Ph.D. Dissertation

EFFICIENT LOCALIZATION ALGORITHMS FOR WIRELESS SENSOR NETWORKS

무선 센서 네트워크 상에서의 효율적인 위치 추정 알고리즘 연구

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이 논문을 공학박사 학위논문으로 제출함

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Abstract

EFFICIENT LOCALIZATION ALGORITHMS FOR WIRELESS SENSOR NETWORKS

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In this dissertation, efficient localization algorithms for wireless sensor networks are represented. Localization algorithms are widely used in commercial systems and application. The localization techniques are anticipated to be developed for various environments and reduce the localization error for accurate location information because the user demands for more accurate positioning systems for medical care, home networks, and monitoring applications in personal range environments. A well-known localization system is GPS, with applications such as mobile navigation. The GPS shows good performance on road or roughly finding location system in outdoor environments but limited in indoor environments. Due to the development of handsets like smart phone, the users can easily receive the GPS signals and other RF signals including 3G/4G/5G signals, WLAN (Wireless Local Area Networks) signals, and the signals from other sensors. Thus, the various systems using localization schemes are developed, especially,

the WSNs (Wireless Sensor Networks) localization system is actively studied in indoor environment without GPS.

In this dissertation, the range-free localization algorithm and the range-based localization algorithm are reported for WSNs localization system. The range-free localization algorithms are proposed before to estimate location using signal database, called signal map, or the anchor nodes of antenna patterns, or ID configuration of the linked anchor nodes, etc. These algorithms generally need to additional hardware or have low accuracy due to low information for location estimation. The range-based algorithms, equal to distance-based algorithms, are based on received signal strength, RSSI, or time delay, TOA and TDOA, between the anchor nodes and a target node. Although the TOA and TDOA are very accurate distance estimation schemes, these scheme have the critical problem, the time synchronization. Although RSSI is very simple to setup the localization system with tiny sensors, the signal variation causes severe distance estimation error. The angle estimation, AOA, provides additional information to estimation the location. However, AOA needs additional hardware, the antenna arrays, which is not suitable for tiny sensors. In this dissertation, range-free and range-based localization algorithms are analyzed and summarized for WSNs with tiny sensors.

The WSNs localization systems are generally used range-based algorithm. The range-based algorithms have major source of distance estimation error, and the distance estimation error causes severe localization error. In this dissertation, the localization error mitigation algorithms are proposed in two dimensional environments and three dimensional environments for WSNs. The mitigation algorithms in two dimensional environments consist of several steps, which are distance error mitigation algorithm, location error mitigation algorithm, and bad condition detection algorithm. The each algorithm is effective to reduce the localization error, but the accuracy of location estimation is the best when they are combined. The performance of proposed

algorithms is examined with variation of received signal strength and it is confirmed that the combined proposed algorithm has the best performance rather than that of conventional scheme and each proposed algorithms. The three dimensional localization uses Heron's formula of tetrahedron to calculate the target height, then transforms a two dimensional location computed by LLSE into a three dimensional estimated location. Simulation results validate the accuracy of the proposed scheme.

Keywords: Localization, Distance estimation, Location error mitigation algorithm, 3D localization algorithm

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Chapter 1. Introduction

Localization algorithms are used in vehicle navigations using GPS, location based service based on smart phone, and other WSNs localization systems. The users who need the accurate location estimation system for various environments are increased. For example, the WSNs localization system can be used in security and safety system for private places and a missing child, emergency control systems for hospital and sanatorium, unmanned robot control system for military, etc. And then, localization systems are demanded for high accuracy and stability. The accuracy of localization system is commonly evaluated RMSE (Root Mean Squared Error) and the stability of localization system is assessed CDF (Cumulative Distribution Function) to check the error distribution. The location estimation error mitigation algorithms are discussed in many years [1]-[3]. Especially, WSNs localization system is studied actively because the WSNs are easy to setup for any environments and extend or link to other sensors. In this dissertation, the localization system with tiny sensors for WSNs is debated and the localization error mitigation algorithms are proposed for high accurate location estimation.

In chapter 2, location estimation schemes for WSNs are discussed. WSNs with tiny sensors are expected to be used widely in indoor localization system. [4]-[6] However, the WSNs localization system in indoor environments has several problems for accurate location estimation. Although the wireless sensors used in indoor environments are smart to transmit or receive signals, they have limitation to extend extra hardware which is additional antennas or signal processing units, etc. Therefore, the WSNs localization system has limitation to choose the distance or angle estimation schemes, TOA, RSSI, and AOA, and generally used RSSI because of simplicity. TOA is the time based distance estimation scheme [7]-[10]. The estimated distances are calculated by the multiplication of speed of light and the time delays between the anchor nodes and a target node. The time synchronization problem is the major source of error in TOA and TDOA. However, it is hard to solve in WSNs with tiny sensors because of hardware limitation. AOA is the one of location estimation scheme using angle estimation [11]-[12]. The angle estimation needs the antenna array and LOS environment. The accuracy of location estimation using AOA depends on the resolution of angle estimation which is generally decided by the number of antennas. Thus, the proposed mitigation algorithms are analyzed using RSSI in this dissertation [13]-[15].

In chapter 3, the location estimation error mitigation algorithms for 2D localization system are proposed. The proposed algorithms are GM (Geometric Mitigation) algorithm, CS (Coordinate Shift) algorithm, and BCD (Bad Condition Detection) algorithm. Each proposed algorithm can mitigate the location estimation error for different motivations. The accuracy of localization system is enhanced by the distance estimation error mitigation, error correction vector, and bad situation elimination. The algorithm of distance estimation error mitigation, GM algorithm [16], is based on CRLB of estimated distances. The overestimated distances caused by distance estimation error should be offset before LLS (Linear Least Square) estimation to prevent severe location estimation error because the matrix for calculation is made from the estimated distances [17]. The error correction vector is calculated from the estimated distances and the angles between the anchor nodes and estimated location by LLS estimation. The estimated location by LLS estimation still has location estimation errors which cannot be offset by the GM algorithm. The error correction vector helps the high accurate performance to reduce the location estimation error. The BCD algorithm provides more accurate performance rather than that of CS algorithm by eliminating the bad situation for location estimation. The thresholds of BCD algorithm prevent severe location estimation errors before location estimation. The details of the proposed algorithms are explained in chapter 3. And the next chapter provides the efficient localization algorithm for 3D location estimation [18]. The conventional 3D location estimation algorithms are reported a hybrid algorithm using distance estimation and angle estimation, and lots of anchor nodes are needed to estimate the 3D location. Although the 3D localization algorithms based on the estimated distances have been proposed recently, these need additional hardware for extra information. The proposed algorithm proceeds in three phases. In the first phase, the offset vector is calculated from the tetrahedron formed by three anchor nodes and the estimated distance between three anchor nodes and a target node. In the second phase, the transformed target location is estimated by two dimensional

LLSE using vector rotations on the plane which is formed by three anchor nodes. Finally, the target location is calculated by the transformed target location and the offset vector.

At the last part of dissertation, many extra works for high accurate location system are summarized. The flip ambiguity is the major issue in localization algorithm parts [19]-[20]. The flip ambiguity problems generate severe location estimation error and are hard to be detected and eliminated. In previous work, the flip ambiguity is considered in co-linear anchor node environments. However, the flip ambiguity problems can occur in any environment even if the anchor nodes are located like a regular polygon. The analysis of flip ambiguity is represented in chapter 5. And the efficient anchor node selection algorithm is also proposed.

This dissertation is organized as follows: Chapter 2 deals with the location estimation schemes for wireless sensor networks localization system. Chapter 3, the efficient localization algorithms for two dimension localization systems are proposed. In Chapter 4, the three dimensional location estimation algorithm for WSNs localization system is described. Extra works for high accurate localization systems are summarized in Chapter 5.

Chapter 2. Location estimation for wireless sensor networks

2.1 Introduction

Common localization methods are range-free algorithm and range-based algorithm. Range-free algorithm, such as the fingerprinting method [21]-[22], Centroid algorithm [23] and SeRLoc(Secure range-independent Localization) [24]. While fingerprinting method has good localization performance in site-specific, it is not practical for wireless sensor networks with tiny sensors due to the large amount of required memory size and limited hardware performance and not feasible in indoor varying environments. The accuracy limitation of Centroid algorithm depends on the number of anchor nodes and other range-free algorithms which include SeRLoc depend on additional hardware performances. Range-based algorithm should estimate the distance or angle using signal strength or time of flight. Time-of-arrival (TOA), time-difference-of-arrival (TDOA), received signal strength indicator (RSSI), and angle-of-arrival (AOA) are commonly used to measure the distance or angle between the anchor node, a known location, and the target node or called blind node.

The major issue of WSNs localization system is the limitation of hardware. Although the location estimation schemes are limited due to this issue, WSNs can provide short range environment with LOS (Line of Sight) by using the network topologies which are centralized, decentralized, and distributed system [25].

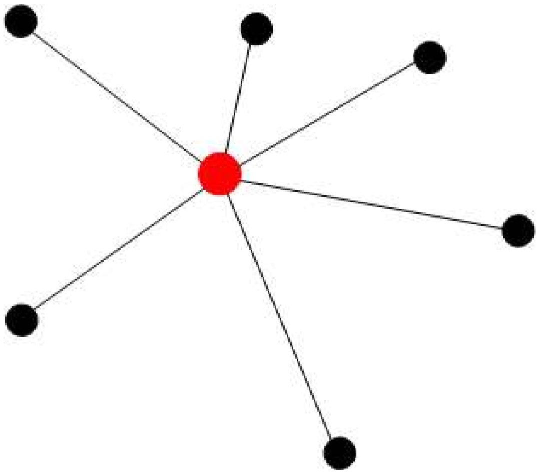


Figure 2.1 Centralized system

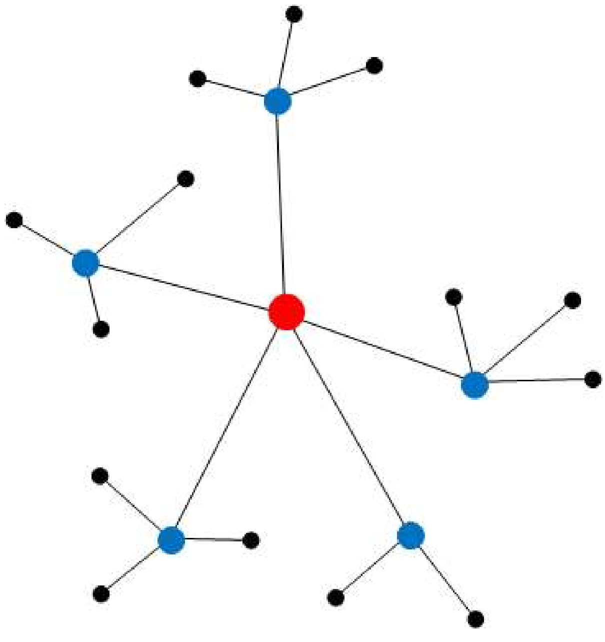


Figure 2.2 Decentralized system

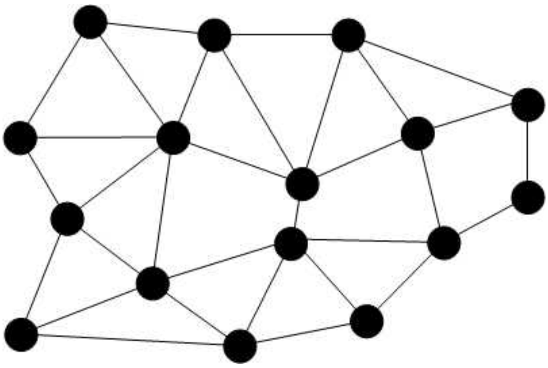


Figure 2.3 Distributed system

The location estimation schemes for WSNs are selected for tiny sensors and appropriate localization system.

This chapter is organized as follows. Section 2.2 presents the range-free location estimation schemes. Section 3.3 provides range-based location estimation schemes and section 3.4 summarizes the localization schemes for wireless sensor networks.

2.2 Range-free location estimation

2.2.1 Cell-ID location estimation

Cell-ID location estimation is typically used in cell phone system [26]-[27]. When the devices (cell phone, wireless sensors, RF tags, etc.) are linked AP (Access Point), the location of devices becomes the location of AP, or the sector of AP. Thus, the accuracy of Cell-ID depends on the range of the AP, and the users can know approximate location not exact position. Although Cell-ID location estimation has very low accuracy, Cell-ID is efficient localization method for reducing the sensing range in broad area because it is very simple method to estimate the location. Moreover, Cell-ID helps the other location estimation to provide the initial location and limitation of location estimation area.

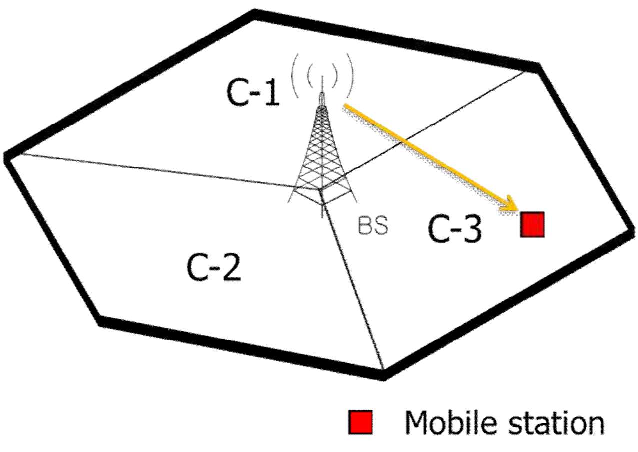
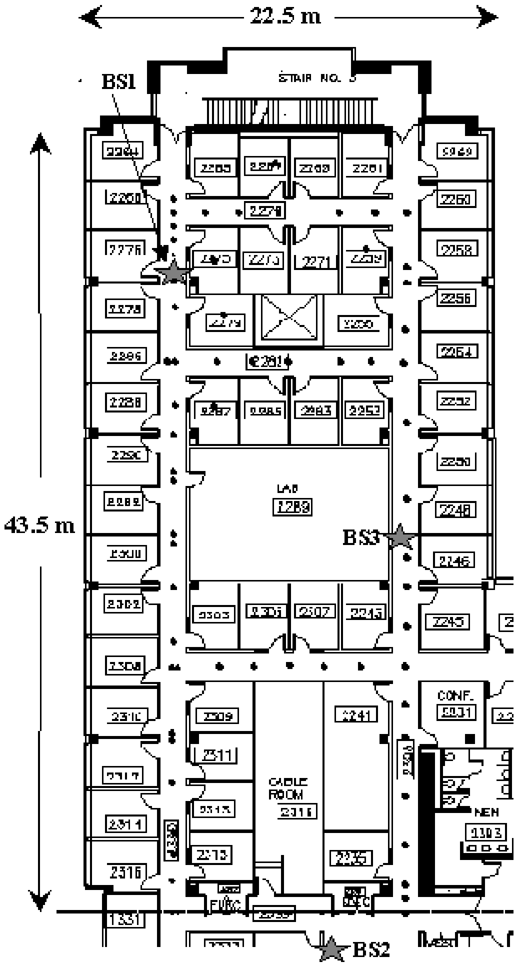


Figure 2.4 Cell-ID location estimation

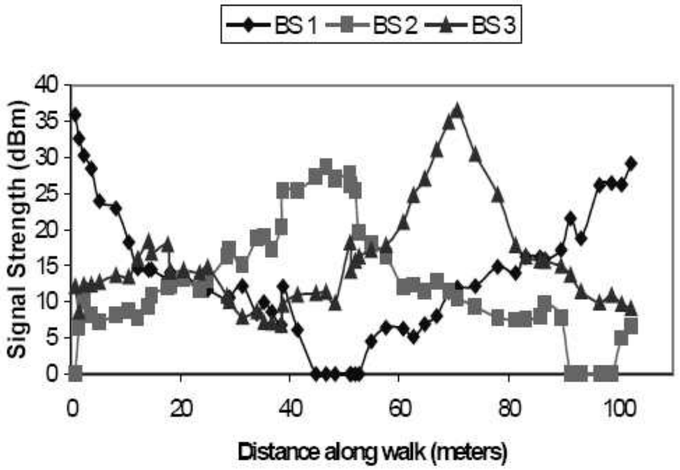
Cell-ID location estimation scheme is very suitable for wireless sensor networks. To do that, lots of access points are needed to satisfy the accuracy of localization system.

2.2.2 Fingerprint location estimation

The typical fingerprint location estimation scheme is proposed in [21]. This scheme provides the high accurate estimated location within 2~3m. The advantages of fingerprint location estimation scheme are high accuracy localization scheme in indoor environments and simple hardware due to RSS based system. The example of fingerprinting method called RADAR system proposed by Microsoft research team is presented briefly in Figure 2.5.



(a) The environment of fingerprinting localization scheme



(b) Signal strength recorded at three base stations

Figure 2.5 Fingerprinting localization scheme proposed by MS research team

Figure 2.5 (a) shows the environment of the experiments. The black dots means that the locations were empirically collected signal strength information. The big stars show the three base station, BS1, BS2, and BS3 also represented in Figure 2.5 (b). When the user walks in this map, the three base stations received signal strength from the user shown in Figure 2.5 (b). The basic approach of location estimation is the calculation of Euclidean distance between the observation set (ss1, ss2, and ss3) and the recorded set (ss'1, ss'2, and ss'3).

$$\mathrm{ED} = \sqrt{(ss1 - ss'1)^2 + (ss2 - ss'2)^2 + (ss3 - ss'3)^2} \qquad (2.1)$$

The location of the user is estimated to location of the one of black dots or the spots which is minimized Euclidean distance. The several schemes for determine the location are proposed in [21].

The fingerprinting localization method is explained how to estimation the location. The analysis of fingerprinting method for WSNs localization system is as follows. Although the advantages of the fingerprinting method are very suitable for WSNs localization system, the accuracy of the location estimation depends on the recorded data and the number of spots shown as the block dots in Figure 2.5 (a). Moreover, the recorded data can be easily distorted by RF signal environment change. When the spots recorded data are increased, the complexity of localization system is also increased because the number of comparison analysis is increased. Thus, the fingerprinting method for WSNs localization system should be check the possibility to setup the system hardware which is considered the capacity of server to save the recorded data, the calculators for location estimation. Especially, the stationary environment should be also allowed for high accuracy of location estimation.

2.2.3 Other range-free location estimation

The other conventional range-free location estimation schemes are explained briefly in this chapter. The Centroid algorithm is also widely used for simple localization system. Centroid algorithm calculates the arithmetic mean position of all linked anchor nodes.

$$(X_t,\ Y_t) = \left(\frac{\sum_{i=1}^{n} X_i}{n},\ \frac{\sum_{i=1}^{n} Y_i}{n} \right) \tag{2.2}$$

Where $(X_t,\ Y_t)$ means the estimated location of a target node, $(X_i,\ Y_i)$ represents the location of the ith anchor node, and the n is the number of linked anchor nodes.

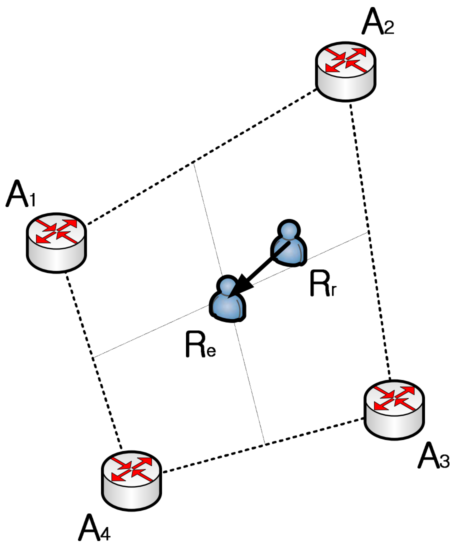


Figure 2.6 Centroid algorithm

Centroid algorithm may be the best solution to estimate the target location for WSNs localization system when the anchor nodes are densely distributed, and besides the calculation for location estimation is very simple like Cell-ID localization scheme. However, the accuracy of centroid algorithm does not increase if the number of linked anchor nodes is increased because the calculation parameter of centroid algorithm is only location of anchor nodes. When the order of anchor nodes which is decided by signal strength is changed, it generates the severe location estimation error. Thus, this algorithm provides low accuracy of location estimation in high noisy environments.

The SeRLoc (Secure range-independent Localization) algorithm is also proposed to estimate location using the antenna patterns.

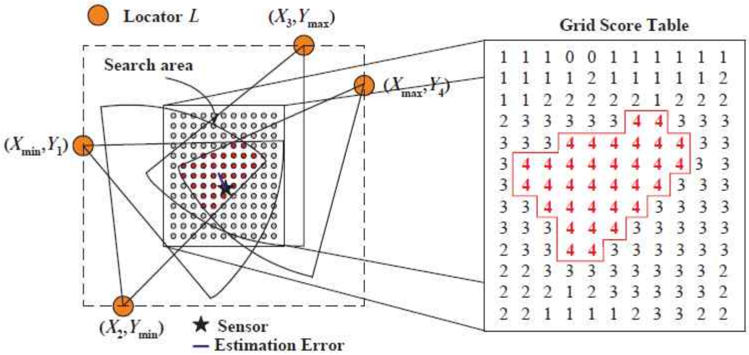


Figure 2.7 SeRLoc algorithm

SeRLoc algorithm is robust against jamming signal and varying sources of errors which are signal distortion, NLOS environment, etc. The antenna patterns from the anchor nodes generate the overlapped area and the location of a target is decided in grid spot of the area. The accuracy of SeRLoc algorithm depends on the beam width of antennas. And the location of a target node should be calculated by the anchor nodes because the target node cannot understand the direction of the anchor nodes even if the target node is conscious of the antenna patterns of the anchor nodes. Thus, SeRLoc algorithm is not suitable for WSNs localization system with tiny sensors.

2.3 Range-based location estimation

2.3.1 Time delay based distance estimation

Time delay based distance estimation is called TOA (Time of Arrival) or TDOA (Time Difference of Arrival). TOA is the calculated by the propagation time of the signal traveling between the anchor nodes and a target node. Although TOA is the robust technique to estimate the distance and location, TOA has several issues before distance or location estimation. The major issue of TOA is synchronization problem. TOA requires all nodes to precisely synchronize each other (Anchor nodes and a target node). The estimated distances by TOA are calculated as follows.

$$\hat{d}_i^{toa} = c \cdot \tau_i^{toa} \tag{2.3}$$

Where the τ_i^{toa} is the time delay between the *i*th anchor node and a target node. c is the speed of light, $c \approx 3 \times 10^8 m/s$. Thus, a small timing error may leads to a large estimation error in the calculation of the estimated distance. Moreover, TOA has another timing issue to check for the distance estimation. The transmitted signal must be labeled with a time stamp which allows the anchor nodes to determine the initial time to calculate the τ_i^{toa}. If the target nodes are increased (increased time stamps), the complexity of localization system is hard to control the initial time which may lead to additional source of error.

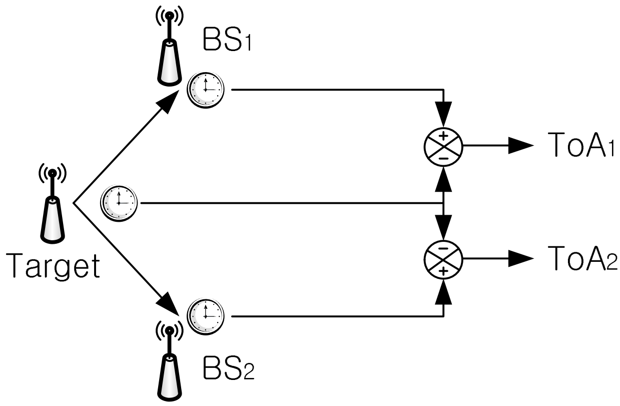


Figure 2.8 Time of Arrival

TDOA estimation requires the measurement of the difference in time between the signals arriving at two anchor nodes. Hyperbolic positioning is the process of locating an object by accurately computing the time difference of arrival of a signal emitted from that object to three or more receivers. TDOA can remove the requirement of synchronizing the target node clock with the anchor nodes clock because all anchor nodes receive the same signal from a target node. When the anchor node clocks are synchronized, the timing error from the arrival time at each anchor nodes can be ignored due to unsynchronized clock is same (the same signal from a target node). Moreover, TDOA needs not the time stamp of a target node because the anchor nodes receive the same signal from a target node. Thus, time synchronization in TDOA estimation is required only the anchor node clocks (AN to AN synchronization).

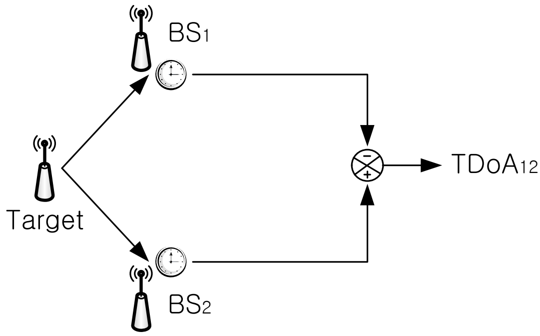


Figure 2.9 Time difference of Arrival

The location estimation using TOA is represented the simultaneous equations of the estimated circle.

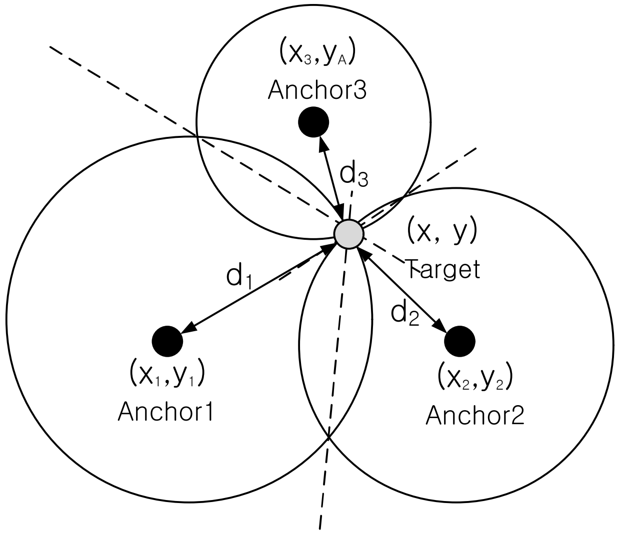
$$(x-x_i)^2+(y-y_i)^2=\hat{d}_{toa,i}^2 \tag{2.4}$$

$(x,\ y)$ is the location of a target node, $(x_i,\ y_i)$ means the location of the anchor nodes, and $\hat{d}_{toa,i}$ is the estimated distance using TOA. The detail calculation of simultaneous equations is expressed in chapter 3. The location estimation using TDOA is calculated by the intersection of at least two hyperbolae which is made from the difference of estimated distances.

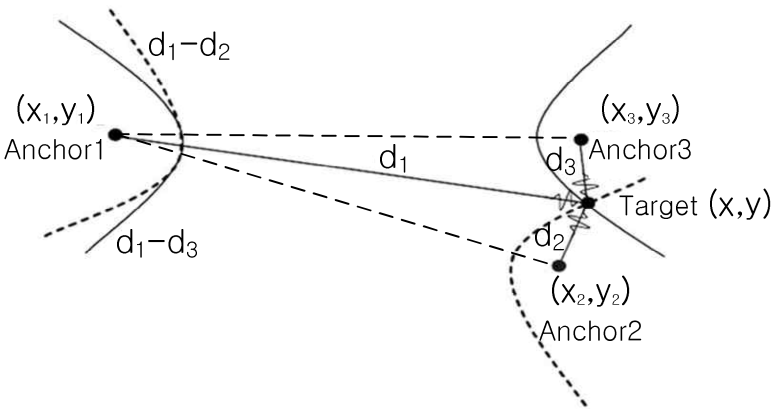
$$\begin{cases} \hat{d}_{12}=\sqrt{\left(x_1-x\right)^2+\left(y_1-y\right)^2}-\sqrt{\left(x_2-x\right)^2+\left(y_2-y\right)^2} \\ \hat{d}_{13}=\sqrt{\left(x_1-x\right)^2+\left(y_1-y\right)^2}-\sqrt{\left(x_3-x\right)^2+\left(y_3-y\right)^2} \end{cases} \tag{2.5}$$

$\hat{d}_{12}$ and $\hat{d}_{13}$ are estimated distance difference from time differences. (Anchor node 1 is basis of calculation)

$$\hat{d}_{1i}=(t_i-t_1)c \tag{2.6}$$



(a) The location estimation using TOA



(b) The location estimation using TDOA

Figure 2.10 TOA vs TDOA location estimation

The both of location estimation scheme, TOA and TDOA, are robust location estimation scheme with high accurate. However, the synchronization issue is very difficult to solve in wireless sensor networks with tiny sensors due to hardware limitation. Several microsecond delay based on the quartz clock causes over hundreds of distance error from (2.3). Thus, WSNs localization system should consider carefully in this matter how to setup under nanosecond delay system or control the synchronization problems for using the TOA and TDOA.

2.3.2 Received signal strength based distance estimation

The major study of location estimation in academia and industry is how to reduce the cost, complexity for feasibility of the location system. Especially, the WSNs localization system has hardware limitation due to tiny sensors. Thus, the RSS-based location estimation scheme is very attractive candidate for WSNs localization system. Although the RSS-based approach is suitable for WSNs localization system, the low accurate distance estimation caused by multipath fading, interferences, and discordance between system environment and wireless channel models should be mitigate to get the acceptable location estimation results. The estimated distances are calculated using path-loss model in RSS-based distance estimation [28]-[30] .

$$PL_i\left(dB\right) = P_0 - 10 \times n \times \log_{10}\left(\frac{d_i}{d_0}\right) + X_{\sigma_i} \qquad (2.7)$$

Where the PL_i is the received signal strength in dB scale related the *i*th anchor node, P_o is the received power at a short reference distance d_o, which is typically 1m. n is the path-loss exponent, X_σ is the log-normal shadowing, expressed in units of dB and related to the distance error.

$$\hat{d}_i = 10^{-\frac{PL_i - Po - X_\sigma}{10 \cdot n}} \qquad (2.8)$$

The estimated distance, $\hat{d}_i$ is calculated by (2.7). PL_i, P_o, and n are the deterministic value. The distance estimation error is caused by X_σ, the shadowing factor which is from signal distortions and fades generated by reflection, scattering, diffraction, and refraction from buildings trees furniture, and other obstructions in the environment. This factor is decided in a random manner because many deployment environments are characterized by randomness. The location estimation using RSS-based approach is the same as that of TOA. The estimated location is calculated by the simultaneous equations of the estimated circles made from distance estimation. In this dissertation, the location estimation error mitigation algorithms are proposed for high accurate localization system based on distance estimation. The proposed algorithms are expected to help RSS-based approach to reduce the lots of distance errors. In this dissertation, the channel model from experiments using ZigBee wireless sensors in indoor environments is used for simulation.

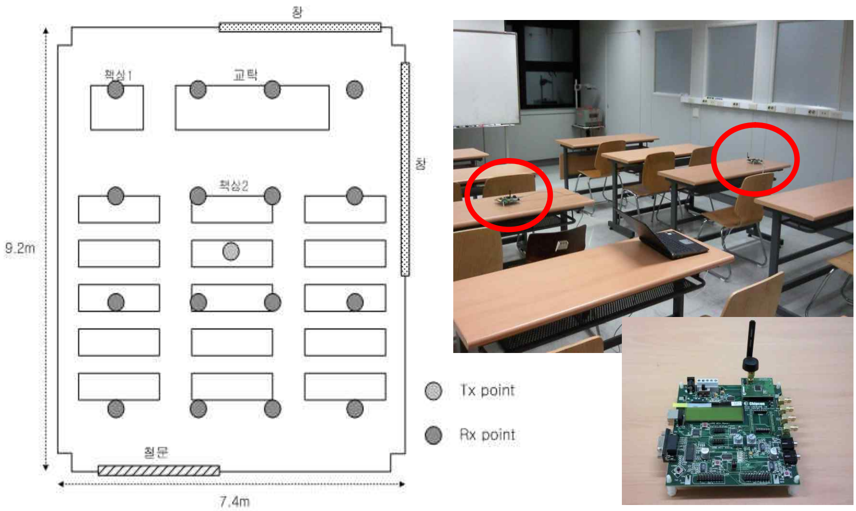


Figure 2.11 The experiment environment

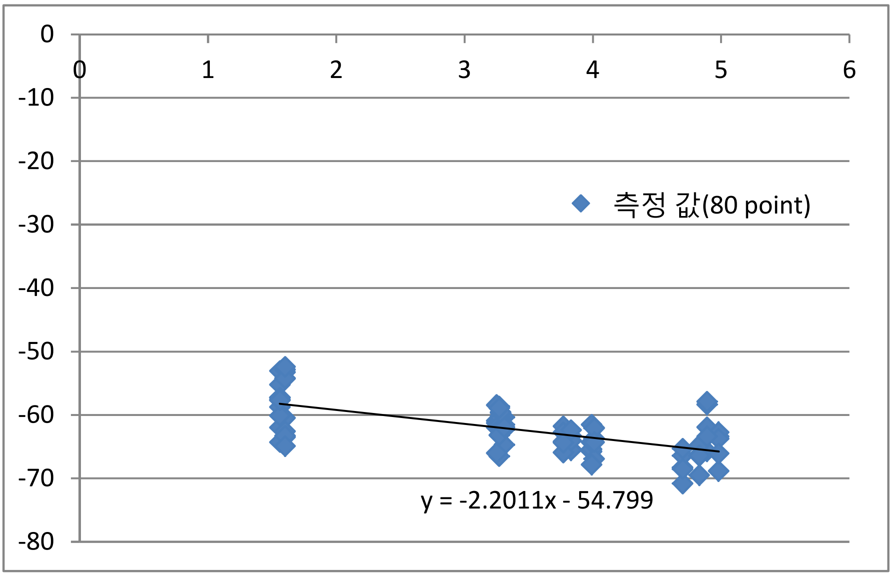


Figure 2.12 The results of experiment

The 5000 times of experiments are shown in each point. The channel exponent is 2.2001, and P_o is -54.799dBm. The standard of P_o in ZigBee wireless sensors is -55dBm. Thus, the experiment is matched for standard very well, and the channel exponent from the experiment is applied to all simulation environments.

2.3.3 Angle of arrival based location estimation

Although (AOA) Angle of Arrival is not the distance based location estimation scheme, the introduction of AOA scheme is briefly represented in this chapter because AOA is widely used in localization system. AOA estimates the angles between the anchor nodes and a target node using the antenna arrays. Antenna array system needs higher complexity and power consumption compared to TOA or RSS-based algorithm. The disadvantages of AOA scheme is not suitable for WSNs localization system, but only two anchor nodes are sufficient to estimate the location of a target node and the information of angle at least coarse information helps the other schemes to reduce the location estimation error. The location estimation using AOA is expressed as follows.

$$\tan\theta_i = \frac{y_m - y_i}{x_m - x_i} \Rightarrow y_m = \tan\theta_i x_m + y_i - \tan\theta_i x_i \tag{2.9}$$

$$\underbrace{\begin{bmatrix} -\tan\theta_1 & 1 \\ \vdots & \vdots \\ -\tan\theta_i & 1 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} x_m \\ y_m \end{bmatrix}}_{\mathbf{x}} = \underbrace{\begin{bmatrix} y_1 - \tan\theta_1 x_1 \\ \vdots \\ y_i - \tan\theta_i x_i \end{bmatrix}}_{\mathbf{b}} \tag{2.10}$$

The target location is calculated by the pseudo inverse of matrix A and the Figure 2.11 helps understand the (2.9) and (2.10).

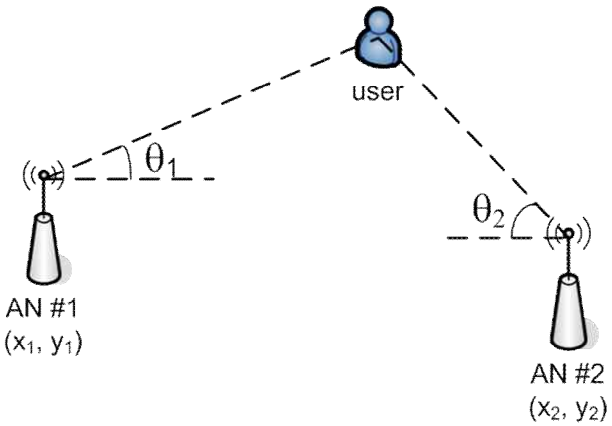


Figure 2.11 AOA location estimation

2.4 Summary

In this chapter, the conventional algorithms for range-free location estimation and the range-based location estimation schemes are summarized for WSNs localization system.

Table 2.1 The range-free location estimation schemes

	Cell-ID
Advantages	Very simple algorithm. (Low complexity)
Weakness	Low accuracy. (Rough estimate)
For WSNs	One of the best scheme for WSNs.
	Fingerprinting algorithm
Advantages	High accuracy. No needs additional hardware.
Weakness	Sensitive about environment change. The performance depends on signal mapping database.
For WSNs	Depends on hardware specification.
	Centroid algorithm
Advantages	Very simple algorithm. (Low complexity)
Weakness	Node selection problem (The order of ANs)
For WSNs	One of the best scheme for WSNs.
	SeRLoc algorithm
Advantages	Robust against jamming signal, varying sources of error.
Weakness	AN needs a particular antenna.
For WSNs	Depends on hardware specification.

Table 2.2 The range-based location estimation schemes

	Time of Arrival
Advantages	High accurate scheme to estimate the location.
Weakness	Time sync. problem with AN to AN and AN to TN
For WSNs	Not suitable for WSNs
	Time Difference of Arrival
Advantages	Eliminate the time sync. Problem with AN to AN. High accurate scheme to estimate the location.
Weakness	Time sync. problem with AN to TN. High complexity of calculation.
For WSNs	Not suitable for WSNs
	Received Signal Strength Indicator
Advantages	No needs additional hardware (very simple)
Weakness	High variation of signal strength (Low accuracy)
For WSNs	One of the best scheme for WSNs
	Angle of Arrival
Advantages	Only two ANs needed to estimate location. Provides additional information for other schemes.
Weakness	LOS should be secured. Antenna array is required.
For WSNs	Not suitable for WSNs. (Only AoA)

Chapter 3. Two dimensional location estimation for wireless sensor networks

3.1 Introduction

Recent, applications contain location based services, which make it easy to find a user's destination. Global Positioning System (GPS) is a well-known localization system and has good performance [31]. However, GPS does not work in urban areas and indoor environments like in building, mines due to GPS signal attenuation. Moreover, the features of GPS are widely known, this signal might be jammed by enemies in wartime situation. To overcome the limitations of GPS, other applications for localization should be developed to enable localization system such as wireless sensor networks (WSNs) in GPS-free environments. While WSNs can help to estimate the location without GPS, it does not ensure exact estimated position because indoor environments contain many objects such as walls, desks, and panels, etc., that disturb the LOS signals. It is known that the topologies of wireless sensor networks can overcome these problems by deploying smart tiny sensors in large numbers. Furthermore, it is known that WSNs guarantee low cost, ease of setup, small size, and low power consumption.

In particular the RSSI positioning systems are simpler than those of TOA, TDOA and AOA. Note that TOA and TDOA are very sensitive to the hardware performance due to need time synchronization among the sources and hard to find the first path in indoor environment with severe multi-path fading channel. AOA needs antenna arrays to find the angle. Furthermore, Line of Sight (LOS) environment should be secured to measure the angles from the target node. These methods are hard to implement using tiny sensors. Thus, RSSI is suitable for WSNs localization in short range indoor environments.

The distance estimation based on received signal strength follows the exponential decay model called the path loss model. The path loss model in indoor environment is commonly treated as Gaussian noise. Its measurement error has a high degree of variation which causes unacceptable error in real

WSNs implementation. The estimated distances including high degree of signal strength variation make it difficult to determine an accurate position because of the avalanche error propagation effect in a distributed localization system.

In this chapter, the several location estimation algorithms are proposed to prevent error propagation of conventional mitigation algorithms. The proposed algorithms are classified the cases of tri-lataration and applied to each appropriate case. The proposed algorithms consist of GM algorithm, CS algorithm and BCD algorithm. GM algorithm can mitigate the estimated distance considered the CRLB of estimated distances and CS algorithm offsets the estimated location using the size and direction of offsetting vector. The offsetting vectors can mitigate the pre-estimated location by shifting their coordinates. Although two mitigation algorithms reduce the estimated location error, GM and CS algorithm use the parameters which are calculated from the uncertain values which are degraded by complex environment. For that reason, the mitigation algorithms using the inaccurate estimated parameters cause the bad location estimation results. The bad condition for location estimation is defined by comparing the differences of each estimated distances based on pre-estimated location. The estimated distances between the anchor nodes and target node, and the distances between the anchor nodes and pre-estimated location are big differences in bad condition to location estimation. The BCD algorithm estimates the bad situations which cannot be offset by the mitigation algorithms. BCD algorithm eliminates the bad condition to improve the accuracy and stability of localization system.

This chapter is organized as follows. Section 3.2 presents the Tri-lateration which is the basis of location estimation. Section 3.3 provides the proposed Geometric clipping algorithm and section 3.4 does the proposed Coordinate shift algorithm. Section 3.5 represents another proposed algorithm, Bad condition detection algorithm and classifies all proposed algorithm for robust localization systems using wireless sensor networks. Finally, the summary is followed in section 3.6.

3.2 Tri-lateration

3.2.1 Linear least square estimation

The linear least square (LLS) estimation is widely used to location estimation method based on estimated distances. Tri-lateration is one of LLS estimation only using three anchor nodes [32]. The LLS estimation using four and more anchor nodes is called multi-lateration.

To estimate the location, the least square (LS) estimation and maximum likelihood (ML) estimation are basically used. The ML estimation is the highest accurate method to estimate the location. However, the complexity is also high if grid or random search is involved, and noised statistics should be known [33]. These disadvantages are hard to apply to localization system with tiny sensors. There are two approaches of LS estimation which are nonlinear and linear estimation. Although nonlinear least square (NLS) estimation is generally high accurate method, it has the same complexity problem like ML [34]-[35]. Moreover, NLS approach needs initial guess to update the LS cost function. According to the initial guess, the global solution may not be guaranteed because of the size of minimizing steps.

The LLS estimation, on the other hand, is generally low accurate method, but it is very simple and global solution is guaranteed by closed form calculation. Above all things, the simple computation is the great advantage for localization with tiny sensors. Thus, we consider the LLS estimation for wireless sensor networks localization. The LLS estimation using three anchor nodes to estimate the location is called tri-lateration. Tri-lateration method estimates an unknown location node (i.e., a target node) using three known fixed locations (i.e., anchor nodes). At the beginning of tri-lateration, three circles are formed from the coordinates of the anchor nodes and the radius of them can be treated as the estimated distance. The general form of LLS estimation for three or more anchor nodes in two dimensional (2D) location estimation systems is shown as.

$$(x-x_i)^2+(y-y_i)^2=\hat{d}_i^2 \tag{3.1}$$

Here, x_i and y_i are the coordinates of the *i*th anchor node and the $\hat{d}_i$ is the estimated distance between the *i*th anchor node and a target node. To simplify the equation to estimate the target location, The simultaneous equations of (3.1) are arranged to a matrix form $Hx = b$, where $x = (x, y)$.

$$H = \begin{bmatrix} (x_2 - x_1) & (y_2 - y_1) \\ \vdots & \vdots \\ (x_N - x_1) & (y_N - y_1) \end{bmatrix} \tag{3.2}$$

$$b = \frac{1}{2} \begin{bmatrix} (\hat{d}_1^2 - \hat{d}_2^2) - (x_1^2 - x_2^2) - (y_1^2 - y_2^2) \\ \vdots \\ (\hat{d}_1^2 - \hat{d}_N^2) - (x_1^2 - x_N^2) - (y_1^2 - y_N^2) \end{bmatrix} \tag{3.3}$$

Where N is the number of anchor nodes which can be used to estimated the location. H is only described by the coordinates of anchor nodes, b is represented by the estimated distance between anchor nodes and target node with the coordinates of anchor nodes. In tri-lateration, the coordinates of target node $(\hat{x}_{lls}, \hat{y}_{lls})$ represented by P_e are given by $P_e = H^{-1}b$. In multi-lateration, using more than three anchor nodes, the coordinates of target node are given by $P_e = (H^T H)^{-1} H^T b$.

3.2.2 The cases of tri-lateration

The distances between the anchor nodes and a target node, and the location of the anchor nodes have estimated with many sources of error in noisy environments caused by multipath signals, diffractions, shadowing effects by the obstacles such as furniture, walls, desks and more which could not be defined. Especially, RSS based on estimated distances have severe errors because of their sensitiveness. The distance estimation error is the major point of the location estimation error. Due to the signal distortion, the received signal strength has a noisy range of measurements, which make several cases of tri-lateration ranging measurements possible .

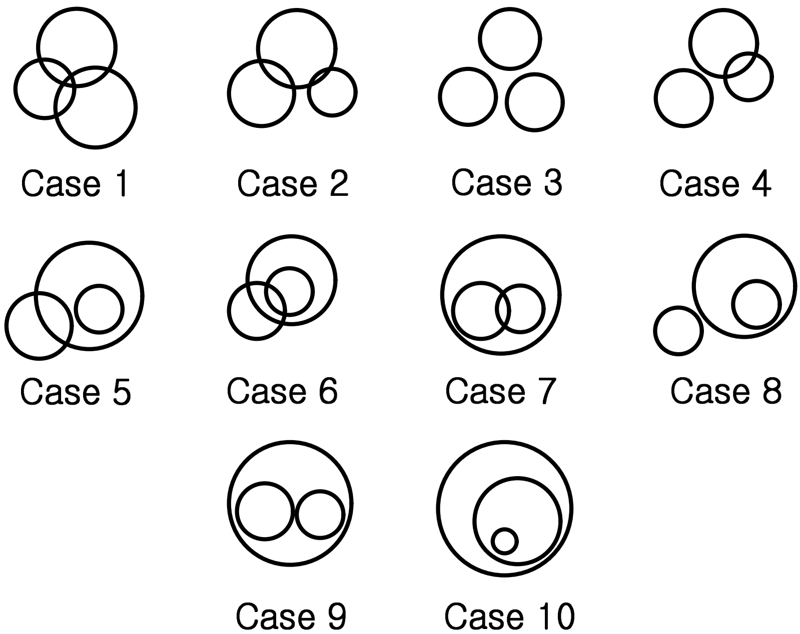


Figure 3.1 The cases of tri-lateration in noisy measurements

Figure 3.1 shows most possible cases of tri-lateration ranging measurements. The circles from the estimated distances and the location anchor nodes, called estimated circles, make the different kinds of the tri-lateration cases. Case 1 is one of the good and expected case of tri-lateration. Case 2, 3, and 4 are also good case of tri-lateration because estimated circles can be offset by each others for tri-lateration included simultaneous equations. Case 5, 6, 7, 8, 9, and 10 are hard to estimate accurate location using tri-lateration. Thinking about the CRLB of estimated distances, the shorter estimated distance is more accurate than others. If the estimated circle includes the other estimated circles, the estimated location is to be very bad. Thus, this or these estimated circles should be mitigated to get the high accurate tri-lateration result. In rest of chapter, several mitigation schemes are proposed to get the precise estimated location in noisy environments

3.3 Geometric mitigation algorithm

3.3.1 Motivation

When large estimated circle includes other estimated circles like in Figure 3.2, the estimated position has a severe error. As shown in the cases 5, 6, 7, 8, 9 and 10 in Figure 3.1, intersection points are not formed since the largest circle includes other circles. The lines, calculated by subtraction from each estimated circle, are generated outside the large estimated circle. This characteristic makes the large error because the estimated position is on the lines and the shortest estimated circle which has lower CRLB is more separated from the estimated position [36]-[37]. Thus, a mitigation algorithm, called the GM (Geometric Mitigation) algorithm [16]. The GM algorithm is a very simple but powerful algorithm to determine the precise positions in cases 5, 6, 7, 8, 9 and 10.

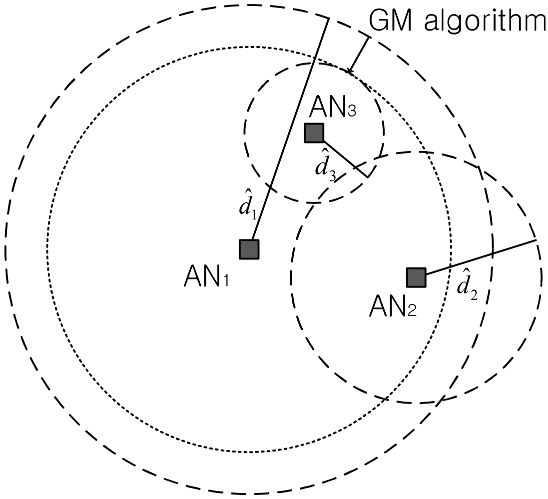


Figure 3.2 The example of geometric mitigation algorithm

Figure 3.2 shows an example of GM algorithm. Long-dashed circles denote the estimated distance from each anchor nodes and a short-dashed circles is mitigated circle by GM algorithm. Notation of ANi means the number of anchor nodes and $\hat{d}_i$ means the estimated distance.

3.3.2 Algorithm explanation

The estimated circle from anchor node 1 includes the estimated circle from anchor node 3 in Figure 3.2, which has lower CRLB of estimated distance. In the geometric method, the estimated circle from anchor node 1 is reduced to meet the end of estimated circle from anchor node 3 to make at least one intersection point. The GM algorithm is summarized as follows.

1. Geometric Mitigation Algorithm

Known a priori : plane equation from anchor node position.

1. Compute the estimated distance $\hat{d}_i$, i = 1, 2, 3
2. Calculate the distance between the anchor nodes, $dist_{ij}$. i = 1, 2, 3 j = 1, 2, 3. $i \neq j$.
3. if $\hat{d}_i > dist_{ij} + \hat{d}_j$
4. $\hat{d}_i = dist_{ij} + \hat{d}_j$ for all i and j.
5. end if.

Figure 3.3 The geometric mitigation algorithm

The anchor nodes of location are known a priori, the distances between the anchor nodes and a target node are estimated by RSS or ToA, and the distances between the anchor nodes can be calculated. From these information, the overestimated distance, including the other estimated circle like in step 3, is clipped by the step 4. Thus, GM algorithm prevents the severe distance estimation error from the overestimated distances by limiting the estimated distances to shorter estimated distances in case of step 3.

3.3.3 Simulation

Simulation results show the performance of the localization algorithms using LLS estimation with GM algorithm. The channel model used in our simulations followed the IEEE 802.15.4a [38] and the simulation field was a 10m by 10m general office environment. Actually, the distance based algorithm like proposed schemes (in section 3.4, 3.5) can be applied to various positioning systems, no matter if the ranging signal is TOA or RSS. In this dissertation, the simulation considers only RSS based system because of hardware limitation. And we set the shadowing factor 1dB to 3dB to follow the common indoor office environment. The anchor nodes were fixed with known positions while one blind node was randomly distributed. The anchor nodes were placed uniformly on a circle with a 3m radius, to achieve the same distance from the center of the simulation field for reducing the location error caused by anchor node biased problem. In the simulation, the location of the unknown sensor nodes is estimated using LLS estimation. The average mean square error in localization performance is calculated and normalized using Monte Carlo simulation [39] as follows,

$$e_{avg} = \frac{1}{N_i} \sum_{i=1}^{N_i} \| P_{real} - \hat{P}_e \| \tag{3.4}$$

where the e_{avg} is the RMSE of location estimation, P_{real} means the real location of the target node, $\hat{P}_e$ is the estimated location of the target node with GM algorithm, and N_i is the number of Monte Carlo simulation, and N_i is 10^5 times of Monte Carlo simulation in all section 3.

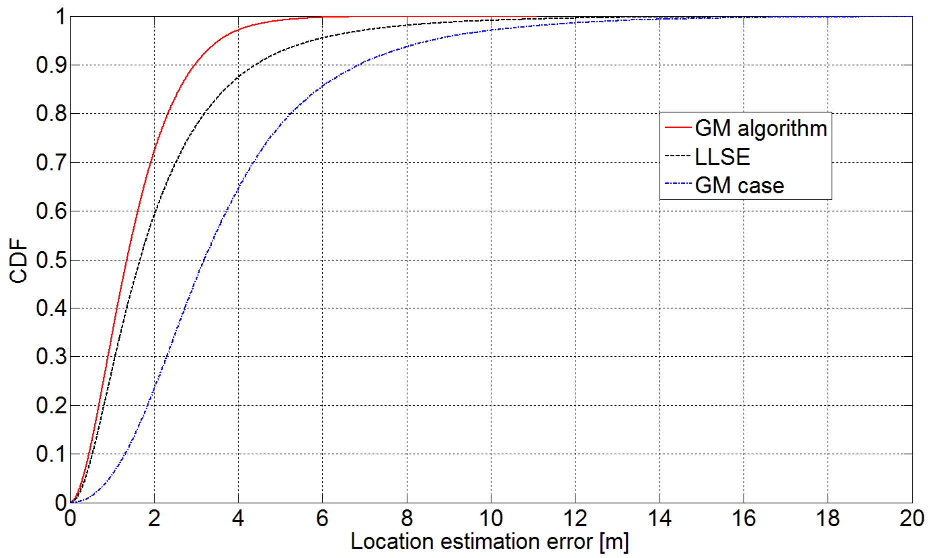


Figure 3.4 The CDF of geometric mitigation algorithm (Shadowing : 2dB)

Figure 3.4 shows the CDF of GM algorithm in 2dB shadowing environment. GM algorithm in legend of Figure 3.4 means the results of LLS estimation including mitigated cases by GM algorithm. LLSE represents the results of LLS estimation without GM algorithm. And GM case shows the results of LLS estimation without GM algorithm in case 5, 6, 7, 8, 9, and 10 of tri-lateration which is able to offset by GM algorithm. The probability of GM case for 10^5 times of Monte Carlo simulation is about 30% (29934 times).

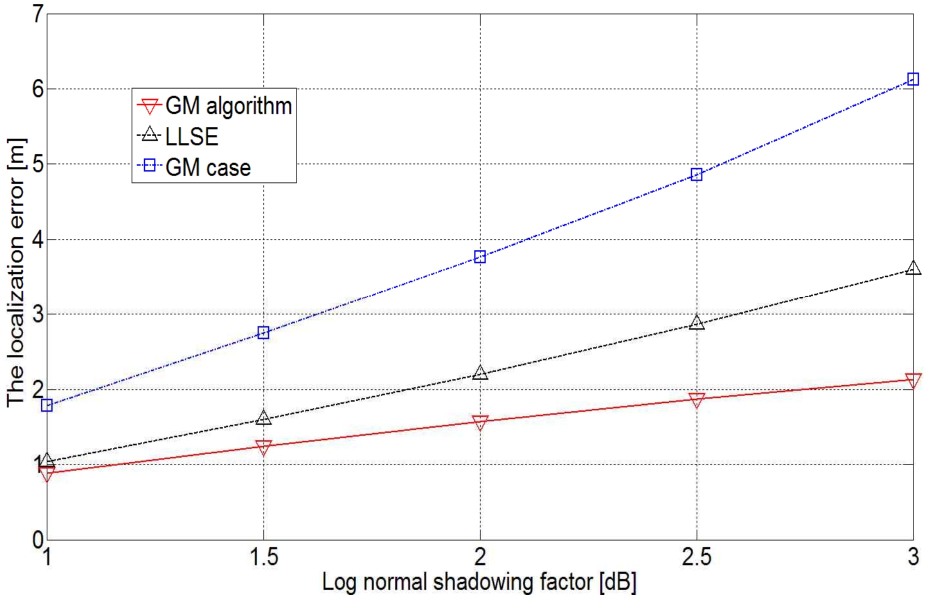
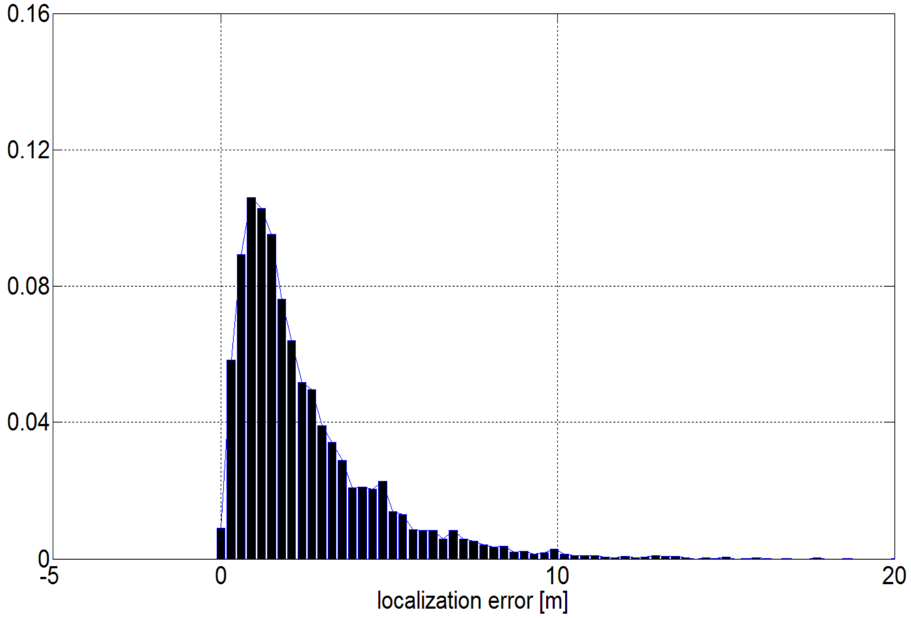
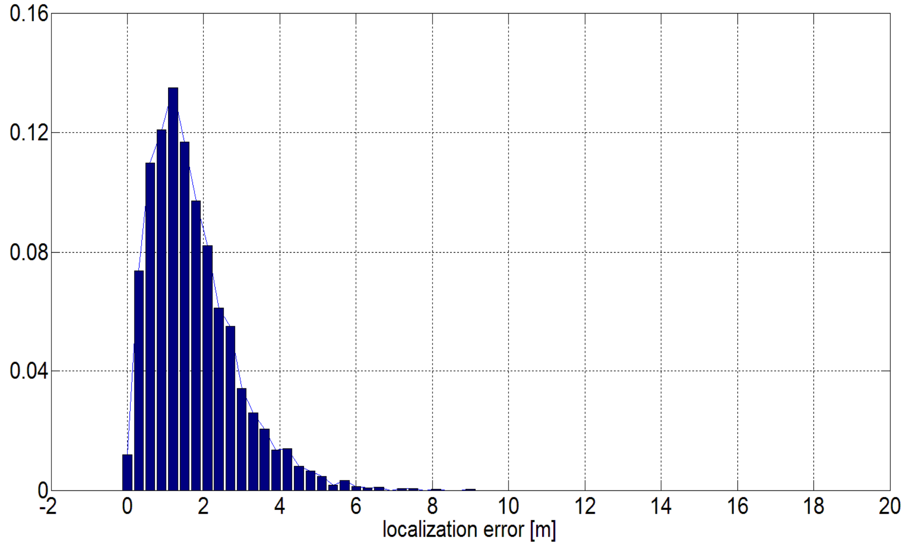


Figure 3.5 The RMSE of geometric mitigation algorithm

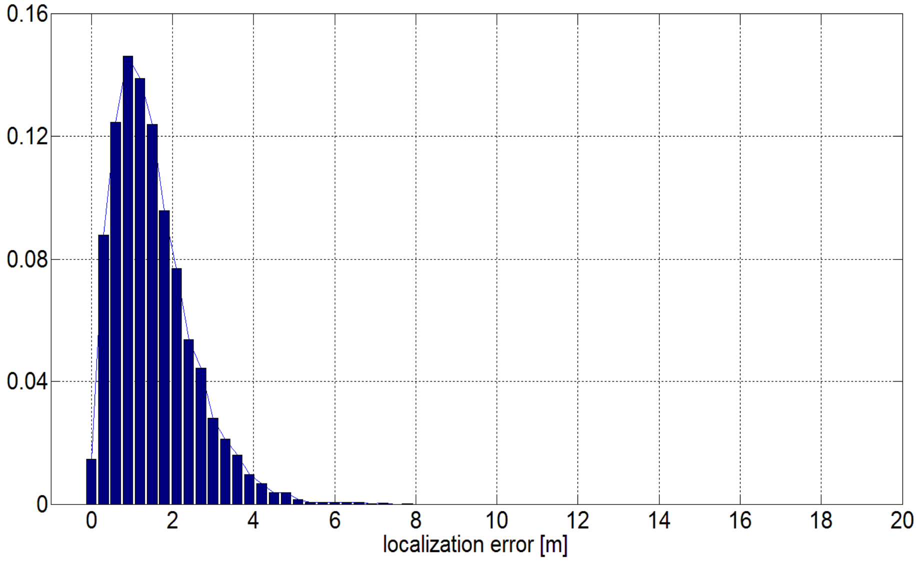
Figure 3.5 shows the RMSE of GM algorithm. The GM algorithm can mitigate the localization errors from the GM cases, and is more effective in severe signal shadowing environment because those cases are frequent in that environment. The localization error is reduced by up to 34.45% in 3dB shadowing environment compared to the LLS estimation without GM algorithm.



a) The histogram of GM cases and case 2, 3, 4 without GM algorithm



b) The histogram of case 1 of tri-lateration



c) The histogram of GM cases and case 2, 3, 4 with GM algorithm

Figure 3.6 The histogram of GM algorithm in three cases (2dB shadowing)

Figure 3.6 shows the histogram of location estimation error using GM algorithm in three cases. Figure 3.6 a) means the histogram of GM cases case 2, 3, 4 without GM algorithm, b) shows the histogram of case 1 of tri-lateration, and c) represents the histogram of GM cases case 2, 3, 4 with GM algorithm. Figure 3.6 a) case has severe localization errors over 19m in 10m by 10m environment. These errors cause the severe error propagation with high probability in WSNs localization system which is connected many tiny sensors each other. Although Figure 3.6 b) shows good error performance rather than that of case a), the critical errors over 5m exist occasionally. Figure 3.6 c) looks similar to case b) because the case 2, 3, and 4, which cannot be mitigated by GM algorithm but are basically good location estimation cases, and GM cases are mitigated by GM algorithm eliminating the overestimated distances. After GM algorithm, the histogram of all cases of tri-lateration except the case 1 is far better than that of case a) and is becoming similar to that of the case b). Thus, the severe location estimation error from the longest estimated distance which includes other estimated distances is mitigated by GM algorithm.

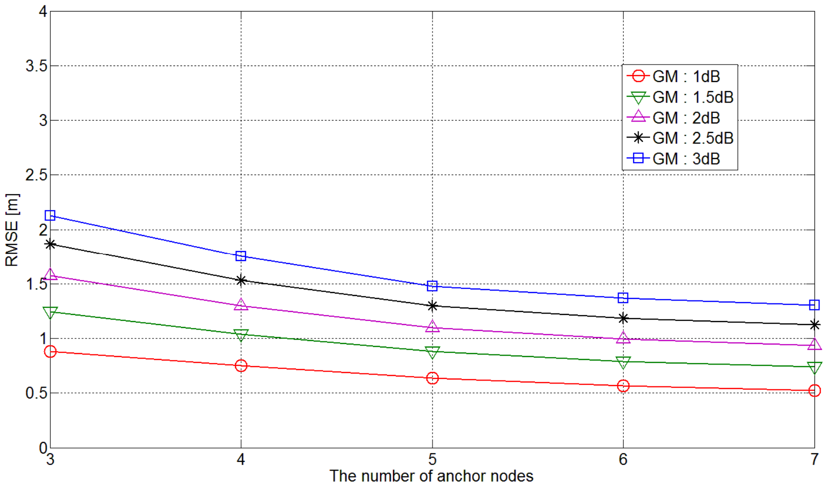


Figure 3.7 The RMSE of GM algorithm in multi-lateration

Figure 3.7 shows the RMSE of GM algorithm in multi-lateration which estimates the location using more four anchor nodes. The proposed GM algorithm provides better localization performance in multi-lateration.

3.3.4 Conclusion

The GM algorithm considered only the estimated distances, not included probability models because the accuracy of estimated distance is decided in distance estimation part, and the estimated distances are assumed that these are the best way to be calculated by the best channel parameters. The GM algorithm works well in all different shadowing environments rather than conventional LLS estimation. Moreover, the severe errors over the half of simulation environment can offset the localization error to case 1 of tri-lateration level. Although the GM algorithm can reduce the location estimation error to mitigate the overestimated distances, it is not enough to expect the accurate location estimation result because this algorithm can be applied only to the particular cases. Thus, the error mitigation algorithms for location estimation are proposed in the next subsection.

3.4 Coordinate shift algorithm

3.4.1 Motivation

Inaccurate estimated distances make hard to decide the exact location shown as chapter 3.3. It is found that some kinds of the positioning errors cannot be reduced the location estimation errors by the GM algorithm to offset the overestimated distances. Thus, we proposed the other algorithm, named Coordination Shift (CS) algorithm [17] to mitigate the location estimation errors that the geometric method cannot deal with.

First of all, the information to estimate location is not enough for high accurate localization system. It is all the localization systems know the locations of anchor nodes, the distances between the anchor nodes, and the estimated distances between the anchor nodes and a target node. Moreover, the estimated distances cannot be offset without channel parameters from the perfect channel estimation for accurate location estimation. Thus, the proposed CS algorithm considers more sources for the location estimation from the estimated target location after GM algorithm, and makes the correction vector. The details of the proposed CS algorithm are expressed in the next subsection.

3.4.2 Algorithm explanation

The CS algorithm begins after GM algorithm to make the error correction vectors. The error correction vector is composed of the error correction angle and the error correction distance. The error correction angle and the error correction distance are calculated from the estimated location of a target node by LLS estimation with GM algorithm. The error correction angle is calculated by the sum of calculated directions between the anchor nodes and the estimated location of a target node. The error correction distance is calculated from the shortest estimated distance and the distance between the anchor node which has the shortest estimated distance and a location of a target node, $dist(P_e, AN_c)$. The difference of distance between the shortest estimated distance and $dist(P_e, AN_c)$ becomes the error correction distance. The CS algorithm has several steps as shown below.

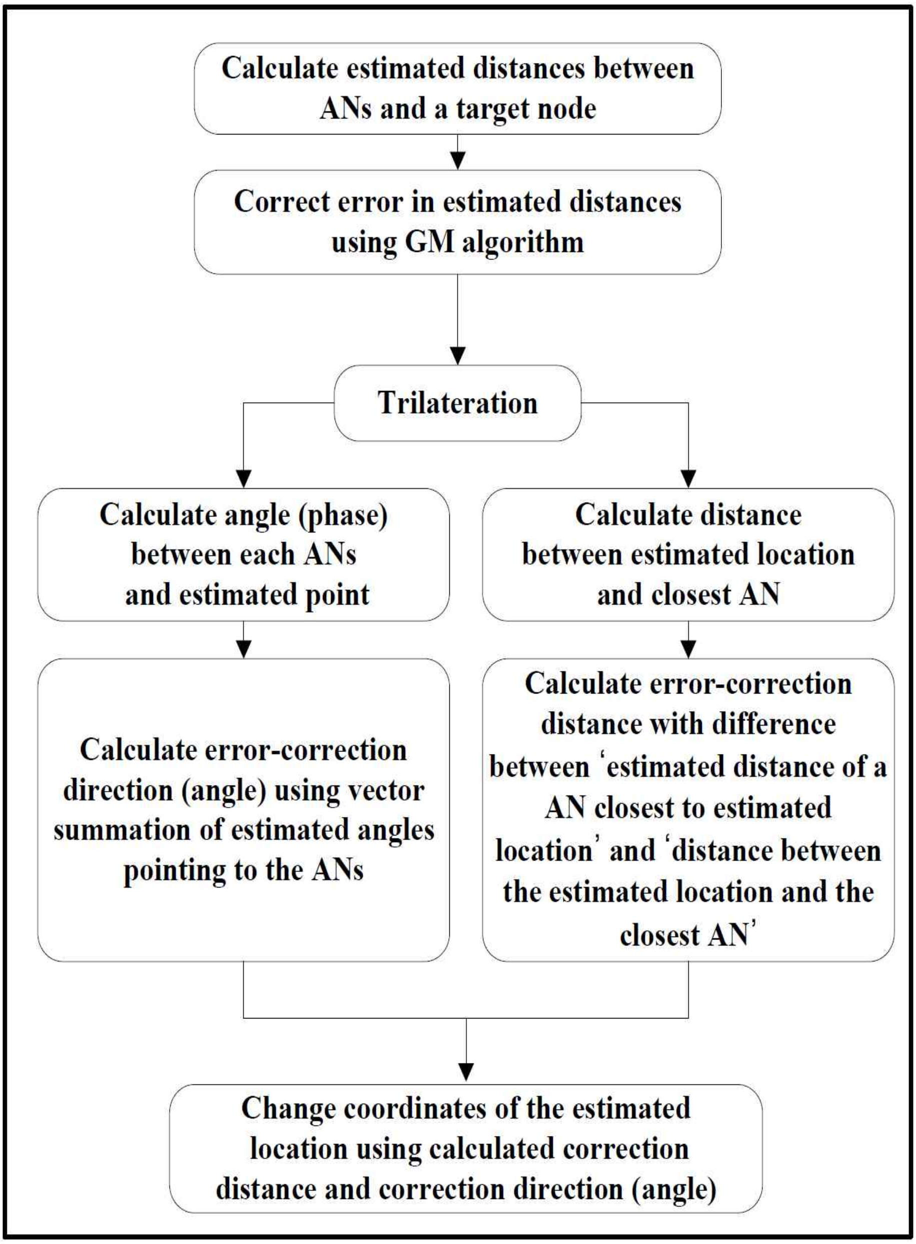


Figure 3.8 The Flow chart of coordination shift algorithm

Figure 3.8 shows the flow chart of the coordination shift algorithm including the GM algorithm. The error correction vector is combined by that angles and distances. Finally, the estimated location using LLS estimation with GM algorithm is error mitigated using the correction vector. Figure 3.9 represents the details of the parameters which are composed of the CS algorithm.

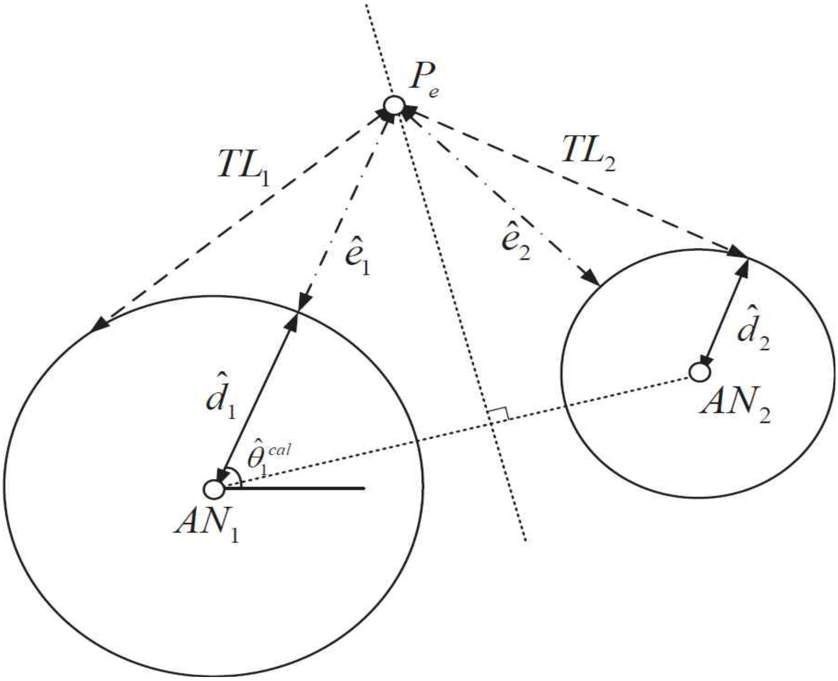


Figure 3.9 The parameters of the CS algorithm

Figure 3.9 shows the parameters of the CS algorithm. P_e = $(\hat{x}_{lls}, \hat{y}_{lls})$ is the estimated position using LLS estimation with GM algorithm, TL_i is the tangential line on the estimated circle, $\hat{e}_i$ is the difference between the estimated distance, $\hat{d}_i$, and $dist(P_e, AN_i)$. $dist(P_e, AN_i)$ means the distance between the P_e and the location of anchor node i. $\hat{\theta}_i^{cal}$ is calculated from P_e and the location of anchor node i.

To obtain the error-correction angle, the angle between each anchor node and the estimated location should be calculated as

$$\hat{\theta}_i^{cal} = \tan^{-1}\left(\frac{y_i - \hat{y}_{lls}}{x_i - \hat{x}_{lls}}\right) \tag{3.5}$$

The error correction angle is computed by the vector sum of the calculated directions, $\hat{\theta}_i^{cal}$. The error correction angle is expressed as,

$$\theta_{cr} = \frac{\mathrm{w}_{\theta i}\hat{\theta}_i^{cal}}{|\,\mathrm{w}_{\theta i}\hat{\theta}_i^{cal}\,|} \tag{3.6}$$

where θ_{cr} is the error correction angle, $\mathrm{w}_{\theta i}$ mean the weighting factors, $\sum \mathrm{w}_{\theta i} = 1$. The weighting factors, $\mathrm{w}_{\theta i}$ are decided by the estimated distances. The shortest estimated distance has the highest confidence that the error correction direction would better to match this estimated circle and the longest estimated distance has the lowest confidence which causes stochastically large errors known by the CRLB of estimated distance. Thus, the weighting factor is focused on the shortest estimated distance and the longest estimated distance. However, it is hard to decided which is the shortest estimated distance or longest estimated distance in noisy environment. When it is hard to decide whether the longest estimated distance or the second length of estimated distance because of little difference between two distances, the weighting vector is to fit only the shortest estimated distance. And if three of the distances have a little differences, the weighting factor is to be equivalent values.

The CS algorithm defined the error correction distance to d_{cr}, which is the distance between the estimated location and the closest anchor node which has the shortest estimated distance for the same reason as the error correction angle. The error correction distance is expressed as,

$$\mathrm{d}_{cr} = \hat{d}_c - \sqrt{(x_c - \hat{x}_{lls})^2 + (y_c - \hat{y}_{lls})^2} \tag{3.7}$$

where the (x_c, y_c) is the location of the closest anchor node, $\hat{d}_c$ means the the shortest estimated distance. Finally, the estimated point is offset by the error correction angle, θ_{cr}, which determines the direction and the error correction distance, d_{cr}, which in turn determines the length and the sign (i.e. positive or negative). The sign of the error correction distance has only a plus sign in case 1 and a minus sign in other cases. The details about the sign of the error correction distance will be touched on next mitigation algorithm. The entire CS algorithm with the calculation of the final mitigated position are summarized as follows.

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2. Coordinate Shift Algorithm

The process after Geometric Mitigation Algorithm.

1. Location estimation using LLSE.

$$(\hat{x}_{lls}, \hat{y}_{lls}) = (H^T H)^{-1} H^T b.$$

2. Calculate the angle between the anchor nodes and estimated location,

$$\hat{\theta}_i^{cal} = \tan^{-1}\left(\frac{y_i - \hat{y}_{lls}}{x_i - \hat{x}_{lls}}\right) \; i = 1, 2, 3.$$

3. Calculate the error correction angle,

$$\theta_{cr} = \frac{w_{\theta i}\hat{\theta}_i^{cal}}{|w_{\theta i}\hat{\theta}_i^{cal}|}$$

4. Calculate the error correction distance

$$d_{cr} = \hat{d}_c - \sqrt{(x_c - \hat{x}_{lls})^2 + (y_c - \hat{y}_{lls})^2}$$

5. Combine the error correction angle and distance to make the correction vector

6. Shift the estimated location with correction vector.

$$(\hat{x}_{cs}, \hat{y}_{cs}) = (\hat{x}_{lls} - d_{cr}\cos(\theta_{cr}), \hat{y}_{lls} - d_{cr}\sin(\theta_{cr}))$$

6. end if.

Figure 3.10 The coordination shift algorithm

3.4.3 Simulation

The environment of simulation is same as the chapter 3.3 for comparing the results of GM algorithm. The simulation considers the accuracy of location estimation.

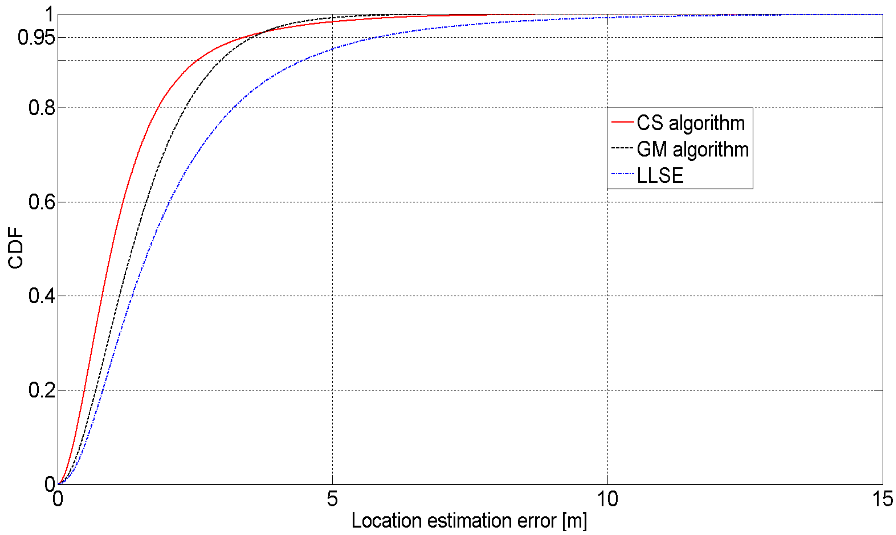

Figure 3.11 The CDF of CS algorithm (2dB shadowing)

Figure 3.11 shows the CDF and RMSE with CS algorithm. The CS algorithm shows better performances than GM algorithm in CDF. The CDF of CS algorithm over 96% is lower than that of GM algorithm, because the 4% of CS algorithm has the probability of false mitigation due to wrong mitigation direction. The wrong mitigation direction occurs when the estimated distances are changed the distance order caused by distance estimation error. This problem is almost frequent in case 1 of tri-lateration. Although the case 1 is commonly good case of location estimation, the wrong cases of estimated distances' order causes the wrong direction of the error correction vector. The problem from the case 1 with distance estimation error is discussed in next subsection.

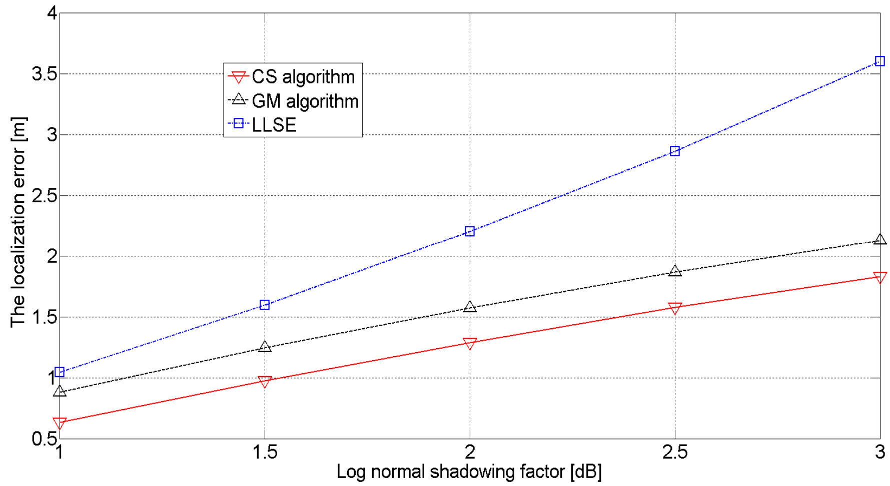

Figure 3.12 The RMSE of CS algorithm

Although the CS algorithm has a little probability of failure, the CS algorithm can mitigate the location estimation error at all shadowing environments rather than that of GM algorithm and conventional LLS estimation as shown in Figure 3.12. The localization error using CS algorithm is reduced by up to 49.25% in 3dB shadowing environment compared to the LLS estimation without GM algorithm and 14.11% compared to the GM algorithm in the same shadowing environment.

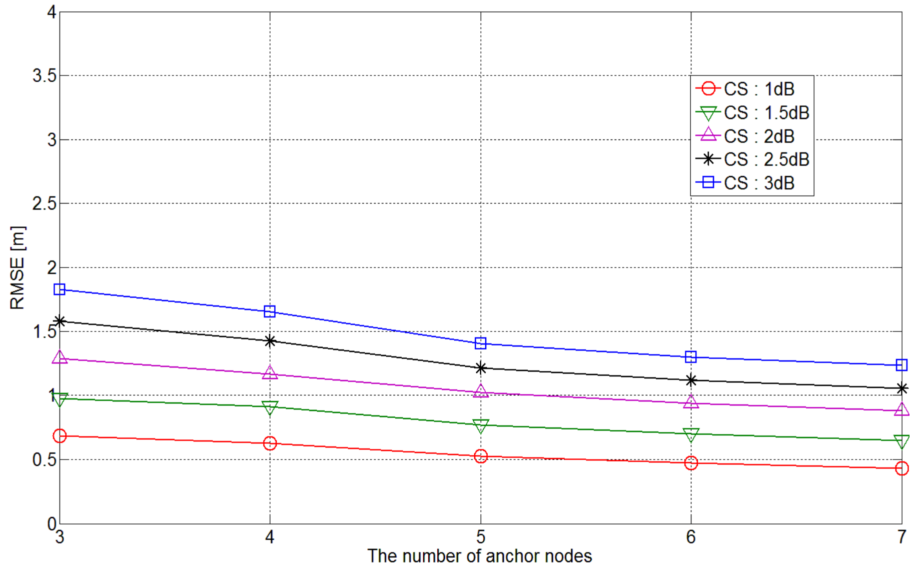

Figure 3.13 The RMSE of CS algorithm in multi-lateration

The RMSE of CS algorithm shows better when the anchor nodes are increased like the GM algorithm. Thus, the proposed CS algorithm provides good localization performance regardless of the number of anchor nodes.

3.4.4 Conclusion

In this section, the CS algorithm is presented for efficient WSNs localization using the received signal strength in an indoor environment. The CS algorithm includes three main factors, a GM algorithm, the error correction angle and the error correction distance. The GM algorithm can mitigate the noisy range of measurements for cases 5, 6, 7, 8, 9 and 10 as shown in section 3.3. The error correction angle and the error correction distance reduce the localization error in other cases that cannot be modified by using the GM algorithm. However, the false alarm of the direction of error correction angle may cause severe trouble in entire WSNs localization. Thus, the false alarm detection algorithm is proposed in the next subsection.

3.5 Bad condition detection algorithm

3.5.1 Motivation

The GM and CS algorithm proposed in former section use the parameters which are calculated from the uncertain values which are degraded by complex environment. For that reason, the mitigation algorithms using the inaccurate estimated parameters cause the bad location estimation results. The bad condition for location estimation is defined by comparing the differences of each estimated distances based on pre-estimated location. The estimated distances between the anchor nodes and target node, and the distances between the anchor nodes and pre-estimated location are big differences in bad condition to location estimation. In this section, the BCD algorithm is discussed to estimate the bad situations which cannot be offset by the proposed mitigation algorithms. The proposed BCD algorithm eliminates the bad condition to improve the accuracy and stability of localization system and classifies the proposed algorithm, GM algorithm and CS algorithm, for WSNs localization system.

3.5.2 Algorithm explanation

The BCD algorithm focuses on eliminating the bad situations which cannot be offset by the mitigation algorithms to improve the accuracy and stability of localization system. The bad condition of the estimation is defined by the estimated distances using the characteristics of tri-lateration. In empirical analysis using Monte-Carlo simulation, the large location error cases have three features. The flip ambiguity is the major feature which causes the large location error in heavy noisy environment. However, we assumed that this problem can be eliminated by the anchor node arrangement and considering in short range environment, relatively low noise environments. One of other source of large location error is the longest estimated distance. Typically, the longest estimated distance is stochastically overestimated. This source of error can be mitigated using the GM algorithm and CS algorithm. The estimated location error from the shortest distance is hard to mitigate because the proposed algorithms is based on the shortest estimated distance which has the lowest CRLB. This situation occurs frequently in case 1. When the channel parameters are known, the ML (Maximum likelihood) and WLLS (Weighted Linear Least Squared) estimation suppress the location estimation error from the variances of signal in all cases of tri-lateration. However, we assumed that the shadowing factor is unknown, it is hard to offset the location estimation error using these schemes. Thus, the proposed BCD algorithm detects the bad situation for estimation, and eliminates this situation to improve the accuracy and stability of localization system for all cases of tri-lateration only uses the estimated distances.

The two characteristics of tri-lateration are shown as follows.

Characteristic 1 : If $\hat{d}_1$ is longer than $\hat{d}_2$ ($\hat{d}_1 > \hat{d}_2$), then the absolute value of $\hat{e}_1$ is shorter than that of $\hat{e}_2$, ($|\hat{e}_1| < |\hat{e}_2|$).

Proof : TL_1 and TL_2 are the same distance distance from any other points on the radical axis. Thus, we can write

1. $dist(P_e, AN_1)^2$ - $\hat{d}_1^2$ = TL_1^2
2. $dist(P_e, AN_2)^2$ - $\hat{d}_2^2$ = TL_2^2
3. $dist(P_e, AN_1)^2$ - $\hat{d}_1^2$ = $dist(P_e, AN_2)^2$ - $\hat{d}_2^2$
4. $(dist(P_e, AN_1)$ + $\hat{d}_1)(\hat{e}_1)$ = $(dist(P_e, AN_2)$ + $\hat{d}_2)(\hat{e}_2)$
5. $(2\hat{d}_1$ + $\hat{e}_1)(\hat{e}_1)$ = $(2\hat{d}_2$ + $\hat{e}_2)(\hat{e}_2)$

since $\hat{d}_1 > \hat{d}_2$ according to the assumption, we get ($|\hat{e}_1| < |\hat{e}_2|$).

Figure 3.14 The characteristic 1 of tri-lateration

The Characteristic 1 shows the distance errors between the $dist(P_e, AN_i)$ and $\hat{d}_i$ expressed by $\hat{e}_i$ have a particular feature. The feature is that the closest anchor node has the largest distance error, $\hat{e}_c$ rather than other anchor nodes, and the sizes of the distance errors are calculated and arranged according to the sizes of estimated distances. Although the shortest estimated distance from the closest anchor node has the highest confidence value, ironically, the distance error from the closest anchor node is the largest value. From this feature, the $\hat{e}_c$ from shortest estimated distance becomes the decision criterion of the BCD algorithm.

Characteristic 2. If $\hat{e}_1$ has a minus sign, $\hat{e}_2$ also has a minus sign.

Proof : According to the characteristic of the radical axis, we have

1. $(dist(P_e, AN_1)$ + $\hat{d}_1)(\hat{e}_1)$ = $(dist(P_e, AN_2)$ + $\hat{d}_2)(\hat{e}_2)$

$dist(P_e, AN_1)$ and $\hat{d}_1$ have an absolute value. Thus, any $\hat{e}_i$, in which i = 1, 2, 3, have the same sign.

Figure 3.15 The characteristic 2 of tri-lateration

The Characteristic 2 shows the sign of the distance errors, $\hat{e}_i$ is the same for all *i*th anchor nodes. This feature means that the direction of error correction vector is not changed when the case of tri-lateration is fixed. The case 1 has minus sign only because the P_e is in the estimated circles shown as Figure 3.1. Thus, it is possible to separate easily the case 1 and other cases for building the BCD algorithm. According to characteristics 1 and 2, the BCD algorithm is proposed as follows.

---

3. Bad Condition Detection Algorithm

The process after Geometric Mitigation Algorithm.

1. Location estimation using LLSE.
   $(\hat{x}_{lls}, \hat{y}_{lls}) = (H^T H)^{-1} H^T b.$
2. Calculate the distance error from P_e,
   $\hat{e}_i = \hat{d}_i - \sqrt{(x_i - \hat{x}_{lls})^2 + (y_i - \hat{y}_{lls})^2}$
3. Set the threshold α_{th}
4. if $\hat{e}_c > \alpha_{th}$
5. then, Bad Condition Detected
6. end if.
7. Return BCD algorithm

Figure 3.16 The bad condition detection algorithm

If the one of channel parameter, X_σ is known value, the threshold, α_{th} is calculated as the CRLB of the longest estimated distance. The square root of CRLB is the standard deviation of estimated distance, which represents the distance error bound. We defined that the longest estimated distance of the square root of CRLB is threshold for BCD algorithm because the $\hat{e}_c$ is hard to exceed the error bound of the longest estimated distance in normal situation. In spite of the fact that the CRLB is calculated using the real distances, the real distances are unknown value. Thus, the estimated distance is used for the threshold calculation.

$$\alpha_{th} = \left(\frac{ln10}{10} \frac{\hat{X}_\sigma}{\text{n}} \right) \cdot \hat{d}_f = \varepsilon_{CRLB}^{est} \cdot \hat{d}_f \tag{3.8}$$

ε_{CRLB}^{est} is calculated with the channel parameters. The shadowing factor can be estimated roughly using the simple data from the anchor nodes which are known their own location. When the shadowing factor is unknown, the threshold, α_{th} consists of two steps only used estimated distances. First, if the $\hat{d}_c$ is very short value rather than other estimated distance, the threshold of $\hat{e}_c$, α_{th}^{short}, becomes $\hat{d}_c$. No matter what $\hat{d}_c$ is very short, $\hat{e}_c$ should not exceed the shortest estimated distance, $\hat{d}_c$. The decision value of the short estimated distance is δ_{th}^{short}, which is calculated by the ratio of estimated distance, $\eta \cdot \hat{d}_c / \hat{d}_f$, and η has 0 to 0.5 depends on system setting. Second, α_{th}^{long}, other case of the α_{th}^{short}, is calculated with the shortest estimated distance, otherwise calculated as the α_{th} using the CRLB. The α_{th}^{long} is decided at the rate of the shortest estimated distance with δ_{th}^{long}, which has 0 to 0.5 depends on system setting because the $\hat{e}_c$ can be expressed by the other estimated distances. The decision of the thresholds in BCD algorithm is summarized as follows:

The decision of threshold in BCD algorithm
When the shadowing factor is roughly estimated.
1. $\alpha_{th} = \left(\frac{ln10}{10}\frac{\hat{X}_{\sigma}}{n}\right) \cdot \hat{d}_f = \epsilon_{CRLB}^{est} \cdot \hat{d}_f$
When the shadowing factor is unknown.
1. If $\hat{d}_c < \delta_{th}^{short}$, $\delta_{th}^{short} = \eta \cdot \hat{d}_c / \hat{d}_f$, $0 < \eta < 0.5$
$\alpha_{th} = \hat{d}_c$
2. else
$\alpha_{th} = \delta_{th}^{long} \cdot \hat{d}_c$, $0 < \delta_{th}^{long} < 0.5$
3. end if

Figure 3.17 The decision of threshold in BCD algorithm

In the BCD algorithm, we considered only plus sign of $\hat{e}_c$, which means that the case 1 is only selected. Although the case 1 is a good case to estimate location in Section II, the case 1 is hard to mitigate the location estimation error using the proposed algorithm. The case 2, 3, and 4 are offset the estimation error each other by the gap of estimated circles, and the case 5, 6, 7, 8, 9, and 10 are mitigated by GM algorithm. Moreover, the case 5, 6, 7, 8, 9, and 10 can make the error correction vector easy because it is simple to separate the order of estimated distances. On the other hand, the case 1 has a wide estimated area which is made from the three estimated circles. In addition, the order of estimated distances are changed by estimation error with high probability rather than other cases, which disturbs the CS algorithm to make the error correction vector. Thus, we eliminate the bad condition in the case 1 (no effective GM algorithm, hard to make the error correction vector in CS algorithm) using the BCD algorithm.

The proposed algorithms, GM algorithm, CS algorithm, and BCD algorithm are combined in efficient WSNs localization algorithm which is named CAS (Classification and Selection) algorithm.

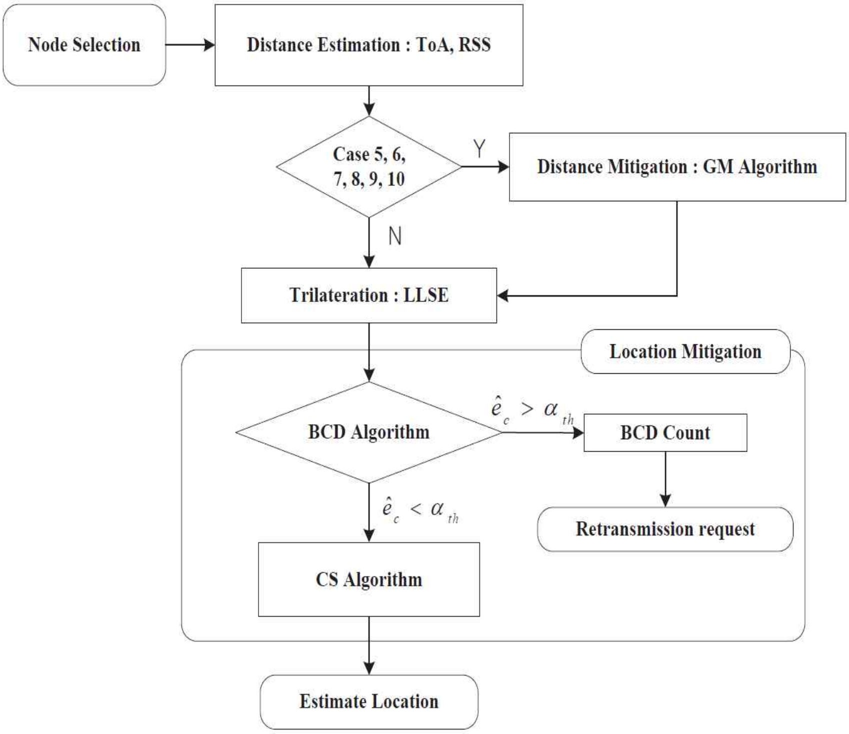

Figure 3.18 The CAS algorithm for WSNs localization system

Although the each proposed algorithms can mitigate the distance and location error, the each proposed algorithms is hard to deal with all cases of tri-lateration. The CAS algorithm controls the proposed algorithms effectively to mitigate all cases of tri-lateration and shows the high accurate location estimation results rather than that of conventional location estimation

3.5.3 Simulation

The environment of simulation is same as the chapter 3.3 for comparing the results of GM algorithm and CS algorithm. The simulation considers the false alarm rate of the BCD algorithm and accuracy of location estimation after eliminating the bad situations.

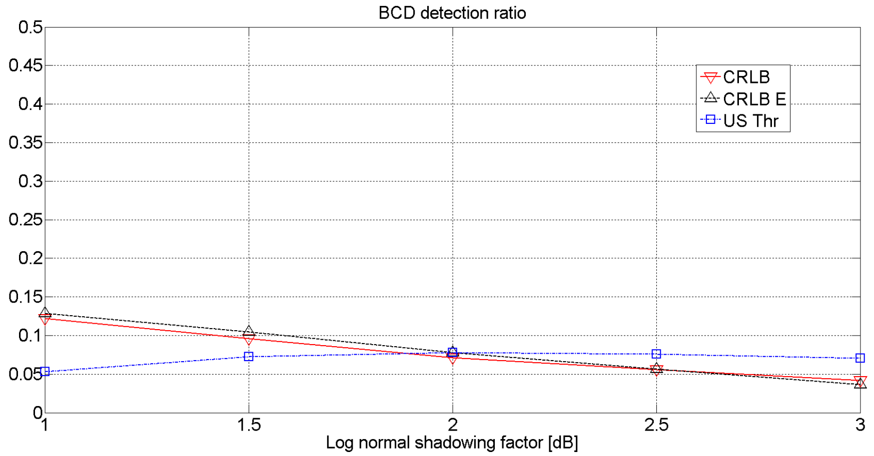

Figure 3.19 The detection ratio of BCD algorithm

Figure 3.19 shows the detection ratio of BCD algorithm. The detection ratio of the BCD algorithm means that the number of detected by the BCD algorithm is divided by total number of simulation. The detection ratio using the threshold from CRLB and estimated CRLB is decreased when the shadowing factor is increased because the CRLB, also estimated CRLB includes the shadowing factor. The value of these thresholds becomes large in high shadowing environment. And then, the number of detection is decreased due to the large value of threshold. The user selected threshold has flatness result comparatively because the user selected threshold does not changed by the shadowing factor (η = 0.5, δ_{th}^{long} = 0.5 in Figure. 3.17). Although the BCD algorithm detects the large error condition to location estimation, the detected cases have not always severe location estimation error. Thus, the false alarm rate of BCD algorithm should be analized.

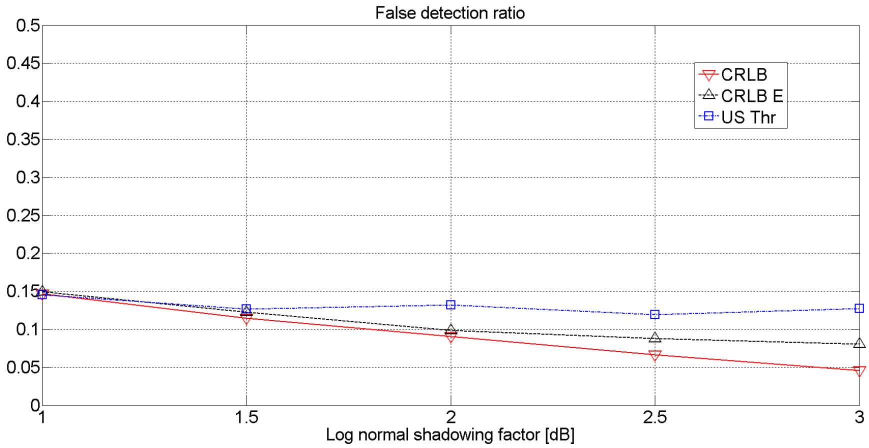

Figure 3.20 The false detection ratio of BCD algorithm

Figure 3.20 shows the false detection ratio of BCD algorithm The false detection ratio means that the number of cases which exceed the half average of location estimation error is divided by the number of the detected by the BCD algorithm. The thresholds made from CRLB, estimated CRLB, and user selection have different ratios. The false detection ratio shows the similar tendency of the detection ratio. The point is, the threshold from CRLB reflects well the noisy channel environments rather than user selected threshold. Even though the threshold from CRLB is better detection performance than user selected threshold, the user selected threshold has also reasonable results for the BCD algorithm and it is more valuable in real localization system because of unknown parameters.

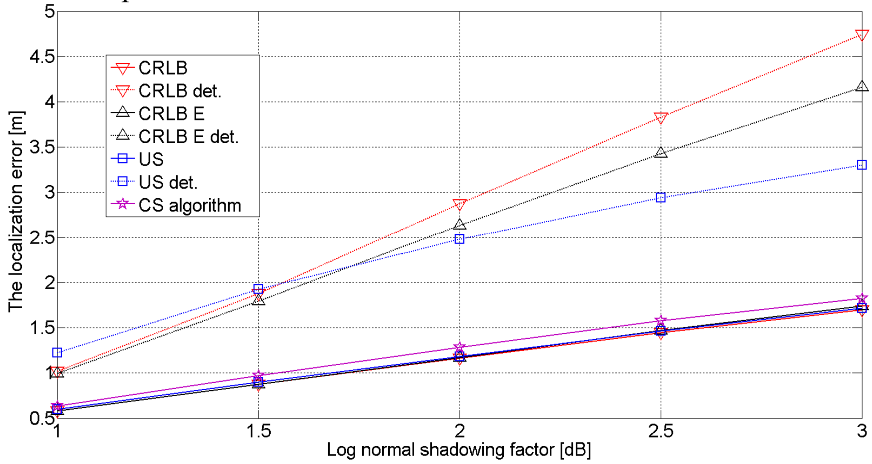

Figure 3.21 The RMSE of CAS algorithm vs CS algorithm

Figure 3.21 shows the RMSE of CAS algorithm versus CS algorithm. The three of BCD algorithm are better localization performance than that of CS algorithm. Even though it seems a little changes in total RMSE point of view, the RMSE of detected cases by BCD algorithm is much higher than that of CS algorithm. The elimination of these cases is very important to the stability of localization system prevent to location error propagation. The CAS algorithm is the best location estimation results rather than that of conventional LLSE or the each proposed algorithm, GM and CS algorithm.

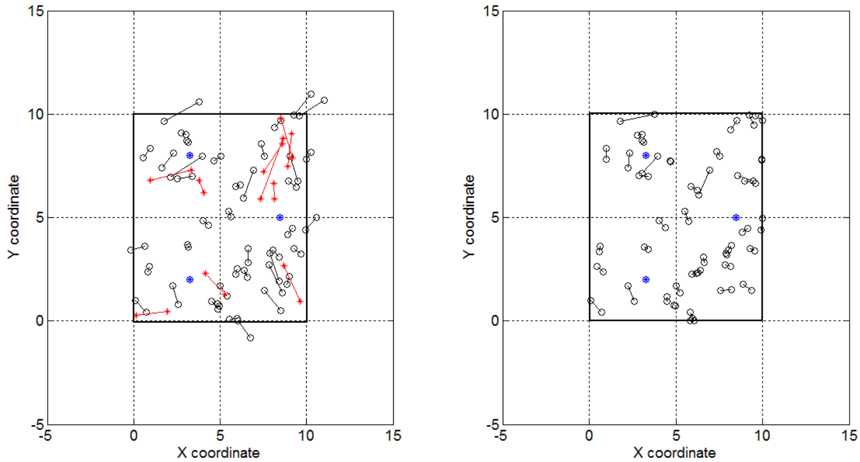

Figure 3.22 The results of CAS algorithm (30 samples, 2dB shadowing)

Figure 3.22 shows the results of CAS algorithm. The coordinates of estimated targets are change by CAS algorithm. The red line cases are detected by BCD algorithm and other cases are mitigated by GM algorithm and CS algorithm. From these results, the CAS algorithm is very effective algorithm for WSNs localization system.

3.5.4 Conclusion

In this chapter, BCD algorithm and CAS algorithm are proposed for WSNs localization system. BCD algorithm can elimiate the bad cases for location estimation in case 1, which is hard to mitigate by GM algorithm and CS algorithm. CAS algorithm combines all proposed algorithms to arrange the efficient localization algorithm for WSNs. The detection ratio of BCD algorithm is under 9% of total number of simulation (over 25% only considered the case 1) in 2dB shadowing, and the false detection of BCD algorithm is about 10% of the cases (under 2.5% for total number of simulation) which are detected by BCD algorithm. The RMSE of CAS algorithm is the best results rather than that of CS algorithm for any thresholds of BCD algorithm. Thus, BCD algorithm is very efficient algorithm to eliminate the cases of severe location estimation error in case 1, CAS algorithm offers the best accuracy localization result for WSNs.

3.5 Conclusion

In this chapter, we proposed a distance error mitigation algorithm and location error mitigation algorithms for high accurate wireless sensor networks localization system. The proposed mitigation algorithms are classified due to the cases of tri-lateration and the thresholds from the BCD algorithm. The proposed algorithms can mitigate all cases of tri-lateration based the shortest estimated distance, and eliminate the situation which is hard to offset by GM algorithm and CS algorithm to improve the estimation accuracy and the stability of localization system. Beyond that the contribution of this work in localization system point of view is twofold. First, the proposed algorithms are very simple to realize in the wireless sensor networks because the proposed algorithms consist of simple comparisons using estimated distance and the information which are known a priori. Second, the proposed algorithms are easily able to expand multi-lateration which uses four and more anchor nodes. There is no limitation from increasing anchor nodes in any proposed algorithms. Thus, the proposed algorithms work well in noisy environments due to robustness and in wireless sensor networks with tiny sensors due to simple algorithm processes.

Chapter 4. Three dimensional location estimation for wireless sensor networks

4.1 Introduction

Currently, node localization is used primarily in medical care systems, security and safety systems, emergency control systems, etc. An accurate node location can afford to help the unmanned systems which can detect and share the information themselves through wireless sensor networks. A well-known localization system, GPS (Global Positioning System) shows good performance in outdoor environments. However, the nodes in indoor, underwater, and tunnel environments for low-cost localization using small devices preclude the use of GPS signals for localization. Although the majority of localization algorithms are believed to provide the fairly accurate of position estimation and solve the geometric problems, most of these have focused solely on 2D analysis [16]-[20]. Of special concern is the fact that 2D algorithms decrease localization accuracy in a practical 3D environment. The 2D localization provides the estimated location which is projected on the same heights of anchors or the ground of the environment. This is not a severe problem when the heights of anchor nodes are similar to those of target nodes. However, it is hard to ignore the difference between the heights of anchor nodes and target node in large-scale environments such as warehouse, large size office, and underwater, because the distance measurement error is increased in proportion to the ignored difference of heights between the anchor nodes and target nodes. The newest study has reported a hybrid algorithm using distance estimation and angle estimation for 3D localization [40]. Another approach for 3D localization utilizes six anchor nodes to reduce the complexity compared with the conventional 3D linear least square estimation (LLSE) algorithm [41]. Although the 3D localization algorithms based on the estimated distances have been proposed recently, these need additional hardware for extra information [42].

In this section, we propose a 3D range-based localization algorithm that has low complexity and low cost. The distance estimate is obtained by using tiny wireless sensors which can measure the signal strength or time delay to estimate the distance and needs no additional hardware. The LLSE is used for low complexity in the proposed algorithm. Since the proposed scheme utilizes Heron's formula of tetrahedron, it requires the estimated distances from only three anchor nodes. In particular, we employ a range-based localization scheme instead of a range-free scheme, since a range-free approach has the limitations of low resolution, and also require additional hardware and large databases. The proposed algorithm proceeds in three phases. In the first phase, the offset vector is calculated from the tetrahedron formed by three anchor nodes and the estimated distance between three anchor nodes and a target node. In the second phase, the transformed target location is estimated by two dimensional LLSE using vector rotations on the plane which is formed by three anchor nodes. Finally, the target location is calculated by the transformed target location and the offset vector.

This chapter is organized as follows. Section 4.2 presents the motivations to set-up the proposed algorithm. Section 4.3 provides the proposed scheme with detail explanations. Section 4.4 shows the simulation results for the proposed algorithm and the improved localization performance. Finally, the conclusion follows in Section 4.5.

4.2 Motivation

4.2.1 Singular matrix problem

The conventional three dimensional linear least square estimation (3D LLSE) is calculated by the equation of spheres from the location of anchor nodes and the estimated distances unlike to 2D LLSE which is calculated by the equation of circles. The equation of spheres for 3D LLSE is as follows:

$$
\begin{aligned}
&(x-x_1)^2+(y-y_1)^2+(z-z_1)^2=\hat{d}_1^2\\
&(x-x_2)^2+(y-y_2)^2+(z-z_2)^2=\hat{d}_2^2\\
&\cdots\cdots\\
&(x-x_N)^2+(y-y_N)^2+(z-z_N)^2=\hat{d}_N^2
\end{aligned}
\tag{4.1}
$$

where (x, y, z) are the coordinates of target node, (x_i, y_i, z_i) means the coordinates of anchor nodes, and $\hat{d}_i^2$ is the estimated distance from the ith anchor node. The equation of spheres is solved from simultaneous equations like 2D LLSE and the coordinates of target node is calculated as follows:

$$
(\hat{x},\ \hat{y},\ \hat{z})=(\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{b} \tag{4.2}
$$

$$
\mathbf{H}=\begin{bmatrix} (x_1-x_N) & (y_1-y_N) & (z_1-z_N)\\ \cdots\cdots\cdots & & \\ (x_{N-1}-x_N) & (y_{N-1}-y_N) & (z_{N-1}-z_N) \end{bmatrix} \tag{4.3}
$$

$$
\mathbf{b}=\frac{1}{2}\begin{bmatrix} x_1^2-x_N^2+y_1^2-y_N^2+z_1^2-z_N^2-\hat{d}_1^2+\hat{d}_N^2\\ \cdots\cdots\\ x_{N-1}^2-x_N^2+y_{N-1}^2-y_N^2+z_{N-1}^2-z_N^2-\hat{d}_{N-1}^2+\hat{d}_N^2 \end{bmatrix} \tag{4.4}
$$

The coordinates of target node are calculated using the pseudo inverse of H matrix. Unlike 2D LLSE, the z component from H matrix causes unexpected error when the differences of z components are too small. This means that the heights of the anchor nodes are almost same as easily shown in indoor environments. Mathematically, this problem is called singular matrix problem. When the z components are too small, the eigenvalue of the z component is too smaller than that of other components. [43] Consequentially, the matrix H has a lack of rank to calculate the inverse matrix of H.

The proposed scheme overcomes this problem using the vector rotation schemes and offset vector which is calculated from the tetrahedron formed by three anchor nodes and the estimated distance between three anchor nodes and a target node. The Levenberg-Marquardt (LM) scheme [44], which is one of the Non-linear least square estimation (NLSE), is compared to the proposed scheme because the conventional 3D LLSE scheme is hard to be compared because of the singular matrix problem.

4.2.2 Short range location estimation

The proposed scheme has several assumptions. First, the four and more anchor nodes should be linked from the target node and the anchor nodes or the target node can estimate the distances. Second, the height of target node is up to 2m to reflect the average human-size in indoor environments. Finally, all nodes lied in the same channel environment. The first constraint means that the matrix of H should be full rank for calculation. The second and last constraints mean that this localization system is short range location estimation system. Actually, the proposed scheme does not concern no matter if the localization environment is small or large size because the users can use the topologies of wireless sensor networks. These assumptions make easy to analyze the proposed scheme for the environment with singular matrix problem that the heights of anchor nodes are almost same, and this assumption is hard to accept in large scale environments like outdoor.

4.3 Algorithm explanation

The proposed localization scheme uses Heron's formula and trilateration. Figure. 4.1 shows how to calculate the three dimensional coordinates from three anchor nodes in the proposed scheme.

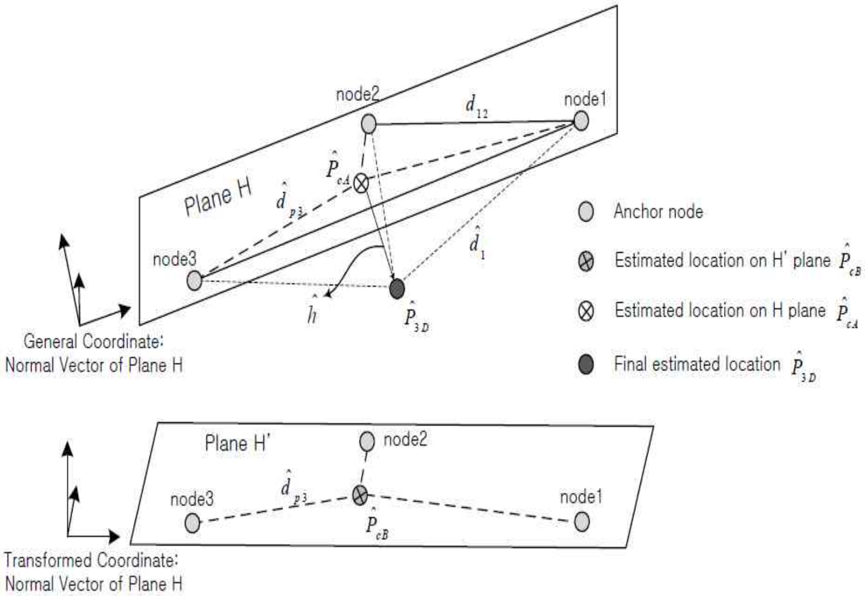

Figure 4.1 Three dimensional positioning scheme using three anchor nodes

We can calculate the distance between the *i*th anchor node and the *j*th anchor node, $\hat{d}_{ij}$ because the location of the anchor nodes is known *a priori*. The estimated distance between the anchor nodes and the target node, $\hat{d}_i$, can be calculated based on RSS or TOA. Thus, we can acquire 3 distances between anchor nodes (i.e., d_{12}, d_{23}, and d_{31}) and 3 estimated distances from anchor nodes (i.e., $\hat{d}_1$, $\hat{d}_2$, and $\hat{d}_3$) for making tetrahedron in order to calculate the height of the target. The area made from three anchor nodes on the plane H is the underside of tetrahedron. The volume of tetrahedron can be calculated by the Heron's formula. Next, the distance between the target node and the plane H, $\hat{h}$ is calculated sequentially. The calculation using the Heron's formula is represented as follows,

$$V_T = \frac{\hat{d}_1 \cdot \hat{d}_2 \cdot \hat{d}_3}{6}\sqrt{1+f(\theta_i)} \tag{4.5}$$

where VT signifies the volume of tetrahedron and $\hat{d}_i$ is the estimated distance from the ith anchor node. The function $f(\theta_i)$ in (4.5) is represented as follows:

$$f(\theta_i) = 2 \cdot \prod_{i=1}^{3} \cos\theta_i - \left(\sum_{i=1}^{3} \cos^2\theta_i\right) \tag{4.6}$$

$$\cos\theta_i = \frac{\hat{d}_i^2 + \hat{d}_j^2 - d_{ij}^2}{2 \cdot \hat{d}_i \cdot \hat{d}_j} \tag{4.7}$$

Although $f(\theta_i)$ looks like the equation having argument of cosine functions with angle variable, the cosine functions in (4.6) are given by the known distances (i.e., d_{ij}, $\hat{d}_i$, and $\hat{d}_j$) using the law of cosines. i denotes the anchor node index with i = 1, 2, 3 and j is the index of the next anchor node defined as j = (i mod 3) + 1. After the volume of the tetrahedron is obtained in (4.5), the distance between the target node and the plane H can be calculated as follows,

$$\left|\hat{h}\right| = 3 \cdot \frac{V_T}{A_V} \tag{4.8}$$

where A_V represents the area of the underside of tetrahedron made from three anchor nodes (i.e., d_{12}, d_{23}, and d_{31}). The direction of $\hat{h}$ is simply calculated from the normal vector of the plane H. $\hat{h}$ is an important parameter to find the height of the target node. To calculate the three dimensional coordinates of the target node, it is necessary to calculate the transformed coordinates of the target node on plane H (i.e., $\hat{P}_{cA}$) using estimated distance projected on the plane H, $\hat{d}_{pi}$ shown in Figure 4.2. $\hat{P}_{cA}$ is the estimated position projected on the plane H in the opposite direction of ˆh and calculated by $\hat{d}_{pi}$ on the plane H. Thus, the $\hat{P}_{cA}$ on the plane H is calculated in the transformed coordinates based on the plane H. In order to specify an arbitrary point in the 3D Cartesian coordinate, three axis should be defined. In this section, the subscript A denotes the general coordinate systems for the localization and the subscript B does the transformed coordinate systems regarding the plane H. The method of transforming the position vector of the A-coordinate system into that of the B-coordinate system is as follows,

$$P_B = C_A^B \cdot P_A \tag{4.9}$$

where P_A and P_B are position vectors in the A and B coordinate systems, respectively. C_A^B represents the transformation matrix that transforms the system from the A-coordinate system to the B-coordinate system. The transformation matrix C_A^B is obtained from the basis vector of the A-coordinate system and the B-coordinate system. Because the A-coordinate system is a general 3D cartesian coordinate, the basis vector of A-coordinate system is simply expressed as

$$X_A = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.10}$$

where the columns of X_A (i.e., α_1, α_2 and α_3) produce the standard basis for R^3. The normalized basis vectors of the B-coordinate system are given as

$$X_B = \left[\beta_1\ \beta_2\ \beta_3\right] = \begin{bmatrix} \vec{n}_{1x} & \vec{n}_{2x} & \vec{n}_{hx} \\ \vec{n}_{1y} & \vec{n}_{2y} & \vec{n}_{hy} \\ \vec{n}_{1z} & \vec{n}_{2z} & \vec{n}_{hz} \end{bmatrix} \tag{4.11}$$

where $\beta_1 = \left[\vec{n}_{1x}\ \vec{n}_{1y}\ \vec{n}_{1z}\right]^T$ and $\beta_2 = \left[\vec{n}_{2x}\ \vec{n}_{2y}\ \vec{n}_{2z}\right]^T$ are arbitrary and independent normalized vectors on the plane H. $\beta_3 = \left[\vec{n}_{hx}\ \vec{n}_{hy}\ \vec{n}_{hz}\right]^T$ represents the normalized normal vector of the plane H. The basis vector, β_1 is calculated by two points of anchor nodes on the plane H and β_3 is obtained from the equation of the plane H defined by three reference nodes. β_2 is easily calculated by vector cross product theorem using two vectors from the plane H. Therefore, the columns (i.e., β_1, β_2 and β_3) are orthogonal and normalized vectors. Subsequently, the transformation matrix C_A^B can be calculated as

$$C_A^B = X_B\left(X_A\right)^{-1} = \begin{bmatrix} \vec{n}_{1x} & \vec{n}_{2x} & \vec{n}_{hx} \\ \vec{n}_{1y} & \vec{n}_{2y} & \vec{n}_{hy} \\ \vec{n}_{1z} & \vec{n}_{2z} & \vec{n}_{hz} \end{bmatrix} \tag{4.12}$$

Note that C_A^B transforms the A-coordinate into the B-coordinate and the inverse matrix of C_B^A transforms the B-coordinate into the A-coordinate. The inverse relation between C_A^B and C_B^A is easily obtained as

$$X_A = C_B^A \cdot X_B \cdot X_A \tag{4.13}$$

Where X_A is identity matrix and C_A^B is the same as X_B which is invertible. So, C_B^A is the inverse matrix of X_B. Now, we calculate $\hat{P}_{cB}$ in Figure 4.1, which denotes the transformed target location on the plane H. The coordinates of the anchor nodes are simply transformed to the plane H coordinate system using the transforming matrix C_A^B. The transformed distance on the plane H, $\hat{d}_{pi}$ is calculated by Pythagoras' theorem using $\hat{h}$ and $\hat{d}_i$. Next, $\hat{P}_{cB}$ can be calculated by 2D LLSE on the plane H using the transformed coordinates of anchor nodes and $\hat{d}_{pi}$.

$$(\hat{x}_{cB},\ \hat{y}_{cB}) = (\mathbf{H}_{cB}^T \mathbf{H}_{cB})^{-1} \mathbf{H}_{cB}^T \mathbf{b}_{cB} \tag{4.14}$$

Where $(\hat{x}_{cB},\ \hat{y}_{cB})$ is transformed target location on plane H, $\mathbf{H}_{cB}$ is two dimensional matrix with transformed coordinates of the anchor nodes. $\mathbf{b}_{cB}$ is the constants from the coordinates of the anchor nodes and the estimated distances projected on plane H. The calculations of each matrix are as follows.

$$\mathbf{H}_{cB} = \begin{bmatrix} (x_1^{cB} - x_N^{cB}) & (y_1^{cB} - y_N^{cB}) \\ \vdots & \vdots \\ (x_{N-1}^{cB} - x_N^{cB}) & (y_{N-1}^{cB} - y_N^{cB}) \end{bmatrix} \tag{4.15}$$

$$\mathbf{b}_{cB} = \frac{1}{2} \begin{bmatrix} (x_1^{cB})^2 - (x_N^{cB})^2 + (y_1^{cB})^2 - (y_N^{cB})^2 - \hat{d}_{p1}^2 + \hat{d}_{pN}^2 \\ \vdots \\ (x_{N-1}^{cB})^2 - (x_N^{cB})^2 + (y_{N-1}^{cB})^2 - (y_N^{cB})^2 - \hat{d}_{pN-1}^2 + \hat{d}_{pN}^2 \end{bmatrix} \tag{4.16}$$

Finally, the location of the target node, $\hat{P}_{3D}$ is calculated by $\hat{P}_{cA}$ which is transformed from $\hat{P}_{cB}$ using transformation matrix C_B^A, and $\hat{h}$.

$$\hat{P}_{cA} = C_B^A \cdot \hat{P}_{cB} \tag{4.17}$$

$\hat{P}_{cA}$ is the projected point of the target node onto the plane H in Cartesian coordinate. $\hat{h}$ represents the distance and direction between the target node and $\hat{P}_{cA}$. $\hat{P}_{3D}$ is calculated as

$$\begin{aligned}\hat{P}_{3D} &= \hat{P}_{cA} - \hat{h} \\ &= \left(\hat{x}_{cA} - \left|\hat{h}\right| \vec{n}_{hx},\ \hat{y}_{cA} - \left|\hat{h}\right| \vec{n}_{hy},\ \hat{z}_{cA} - \left|\hat{h}\right| \vec{n}_{hz} \right)\end{aligned} \tag{4.18}$$

where $(\hat{x}_{cA}, \hat{y}_{cA}, \hat{z}_{cA})$ are coordinates of $\hat{P}_{cA}$ and $(\vec{n}_{hx}, \vec{n}_{hy}, \vec{n}_{hz})$ are directions of $\hat{h}$ which are calculated by the equation of the plane H. The steps of the proposed algorithm using three anchor nodes are summarized below.

Algorithm 1 Proposed Semi-Three Dimension Localization

Known *a priori*: plane equation from anchor node position.

1) Compute the estimated distance $\hat{d}_i$, i $= 1, 2, 3$
2) Calculate the volume of tetrahedron V_h
3) Calculate the length of $\hat{h}$
4) Compute the transformed distance $\hat{d}_{pi}$, i $= 1, 2, 3$
5) Compute the transformed coordinates of anchor nodes.
6) Calculate the position $\hat{P}_{cB}$ on the transformed plane H using two dimensional least square estimation with $\langle 4 \rangle, \langle 5 \rangle$.
7) Compute the $\hat{P}_{cA}$.
8) Compute the $\hat{P}_{3D}$ using $\langle 7 \rangle$ and the normal vector of the plane H.
9) End

Figure 4.2 Proposed Semi-Three Dimension Localization

The result of $\hat{P}_{3D}$ can be considered as a semi-3D location estimate, because $\hat{P}_{3D}$ needs a pre-set direction of $\hat{h}$. Assuming that the direction of $\hat{h}$ is known, we use only three distance estimates $\hat{d}_1$, $\hat{d}_2$, and $\hat{d}_3$, which implies that the proposed scheme requires only three anchor nodes. Considering that a human is located generally lower than references and an aircraft is located generally higher than references, we can simply set up the direction of $\hat{P}_{3D}$ according to a type of target. However, we also have to consider the case where the direction of $\hat{h}$ cannot be predetermined. In this case, the proposed scheme requires at least four anchor nodes. Let the number of anchor nodes in the system be N. We can choose three anchor nodes among N anchor nodes and perform the proposed scheme to obtain the 3D location estimate. For all combination of anchor nodes, we can have $\begin{pmatrix} N \\ 3 \end{pmatrix}$ 3D location estimates and easily find the direction of $\hat{h}$ by comparing the estimates as in the conventional 3D schemes. Further, we take the average of the estimates as the

final estimate of the proposed scheme. It is also noteworthy that the proposed scheme can solve the singular matrix problem caused when the heights (i.e., the z-components) of anchor nodes have almost similar values [44]. The estimated position in the conventional scheme may not be correct because the eigenvalue corresponding to z-component in the least square matrix is very small compared to the others. However, the estimated position in the proposed algorithm is stabilized even when the singular matrix problem occurs, because the 2D LLSE on the transformed plane H in the proposed scheme does not consider the heights of the anchor nodes. Therefore, it is possible to set up the anchor nodes freely in practical indoor environments, where the heights of anchor nodes become nearly close to each other with a high probability.

4.4 Simulation

In this section, we present simulation results to verify the accuracy of the proposed scheme. We assume that the simulation field is a 10 m by 10 m office environment. The ranging error is modeled as a zero-mean Gaussian random variable, of which the standard deviation is given as *p*% of the distance.

$$\hat{d}_i \sim N(d_i,\ \frac{p}{100} \cdot d_i) \tag{4.19}$$

Where d_i is the distance between the target node and the *i*th anchor node. The variance of the ranging error is known to increase with d_i [37]. The Cramer-Rao lower bound (CRLB) which provides a lower bound on the variance of the distance estimation is expressed based on the distance measurement. Thus, the ranging error model in our simulation follows the general form based on the distance measurement, because the proposed scheme can be applied to various positioning systems, no matter if the ranging signal is TOA or RSS.

The anchor nodes are placed on the boundary of the field and separated each other with 2π/N. The height of the anchor node is set to be 3 m with 1 m standard deviation to reflect the general environment. The target node is placed uniformly on the field and the height of target node is ranging from 0 m to 2 m to reflect the average human-size. The root mean square error (RMSE) in localization performance is calculated as,

$$e_{avg} = \frac{1}{N_i} \sum_{i=1}^{N_i} \left\| P_{real} - \hat{P}_{3D} \right\| \tag{4.20}$$

where e_{avg} is the RMSE of the localization schemes, P_{real} is the real 3D location of the target node, $\hat{P}_{3D}$ is the estimated 3D location of the target node, and N_i is the number of Monte-Carlo simulation. From simulation results, we found that the proposed scheme has no location estimation error when p = 0 shown in Figure 4.3.

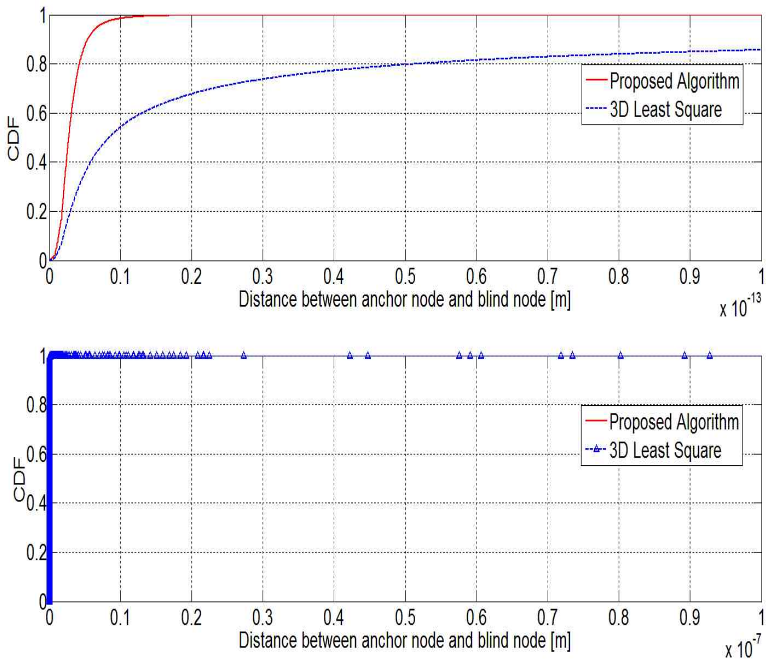

Figure 4.3 The CDF of localization error using the proposed scheme and conventional LLSE scheme in error free condition

Figure 4.3 shows the CDF of localization error using the proposed scheme and conventional LLSE scheme in error free condition. The distance error in upper side of Figure 4.3 represents the fixed point error from MATLAB program. We can notice that the fixed point error of the proposed scheme is smaller than that of the 3D LLSE scheme because the proposed scheme is more simple calculations which are composed of the 2D LLSE and vector rotations rather than three dimensional matrix calculations. The sizes of distance error are very small and hard to separate the distance errors between the proposed scheme and conventional 3D LLSE scheme in down side of Figure 4.3. Thus, both schemes do not have calculation errors in error free condition.

For comparison, we also evaluated the localization errors of the conventional 3D LLSE and 3D Levenberg-Marquardt (LM) schemes. The conventional 3D LLSE scheme needs four anchor nodes for making inverse matrix to find the 3D location even if the direction of $\hat{h}$ is provided. Since the 3D LLSE scheme has singular matrix problems, we evaluated the localization errors of the 3D LLSE scheme after setting the upper limit of the estimated height of target node as 2 m. The LM scheme can avoid the singular matrix problems using non-negative scalar in Hessian matrix. Although the 3D LM scheme can estimate the 3D location using the direction of $\hat{h}$ and three anchor nodes, the iterative descent techniques have some drawbacks. First, the 3D LM scheme requires an initial location estimate before beginning iterations. Further, the iteration process of the LM scheme inevitably results in heavy computations. In order to evaluate the performance of the 3D LM scheme, we set the maximum number of iterations to be 100 and let the iteration continue until the localization estimate converges or the iteration reaches the maximum number of iterations.

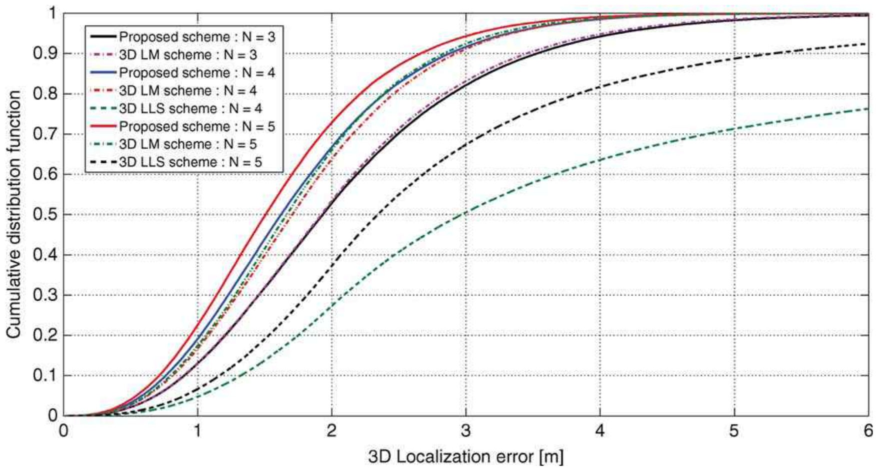

Figure 4.4 CDF of localization errors for the proposed scheme and the conventional schemes when p = 20

Figure 4.4 shows the CDFs of the localization errors of the proposed scheme and the conventional schemes when p = 20 [45]. Note that the small difference between the heights of anchor nodes results in frequent occurrence of the singular matrix problem in the 3D LLSE scheme. However, the 3D LM scheme is relatively free from the difference between the heights of anchor nodes, such that it is appropriate to set the same heights of anchor nodes as in the proposed scheme. As shown in Figure 4.4, the proposed scheme shows the better accuracy of location estimation compared to the 3D LLSE scheme in the entire localization error range. Even though the number of anchor nodes increases, the 3D LLSE scheme still suffers from the singular matrix problem because of the ranging errors. It is also observed that the 3D LM scheme enhances the localization accuracy compared to 3D LLSE scheme and provides almost the same performance of the proposed scheme. However, it should be noted that the proposed scheme requires the 2D LLSE and a few simple calculations, which has lower computational complexity than only a single iteration of the 3D LM scheme. Moreover, the 3D LM scheme executes about 40 iterations for convergence, which leads to huge computation complexity. Consequently, the proposed scheme provides the localization accuracy comparable to the 3D LM scheme as shown in Figure 4.4, while it requires significantly low computational complexity. It is also observed that the localization accuracy of the proposed scheme is enhanced as the number of anchor nodes increases.

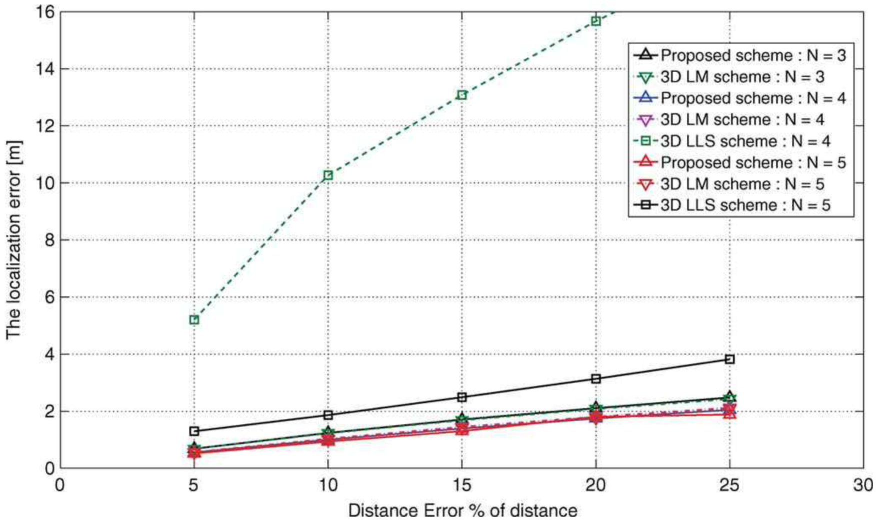

Figure 4.5 RMSE of the proposed 3D localization algorithm and the conventional 3D localization algorithms.

Figure 4.5 compares the RMSE of the proposed scheme and the conventional 3D LLSE and 3D LM schemes. The accuracy of the 3D LLSE scheme is the worst out of three schemes in all ranges of p due to the singular matrix problem. Observing the RMSE of the 3D LLSE scheme in Figure 4.5, we can conclude that the slightly difference between the heights of anchor nodes highly degrades the performance of the conventional closed-form algorithm. However, the RMSE of the proposed scheme is almost the same as that of the 3D LM scheme. However, unlike the 3D LM scheme, the proposed scheme does not require any iteration and initial location estimation.

4.5 Conclusion

In this chapter, we proposed a new semi-3D localization scheme using the Heron's formula of tetrahedron and the 2D LLSE. The proposed scheme is a range-based positioning algorithm which can use the received signal strength indicator and the closed-form calculations without singular matrix problem. The contribution of this work is twofold. First, the proposed scheme can estimate the 3D position with low-complexity, whereas the conventional 3D iterative descent algorithm requires heavy computations. Second, the proposed scheme can estimate the 3D position without singular matrix problems in practical environments even though it uses a simple closed-form algorithm.

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초 록

본 논문에서는 센서 네트워크 기반 위치 추정 방식에서의 오차 보정 알고리즘에 대한 연구를 소개하였다. 센서 네트워크 기반 위치 추정 시스템의 특징은 간단한 하드웨어로 구성되어야 하며 많은 수의 센서를 이용할 수 있기 때문에 LOS 환경을 구축하기 쉽다는 장점이 있다. 위치 추정 방식은 크게 거리 추정 기반 위치 추정 방식과 추정 거리 없이 위치를 추정하는 방식으로 나뉜다. 우선 추정 거리 없이 위치를 추정하는 방식은 주로 특수한 하드웨어에 의존하거나 매우 간단한 방식을 선택하여 대략적인 위치를 얻을 때 유용하게 이용된다. 센서 네트워크가 가지는 하드웨어의 한계 문제를 해결할 수 있는 반면에 위치 추정 정확도가 많이 떨어지는 방식이나 신호 mapping을 위한 데이터베이스 구축을 해야 되는 등의 많은 사전 작업이 필요한 방법이기 때문에 제대로 된 센서 네트워크 기반 위치 추정 시스템을 구축하기엔 고려해야 될 사항이 많다. 이에 반에 거리 추정 기반 위치 추정 방식은 신호세기, 신호의 지연 시간을 통해 거리를 추정하고 이 값을 기반으로 하여 위치를 추정하는 방식이다. 따라서 추정 거리 정확도에 따라 위치 추정의 결과 값이 많이 달라지게 되는데, 센서 네트워크를 기반으로 위치 추정 시스템을 구축하기 위해서는 신호 세기로부터 거리를 추정하는 방식인 RSSI 방식이 널리 쓰이고 있다. 신호의 지연 시간을 통해 거리를 추정할 경우 신호 처리에 의한 추정 거리 계산은 매우 정확할 수 있지만 기준 노드와 타겟 노드간의 시간 동기화 문제는 작은 센서를 이용하는 시스템에서는 이용하기가 힘들기 때문이다. 이에 따라, 신호 세기 기반 거리 추정 및 위치 추정 시스템을 고려하여 신호 세기의 변화로 인한 거리 오차 제거 및 추정 위치 보정 알고리즘을 제안하였다. 또한 2차원, 3차원으로 나누어 효율적인 위치 추정 알고리즘을 제안하여 보다 다양한 위치 추정 시스템을 구축 할 수 있도록 하였다.

효율적인 2차원 위치 추정 알고리즘은 크게 3가지로 나눌 수 있다. 추정 거리를 보정하여 정확한 위치를 찾을 수 있도록 하는 GM 알고리즘, GM 알고리즘으로 보정할 수 없는 삼변측량법 경우들까지 보정할 수 있는 CS 알고리즘, CS 알고리즘으로 보정하기 전에 미리 위치 추정하기 힘든 경우들을 제거하여 위치 추정 시스템의 안정성 및 정확도를 향상시켜주는 BCD 알고리즘을 제안하였다. 각 알고리즘은 모두 신호세기 기반 몬테-카를로 시뮬레이션으로 분석하였으며 각 알고리즘의 성능, 알고리즘을 결합하였을 때의 성능 등을 기존의 최소제곱법과 비교하면서 자세히 분석하였다.

3차원 위치 추정 알고리즘은 크게 2가지 장점이 있다. 헤론의 부피공식을 이용하여 보정 요소를 계산하고 간단한 좌표계 회전을 통해 3차원 알고리즘을 2차원으로 투영시켜 복잡도를 매우 낮췄으며, 기존의 3차원 알고리즘에서 발생하였던 singular 행렬 문제를 매우 간단하게 해결하였다. 제안한 알고리즘의 성능은 위와 같이 몬테-카를로 시뮬레이션을 통해 기존의 최소제곱법과 비교 및 분석하였다.

본 논문에서 제안된 위치추정 알고리즘은 실제 위치 추정 시스템이 구동 될 환경을 고려하여 제안하였기 때문에 다양한 실제 환경 및 시스템에서 위치 추정 기술을 적용하는데 큰 도움이 될 것으로 생각한다.

주요어 : 2차원 위치 추정 알고리즘, 3차원 위치 추정 알고리즘, 최소제곱법, 무선센서네트워크, 오차 보정 알고리즘, 실내 채널 모델링.

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