MULTI-HOP LOCALIZATION IN LARGE SCALE DEPLOYMENTS

by

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Abstract

The development of Wireless Sensor Networks (WSNs) is enabled by the recent advances in wireless communication and sensing technologies. WSNs have a wide range of scientific and commercial applications. In many applications the sensed data is useless if the location of the event is not associated with the data. Thus localization plays a substantial role in WSNs. Increased dependence on devices and sensed data presses for more efficient and accurate localization schemes. In many Internet of Things (IoT) deployments the area covered is large making it impossible to localize all devices and Sensor Nodes (SNs) using single-hop localization techniques. A solution to this problem is to use a multi-hop localization technique to estimate devices’ positions. In small areas SNs require at least three anchor nodes within their transmission range to estimate their location.

Despite numerous existing localization techniques, the fundamental behavior of multi-hop localization is, as yet, not fully examined. Thus, we study the main characteristics of multi-hop localization and propose new solutions to enhance the performance of multi-hop localization techniques. We examine the assumptions in existing simulation models to build a more realistic simulation model, while studying and investigating the behavior of multi-hop localization techniques in large scale deployments before the actual deployment. We find that the introduced error follows the
Gaussian distribution, but the estimated distance follows the Rayleigh distribution. We use the new simulation model to characterize the effect of hops on localization in both dense and sparse multi-hop deployments. We show that, contrary to common beliefs, in sparse deployments it is better to use long hops, while in dense deployments it is better to use short hops. Using short hops in dense deployments generates a large amount of traffic. Thus we propose a new solution which decreases and manages the overhead generated during the localization process. The proposed solution decreased the number of messages exchanged by almost 70% for DV-Distance and 55% for DV-Hop. Finally, we utilize mobile anchors instead of fixed anchors and propose a solution for the collinearity problem associated with the mobile anchor and use Kalman Filter (KF) to enhance the overall localization accuracy. Through simulation studies, we show that the scheme using a Kalman Filter decreases the estimation errors than using single direction by 31% and better than using weighted averages by 16% . As well, our new scheme overcomes the collinearity problem that appears from using mobile anchor nodes.
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Statement of Originality

I hereby certify that this Ph.D. thesis is original and that all ideas and inventions attributed to others have been properly referenced.
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List of Acronyms

AoA  Angle of Arrival

AHLoS  Ad-Hoc Localization System

CR  Concentric Ring

CG  Centrifugal Gradient

DG  Distorted Gradient

DSSS  Direct Sequence Spread Spectrum

DoA  Direction of Arrival

DV  Distance Vector

GPS  Global Positioning System

IoT  Internet of Things

KF  Kalman Filter

LoS  Line of Sight

MDS  Multi-Dimensional Scaling
SN  Sensor Node

SNR  Signal to Noise Ratio

PoA  Phase of Arrival

RSSI  Received Signal Strength Indicator

RToA  Round-trip Time of Arrival

RF  Radio Frequency

ToA  Time of Arrival

TDoA  Time Difference of Arrival

UWB  Ultra Wide Band

WSN  Wireless Sensor Network
Chapter 1

Introduction

Rapid evolution in wireless communication and electronic technologies have substantially decreased the cost and size of embedded devices with sensing, processing and communication capabilities. These Sensor Nodes (SNs) can be easily deployed in pre-determined locations or in an ad hoc manner forming a unique network paradigm called Wireless Sensor Network (WSN) [4–6]. This network paradigm has several characteristics such as: deployment manner, system lifetime, limited resources, scalability, and cooperation that result in some challenges to be taken into consideration.

A sensing unit, a processing unit, a transceiver unit, a power, and unit location finding system are the main components of a typical SN in addition to a mobilizer unit which considered a secondary component as shown in Figure 1.1 [5, 7].

WSNs have made ubiquitous monitoring and tracking applications cost-effective by enabling the collection of data from hundreds of different locations in large scale deployments [8]. These advancements have facilitated a new vision where information from millions or even billions of SNs can be collected, processed and exploited collaboratively within a global Internet of Things (IoT) [9]. The IoT emphasizes a paradigm
shift in the next generation Internet that allows for the connectivity of multitudes of users and devices. The essential concept is to connect a variety of communicating Things with each other through a unique addressing technique using the Internet [10].

Great dependence in the IoT will be on wireless connectivity and identify the location of Things. Energy consumption, storage management, heterogeneity of devices and communication bandwidth are major challenges facing this emerging paradigm. As well, Things have to be locatable and addressable in order to be tracked and accessible in application domains such as geographic routing, marketing, data aggregation algorithms and environmental monitoring applications [11]. Given the sheer number of Things involved, in addition to projected variance in their location/mobility profiles, it becomes crucial to understand how current localization systems can cope with both scale and mobility, as well as satisfying the requirements of promptness and accuracy in the localization procedure [12].

A central functionality in the IoT is the physical location of SNs [13, 14]. As in many applications the sensed data is useless if the location of the event is not associated with the data. Thus it is important to pinpoint the location of the event.
in order to take the correct action. A simple solution is to add a Global Positioning System (GPS) to every SN to locate their locations. However, it is desirable to decrease the cost of SNs as much as possible because GPS circuitry is costly, makes the SN bulky, and raises its energy requirements. Since WSN would have hundreds or even thousands of SNs, it is better to decrease the cost of SNs. Another solution is through location knowledge of other SNs called anchor nodes in the WSN using distance and bearing measurements such as signal strength, time of arrival or network information. Therefore, an accurate localization technique is required to estimate the location of SNs without the aid of GPS.

WSN localization techniques mainly estimate the location of unlocalized SNs with the aid of anchor nodes, which can be either dedicated SNs, i.e., base stations, or realized through SNs with more capabilities relative to other SNs in the network, including the ability to know their own absolute location. Anchor nodes know their absolute locations by either using a GPS, or by being attached to predefined locations with known coordinates. To localize SNs, anchor nodes broadcast their location with the operating instructions to SNs, which use the received locations of anchor nodes to estimate their own locations.

Depending on the application and size of the terrain, localization techniques can either be single-hop or multi-hop. In a small scale deployment, using single-hop techniques, unlocalized SNs require a minimum of three anchor nodes in 2-D and four anchor nodes in 3-D within their transmission range in order to estimate their location. However in a large scale dense deployments, the sensed area is vast. In such deployments most of SNs are not located in the transmission range of three anchor nodes at the same time unless the number of anchor nodes is increased to cover the
whole sensed area by at least three anchor nodes. Thus a multi-hop localization technique is used to estimate the locations of SNs in large scale deployments. Multi-hop localization uses two or more wireless hops to convey location information from anchor node to SN.

1.1 Motivations

In large scale deployments, as the sensed area increases the localization error increases. The localization error is defined as the Euclidean distance between the estimated location of the SN and its actual location. An understanding of the relation between number of hops, transmission range and localization error will help to improve the localization accuracy for SNs in large deployment scenarios. Intuitively, decreasing the transmission range would increase the number of packet used in the localization process, which would shorten the lifespan of the SNs. Meanwhile, increasing the lifespan of the SNs is important as it should be operational for several months or even years without changing their batteries. Also, decreasing the number of packets exchanged between the nodes is essential as the generated traffic could increase the collision rate, which could also affect the overall localization process. Thus we need to understand the behavior of different localization techniques and to understand the relation between hop count, transmission and localization error. Also, we need to reduce the traffic generated from localization algorithms.

Most multi-hop localization schemes require a high-density deployment of anchor nodes to ensure SNs have enough references to estimate their locations. However, anchor nodes are more expensive than SNs and they have a limited use after the localization process is completed as the anchor nodes would then act as normal SNs.
1.2. THESIS OBJECTIVES

The current research direction in WSN localization moves toward designing new localization schemes that use mobile anchors to decrease the cost of the entire network [15,16]. Thus, we need to use a mobile anchor instead of stationary anchors to localize SNs.

1.2 Thesis Objectives

The intention of this research is to study the fundamental behavior of multi-hop localization techniques in large scale deployment scenarios. The proposed work provides an intensive study about simulating error model for multi-hop localization technique and propose a new error representation that is more realistic. We study the effect of extrinsic errors on multi-hop localization. A common belief by researchers in multi-hop localization techniques is: by increasing the number of hops between the anchor nodes and SNs, this will increase the localization error. However, in this study we show that this belief is not always the case. Indeed, there are conditions where using a larger number of hops gives a better localization accuracy than using a smaller number of hops.

The traffic generated from using localization techniques would affect the performance of the localization process especially in the mobile environment. To reduce the traffic generated from the localization process, we propose a new scheme that would aggregate the locations of multiple anchors before forwarding the packet. We also explore the use of mobile anchors to localize SNs in isolated environments. The SNs estimate their positions from multiple mobile anchors, which decrease the effect of the error propagation. A Kalman Filter (KF) is used to decreases the localization error coming from the longer hop direction, based on the information coming from the shorter hop direction.
1.3 Thesis Contributions

In this document we first examine the assumption of the error model used in previous simulation models by using real measurement and propose a new representation for the estimated distance between SNs making our simulation model more realistic. We then use the new simulation model proposed to study the performance of multi-hop localization in a static network by studying the relation between the transmission range of SNs and localization accuracy. Following, we propose a new scheme that reduces the number of packets exchanged between SNs during the localization process. Finally, we utilize smart vehicles as mobile anchors to localize isolated SNs.

The main contributions of this thesis are as follows:

- Creating a more realistic simulation model to simulate the localization error to represent actual measurement used to estimate the distance between SNs. Previous simulation models added Gaussian noise to the actual distance between SNs. However in this work, we show that the simulation can be more accurately represented by using Rayleigh distribution instead of using Gaussian distribution. By analyzing real measurements we show that using Rayleigh distribution gives a more realistic representation of the localization error. Then we show, by using multi-hop simulation, the difference between using Gaussian and Rayleigh distribution to validate our model.

- Characterizing the error behavior of multi-hop localization, studying the effect of changing the transmission range of SNs and observing how changing the number of hops affects the localization accuracy. Existing work lacks quantitative
analysis of the relation between the hop numbers, transmission range and localization accuracy. Researchers in multi-hop localization share a common belief that by increasing the number of hops between the anchor nodes and SNs, this will increase the localization error, in our study we show that this is not always the case. Indeed, there are conditions, under which, using a larger number of hops gives a better localization accuracy than using a smaller number of hops.

- Characterizing the overhead and the amount of traffic generated during the localization process. We study how the density of SNs would affect the number of generated packets during the localization process. We also check the overhead resulting from the mobility of the SNs and check the different parameters that have an effect on the amount of traffic generated. Then, we propose a new solution to reduce the number of packets exchanged between SNs without negatively affecting the accuracy of localization. By reducing the traffic generated, the lifespan of SNs will be longer.

- Utilizing smart vehicles to act as mobile anchors that localize SNs in an isolated environment. However, using a mobile anchor raises the collinearity problem if the mobile anchor moved in straight trajectory. In this research work, we propose a new scheme to overcome the collinearity problem regardless of the trajectory the mobile anchor used to localize SNs. After that we decrease the localization error in the center of the WSN using KF.

1.4 Thesis Outline

The remainder of this document is organized as follows: Chapter 2 presents the background and literature survey in WSN localization. In Chapter 3 we create a realistic
1.4. THESIS OUTLINE

simulation model to estimate the distance between SNs using RSSI. Chapter 4 covers the effect of the transmission range of SNs in a multi-hop localization environment and how this impacts the localization accuracy. Chapter 5 proposes a new aggregation scheme that reduces the number of packets exchanged during the localization process. We evaluate the proposed scheme using various operational aspects, including number of packets sent, collisions, localization accuracy, in addition to the percentage of unlocalized SNs. Chapter 6 introduces a new localization scheme to localize isolated SNs using a mobile anchor that moves in a collinear or non-collinear trajectory. This scheme benefits from the estimated distance between neighbor nodes and additional information provided by another mobile anchor which moves in the opposite direction to identify the flow direction of the packets and increase the localization accuracy. Finally, Chapter 7 concludes this document by highlighting the main issues addressed in this thesis and outlining future research directions.
Chapter 2

Background

This chapter presents the background material and surveys previous research related to the work in this thesis. Section 2.1 starts with an introduction to WSN localization. Section 2.2 overviews the different measurement techniques used in WSN localization. Section 2.3 discusses the different localization techniques used to estimate the locations of SNs. Multi-hop localization is discussed in Section 2.4. Section 2.5 explains the flip ambiguity problem. Section 2.6 presents previous works using mobile anchor. Finally a brief summary is given in Section 2.7.

2.1 Introduction

A WSN is composed of SNs which have sensing functionalities to monitor physical properties such as pressure, humidity, and temperature, as well as moving objects [4–6]. SNs have a small processor, limited power supply, memory, and a short range wireless transceiver [7]. The sensed information is propagated towards a SN located at the edge of the WSN that is connected to a server called a sink node. Usually
intermediate SNs forward the information to the sink node in order to process and store the sensed information.

In the context of WSNs localization is the process of identifying and estimating the location of SNs. There are two types of SNs in WSN localization. The first type is called anchor or beacon nodes, which are SNs that know their location either by using GPS or by manual configuration during the deployment phase. The other SNs that do not know their location are called unlocalized SNs [17–20]. Different localization techniques are proposed to estimate the location of the unlocalized SNs.

The localization process consists of two phases. The first phase involves estimating the distance or the angle between SNs using one of the measurement techniques. The second phase uses the distance or angle information to estimate the location of SNs using a localization technique. Location estimation can be either centric or distributed. In centric localization, the localization process is done in a single location based on distance or angle information collected from the SNs, while in a distributed system each SN estimates its location. Distributed localization systems are scalable but they require that SNs have enough processing power to estimate their location.

### 2.2 Measurement Techniques

In this section, we discuss the different measurement techniques that are used to estimate the distance or the angle between SNs. Measurement techniques in WSN localization are classified into four categories: RSSI based, time based, angle based and phase based as shown in Figure 2.1
2.2. MEASUREMENT TECHNIQUES

Figure 2.1: Different estimation techniques used in WSN.

2.2.1 Received Signal Strength Indicator (RSSI) Based Techniques

RSSI indicates the relative power level of the signal received by the antenna of the receiver. The lower the RSSI number, the higher the signal attenuation due to energy loss as it travels through the air. Therefore RSSI distance measurement techniques are based on the fact that the strength of the signal is inversely proportional to the distance between the transmitter and the receiver [2,21–25]. Thus, understanding the characteristics of signal attenuation helps to map the RSSI to the actual distance.

RSSI mapping methods are classified into Analytical and Empirical models. Analytical models map the RSSI to the actual distance using a path-loss propagation model, which is a model of electromagnetic wave as it propagates through space. In this case, the rate at which the signal attenuates over distance is assumed to be previously known. Empirical models map the actual distance to a RSSI profile created during the deployment phase i.e., based on measurements of the actual deployment and RSSI.
2.2. MEASUREMENT TECHNIQUES

Table 2.1: Typical values for the path-loss exponent [1].

<table>
<thead>
<tr>
<th>Environment</th>
<th>Path-loss exponent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free space</td>
<td>2</td>
</tr>
<tr>
<td>Urban area</td>
<td>2.7 - 3.5</td>
</tr>
<tr>
<td>Shadowed urban area</td>
<td>3 - 5</td>
</tr>
<tr>
<td>In-building Line of Sight (LoS)</td>
<td>1.6 - 1.8</td>
</tr>
<tr>
<td>Obstructed in building</td>
<td>4 - 6</td>
</tr>
</tbody>
</table>

Analytical-Mapping Model:

In an analytical mapping model, the distance is estimated from the received power of the signal using a mathematical equation. In the free space model the RSSI is inversely proportional to the square of the distance $d$ between the transmitter and the receiver. The relation between the received power $P_r(d)$ and the distance $d$ in the free space model can be represented by using the Friis equation [26]

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2} ,$$  \hspace{1cm} (2.1)

where $P_t$ is the transmitted power, $G_t$ and $G_r$ are the transmitter and receiver antenna gain respectively and $\lambda$ is the wavelength of the transmitted signal in meters.

The transmitted signal is affected by phenomena called reflection, diffraction and scattering, making the free space model idealistic [27, 28]. Thus a path-loss propagation model is used to model the RSSI of $P_r(d)$ at any value of $d$ at a particular location as a log-normal distributed random variable using the following equation:

$$P_r(d) = P_0(d_0) - 10n_p \log \left( \frac{d}{d_0} \right) + X_\sigma,$$  \hspace{1cm} (2.2)

where $P_0(d_0)$ is a known reference power in dBm at a reference distance $d_0$, $n_p$ is the
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path-loss exponent that measures the rate at which the RSSI decreases with distance. Typical path-loss values for different environments are listed in Table 2.1 [1]. $X_\sigma$ is a zero mean Gaussian distributed random variable with standard deviation $\sigma$ and it accounts for the random effect of shadowing [26].

By solving equation 2.2 the maximum likelihood estimate of the distance $d$ between the transmitter and the receiver is as follows

\[
\hat{d} = d_0 \left( \frac{P_r(d)}{P_0(d_0)} \right)^{-1/n_p}
\] (2.3)

Thus the estimated distance, $\hat{d}_{ij}$ between the transmitter $i$ and the receiver $j$ can be related to the actual distance using the following equation

\[
\hat{d}_{ij} = d_{ij} e^{\frac{\sigma^2}{2\eta n_p^2}}
\] (2.4)

where $\eta = \frac{10}{\ln(10)}$. The expected value of $\hat{d}_{ij}$ thus becomes

\[
E(\hat{d}) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} d_{ij} e^{\frac{X_\sigma}{\sqrt{2\eta n_p}}} e^{-\frac{X_\sigma^2}{2\sigma^2}} dX_\sigma = d_{ij} e^{\frac{\sigma^2}{2\eta n_p^2}}.
\] (2.5)

Here, the rate in which the signal attenuation over distance is assumed to be previously known. After solving equation 2.3 and 2.5, a biased estimate of the true distance is given by

\[
\hat{d}_{ij} = d_0 \left( \frac{P_{ij}}{P_0(d_0)} \right)^{-1/n_p} e^{\frac{\sigma^2}{2\eta n_p^2}}.
\] (2.6)

The path-loss log normal shadowing model assumes that the uncertainty is modeled as white noise. However, such an assumption is not true as the log normal shadowing model typically depends on the environment and on the interference factors.
affecting the signal propagation. The main factor that affects the signal propagation is the dynamic signal distortion caused by i) random multi-path propagation, ii) movement of objects and/or persons in the deployment area or iii) various weather conditions. In most cases RSSI analytical models give better results in outdoor than indoor environments, as RSSI models are badly affected by multi-path, fading, reflection, refraction and shadowing by the walls in the indoor environment. Analytical mapping models are a plausible solution as they do not require any additional hardware and they give a reasonable localization accuracy [18,29].

**Empirical-Mapping Models**

An empirical model maps the RSSI to distance through experimental measurements and statistical analysis of collected data. The collected data is mainly based on fingerprinting the environment through extensive measurements gathered either offline by a priori measurements during the deployment phase or online using sniffing devices [30,31].

Constructing empirical models typically involves two phases *training* and *estimation* phases. In the training phase, the RSSI signal is measured at different locations in the deployment area to form a radio map that represents the signal strength for each anchor node in all the possible locations that the SNs can be located. In the estimation phase, the SN compares the value of the RSSI with the closest value saved in the radio map.

The empirical map model gives a better location accuracy estimation compared to the analytical models [22,32,33]. The accuracy of the empirical model increases as the number of the RSSI measurements collected during the training phase is increased.
However, empirical models are badly affected by the following drawbacks: 1) the training phase can be too complex, with a complexity that increases with the increase of the area of the deployment environment; 2) any modification in the deployment environment, such as change the location of objects, would have a direct impact on the validity of the radio map created in the training phase. These two drawbacks are reduced by minimizing the human interaction during the fingerprinting phase by automating the radio map construction process. This enables regenerating the radio map whenever there is a change in the deployment area [34].

The construction of the map starts with subdividing the area into small cells. The collection process starts when anchor nodes transmit radio signals, which is received by the calibration SN for a certain period of time at a fixed location. The process is repeated for every cell in the deployment area. The received RSSI is stored in a vector data $m_{i,j}$ in a database, where $i$ denotes the $i^{th}$ cell and $j$ represents the $j^{th}$ anchor node. The set of $m$ vectors is called the radio map. The radio map can also include other information that would be useful for the localization process such as the median RSSI value in the center of the cell along with the minimum and maximum values recorded in the cell [35,36].

### 2.2.2 Time Based Techniques

Time based techniques rely on calculating the propagation time traveled by the signal between the transmitter and receiver. The signal used could be electromagnetic, acoustic or ultrasound.

The time based model is divided into three main categories: Time of Arrival (ToA), Round-trip Time of Arrival (RToA) and Time Difference of Arrival (TDoA).
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![Diagram of Time-based Localization Techniques](image)

Figure 2.2: Time based localization techniques.

**Time of Arrival (ToA)**

ToA (also called Time of Flight) is calculated through estimating the distance between SNs by calculating the one way propagation time of the signal between two highly synchronized SNs. Algorithms for computing ToA benefits from the knowledge of the propagation speed of the transmitted signal [37–39]. The distance is estimated using ToA by the following equation:

\[ d = c_r \times (t_1 - t_0), \]  

(2.7)

where \( c_r \) refers to the speed of the transmitted signal, \( t_0 \) and \( t_1 \) represent the transmission and reception time respectively as shown in Figure 2.2(a).

Two types of signals, Direct Sequence Spread Spectrum (DSSS) or Ultra Wide Band (UWB) can be used in ToA [20]. Greater accuracy can be achieved by using UWB technology than using DSSS because the propagation speed of ultrasound signals is slower (approximatively 331.4 ms/s) than DSSS signals and secondly, UWB has a larger bandwidth (\( \geq 500 \) MHz). Previous results show that the location estimation accuracy with UWB radios can be accurate up to 2 cm in good conditions.
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with direct LoS propagation. However, by using DSSS the accuracy is roughly from 5 m to 10 m. Nevertheless, Radio Frequency (RF) based ToA is used in the GPS systems where they use a high clock synchronization and the distances traveled by the RF signal are very long.

The main disadvantages of ToA are: 1) SNs must be highly synchronized, which requires high clock resolutions. 2) Localization accuracy depends on the signal bandwidth, which means that increasing the bandwidth improves the localization accuracy as in the case of using UWB Technology. 3) ToA is very sensitive to multi-path effect, which requires direct LoS between transmitter and receiver as the blockage of the direct path would increase the localization error. 4) The added cost to the price of the SN by installing a highly accurate clock [40].

**Round-trip Time of Arrival (RToA)**

To avoid ToA’s synchronization constraints, RToA involves measuring the two way propagation (round-trip) time at the transmitter side instead of calculating the one way propagation time at the receiver side [41, 42]. Since the same clock is used to calculate the round-trip at the transmitter side, the synchronization requirement is relaxed. However, a major source of error is the signal processing delay at the receiver side. This delay must be estimated and subtracted from the round trip time to reduce the distance estimation errors. The internal signal processing delay in the receiver can be either pre-calibrated in advance or measured by the receiver, and then sent back to the transmitter to be subtracted. The distance is estimated using RToA using the following equation:
where $c_r$ refers to the speed of the RF signal and $(t_1 - t_0)$ represents the round-trip time of flight as shown in Figure 2.2(b). RToA gives a very high accuracy. However, it should to be noted that the accuracy of RToA is also limited by the effect of multi-path and the unavailability of LoS.

### Time Difference of Arrival (TDoA)

In TDoA the distance between two SNs is estimated by measuring the time difference between two different signals that have different propagation speeds by the same receiver [39, 43]. RF and ultrasound signals are the most common signals used in TDoA, as RF is $10^6$ times faster than ultrasound signals (acoustic signals sometimes replace the ultrasound signals), which makes the time difference between the two signals long enough to estimate the time difference between the two signals received by the receiver SN. The RF and ultrasound signals are transmitted at the same time. The receiver SN uses the arrival time of the RF signal as a time reference then subtracts the arrival time of the ultrasound signal to calculate the delay between both signals. The distance $d$ between the transmitter and the receiver is calculated according to the following equation:

$$d = \frac{c_r \times (t_1 - t_0)}{2}$$

where $c_r$ and $c_u$ are respectively the propagation speed of the RF and ultrasound signals, while $t_1$ and $t_2$ are their reception times respectively at the receiver side as shown in Figure 2.2(c). Thus, the synchronization requirement of ToA techniques and
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Priyantha et al. showed that TDoA can provide a distance accuracy of 5 cm as shown in the Cricket platform [44].

As mentioned above, methods for estimating TDoA provide high accuracy and do not require synchronization between SNs. However, the major drawback of this technique is the requirement of two different transceivers, which would have a negative impact on the cost of the SN and the complexity of its design [39].

2.2.3 Angle Based

Another category of measurement techniques in WSNs are those that calculate Angle of Arrival (AoA) or Direction of Arrival (DoA). These techniques rely on calculating the angle between an unlocalized SN to an anchor node with respect to a referenced direction. This angle is also known as orientation [45]. The reference direction is called absolute orientation if it refers to the North direction, i.e., angle 0°. Figure 2.3(a) illustrates the concept of the absolute reference direction. However, if the reference direction with respect to the North direction is known in advance, it is
called a relative orientation [24]. In this case, each SN could have its own orientation axis that is different from other SNs orientation as shown in Figure 2.3(b). For both absolute and relative orientation two anchor nodes are sufficient to estimate the location of unlocalized SN. However, if the reference direction is unknown, three non-collinear anchor nodes are required to estimate the location of the unlocalized SN. In this case, the reference direction is determined by utilizing the angle of the third anchor node as illustrated in Figure 2.3(c).

The advantage of AoA techniques is that they do not require time synchronization and only use two anchor nodes if the reference direction is known. However, AoA techniques suffer from three main disadvantages. First, AoA requires expensive equipment in order to estimate the angle between the unlocalized SNs and anchor nodes. Second, the hardware and computation paradigms of the angle estimation are very complex. Third, the direction of the antenna, noise, shadowing and multi-path effect have a direct impact on the accuracy of the measurements of AoA, which affects the accuracy of the angle’s estimation. AoA mainly relies on a direct LoS between the transmitter and the receiver. Different maximum likelihood algorithms are proposed in the literature to decrease the effect of the multi-path propagation and increase the estimation accuracy [46–48]. There are two main fundamental techniques to estimate the angle between anchor nodes and unlocalized SN. The two techniques are beamforming and phase interferometry.

**Beamforming**

The Beamforming technique uses a type of a receiver antenna that has an anisotropy pattern, i.e., a directional antenna. Figure 2.4 shows the beam pattern of a typical
anisotropic antenna. Typically, the measurement unit is smaller than the wavelength of the signals in order to have a reading with reasonable accuracy. The receiver antenna rotates on its axis either electronically or mechanically. The direction with the maximum received signal strength is considered as the direction of the transmitter.

Usually the transmitted signal has a varying amplitude and signal strength over time that the receiver cannot identify the direction with the strongest signal. To overcome this variation of signal strength generated from the transmitter over time is to use a second non-rotating omnidirectional antenna at the receiver. By normalizing the signal strength received by the rotating anisotropic antenna with respect to the signal strength received by the non-rotating omnidirectional antenna, the impact of varying signal strength can be largely eliminated.
Phase Interferometry Techniques

Phase interferometry techniques use an array of antennas or a large receiver antenna (relative to the wavelength of the transmitter signal), which exploit the finite propagation speed of waves. Figure 2.5 shows an antenna array of $N$ antennas where adjacent antennas are separated by a distance $d$. The distance between a transmitter to the $k^{th}$ antenna is approximated by the following equation [57]:

$$R_k = R_0 - kd \cos(\theta)$$  \hspace{1cm} (2.10)

where $R_0$ is the distance between the transmitter and the first antenna i.e. $0^{th}$ antenna, and $\theta$ is the direction of the transmitter with respect to the antenna array. The phase difference of the transmitted signals received by adjacent antenna array
have a phase difference of $2\pi \frac{d \cos(\theta)}{\lambda}$, where $\lambda$ is the wavelength of the transmitted signal. This allows the SNs to obtain the direction of the transmitter from the measurement of the phase difference. This approach works quite well for high Signal to Noise Ratio (SNR) but may fail in the presence of strong co-channel interference and/or multi-path signals.

2.2.4 Phase of Arrival (PoA) Techniques

The PoA also known as received signal phase estimates the distance between SNs by using the phase difference of the received signal between the transmitter and receiver [20, 49]. By assuming that the SNs emit pure sinusoidal signals with zero phase offset and same frequency of the form $S_i(t) = \sin(2\pi ft + \phi_i)$ where $f$ is the emitted frequency and $\phi_i$ is the phase where $\phi_i = (2\pi fd_i)/c$, where $c$ is the propagation speed of the signal, and $d_i$ is the distance between transmitter and receiver. PoA works effectively when the maximum distance is shorter than the signal wavelength, i.e., $0 < \phi_i < 2\pi$. Therefore the distance between the transmitter and receiver is estimated using the following equation:

$$d_i = \frac{c\phi_i}{2\pi f} \quad (2.11)$$

PoA requires a LoS path to get reasonable accuracy. Usually PoA is used in a combination with RSSI or ToA to improve the localization accuracy level.

2.3 Location Estimation Techniques

In this section, we discuss the principles of one-hop localization measurement techniques discussed in the previous section in which the unlocalized SN to be localized
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is the one-hop neighbor of a sufficient number of anchors.

The main localization techniques are lateration using Linear Least Square, Bounding Box and angulation using Linear Least Square. Both lateration and Bounding Box uses distance estimation techniques, while angulation estimation techniques use AoA measurements.

2.3.1 Multilateration using Linear Least Square

Multilateration is a localization technique that uses distance information such as RSSI or ToA from anchor nodes to estimate the location of an unlocalized SN. In the ideal case, multilateration assumes that the distance measurements are accurately estimated and noise free. Figure 2.6(a) shows that the three circles intersect in a single point which represents the location of the SN. Each circle represents the distance between itself and unlocalized SN.

However, such a situation is not usually applicable as the accuracy estimation of distance measurements are easily affected by surrounding noises. These inaccuracies

![Figure 2.6: The difference between trilateration with noise free and noisy distance measurements.](image)
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prevent the circles to intersect in a single point making the localization process more challenging. Figure 2.6(b) shows that the three circles do not intersect in a single point. A possible solution to estimate the SN location is to use the least squares optimization technique [50].

The multilateration process to estimate the location of the unlocalized SN is achieved by solving three or more of the linear equation systems using:

\[
(x_i - x)^2 + (y_i - y)^2 = d_i^2
\]

(2.12)

where \(x\) and \(y\) are the coordinates of the unlocalized SN, and \(x_i\) and \(y_i\) are the coordinates of a minimum of three non-collinear anchor nodes involved in the localization process. The linear equation system would give an exact and unique solution if the circles intersect in one point, in an ideal noise free environment. However, there is white noise added to the actual distance while using distance estimation techniques, which creates multiple solutions in the area of intersection of the three circles as shown in Figure 2.6(b). To solve such a problem, the system can be linearized by subtracting equation 2.12 for anchor \(i\) from the equivalent equation for anchor 1, which results in the following equation:

\[
x_i^2 + y_i^2 - x_i^2 - y_i^2 + 2x(x_i - x_1) + 2y(y_i - y_1) = d_1^2 - d_i^2
\]

(2.13)

After solving the previous equation, we get:

\[
2x(x_i - x_1) + 2y(y_i - y_1) = d_1^2 - d_2^2 + x_i^2 + y_i^2 - x_1^2 + y_1^2
\]

(2.14)
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The system can be written in matrix notation as:

\[ AX = B \]  \hspace{1cm} (2.15)

where \( X = [x, y]^T \) represents the unlocalized SN location,

\[
A = 2 \begin{bmatrix}
  x_2 - x_1 & y_2 - y_1 \\
  x_3 - x_1 & y_3 - y_1 \\
  \vdots & \vdots \\
  x_n - x_1 & y_n - y_1 
\end{bmatrix} \hspace{1cm} (2.16)
\]

and,

\[
B = \begin{bmatrix}
  (d_1^2 - d_2^2) + (x_2^2 + y_2^2) - (x_1^2 - y_1^2) \\
  (d_1^2 - d_3^2) + (x_3^2 + y_3^2) - (x_1^2 - y_1^2) \\
  \vdots \\
  (d_1^2 - d_n^2) + (x_n^2 + y_n^2) - (x_1^2 - y_1^2)
\end{bmatrix} \hspace{1cm} (2.17)
\]

Thereby, after solving the previous equation for the linear least squares problem by using Cholesky factorization to estimate the values of \( x \) and \( y \) coordinates of the SNs. The SNs locations can be estimated using the following formula:

\[ X = (A^T A)^{-1} A^T B \]  \hspace{1cm} (2.18)
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2.3.2 Bounding Box

The Bounding Box localization techniques (also known as the minmax algorithm) is another computationally efficient alternative to trilateration that relies on the intersection of rectangles instead of circles to estimate the location of an unlocalized SN. The main idea is to draw a bounding box for each anchor node using its location and distance estimate, then to determine the intersection of these rectangles. The location of the unlocalized SN is estimated as the center of the intersection rectangle. The minmax method provides a solution very close to the ideal solution obtained through trilateration, with much less computational requirements. Formally, the bounding box pertaining to an anchor \( N_i \) is constructed by subtracting its distance estimate \( d_i \) from its location \([x_i, y_i]\) using:

\[
[x_i - d_i, y_i - d_i] \times [x_i + d_i, y_i + d_i]
\]  

(2.19)

The intersection of the Bounding Boxes is computed by taking the maximum of all coordinate minimums and the minimum of all maximums:

\[
[max(x_i - d_i), max(y_i - d_i)] \times [min(x_i + d_i), min(y_i + d_i)]
\]  

(2.20)

It is noted that the accuracy of bounding box method is less than the lateration techniques, but with less computation cost makes it suitable to be used with SNs with low processing power capabilities.
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2.3.3 Angulation using Linear Least Square

Angulation is another localization technique that uses the angle information and the triangles properties in order to determine the location of unlocalized SNs. As discussed in Section 2.2.3, the location of unlocalized SNs can be estimated using two anchor nodes in a 2D and in 3D space, triangulation is possible if the measurement of the height is available. In this case there are two situations that may arise with triangulation: 1) the distance between the two anchor nodes is known, and 2) the distance between the two anchor nodes is unknown.

In the first situation, the two anchor nodes A and B are separated by the distance $d_{AB}$, SN C is the unlocalized SN that needs to be localized, and $\hat{CAB}$ and $\hat{ABC}$ are the two estimated angles using AoA, then the location of the unlocalized SN C is estimated by calculating the sides of the triangle ABC by using the trigonometry laws of sines and cosines. Unlocalized SN C is located at the distance $d_C$ at the perpendicular to line (A, B) as shown in Figure 2.7 such that

$$d_C = \frac{d_{AB} \sin(\hat{CAB}) \sin(\hat{ABC})}{\sin(CAB + ABC)}.$$  \hspace{1cm} (2.21)
In the second case, SN estimates the angle $\theta_i$ of the signal received from anchor node $i$. In this case, the equation can be represented as follows:

$$(x_i - x) \sin(\theta_i) = (y_i - y)\cos(\theta_i)$$  \hspace{1cm} (2.22)

and, in matrix form:

$$AX = B$$  \hspace{1cm} (2.23)

where,

$$A = \begin{bmatrix} -\sin(\theta_1) & \cos(\theta_1) \\ -\sin(\theta_2) & \cos(\theta_2) \\ \vdots & \vdots \\ -\sin(\theta_n) & \cos(\theta_n) \end{bmatrix}$$  \hspace{1cm} (2.24)

and,

$$B = \begin{bmatrix} y_1 \cos(\theta_1) - x_1 \sin(\theta_1) \\ y_2 \cos(\theta_2) - x_2 \sin(\theta_2) \\ \vdots \\ y_n \cos(\theta_n) - x_n \sin(\theta_n) \end{bmatrix}$$  \hspace{1cm} (2.25)

Thereby, the location of unlocalized SN can be estimated as:

$$X = (A^T A)^{-1} A^T B$$  \hspace{1cm} (2.26)
2.4 Multi-hop Localization

The techniques discussed in the previous sections are all single hop localization, however WSNs usually use multi-hop communication especially when the sensed area is large. Thus several multi-hop localization techniques are proposed to estimate the location of SNs [18,19].

Multi-hop localization techniques can be distance based or connectivity based. In connectivity based techniques the SNs obtain the absolute measurements of SN distances using RSSI, ToA, or TDoA [51–53], while in distance based techniques the SNs use the connectivity information to estimate the location of SNs based on the location of the anchor nodes [51,54–57].

For distance based multi-hop localization techniques Niculescu and Nath propose Distance Vector (DV)-Distance, where the anchor node sends beacon packets to all its immediate neighbors [51]. Immediate (first-hop) neighbors to the anchor node estimate the distance to the anchor by using signal strength measurement. These neighboring SNs then forward the beacon packet to the second-hop neighbors to infer the distance to the anchor, and so on until the network is completely covered in a controlled flooding manner. Once an unlocalized SN has three or more distances estimated to different anchor nodes, it computes its location using multi-lateration.

Stoleru et al. propose a technique called MDS-MAP that uses Multi-Dimensional Scaling (MDS) to determine SN locations by using only connectivity information [52]. The operation of MDS-MAP consists of three steps: 1) finding the shortest paths for all pairs; 2) applying classical MDS to the distance matrix; 3) using three or more anchor nodes to transform the relative map to locations based on the locations of the anchor nodes.
Figure 2.8: (a) The shortest path between source and destination is close to a straight line. (b) The shortest path between source and destination is curved caused by the hole between them.

Wu et al. propose a self-configurable technique for multi-hop wireless networks [53]. A number of SNs at each corner of the network serve together as anchor for estimating the distances by a Euclidean distance estimation model. The authors use ToA to estimate the distance for each hop. Once ToA information is received by an SN, the sum of these distances is computed by minimizing an error objective function.

The above solutions work well in isotropic networks, i.e., networks where the hop count between two SNs is proportional to their geometric distance. The techniques, however, exhibit a dramatic decrease in performance when used in anisotropic networks, i.e., with non-uniform SN distribution where there is a concave region at its center. Figure 2.8 shows the differences between isotropic and anisotropic networks. Li and Wang mined the characteristic of anisotropic WSN when anchor SNs send non-uniform beacon packets [58]. They use the mined network connectivity characteristics to make appropriate adjustments on measured distance between SNs based on the directions of packet and degrees of inflections. Their simulation results show
that their technique gives higher localization accuracy than DV-distance especially when the SNs are not deployed uniformly.

Xiao et al. solve the problem of anisotropic network by defining three different patterns based on number of hops and LoS rule [57]. The three patterns are:

1. Concentric Ring (CR) pattern, in which the SN is within few hops from the anchor node, in this case SN is treated as it is in isotropic anchor.

2. Centrifugal Gradient (CG) pattern, in which the SN is far from the anchor node, in this case SN is treated as anisotropic where they use a proposed solution named DiffTriangle that tolerates the inaccurate hop size estimates.

3. Distorted Gradient (DG) pattern which is considered the worst pattern, in which the LoS rule is breached by an object, in this case the packet is dropped.

SNs estimate their locations using weighted multilateration after they collect sufficient distance estimated from different anchors using CR or CG patterns only. They show that using analytical analysis and simulation that their solution for anisotropic gives a higher localization accuracy compared to previous localization solutions that declare they tolerate network anisotropy.

For connectivity based multi-hop localization Niculescu and Nath propose DV-Hop, which operates in three stages [51]. First, the algorithm computes the number of hops for all the SNs to the anchor nodes. Next, the anchor node gets the number of hops required to reach the other anchor nodes, calculating the average length for one hop by dividing the total distance by the number of hops. SNs then estimate the distance by multiplying the number of hops by the average length for one hop.
Savarese et al. [54] propose another technique based on connectivity called Ad-Hoc Localization System (AHLoS) algorithm, where a small fraction of SNs have the knowledge of their location to estimate the location of other SNs using a collaborative and iterative multi-lateration algorithm. In AHLoS at least three SNs know their location in order to estimate the location of other SNs. Nagpal et al. [55] calculate a global coordinate system for the whole network by estimating the Euclidian distance of each hop between SNs. The SNs use the number of communication hops to estimate how far they are from anchor nodes. When an SN receives at least three different locations from different anchor nodes, the SN combines the distance from the anchor nodes and estimates its location based on the hop count to each anchor. Akbas et al. [56] localize the location of SNs floating in the Amazon river based on stationary anchor nodes placed at the bank of the river. Their localization algorithm uses multi-hop between SNs and anchor nodes. Each SN keeps a single weight value for each anchor it is associated with. The saved weight represents how far the SNs are to each anchor node. The anchor node uses these weights to estimate the SNs location.

2.5 Flip Ambiguity

The term “flip ambiguity” labels the confusion of estimating the correct location of the SN resulting from collinear anchor nodes. As illustrated in Figure 2.9, anchor nodes $a$, $b$, and $c$ are collinear. SN $n$ estimates its location through measurements $d_a$, $d_b$, and $d_c$ [59]. Each measurement defines a ranging circle centered at the anchor node. Due to measurement errors, the three measured circles do not intersect at a common point, which causes ambiguities in determining whether the location of the SN is $n$ or $n'$ [60].
The problem of flip ambiguity is approached from different perspectives in the literature. The work done by Eren et al. and Goldenberg et al. test the unique localization conditions and construct localizable networks using global rigidity theory [61, 62]. A graph $G$ is considered a globally rigid if and only if $G$ is a complete graph and each vertex is connected with at least three vertices. The authors show that maintaining a global rigidity in the localized networks decreases the collinearity of anchor nodes. However, it is hard to maintain the global rigidity of the network unless it is compensated by a priori information from the network [61].

Localization algorithms in [60, 63] identify possible flip ambiguities caused by collinearity of anchor nodes and decrease the effect of flip ambiguity during the localization processes. Moore et al. propose a robust quadrilaterals localization technique to identify possible flip ambiguities in fully connected sensor quadruples [60]. The technique has two steps. In the first step, the distance measurement between two anchor nodes $S_A$ and $S_B$ is used to estimate the two possible locations of the unlocalized SN $S_D$. In the second step, a third anchor SN $S_C$ is used to decide which of
the two possible locations for the unlocalized SN satisfy the distance constraint. If both locations satisfy the condition, the technique will ignore this SN. In [63] Sottile and Spirito note that if sensors $S_A$ and $S_C$ are used in the first step in [60] instead of sensors $S_A$ and $S_B$, and sensor $S_B$ is used in step 2 instead of sensor $S_C$, this may result in a different value for the robustness criterion, which would affect the overall localization performance. Such dependency is eliminated by including all three permutations when localizing $S_D$ i.e., $(S_A, S_B, S_C)$, $(S_A, S_C, S_B)$ and $(S_B, S_C, S_A)$. This inclusion, however, increases the computational complexity of the algorithm.

To reduce the error caused by trilateration, Yang et al. [64] propose a sequential localization technique that estimates SNs location and controls the errors introduced in each step. In their sequential technique, a set of anchor nodes are chosen and the expected error is tracked in each step to minimize the error. However, flip ambiguity cannot be avoided by error control alone as it can be triggered even by the smallest errors if the anchor nodes used to localize the SN are collinear. Basu et al. solved the problem of collinearity by using both distance and angle measurements [65], where the localization problem is transferred to a convex form and solved using linear programming. However, the technique by Basu et al. cannot work if either the distance or angle measurement does not have a clear boundary. Moreover, the technique depends on the knowledge of both distance and angle measurements, which requires additional hardware. To identify and reduce the error caused by flip ambiguities, Kannan et al. introduce a technique that recognizes SNs with possible flips using simulated annealing, and offer a refined technique through the use of a ranging model and a bounder check, despite the refinement, however, the technique may not identify all flips [66].
2.6. LOCALIZATION USING MOBILE ANCHOR

The localization techniques above use fixed anchor nodes. In order to reduce the number of anchor nodes in the sensing area and to overcome the constraints of the short transmission range for anchor nodes, the usage of mobile anchors in WSNs have attracted researchers attention recently [17]. The mobile anchor moves in the sensing area to assist the unlocalized SNs to estimate their location. The main advantage of using mobile anchors is the cost reduction of the WSN since using one single mobile anchor is equivalent to many virtual anchors at specific locations [15,16].

Ssu et al. use mobile anchor nodes that move in random paths using the random waypoint model to localize SNs [67]. In their technique a mobile anchor broadcasts beacon packets that contains its ID, location, and timestamp periodically. Each SN stores a set of *beacon points* and *visitor lists*. The beacon points contain only the entry and exit point to the transmission range of the SN. This is done by the help of the visitor lists by storing the IDs of mobile anchors whose beacon packet is received by the SN and their associated lifetime.

Figure 2.10: Beacon Point selection.
In Figure 2.10 $P_1$, $P_4$, $P_8$, and $P_{10}$ represent the beacon points. When a SN receives a beacon packet from a mobile anchor, the SN first checks whether the anchor ID is saved in the visitor list. If not, the SN adds the anchor node record in the beacon points as $(ID_i, location_i, timestamp_i)$ and in the visitor list as $(ID_i, lifetime_i)$. Otherwise, the beacon packet is added to a temporary list and the lifespan of the mobile anchor point in the visitor lists will be extended. When the lifetime of the anchor point is expired, the corresponding entry in the visitor list is removed and the last beacon packet in the temporary list of the anchor point is moved to the beacon point list. After that the SN uses the beacon point to estimate its location. Ou and He show that localization using mobile anchor nodes that move randomly results in poor performance in terms of localization time and accuracy [68].

To overcome the poor performance of random movement for mobile anchor nodes, a predefined trajectory for a single mobile anchor is used. Sichitiu and Ramadurai introduced the concept of mobile anchor trajectory [69]. In their work they raised these two interesting questions: “What is the optimum beacon trajectory and when should the beacon packets be sent?”. Sichitiu and Ramadurai did not answer the two questions, but they made important remarks regarding the characteristic that the path trajectory should have and how often the anchor node should send the beacon packet. They suggested that the mobile anchor trajectory must be planned in a way that all the possible locations for SNs should be fully covered by at least three non-collinear beacons from the mobile anchor. Also the trajectory of the mobile anchor should be as tight as possible to increase the localization accuracy.

Koutsonikolas et al. propose three pre-determined path techniques for a single mobile anchor [70] namely $SCAN$, $DOUBLE\, SCAN$, and $HILBERT$. In the three path
planning techniques they covered the two questions raised by Sichitiu and Ramadurai [69]. In SCAN, the trajectory of the mobile anchor is parallel to single dimension either the x-axis or y-axis as shown in Figure 2.11(a). The distance between two successive segments of the trajectory is at most twice the communication range of the
SN. The main advantages of SCAN are simplicity, easy of implementation and uniform coverage. However, SCAN suffers from collinearity which has a direct impact on the localization accuracy as the mobile anchor moves in straight paths. DOUBLE SCAN overcomes the collinearity problem raised in SCAN by moving the mobile anchor in both the x and y directions instead of a single direction as shown in Figure 2.11(b). Although DOUBLE SCAN improves the localization accuracy of SNs, but this was at the cost of increasing the distance traveled by the mobile anchor. The trajectory of DOUBLE SCAN is doubled compared to that of SCAN, and thus the energy overhead increases accordingly. In HILBERT, they reduced the path length and overcame the collinearity problem by creating several points in a higher dimensional space by dividing the 2-D space into $4^n$ square cells and connects the centers of those cells using $4^n$ as shown in Figure 2.11(c). Results show that HILBERT gives the best localization accuracy especially when the trajectory of the mobile anchor has a high resolution.

Huang and Zaruba presented two further path planning techniques designated as CIRCLES and S-CURVES [71]. In CIRCLES, the mobile anchor moves in a path that consists of a sequence of concentric circles, where its center is the center of the deployment area as shown in Figure 2.11(d). S-CURVES is based on SCAN but instead of moving in simple straight lines, the mobile anchor moves in an S-shaped curves as shown in Figure 2.11(e). They showed that CIRCLES and S-CURVES gives a higher accuracy and a similar path length compared to SCAN and HILBERT are proposed by [70]. Hu et al. used a spiral trajectory to localize SNs as shown in Figure 2.11(f) [72]. Spiral trajectory has a similar accuracy to CIRCLES, but has a shorter trajectory.
2.6. LOCALIZATION USING MOBILE ANCHOR

Han et al. propose LMAT [59]. LMAT is based on an equilateral triangle trajectory for mobile anchor as shown in Figure 2.11(g). Their aim is to optimize the trajectory of the mobile anchor and maximize the localization accuracy of unlocalized SNs. They showed through different simulations that LMAT gives a higher localization accuracy compared to SCAN, HILBERT and SPIRAL trajectories. Moreover LMAT lowers the energy consumption of the WSN as LMAT has a shorter trajectory.

Predetermined trajectories are efficient if the deployment area has a regular shape (i.e., square or rectangle) and the density of sensors is uniform, but can lead to wasteful anchor movement in irregular areas and non-uniform sensor density. Several dynamic trajectories are proposed to consider non-uniform SN’s deployments in the sensing field [73–75]. In dynamic trajectory path planning, the mobile anchor node sends a start packet all over the network and when an SN receives the start packet it adds the neighbor SNs surrounding it and then the SN forwards the packet. When the anchor node receives the start packet back, it calculates the shortest path to localize all SNs based on the topology information thus becoming a graph traversing problem. Li et al. propose a breadth first and backtracking greedy algorithm to build the dynamic path [74]. The breadth first starts at a given SN, which represents level 0. In the first stage a mobile anchor visits all SNs at level 1 then SNs at level 2 and so on. The algorithm terminates when every SN has been visited in a previous point. The greedy algorithm is connected to the backtracking algorithm generated from the breadth first. When the mobile anchor finishes visiting all the SNs in a given area, it then sets the nearest SN, that it has not visited, as a new start and continues to run Greedy Algorithm. The algorithm stops when the mobile anchor has
visited all the SNs. Li et al. suggested to used depth first instead of breadth first [73]. They define the traversing problem as the traveling salesman problem. A minimum spanning tree was used to solve the traversing problem, where the repeated SN that is visited multiple times to be removed from the sequence. They show that they have a shorter path than [74].

Wang et al. propose a stitching technique where the anchor node sends a start packet all over the network [75]. When a SN receives the start packet it adds the neighbor SNs surrounding it and then the SN forwards the packet. When the anchor node receives the start packet back, it calculates the shortest path to localize all SNs. To avoid the collinearity problem for the mobile anchor node, the mobile anchor moves in half-circles around the unlocalized SNs. Kim et al. suggest that mobile anchor should move in equality triangles trajectory with the length of its sides equal to the SNs transmission range [76]. In their technique, the mobile anchor first broadcasts three beacon packets. The SNs start to broadcast these packets and reply to the mobile anchor with a request. The mobile anchor after that plans its trajectory based on the received request packets. Chang suggested that mobile anchor moves around the sensing field [77]. The anchor node moves around the sensing field to divide the network into different regions, after that the mobile anchor node determines the shortest trajectory for each region.

Ou [68] propose a path planning technique, which ensures that the trajectory of the mobile anchor minimize the localization error of all SNs and ensures that all SNs are localized. Also, they proposed an obstacle-resistant trajectory to deal with obstacles found in the deployment area. However, the drawback of Ou’s technique is the path taken by the mobile anchor is longer than other dynamic trajectories.
2.7 Discussion

In this chapter, we give the background material of different approaches used to localize SNs in WSN. Different estimation techniques that are used to estimate the distance or the angles between SNs are presented. Later we discuss different localization techniques used to estimate SN locations using one of the estimation techniques. To estimate SNs location at least three anchor nodes are required in its transmission range. However, in large deployments not all the SNs can be covered by a single-hop with three anchor nodes, a multi-hop localization technique is used to localize SNs. We presented the two major categories of multi-hop localization techniques. The first category is distance based that relies on the individual inter-sensor distance data. The second category, connectivity based or range free localization techniques, do not depend on any of the distance measurement techniques. This approach is based on connectivity information to estimate the locations of the unlocalized SNs. In multi-hop localization, there is a greater potential that the anchor nodes used for localization are on the same line which cause the collinearity problem. We presented the solution proposed in the literature to detected and overcome the collinearity problem. Recently, researches have favored using mobile anchors over using a large number of stationary anchors to lower the cost of the WSN.

Previous researches ave proposed various multi-hop localization techniques [17, 18, 51–56, 61, 62]. However, these proposed localization techniques face several major challenges especially in outdoor large scale deployments such as: 1) The area required to cover is very large. 2) The high density of SNs has a direct impact on the traffic generated and the number of packets exchanged between SNs. 3) The mobility of the anchors and/or SNs. 4) The effect of the transmission range of anchor nodes and
2.7. DISCUSSION

SNs on localization accuracy. 5) The inaccurate location of anchor nodes. 6) The collinearity problem when a mobile anchor moves in a straight trajectory. Our aim in this research is to examine and study the characteristics of multi-hop localization and propose solutions to enhance the performance of multi-hop localization techniques.
Chapter 3

Creating a Realistic Simulation Model

Localization plays a substantial role in the future Internet, especially within the context of the IoT. Increased dependence on devices and sensed data presses for more efficient and accurate localization techniques. Evaluating multi-hop localization techniques in large areas is expensive and time consuming, especially if the experiments involve hundreds or thousands of SNs in an area that covers hundreds of square meters. Using network simulation provides a rich opportunity for efficient experimentation, as simulation gives practical feedback before designing real world systems. This allows us to determine the correctness and efficiency of the localization techniques before the actual deployment of the SNs. Therefore, a simulation environment that can capture what happens in the real deployment is required. In this chapter, we create a more realistic representation for distance measurement errors.

Existing works have assumed that the measurement error added to the estimated
3.1. PREVIOUS WORK

distance follows a normal distribution, and uses this assumption to simulate SN local-
ization. We create a more realistic simulation model. We show that the simulation is more realistic by using Rayleigh distribution for the estimated distance instead of using Gaussian distribution. We show through obtaining real measurements that using Rayleigh distribution gives a more realistic representation of the localization error. Moreover, we show, by using multi-hop simulation, the difference between using Gaussian and Rayleigh distribution.

The remainder of this Chapter is organized as follows: The background is covered in Section 3.1. The error component used to estimated the distance between SNs is presented in Section 3.2. The results and our findings are covered in Section 3.3. The conclusion is given in Section 3.4.

3.1 Previous Work

Estimating the distance between a pair of SNs is the main component of localizing SNs discussed in Section 2.2. RSSI and Time based measurement techniques are the most common ranging techniques used in WSN localization. Both techniques are prone to noise causing the estimated distance to be imprecise [25]. Time base techniques are relatively immune to most sources of noise including signal attenuation, refraction and reflection as time based techniques rely on the signal speed. However, the main source of errors are the absence of LoS between SNs and the processing time of the packets. On the other hand, RSSI techniques are sensitive to channel noise, interference and reflections as they estimate the distance using the strength of the received radio frequency signal. RSSI techniques use either RSSI profiling measurements or estimating the distance via the analytical model by mapping the RSSI to distance
using the path-loss propagation model as discussed in the background Chapter 2.

Previous works in localization that use RSSI and ToA in their theoretical analysis or simulation usually adopt the noisy disk model to estimate the distance between SNs. Motivational for this adaptations include: 1) Evaluating and comparing different localization techniques; 2) mathematically deriving the maximum likelihood for localization; and/or 3) studying the lower bounds on localization error.

The noisy disk model has two components: node connectivity and error. The node connectivity component represents the actual distance between the two SNs, while the noise component represents the noise distribution of the estimated distance and the actual distance. Different localization problems are discussed by Whitehouse et al. [25], Savvides et al. [78], Chang et al. [79] and Sheng and Hu [80] and they all adopted the noisy disk model using the Gaussian noise that defines the estimated distance between the $i^{th}$ and $j^{th}$ SN is represented as follows:

$$d_{i,j} = d_{j,i} = r_{i,j} + \varepsilon_{i,j} \quad \forall i, j = 1, 2, \ldots, M \quad (3.1)$$

where $r_{i,j} = \| x_i - x_j \|$ is the noise free distance between node $i$ and $j$, and $\varepsilon_{i,j} \sim \mathcal{N}(0, \sigma_{i,j}^2)$ represents the uncorrelated noise, where $\sigma_{i,j}^2$ is assumed to be accurately estimated and is known a priori [78, 79].

Liu et al. proposed an iterative least square method to localize SNs using small numbers of anchors [81]. They propose an error control mechanism that uses an error registry to prevent error from propagating and accumulating during the iteration process. They evaluated their algorithm using MATLAB to simulate three different noise models. The description of the experiments are as follows:

1. They did not add any noise to the distance.
2. They added Gaussian noise to the distance similar to Eq 6.1 and fixed the $\sigma$ to 1.7 inches.

3. They used the following equation:

$$z = \begin{cases} 
    d + \varepsilon_1 & \text{if } d < d_0, \text{ where } \varepsilon_1 \sim \mathcal{N}(0, \sigma_1) \\
    d_0 + \varepsilon_2 & \text{otherwise, where } \varepsilon_2 \sim \mathcal{N}(0, \sigma_2) 
\end{cases} \quad (3.2)$$

where $d_0 = 120$ inches and $\sigma_2 = K \sigma_1$ where $K$ is a large number ($10^6$). As they assume that the noise increases rapidly when the distance exceeds a certain threshold.

To take the distance between SNs into consideration, Chan et al. [82] added a zero-mean white Gaussian process with the variance $\sigma^2 = \frac{d_m^2}{\kappa}$ to propose a new weighted multidimensional scaling for localization technique, where $\kappa$ is a constant used to make longer distances have a larger measurement error. So and Chan [83], Wei et al. [84] and Qin et al. [85] take the quality of the channel into consideration and replaced constant $\kappa$ with the SNR in the equation of the variance of the zero-mean white Gaussian process with variance. The equation they used is as follows:

$$\sigma^2 = \frac{d_m^2}{SNR}, \quad (3.3)$$

where $SNR$ is the signal-to-noise ratio and $d_m^2$ is the actual distance.

### 3.2 Error Modeling

As discussed in the previous Section 3.1, existing works simulate the noise added to the distance as accurately as possible in order to make their findings close to real WSN deployments. All the previous work added the Gaussian noise to the actual
3.2. ERROR MODELING

Figure 3.1: The estimated distance between SN$_i$ and SN$_j$ is resulted from the displacement in both x and y. The SN can be estimated in any location inside the dotted circle.

distance similar to equation 3.1 with different variations to the variance. However, the Gaussian error introduced to the estimated distance is added to the displacement of SN location, i.e., in the x and y co-ordinate, not to the absolute distance, i.e., $d_{i,j}$, between the SNs. Figure 3.1 shows that the error added to the estimated distance $d_{i,j}$ results from the displacement in both $x$ and $y$ of the SN location. If we assumed that the displacement in $x$ and $y$ follows the Gaussian distribution:

\[ x_{est} = x_j + x_{err} \quad \text{where} \quad x_{err} \sim \mathcal{N}(0, \sigma^2), \quad (3.4) \]

and,

\[ y_{est} = y_j + y_{err} \quad \text{where} \quad y_{err} \sim \mathcal{N}(0, \sigma^2), \quad (3.5) \]

therefore the estimated distance can be represented as follows:

\[ d_{i,j} = \sqrt{(x_{est} - x_i)^2 + (y_{est} - y_i)^2}, \quad (3.6) \]
by substituting equation 3.4 and 3.5 in equation 3.6, then we will have:

\[ d_{i,j} = \sqrt{(x_j - x_i + x_{err})^2 + (y_j - y_i + y_{err})^2} \]

where \( x_{err} \) and \( y_{err} \) are independent normal random variables, which is the case in equation 3.7. Therefore \( d_{i,j} \sim Rayleigh(\sigma_{i,j}) \).

From the definition of the Rayleigh, \( \gamma \sim Rayleigh(\sigma) \) if \( \gamma = \sqrt{X^2 + Y^2} \), where \( X \) and \( Y \sim \mathcal{N}(0, \sigma^2) \) are independent normal random variables, which is the case in equation 3.7. Therefore \( d_{i,j} \sim Rayleigh(\sigma_{i,j}) \).

To validate that \( d_{i,j} \sim Rayleigh(\sigma_{i,j}) \), we use real data provided by Patwari et al. \cite{2}. The choice of using this data set is motivated by the enhancements they did for the RSSI model to estimate the distance between SNs and they reached 2-m location error using the RSSI. In their experiment, they used a wideband DSSS transceiver (Sigtek ST-515). They maintain the SNR > 25 db during the experiment to reduce the effect of the noise and ISM-band. They modeled the wideband radio channel impulse response as a sum of attenuated signal, phase-shifted and multi-path \cite{26,86}.

Patwari et al. deployed 44 SNs within a 14 \times 13 m area as shown in Figure 3.2. The distance between each SN pair is estimated using RSSI measurements to have in total 44 \times 43 = 1892 measurements. The histogram of the absolute noise, i.e., \( \varepsilon_{i,j} \), resulting from estimating the distance between the SNs is plotted as shown in Figure 3.3(a). The output of the histogram follows a Gaussian distribution with \( \mu = 0.4 \) and \( \sigma^2 = 8.41 \). The data can be replicated easily using the same values as shown in Figure 3.3(b). Previous works have shown a similar finding. They use such finding and suggest that the added noise to actual distance follows the Gaussian distribution. They therefore added the generated noise to the absolute distance to represent the estimated distance. However, when the histogram of the estimated distance is plotted,
3.2. ERROR MODELING

Figure 3.2: Map locates the actual locations for SNs (● #T). The RSSI is used to estimate the distance between each SN pair. The distances are estimated by [2].

i.e., the actual distance with the noise \( d_{i,j} = r_{i,j} + \epsilon_{i,j} \), using the real data the result follows the Rayleigh distribution with \( \sigma = 6.6 \) as shown in Figure 3.4(a).

When we replicate the estimated distance by adding Gaussian noise resulting from Figure 3.3(b) to the actual distance using the following equation 6.1, the estimated distance follows the normal distribution with \( \mu = 7.7 \) and \( \sigma^2 = 4.7 \) as shown in Figure 3.4(b). However, by using equation 3.7, we get a Rayleigh distribution with \( \sigma = 6.72 \) as shown in Figure 3.4(c). The histogram resulting using equation 3.7 gives a realistic representation of the error, as it gives an almost similar distribution resulting from using the estimated distances using real measurements. This means the added noise is not a pure Gaussian distribution and it is affected by the change in both \( x \) and \( y \) co-ordinates.
3.3 Simulation and Discussion

We performed two different experiments using simulation to study the effect of adding Rayleigh distribution using equation 3.7 to the distance error between SNs instead of adding Gaussian using equation 6.1. In the first experiment, we study the effect of the transmission range on localization accuracy, while in the second experiment, we study the effect of changing the number of anchors on localization accuracy.

In the simulation, we use ns-3 to study the effect of using Normal versus Rayleigh...
3.3. SIMULATION AND DISCUSSION

(a) Actual distance measurements follow Rayleigh distribution

(b) Estimated distance measurements using equation 6.1 follow Normal distribution

(c) Estimated distances measurements using equation 3.7 follow Rayleigh distribution

Figure 3.4: The distance measurement \( (d_{i,j} = r_{i,j} + \varepsilon_{i,j}) \) histogram and its distribution fit.

distribution on multi-hop localization technique that uses DV-Distance [87]. A number of 500 SNs are randomly placed an area of 200 \( \times \) 200 \( m^2 \). In the first experiment we placed four anchor nodes at the edge of the simulated area, while in the second experiment we placed the anchor nodes randomly inside the simulated area. The same \( \sigma^2 \) is used for both Gaussian and Rayleigh distribution. All the results are from
3.3. SIMULATION AND DISCUSSION

Figure 3.5: Goodness of fitness for the actual distance using Gaussian distribution and Rayleigh distribution. It is clear that the actual distance follow the Rayleigh distribution not the Gaussian distribution.

3.3.1 Effect of Changing the Transmission Range of SNs

In the first experiment, we study the effect of localization error when we increase the transmission range for SNs. In order to minimize the effect of placing the anchor nodes on the transmission range, we placed four anchor nodes at the corner of the simulated area. The transmission range of the anchors and SNs are increased gradually from 20 m to 100 m in increments of 20 m.

Figure 3.6 shows the relation between increasing the transmission range and localization error. When the error is small ($\sigma^2 = 2$), the localization error is the same for both Gaussian and Rayleigh distribution as shown in Figure 3.6(a). The localization accuracy decreases as we increase the transmission range except when the transmission range is 20 meters. The reason that the localization error is high when transmission range = 20 is the density of the SNs is not that high, which leads the
3.3. SIMULATION AND DISCUSSION

Figure 3.6: The relation between transmission range and localization error. Number of anchors = 4 at the edge of the studied area.

SN to take a larger number of hops to reach the anchor node. In the next chapter we study the effect of transmission range on localization accuracy in detail.

However, when the error is large ($\sigma^2 = 8$) and transmission range is small (20 meters), the difference between Gaussian and Rayleigh distribution is at maximum (12 meters). As we increase the transmission range, the difference between Gaussian and Rayleigh distribution decreases, until both Rayleigh and Gaussian distribution have similar localization error when the transmission range = 60 meters as shown in Figure 3.6(b).
3.3. SIMULATION AND DISCUSSION

Figure 3.7: The relation between $\sigma^2$ and localization error using 4 anchor nodes located at the edge of the simulated area.

This means when the transmission range is small the difference between using Gaussian and Rayleigh increases as the variance of the error increases. Also, when the transmission range is large both Rayleigh and Gaussian give similar localization error as the variance of the error increases. To validate our findings and check the effect of the variance on the localization error, we fixed the transmission range and increased the value of the variance gradually. When the transmission range = 20 meters the difference between using Gaussian and Rayleigh increases rapidly until the difference reaches 12 meters as shown in Figure 3.7(a). However when the transmission range =
3.3. SIMULATION AND DISCUSSION

Figure 3.8: The relation between number of anchors and localization error when the transmission of the sensor node = 20 meters.

60 meters the difference between using Gaussian and Rayleigh increases slowly until the difference is 2 meters as shown in Figure 3.7(b). Results in Figure 3.7 validate the findings in Figure 3.6.

3.3.2 Effect of Changing the Number of Anchor Nodes

In the second experiment, we study the effect of localization error when we increase the number of anchors. The anchor nodes are placed randomly in the simulated area and the number of anchor nodes are increased gradually. In the first experiment, we
3.3. SIMULATION AND DISCUSSION

Figure 3.9: The relation between number of anchors and localization error when the transmission of the sensor node = 40 meters.

We find that as we increase the transmission range the Gaussian and Rayleigh converge to give the same localization accuracy. We repeated the experiment using two different transmission ranges 20 and 40 meters respectively.

Figure 3.8 and 3.9 shows the relation between the number of anchor nodes and localization error when the transmission range of the SNs is fixed to 20 and 40 meters respectively. As expected as we increase the number of the anchor nodes the localization error decreases. This behavior is the same when we add Gaussian or Rayleigh
3.3. SIMULATION AND DISCUSSION

Figure 3.10: The relation between variance and localization error using 7 anchor nodes located randomly in the simulated area.

distribution to the actual distance between nodes. However, when the transmission range is small (20 meters) and the variance is small \((\sigma^2 = 2)\), both Gaussian and Rayleigh distribution give the same localization error as shown in Figure 3.8(a). When the variance is large \((\sigma^2 = 8)\), the difference between the Rayleigh and Gaussian increases to become 12 meters on average as shown in Figure 3.8(b). When the transmission range increases, the difference between using Gaussian and Rayleigh decreases as shown in Figure 3.9(a) when \(\sigma^2 = 2\) and Figure 3.9(b) when \(\sigma^2 = 8\).

To see the effect of the variance on the localization error, we fixed the number
of anchor nodes to seven and increased the value of $\sigma^2$ gradually. Results in Figure 3.10 show a similarity to Figure 3.7. When the transmission range = 20 meters the difference between using Gaussian and Rayleigh increases rapidly until the difference reaches 16 meters as shown in Figure 3.10(a). However when the transmission range = 40 meters the difference between using Gaussian and Rayleigh increases slowly until the difference is 5 meters as shown in Figure 3.10(b).

3.4 Conclusion

In this Chapter, the error model introduced to estimate the distance between SNs using RSSI is investigated in order to create a more realistic simulation model for multi-hop localization. There has been a belief in the literature that the Gaussian noise is added directly to the distance, which makes the estimated distance follow the Gaussian distribution for the distance. We assess such belief by showing that the introduced error follows the Gaussian distribution, but the estimated distance follows Rayleigh distribution. This Rayleigh distribution is introduced by adding the introduced error to the x and y coordinates to the SN location while calculating the distance. After that we compared the difference between representing the estimated distance using Gaussian and Rayleigh distributions. Our results show that as we decrease the transmission range of the SNs, the difference between using Gaussian and Rayleigh increases. The same effect also appears when we increase the $\sigma^2$. Thus, it is recommended to add noise to the x and y co-ordinate (Rayleigh distribution) not to the whole distance (Normal distribution) to have an accurate estimation for the distances between SNs especially in highly dense deployments.
Chapter 4

Characterizing the Error in Multi-hop Localization

Localization estimation errors can be broken down into extrinsic or intrinsic error [88]. An intrinsic error is usually caused by the imperfections of the sensor hardware and/or software, while an extrinsic error is attributed to the physical effects on the measurement channel and multi-hop communication. Savvides et al. [88] studied a range of intrinsic error characteristics for different measurement technologies, however they did not study the effect of extrinsic error.

In this Chapter, we characterize the effects of extrinsic errors on multi-hop localization. A common belief held by researchers in multi-hop localization techniques is that by increasing the number of hops between the anchor nodes and SNs, the localization error will increase. However, in this study we show that this is not always the case. Indeed, there are conditions where using a larger number of hops results in better localization accuracy than using a smaller number of hops.

The remainder of this chapter is organized as follows. A background of multi-hop
localization techniques used in this chapter is covered in Section 4.1. The performance evaluation setup is presented in Section 4.2. The results and discussion about the findings are discussed in Section 4.3. Conclusions are given in Section 4.5.

4.1 Multi-hop Localization Techniques

In this work, we adopt two generic techniques that represent the two major categories of multi-hop localization techniques. DV-Hop represents the connectivity based category, while DV-Distance represents the distance based category [51]. In the following subsection, we give an overview of DV-Hop and DV-Distance.

4.1.1 DV-Hop Localization Technique

The DV-Hop localization technique has two stages. In the first stage the anchor nodes broadcast their actual locations to the SNs. The SNs keep the shortest number of hops to each anchor node along with the anchor node’s location. Thus at the end of the first stage, each SN maintains a table of \( \{x_i, y_i, h_i\} \), where \( x_i \) and \( y_i \) are the coordinates of anchor \( i \) and \( h_i \) is the shortest number of hops to reach anchor \( i \). SNs exchange the shortest hop location packets only with their neighbors. When an anchor node receives a location packet from other anchor nodes, it estimates the average distance for a single hop for the entire network. The average distance of a single hop of anchor \( i \) is calculated as follows:

\[
c_i = \sum_{j=1}^{M} \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{h_j}, \text{ where } i \neq j.
\] (4.1)

In the second stage, the anchor nodes broadcast their estimates of the average distance for a single hop. SN saves the average single hop from the closest anchor
node and forwards it to its neighbors. The SNs use the received average distance for a single hop and multiply it with the total number of hops for each anchor node using the information saved in the table \( \{x_i, y_i, h_i\} \). Finally, these values are then plugged in the multilateration equation described in the next subsection. The error in the DV-Hop localization technique appears since it assumes all hops to have the same value.

Figure 4.1 shows an example of DV-Hop. SNs A\(_1\), A\(_2\) and A\(_3\) are anchor nodes. Anchor node A\(_1\) has both the Euclidean distance and hop numbers to anchor nodes A\(_2\) and A\(_3\). Anchor node A\(_1\) calculates the average distance for a single hop in meters as follows \((150 + 50)/(5 + 3) = 25\) meters. Anchor node A\(_1\) then broadcasts the average distance for a single hop to the network. In a similar way, anchor node A\(_2\) and A\(_3\) computes the average distance for a single hop \((50 + 65)/(3 + 4) = 16.43\) and \((65 + 150)/(4 + 5) = 23.89\) respectively. The SN receives the average distance for a single hop from anchor nodes. The SN only saves the average hop distance received from the closest anchor node. For SN\(_i\) the nearest anchor node is L2, thus it saves the average hop distance received from A\(_2\). SN\(_i\) estimates the distances to the three
anchor nodes would be: $A_1 = 2 \times 25$, $A_2 = 2 \times 16.43$, and $A_3 = 3 \times 23.89$. These values are then plugged into the triangulation procedure to calculate the estimated location of the SNs.

### 4.1.2 DV-Distance Localization Technique

The DV-Distance localization technique has only one stage, in which the anchor nodes broadcast their locations to the entire network. The location packet contains the actual location $x_i, y_i$ of anchor node $i$ and the total distance traveled $d_i$. The anchor node initializes the distance to zero. When a SN receives the packet, it estimates the distance the packet traveled for a single hop using either RSSI or ToA. After which the SN node adds the estimated distance to the total distance traveled by the packet and forwards the packet.

Thus, each SN maintains a table of $\{x_i, y_i, d_i\}$, where $x_i$ and $y_i$ are the coordinates of anchor $i$ and $d_i$ is the cumulative traveling distance estimated in meters from anchor node $i$. The DV-Distance technique is prone to distance estimation errors due to: obstacles between two SNs, multi-path fading, noise interference, and irregular signal propagation. However, the hops between SNs are not assumed to have the same distance.

### 4.2 Performance Evaluation Setup

In the simulation, we use ns-3 [87] using the error model proposed in Chapter 3 to study the effect of multi-hop on DV-Hop and DV-Distance localization techniques. The WSN is deployed with N unlocalized SNs and four anchor nodes. Different numbers and locations of anchor nodes have been experimented with and resulted in
4.2. PERFORMANCE EVALUATION SETUP

(a) Random Deployment  
(b) Fixed Grid Deployment  
(c) Dynamic Grid Deployment

Figure 4.2: Example for the different deployment strategies used for WSNs. The transmission range of SNs in this example is 50 meters.

similar observations. The simulation area is set to be $200 \times 200 \text{ m}^2$. To minimize the effect of the anchor nodes location on localization accuracy and to overcome the collinearity effect, the four anchor nodes are placed at the four corners of the simulation area. The collinearity problem appears when the anchor nodes are on the same line [59]. In this case, it is hard to identify whether the SN is on the left or right of the anchor nodes, which causes the location of the SN to be flipped [60].

The measurement noise used in estimating the distance for DV-Distance is a zero-mean White Gaussian process with variance $\sigma^2_{i,j} = d^2/\text{SNR}$ added to the $x$ and $y$ coordinates as discussed in Chapter 3. We use two values for SNR: SNR = 10 db is used to represent a communication channel with a high noise and SNR = 30 db is used for a communication channel with low noise. All results are averages of ten different independent runs with distinct random seeds.

To study the effect of multi-hop communication on localization accuracy, we estimate the location of the SNs using five different transmission ranges of SNs, ranging from 20 meters to 100 meters with a step of 20 meters. We consider three different
4.2. PERFORMANCE EVALUATION SETUP

deployment scenarios to understand the effect of multi-hop on localization accuracy. Figure 4.2 shows the different deployment scenarios used in the simulation when the transmission range is set to 50 meters. The first scenario represents a practical scenario, where SNs are deployed randomly in the sensor area as shown in Figure 4.2(a) with a total of 500 SNs. The second and third scenarios, represents controlled deployments, enabling a better understanding of the effects of the errors. In the second scenario, the SNs are deployed in a fixed grid with a 10 meter step between SNs with a total of 500 SNs as shown in Figure 4.2(b). In the third scenario, the SNs are deployed in a dynamic grid, where the number of SNs and their placement are changed based on the SN transmission range as shown in Figure 4.2(c). The number of SNs used in the dynamic grid is calculated using the following equation:

\[
= \left( \frac{\sqrt{(\text{Sim. Width})^2 + (\text{Sim. length})^2}}{\text{trans. Range}} + 2 \right)^2, \tag{4.2}
\]

while the vertical step is calculated using the following equation:

\[
= \frac{\text{Sim. width} \times \text{trans. Range}}{\sqrt{(\text{Sim. Width})^2 + (\text{Sim. length})^2 + \text{trans. Range}}} \tag{4.3}
\]

and horizontal step is calculated using:

\[
= \frac{\text{Sim. length} \times \text{trans. Range}}{\sqrt{(\text{Sim. Width})^2 + (\text{Sim. length})^2 + \text{trans. Range}}.} \tag{4.4}
\]

To make the fixed grid deployment more realistic, we assume that there is randomness in the deployment of individual SNs. The randomness is modeled by a random error disk with a radius of 1 meter [89]. The second scenario represents a dense deployment of SNs, in which more SNs are covered by increasing the transmission
range. While, the third scenario represents a sparse deployment where SNs are only covered by the boarder of the maximum transmission range. For example in Figure 4.2(b) when the transmission range is 50 meters, there are more than 50 SNs covered, where 3 or 4 of them are within 10 meters away from the anchor nodes, while there are around 10 SNs that are almost 50 meters away and the rest of the SNs are in between. This variant of distance increases the overall localization error. Where as in Figure 4.2(c) when the transmission range is 50 meters, we only have 3 nodes which are approximately 50 meters away from the anchor node.

4.3 Results

For all the experiments we performed, it is clear that DV-Hop localization technique outperforms DV-Distance technique when the SNR is low. Previous works have also pointed to such findings such as [19]. However, when the SNR increases the performance of DV-Distance improves. In the following subsections, we discuss the results for using random deployment, fixed grid and dynamic grid.
4.3. RESULTS

Figure 4.4: The effect of dense and sparse deployment on localization accuracy.

4.3.1 Random Deployment

In the first scenario, we deployed 500 SNs randomly. Figure 4.3 shows that using shorter hops gives a higher accuracy, for both DV-Hop and DV-Distance localization techniques. The average accuracy decreases when we increase the transmission range of the SNs for both DV-Hop and DV-Distance except when the transmission range is 20 meters.

The decrease in accuracy of DV-Hop is larger than DV-Distance when we increase the transmission range (the error in DV-Distance with 30 db is almost constant). The accuracy of DV-Hop decreased by 11% while the accuracy of DV-Distance decreased by 8%, for SNR = 10 db and 2% for SNR = 30 db when the transmission range of the sensor nodes increases from 40 meters to 100 meters. Figure 4.4 illustrates why the localization error increases when the transmission range of the SN is increased to 20 meters.
In Figure 4.4(a) the transmission range of the SNs is set to 20 meters and the distance between anchor node A and SN is 48 meters. Thus the packets that are used to estimate the distance between A and SN are from SN, SN, and SN respectfully. In DV-Distance, by adding the actual distance of the 4 hops we get a distance of 65 meters, where the actual distance is 48 meters. The same effect applies when the DV-Hop is used, since we have four hops and if we assumed that the average hop distance is 15 meters, then the total estimated distance is 60 meters. However when the transmission range is 40 meters the estimated distance is estimated through 2 hop only, which increases the estimation accuracy. By increasing the density of SNs by adding an extra SN between A and SN as shown in Figure 4.4(b). The estimated distance become 51 meters if we used DV-Distance and 45 meters if we used DV-Hop, which is very close to the actual distance.

To validate such an assumption, we repeated the experiment using different number of SNs: 400, 500 and 600 in the same area. Figure 4.5 shows that as we increase the number of SNs the localization accuracy increases when the transmission range of the SNs is equal to 20 meters for both DV-Hop and DV-Distance. However the change in the localization accuracy is insignificant when the transmission range is larger than 40 meters.

In general, this result shows that in highly dense deployments it is better to have a larger number of hops with shorter transmission ranges (around 40 meters) than to have a small number of hops with larger transmission ranges. These findings are in contrast to an earlier belief that using shorter hops would give better accuracy. In order to understand the reason for such behavior, we use the two controlled experiments: fixed and dynamic grid explained in the previous section.
4.3. RESULTS

Figure 4.5: Relation between SN transmission range and localization error when we increase the number of SNs.

4.3.2 Fixed Grid

In this scenario SNs are deployed in a fixed grid in the sensed area. Figure 4.6 shows the accuracy for localizing SNs when the SNs are placed in a fixed grid. Neither the
4.3. RESULTS

The localization accuracy using fixed grid deployment for SNs is shown in Figure 4.6. As the transmission range for SNs is increased from 20 meters to 100 meters, the localization error increases for all methods. However, the accuracy of DV-Hop localization is reduced by 27% whereas the accuracy of DV-Distance only decreases by 12% and 10% for SNR = 10 db and 30 db respectively. This result supports the previous finding that using shorter transmission for SNs decreases the overall localization error. The only difference with the previous finding is at transmission range = 20 meters using fixed grid deployment gives a higher localization accuracy than using random deployment. The reason is in fixed grid the shortest path is always granted shown in Figure 4.4(b).

Figure 4.6: The localization accuracy using fixed grid deployment for SNs.

Figure 4.7: Explain the difference between dense and sparse deployment for DV-Hop.

The number of SNs nor the distance between the SNs is changed when we increase the transmission range for SNs. The accuracy of DV-Hop localization is reduced by 27% when the transmission range is increased from 20 meters to 100 meters. Whereas the accuracy of DV-Distance only decreases by 12% and 10% for SNR = 10 db and 30 db respectively. This result supports the previous finding that using shorter transmission for SNs decreases the overall localization error. The only difference with the previous finding is at transmission range = 20 meters using fixed grid deployment gives a higher localization accuracy than using random deployment. The reason is in fixed grid the shortest path is always granted shown in Figure 4.4(b).
The reason that the localization accuracy decreases for DV-Hop as we increase the transmission range (decreasing the number of hops) is explained in Figure 4.7. If we assume the distance between $A_1$ and $A_2$ is 100 meters. In the ideal case when there is 1 SN between the two anchor nodes as shown in Figure 4.7(a), both anchor nodes calculate that the average hop distance is 50 meters as the packet reached $A_2$ in 2 hops. Thus when $N_1$ multiples the average hop distance which is 50 by the number of hops which is 1, we get 50 meters which is a highly accurate estimation. However, this is not the case in a dense deployment. Figure 4.7(b) shows that there are 5 SNs between the two anchor nodes. The minimum number of hops between $A_1$ and $A_2$ is 2 hops through $SN_3$. Thus the average hop distance is 50 meters. When $SN_1$, $SN_2$ and $SN_3$ estimate the distance between themselves and $A_1$ by multiplying the average hop distance which is 50 meters by the number of hops which is 1, we get 50 meters which is an accurate estimation for $N_3$ only.
4.3. RESULTS

4.3.3 Dynamic Grid

In this scenario we use a dynamic grid, i.e., the spacing between SNs increases as we increase the transmission range of SNs. Figure 4.8 shows that as we increase the transmission range, the overall localization accuracy improves for both DV-Hop and DV-Distance using SNR = 30 db and descends for DV-Distance using SNR = 10 db. This result was as expected, however, the accuracy decreased dramatically when we used DV-Distance using SNR = 10 db. The previous results show that in sparse deployments it is better to have a lower number of hops with longer transmission ranges.

To explain why DV-Distance with high noise (low SNR value) has poor accuracy in a sparse deployment when using longer transmission ranges, refer to Figure 6.2. When the distance between the anchor nodes and the SN is accurately estimated the area we perform multilateration is relatively small, which increases the localization accuracy as shown in Figure 6.2(a). However, when the error for the estimated distance is high, the area on which we perform multilateration is larger. This increases the error
4.4. DISCUSSION

Figure 4.10: Number of packets generated during the localization process.

for the estimated location. Thus when we use DV-Distance in an environment that
has a high noise level in the channel it is better to use shorter hops with a shorter
transmission range than to use a long transmission range.

4.4 Discussion

Previous results show that to achieve high localization accuracy in highly dense de-
ployments it is better to use short transmission ranges for the SNs. However, by
decreasing the transmission range the number of packets transmitted in the network
will increase as shown in Figure 4.10. The number of packets sent decreased by 62%
and 48% for DV-Distance and DV-Hop respectively as we increased the transmission
range from 20 meters to 100 meters.

As the number of packets transmitted increases in the network, the number of
collisions will increase which will have a direct impact on the overall localization
accuracy. Figure 4.10 shows that DV-Hop generates twice the packets generated by
DV-Distance. Also, as we increase the transmission range the number of packets
transmitted decreases gradually. Thus it is important to study the effect of packets
transmitted during the localization process.

4.5 Conclusion

In this chapter, we characterize the effect of number of hops in multi-hop localization techniques. There has been a belief in the literature that the smaller the number of hops the greater the accuracy. We assess this belief for representative generic techniques of range based and range free localization. We consider a number of sensor nodes deployment and anchor node placement scenarios. Deployment scenarios considered include random, fixed grid, which represents a controlled dense deployment, and dynamic grid, which represents a controlled sparse deployment. Our results show that using a larger number of hops with a shorter transmission range in dense deployments provide a higher accuracy than using a small number of hops with a larger transmission range. In sparse deployments with a noisy channel it is also better to use a large number of hops with a shorter transmission range for a range based localization technique. In general, range free localization performs better than range based localization under noisy communication channels. The findings of this work show that the choice of localization techniques (with or without multi-hopping) is dependent on deployment setting and channel conditions.
Chapter 5

Managing Overhead in Large Scale Deployments

In the previous chapter, we show that to achieve high localization accuracy in highly dense environments, it is better to use short transmission ranges for the SNs. However, using short transmission range for SN in highly dense deployments will increase the number of packets transmitted in the network. Given the sheer number of SNs involved in the large scale deployments, in addition to projected variance in their location/mobility profiles, it becomes necessary to propose a solution to multi-hop that can cope with both scale and mobility of SNs.

In this chapter, we propose an aggregation technique to be used in multi-hop localization that will decrease the number of packets generated during the localization process. We investigate the impact of the proposed aggregation technique and compere the overhead generated in large scale deployments. Moreover, we check the impact of SNs scalability and mobility on the multi-hop aggregation technique and study the affect of aggregation technique on the number of packets generated during
the localization process. Our interest spans the aspects of both network requirements and localization accuracy.

To study the proposed aggregation technique, we add the aggregation technique to a representative system for wireless multi-hop localization technique selected for its operational efficiency and accuracy that deals with SNs mobility [56]. The system depends on fixed anchor nodes that are aware of their location and sensor network responding and processing localization information send by the anchors, and is implemented with modifications to enhance localization accuracy. The testing involves increasing the size of the sensor network, in addition to increasing SN mobility. Operational aspects such as the number of packets generated, received and dropped, the number of collisions, localization accuracy and percentage of unlocalized SNs are all measured. Results invariably indicate definite scalability issues at the different layers of operation. Moreover, we illustrate that substantial gains can be achieved using the proposed packet aggregation.

The remainder of this chapter is organized as follows. The proposed packet aggregation is proposed in Section 5.1. Section 5.2 provides the evaluation environment, giving an overview of the representative system for wireless multi-hop localization, elaborating on the implemented modifications and describing the suggested enhancement. Section 5.3 presents the simulation setup and metrics we are going to use to evaluate our proposed solution. Section 5.4 discusses the results. Finally, Section 5.6 concludes and alludes to possible future directions.
5.1 Aggregate Multi-hop Localization Packets

In previous localization techniques proposed, when an SN receives a packet containing the anchor node’s location, the SN forwards this packet to the surrounding SNs at once. This behavior (receive then forward) generates huge traffic from SNs that affects the performance of the transmission. This may be acceptable in sparse WSN deployments, but it adversely affects the performance of the communication in high dense deployments. The reason for the huge traffic generated is that the packet is broadcasted to all neighbor SNs. Thus it is important to reduce the number of packets generated while implementing the localization algorithm.

To solve this problem, we propose that SNs only transmit localization packets in a predefined time. This means when a SN receives a packet it first stores the packet and aggregates it with the previous received packets. When the timer for the transmitter expires the SN forwards the aggregated packet. In connectivity based localization techniques SNs aggregate two types of packets, the first packet is for the anchor location packet, while second is for the average hop packet. After applying this behavior (receive, save then forward), the number of packets sent is reduced dramatically.

Figure 5.1 shows the number of packets sent to localize both DV-Hop and DV-Distance. The number of packets decrease for DV-Distance by almost 70% when the transmission range of SNs is 20 meters and 50% when the transmission range of SNs is 100 meters. For DV-Hop the number of packets decreased by 55% and 40% when the transmission range of SNs is set to 20 and 100 meters respectively. From the above result it is clear that the aggregation technique we propose dramatically decreases the number of packets sent without affecting the localization accuracy. In
the rest of the chapter, we investigate the impact of scale on wireless multi-hop
and check the effect of using the aggregation concept on the performance of the
localization accuracy. To achieve this objective, we plan to use a representative
system for wireless multi-hop localization. The results from the previous chapter
shows that using connectivity based localization techniques perform better than using
range based localization techniques in noisy deployments. Also connectivity based
localization techniques generate twice the number of packets generated by distance
based localization techniques. That is why we use a connectivity based localization

Figure 5.1: Number of packets sent to localize SNs.
technique in the rest of this chapter.

5.2 Evaluation Environment for Mobile SNs

Our evaluation environment relies on the wireless multi-hop localization system proposed by Akbas et al. in [56]. This choice was motivated by the general applicability of wireless multi-hop localization to both multi-hop and single hop localizations. It was also motivated by the projected nature of how Things communicate in the IoT. More importantly, our own validations indicate that the system possesses a relatively higher operational efficiency, in addition to a robustness in localizing SNs at different mobility speeds.

The system relies on both anchor nodes and a sensor network. Each anchor node periodically sends what is called weight update packet to all its neighboring SNs that contains the anchor node’s address (anchor ID) and the value of its own weight parameter $k$. During initialization the value of $k$ is the same for all anchor nodes.

When a SN receives a weight update packet, it will first decrease the weight value by one. If the weight value reaches zero, the SN drops the packet, otherwise the SN forwards the packet to the surrounding SNs. Each SN saves the highest received weight for each anchor node in its weight table. Figure 5.2 shows an example of the weight table. The SN could save multiple weights for different anchor nodes, but it should save a single weight for each anchor node. The weight saved at the SN indicates how many hops this SN is away from the anchor node it saves a weight of.

In operation, a SN differs from an anchor node in that the SN will forward the weight update packet if the weight did not reach zero, while the anchor node will drop the packet after it saves the weight value in the weight table.
After the SNs build their weight tables as shown in Figure 5.2, they will forward their weight table periodically to the anchor nodes. The aim in sending the weight table is to enable the anchor node to calculate the estimated distance between an anchor node and all the SNs associated with the anchor node. The time to live for the packet is set with the maximum weight value saved in the table.

As the SNs move around the network, the weight values saved by the SNs do not represent the number of hops between the SN and the anchor node. This means the SNs have to update their weight table periodically. In order to do so, each SN saves the time it received the weight update packet. After that the SN subtracts the saved
time with the current time while sending the weight table packet. If the subtracted time exceeds a given threshold, the SN decreases the weight value by 1 until it reaches zero.

When a SN receives a weight table packet it simply forwards that table to the surrounding SNs. Meanwhile, when an anchor receives a weight table packet, it starts to process the packet to calculate the estimated distance between itself and all the SNs that send the weight table packet using the following equation:

\[
d_{a,s} = w_{a,s} \times h_a
\]  

(5.1)

where \(d_{a,s}\) represents the estimated distance between anchor node \(A\) and SN \(S\), \(w_{a,s}\) is the weight of SN \(S\) for anchor node \(A\) and \(h_a\) is the average 1-hop distance of anchor \(A\). After calculating the estimated distance for all the SNs affiliated with the anchor node, the anchor node forwards these values to the sink SN.

Upon investigation, however, we observed that the accuracy of this equation can be improved by subtracting the weight of anchor node from \(w_{a,s}\), as follows:

\[
d_{a,s} = (k_a - w_{a,s}) \times h_a
\]  

(5.2)

where \(k_a\) is the weight of anchor node \(A\). Our implementation utilizes this modification.

The sink SN uses all the received estimated distances “\(d_{a,s}\)” for every SN calculated by anchor nodes. For a given SN, if at least three estimated distances are calculated for different anchor nodes, then the location of this SN can be estimated using the multi-lateration technique.
5.3 Simulation Setup

We extend the ns-3 [87] and utilize BonnMotion to generate various mobility traces based on the random Waypoint mobility model [90]. In the setup, SNs are uniformly distributed in a simulated area of $100 \times 100$ unit blocks. The choice of area is made to ensure the full connectivity of the wireless sensor networks when even the least number of SNs is distributed, which is 25 SNs. In the following evaluations, an anchor node sends a weight update packet every 10 seconds. The transmission range for SNs is set to 40 meters, and the anchor nodes and sink SN are connected through a high-speed backbone network. In the beginning 25 anchor nodes in addition to 1 sink SN are used. Simulations are made to run for a period of 100 seconds. Impact of scale is evaluated through varying size of the sensor network from 25 SNs to 200 in increments of 25 SNs. The effect of mobility is verified through varying mobility speeds based on the Random Waypoint model, and detailed below in the relevant experiments. The performance metrics are averaged over ten different topology runs generated using distinct random seeds.

In our evaluations, we investigate several aspects of operation. We describe below our findings giving performance metrics that best illustrate the impact of scale and mobility on wireless localization algorithms. The metrics are defined as follows:

- **Total number of packets sent**: Comprises the total number of packets transmitted for two types of packets. The first type includes weight update packets, which are generated by anchor nodes and forwarded by the SNs. The second includes the weight table packets, which are generated and forwarded by SNs.

- **Total number of packets received**: The total number of packets received at anchor nodes and SNs.
• **Total number of packets dropped** Comprises the packets dropped due to redundancy, i.e., a weight update or weight table packets that have already been received.

• **Total number of packet collisions:** Reports the number of packet collisions at the MAC layer.

• **Mean error in Euclidean distance:** Reports the mean error in computing the Euclidean distance between estimated location and actual location for each SN.

• **Percentage of unlocalized SNs:** Localizing any SNs requires at least three reports. This metric reports the percentage of the SNs for which at least three distance reports were not received.

### 5.4 Results

In addition to investigating the effect of scale and speed on multi-hop localization, we also investigate the possible improvements provided by the simple aggregation discussed in Section 5.1. Consequently, the figures discussed below show the localization results for both with and without the proposed aggregation technique.

#### 5.4.1 Elaboration on the Selection of the Simulation Area.

This section elaborates on the selection of a $100 \times 100$ unit for the following sequence of results. To ensure neutrality, we seek an area that would eliminate the effect of connectivity on the results. An area that ensures full connectivity when the least number
of SNs is distributed, 25 SNs in our case, would consequently ensure connectivity for a higher number of SNs.

In order to investigate the effect of a simulated area on SN connectivity, a scenario is used where only 25 anchor SNs and 25 SNs are simulated. The weight parameter, \( k \), is set to four to allow SNs to connect to anchor nodes using four hops. Figure 5.3 shows the simulated area represented relative to the percentage of SNs that failed to be localized. Confirming intuition, as the simulation area increase the percentage of SNs that are not localized also increases. A 100 \( \times \) 100 simulation area, however, satisfies our connectivity objectives.

5.4.2 Impact of Network Size

In order to investigate the effect of scalability on localization, the number of SNs is increased from 25 to 200 by increasing 25 SNs each time. The weight parameter, \( k \), is set to 4 to allow SNs to connect to anchors node using 4 hops. The impact of network size is evaluated both in a static (no mobility) scenario and a mobile scenario. In the
5.4. RESULTS

Figure 5.4: The effect of increasing the number of SNs on the evaluation metrics - static setting with weight $k = 4$.

latter, a SN’s speed ranges between 4.5 km/h and 5.5 km/h, which is the average speed of a pedestrian. The results for the static and mobile scenarios are respectively shown in Figure 5.4 and Figure 5.5. In each, the sub-figures illustrate the impact on the total numbers of (a) packets sent (b) packets received (c) packets dropped and (d) packet collisions.

The value of the different metrics consistently increases as the number of SNs is increased. This is observed in both static and mobile settings. When aggregation is not employed, despite the redundancy check, a great number of packets are generated. For example, at 125 SNs, 150,000 packets are either sent or forwarded in the static setting as shown in Figure 5.4(a), while almost 2,000,000 packets are received as shown in Figure 5.4(b). A similar trend can also be observed in the mobile setting (100,000 to 800,000 at 125 SNs). Note that this great discrepancy is due to the
5.4. RESULTS

Figure 5.5: The effect of increasing the number of SNs on the evaluation metrics - mobile setting (4.5 5.5 Km/hr) with weight k = 4.

The broadcast nature of the wireless medium, i.e., all receivers in the vicinity of a sender or forwarder SN receive the broadcasted packet. This very nature also justifies the numbers of packets dropped and collisions as shown in Figures 5.4(c) and 5.4(d). Lesser numbers are also experienced in the mobile setting as SNs move beyond each other’s vicinity more frequently.

The impact of the suggested aggregation is apparent in both Figure 5.4 and Figure 5.5. Recall that the aggregation simply involves the use of a hold time prior to forwarding received packets and tables while aggregating them in one transmission. In the static setting, this modification reduces the number of sent and forwarded packets from almost 300,000 to less than 20,000 at 200 SNs as shown in Figure 5.4(a), and relatively diminishes the number of collisions experienced in the network as shown in Figure 5.4(d). Similar trends can also be observed in the mobile setting.
Figure 5.6: Metrics calculated using different speed using 25 SNs.

as shown in Figure 5.5.
5.4. RESULTS

Figure 5.7: Metrics calculated using different speed using 200 SNs.

5.4.3 Impact of Mobility

The experiments discussed in the previous subsection were concerned with isolating the impact of network size. Here, we isolate the impact of mobility on localization,
and continue to identify the effect of the suggested aggregation. In the scenario employed, mobility speed ranges between 1 m/s to 9 m/s (= 32 km/h). In Figures 5.6 and 5.7, we show two sets of results, one for 25 SNs and the other for 200 SNs respectively. Figures 5.6(a), 5.6(b), 5.6(c) respectively show the total collisions, mean error in Euclidean distance and percentage of computable SNs for 25 SNs; Figures 5.7(a), 5.7(b), 5.7(c) show the same for 200 SNs.

In terms of collisions, Figure 5.6(a) and 5.7(a) confirm trends that were discussed above. Here, however, we note a general reduction in the number of collisions as the mobility increases. As noted above, this decrease is justified by the network’s variations in topology rather than the operational qualities of localization. SN mobility reduces the possibility of receiving a packet, in turn reducing the load of packets sending and forwarding on the medium which results in reducing the number of possible collisions. It is more critical however, to observe the impact of aggregation on collisions, which can be justified by substantial reduction in the ending and forwarding load as a result of aggregation.

The remaining sub-figures illustrate further operational advantages of suggested aggregation. The localization employed relies on an over determined computation, whereby localization accuracy improves as more packets are received per a localized SN. This increase in accuracy is apparent in Figure 5.7(b), and is sustained as SN mobility is increased. Meanwhile, while Figures 5.6(c) and 5.7(c) illustrate the impact of mobility on the percentage of unlocalized SNs, they also show the impact of aggregation in reducing this percentage - especially at higher SN mobility.
5.5 Discussion and Further Observations

In addition to other extensive evaluations, the above results indicate a need for carefully designed localization algorithms. Even for the proposed aggregation technique, further optimization remains possible. For example, the exact relationship between hold time and mobility need to be further explored. Another issue of concern is that of MAC operation, especially when it comes to functionalities such as localization. This impact of MAC is apparent in Figures 5.4(d) and 5.5(d) which show the number of collisions in MAC layer, which even after aggregation is quite substantial.

It is also important in optimizing or re-designing the localization procedures to keep in mind the ultimate objective, which is accurate localization. In investigating the suggested aggregation, we explored its impact on localization accuracy, or
rather error. Figure 5.8 shows the mean localization error for the static and mobile settings discussed in Section 5.4.2 above. In the figure, it can be observed that aggregation reduces the localization error. This decrease in error results specifically from aggregation connecting the SNs to more anchors.

Enhancements to localization procedures are hence required to be made at several layers, especially when it comes to accommodating scale and mobility. In this study, we initially isolated the localization functionality from other network operations. We understand, however, that more elaborate studies can identify further optimizations, where enhancements such as packet sharing between different functionalities can be explored. Such an expansive view is indeed the subject of our future investigations.

5.6 Conclusion

In this chapter, we propose a new aggregation technique that manages the overhead generated from localization algorithms in large scale deployments. We investigate the impact of using the aggregation techniques in different scales and mobility scenarios. Our investigations examined various operation aspects, including number of packets transmitted and received, network collisions, localization accuracy and percentage of unlocalized SNs. The results presented in this chapter show that the aggregation technique complements the localization technique, and is specifically useful in enhancing the localization performance and enhances the performance of the WSN. Collectively localization techniques play a crucial role in WSNs, where location based services and functionalities are important for both the network and the users. It is more important to simultaneously reduce the network requirements and enhance the accuracy of localization procedures in large network deployments.
Chapter 6

Employing Mobile Anchors in Large Scale Deployments

Many WSNs applications involve random deployment of SNs in isolated terrains with no central access roads, e.g., dense rain forest or expanded rocky areas. Due to the limited transmission range of WSNs, SNs collect information about the environment and send the collected information to the SNs at the edge of the topology using multi-hop communication. Figure 6.1 shows an example of isolated SNs. To localize SNs isolated from the network edge, a multi-hop localization technique is needed. As the processing of the location information propagates to the isolated nodes, error accumulates, decreasing the estimation accuracy as the number of hops increases [51].

Localizing SNs using multi-hop techniques involves deploying anchor nodes that broadcast their location information with operation instructions to the SNs. In turn, SNs would utilize this information to estimate their own location. These techniques commonly relied on high-density deployment of costly anchor nodes to ensure the
availability of sufficient reference points for all SNs. Such assumptions become problematic in the context of IoT, where densities of SNs or Things are expected to be higher, more ad hoc, and spread over wider areas, and where the use of dedicated “anchoring” becomes eventually both costly and ineffective.

While IoT emerges with its unique challenges, it also brings forth unique opportunities. A relevant example can be readily seen in the ubiquity of today’s smartphones that possess a collective capability of communication, processing, storage, recording (audio, image and video), and localization (GPS and assisted GPS). However, a more pronounced manifestation of an IoT opportunistic resource are smart vehicles that interact not only with navigation and broadcast satellites, but also with passenger smartphones, roadside components, and other vehicles on the road. In this work we capitalize on the emergence of these smart vehicles, specifically by using them as mobile anchors. When smart vehicles move in straight trajectories, the flip ambiguity problem results as discussed in Section 2.5. To overcome flip ambiguity, we propose a new localization technique that estimates the distance between two nodes using RSSI measurements. SNs then estimate their location using the estimated distance and laws of trigonometry [91].
In this chapter, we propose a new and robust localization technique that uses smart vehicles to localize isolated SNs. In the proposed technique, the SNs estimate their locations from multiple directions, which decreases the effect of the error propagation. After this process, a KF is used to decrease the localization error coming from the longer hop direction, based on the information coming from the shorter hop direction. Simulation results show that using information from two different directions significantly increases localization accuracy.

The remainder of this chapter is organized as follows. Section 6.1 offers a concise definition of the problem being addressed and details the proposed solution. Section 6.3 details the simulation environment used for validation and analysis, along with results and discussions. Finally, conclusions are made in Section 6.4, along with an elaboration on possible future directions.

6.1 Problem formulation

We consider a two-dimensional WSN localization problem, where there are two roads at both ends of the sensing area as shown in Figure 6.1. Assume that there are $M$ SNs that are deployed randomly in the sensing area, where the SNs need to localize their locations. The location of $i^{th}$ SN is denoted by $x_i = [x_i \ y_i]^T$. The distance measured between the $i^{th}$ and $j^{th}$ SN is:

$$d_{i,j} = d_{j,i} = r_{i,j} + \varepsilon_{i,j} \quad \forall i, j = 1, 2, \ldots, M$$ (6.1)

where $r_{i,j} = \|x_i - x_j\|$ is the noise free distance between SN $i$ and $j$, and $\varepsilon_{i,j} \sim \mathcal{N}(0, \sigma_{i,j}^2)$ represents the uncorrelated noise. The $\sigma_{i,j}^2$ is assumed to be accurately estimated and is known a priori [84]. Let $\alpha_i^l$ and $\alpha_i^r$, $\forall i = 1, 2, \ldots, n$, respectively be
the locations where the left and right mobile anchor nodes broadcast their locations while they are moving along the edges of the sensing area. The mobile anchor sends its location in the location packet that is sent to localize the SNs. Each SN localizes its location two times from the left and right sides and saves the number of hops to the left and right edge. The estimated locations of \( i^{th} \) SN from the left and right side that are \( p \) and \( q \) hops away from the left and right anchor nodes are represented by \( \tilde{x}_{l,p}^i \) and \( \tilde{x}_{r,q}^i \), respectively. For example, \( \tilde{x}_{l,3}^k \) means SN \( k \) received a packet that is 3 hops away from the left edge.

### 6.2 Robust Multi-hop Localization Technique

The robust multi-hop localization technique using multiple directions is described in detail in this section. The two main goals for this approach are: 1) to enhance the location estimation of localized SNs without deploying anchor nodes in the sensing area as the cost of anchor nodes is much higher than normal SNs and 2) to propose a solution that overcomes the collinearity problem that appears from using a mobile vehicle that moves in straight lines. To simplify the description of our technique, and without loss of generality, we review the operation of the technique using only two mobile anchors, each sending location packets from a different direction. In the following, we first describe how location packet is processed. Next, the proposed technique used to estimate the SN location is discussed. Finally, we introduce the KF that is used to reduce the localization errors.
Algorithm 1: Processing the location packet at Node $k$.

```plaintext
Function CheckPosMsg(recSeqNum, recHopNum, srcIP, $x_i$, $d_{ik}$)
switch unknownPosMap, leftPosMap and rightPosMap do
  case unknownPosMap, leftPosMap, rightPosMap are empty
    Add $x_i$ to unknownPosMap;
    savedUnknownHopNum $\leftarrow$ recHopNum;
    if recHopNum $== 1$ then unknownNodeState $\leftarrow$ borderNode;
    else unknownNodeState $\leftarrow$ normalNode;
  case leftPosMap and rightPosMap are empty
    $y_{avg} \leftarrow \text{GetYAverage}(unknownPosMap);
    if $|y_{avg} - y_i| < \epsilon$ then
      Add $x_i$ and $d_{ik}$ to unknownPosMap;
      break;
    else
      Move unknownPosMap to leftPosMap;
      rightNodeState $\leftarrow$ normalNode;
      if recHopNum $== 1$ then rightNodeState $\leftarrow$ borderNode;
      else rightNodeState $\leftarrow$ normalNode;
      Add $x_i$ and $d_{ik}$ to rightPosMap;
      if leftNodeState is borderNode then
        EstimateNodeKPos(leftPosMap, left);
      else
        Move unknownPosMap to rightPosMap;
        if recHopNum $== 1$ then rightNodeState $\leftarrow$ borderNode;
        else rightNodeState $\leftarrow$ normalNode;
        Add $x_i$ and $d_{ik}$ to leftPosMap;
    Forward the received packet;
  case leftPosMap and rightPosMap are not empty
    $y_{avg} \leftarrow \text{GetYAverage}(leftPosMap);
    if $|y_{avg} - y_i| < \epsilon$ then
      if recHopNum $> savedLeftHopsNum$ then return (Packet coming from longer route);
      Add $x_i$ to leftPosMap;
    else
      if recHopNum $> savedRightHopsNum$ then return (Packet coming from longer route);
      Add $x_i$ and $d_{ik}$ to rightPosMap;
      if leftNodeState is borderNode then
        EstimateNodeKPos(leftPosMap, left);
      else
        Forward this packet;
```

6.2.1 Processing the Location Packet

Each SN estimates its location $\tilde{x}_i$ using location coming from the left ($\tilde{x}_i^{lp}$) and right ($\tilde{x}_i^{rq}$) directions. The SNs, therefore, need not know the direction of the packet to estimate location. Each SN requires a minimum of two SNs, with a known location from each direction, in order to estimate its location from one direction. This localization technique contains two phases of location packets. The first location packet
6.2. ROBUST MULTI-HOP LOCALIZATION TECHNIQUE

Algorithm 2: Packet direction is known. The packet is coming from the left direction.

1 Function CheckPosMsgDirKnown (seqNum, hopNum, srcIP, $x_i, d_{ik}, \text{msgDir}$)  
2 \hspace{1em} if msgDir == left then  
3 \hspace{2em} if hopNum > savedLeftHopsNum then \hspace{1em} \hspace{1em} return (Packet coming from longer route);  
4 \hspace{2em} savedLeftHopsNum ← seqNum for srcIP;  
5 \hspace{2em} Add $x_i$ and $d_{ik}$ to the leftPosMap;  
6 \hspace{2em} if size of leftPosMap > 2 then  
7 \hspace{3em} EstimateNodeKPos(leftPosMap, left);  
8 \hspace{2em} else if msgDir == right then  
9 \hspace{3em} if hopNum > savedRightHopsNum then \hspace{1em} \hspace{1em} return (Packet coming from longer route);  
10 \hspace{3em} savedRightHopsNum ← seqNum for srcIP;  
11 \hspace{3em} Add $x_i$ and $d_{ik}$ to the rightLocationMap;  
12 \hspace{3em} if size of rightPosMap > 2 then  
13 \hspace{4em} EstimateNodeKPos(rightPosMap, left);  

phase is when the direction of the packet is unknown, while the second location packet phase is when the direction of the packet is known and the location of the SNs at the border is estimated.

The first phase location packet has three different maps: unknownPosMap, leftPosMap and rightPosMap. The unknownPosMap saves anchor SN locations along with the distance between the anchor node and itself when the direction of the packet is unknown at the beginning. The leftPosMap and rightPosMap are used when the SN has enough information that enables the SN to identify whether the packet is coming from the right or left direction. This localization technique has three cases, as shown in Algorithm 1, to process the location packet: case 1 is used when the three Maps are empty; case 2 when the leftPosMap and rightPosMap are empty; and
6.2. ROBUST MULTI-HOP LOCALIZATION TECHNIQUE

case 3 when leftPosMap and rightPosMap contains data.

In case 1, when the three maps are empty, this means that this is the first location packet received by the SN. The location of the anchor and the estimated distance is saved in unknownPosMap. After that, the SN checks the number of hops, if it is equal to 1 then the SN declares itself to be a border SN otherwise it is a normal SN.

For case 2, when leftPosMap and rightPosMap are empty, it means the direction of the packet is not identified yet. Thus the SN has to identify whether the received packet is coming from the same direction or from the other direction. This process is done as follows. First, the SN calculates the average of \( y \) in unknownPosMap. It then compares the \( y_{avg} \) with the received \( y_i \). If the difference between them is smaller for a given threshold, it means that the change in \( y \) is very small, and the packet is coming from the same direction as the previous packets. In this case, the SN verifies that the packet is not coming from a longer route and then adds the received anchor SN location to the unknownPosMap. However, if the difference between \( y_{avg} \) and received \( y_i \) is greater than the given threshold, then this means the packet is coming from the other direction. If the received \( y_i \) is less than the saved average \( y_{avg} \), then the received packet is coming from the left direction. Thus the location of the anchor node is saved in leftPosMap and unknownPosMap is copied to rightPosMap and vice versa if the received \( y_i \) is greater than the saved average \( y_{avg} \). Finally, the SN forwards the location packet.

For case 3, when leftPosMap and rightPosMap are not empty, it means that the direction of the packet can be determined. To identify the direction of the received packet, the SN estimates the average \( y \) of one of the saved maps (in our case, we chose average of leftPosMap). If the difference between \( y_{avg}^{left} \) and received \( y_i \) is less than a
given threshold, this means the packet is received from the left direction, otherwise it means it is coming from the right direction. If the packet is coming from the left direction, the SN checks that the packet is not coming from a longer route. After that, the anchor node location is added to the leftPosMap and vice versa if it is coming from the right direction. Then the SN checks its status, if it is a normal SN then it will forward the received location packet. But if it is a border SN, it estimates its location then forwards its location to the surrounding SNs.

When an SN in the middle receives a second phase location packet, it processes the second phase location packet as follows. The SN checks the number of hops of the received packet. If the received number of hops is larger than the saved number of hops, the SN discards the packet as it is coming from a longer route. Otherwise, the SN saves the received number of hops and this hop number represents how far the SN is from the edge in which the received direction. The SN then saves the location of the SN that sends the location packet. Algorithm 2 shows the main procedure to check the packet with known direction.

### 6.2.2 Estimating the SN Location.

After an SN receives two or more location packets that have the same number of hops, it estimates the three distances $d_{i,j}, d_{i,k}, d_{j,k}$ for each pair as shown in Figure 6.2, where the locations of $x_i$ and $x_j$ are previously known (i.e., two different locations for two mobile anchor nodes or normal SNs that have estimated their location in a previous step) and $x_k$ is the location of SN $k$ that needs to estimate its location.

In order to estimate $x_k$, we need to estimate the coordinates of point $x_l$ representing the intersection between $d_{i,j}$ and the height $h$ of triangle $d_{i,j}, d_{i,k}, d_{j,k}$. The
6.2. ROBUST MULTI-HOP LOCALIZATION TECHNIQUE

coordinates of \( x_l \) are calculated as follows:

\[
\begin{bmatrix}
x_l \\
y_l
\end{bmatrix} = \begin{cases}
\begin{bmatrix}
x_i \\
y_i
\end{bmatrix} + \frac{l}{d_{i,j}} \begin{bmatrix}
x_j - x_i \\
y_j - y_i
\end{bmatrix} & \text{for } \hat{D}_{j,k} \leq 90 \\
\begin{bmatrix}
x_i \\
y_i
\end{bmatrix} + \frac{l}{d_{i,j}} \begin{bmatrix}
x_j - x_i \\
-(y_j - y_i)
\end{bmatrix} & \text{otherwise}
\end{cases}
\]

for \( D_{j,k} \leq 90 \),

\[
l = \sqrt{h^2 + d_{i,k}^2 - (2 \times h \times d_{i,k} \times \cos(\hat{L}))}.
\]
In order to calculate \( l \) we need to calculate \( h \) and angle \( \hat{L} \). \( h \) is given by:

\[
h = \frac{2 \times d_{i,k} \times d_{i,j} \times \sin (\hat{D}_{j,k})}{d_{i,j}}.
\]  

(6.4)

where the angle \( \hat{D}_{j,k} \) is calculated using:

\[
\hat{D}_{j,k} = \cos^{-1}\left(\frac{d_{i,j}^2 + d_{j,k}^2 - d_{i,k}^2}{2 \times d_{i,j} \times d_{j,k}}\right),
\]  

(6.5)

and the angle \( \hat{L} \) as:

\[
\hat{L} = \begin{cases} 
90 - \hat{D}_{j,k} & \text{for } \hat{D}_{j,k} \leq 90 \\
\hat{D}_{j,k} - 90 & \text{otherwise}
\end{cases}
\]  

(6.6)

After estimating the coordinates of \( x_l \), we get the slope between SN \( i \) and \( j \) to calculate \( x_k \) to consider the shift in \( x \) and \( y \) coordinates caused by the slope of the line \( m_{d_{i,j}} = \tan^{-1}\frac{y_j - y_i}{x_j - x_i} \). This allows us to estimate the location of the SN using collinear and non-collinear anchor nodes.

SN \( k \) estimates its location based on the direction of the packet. Thus, if the packet is coming from the left direction, SN \( K \) estimates \( \tilde{x}_{l,p}^k \) by:

\[
\tilde{x}_{l,p}^k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_l \\ y_l \end{bmatrix} + h \begin{bmatrix} \sin(m_{d_{i,j}}) \\ -\cos(m_{d_{i,j}}) \end{bmatrix}.
\]  

(6.7)

Otherwise, if the packet is coming from the right direction, SN \( k \) estimates \( \tilde{x}_{r,q}^k \) by:

\[
\tilde{x}_{r,q}^k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_l \\ y_l \end{bmatrix} + h \begin{bmatrix} -\sin(m_{d_{i,j}}) \\ \cos(m_{d_{i,j}}) \end{bmatrix},
\]  

(6.8)

where \( \tilde{x}_{l,p}^k \) is the estimated location from the left direction that is \( p \) hops away from
the left edge and $\tilde{x}_k^{r,q}$ is the estimated location from the right direction that is $q$ hops away from the right edge. Algorithm 3 shows the procedure for estimating the SN’s location from the left and right directions.

After SN $k$ estimates its direction from both directions, the SN can use the mean to estimate its location. However, the estimated location from the direction with the larger number of hops contains more errors than the direction with the smaller number of hops (i.e., if $q < p$, then $\tilde{x}_k^{r,q}$ is more accurate than $\tilde{x}_k^{l,p}$). Using the mean the SN does not take into consideration the error propagated for each hop. Thus, the weighted mean can be used to consider the propagation error for each hop. The weighted mean estimation is calculated as follows:

$$\tilde{x}_k = \frac{(\tilde{x}_k^{l,p} \times q) + (\tilde{x}_k^{r,q} \times p)}{p + q}.$$  

(6.9)

However, the weighted mean does not take into consideration the error gained from each hop, which motivates our use of Kalman filtering.

### 6.2.3 Location Enhancement Using the Kalman Filter

We propose to use KF in place of the weighted mean. KF is an optimal estimation tool that enhances one measurement giving a more accurate measurement from another source using a sequential recursive algorithm [3]. We use a KF that corrects the estimated location of the side that has the larger number of hops using the information provided from the side that has the smaller number of hops. This helps to estimate the error resulting from the larger number of hops. Figure 6.3 shows the KF block diagram used in this study.

In order to complete the development of the state-space of the discrete time KF
Algorithm 3: Estimate the location of SN k

1. **Function** `EstimateNodeKPos (posMap, msgDir)`
2. 
   ```
   Function EstimateNodeKPos (posMap, msgDir)
   counter ← 0
   foreach x_i and d_i,k in posMap do
     foreach x_j and d_j,k in posMap do
       if x_i == x_j then Continue;
       counter + +;
       d_{i,j} ← \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2};
     Calculate l = \sqrt{h^2 + d_{i,k}^2} - (2 \times h \times d_{i,k} \times \cos(\hat{L})};
     if \hat{D}_{j,k} \leq 90 then
       \hat{L} ← 90 - \hat{D}_{j,k};
       x_l ← x_i + \frac{l}{d_{i,j}} \times (x_j - x_i); \\
       y_l ← y_i + \frac{l}{d_{i,j}} \times (y_j - y_i);
     else
       \hat{L} ← \hat{D}_{j,k} - 90;
       x_l ← x_i + \frac{l}{d_{i,j}} \times (x_j - x_i); \\
       y_l ← y_i + \frac{l}{d_{i,j}} \times -(y_j - y_i);
     Calculate m_{d_{i,j}} = \tan^{-1} \frac{y_j - y_i}{x_j - x_i};
     if msgDir == left then
       p ← savedLeftHopNum;
       estimate \hat{x}^{l,p}[counter] using eq 6.7;
     else if msgDir == right then
       q ← savedRightHopNum;
       estimate \hat{x}^{r,q}[counter] using eq 6.8;
     if msgDir == left then
       \hat{x}^{r,p}_k ← GetAverage(\hat{x}^{l,p})
     else if msgDir == right then
       \hat{x}^{r,q}_k ← GetYAverage(\hat{x}^{r,q})
   ```

3. equations, the system’s dynamic and measurement models for the SN have to be defined. The system static and measurement model equations if \( p < q \) (\( \hat{x}^{l,p}_k \) and \( \hat{x}^{r,q}_k \) are switched if \( q < p \)) are represented as follows, respectively:

   \[ \hat{x}^{r,p}_k = \phi_k \hat{x}_k + \omega_k^p \]  
   \( (6.10) \)
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Figure 6.3: The KF left/right integration for \( p < q \) [3].

\[
z_k = \mathbf{x}_k^{l,q} = H_k \mathbf{x}_k + v_k^q
\]  
(6.11)

where \( \mathbf{x}_k \) is the actual location of the SN, \( \phi_k \) is a static transmission matrix that relates \( \mathbf{x}_k \) with its previous state. Since there is no change in the SN state, i.e., location, the \( \phi_{k,k-1} \) matrix is represented as an identity matrix, \( Q_k^p = E[\omega_k^p (\omega_k^p)^T] \) and \( R_k^q = E[v_k^q (v_k^q)^T] \) are the covariance matrices for the \( p \) and \( q \) hop count coming from the left and right directions. \( Q_k \) and \( R_k \) are assumed to be uncorrelated as they are received from two different directions with different numbers of hops.

Cho et al. calculate \( Q_k \) and \( R_k \) for single hop as \( \frac{R_3}{2} \times I \), where \( R \) is the normal distribution of error placement for a single hop [92]. In order to calculate \( Q_k \) and \( R_k \) for multi-hops, we expanded their proof to calculate \( Q_k \) and \( R_k \) for multiple hops. \( Q_k^p \) and \( R_k^q \) are calculated in our work as follows:

\[
Q_k^p = E[\omega_k^p (\omega_k^p)^T] = \begin{bmatrix}
\frac{\sum_{i=1}^{p}(\sigma_i^3)^3}{2} & 0 \\
0 & \frac{\sum_{i=1}^{p}(\sigma_i^3)^3}{2}
\end{bmatrix}
\]  
(6.12)
Table 6.1: A Summary of Kalman Filter equations for $p < q$.

<table>
<thead>
<tr>
<th>Kalman Filter Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariance matrix initialization:</td>
</tr>
<tr>
<td>$P_0 = E((x - \tilde{x}_0)(x - \tilde{x}_0)^T)$ (6.14)</td>
</tr>
<tr>
<td>State estimate extrapolation:</td>
</tr>
<tr>
<td>$\tilde{x}<em>k(-) = \phi_k \tilde{x}</em>{k-1}(+)$ (6.15)</td>
</tr>
<tr>
<td>A priori covariance matrix:</td>
</tr>
<tr>
<td>$P_k(-) = \phi_k P_k(+) \phi_k^T + Q_{k-1}$ (6.16)</td>
</tr>
<tr>
<td>Kalman gain matrix:</td>
</tr>
<tr>
<td>$K_k = P_k(-)H_k^T(H_k P_k(-)H_k^T + R_k)^{-1}$ (6.17)</td>
</tr>
<tr>
<td>Update the estimated location:</td>
</tr>
<tr>
<td>$\tilde{x}_k(+^1) = \tilde{x}_k(-) + K_k(\tilde{x}_k^l - H_k \tilde{x}_k(-))$ (6.18)</td>
</tr>
<tr>
<td>A posteriori covariance matrix:</td>
</tr>
<tr>
<td>$P_k(+) = (I - K_k H_k) P_k(-)$ (6.19)</td>
</tr>
</tbody>
</table>

$$R^p_k = E[\nu_k^q (\nu_k^q)^T] = \begin{bmatrix} \sum_{i=1}^{q} (\sigma_i^q)^3 & 0 \\ 0 & \sum_{i=1}^{p} (\sigma_i^p)^3 \end{bmatrix}$$ (6.13)

where $\sum_{i=1}^{p} \sigma_i^2$, is the summation of the uncorrelated noise in Equation 6.1 from hop 1 to hop $p$ and similar for $\sum_{i=1}^{q} \sigma_i^2$.

The KF equations used in this study are summarized in Table 6.1. The steps using KF are as follows if $p < q$ ($\tilde{x}_k^{l,p}$ and $\tilde{x}_k^{r,q}$ are switched if $q < p$). First, the covariance matrix is initialized at the left border SN using Equation 6.14. After that, the SN calculates the priori covariance and Kalman gain matrices using Equations 6.16 and 6.17. Then, the right location $\tilde{x}_k^r$ is updated to $\tilde{x}_k^r$ using Equation 6.18. Later, the SN calculates the posteriori covariance matrix using Equation 6.19 using the computed values of $K$, pervious state of $\tilde{x}_k^r(-)$ and the accurate data $\tilde{x}_k^l$ in Equations 6.17, 6.15 and 6.16 respectively. Finally, the SN forwards the Posteriori $P_k(+)$. matrix to the
next hop SNs to be used as the priori covariance matrix $P_k(-)$. The SNs that are
away from the edge of the network do the same steps except they use the received
posteriori covariance matrix instead of creating a new one. Finally the SNs estimate
their new location using the following equation:

$$\tilde{x}_k = \frac{\tilde{x}_{k}^{l,p} + \tilde{x}_{k}^{r,q}}{2}$$

(6.20)

6.3 Performance Evaluation

In this section we evaluate the performance of the proposed technique in three different
scenarios. The first scenario compares the error between using fixed anchor nodes
against using mobile anchor nodes. To do so, we first calculate the number of fixed
anchors required to cover a road with a given length, then perform the comparison
between using fixed and mobile anchors. In the second scenario we investigate the
accuracy of the localization estimation as the number of hops increases. Finally in the
third scenario we compare the effect of increasing the number of hops by increasing
the width of the simulation area.

The metric utilized in the first scenario is the localization mean error after esti-
mating the location using KF as in equation 6.20. In the second and third scenarios,
we compare four different estimation techniques for our localization technique: 1) using one direction that has fewer number of hops, 2) using the mean of both sides,
3) using the weighted mean of both sides using equation 6.9, and 4) using KF using
equation 6.20 against DV-Distance localization technique [51]. The anchor nodes
used for DV-Distance are fixed on the edge of the simulated area. Our simulations are
made in ns-3 [87] using the error model proposed in Chapter 3. The communication
range of anchors and SNs are set to 30m. All results are averages of ten different independent runs with distinct random seeds.

6.3.1 Minimum Number of Static Anchor Nodes

Before we compare the result between using mobile against static anchor nodes, we need to identify the minimum number of static anchors on each side of the road that are required to replace the mobile anchor. To facilitate the illustration, we assume that the static anchor nodes are placed in a straight line, and that transmission ranges
are fixed and are not effected by signal distortion, i.e., have a perfectly circular shape.

The scenario considered in Figure 6.4 where SN A and C are almost on the same border line. However SN A is only covered by 1 anchor node “x₂”, while SN C is covered by 2 anchor nodes “x₁ and x₂”. This means that not all SNs on border line 1 are guaranteed to be covered by 2 anchor nodes. On the other hand, SN B by comparison is covered by 3 anchor nodes, which means that SNs on border 2 are guaranteed to be covered by at least 2 anchor nodes. This line is defined by the point of intersection between the two circles x₁ and x₃, which is the location of SN B. Thus, to measure the distance between the anchor nodes “d”, we have to know how far the border line of the isolated SNs is from the line where the anchor nodes are located. The distance between the line of anchor nodes and the border SN is represented by the symbol h.

The distance between two anchor nodes can be calculated using triangle x₁, x₂ and SN₀. Since we have two known sides, which are how far the SNs are far from the anchor nodes represented by h and the transmission range for the anchor node represented by r, we can get the length of the third side using Pythagoras theorem formula. Thus the distance between two anchor nodes can be calculated as:

\[ d = \sqrt{r^2 - h^2} \]  

(6.21)

Therefore, the number of SNs required to cover each side is given by the following equation:

\[ \text{Number of anchor nodes} = \frac{l}{\sqrt{r^2 - h^2}} + 1 \]  

(6.22)
6.3. PERFORMANCE EVALUATION

The Total Width of the Simulated Area

Figure 6.5: Comparison between static and mobile anchor nodes.

where \( l \) is the length of the road. Thus the number of SNs is directly proportional with the height of the simulated area, and inversely proportional with the transmission range and how far the SNs are from the border.

### 6.3.2 Static vs. Mobile Anchor Nodes

After we identified the minimum number of static nodes that are required to cover each side of the road in the previous subsection, in this subsection we compare the performance of static and mobile anchor nodes. 500 SNs are deployed randomly in a simulated area with a width of 100 m and the length of the road is changed from 100 m to 400 m in 50 m increments. For the static nodes approach, SNs are fixed in their location and the distance between fixed anchor nodes is calculated based on section 6.3.1. The location of the static SN is assumed to arrive accurately at the SNs, while a fixed error is introduced in the mobile anchors location broadcasts. The error is equal to 10% of the distance between the road and the sensor network.

Figure 6.5 shows the average location error for fixed and mobile anchor nodes, these results for both of them is after using the KF. Figure 6.5 shows that the accuracy
of using fixed anchors is very similar to using the mobile anchors. However, static anchors give a little higher location accuracy than mobile anchors. Although there is a location error introduced to the location of the mobile anchor, the difference between the accuracy of using a mobile anchor with inaccurate location is less, around 0.5 m, which is much lower than the error introduced to the mobile anchors. This is because the KF enhances the estimated localization.

### 6.3.3 Localization Error per Number of Hops

In this scenario, we examine the localization error for each hop as the number of hops of the shortest side increases in the same simulation area. We randomly deploy 200 SNs in a simulation area 400 m × 100 m, since we are interested in studying the effect of number of hops on our localization accuracy, which is affected by the width of the simulated area. Thus we increase the width of the simulated area to be 4 times its length. The maximum number of hops from one end to the other using the above dimension is 17. For DV-Distance, the number of fixed nodes is calculated using equation 6.4 in subsection 6.3.1.

Figure 6.6 illustrates that using mean estimation for our techniques shows a similar trend as using DV-Distance, as the localization accuracy is worse at the edges and improves in the middle of the simulation area. This shows that DV-Distance technique works similar to the mean estimation, i.e., give similar weight to the longer and shorter hops. For all other estimation techniques as the number of hops increases the localization error increases. Figure 6.6 shows that using KF gives the least estimation error, while the mean estimation gives the highest estimation error. The mean estimation gives the worst results when the difference between the number of
hops is larger as the error from the direction that has a larger number of hops is huge, which affects the overall estimation accuracy when we take the mean. However, by taking the weighted mean, we give a lower weight for the estimation from the direction that has a larger number of hops. The improvement of KF over the weighted mean is between 19% and 13% with an overall mean of 15.6%. Estimating the location using shortest hop only, weighted mean and KF gives a very high accuracy when the difference between the two directions is the maximum, i.e., near the edge of the simulation area. However, the estimation error for shortest hop only is higher than weighted mean and KF for SNs that are four hops away from the edge of the network and reaches the maximum in the middle of the network performance is worse than the KF by 51.7%. This is because using shortest hop only does not benefit from the information coming from the other direction. Moreover, using our technique with KF is better than using DV-Distance technique by 28% on average.
6.3. PERFORMANCE EVALUATION

6.3.4 Localization Error per Width Change

In this scenario, we compare the overall localization error as we increase the number of hops by increasing the simulation area. We randomly deployed 200 SNs in a simulation area with a length of 100 m and the width of the simulation area is changed from 200 m to 400 m in 40 m increments.

Figure 6.7 shows that using the mean gives the worst localization accuracy, while using the KF gives the best accuracy. KF gives better localization accuracy than weighted mean by 15.6% on average and better than a single side by 31% on average. The DV-Distance localization technique gives a better accuracy than using the mean, however its localization performance is worse than Shortest distance only, weighted mean and using KF. The reason that the KF gives a better result than the weighted mean is the KF estimates and assigns the weights automatically. Moreover, KF takes into consideration the propagation error per hop, while the weights in the weighted mean are fixed and the propagation errors per hop are not taken into consideration.
In this chapter we employ mobile anchors to localize isolate SNs in large scale deployments. We propose a new localization scheme to localize SNs using two mobile anchor nodes through multi-hop. Our new scheme is divided into two phases. The first phase, the scheme estimates the location for each node from two different directions using the estimated distance between nodes and the flow direction of the message. The second phase, we apply Kalman Filter to improve localization accuracy. Simulations results show that the proposed scheme, which estimates locations from both directions, gives better results than estimating the location from a single direction especially when the number of hops increases. Moreover, the results show that using Kalman Filter increases the accuracy of our scheme.

To achieve a similar localization accuracy either to use a high density of stationary SNs, which increases the cost of the WSN, or to use a mobile anchor that have to access the isolated area, which is not feasible in some deployments. Moreover, our new localization scheme estimates the location of SNs using collinear and non-collinear mobile anchor nodes, where in previous work they have to ensure that the path of the mobile anchor does not move in a collinear trajectory.
Chapter 7

Summary and Conclusions

The last decade has witnessed a growing interest in WSN localization due to its unique potential in a wide range of environmental, scientific, civilian and military applications. However, this critical missions require a high level of localization accuracy to ensure precise location of the sensed data within a reasonable cost. Knowing the position of sensor nodes in environmental monitoring is useful to identify the location of events. In large scale deployments the area covered is very large making it impossible to localize all SNs using single-hop localization techniques. A solution to this problem is to use a multi-hop localization technique to estimate SN positions.

Evaluating multi-hop localization techniques in large areas is expensive and time consuming, especially if the experiments involve hundreds or thousands of SNs in an area that covers hundreds of square meters. Thus, creating a realistic simulation model is required, using a network simulation provides a rich opportunity for efficient experimentation, as simulation gives practical feedback before designing real world systems. This allows us to determine the correctness and efficiency of the localization
techniques before the actual deployment of the SNs. Thus, we build a realistic simulation model to use to study and investigate the behavior of multi-hop localization techniques in large scale deployments and propose new schemes for multi-hop localization. After that we characterize the error behavior in multi-hop localization. We show that in dense deployments it is better to decrease the transmission to achieve high localization accuracy, which will generate a large amount of traffic. Thus we proposed a new solution that decreases the number of packets generated in highly dense deployments. In all the previous studies we used fixed anchor nodes, thus we proposed to use a mobile anchor in multi-hop deployment and propose solutions for the collinearity of anchor nodes and to increase the overall localization accuracy of the network.

The work presented in this thesis is summarized in Section 7.1. Future research directions are highlighted in Section 7.2.

7.1 Summary

In Chapter 3, we studied the error model used to introduce the error to the actual distance between SNs in the simulation model. Previous simulation models added Gaussian noise to the actual distance between SNs. However we show that the estimated distance follows Rayleigh distribution not Gaussian distribution. This Rayleigh distribution is introduced by adding the introduced Gaussian error to the x and y coordinated to the SN position while simulating the RSSI estimated distance.

In Chapter 4, we characterized the relation between number of hops and localization accuracy. Three deployment scenarios are considered to perform such study including: random deployment that represents a real deployment scenario, fixed grid
that represents a controlled dense deployment, and dynamic grid that represents a controlled sparse deployment. Our results show to achieve high localization accuracy in high dense SN deployment it is better to use a larger number of hops with a shorter transmission range, while in sparse SNs deployment it is better to use a small number of hops with a longer transmission range. If DV-Distance is used in a high noisy channel it is better to use a large number of hops with a shorter transmission range in all scenarios. In general unless you have highly accurate distance estimation mechanism, it is better to use connectivity based localization technique than to use range based localization.

In Chapter 5, we proposed a new aggregation technique that substantially decreases the number of packets send during the localization process. We investigate the performance of scale and mobility on multi-hop localization with and without the proposed aggregation technique. We show that how the density and mobility of SNs would affect the accuracy of the localization techniques.

In Chapter 6, we proposed a new localization technique to localize SNs using two mobile anchor nodes through multi-hop. Our new technique is divided into two phases. The first phase, the technique estimates the location for each node from two different directions using the estimated distance between nodes and the flow direction of the packet. The second phase, we apply Kalman Filter to improve localization accuracy. Simulation results show that the proposed technique, which estimates positions from both directions, gives better results than estimating the position from a single direction especially when the number of hops increases. Moreover, the results show that using Kalman Filter increases the accuracy of our technique.
7.2 Future Work

Several future research problems can be derived from our work thus far. In this section we point out the future work that can be done for each chapter.

In Chapter 3, we assumed the noise added to the $x$ and $y$ follows normal distribution that have the same $\sigma$, and by squaring the two values and taking the square root the estimated distance follows the Rayleigh distribution. An interesting part to investigate is if the noise added to the $x$ and $y$ follows normal distributions that have different $\sigma$ in this case the estimated distance would follow Chi distribution.

In Chapter 4, we studied the effect of hops on localization accuracy for an isotropic network. However, it would be feasible to extend the study for anisotropic network. In this case the non-uniform SNs will have a different effect on the average hop metric used in the localization technique. A good understanding for the hops behavior in anisotropic network would definitely help in improving the localization performance in such networks.

In Chapter 5, we investigate the effect of aggregating the localization packets, which resulted in substantial enhancement in both network operation and accuracy. A future project could be to identify possible enhancements by exploring cross-layer design and packet sharing between different network functionalities.

In Chapter 6, we proposed a localization technique using mobile anchor for 2-D, which covers most of network deployments as they are usually deployed on flat areas. However in some cases the terrain is 3-D as the case in mountain deployment to sense the falling rocks, or underwater deployments to monitor water pollution. In such cases a 3-D solution is required. In the 3-D environment the coplanarity condition applies, where the anchor node moves on the same plane.
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