Doctoral Thesis

Incorporating Reliability of Anchors for Proximity-based Mobile Localization in Wireless Sensor Networks

by

Zulfazli Bin Hussin

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Graduate School of Applied Informatics

University of Hyogo

Abstract

Wireless Sensor Network (WSN) is a domain in ubiquitous computing technologies, which can connect the sensor nodes with outside worlds. In WSN, localization is a process that deals with how to use information from sensor nodes to determine the unknown locations of sensor nodes. Localization methods which have the ability to perform high efficiency of localization in a low cost environment with easy deployment have attracted a great deal of attention.

Proximity-based localization is a method that can deal with solutions of localization in easy deployment. In proximity-based localization, the information about connections between neighboring sensor nodes has been exploited without measuring exact distance between sensor nodes. In proximity-based localization, there are various types of physical properties of radio signals which have been used to determine the distance between sensor nodes such as Time-of-Arrival (ToA), Time-Difference-of-Arrival (TDoA), Angle-of-Arrival (AoA) and Received-signal-strength (RSS). Proximity-based localization that utilized RSS has become popular because of its inexpensive solution to the problems of localization. RSS provides useful information that is distantly related in addition to indicating connectivity information between neighboring nodes. The majority of proximity-based localization methods assume the presence of anchors, which know their exact locations in advance. Anchors can be used as reference locations to determine the location of sensor nodes, called as estimated position.

The purpose of this PhD thesis is to propose a new solution of mobile localization, which employs the proximity information of anchors by using RSS. In most proximity-based localization, the location of a sensor node is determined by calculating the average location of anchors, which are located in the communication range of the sensor node. We assume that a sensor node can communicate with anchors which are located within the communication range of sensor node. Although the anchors are always assumed to be precisely deployed at their predetermined locations, we consider this assumption is not realistic. It is difficult to maintain such positions in a real environment without providing a particular monitoring system for each anchor to assure their locations. Many studies have been reported on improving the localization accuracy of sensor node, however, most of the studies did not address the problem of how to assure the location of anchors in estimating the location of a sensor node. In this PhD thesis, we select appropriate anchors for the localization, instead of using all possible anchors.

We define the problem of determining the anchors by comparing the radio propagation in a noise-free environment and in a noisy environment. In a noise-free environment, radio propagation is ideal, a sensor node can communicate with anchors located in a perfect circle centered on a sensor node with a radius, which is equal to its standard interrogation. Average of anchors might close to the center of a perfect circle of the

communication area which denotes to the true position of a sensor node. On the other hand, in a noisy environment, the radius of the circle (which is imperfect) are varied significantly in different angle of circle due to the noise of radio propagation of sensor node. The variation of radius contributes to the inefficiency of average-based calculation of the estimated position of the sensor node. To solve this problem, the anchors could be selected based on their distance to the center of the circle. Less variation of their distances could provide the closer average position to the center of circle. We assume that the selection of anchors is reliable if they have less variation of distances to a sensor node. However, location of center of circle is unknown. Hence, we use a designated parameter to represent the center of circle in order to select the anchors. We call the parameter as *Reference point*.

The objective of this PhD thesis is to propose a new method of selecting the reliable selection of anchors by evaluating the distance between the location of average of appropriate anchors and *Reference point* in noisy environments. We call the location of average as *Indicators point*. *Indicators point* is used as a metric to measure whether the selected anchors have less variety of their distance to the *Reference point* or not. We select the anchors based on two types of *Reference point*, static *Reference point* and dynamic *Reference point*. In the selection of anchors based on static *Reference point*, we assume a mobile receiver travels in a connection of straight lines. Each line contains two anchors located at the edges of it. *Indicators point* is calculated from the average of selected anchors at the lines. We call the locations of mobile receiver located between two anchors at each interval time unit as footprints. *Reference point* is calculated using the average of three footprints which have largest RSS. We select the anchors, which have the smallest distance between *Reference point* and *Indicators point* based on the genetic algorithm approach. The estimated location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors. The feature of this method is to provide the ability to distinguish an estimated position based on *Indicators point* by comparing the distances of both estimated position and *Indicators point* to *Reference point*. As for the results of simulation experiment, we demonstrated that we were able to distinguish the reliable selection of anchors, where 89% of estimated position from reliable selection of anchors were improved their localization error for about 53% lower than the localization error of sensor nodes determined from all anchors.

In the selection of anchors based on dynamic *Reference point*, we suppose that the anchors are located at the locations of mobile receiver in each interval time unit. Anchors are divided into multiple sets based on their RSS measurement. Multiple *Indicators points* are calculated from the average of selected anchors of each set. The concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. Initially, *Reference point* is determined randomly at a known location. In determining the location of a sensor node, *Reference point* iteratively improves its location approaches to an area which has a high density of *Indicators points*. The feature of this method is to provide the ability for a sensor node to determine its location by using anchors selectively without using any static *Reference point* or objects. As for the results of simulation experiment, we have demonstrated that more than 80% of sensor nodes have improved their *Reference points* below 2m of distance between *Reference points* and true position of sensor nodes. The results of the experiments in this PhD thesis indicate that our proposed method can improve the efficiency of average-based calculation for proximity-based localization.

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1 Introduction

1.1 Background

Ubiquitous computing is a concept describing interconnection of pervasive and intelligent networked computers embedded in objects, including users. Thus, human life becomes more comfortable by enabling objects to interact and cooperate with each other [1]. Communication between such ubiquitous embedded devices and outside worlds (humans or computers) inspires large amount of information gathered in the ubiquitous computing to be applied in many services or applications. In the ubiquitous environment, a user can exchange data and sense changes by using intelligent devices which are embedded with inertial sensors, accelerometers, cameras, digital compasses or orientation sensors.

The advancement of ubiquitous computing technology has encourages the wide use of sensor network applications. The benefits of sensor network application are not only to the communications and computation of resources, but also to the contextual information such as human activities, objects in the surroundings or temperature changes in the environments. Ability of context-aware applications to obtain contextual information can allow users to apply this information for various types of services that connected to the intelligent devices. In order to perform high-quality of context-aware services that use various types of context data, it is necessary to incorporate the information that collected virtually from computers (e.g. Internet, cloud data, processed information) to the real environment (e.g. Environment sensor, actuator, camera). Hence, connection between such devices is the important domain to overcome the problem incorporate the resources in the virtual space to the resources from the real space.

A sensor network is effective for the time-critical services that allow the information from intelligent devices or computers to communicate with each other in a timely manner without using any fixed network infrastructure. For instance, MicroElectroMechanical Systems (MEMS) devices are employed in the home monitoring system to detect brightness changes, temperature of rooms or human body and movement of users. In home monitoring system, MEMS devices are used for automatically control the direction and temperature of air-conditioning system. Home monitoring system has been proposed in [2] for collection of sensor data at home to recognize a daily activity patterns of an elderly person. This system uses cameras and sensors for automated medical supervision to allow elderly person to stay at home safely and to reduce the costs of long hospitalizations. By combining the video analysis of cameras and environmental analysis of sensors, they construct a model of daily life activities of a person at each instant. If the incidents are detected from the recognized events, the system alerts an operator to provide supports in preventing critical incidents.

The emergence of ubiquitous computing technology has also helped the manufactur-

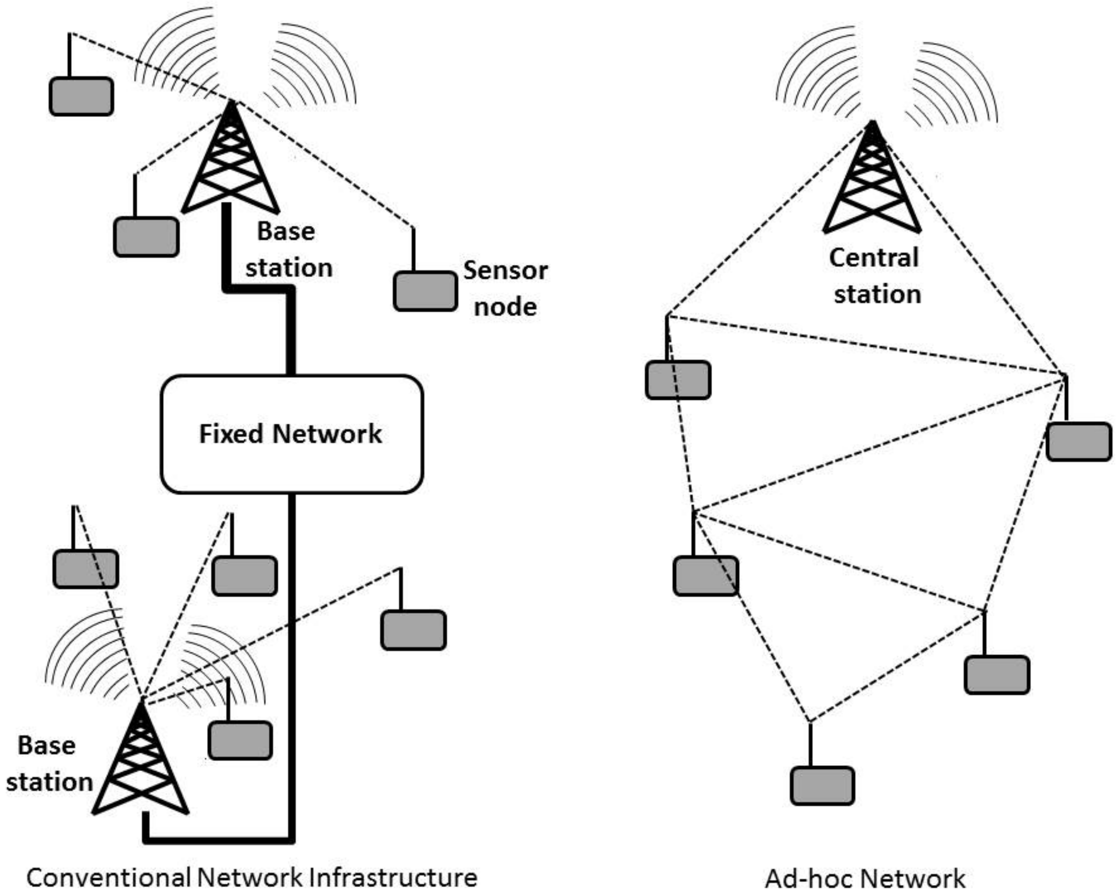


Figure 1: The concepts of conventional network infrastructure and ad-hoc network

ing enterprises to deal with the customer-centric demands in enhancing the total performance of the entire life cycle of their business. Ford [3] has adopted the Radio Frequency (RF) based system for their part replenishment system to keep inventory levels as low as possible. This system allows a worker to replenish an item by using RF transponder to retrieve an item ID of the requested item. The RF transponder transmits the information to the central server through wireless connection. RF signals from transponder are exploited to calculate the location of the replenished item automatically. An order of a particular item will be sent to the supplier automatically if the inventory level of an item is below a stock level. Localization that used an RF based system which exploits the wireless network system is proven to benefit the solution for a problem of time critical task in supply chain management.

Infineon has used the temperature sensors to record temperature data for monitoring the transportation of temperature sensitive chemical products [4]. The temperature data that are collected from portable devices (embedded with infrared sensor) are converted to XML format and transferred to the central server. By monitoring temperature history during the transportation of the products continuously, they can respond immediately to the damages of the products that exposed to the hot temperature.

British retailer Sainsbury allows full visibility of their products by using packaging crates that are attached with RFID smart tags [5]. The tags have a record of the data on expiry date information of the products. These informations are collected by using a mobile receiver and then sent to the central server that controls the distribution process. When retrieving the products, workers at the warehouse check the location of the products based on the informations supplied by the system. The products that are close to their expiry date are recognized by the system and are picked earlier by the workers. This system can localize the products without need of workers to search the products and simultaneously improve their replenishment planning for distribution center.

Exploiting wireless network in problems solving for manufacturing enterprises encourages the emergence of sensor network technologies. Computational devices in sensor networks can connect the computed information to the physical environment directly or indirectly with less effort and cost-efficient. Requirement of wireless network for sensors to communicate with each other or interact with the real environment without fixed network infrastructure is at the focus of attention.

Wireless Sensor Network (WSN) is a collection of sensor nodes that have sensing and computational capabilities which are connected by wireless communication links [6]. WSN can solve the problem of connecting intelligent devices with the physical environment. Ad-hoc networks are often used in WSN to provide sensor nodes the networking applications without the fixed network infrastructure such as wireless cellular communication system. As shown in the Figure 1, each sensor node in an ad-hoc network has a ability to communicate with each other. On the other hand, sensor nodes in the conventional network infrastructure can be connected only by using fixed network. Each sensor node in an ad-hoc network has a capability to communicate with each other by using a radio transmitter equipped with them. Unlike conventional network infrastructure, a base station, which controls the transmission in conventional network infrastructure is not required for ad-hoc networks. Sensor nodes in an ad-hoc network are connected through gateways, central station, fixed network and the internet.

In WSN, the large number of intelligent devices are equipped with sensors to collect data or information from the real environment. Sensors cooperate with each other to retrieve raw information from distributed devices. It translates and processes the raw data into the meaningful information that can be applied to a user. Intelligent devices that are equipped with actuator in the wireless network manipulate the real environment to act upon a surrounding environment. They are usually densely deployed in a wide area for object monitoring and target tracking. Various applications of WSN for a large scale of environmental monitoring systems have been proposed mainly for military [7], application for disaster [8] and application for smart environment monitoring [9]. Physical experiments of WSN have been done in many proposals which provide the effectiveness of the use of WSN. Some of the proposals have demonstrated the use of the WSN in limited resources and scale, and the ability of WSN applications for the real deployment.

WSN can facilitate many existing applications and bring into existence of other new applications. The needs to develop actual WSN applications which is low-cost, programmable and easy to deploy can envisage the applications to obtain physical parameters that can be integrated with WSN. In [10], the students in kindergarten are tracked by RF receivers attached to the ceiling of a classroom. The students wear *iBadges*, the smart badge embedded with a sensor node that can transmit signals to receivers. The receivers are deployed at fixed locations, which are used as reference coordinates to compute positions of the students. The signals received from *iBadge* are exploited to calculate their distance to the receivers and sent to the central server for location estimation. In *SmartTable* [11], the sensor nodes are attached to a table surface for observing the level of interaction with toys and objects among students during the activities that occur on the tables. The observation results are stored in the central server for teachers' reference and can be used to improve the effectiveness of activities in a classroom.

In the management of commercial buildings, WSN has been applied in their HVAC (Heating, Hentilating and Air-Conditioning) system to improve human comfort and reduce energy consumption. In [12], multiple of sensor nodes are employed to control HVAC systems in a building. A number of information such as temperature, humidity, clothing insulation and air velocity are measured by using multiple wireless sensors to control temperature in rooms. Moreover, energy consumption of a building is optimized by monitoring temperature in the rooms respectively, and control the energy consumption under the energy constraint according to the owner of a building. In [13], the mathematical model constructed from highly dynamic outputs of wireless sensor nodes has been developed to utilize the building layout information. The information of building layout can be used to achieve evacuation path planning for users in a building. Since each evacuation path is planned according to the layout of a building, this work demonstrates the effectiveness of a WSN system in assuring the safety of occupants in an emergency situation although a layout of a building is changed during the emergency.

Many of these applications are aware of sensor node locations in the physical world such as determining the location of students [10] and location of toys or objects on the table in kindergarten [11]. The location informations of sensor nodes equipped in the kitchen, living room and dining room are used to control HVAC system in the house [12]. Detecting the locations that are moved or changed has benefited the evacuation path development in a building [13]. Obviously, WSN applications have given advantages to the applications that utilize object tracking application or activity monitoring applications. Many of the WSN applications are not particularly useful if the information about the location of an objects or/and sensor nodes cannot be determined by WSN systems. The appropriate sensor technology of actual sensing and actuating can envisages the new useful information from physical environment. Physical parameters can be used by integrating these parameters with WSN to develop a localization method in WSN application which is low-cost, programmable and easy to deploy. Localization methods that have the ability to perform high accuracy of position estimation in a low cost environment with easy deployment of WSN has attracted a great deal of attention.

1.2 Motivation

Localization is fundamentally a serious problem that deals with how to use information from sensor nodes to determine position coordinates for many applications. For example, in the distribution center, locating an item has been a critical process since poor performance results in unsatisfactory customer services (long processing and lagged delivery) and high costs. Suppose that a sensor node is attached to an item at a distribution center. Placing an item at a fixed location at a distribution center makes it easier to locate it. Fixed location for items accordingly, however, is not always the most space-efficient method of storage for products that are less predictable due to uncertain demand [14]. In contrast, random-location storage uses less storage space even though it requires the use of a locator to identify the locations of items. A straightforward solution would be to equip all items with GPS-equipped sensor nodes. Sensor nodes that are equipped with GPS can provide them with the exact locations of items. Embedding GPS-equipped sensor nodes in a large amount of items or objects, however, could be insufficient and costly. Appointing the coordinates information to sensor nodes that are embedded into the environment is not effective because of cost and deployment limitation. Physical parameters that are obtained from the observations from sensor nodes can be exploited to perform the localization of sensor nodes.

We consider three main approaches to determine the location of sensor node in WSN environment, scene analysis techniques, multilateration techniques and proximity-based techniques. In scene analysis techniques, the data of prior measurements are stored in the database to perform localization [15, 16, 17]. The locations of sensor nodes can be derived by comparing the analyzed information of unknown sensor nodes or objects in an environment with the measurements data in the database. These informations can be analyzed by using camera sensors or precise distance measurement. The analyzed informations can be used to indicate whether an unknown sensor node or object is located in the vicinity of reference objects (with known location) or not. It also can be used as the origin of the virtual coordinate system to determine the location of an unknown sensor node in WSN. The cost and effort that required for explicit measurement in priori for the localization is a drawback of this approach. Multilateration techniques do not employ the explicit measurement to be stored in a database for the localization [18, 19, 20, 21]. These techniques employ accurate measurements of the distance between sensor nodes in WSN. Triangulation equation is employed to calculate the position of a sensor node based on the known positions of anchors during the localization. Here, anchors is a reference sensor node with known location. It is difficult to assure the localization accuracy with exact distance measurements between sensor nodes due to the uncertainties of radio propagation. Distance measurement between sensor nodes is contaminated by highly dynamic environment and never perfect. On the other hand, proximity-based localization has exploited the information in connection between neighboring sensor nodes to perform localization in WSN [22, 23, 24, 25]. Assuming the presence of reference positions or anchors (with predetermine information of accurate positions) in the environment, proximity-based localization have demonstrated the solutions of localization in easy implementation of WSN. Sensor nodes that located in the wireless communication range of anchors can be used to determine the location of sensor nodes. Proximities information between sensor nodes and anchors is exploited without accurate measurement of distance between each of them in WSN. Majority of proximity-based localization techniques employ Received Signal Strength (RSS) as a parameter to measure the information of the connection between sensor nodes and anchors. Proximity-based localization can provide a low-cost implementation and easy deployment solutions for WSN.

The proximity-based localization based on RSS has become popular because it is an inexpensive solution to the problem of localizing target nodes in easy deployment. Compared to various physical properties of radio signals, such as Time of Arrival (ToA) [26], Time Difference of Arrival (TDoA) [27] or Angle of Arrival (AoA) [28], RSS is an attractive approach for the localization in WSN because it can easily be obtained through existing wireless devices without the need for any additional hardware. The major challenge in RSS-based positioning approaches is to estimate accurate positioning results from RSS measurement. The variation in RSS that change over time and space due to dynamic and unpredictable signal propagation has make it more challenging to obtain accurate positioning results. RSS is not considered to be a good choice for estimating physical distances in many scenarios that involve unknown radio path loss factors, hardware discrepancies, and antenna orientation [29, 30]. The RSS, however, provides useful information about indicating the connectivity information between neighboring nodes. These informations can be used as a metric to estimate the position of target nodes without computing the actual distance between nodes [22, 31].

In the proximity-based localization, RSS measurement has been exploited without measuring actual distance to measure the connectivity among sensor nodes in WSN. The majority of the proximity-based localization methods that used RSS measurement assume the presence of anchors that know their exact locations in advance. Anchors that are located in the communication range of sensor nodes can be used as reference locations to determine the location of sensor nodes. The location of a sensor node is estimated based on the connectivity information between neighboring sensor nodes and anchors. Comparing with the scene analysis technique and multilateration technique, the localization that used proximities information of sensor nodes and anchors is relatively robust to the dynamic environment of wireless communication.

The purpose of this PhD thesis is to propose a new solution of mobile localization, which employs the proximity information of anchors by using RSS. In most proximity-based localization, the location of a sensor node is determined by calculating the average location of anchors, which are located in the communication range of the sensor node. We assume that a sensor node can communicate with anchors which are located within the communication range of sensor node. Although the anchors are always assumed to be precisely deployed at their predetermined locations, we consider this assumption is not realistic. It is difficult to maintain such positions in a real environment without providing a particular monitoring system for each anchor to assure their locations. Many studies have been reported on improving the localization accuracy of sensor node, however, most of the studies did not address the problem of how to assure the location of anchors in estimating the location of a sensor node.

1.3 Objective

The objective of this PhD thesis is to propose a new method of selecting the reliable selection of anchors by evaluating the distance between the location of average of appropriate anchors and *Reference point* in noisy environments. In a noise-free environment, as shown in Figure 2, radio propagation is ideal. A sensor node can communicate with anchors located in a perfect circle centered on a sensor node with a radius, which is equal to its standard interrogation. Average of anchors might close to the center of a perfect circle of the communication area which denotes to the true position of sensor node. On the other hand, in a noisy environment, the radius of the circle (which is imperfect) are varied significantly in different angle of circle due to the noise of radio propagation of sensor node. The variation of radius contributes to the inefficiency of average-based calculation of the estimated position of a sensor node. To solve this problem, the anchors could be selected based on their distance to the center of the circle. Less variation of their distance could provide the closer average position to the center of circle. However, location of center of communication range is unknown. Hence, we use a designated parameter to represent the center of circle in order to select the anchors. We call the parameter as *Reference point*.

In selecting the anchors, we evaluate the distance between the location of average of selected anchors and *Reference point* in noisy environments. We call location of average

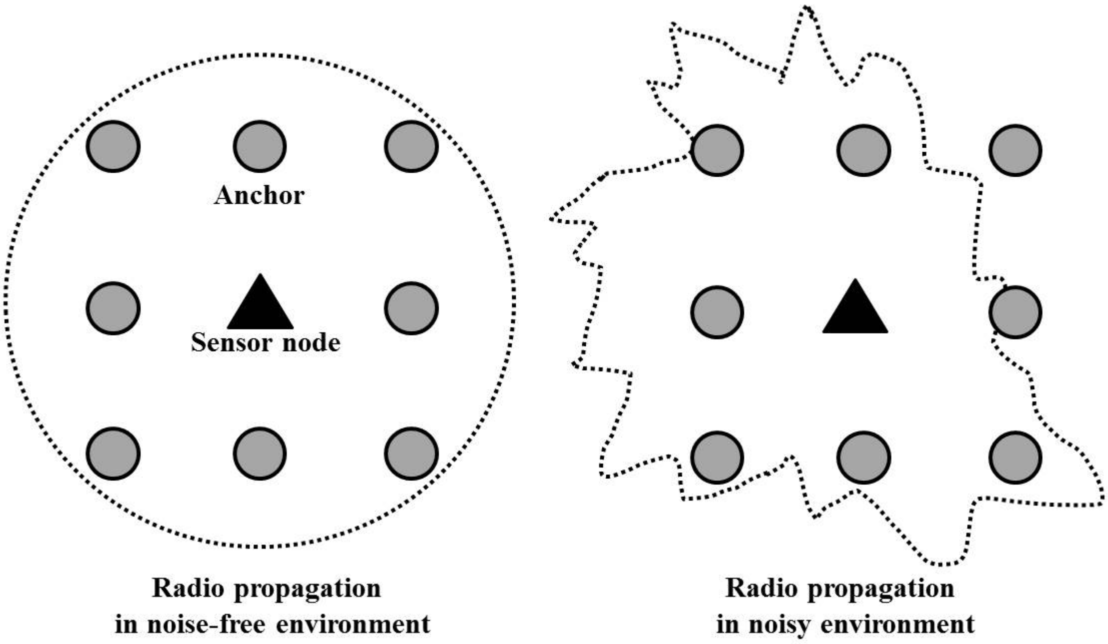


Figure 2: The comparison of radio propagation in noise-free environment and noisy environment

as *Indicators point*. *Indicators point* is used as a metric to measure whether the selected anchors have less variety of their distance to the *Reference point* or not. We select the anchors based on two types of *Reference point*, static *Reference point* and dynamic *Reference point*. In the selection of anchors based on static *Reference point*, we assume a mobile receiver travels in a connection of straight lines. Each line contains two anchors located at the edges of a line. *Indicators point* is calculated from the average of selected anchors at the lines. We call the locations of mobile receiver located between two anchors at each interval time unit as footprints. *Reference point* is calculated using the average of three footprints which have largest RSS. We select the anchors, which have smallest distance between *Reference point* and *Indicators point* based on the genetic algorithm approach. The estimated location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors. The feature of this method is to provide the ability to distinguish an estimated position based on *Indicators point* by comparing the distances of both estimated position and *Indicators point* to *Reference point*.

In the selection of anchors based on dynamic *Reference point*, we suppose that the anchors are the locations of mobile receiver at each interval time unit. Anchors are divided into multiple sets based on their RSS measurement. Multiple *Indicators points* are calculated from the average of selected anchors of each set. The concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. Initially, *Reference point* is determined randomly at a known location. In determining the location of a sensor node, *Reference point* is improved iteratively approaches to an area which has a high density of *Indicators points*. The feature of this method is to provide the ability for a sensor node to determine its location by using anchors selectively without using any static *Reference point* or objects.

We describe the structure of this PhD thesis as follows: Chapter 2 presents an overview of localization techniques for WSN. Furthermore, we described the previous works about the localization solution regarding the uncertainties of RSS measurement to achieve high-efficiency localization.

Chapter 3 describes the problem of selecting the anchors in proximity-based localization. More concretely, a special attention has been given to the average-based calculation of anchors which is employed in many proximity-based localization. Anchors are affected by the errors from radio propagation effects such as multipath and fading, we address the solutions on selecting an appropriate anchors fro the localization, instead of using all anchors in the localization. We propose the methods of selecting the anchors by observing the relation of distance function between the average position calculated from selected anchors with an *Indicators point*. This relation is used as a parameter to measure whether the average position is located close to the center of communication range or not.

Chapter 4 is devoted to present our proposed proximity-based mobile localization method that utilized the selection of anchors based on static *Reference point* [32, 33]. More concretely, the RSS measurement is utilized to measure the proximities of sensor nodes with anchors in the localization. RSS measurement is converted into distance by using fuzzy logic approach to indicate the distance between an anchor and a sensor node. We carried out the simulations and experimental results to evaluate the performance of our proposed method.

Chapter 5 focuses on proximity-based mobile localization that utilized the selection of anchors based on dynamic *Reference point* [34]. More concretely, the location of a sensor node is determined by using the concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. *Reference point* is improved iteratively approaching to an area which has high density of *Indicators point*. We carried out the simulations and experimental result to evaluate the performance of our proposed method.

Chapter 6 concludes this PhD thesis with a summary of the obtained simulation and experimental results. The limitation of these studies and some suggestions for future work are also presented.

2 An overview of localization techniques for wireless sensor networks

In this chapter, we present an overview of the methods for determining the location of sensor nodes in WSN as shown in Figure 3. The localization methods in WSN are divided into two types of localizations, anchor-based localization and anchor-free localization. These methods are discussed in this chapter, including the properties of anchor-based localization methods that employ the mobile receivers in their localization methods, the previous localization techniques, radiolocation techniques and the solutions for improving the efficiency of radiolocation methods.

2.1 Anchor-based localization and anchor-free localization

Anchor-free localization methods do not depend on the existence of anchor or reference objects [35, 36]. These methods typically begins with an initial coordinate assignment based on the connectivity between sensor nodes [35] or by selecting a small set of sensor nodes and assigning coordinates to them [36]. Then, each sensor node uses the most recently computed coordinates of neighboring sensor nodes to recompute its own coordinates repeatedly until the position of all sensor nodes have converged. A drawback of anchor-free localization methods is that they are prone to error because of a poor overall coordinate assignments. The efficiency of the methods depends heavily on the initial coordinate assignments. Assigning a good initial coordinate without any reference position or objects is not easy, especially in the anisotropic topology which can be caused by the irregular shape of the area or by obstacles within the area. The efficiency of the localization in such environments can be improved by using the knowledge of the absolute positions of anchors.

The majority of localization methods in WSN assume the presence of anchors that know their exact positions in advance [22, 23, 37, 38, 39, 40, 41, 42, 43]. Anchors are utilized as reference positions for determining the location of sensor nodes. The location of anchors can be obtained by installing the anchors at predetermine location in the localization area or by using a global positioning system (GPS). Anchors or location-aware receivers receive signals from a sensor node and calculate the unknown location of sensor nodes located within their vicinity.

2.2 Receiver-assisted localization

Receiver-assisted localization has attracted a great deal of attention in estimating the positions of objects that are equipped with sensor nodes by using mobile receivers. A receiver receives signals from a sensor node and computes its location. There are two types of

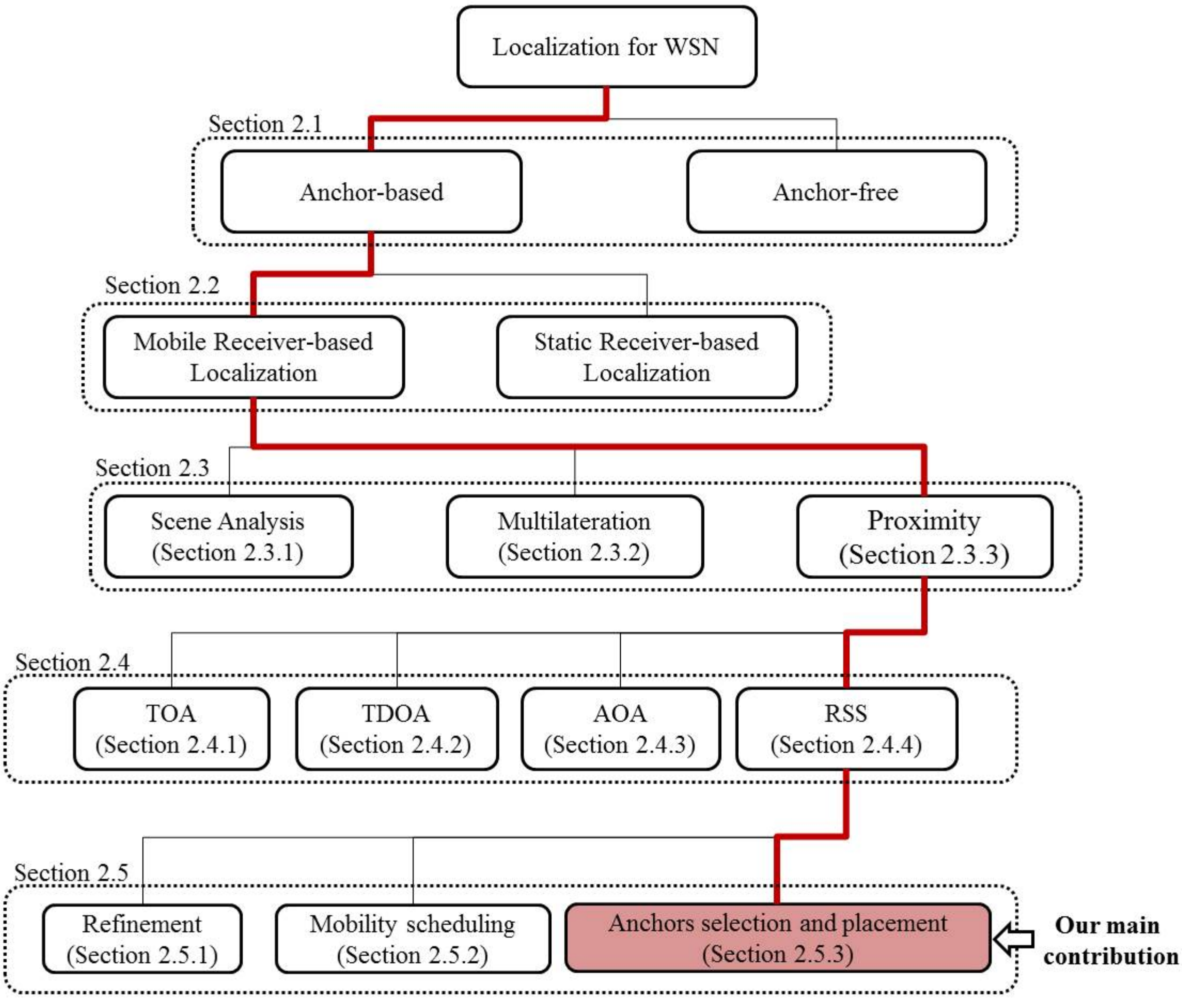


Figure 3: Overview of localization method for WSN

receiver distribution which are used to detect a sensor node. One is to deploy many fixed receivers which cover particular regions [44, 45] and another way is to use a mobile receiver to do a location sensing [46, 47, 48].

In [44], passive method and active method of RFID system have been employed in the localization to locate the RFID receivers and tags in the predetermined arbitrary coordinate system. RFID receivers and tags are used as anchors (with known coordinates) to determine the location of the target receivers and target tags (without known coordinates). Anchors are deployed in a specific location on a floor or a ceiling in a hexahedron-shaped space. In the passive method, the location of target tags are calculated by using the responding anchors that are deployed in the areas. Nelder-Mead nonlinear optimization scheme is used to minimize the errors of the localization based on the accurate locations of responding anchors. In the active method, anchors are used to collect the signals from moving receivers (without known coordinates) continuously. The location of moving tar-

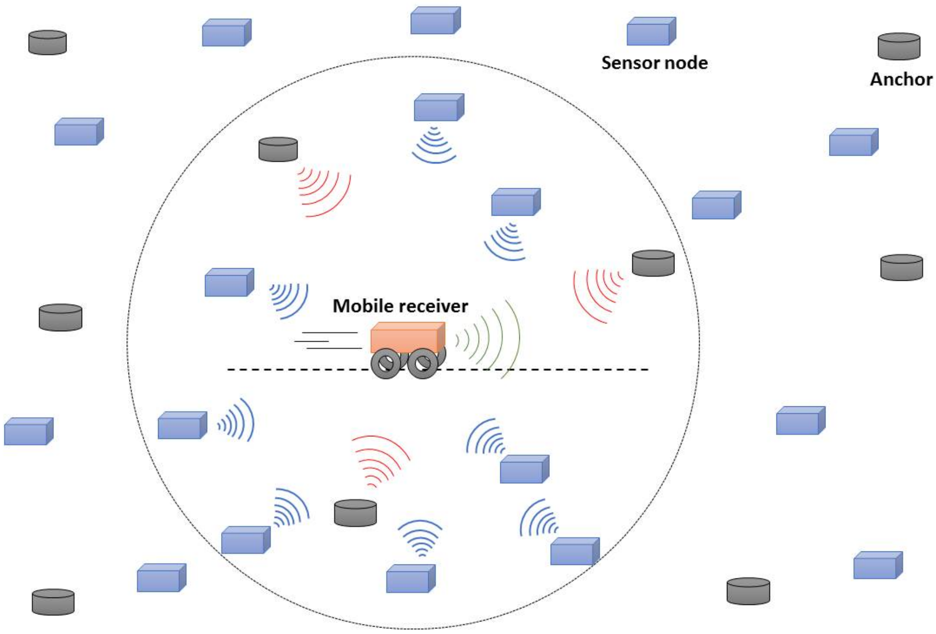


Figure 4: Receiver-assisted localization in WSN that used mobile receiver to receive signals from sensor nodes

get receivers are estimated for each interval time unit based on the location of anchors.

In [49], the multi-path reflection effect is exploited to detect an object located between a pair of receivers. This effect occurs from the reflection of signal by ceiling or wall in a building. The regular and irregular of signal information from both receivers is utilized to detect an object located between the receivers. The regular signal is a non-light-of-sight (NLOS) signal transmitted from one receiver to another without any objects located between them. The irregular signal is a signal reflected from the objects located between the receivers. The weight of the presence of an object is calculated by comparing the difference of regular signals and irregular signals. The weight indicates the possibility of the existence of an object on the link between the receivers. In their extended research [45], they deployed three receivers on a ceiling in a triangle-shape area and each receiver continuously communicates each other to detect the existence of an object. The map of connection of signal between the receivers is constructed to represent the map of links of three receivers. The weight is computed at each link if an object is located within this map. If an object is closer to one link, the weight of the link is becoming larger than the weight in other links. These weights are used to estimate the exact location of an object in the map of links.

Another way is to use a mobile receiver to do a location sensing. Since a mobile receiver is portable and easy to use, it is suitable for location sensing in a large area (e.g. Distribution centers). Figure 4 shows a mobile receiver receives signals from sensor nodes that are located in its wireless communication range. The signals contain an information that describes the relation between mobile receiver (anchor) and sensor nodes such as signal strength, departure time and arrival time of a signal, angle of direction of a signal, location information of anchors and the proximities information between anchors and sensor nodes. These informations are exploited to calculate the locations of sensor nodes. In general, the reading range of a mobile receiver is around a few meters with an additional modular [50]. In the near future, the ability of mobile receiver will be improved due to new antenna designs. Therefore, the localization methods that use mobile receiver may become a widely used approach.

In [46], the locations of sensor nodes are estimated by using location information from GPS-equipped mobile receiver. Mobile receiver is equipped with a GPS system to obtain its current position and transmits the messages that contain its location information to the sensor nodes within its wireless communication range. Sensor nodes use these messages together with the signal strength measurement that measured from the received message to compute its position. In this method, Bayesian inference approach has been employed to update the estimated location of sensor nodes periodically.

In [47], the locations of mobile devices (e.g. Smartphones, router and remote control) are estimated by using the context entities information from the mobile devices such as data volume, frequency, resource availability for each target mobile device. The GPS-equipped devices are used as anchors to obtain the context information from a target mobile devices. This method uses the context information to combine with the position information from anchors to build high-precision tracking system for mobile devices.

In [51], the sensor nodes are attached with an acoustic sensor board to measure the time difference of arrival (TDOA) of the acoustic signals between mobile receiver and the sensor nodes. Ranging information calculated from the time measurement of acoustic signals is used to estimate the position of sensor nodes. Acoustic signal is converted into distance by using the least-squares approach. This method employs non-linear optimization which improves the position of sensor nodes iteratively based on the distance between sensor nodes and mobile receiver. The drawbacks of this method is the requirement of line-of-sight (LOS) environment for acoustic signal transmission between mobile receiver and sensor nodes. Moreover, this method requires an assignment of initial position of sensor nodes. The poor accuracy of the initial position can contributes to the inefficiency of the localization.

In [48], the signal strength is measured from target sensor nodes by using mobile robots to perform localization for the sensor nodes which are located within the transmission range of mobile robots. Static receivers are deployed in the localization areas and used as anchors to help the system to localize sensor nodes. Mobile robots receive messages from static receivers which contain the estimated positions of the present location of mobile robots. The estimated location is combined with the measured RSS from target sensor nodes to perform the localization of target sensor nodes that are located in the vicinity of mobile robots.

2.3 Localization techniques

It is useful for a sensor node in WSN to be aware of its location in the physical environment. Localization of sensor nodes in WSN is a fundamental serious problem that deals with how to use information from sensor nodes to determine position coordinates. Providing coordinates information for each sensor node deployed into the environment is not an effective way because of cost and deployment limitation. We consider three main approaches to determine the location of sensor nodes that have been extensively researched recently.

1. Scene analysis: This technique employs camera or/and sensors to perform scene analysis in determining the location of sensor nodes. This technique analyzes the characteristic of objects or a person in an environment from a data taken by cameras or/and collected by sensors. The analyzed information is compared with prior information (analyzed data which is stored in database) to determine the location of sensor nodes.

2. Multilateration: The geometry element of wireless connection links within sensor nodes and anchors is exploited to determine the location of sensor nodes. The wireless communication links are utilized to solve mathematical equations of multilateration problems in calculating the exact location of sensor nodes.

3. Proximity: The neighborhood information of sensor nodes and anchors is exploited to determine the approximate distance between sensor nodes and anchors for the localization of sensor nodes.

2.3.1 Scene analysis

In scene analysis technique, the locations of a sensor node is determined by analyzing the pictures taken by the cameras. This technique requires considerable computational effort which is difficult to be applied in WSN that employ small and low-cost devices with a limited computation capability.

Other approaches that used in scene analysis technique is to determine the location of a sensor node by using prior measurement information from database such as RSS measurement, radio wave propagation patterns or the accurate location of anchors. The properties of the analyzed information in database are compared with the measurement

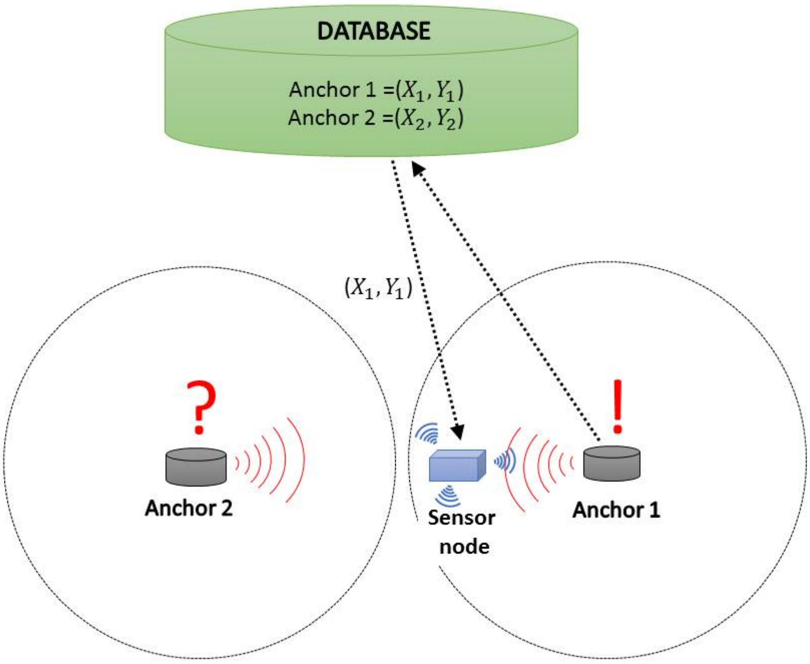


Figure 5: Determining a sensor node location by comparing prior measurement information of anchor position

of a sensor node. Figure 5 shows the estimation of the location of a *Sensor node* based on the location of *Anchor 1* and *Anchor 2* from database. (X_1, Y_1) and (X_2, Y_2) are the coordinates of *Anchor 1* and *Anchor 2* respectively, which is stored in the database before the localization is performed. The location of *Sensor node* is determined by comparing observation results from anchors. The existence of *Sensor node* in the wireless communication range of *Anchor 1* is used as a observation result to choose which location in the database should be used to determine the location of *Sensor node*. Here, the location of nearest anchor (which is *Anchor 1* as shown in the figure) is used to estimate the location of *Sensor node*. As shown in this figure, the location of *Sensor node* is determined as same as the location of *Anchor 1* according to the comparison of observation results from both anchors.

There are many researches have employed the scene analysis technique in their localization methods. In [15, 16], They use infra-red (IR) signals technologies to determine the location of the RFID tags. These tags are embedded with IR transceiver which can transmit a unique code and receive signals from sensors deployed in the environments. Sensors are deployed at fix location and transmit the signals to the RFID tags if they are located within their communication range.

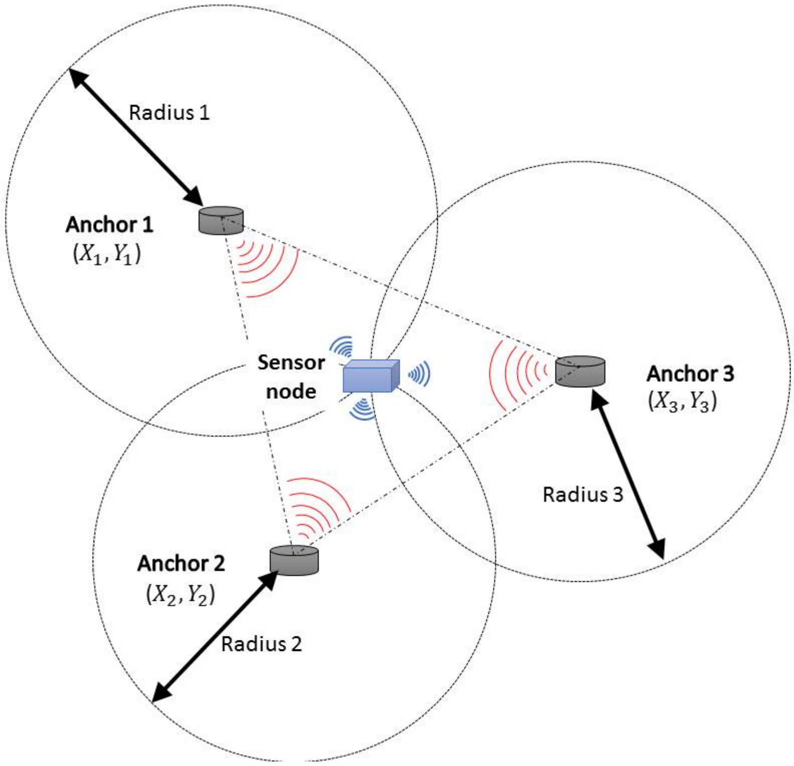


Figure 6: Measurement of accurate distance between a sensor node and anchors to perform multilateration

[17] has used a radio-frequency (RF) technology to determine the location of sensor nodes due to the limitation of range distance of IR and deployment cost as used in [15, 16]. In [17], they consider a data collection step in offline phase and localization step in online phase. In offline phase, the location of sensor nodes (anchors) are measured with explicit measurement instruction and stored in the database. The RSS is measured at each point of location which is determined before the measurement. Then, measurement information of signal strength and coordinates of measurement points is stored in a database which will be used in the online phase. In online phase, location of a target sensor node (with unknown location) is estimated by comparing the signal strength measurement information of a sensor node with the measurement information (signal strength and location of reference positions) in the database.

2.3.2 Multilateration

Geometry element can be extracted from the connection links within sensor nodes in WSN. The geometry information from the links provides the notable information to solve mathematical problems of the links such as lengths, angles or areas. Lateration and angulation are used in the multilateration-based localization techniques which employ the geometry elements of the links in determining the location of sensor nodes. Figure 6 shows the multilateration-based localization technique that determines the location of a *Sensor node* from the intersection of three circles of wireless communication range of *Anchor 1, Anchor 2* and *Anchor 3*. Suppose $(X_1,Y_1),(X_2,Y_2)$ and (X_3,Y_3) are the coordinates of *Anchor 1, Anchor 2* and *Anchor 3* respectively, the location of *Sensor node* is determined by using trilateration equation based on the coordinates of anchors and the distances between anchors and *Sensor node*. Here, the distances between anchors and *Sensor node* are given as *Radius 1, Radius 2* and *Radius 3*. These distances are determined based on the measurement of signals from *Sensor node* at each anchor. Since the distance measurement of *Radius 1, Radius 2* and *Radius 3* are contaminated with noises and never perfect, the intersection of the circles of a wireless communication range of anchors will not give a result in a single point. Therefore, it is difficult to obtain an accurate single intersection point by using the distance measurement of *Radius 1, Radius 2* and *Radius 3*. The accuracy of distance measurement is trivial to the accuracy of the localization.

The incremental algorithm [18] uses the location information of anchors to localize a sensor node by applying the signal strength measurement between anchors and a sensor node. Geometry information of links between anchors has been used to solve a triangulation problem to calculate iteratively the coordinates of a sensor node. Every sensor node is assigned with the initial location as the origin of their coordinate system and estimate their own position by using multilateration technique based on the location of at least four anchors. Then, each sensor node uses the most recently computed coordinates of neighboring sensor nodes to recompute its own coordinate repeatedly until the position of all sensor nodes have converged. The accuracy of this algorithm heavily depends on the initial coordinate assignments and the accuracy of distance measurement between anchors and a sensor node in each iteration.

The Maximum Likelihood Estimation (MLE) is applied in [19] combines with signal strength measurement to perform multilateration by using the locations of anchors (sensor nodes that deployed in the environment with known location) [19]. Distance measurement of pairs of target sensor nodes is used in the multilateration equation to localize the target sensor nodes. MLE is used to iteratively reduce errors of the localization by using the estimated location of target sensor nodes.

Time rounds scheme has been applied in [20] to perform iterative localization in WSN. This method consists of two phases, localization phase and data transmission phase. In the localization phase, the location of a target sensor node is estimated by using anchors (with known positions) based on the measurement of signal strength from a sensor node in the environment. Then, the estimated location is transmitted to the neighboring sensor nodes in the data transmission phase to help the localization of other target sensor nodes.

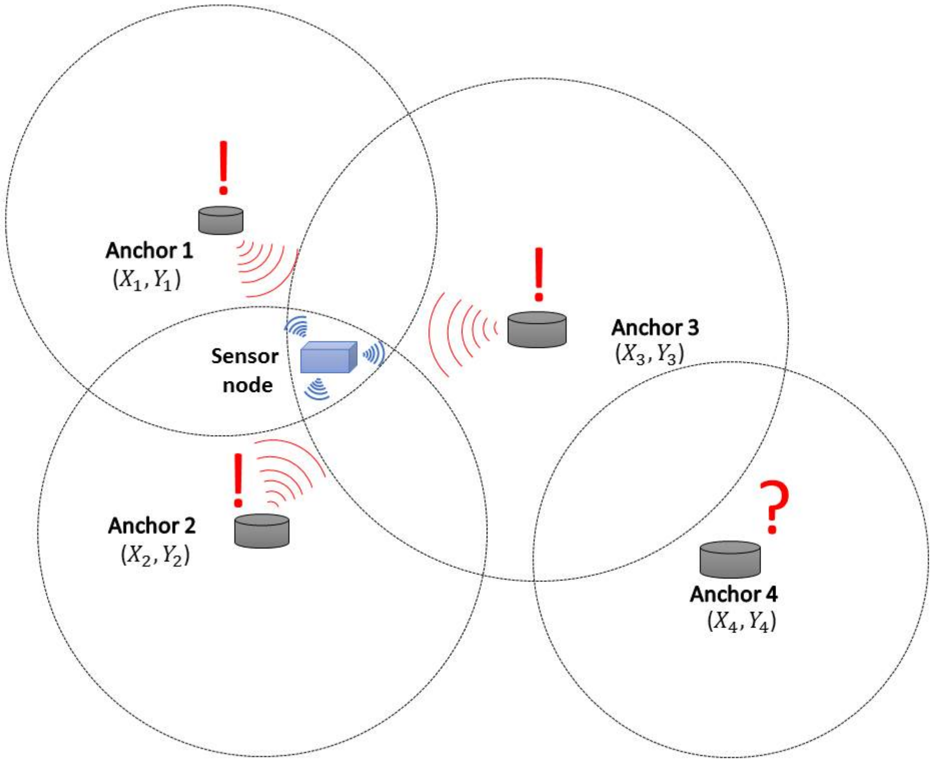


Figure 7: Determining location of a sensor node from connectivity information between anchors.

Each iteration of transmission is synchronized within sensor nodes, including anchors by using a periodic timer embedded in each sensor node and anchor.

In [21], the coordinates of anchors and the distance measurement between a sensor node and anchors are used in multilateration equations to calculate the location of a sensor node. This method considers the variation of attenuation in the signals transmission among sensor nodes and anchors has deteriorates the accuracy of distance measurement. In order to improve the accuracy of distance measurement, the attenuation coefficient of all transmitted signals are calibrated according to radio propagation characteristic in the environment to increase the accuracy of localization.

2.3.3 Proximity

Localization based on the proximity technique exploits the connection between sensor nodes and anchors in an environment. The connectivity information between sensor nodes and anchors can be used to determine the existence of sensor nodes or anchors in their vicinity. The majority of the proximity-based localization methods assume the presence of anchors that know their exact positions in advance. Proximity information of several anchors can be analyzed by a sensor node for approximate positioning in WSN [22, 23].

This type of localization technique is most similar to the coarse-grained localization which exploits the wireless connectivity information between neighboring sensor nodes to perform localization. On the other hand, fine-grained localization employs the measurements of exact distances or angles relative to the location of reference positions or neighboring sensor nodes. Unlike fine-grained localization, coarse-grained localization is relatively robust to the error from noisy environments. The ability to perform the localization without the precise measurement of distance can avoid the errors from distance measurement in noisy environment.

In most proximity-based localization, location of a sensor node is estimated by computing the average locations of anchors, which are located in the wireless communication range of a sensor node [22, 23, 37, 38, 39, 40, 41, 42, 43]. As shown in Figure 7, by exploiting the wireless connectivity between sensor node and anchors, *Sensor node* can determine whether the anchors are located in the proximity of its location. Given the locations of four anchors, *Anchor1, Anchor 2, Anchor 3* and *Anchor 4* as $(X_1,Y_1),(X_2,Y_2),(X_3,Y_3)$ and (X_4,Y_4) respectively, *Sensor node* is able to recognize these anchors which are located within its communication range. Given the coordinates of the recognized anchors are $(X_1,Y_1),(X_2,Y_2)$ and (X_3,Y_3), the location of *Sensor node* can be calculated by using the average of the coordinates of recognized anchors without using the measurement of distance between *Sensor node* and each anchor. *Anchor 4* is not consider as the recognized anchor because of its location located outside the communication range of *Sensor node* as shown in this figure.

Many researches have employed the proximity-based localization to avoid the precise measurement of distance between sensor nodes. In [22], they use Received Signal Strength (RSS) as a parameter to measure the signals transmitted from RF transceivers which are used as anchors for the localization system. The perfect circle of wireless communication range from target sensor nodes and RF transceiver is assumed in the environment to estimate the location of target sensor nodes. Average of known positions of anchors that are located in the coverage of target sensor nodes are utilized as the estimated location of target sensor nodes. The RSS from target sensor nodes measured by the RF transceivers is used to make sure that all anchors are located at the same distance to the target sensor nodes. Here, distance is derived from the RSS of transmission between an anchor and a sensor node.

In Monte Carlo Localization (MCL) method [23], the localization of target sensor nodes is performed by using the reference nodes that are deployed in a priori. The reference nodes, however, do not have the information about their position. The target sensor nodes and reference nodes have a fixed wireless transmission range. There are two steps in estimating the position of sensor nodes. A prediction step and filtering step. The position of a target sensor node is localized at each interval of time and stored at each target sensor node in the prediction step. In filtering step, new information on the observation from reference nodes is used to improve the location that estimated in the prediction step. The posterior distribution of estimated location is represented by a set of weighted samples. These samples are selected randomly and determined as the initial samples of the distribution. Uncertainties of radio propagation in selecting the initial samples can deteriorates the accuracy of initial samples which are critical to the localization accuracy.

In multi-dimensional scaling (MDS) methods, the connectivity of sensor nodes is used to determine their initial locations (initial step) and repeatedly improve their positions (improvement step). In an initial step of MDS, all target sensor nodes determine their positions by using the connectivity information on them. Then, these location information is improved by MDS iteratively by using the number of hop-count of their neighboring sensor nodes. The improvement of the location information will be properly normalized if the anchors with absolute position are available in the environment.

In [24], estimated distances between pairs of target sensor nodes are used in MDS to calculate the relative location of target sensor nodes. MDS-MAP is applied to construct a relative map which represents a relative location of neighboring sensor nodes. A relative map is transformed into an absolute map if anchors or sensor nodes that have absolute location information are available in the map. In MDS-MAP, relative map is constructed from the estimated distance matrix of neighboring sensor nodes. Here, hop-counting is used to represent a distance parameter in constructing the relative map. This method requires the construction of a relative map at each sensor node. These maps are merged to generate a global map. The merging process can slow down the computation speed if there are too many common sensor nodes in the relative map. In [25], the computation speed is improved in constructing a relative map at each sensor node by filtering the sensor nodes in a merging process. The neighboring sensor nodes are chosen randomly in the merging process, instead of using all sensor node information in the relative map.

Since the localization accuracy of the above methods depends on the numbers of deployed anchors in the areas, we find it difficult to employ the methods in a large area such as distribution center or warehouse. A number of receivers and their distributions have a direct impact to the accuracy of localization. A large number of distributed receivers will lead to improve the accuracy of the localization. However, the costs of deployment will increase if a large number of anchors are deployed into the large areas. The deployment of a large numbers of fixed anchors for accurate localization are expensive in the environments that changed accordingly such as in flexible distribution center automation system. The locations of racks or the location of storage of particular items are frequently changed due to the changes of market trends. The redeployment of sensor nodes and anchors in an environments that are frequently changed is time-consuming and costly. Therefore, it is important to improve the efficiency of proximity-based localization methods in a low-cost

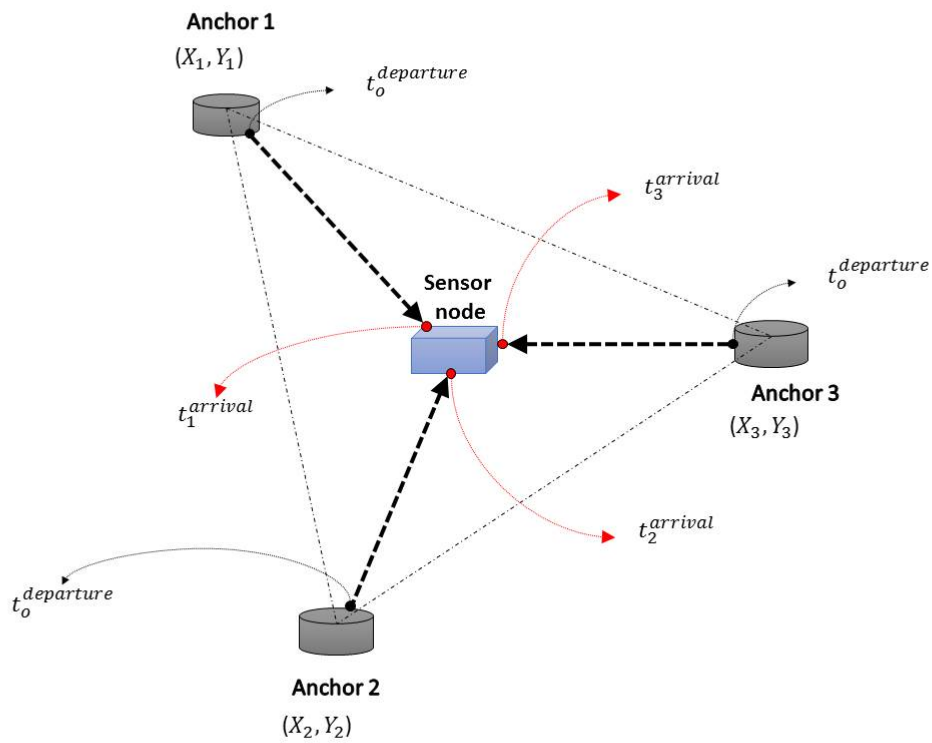


Figure 8: Measuring time of arrival (TOA) of signal from anchors where the time of departure of the signals are synchronized within all anchors

environment with easy deployment of WSN.

2.4 Localization based on radiolocation methods

Recently, various of researches concentrate on determining the location of sensor nodes based on the combination of sensor nodes without GPS capability and with the GPS-equipped sensor nodes. The combination can increase the efficiency of localization which can be applied in indoor and outdoor environments. Radiolocation methods have been employed in many GPS-less localization systems to measure a distance between transmitter and receiver. In this section, we discuss several previous researches that use radiolocation methods for localization in WSN.

2.4.1 Time of arrival

Time of Arrival (TOA) is a technique that used the propagation time of the signal during the transmission between sensor nodes and anchors. This technique requires the synchronized and accurate timer of all sensor nodes (transmitter and receiver) to allow both transmitter and receiver to send and receive signals in the same timestamp. This requirement is to make sure the accurate measurement of distance according to the trip time of a signal. As shown in Figure 8, the difference between a synchronized time of departure of a signal from all anchors, $t_0^{departure}$ and time of arrival of signals from each anchors, $t_1^{arrival}, t_2^{arrival}$ and $t_3^{arrival}$ are used to measure the distances between a *Sensor node* and *Anchor 1, Anchor 2* and *Anchor 3* respectively. These distances are used with coordinates of anchors as $(X_1, Y_1), (X_2, Y_2)$ and (X_3, Y_3) to estimate the location of *Sensor node*.

In [52], the location of a sensor node is determined by using TOA localization method which measures the arrival time of signals from fixed anchors. Instead of assuming all signal measurement is equally reliable, the signals are filtered depending on their distance with anchors. They assumed that the signal transmission of a pair of sensor nodes (transmitter and receiver) is more reliable if they are located near to each other compared to a pair of sensor nodes that located far away to each other. Here, the receivers are used as the anchors with known location.

In [53], different from [52], the anchors that located in the NLOS environment are filtered from the calculation due to the poor accuracy of TOA localization in non-light-of-sight (NLOS) environment. Here, NLOS is an environment of which the signal transmission is obstructed or reflected by the obstacles between a sensor node and an anchor during the transmission of signals. On the other hand, light-of sight (LOS) is an environment of which the signals transmitted directly to the receiver without any obstacle during the transmission. The simulation results have shown that the localization accuracy in LOS environment outperformed the accuracy from NLOS environment. However, this technique requires additional devices or circumstances to verify the synchronization of time of departure is properly made.

2.4.2 Time difference of arrival

Time Difference of Arrival (TDOA) is a technique that measures the difference of arrival time from two transmitters. Unlike TOA techniques, the time of departure are measured accordingly without synchronization of time between sensor nodes or anchors. As shown in Figure 9, the differences of time of departure, $t_1^{departure}, t_2^{departure}$ and $t_3^{departure}$ and time of arrival of signals $t_1^{arrival}, t_2^{arrival}$ and $t_3^{arrival}$ are measured to determine the distances between a *Sensor node* and *Anchor 1, Anchor 2* and *Anchor 3* respectively. Here, anchors are used as transmitters to send and receive signals from a *Sensor node*. The location of a *Sensornode* can be derived from the location of anchors, $(X_1, Y_1), (X_2, Y_2)$ and (X_3, Y_3) with the distance information from the calculated TDOA signals.

In Cricket [54], RF transceiver (sensor node) and RF receiver (anchor) are equipped with ultrasonic transceiver to filter the measurement taken from NLOS environment in their localization. RF signals are used to synchronize the transmission of ultrasonic pulse from multiple transceivers to a receiver. A receiver measures the difference of an ar-

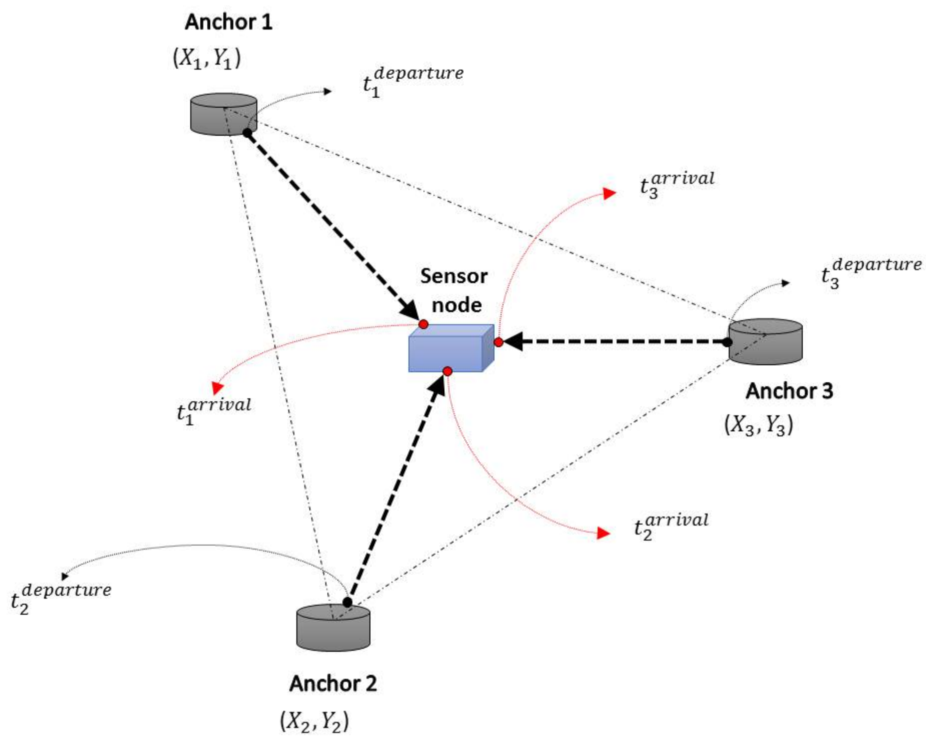


Figure 9: Measuring the difference between unsynchronized time of departure and time of arrival of signal from anchors

rival time of ultrasonic signals from the transceivers to estimate the distance between the transceivers. Receivers only accept ultrasonic pulse signal from transceivers which arrived within the overlap time of arrival of RF signal to avoid the unreliable ultrasonic signals (e.g. Affected by fading effect from obstacles). A receiver has functionality to respond the RF signals by sending the estimated locations and location information of receivers (anchors) to the transmitter (sensor node).

In [55, 51], the position of a pair of transceivers (sensor nodes) is determined by sending signals to the receivers (anchors) with the same time interval. By comparing the number of received signals in particular time, the difference of the number of received signals is derived to estimate their distance. The estimation of distance is sent to the central server for determining the location of both transceivers.

Although TDOA technique can be performed without synchronization of time of departure between sensor nodes or anchors, the requirement of LOS environment in their measurement is problematic. It is difficult to maintain such environment in many WSN applications such as replenishment system in distribution center or activities recognition system in kindergarten.

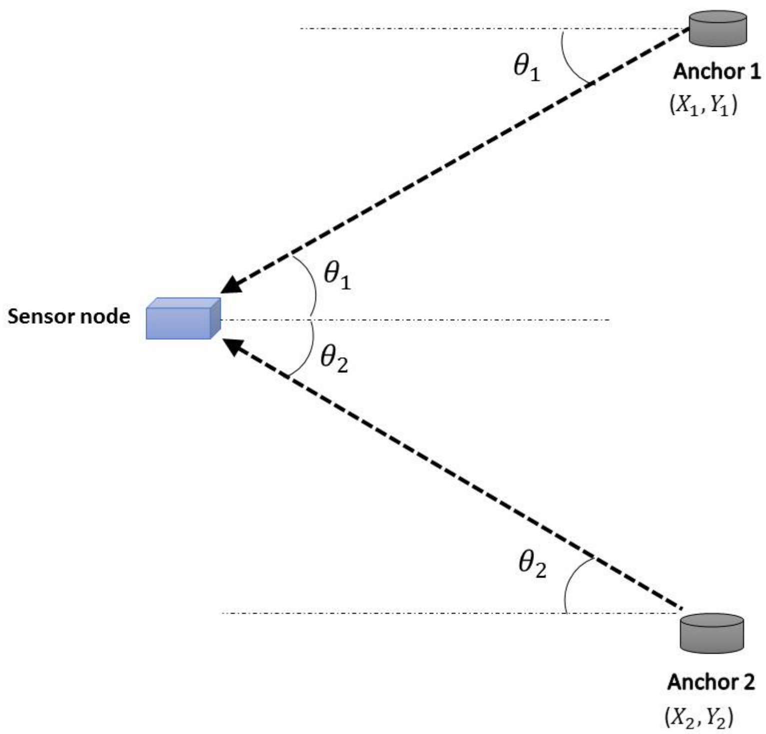


Figure 10: Measuring angles of sensor node direction from anchors

2.4.3 Angle of arrival

Angle of arrival (AOA) technique is a technique to measure the direction of the sources of signals (transmitters) from a sensor node as shown in Figure 10. The angles of directions of signals from *Anchor 1* and *Anchor 2* to *Sensor node* are measured as θ_1 and θ_2 respectively to determine the location of *Sensor node*. The location information of anchors, (X_1, Y_1) and (X_2, Y_2) and the angles of direction, θ_1, θ_2 to calculate the location of *Sensor node*. Array of antennas [56] is used to measure the direction of incoming signals by exploiting the overlapping radio signals to create different amplitude of wave at different direction.

In [57, 58, 56], linearization approach is used to solve triangulation problems by using the information from angle measurement. The measurement of an angle of a signal direction is measured by using antenna arrays. In [57], signal strength with a fixed maximum communication range is used to construct feasible regions of anchors in the localization. The location of sensor nodes are determined by using the angles of direction of anchors and a radius of the maximum communication range. These informations are combined with the known locations of anchors to solve the linearization equation problem in determining the location of a sensor node. The overlapped feasible regions within target sensor nodes are exploited in calculating the location of a sensor node to increase the localization

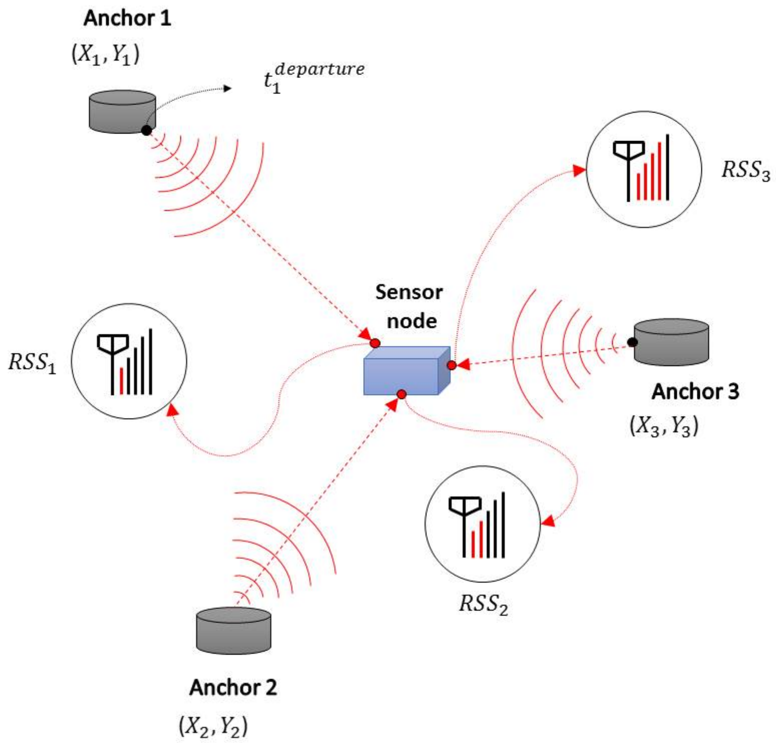


Figure 11: Measuring Received Signal Strength (RSS) from anchors

accuracy.

In [58], three numbers of transmitters (anchors) are used in the measurement of angle. Linear equation is employed to calculate the angles of signal directions from two transmitters. Several pairs of transceivers are used to calculate angles from several pairs of equations to improve the errors from the measurement of angles. The weighted calculated angles is compared to determine the most accurate angle measurement among pairs of equations. The requirement of additional devices to measure the angle of direction of a signal is a drawback of this technique.

2.4.4 Received signal strength

Received Signal Strength (RSS) technique utilizes the path loss effect in radio propagation to estimate distance between sensor nodes. If a signal is transmitted from transmitter to receiver, the difference value of signal strength at transmitter and receiver is used as a function of distance. As shown in Figure 11, *Sensor node* measures the RSS of $Anchor1, Anchor2$ and $Anchor3$ as RSS_1, RSS_2 and RSS_3 respectively. The measurement are applied in the function of distance for determining the position of *Sensor node*. The RSS values are used with the locations of anchors $(X_1, Y_1), (X_2, Y_2)$ and (X_3, Y_3) in calculating the position of *Sensor node*.

Theoretical or empirical models are used in a range-based localization techniques to translate RSS into distance. Range-based localization can achieve better accuracy, but is costly in requiring either pre-node ranging hardware [54] or careful system calibration and environment profiling [17, 59], and thus it is not appropriate for large-scale sensor networks. The correlation of noise due to shadowing from obstacles in wave propagation has been exploited to estimate the locations of the transmitters [60]. Cumulative errors in measurement with positioning methods have been treated as problems with localization where data sampled over time have generated points in high dimensional space [61, 62, 63]. The multi-dimensional scaling (MDS) model has been used to reduce dimensionality to estimate locations [61]. However, the linear relationship requirement between correlation coefficients and radial distance in MDS has restricted its applications to wireless environments where RSS correlations are highly nonlinear if there is a radial distance [64] between receivers. Manifold learning (reduced nonlinear dimensionality) algorithms such as Isomap, Local Linear Embedding (LLE) and Hessian LLE have been used to centralize localization [62, 63]. The linearity between correlation measurements and radial distance is restricted in these approaches to a small area containing K nearest neighbors. However, the linearity between RSS and radial distance does not hold in Li and Liu [64], even in the immediate vicinity of operating frequencies greater than 10 MHz.

Range-free approaches localize sensor nodes based on simple sensing, such as wireless connectivity [31, 24, 65] and anchor proximity [22, 66, 67]. Wireless connectivity information between neighboring sensor nodes is used to estimate the location of a target sensor node by using MDS [24]. Their major limitation is that they all rely on a large number of uniformly-distributed anchors in the networks. Embedding the combinatorial Delaunay complex in the landmark Voronoi diagram [65] has improved the localization of target nodes in various network topologies. However, using a number of landmarks or anchors to achieve precise accuracy in localization is costly.

The approximate-point-in-triangulation (APIT) algorithm [66] is proposed for area-based range-free localization, where all sensor nodes are localized by using the location information of GPS-equipped anchors. The areas occupied by sensor nodes are divided into many triangular regions between anchors in this approach by using the location information provided by GPS. This approach provides excellent accuracy when irregular radio patterns and random node placements are considered. However, the large number of distributed anchors will counteract problems such as high deployment costs when applied to large areas. In Centroid [22], all possible anchors broadcast their location information to all other target sensor nodes. The target sensor nodes use the location information from the anchors that are located in their vicinity to estimate their own location coordinates. The main difficulty with the centroid is the large number of anchors to be considered in the localization. Moreover, if anchors are not uniformly distributed, the distance between them and target nodes varies, which deteriorates the efficiency of localization. It is necessary to take into consideration the distance between the anchors and target nodes to solve this problem. The distances between anchors and target nodes are considered in the distance vector-hop (DV-hop) localization algorithm [31] and resilient Ethernet protocol (REP) [67] as a form of hop counting, which is a range-free approach that does not use RSS to compute the distance between nodes. DV-hop performs well when deployed sensor nodes have a regular density and distances between them. However, the result of the estimation may not be optimal if the radio patterns are irregular and random node deployment is used in practice.

The accuracy of localization in range-free approaches are subject to the effect of radio patterns that affect variations in the estimation of the radial distance between nodes. Many of these techniques uses an average of all anchor positions in their communication range [22, 23, 37] or in the same hop-count values [31] to localize the target nodes, which underestimated the variations in the radial distance thereby causing large localization errors. Deterioration of efficiency of the localization is caused by variations in the radial distance that result from target sensor nodes that have not been uniformly deployed. The variation of radial distances is occurs from the complex and dynamic of RSS values in wireless environments. It is a challenging task to select an efficient RSS values that can provide small variations in the radial distance.

2.5 Improving efficiency of radiolocation methods

Localization based on radiolocation methods have a common problem in obtaining accurate estimations of location. Variations of radio signals give an impact to the localization efficiency due to the dynamic environment effects such as the multi-path effect, path-loss effect, shadow fading effect from obstruction, mobility of receivers or sensor nodes, temperature and antennas implementation. In this section, we describe three types of techniques to improve the efficiency of the radiolocation methods as below:

1. **Refinement**: Removing noise from radio signals statistically by using the series of measurements or estimation.

2. **Mobility scheduling**: Planning moving path of mobile receiver to measure sufficient signals.

3. **Anchors selection and placement**: Selecting appropriate anchors and planning the placement of anchors.

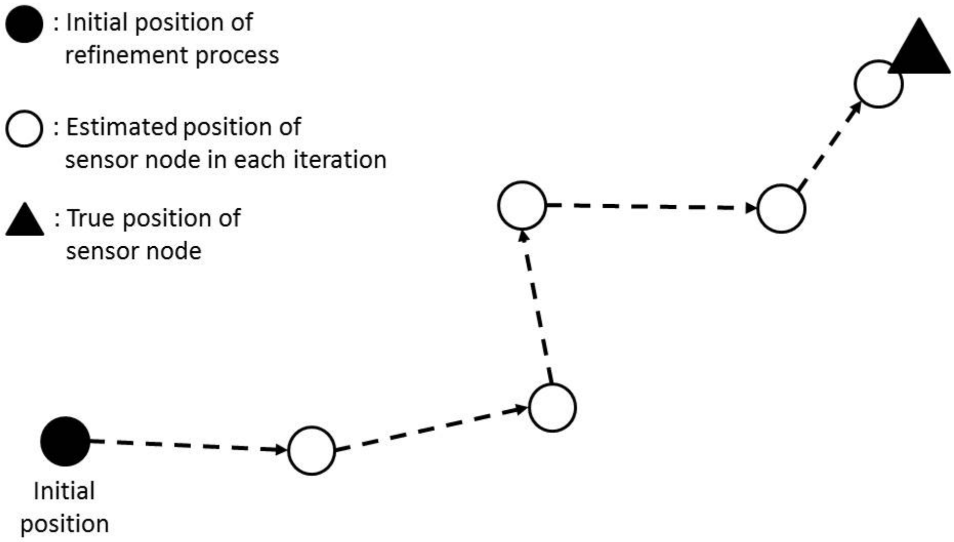


Figure 12: Refinement process in improving the efficiency of localization

2.5.1 Refinement

Refinement process is the process of removing noise from transmitted radio signals in the localization. As shown in Figure 12, the localization of a sensor node is performed iteratively to improve the location estimation based on the measurement in each iteration. Generally, initial position is used to start the refinement process. The initial position is improved by using the measurement based on the current state of the environment. This technique has been applied in many mobile localization methods which applied a nonlinear measurement model as a localization model for locating sensor nodes based on RSS measurements [48, 68]. In [48], robust extended Kalman Filter is used to remove the uncertainties in the RSS measurements. The RSS measurements are then used to estimate a sensor node location which is considered as system state in a nonlinear dynamic system. Mobile robot receives the signals from sensor nodes that are located within its communication range periodically and estimate the position of sensor nodes concurrently by using the refined RSS of signals from sensor nodes. Fading noise in RSS measurement is eliminated statistically based on the RSS measurements that taken over a period of time. The static anchors are deployed in the localization areas that are used as reference locations. The locations of the anchors are precisely determined before the localization. Although the signal measurement of RSS is refined from noise of a dynamic environment, the anchor positions still remain unreliable. Localization accuracy of sensor nodes becomes progressively worse if the anchor positions are affected with position errors or signal propagation errors.

In [68], Monte Carlo sampling operation is used to perform Bayesian filtering on lo-

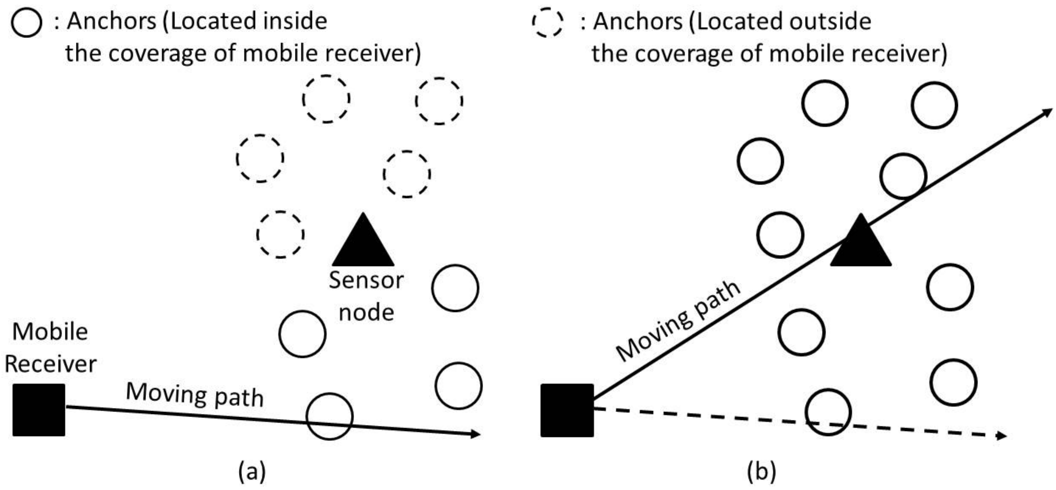


Figure 13: Change the path of mobile receiver in improving the efficiency of localization

cation distribution of sensor nodes. The initial distribution of sensor nodes is assumed as a set of weighted uniformly distributed sensor nodes. Mobile receivers are used to measure the signals from sensor nodes for each interval time. A current location information of a mobile receiver is used as anchors (reference distribution) that is known in a priori. Starting with equal weights for all sensor nodes, the distribution is updated on each state of continuous state space. Mobile receivers collect information from sensor nodes for the location estimation. Various types of measurements have been in this method used for collecting range sensory data from neighbors such as AoA measurement, TOA measurement, RSS measurement and connectivity between a pair of sensor nodes. During the estimation of locations, anchors are expected to be located at accurate position which is problematic in real deployment of WSN. In a real environment, the additional of devices (robot, sensors) is required to monitor the anchor locations to be exactly located at predetermined location which is costly and complicates the deployment of WSN.

2.5.2 Mobility scheduling

Mobility scheduling is a method of planning a moving path of a mobile receiver to perform localization in WSN effectively. The moving path is planned to collect sufficient signals from sensor nodes. For instance, as shown in Figure 13(a), a mobile receiver's path can only measure the signals from 4 anchors which are located in one side of *Sensor node*. Since the large numbers of anchors can improve the localization efficiency, the moving path. As shown in Figure 13(b), a moving path of mobile receiver is changed to the path of where more anchors could be available in collecting the signals for the localization.

In [69], a mobile receiver moves in straight lines in WSN environment to localize the sensor nodes. The path of mobile receiver is assumed to cover all sensor nodes in the WSN based on the prior information of WSN deployment. Localization is performed by using precise location information (as anchors) on arrival/departure of the mobile receiver within the communication range of a sensor node. The variance of RSS measurement is employed to construct the relation of connection between mobile receiver and sensor nodes.

In [70], the optimal fixed path of mobile receiver is designed to perform localization in WSN. Sensor nodes are deployed uniformly in WSN. Based on prior information about deployment area, the fix path of the mobile receiver (defined as anchors) is constructed to perform localization of sensor nodes. RSS measurement is used to perform multilateration techniques for localization of sensor nodes. Although the path is planned to reduce the collinearity in multilateration to increase the localization accuracy, the authors did not provide the solutions of noises from mobile receiver. Since the location of anchors is also used in the multilateration, the errors from mobile receiver can also affect the localization efficiency.

In [71], mobility of multiple mobile receivers has been used to determine the location of a target sensor node. A target sensor node transmits its signals to the mobile receivers that are moving within its communication range. The path of multiple mobile receivers are used in a linear equation to derive an intersection of perpendicular from each path to determine a sensor node location. While mobile receivers are equipped with GPS devices to aware of its location as anchors, the mobility of mobile receiver constructs a multiple line of moving path, in which each of line represent a linear equation of a line. Perpendicular of a line is derived from the nearest points on a line to a target sensor node. Estimation of the location of a sensor node based on perpendicular of multiple linear equations. This can complicates the problems in solving the linear equations since the nearest points in the lines would be varied significantly due to the uncertainty of radio propagation. Moreover, it is difficult to assure the mobile receivers to precisely move in a straight line. The straight lines might contribute to variation of intersection points. The variation of intersection points computed from the perpendicular of the lines might deteriorate the localization efficiency.

The uncertainty of the radius of circle of communication range constructed from the single RSS level of radio propagation has give an impact to localization efficiency if the location of a sensor node is computed using multilateration technique. Instead of using only single of a circle of communication range, [37] has used overlapped of two circles defined by different RSS level centered at the same anchors. The additional static anchors are used to assist the mobile receiver in determining the location of a sensor node. By using characteristic of the overlap circular shape of the wireless communication range between two anchors, the authors construct the grid area which represent the intersection

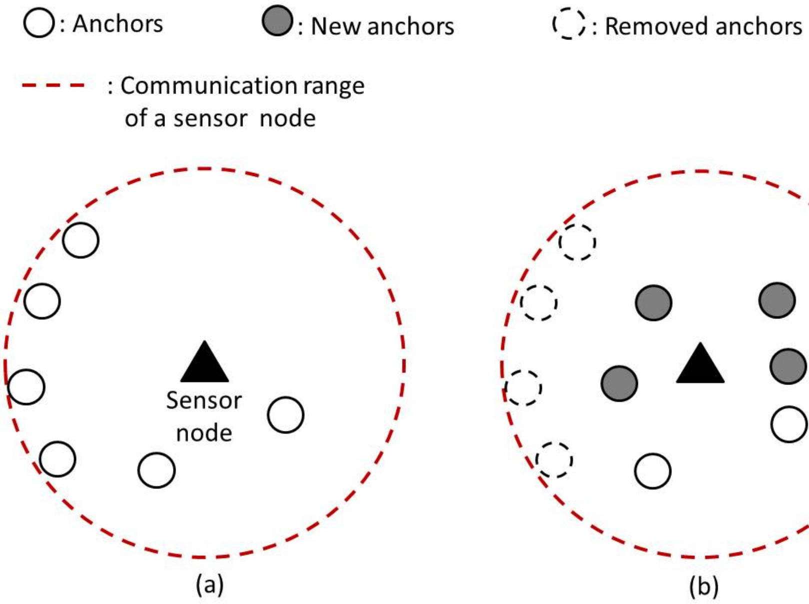


Figure 14: Remove insufficient anchors and place the new anchors and the path of mobile receiver in improving the efficiency of localization

area of overlapped circular shape from more than three anchors, including an overlapped circle of communication range from mobile receiver to compute its position. Overlapped circles of a sensor node represent two circles of ranging areas centered at the same position called inner ring and outer ring. The outer ring is an area where a target sensor node is included in the ring and inner is an area where a target sensor node is not included inside the ring. Length of radius of each ring is measured by RSS of an anchor. Intersections of overlap rings from multiple anchors included mobile receiver are defined by using the length of radius to determine the coordinates of the intersection points. The location of a sensor node is computed from the average of these intersection points. Uncertainties from RSS for accurate distance measurement in constructing the rings is unfeasible for efficient estimation of sensor nodes. Moreover, deployment of a large number of static anchors in a large area to create more intersection points is costly. The location of anchors must be monitored by using special monitoring system to assure its locations are not moved or changed by any natural phenomena such as wind or animals.

2.5.3 Anchors selection and placement

The reliability of anchors in WSN deployment is important as the efficiency of localization of sensor nodes will increase if errors from anchors can be improved. For instance, as shown in Figure 14(a), given the calculation in estimating the location of *Sensor node* as the average of anchors located in its vicinity as employed in [22], the localization of *Sensor node* might be affected by the anchors located at the edge of the communication range of *Sensor node*. The variation of distance between anchors and *Sensor node* can deteriorates the efficiency of the localization based on average of anchors. This can be improved by locating the new *Anchors* and by removing the anchors which are distantly located from a sensor node as show in Figure 14(b). The signals transmission from the anchors which are located near to a sensor node is more reliable than the anchors located far away from a sensor node [52].

In [72], the authors have applied an extended Ad Hoc Positioning System (APS) algorithm from [28] which selectively employs best three numbers of anchors that have the nearest location of the true position of target sensor nodes. Distance measurement is employed in determining three best anchors for the sensor node localization. They have applied AOA ranging and RSS technique to measure the exact distances between sensor nodes and anchors. Multilateration is employed to compute the estimation of sensor node's location based on the known position of selected best anchors. The simulation experiment results show that the average estimation error and C-shape topology have improved compared with the one that applied in the original APS algorithm. They assume a precise distance measurement (AOA and RSS) is performed well in light-of-sight (LOS) environment where there is no obstruction between sensor nodes and anchors. However, the measurement accuracy might deteriorate in non-light-of-sight (NLOS) environment because of fading effect occurs from the obstruction between the transmission.

Virtual Coordinate System (VCS) is used in [73] to avoid the use of exact distance measurements or RSS measurement for selecting reliable selection of anchors in determining the location of a sensor node. VCS is a coordinate system that built virtually based on a pair of connection of anchors and a target sensor node. Different from the classical VCS scheme [74], [73] considers the use of angles and direction information to specify the VCS of a pair of anchors that located in the communication range of a target sensor node. The rectangular grid coordinate system is derived from the anchors. A target sensor node is located in the coordinate system for the localization. Anchors that are used in VCS are selected based on their ability to find the neighbors which can connect its signal transmission to a target sensor node. The anchors are selected from the subsets of sensor nodes, which are able to find the neighbors in their vicinity. The selection of anchors that cannot find their closest neighbor is avoided from the calculation to prevent the degradation of routability of anchor connection. However, since the coordinate system is based on hop-count of the connection between anchors and a target sensor node, the assurance of exact coordinates of anchors still remains a problem. The distance measurement of each hop is needed in a real environment to determine the exact location of a target sensor node. Moreover, position changes of anchors or sensor nodes are prohibited during the localization, which complicates the WSN deployment in the area where the flexibility of the sensor node deployment is unavoidable in many WSN environment.

In [75], reliable anchors are selected according to its minimum hop length estimation in WSN. Anchors are deployed in their predetermined location before performing the localization. The sensor node positions are estimated based on the position information of anchors and hop-count measurement. Each anchor transmits their signals in ad-hoc based networks to other anchors by passing through the sensor nodes that located between them. In isotropic networks, the average length of hop count between two anchors might be minimal if the deployment of sensor nodes that located within the two anchors are uniformly distributed without any obstruction. However, the shortest path of transmission between anchors become longer if there is an obstacle located between the two anchors. The average length of hop-count might be increase due to the existence of obstacles between anchors or the degradation of sensor node density in WSN. The increment of average length of hop-count can deteriorates the efficiency of the localization. Hence, [75] use the selection the anchors that have a minimum average length of hop count during the transmission. However, the reliable anchors only can be derived effectively in high-density of anchors WSN deployment which is costly. The errors of distance measurement of the length of hop-count still remain a problem for the localization, although the average length of hop-count is minimized. Moreover, the need of accurate distance measurement in determining the location of a sensor node by using selected anchors is unfeasible in highly dynamic environments.

In [76], multiple number of mobile receivers are used in the WSN environment to estimate the location of sensor nodes. This research considers the deployment of static anchors with predetermine location in the WSN areas. By exploiting the moving path of mobile receivers which aware of its locations, the intersection of effective areas constructed from both mobile receivers and static anchors is employed to define the most effective location or region in estimating the location of sensor nodes. Each static anchor has its own rectangular of effective area. The moving path of mobile receivers is guided by these rectangular areas to construct more effective intersection area. Assuming the estimation can be performed effectively in these effective areas, mobile receivers select the rectangular of effective area to create more intersections. More intersections can increase the weight of effectiveness and reliability of the areas which contribute to the high efficiency of localization. The locations of sensor nodes are estimated using the intersection point of a pair of diagonal lines in the rectangular areas. The use of the large number of static anchors to cover the sensor nodes areas is a drawback of this method. Static anchors are effective in a small WSN environment, however, the need of explicit deployment of static anchors in a large area is costly. Moreover, it is difficult to deploy in an environment which is always change its layout or arrangement of its area. The redeployment of static anchors in such environment is insufficient and costly.

In the next chapter, we describe our proposed method that can improve the localization efficiency by selecting sufficient anchors for sensor node localization without any deployments of reference objects or any additional monitoring devices in assuring the location of anchors.

3 Selection of anchors

In this chapter, we describe the problem of determining the selection of anchors in proximity-based localization. Majority of the solutions of proximity-based localization in WSN need a specific requirement in order to achieve a high efficiency of localization. The specific requirement in the localization such as good initial coordinates assignment [18] or specific distances between neighboring nodes [77] are used to derive the unknown location of a sensor node. In a real environment, it is difficult to maintain such environment. Initial location has been utilized as reference objects or locations, which we call it as anchors, to perform the estimation of the location of a sensor node. Most of the localization methods have exploited the location information from all available anchors that located in the wireless communication range of a sensor node to perform the localization. This is problematic because the anchors might contain an error due to highly dynamic environment in the real deployment of WSN.

We address the solutions to select the reliable selection of anchors, rather than using all anchors in the localization. Here, reliable selection of anchors denotes the subset of anchors which have an ability to provide their information (e.g. RSS value, position) in minimum amount of errors. We take into account of the impact of errors from natural phenomena (e.g. accidentally moved the anchors from its predetermined location, misplacement of anchors), arbitrary deployment of anchors, and radio propagation effects in noisy environment (e.g. multipath or fading). These impact could affect whether an anchor should be used or not in calculating the position in the estimation. Many of the previous researches have performed the good performance of their localization method, however, most of researches did not address the problem of how to assure the reliability of selection of anchors in estimating the location of a sensor node.

3.1 Problem definition

In most proximity-based localization, location of a sensor node is estimated by computing the average locations of anchors, which are located in the wireless communication range of a sensor node [22, 23, 37, 38, 39, 40, 41, 42, 43]. Estimating the location by computing an average of anchors is not the best solution for high accuracy location estimation, however, it is easy to implement in the low-cost intelligent devices. Considering the errors from natural phenomena, arbitrary deployment of anchors and radio propagation in noisy environment could affect whether an anchor should be used or not in calculating the average of anchors, we select the reliable selection of anchors for the estimation, instead of using all possible anchors. We describe the scenarios that could affect the reliability of anchors as follow:

- **Errors from natural phenomena**: Although the anchors are always assumed to be

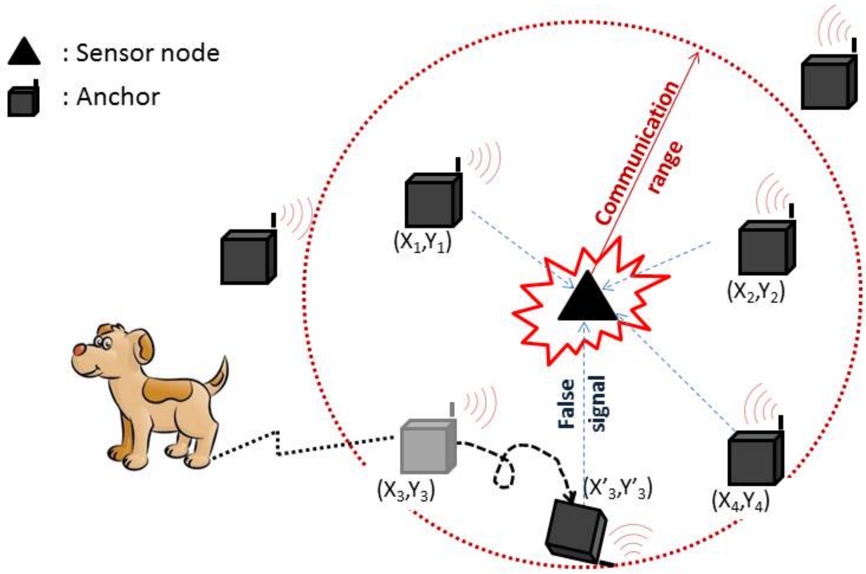


Figure 15: Errors from natural phenomena

precisely deployed at their predetermined positions, we consider this assumption is not realistic. For example, as shown in Figure 15, even if the initial location of anchors was known as $(X_1,Y_1),(X_2,Y_2),(X_3,Y_3)$ and (X_4,Y_4), the final object distribution may be different (e.g., moved by wind, animal or people). In this figure, location of an anchor (X_3,Y_3) has been accidentally moved to (X_3',Y_3') by an animal and this will affect the calculation of average in estimating the location of a sensor node. It is important to update the location of an anchor to avoid the difference of location information between predetermined location of anchor and the location of anchor in a real environment. It is difficult to maintain such positions in a real environment without providing a particular monitoring system for each anchor to assure their locations.

- **Arbitrary deployment of anchors**: Localization based on the average of anchors is effective if anchors are deployed uniformly around the vicinity of a sensor node as $(X_1,Y_1),(X_2,Y_2),(X_3,Y_3)$ and (X_4,Y_4) as shown in Figure 16(a). Average of all anchors can derive the center position of circle of wireless communication range, which is denotes to the true location of a sensor node. On the other hand, the calculated location from the average of anchors which are deployed arbitrary in the environment as shown in Figure 16(b) is not exactly belong to the center location of the circle due to the variation of distance between anchors and a sensor node. The difficulty in obtaining the average of anchors which is located close to the center of circle is the drawback of the average-based localization in the arbitrary deployment of anchors.

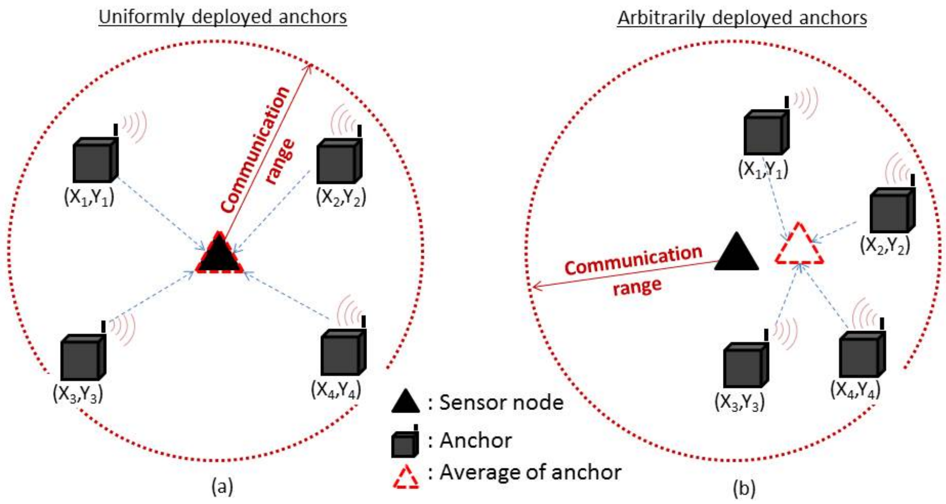


Figure 16: Effect from arbitrary deployment of anchors

- **Radio propagation effect in noisy environment**: Assuming the propagation of wireless signals is ideal in a noise-free environment, a sensor node can communicate with anchors located in an area of perfect circle at $(X_1,Y_1),(X_2,Y_2),(X_3,Y_3)$ and (X_4,Y_4) as shown in Figure 17(a). This perfect circle is centered at the location of a sensor node with a radius that is equal to its standard interrogation. The estimated position from the average of all anchors should be located at the center of a perfect circle of the communication range. On the other hand, in a noisy environment, the radius of the circle (which is imperfect) of wireless communication range are varied significantly in different angle of circle due to the errors of radio propagation as shown in Figure 17(b). For example, although four anchors are deployed at the same distance with a sensor node at $(X_1,Y_1),(X_2,Y_2),(X_3,Y_3)$ and (X_4,Y_4), another anchor at (X_5,Y_5) which is located with different distance (distance between anchor and a sensor node) from the other four anchors might be included into the communication range of a sensor node due to the uncertainties of radio propagation. This results the diversely-located anchors in the imperfect circle of wireless communication range centered at a sensor node although most of the anchors are deployed uniformly in the vicinity of a sensor node. The diversely-located anchors can contribute to the inefficient of average-based calculation in estimating the location of a sensor node.

The variation of radius or distance between anchors and a sensor node in a circle contribute to the inefficiency of average-based calculation in the localization. Nonetheless, the anchors could be selectively used for improving the efficiency of average-based calculation in determining the location of a sensor node. The anchors can be selected by observing the distance between average of selected anchors to the center of circle. We

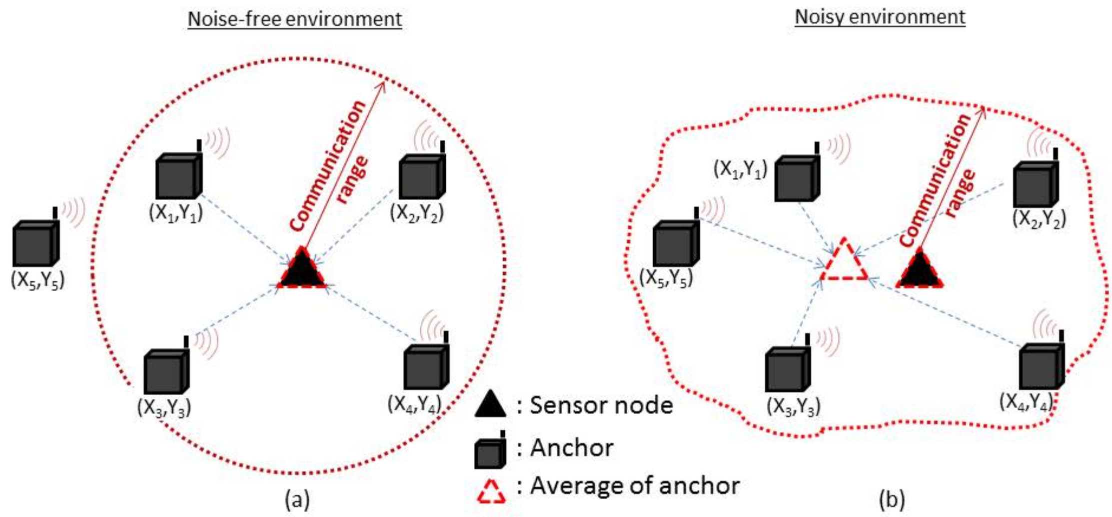


Figure 17: Radio propagation effect in noisy environment

call the average of selected anchors as *Indicators point*. *Indicators point* is used as a metric to indicate the reliability of the selection of anchors. Since the center location of the circle is unknown, we use a designated parameter to represent the center of circle in order to determine the reliable selection of anchors. We call this parameter as *Reference point*. The closer *Indicators point* to *Reference point*, the higher reliability of selection of anchors.

3.2 Determination of selection of anchors

In determining the selection of anchors, we observe the relation of distance function between *Indicators point* and *Reference point* iteratively based on Genetic Algorithm (GA). The problem of selecting optimal selection of anchors from the large amount of anchors is a combinatorial problem. It is difficult to find an optimal selection by enumerating all possible selections of anchors, GA approach can be used to solve a problem by searching a global solution and updating it to improve a global solution toward the optimum. In this PhD thesis, estimated position is calculated from optimum selection of anchors. We describe our proposed method of selection of anchors in improving the global solution toward the optimum solution by using GA.

We assume that a mobile receiver travels within a sensory boundary field that is deployed by sensor nodes. All sensor nodes transmit their wireless signals to mobile receiver on a periodic basis. The mobile receiver travels and collects the wireless signals from sensor nodes at the t time unit. The mobile receiver and sensor nodes are able to communicate within their wireless communication range. Every time the mobile receiver receives a signal from a sensor node i, it measures the RSS value of a signal and then

Table 1: The coordinates of anchors and the distance between sensor node i and anchors respectively.

Anchor	**Coordinate,** (X_j, Y_j)	**Distance between sensor node** i **and anchor,** d
A_1	$(1,7)$	$d_1 = 6.3$
A_2	$(5,7)$	$d_2 = 2.8$
A_3	$(8,7)$	$d_3 = 2.2$
A_4	$(8,3)$	$d_4 = 2.2$
A_5	$(5,4)$	$d_5 = 2.2$
A_6	$(1,5)$	$d_6 = 6.0$

stores it as a tuple $(t, r_{i,t})$, where t is the time denoted as $t = t_1, t_2, \ldots, t_\tau$ and $r_{i,t}$ is an RSS value from sensor node i denoted as $r_{i,t} = r_{i,t_1}, r_{i,t_2}, \ldots, r_{i,t_\tau}$. Each tuple contains a different RSS value, each of which is collected from a different position of a mobile receiver in each t. We call the locations of the mobile receiver at each time unit as anchors. The selection of anchors is assumed as the best selection of anchors (optimum solution) if the *Indicators point* of the selected anchors is located close to the *Reference point*.

It is important to understand the effect of distance between anchors and a sensor node in determining the location of a sensor node from an average of anchors. We describe the effect of variation of distance in calculating the average of anchors for the localization of a sensor node as shown in Figure 18 and Figure 19.

For example, as shown in Figure 18, a mobile receiver travels around a sensor node i and measures a distance d (converted from RSS) as $d_1, d_2, \ldots, d_6$ for each interval time unit. Since we do not assume the presence of fix anchors, we suppose the anchors (location of the mobile receiver at each t) as $A_1, A_2, \ldots, A_6$. We calculate the average of anchors as employed in [22] to determine the location of a sensor node i as below:

$$S_i = \frac{\sum_{j=1}^{n} X_j, Y_j}{n} \tag{1}$$

where n is a number of selected anchors located at coordinate (X_j, Y_j) within the communication range of sensor node i and S_i is a estimated location of sensor node i. Table 1 shows the coordinates of anchors and the distance between sensor node i and anchors respectively.

Assuming there are three selections of anchors, $Selection_{all}, Selection_1$ and $Selection_2$ as shown in Figure 19, we demonstrate the impact of variation of distance d to the cal-

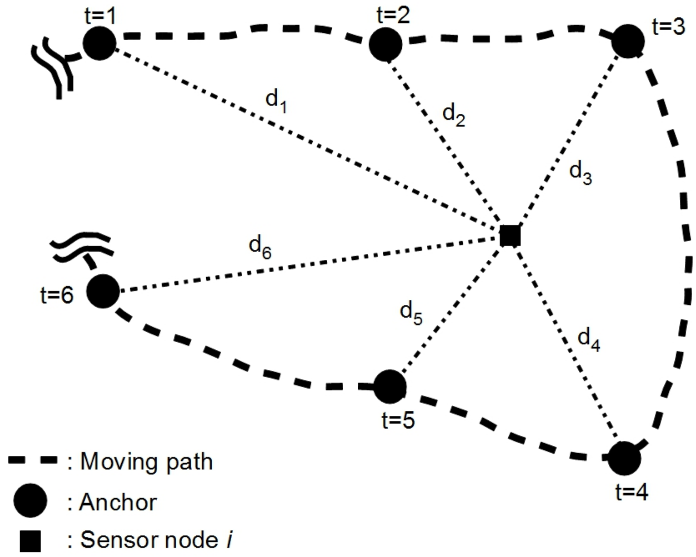


Figure 18: Variations in distance using average of anchors

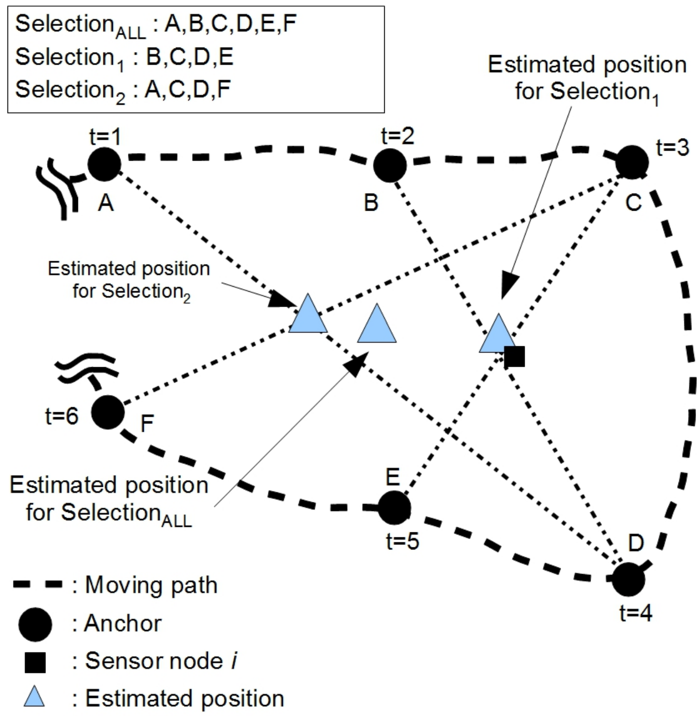


Figure 19: Comparison of localization performance with two different anchor selection

culation of S_i. By comparing the average of anchors from three selections, an average of anchors from $Selection_1$ has the closest distance to the location of sensor node i. As shown in Table 2, the efficiency of the localization is highly depends on the variation of distance from a sensor node to each anchor. Here, the variation of distance denotes the difference between largest d and smallest d in a selection. The calculation of S_i from $Selection_1$ is

Table 2: Impact of variation of distance d to the calculation of S_i.

Selection of anchors	**Distance between S_i and true location of sensor node i**	**Variation of d (Difference between largest d and smallest d in the selection**
$Selection_{all}$	2.4	4.1
$Selection_1$	0.6	0.6
$Selection_2$	4.1	4.1

more accurate than $Selection_{all}$ and $Selection_2$. The variation of d in $Selection_1$ is the smallest among three selections. The variation of distance in $Selection_{all}$ and $Selection_2$ have given a significant error in average calculation in determining the location of a sensor node i. Less variation of distance between sensor node i and each anchor in $Selection_1$ (d_2, d_3, d_4, d_5) reduces the error in average calculation which contribute to high-efficiency of the estimation.

In a real environment, however, it is unable to define the variation of distance between anchors and the center of circle of a sensor node because the real position of a sensor node is unknown. Therefore, we use a *Reference point* to represent the center of circle. In this PhD thesis, we select the anchors based on two types of *Reference point*, static *Reference point* and dynamic *Reference point*. In the selection of anchors based on static *Reference point*, we assume a mobile receiver travels in a connection of straight lines. Each line contains two anchors located at the edges of a line. *Indicators point* is calculated from the average of selected anchors in the lines. *Indicators point* is used as a metric to measure whether the selected anchors have less variety of their distance to the *Reference point* or not. We call the locations of mobile receiver located between two anchors at each interval time unit in a line as footprints. *Reference point* is calculated using the average of three footprints which have largest RSS. We select the anchors, which have smallest distance between *Reference point* and *Indicators point* based on the genetic algorithm (GA) approach. The estimated location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors. The feature of this method is to provide the ability to distinguish an estimated position based on *Indicators point* by comparing the distances of both estimated position and *Indicators point* to *Reference point*.

In the selection of anchors based on dynamic *Reference point*, we suppose that the anchors are the locations of mobile receiver at each interval time unit. Anchors are divided into multiple sets based on their RSS measurement. *Indicators point* are calculated from the average of selected anchors of each set. The concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. Initially, *Reference point* is determined randomly at a known location. In determining the location of a sensor node, *Reference point* is improved iteratively approaches to an area which has a high density of *Indicators points*. The feature of this method is to provide the ability for a sensor node to determine its location by using anchors selectively without using any static *Reference point* or objects.

In both methods of selection of anchors, the best selection of anchors is defined as the optimum solution in GA. Here, we call the selection of anchors in each iteration of GA, a local solution. Global solution of anchors is selected from multiple of local solutions. The global solution is updated toward the optimum which is defined as the optimal solution to the problem. Anchors that are located in the communication range of a sensor node are assumed as the population of samples in determining multiple numbers of local solutions.

3.3 Searching a reliable selection of anchors

3.3.1 Genetic algorithm overview

Genetic Algorithm (GA) is a search algorithm that searches an optimal solution to solve a combinatorial problem such as NP-complete Traveling Salesman Problem (TSP) [78]. GA is a popular approach to solve global optimization problem of finding the optimal solution among a number of local solutions to the problem. Being different with other algorithm in stochastic optimization, GA is an approach that uses multiple local solutions for the problems in searching a global solution and updating it to improve a global solution. The global solution is updated toward the optimum which is defined as the best solution to the problem. In GA, multiple local solutions are considered simultaneously in improving a global solution and iteratively transform the population samples to determine another local solution.

In GA, the concept of the natural evolution of the fittest of a species is applied in determining the survival of the fittest. The fittest that survived in the natural evolution is a global solution to the population. Initially, the initial population is generated as an initial population of sample to perform GA. Usually, the individual solution from initial population is determined randomly as initial solution. In determining global solution, initial solution is improved iteratively and move to a point where the fitness function of

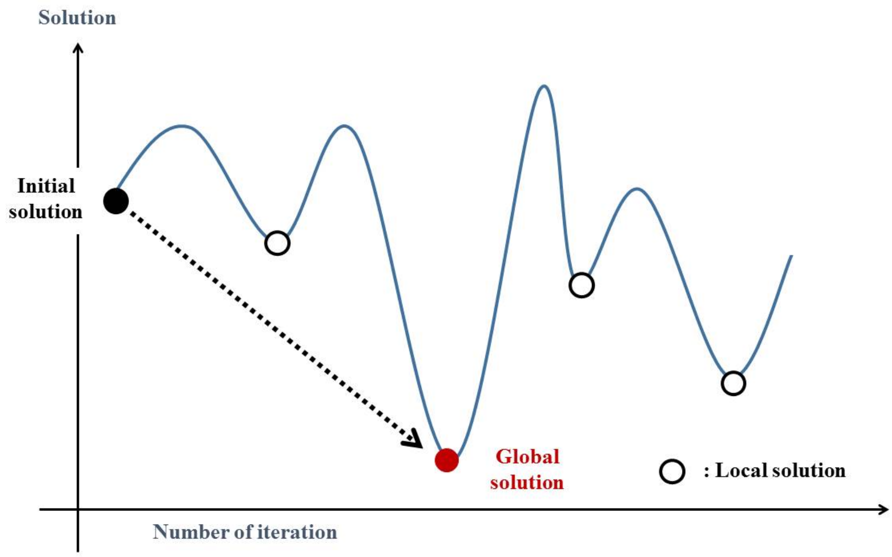


Figure 20: Improvement of local solutions to a global solution in GA

a population is optimized. Here, fitness function is a function to determine a solution of each population. Figure 20 shows the improvement of local solutions to a solution where the fitness function is optimized. In this figure, fitness function is optimized when the solution value is at the lowest value of solution among populations in the iterations. A population that has an optimal value of fitness is assumed as the global solution to the problem.

At the beginning of an iteration, multiple of candidate populations are generated from initial population. Here, we call the candidate populations, a *chromosomes*. The generation process of new chromosomes for each iteration is applied for the transformation of chromosomes in finding new local solutions for candidate populations to the problem. Here, we call the new chromosomes from the generation process, an $offsprings$. In the generation process, the fitness function is applied to evaluate the fitness of every chromosome.

Crossover operator is applied in the generation process of offsprings. Crossover operator is used to evolve the local solution in determining global solution to the problems. It creates a pair of new chromosomes (offsprings) from a pair of parent chromosomes. In the generation process of offsprings, the crossover operator separates each chromosome into two sets and exchange a separated sets each other to form a new offspring chromosomes. If no crossover was performed, new offspring chromosomes are an exact copy of a parent chromosome. Figure 21 shows the example of the crossover operation from a pair of parent chromosomes to generate a pair of child chromosomes (offsprings). This example illustrates the crossover is performed at one single point which is selected ran-

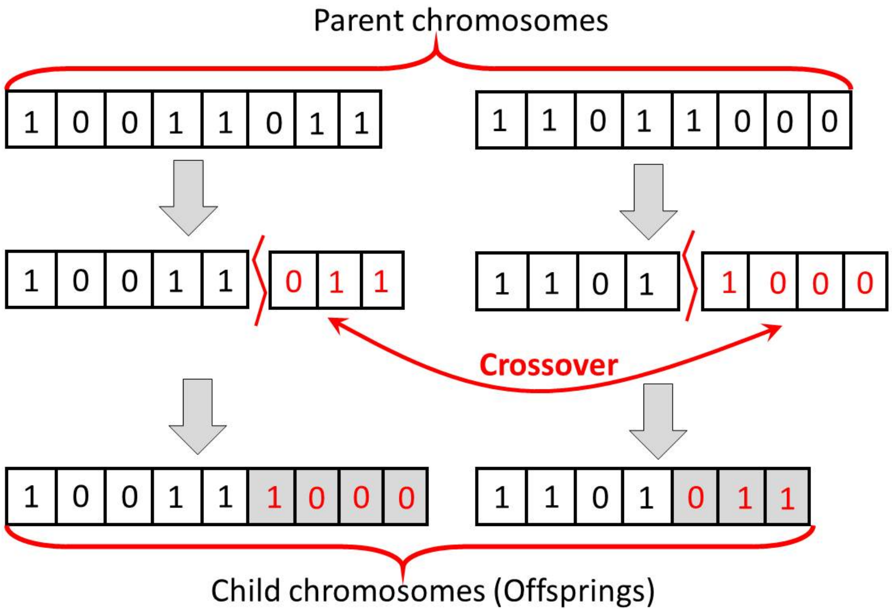


Figure 21: Example of crossover operation from a pair of parent chromosomes

domly. Each parent chromosomes are divided into two groups at the points of where a single point is selected. Each parent chromosome interchanges the one of their divided group with one another to generate child chromosome.

In GA, it is difficult to define whether the algorithm has converged across the iteration effectively or not. In determining the numbers of iteration, [79] has applied the solution in fitness function that satisfies a particular threshold value to stop the iteration in GA. The differences of maximum value and minimum value in N number of populations are evaluated to specify the stopping point of the iteration. If the difference of maximum and minimum are close to each other, where the difference value is smaller than the threshold of closest different value, the iteration in GA is stopped. However, the author did not provide the results that the algorithm has found its global solution. In this PhD thesis, the numbers of iteration is determined empirically during the simulations.

3.3.2 Searching the selection of anchors based on genetic algorithm

The optimal solution of the problem in selecting reliable selection of anchors is determined based on GA approach. We assume the optimal solution in GA is the best selection of anchors to determine the location of a sensor node. In determining the best selection of anchors, initially, all anchors that are located in the communication range of a sensor node are assumed as the initial population of GA. A pair of chromosomes are generated from initial population. Here, the chromosomes is the local solution of the first iteration of GA. We evaluate the fitness function of a pair of chromosomes in each iteration of the GA. A

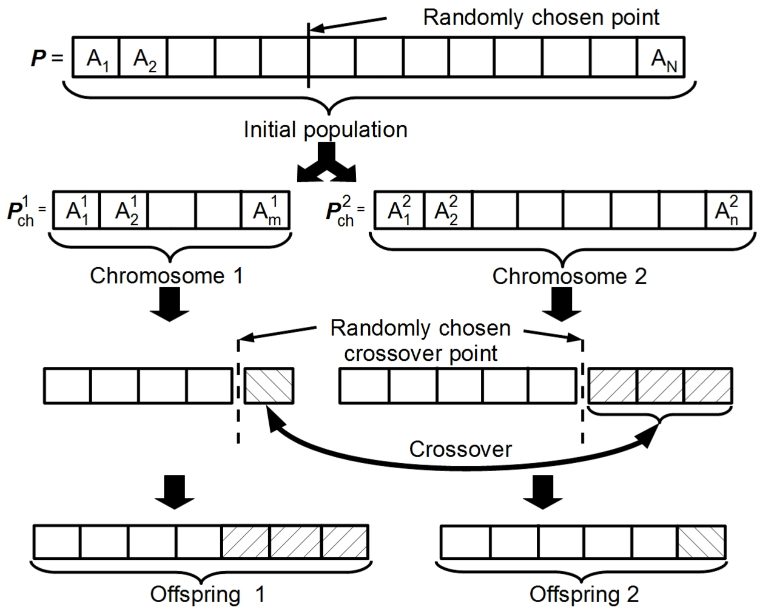


Figure 22: The chromosome representation and generation process in GA

chromosome that has optimum of fitness function is determined as local solution. At the beginning of the iteration, a local solution is used as a global solution. Every selection of anchors are evolving in each iteration to generate new selection of anchors (offsprings). A local solution is determined from a pair of offsprings. Local solution is compared with the current global solution. A local solution that has an optimum of fitness function are assumed as a new global solution of an iteration.

Fitness function is used to determine the local solution and global solution in each iteration of GA. Fitness function represent the euclidean distance of *Indicators point* (average position of selection of anchors) to *Reference point*. *Reference point* is a particular parameter value determined from the information of anchors that used in our methods respectively. Here, we assume the closest distance between *Indicators point* and *Reference point* as the optimum value of the fitness function. We will describe more about *Reference point* in the Chapter 4 and Chapter 5.

We illustrate the chromosome representation and the generation process in GA in Figure 22. As shown in Figure 22, assuming $P = A_1, A_2, \ldots, A_N$ is an initial population that contains the N numbers of anchors. All anchors in P are located in the communication range of a sensor node. P is divided into two chromosomes at one single randomly chosen point as $P^1_{ch} = \{A^1_1, A^1_2, \ldots, A^1_m\}$ and $P^2_{ch} = \{A^2_1, A^2_2, \ldots, A^2_n\}$. A pair of offsprings is generated from an interchange of divided group in each chromosome. These divided groups in each chromosome are produced by the single point crossover operation as described in the section before. The pseudocode for the GA in determining the global solution to the localization problem is given in Algorithm 1. The GA is repeated by using new offspring until the number of the iteration of computation satisfies a bound (for example, 100). It is assumed that the global anchor selection is a selection of anchors in an offspring that have an optimum fitness function where the distance of *Indicators point* of selected anchors in an offspring is the closest to the *Reference point* among all chromosomes.

Algorithm 1 Selection of anchors with GA

$m \leftarrow rand()$
$Indicators\_point1 \leftarrow Chromosome, P^1_{ch} = \{A^1_1, A^1_2, \ldots, A^1_m\}$
$Indicators\_point2 \leftarrow Chromosome, P^2_{ch} = \{A^2_1, A^2_2, \ldots, A^2_n\}$
$F1 \leftarrow$ Distance between center of $Indicators\_point1$ and $Reference\_point$
$F2 \leftarrow$ Distance between center of $Indicators\_point2$ and $Reference\_point$
while $loop < MAXLoop$ **do**
  if $F1 < F\_global$ **then**
    $Best\_selection \leftarrow Indicators\_point1$
    $F\_global \leftarrow F1$
  end if
  if $F2 < F\_Best$ **then**
    $Best_selection \leftarrow Indicators\_point2$
    $F\_global \leftarrow F2$
  end if
  $crossover()$ // Generation of offspring
  $Indicators\_point1 \leftarrow Offspring1$
  $Indicators\_point2 \leftarrow Offspring2$
  $F1 \leftarrow$ Distance between center of $Indicators\_point1$ and $Reference\_point$ after crossover
  $F2 \leftarrow$ Distance between center of $Indicators\_point2$ and $Reference\_point$ after crossover
  $loop \leftarrow loop + 1$
end while

Efficiency of localization that use the average of anchors is obviously affected from the variation of the distance between anchors and a sensor node. However, since the real position of a sensor node is unknown, it is difficult to configure the variation of distance. Consequently, we use distance between *Indicators point* and *Reference point* as a metric to measure whether the selection of anchors in GA is located close to the center of communication range or not. We utilize this characteristic to measure the variation of distance for each chromosome in determining optimal solution (best selection of anchors) based on two types of *Reference point*, static *Reference point* and dynamic *Reference point*. In

Chapter 4, we describe the proximity-based localization which utilized the anchors selectively based on the static *Reference point* by using GA approach. In Chapter 5, we describe the proximity-based localization which utilize a dynamic *Reference point*, which is improved iteratively to determine the location of a sensor node.

4 Selection of anchors based on static *Reference point*

In order to determine the reliable selection of anchors, we use a distance between *Indicators point* and *Reference point* as a metric to measure whether the selection of anchors in GA is located close to the center of communication range or not. In this chapter, we utilize this characteristic to measure the variation of distance for each chromosome in determining best selection of anchors based on the static *Reference point*. Static *Reference point* is employed to represent the center of communication range of a sensor node. A single location of *Reference point* that is determined initially is used in all iteration for determining the best selection of anchors. A static *Reference point* provide the ability for *Indicators point* to indicate the reliability of the selection of anchors. By comparing the distances of both estimated position of a sensor node and *Indicators point* to *Reference point*, the estimated positions of sensor nodes in WSN can be distinguished according to the reliability of every selections of anchors.

4.1 Overview of geometric anchor selection method

The variation of the distance between anchors and a sensor nodes could obviously contribute to the deterioration of efficiency in the localization that used average of anchors. The efficiency of the localization can be improved by reducing the variation of the distance between anchors and a sensor node. In order to reduce the variation of distance, we select the anchors that have less variation of distance between the anchors and a sensor node. We assume that the selection of anchors is reliable if their distances to a sensor node are not varied significantly. However, it is not easy to select a reliable selection of anchors according to their distance to a sensor node as a true location of a sensor node is unknown. The location of a sensor node only can be determined after the selection of anchors. To solve this problem, we proposed a method to select the anchors which have less variation of distance to a sensor node without using any information of sensor node location based on GA approach.

Suppose that when a mobile receiver traveling between two points, they are traveling in a connection of multiple straight lines which lastly become one trajectory. We use the characteristic of these straight lines to build a population samples to determine the best selection of anchors by using GA approach. Each line contains two anchors located at the edges of a line. *Indicators point* is calculated from the average of selected anchors in the lines. We call the locations of mobile receiver located between two anchors at each interval time unit as footprints. We suppose a particular static *Reference point* to represent the center of circle in determining the selection of anchors. We select the anchors, which have smallest distance between *Reference point* and *Indicators point* based on the GA approach. The estimated location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors.

In determining the reliable selection of anchors, we utilized a static *Reference point* which is denotes a reference location that calculated from an average of footprints that have largest RSS values in the vicinity of a sensor node. In this PhD thesis, minimum number of anchors (three anchors) are used to prevent errors that could occur from more anchors that are used to determine *Reference point* as described in [28, 52, 72, 29]. In the WSN environment that deployed with high density of anchors, more anchors could be used to determine the *Reference point* to perform proximity-based localization.

An *Indicators point* is used together with a *Reference point* to find the best selection of anchors in determining the location of a sensor node. *Indicators point* denotes the centroid of the geometric shape of combination of lines connected by selected anchors. The RSS measurement from each footprints is used to construct the lines. The distance information in each footprint is obtained from a conversion of RSS measurement based on the fuzzy logic approach and not a precise distance measurement. Distance information is used as a connectivity constraint between each footprint and a sensor node to indicate the footprints are located in a straight line.

In determining the population of samples to perform GA, we apply these lines to retrieve the anchors from the footprints. A mobile receiver measure an RSS from a sensor node in each time unit and stored in a node tuple for a footprint to construct a line. RSS measurements are converted into distance, d respectively, which represents a distance between a footprint and a sensor node. Footprints are divided into sets of lines according to d measured at each footprints. Anchors are the subset of footprints which are located at the edges of each line.

4.2 Construction of population samples

Population samples is constructed from the lines and each line represent the set of footprints. The lines is constructed according to d converted from RSS measurement at each footprint. In this section, we present the conversion of RSS measurement into distance d by using fuzzy logic approach. The construction of lines are also presented in this section which represent the population samples of GA in determining the best selection of anchors.

4.2.1 Conversion of RSS to distance by using fuzzy logic

We apply the fuzzy logic approach to convert the measurement of RSS from a sensor node to distance as described in [80]. Fuzzy logic approach demonstrates its inexpensive and robust way to deal with highly complex and variable models of noisy and uncertain

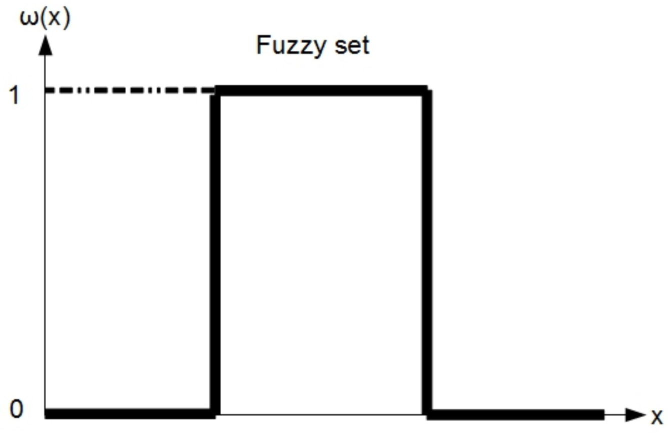


Figure 23: Binary membership function for a fuzzy set

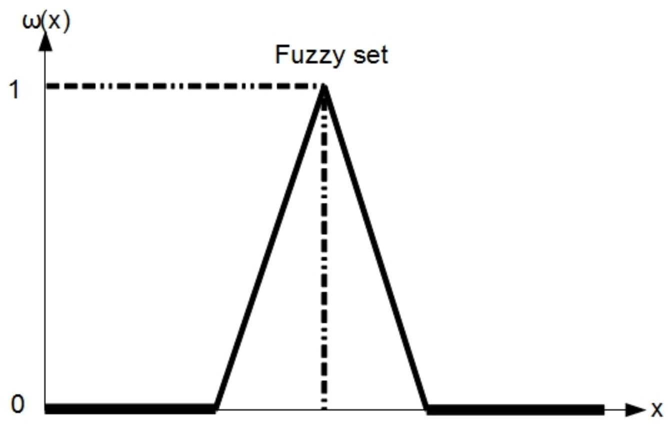


Figure 24: Triangular membership function for a fuzzy set

environments [80]. Since the use of RSS to determine distance between sensor nodes is not accurate due to the effect of uncertainties of radio propagation, we consider the two types of fuzzy sets, input fuzzy sets and output fuzzy sets for the conversion.

Fuzzy logic provides fuzzy set to solve the problems with imprecise input of information. Here, fuzzy set is a set of uncertainty of objects that can be used to determine the ambiguity of a result. Fuzzy set in a fuzzy logic approach contain a result that define the uncertainties of membership of set. The membership function is used to define the degrees of membership of certain input information to the fuzzy set. In [81], membership function is extended to which a degree of membership is represented by the set of number $\{0,1\}$, where each 0 and 1 denoted no membership and full membership respectively as

Table 3: Input fuzzy sets and output fuzzy sets.

Input fuzzy sets (RSS, *dB*)	**Output fuzzy sets (Distance, *m*)**
0	0
-86.7	70
-100.9	140
-109.2	210
-115.0	280
-119.6	350
-123.3	420
-126.4	490
129.2	560
131.6	5630
133.7	700
135.7	770
137.4	840
139.1	910
140.6	980

shown in Equation 2 as shown below:

$$\omega(x) = \begin{cases} 0, & \text{if} \quad x \text{ is no membership} \\ 1, & \text{if} \quad x \text{ is full membership} \end{cases} \tag{2}$$

where $\omega(x)$ is a degree of membership of x to a fuzzy set where the value is represented as 0 and 1. Figure 23 shows a binary membership function as described in Equation 2. In [82], triangular membership function is presented to improve the flexibility of membership function which can be applied to maximize the efficiency of various applications as shown in Figure 24. Here, $\omega(x)$ is a degree of membership of a fuzzy set as give as below:

$$\omega(x) \in [0, 1] \tag{3}$$

where $\omega(x)$ is represented by the real continuous interval $[0,1]$.

In the conversion of RSS to distance, we apply the fuzzy sets to convert the values by using input fuzzy sets and output fuzzy sets. Table 3 shows the values of RSS and converted distance values which are applied as input fuzzy sets and output fuzzy sets respectively. Each value has full membership of a their own fuzzy set. Input fuzzy sets represent the RSS values which are determined in a priori. Output fuzzy sets here represent the distance values which are the results of converted RSS value from each input fuzzy sets by using log-distance path loss model [83] as follows:

$$PL = PL_o + 10\gamma log \frac{d}{d_o} \tag{4}$$

Path loss, PL is a distance-dependent loss of wireless signal power, which we use as RSS to measure the loss of wireless signal power from a target sensor node to a mobile receiver. d_o is the reference distance (i.e., $1m$) and PL_o denotes the path loss in decibels at d_o, which was assumed to be $47dB$ according to measurement in [84]. The d is the distance between target sensor nodes and a mobile receiver. The γ refers to the path loss exponent, which depends on channels and the environment. According to residential indoor models [84], the path loss exponent, γ, in this model is a random variable. and requires sufficient measurements on the spot in various residential environments before effectively being applied to generic scenarios. We have used the measurements in [85] which denote the value of average path-loss exponents as 1.9 in an engineering building.

The degrees of membership, $\omega(x)$ is calculated by using RSS values obtained from RSS measurement during the localization by using a triangular membership function as described in [82, 80] as follows:

$$\omega(x) = \begin{cases} 0, & \text{if } r < a \\ (r-a)/(b-a), & \text{if a} \leq \text{r} \leq \text{b} \\ (c-r)/(c-b), & \text{if b} \leq \text{r} \leq \text{c} \\ 0, & \text{if } r > c \end{cases} \tag{5}$$

where, a, b, c is parameters in fuzzy set as shown in Figure 25. The membership value of RSS input, $\omega(r)$ is converted to get an output value which is approximate by using a fuzzy rule in the mapping process [80]. We call degrees of membership a fuzzy number, $\omega(r)$ as described in Equation 5, where r denotes RSS input value measured by a mobile receiver during the localization. A fuzzy number is an imprecise number rather than exact number in a collection of discrete objects (RSS values) called fuzzy set as shown in Figure 25. Fuzzy number is defined by a membership value ranges in degree between 0 and 1.

The RSS measurements are converted into distance by mapping the $\omega(x)$ from input fuzzy sets to output fuzzy sets. $\omega(x)$ are used to determine a distance value by using a set

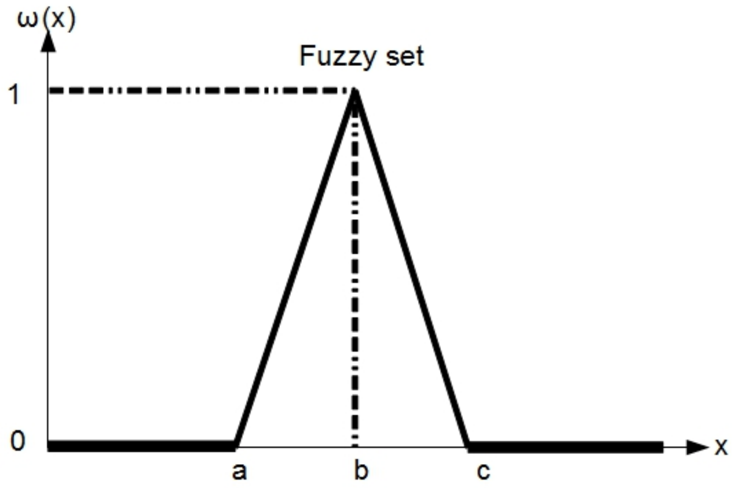


Figure 25: Triangular membership function in the conversion of RSS to distance

of rules in the mapping process. Each rule describes the relation of RSS fuzzy sets (input fuzzy set) to distance fuzzy set (output fuzzy set) according to the measurement of RSS (input value). Fuzzy rule is a form of IF-THEN statement that relates input and output variables. IF statement contains input variables of RSS value, r and the THEN statement contains output variables of distance, d.

In the mapping process, as described in Figure 26, an input of RSS value, r intersects at two different fuzzy sets which give two different fuzzy numbers for each set. Each fuzzy set has a fuzzy rule which translates the RSS fuzzy set to the distance fuzzy set as below:

IF RSS is set $\alpha(r)$ THEN DISTANCE is set $\alpha(d)$
IF RSS is set $\beta(r)$ THEN DISTANCE is set $\beta(d)$

Then we compute the center of gravity as $G = \{G_A, G_B\}$ of the trapezium formed at the distance fuzzy set. A trapezium area denotes a degree of membership for each output fuzzy set formed by $\omega(x)$ from an input fuzzy set. We compute the average of all G as an output value for distance, d. Average value gives a mean of degrees of membership from the output fuzzy sets in order to determine a distance value from trapezium areas of output fuzzy sets.

4.3 Construction of lines

To understand how the movement of a mobile receiver will construct the lines, we have to understand the effect of the distances when a mobile receiver travels on its path as shown in Figure 27. As shown in Figure 27(a), a mobile receiver receives a wireless signal from

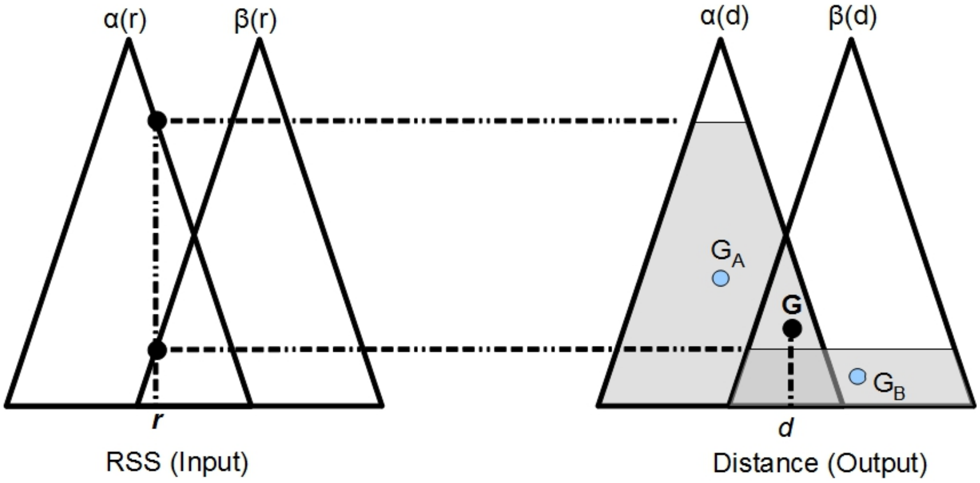
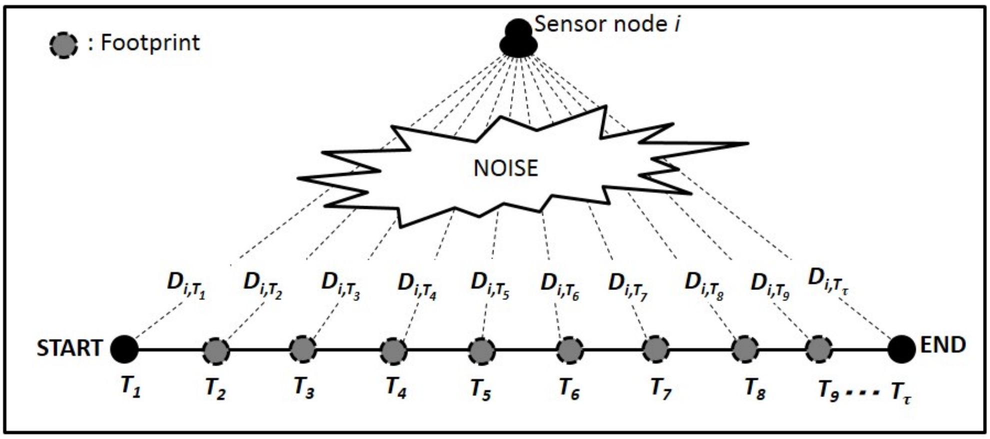


Figure 26: Mapping process

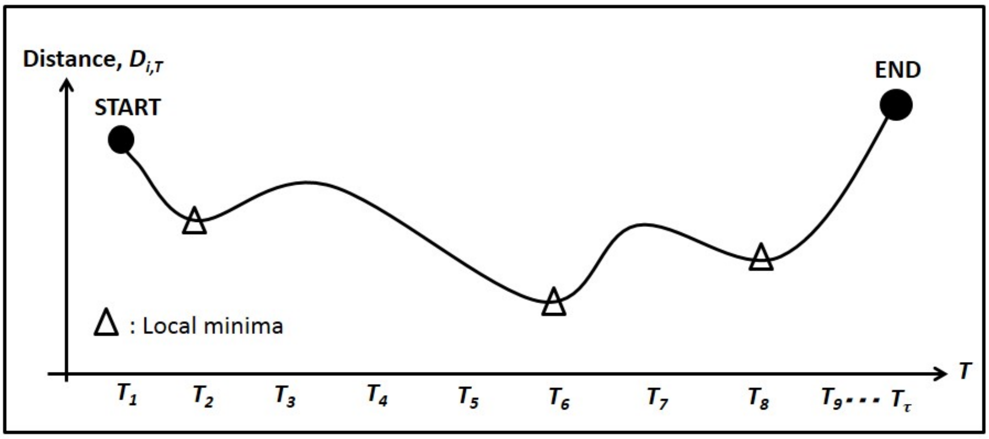
a sensor node i and measures a RSS at time unit T. The measured RSS is affected by noise of signal propagation in the environment. RSS is converted into distance, $D_{i,T}$ as described in Section 4.2.1. A mobile receiver travels in each T and measures a distance $D_{i,T} = D_{i,T_0}, D_{i,T_1}, D_{i,T_2}, \ldots, D_{i,T_\tau}$ where $T = T_0, T_1, T_2, \ldots, T_\tau$.

Although a mobile receiver moves from START point to END point of a straight line, the distance value in footprints does not seem to follow a monotonic path and produce multiple of local minimum between these two points as shown in Figure 27(b). This is a result from the variation of RSS due to dynamic and unpredictable signal propagation. We assume that a set of consecutive footprints which has one local minimum of distance is a set of footprints that moves in a straight line.

As shown in Figure 28, we assume that a set of footprints is a combination of two kinds of sets of footprints, D^{dec} and D^{inc}. Here, D^{dec} is a set of footprints that having its distance decrease monotonically and D^{inc} is a set of footprints which the distances increase monotonically. At time $T = t_\lambda$, we compare the value of $D_{i,T}$ at time $T = t_\lambda$ and $T = t_{\lambda+1}$. If $D_{i,t_\lambda} > D_{i,t_{\lambda+1}}$, then we define Di,t_λ as a set of D^{dec}. We continue this step until we find the local minimum, D_{i,t^c} where $D_{i,t^c} = D_{i,t_{\lambda+\alpha}}$ if $D_{i,t_{\lambda+\alpha}} < D_{i,t_{\lambda+\alpha-1}}$ and $D_{i,t_{\lambda+\alpha}} < D_{i,t_{\lambda+\alpha+1}}$. In the definition of D^{inc}, if the mobile receiver moves β times after t_c, we define $D_{i,t_{\lambda+\alpha+\beta}}$ as a set of D^{inc} if $D_{i,t_{\lambda+\alpha+\beta}} > D_{i,t_{\lambda+\alpha+\beta+1}}$. Then, D^{dec} and D^{inc} are combined to construct a set distance , $D_{i,t} = D_{i,t_\lambda}, D_{i,t_{\lambda+1}}, \ldots, D_{i,t_{\lambda+\alpha}}, D_{i,t_{\lambda+\alpha+1}}, \ldots, D_{i,t_n}$ for one straight line where $t_n = t_{\lambda+\alpha+\beta}$. Here, D_{i,t_n} is also a member of D^{dec} for the next consecutive line. Suppose that each footprint, $F_{i,j,t}$ is stored with a tuple $< i, j, D_{i,t}, FP_{i,j,t}, t >$, a set of consecutive footprints for one straight line is constructed as $F_{i,j,t} = F_{i,j,t_\lambda}, F_{i,j,t_{\lambda+1}}, \ldots, F_{i,j,t_n}$ as shown in Figure 29. Here, $FP_{i,j,t} = (X^{FP}_{i,j,t}, Y^{FP}_{i,j,t})$ is a coordinate of a footprint at time



(a)



(b)

Figure 27: Construction of lines

unit $t = t_\lambda, t_{\lambda+1}, \ldots, t_n$ and j is the number of a line. We suppose the footprints located at t_λ and t_n represent the anchor of line j. Given the number of lines for one trajectory as $j = 1, 2, \ldots, N$, we suppose that the anchors, $A_i = A_{i,1}, A_{i,2}, \ldots, A_{i,2N}$ are the subset of footprints which located at the both edges of each line where $A_i = \{F_{i,j,t} | F_{i,j,t} = F_{i,j,t=t_\lambda} \wedge F_{i,j,t} = F_{i,j,t=t_n} \wedge 1 \leq j \leq N\}$. We utilize A_i as the population samples of GA in determining the best selection of anchors for the localization of sensor node i.

4.4 Selection phase and estimation phase in geometric anchor selection

In determining the location of a sensor node, we consider two phases of localization, a selection phase and an estimation phase. In the selection phase, an *Indicators point*

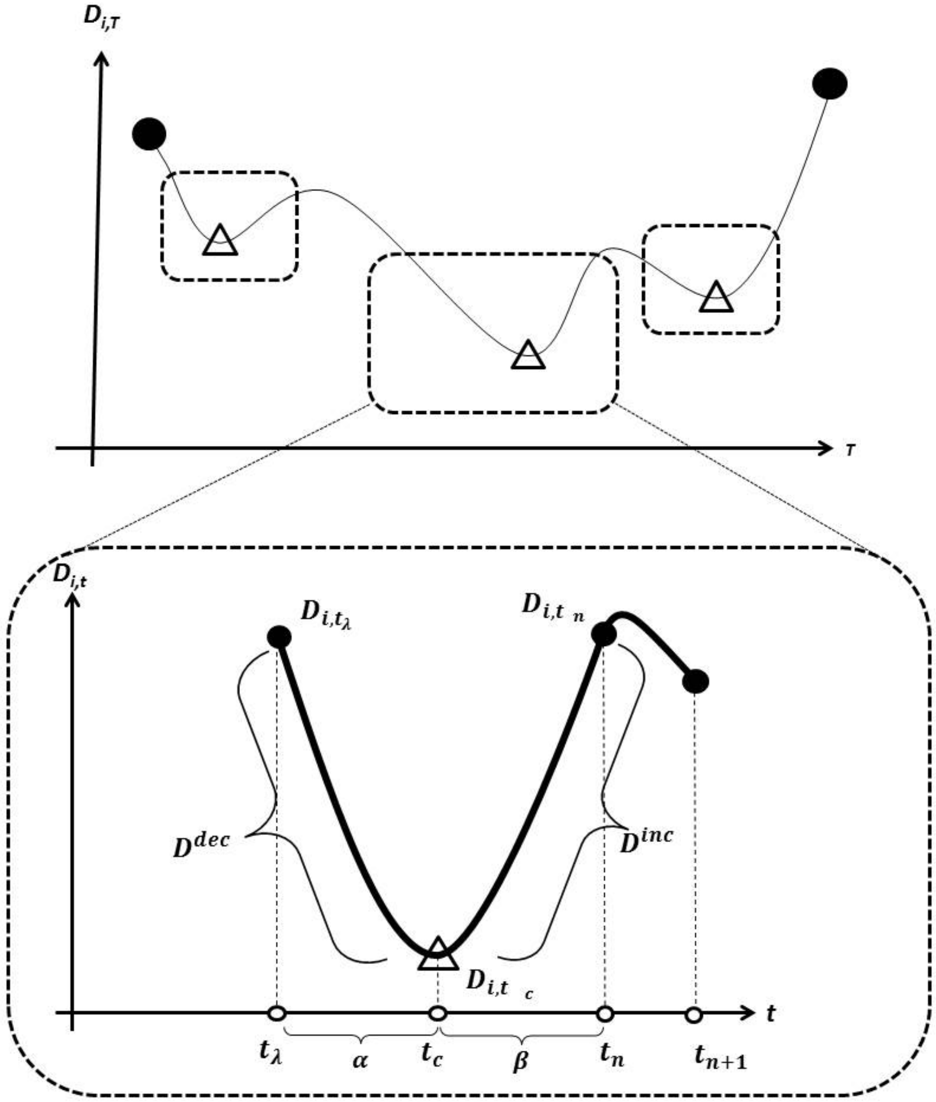


Figure 28: Construction of lines

is used together with a *Reference point* which is calculated from the average position of three footprints that have largest RSS. We select the selection of anchors that have smallest distance between a *Reference point* and an *Indicators point* iteratively based on the GA approach.

In the estimation phase, the location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors.

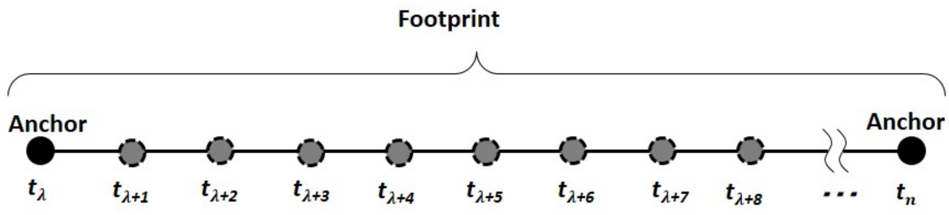


Figure 29: Definition of footprints and anchors in a line

4.4.1 Selection phase

In selection phase, we iteratively observe the relation of distance function of *Indicators point* and *Reference point* to find the best selection of anchors. *Reference point* is utilized to represent the center of communication range of a sensor node in order to find the best selection of anchors. The best selection of anchors is selected according to the distance of *Indicators point* and *Reference point* by using GA approach. Here, *Indicators point* is the average position of selected anchors. We assume that when an *Indicators point* is located close to a *Reference point*, the selection of anchors have less variety of their distance to the center of communication range of a sensor node. The *Reference point* is determined from the average position of three footprints that have largest RSS. Considering the errors of RSS measurements deteriorates over distance exponentially as explained in [28, 52, 72, 29], the nearest location of footprints might have less error of RSS compared to the footprints that located far from a target sensor node.

Assuming we have in total N of lines in population P_i of a sensor node i, we suppose all lines in population P_i as an initial population $P_i^{init} = \{L_{i,1}, L_{i,2}, \dots L_{i,N}\}$. Each line contains a pair of anchors where $L_{i,j} = \{A_{i,j,k_j}\}$. Here, $k_j = 1,2,\dots$ is a number of anchors located in line $L_{i,j}$. The pseudocode for the GA in determining the selection of anchors is given in Algorithm 2. Initially, we define the average of anchors in P_i^{init} as *Indicators point* $IP_i = (X_i^{IP}, Y_i^{IP})$ which is calculated from equation as below:

$$IP_i = (\frac{\sum_{k=1}^{M} X_{i,j,k_j}}{M}, \frac{\sum_{l=1}^{2N} Y_{i,j,k_j}}{M}) \tag{6}$$

where $(X_{i,j,k_j}, Y_{i,j,k_j})$ is a coordinate of an anchor A_{i,j,k_j} and M is a number of anchors from the lines in a population. *Reference point* $RP_i = (X_i^{RP}, Y_i^{RP})$ is determined from the three footprints that have largest RSS values of sensor node i. Given the three footprints that have largest RSS as $FP_{i,j,t}^{Lar}$ for $Lar = 1,2,3$, we compute a *Reference point* as follows:

$$RP_i = (\frac{X_{i,j,t}^{FP^1} + X_{i,j,t}^{FP^2} + X_{i,j,t}^{FP^3}}{3}, \frac{Y_{i,j,t}^{FP^1} + Y_{i,j,t}^{FP^2} + Y_{i,j,t}^{FP^3}}{3}) \tag{7}$$

where $(X_{i,j,t}^{FP^1} + Y_{i,j,t}^{FP^1}), (X_{i,j,t}^{FP^2} + Y_{i,j,t}^{FP^2})$ and $(X_{i,j,t}^{FP^3} + Y_{i,j,t}^{FP^3})$ are the coordinates of $FP_{i,j,t}^1, FP_{i,j,t}^2$ and $FP_{i,j,t}^3$ respectively.

Algorithm 2 Selection of anchors with GA

$P\_Init \leftarrow P_i^{init} = \{L_{i,1}, L_{i,2}, \ldots, L_{i,N}\}$
$m \leftarrow rand()$
$IP1 \leftarrow Chromosome, P_i^{ch1} = \{L_{i,1}, L_{i,2}, \ldots, L_{i,m}\}$
$IP2 \leftarrow Chromosome, P_i^{ch2} = \{L_{i,m+1}, L_{i,m+2}, \ldots, L_{i,N}\}$
$F1 \leftarrow$ Distance between center of $IP1$ and RP
$F2 \leftarrow$ Distance between center of $IP2$ and RP
while $loop < MAXLoopCount$ **do**
    if $F1 < F\_global$ **then**
        $P\_Best \leftarrow P_i^{ch1}$
        $F\_global \leftarrow F1$
    end if
    if $F2 < F\_global$ **then**
        $P\_Best \leftarrow P_i^{ch1}$
        $F\_global \leftarrow F2$
    end if
    $crossover()$ // Generation of offspring
    $P\_ch1 \leftarrow Offspring1$
    $P\_ch2 \leftarrow Offspring2$
    $F1 \leftarrow$ Distance between center of $IP1$ and RP after crossover
    $F2 \leftarrow$ Distance between center of $IP2$ and RP after crossover
    $loop \leftarrow loop + 1$
end while

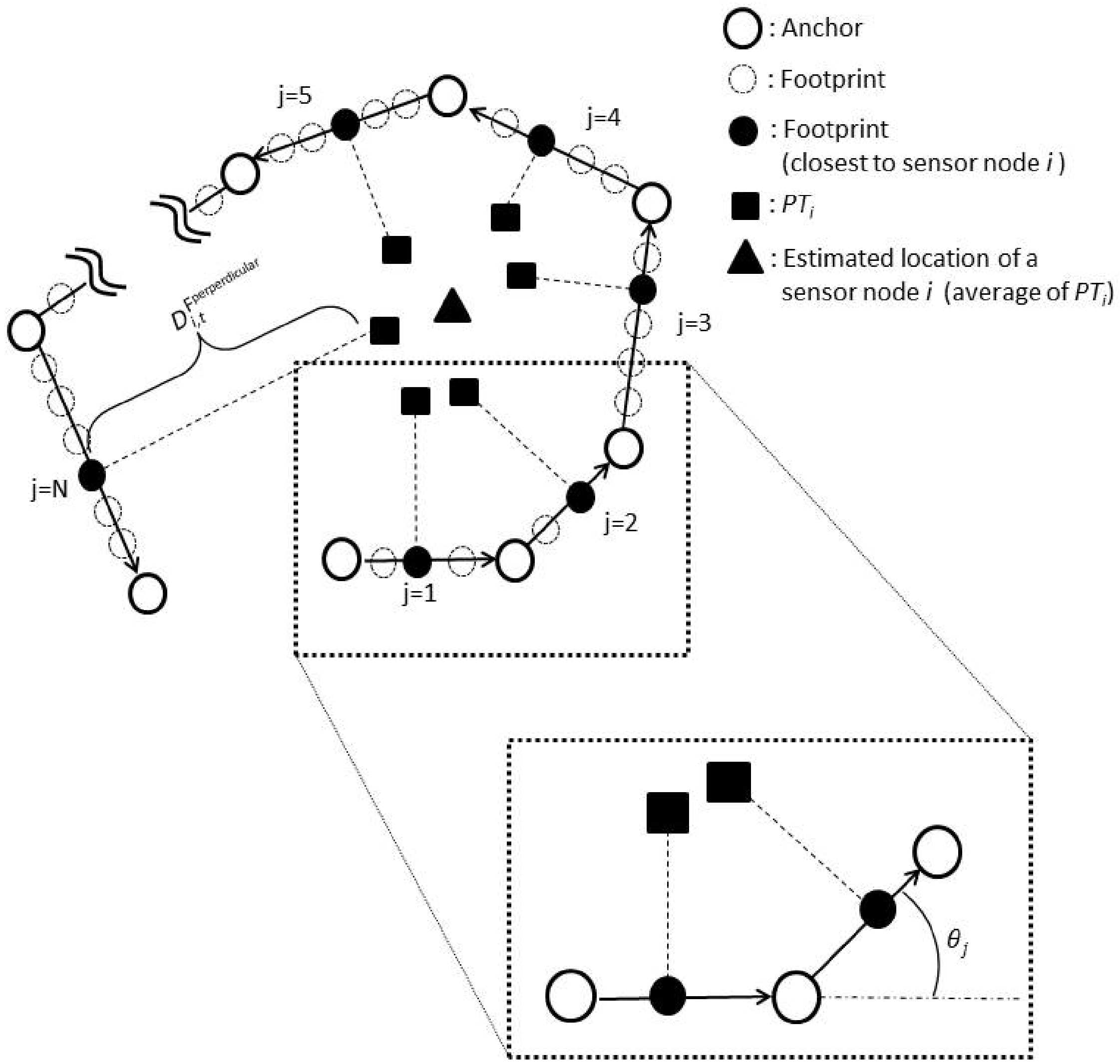


Figure 30: Computation of the location of a sensor node

In GA, we improve an initial solution of a sensor node i iteratively and move to a point where the fitness function of a population is optimized. Fitness function is a function to determine a solution of a population. Here, we suppose the initial population of anchors P_i^{init} as an initial solution of GA. Initial solution is improved in each iteration of GA. In determining the optimum solution of GA, we find the global solution among local local solutions and updating it to improve global solution toward the optimum. Global solution which is improves its location across iteration of GA and survived until the last iteration of GA is assumed as best solution, which is the best selection of anchors.

In generation process of GA, the fitness of a sensor node i, F_i is calculated from the

Euclidean distance between *Indicators point* and *Reference point* as follows:

$$F_i = \sqrt{(X_i^{IP} - X_i^{RP})^2 + (Y_i^{IP} - Y_i^{RP})^2} \quad (8)$$

In the next iteration, we divide the initial population of P_i^{init} into two sets of anchors, P_i^{ch1}, P_i^{ch2} to represent two chromosomes in GA. Each chromosome represents a local solution in GA which is selected arbitrarily from the available anchors in P_i^{init}. We compute the fitness of each local solution respectively as F_i^1 and F_i^2. The global solution is determined from a pair of local solution based on their fitness by comparing F_i^1 and F_i^2. A local solution which has a smaller fitness is selected to represent the global solution of an iteration, $P_i^{global} = \{L_{i,1}, L_{i,2}, \ldots\}$. P_i^{global} which has improved its location across iteration of the GA and survived until the last iteration of the GA is assumed as optimum solution of GA, P_i^{Best}. The anchors which are selected in optimum solution are assume as the best selection of anchors.

4.4.2 Estimation phase

The computation of estimated position of sensor node i in estimation phase is based from the best selection of anchors in P_i^{Best} that determined in GA. The location of a sensor node i is calculated from the average of points, each of which is located at the shortest perpendicular distance of a footprint in a line between a pair of anchors in P_i^{Best} as shown in Figure 30. Given these points as $PT_i = \{PT_{i,1}, PT_{i,2} \ldots, PT_{i,N}\}$, we calculate the estimated position of a sensor node i as follows:

$$(X_i^{EP}, Y_i^{EP}) = \left(\frac{\sum_{j=1}^{N} X_{i,j}^{PT}}{N}, \frac{\sum_{j=1}^{N} Y_{i,j}^{PT}}{N}\right) \quad (9)$$

where $PT_{i,j} = (X_{i,j}^{PT}, Y_{i,j}^{PT})$ is a coordinate of PT_i in j-th line of sensor node i. We assume that a mobile receiver moves in a route on which the angle of turn for j-th line, θ_j is known in advance. We use this information to compute PT_i as follows:

$$X_{i,j}^{PT} = X_{i,j,t}^{F^{perpendicular}} + (D_{i,t}^{perpendicular} \times \sin\theta_j) \quad (10)$$

$$Y_{i,j}^{PT} = Y_{i,j,t}^{F^{perpendicular}} + (D_{i,t}^{perpendicular} \times \cos\theta_j) \quad (11)$$

where $(X_{i,j,t}^{F^{perpendicular}}, Y_{i,j,t}^{F^{perpendicular}})$ is a coordinate of footprint that has a closest distance among other footprints in line j of a sensor node i and $D_{i,t}^{perpendicular}$ is a value of a distance between a footprint and sensor node i.

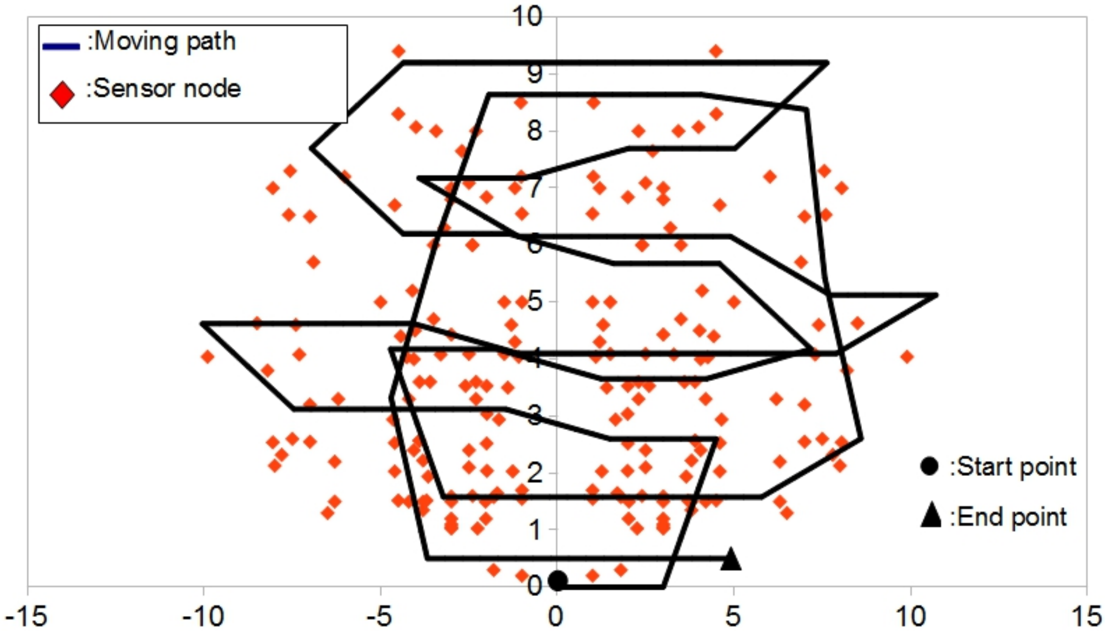


Figure 31: Experiment on the various location of sensor nodes

4.5 Simulation experiment

In this section, we present the simulation experiments to evaluate the performance of proximity-based localization which utilized the anchors selectively based on the static *Reference point*.

4.5.1 Simulation setup

In order to evaluate the performance of this method, we carried out an experiment to determine the effectiveness of the proposed method. We deploy 200 target sensor nodes randomly in $10m \times 20m$ two dimension area as shown in Figure 31. We evaluate the error of the estimated location of a sensor node which utilized the selection of anchors based on the static *Reference point* with a variation of sensor node locations. In this experiment, a mobile receiver travels in a path at a constant speed and receives wireless signals from all sensor nodes in each time unit. Localization of all sensor nodes is performed simultaneously when a mobile receiver has reached to the end point of the path.

We consider the simulated radio propagation model from sensor nodes. Since the perfect circular radio model is invalid to be used for WSN simulation [86], we have adapted *DOI* (Degree of Irregularities) parameter in the simulated radio propagation model of our simulation experiment as used in [66]. In the next section, we describe the simulated radio propagation model that has been used in the simulation experiment.

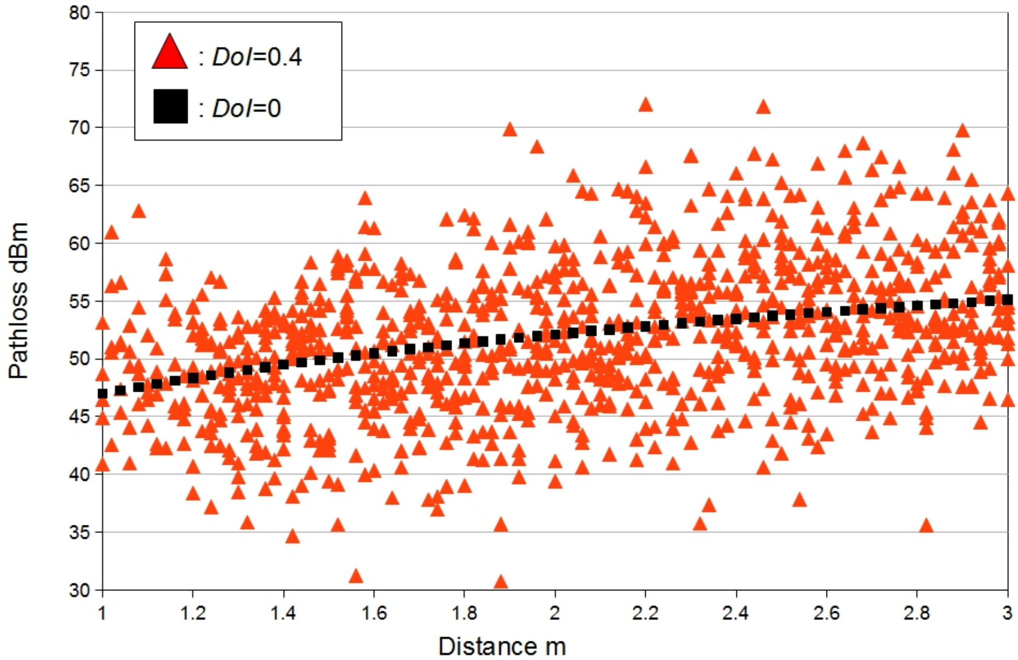


Figure 32: Plot of path loss values

4.5.2 Simulated radio propagation model

In this section, we present the simulated radio propagation model that has been applied in our simulation experiment. The radio transmission of sensor nodes is derived from a path loss model of signal transmission from sensor nodes. We used an extended model of log-distance path loss as described in Equation 4 by combining it with the *DoI* model [66]. The log-distance path loss model is used in many indoor and outdoor environments.

The RSS measurement was a value from our degree of irregularities (*DoI*) extended log-distance path loss in Equation 12 as below:

$$PL = \{(PL_o + 10\gamma log\frac{d}{d_o}) \times (1 \pm (rand() \times DoI))\} + S \tag{12}$$

Here, d_o is the reference distance (i.e., $1m$) and PL_o denotes the path loss in decibels at d_o, which was assumed to be $47dB$. The d is the distance between sensor nodes and the mobile receiver computed from the real coordinates of the simulation system. The γ refers to the path loss exponent, which depends on channels and the environment. According to residential indoor models [84], the path loss exponent, γ, in this model is a random variable, and requires sufficient measurements on the spot in various residential environments before effectively being applied to generic scenarios. Hence, we have used the measurements in Sohrabi et al. [85] in this PhD thesis, which denote the value of average path-loss exponents as 1.9 in an engineering building. S is log-normal shadow fading. The S is usually a random variable with a Gaussian distribution with zero mean and standard deviation σ, which was assumed to be 5.7 according to Sohrabi et al. [85]. The DoI is the radio irregularity and $rand()$ is a random number, $\mathcal{U}(0,1)$.

Figure 32 shows the plot of path loss values of the particular distance by using Equation 12 where $DoI = 0.4$. As shown in a figure, the path loss values are varied significantly due to the effect of $rand()$. We simulate path loss model by using DoI parameter, rather than increases smoothly through distance as demonstrated in a model with $DoI = 0$. Table 4 shows the parameters that used in the experiment. The results of the evaluation experiment are presented in the next section.

Table 4: Simulation parameters

RSS, dB	**Distance,** m
Reference distance, d_o	$1m$
Path loss, PL_o	$47dB$
Distance between a sensor node and anchors, d	$d \in \mathbb{R}$
Path loss exponent (engineering building), γ	1.9
Log-normal shadow fading (engineering building), S	5.7
Radio irregularity, DoI	0.4
Random number, $rand()$	$rand() \in \mathbb{R}$

4.5.3 Results

In this section, we present the results of a simulation experiment in evaluating the performance of the proximity-based localization that utilized the anchors selectively based on the static *Reference point*. We define the criterion for the localization error to be the difference between the estimated location of a sensor node and the true position of a sensor node. The localization error shows the degree of the localization efficiency that the method can perform. Each sensor node has a poor localization efficiency if it has a large position error. In the phase of searching the best selection of anchors in GA, we find a selection of anchors for each sensor node which has the closest of the *Indicators point* to

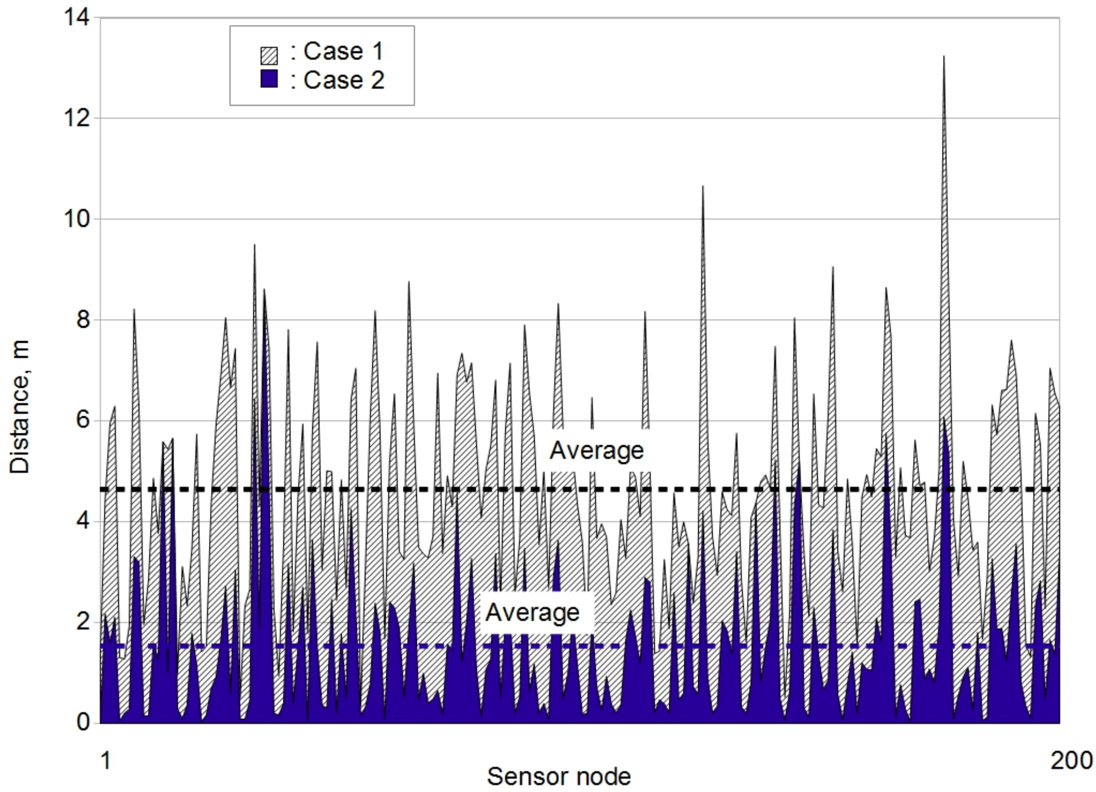


Figure 33: Values A of sensor nodes

Reference point in each iteration.

We investigate the effect of optimization of population of anchors on the localization efficiency in estimating the location of a sensor node. We compare the efficiency of the localization in two cases:

- **Case 1** : The localization based on all anchors.
- **Case 2** : The localization based on the best selection of anchors.

In the first case, all anchors located in the communication range of a sensor node is utilized without searching best anchor selection from GA. On the other hand, in the second case, the best selection of anchors selected in GA is utilized in the localization of a sensor node. We characterize three interests of values to simplify the explanation of our investigation as follows:

1. Value A: Difference of *Indicators point*, IP_i and *Reference point*, RP_i.
2. Value B: Difference of *Indicators point*, IP_i and estimated location of a sensor node, (X_i^{EP}, Y_i^{EP}).

3. Value C: Difference of estimated location of a sensor node, (X_i^{EP}, Y_i^{EP}) and real coordinate of sensor nodes which is also defined as a localization error of the estimated coordinate.

As shown in Figure 33, the distance between a RP_i and IP_i has improved for each sensor node for about 67% averagely in *case 2*, compare with the average of values A in *case 1*. However, we observed that not all target sensor nodes improved their values B and there was an increment of values B in *case 2* compare with the localization in *case 1* as shown in Figure 34 even though the IP_i have improved its location approaching to RP_i. The increment was resulted from error (e.g. Uncertainties of signal propagation model) in distance measurement, d and average calculation due to arbitrary deployment of anchors. Figure 35 shows the localization error by using our method. We found that 65% of the sensor nodes have improved their localization error in *case 2* compare with the localization error in *case 1*. We study the relation of values A, B and C to verify if these values can be used to indicate the reliability of anchors. The estimated position of a sensor node is assumed reliable if it satisfies the following conditions in their localization:

1. Decrement of values A in localization by using the best selection of anchors.
2. Decrement of values B in localization by using the best selection of anchors.

Figure 36 shows the values B of distinguished sensor nodes whose satisfy the condition as described above. The number of distinguished sensor nodes was 112 which was 56% from all sensor nodes in the experiment. The average of values B has decreased for about 35% averagely in localization of *case 2* compare with the localization in *case 1*. We observed that about 89% of distinguished sensor nodes have improved in their localization error by using our method as shown in Figure 37. The average of values C has improved for about 53% averagely for the results of the localization of *case 2* of distinguished sensor nodes, compare with the localization of *case 1* of distinguished sensor nodes. By using the above condition in determining the reliable selection of anchors, we are able to distinguish the estimations that are used reliable selection of anchors.

4.6 Conclusion

We have proposed the selection of anchors based on static *Reference point* in proximity-based localization which exploit the RSS measurement in indicating the connectivity information of sensor nodes and anchors or footprints. We convert the RSS measurement into distance by using fuzzy logic to overcome the uncertainties of signal propagation in the localization of sensor nodes. In this study, we demonstrated a method of selection of anchors to improve the efficiency of average-based calculation in estimating the position of sensor nodes. We have proposed the method for selecting the less reliable selection of anchors based on GA approach. This method provides the ability to distinguish the esti-

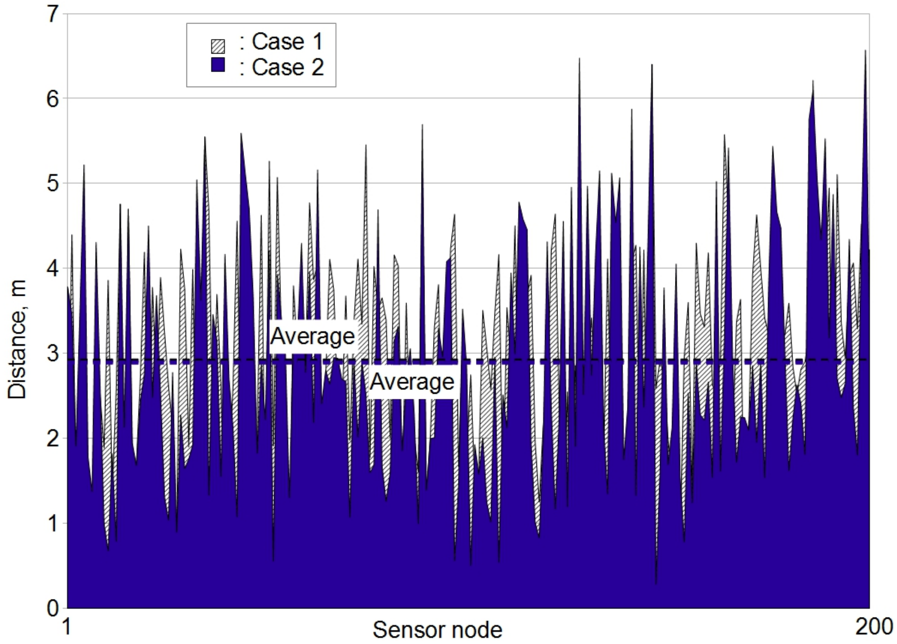


Figure 34: Values B of sensor nodes

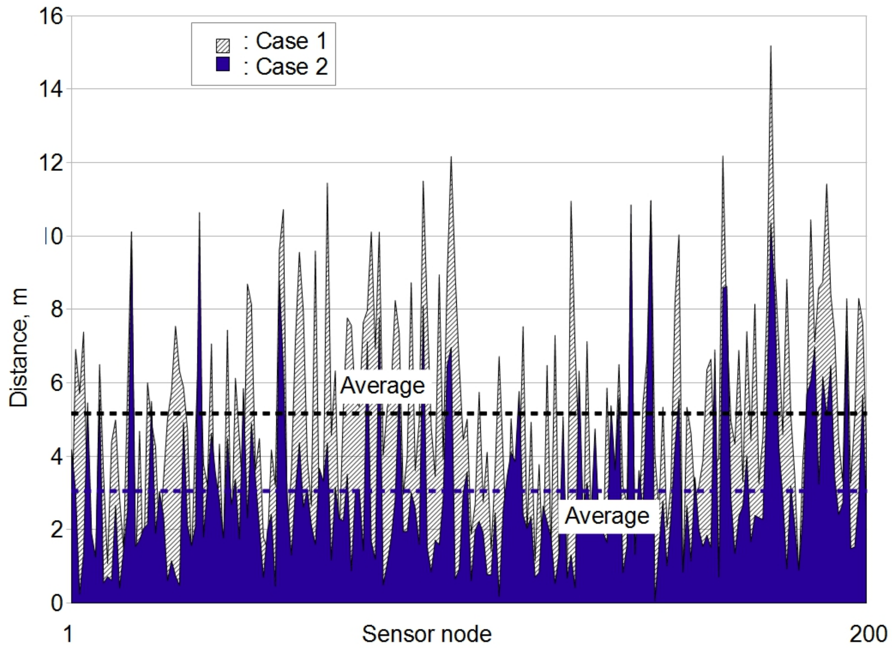


Figure 35: Values C of sensor nodes

mated position of sensor nodes. The experiment results prove that not less than 89% of the distinguished sensor nodes improved for about 53% of their localization error averagely.

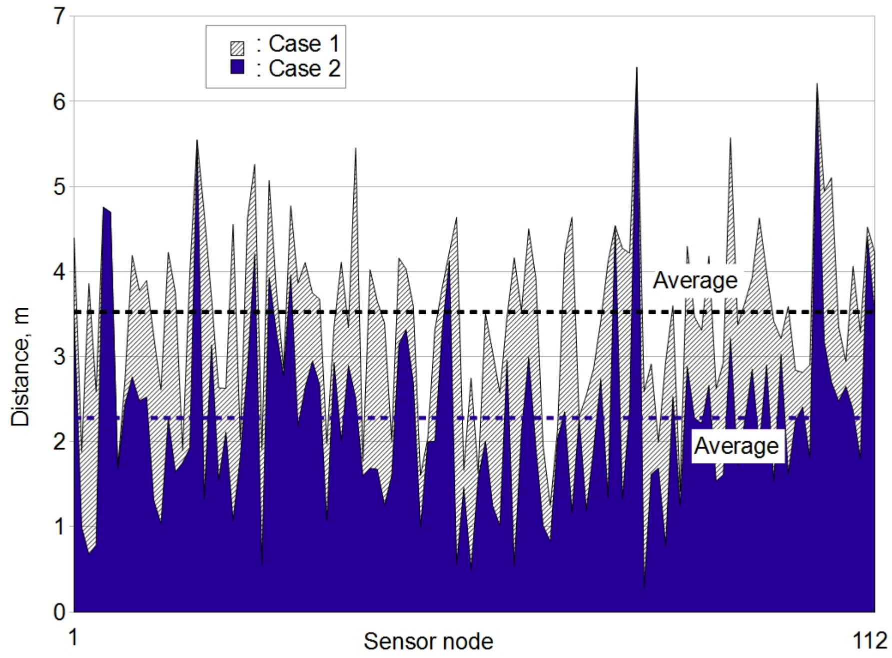


Figure 36: Values B of selected sensor nodes

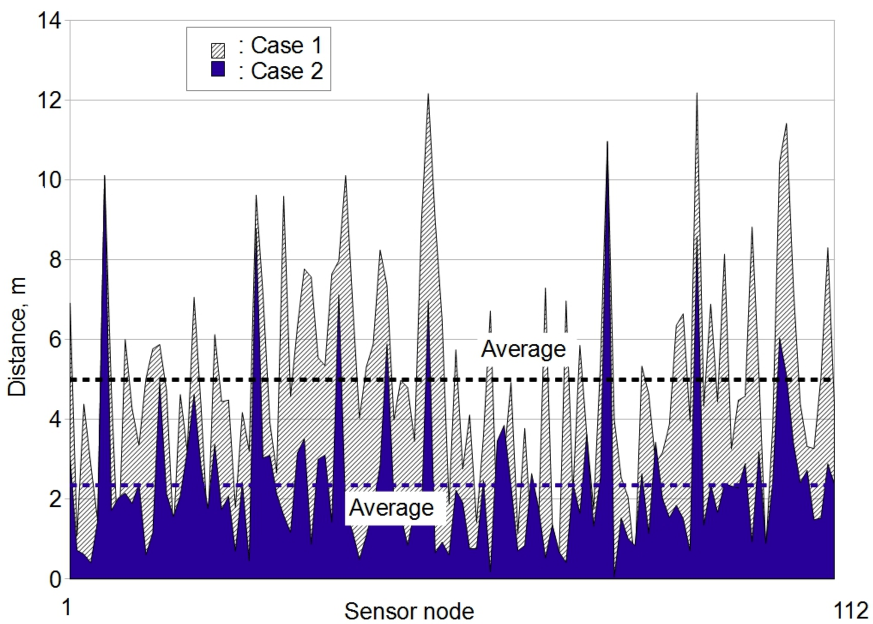


Figure 37: Values C of selected sensor nodes

In the selection of anchors based on the static *Reference point*, we found that the conversion of RSS to distance has give an impact to the error of distance measurement in determining a length of radius of wireless communication. Although this effect is minimized by applying fuzzy logic in conversion of RSS to distance, the effect of arbitrary deployment of anchors has deteriorates the uncertainty in radius of circle. Estimated location of a sensor node is exactly at the centered of perfect circle of communication range of a sensor node if the anchors are located uniformly in the vicinity of a sensor node. In the arbitrary deployment of anchors, the coordinates of selected anchors can be varied differently which deteriorates the error in average-based calculation of estimated position of a sensor node. In the next chapter, in order to solve this problem, we apply the proximity-based localization that utilized the selection of anchors based on the dynamic *Reference point* which improve the position of *Reference point* iteratively during the localization. In this method, we present the method of selecting the anchors without converting the RSS into distance. The *Reference point* is determined repeatedly, rather than using a single *Reference point*.

5 Selection of anchors based on dynamic *Reference point*

In this chapter, we present the proximity-based localization that utilized the anchors selectively based on dynamic *Reference point*. In this method, the selection phase and estimation phase are performed repeatedly in improving an *Indicators point* approaches to the true location of a sensor node. We use the multiple selections of anchors which have its own *Indicators point* in every selection. The concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. Unlike the method described in Chapter 4, *Reference point* is determined repeatedly in each loop of estimation. *Reference point* improves its location approaching to the true location of a sensor node. The improvement of *Reference point* relies upon the concentration of *Indicators point*. The major contribution of this method is to provide the ability for sensor node to determine its location efficiently by using selected anchors without using any static reference positions or objects. We carried out the simulations and experimental results to evaluate the performance of our proposed method.

5.1 Overview of selection of anchors based on dynamic *Reference point*

Table 5: Set of anchors.

Set, q	**RSS [dB],** PL
1	$41.5 < PL \leq 42.5$
2	$42.5 < PL \leq 43.5$
3	$43.5 < PL \leq 44.5$
4	$44.5 < PL \leq 45.5$
5	$45.5 < PL \leq 46.5$
6	$46.5 < PL \leq 47.5$
7	$47.5 < PL \leq 48.5$
8	$48.5 < PL \leq 49.5$
9	$49.5 < PL \leq 50.5$
10	$50.5 < PL \leq 51.5$

In this method, the selection of anchors is determined by using multiple population samples of anchors. Each population is corresponds to the particular range level of RSS that measured from a sensor node. RSS measurements are varied differently and grows exponentially to distance due to log-distance path loss effects. This effect can deteriorate the fluctuation of the radius distance between anchors and the center of circle of communication range. Hence, unlike method presented before, we divided RSS measurement into a number of sets as shown in Table 5 according to their RSS value without converting the RSS into distance. Here, set q is corresponds to the particular radius distance of communication range centered at a sensor node. Selection of anchors is performed in each set q according to which set the anchors belong. Suppose the available anchors that located in the wireless communication range of a sensor node i as $A_{k_q,q} = \left(X^{anchor}_{k_q,q}, Y^{anchor}_{k_q,q}\right)$, we divide all available anchors into s sets of RSS range level. Here, $A_{k_q,q}$ denotes k_q-th anchors in set q where $k_q = 1,2,\ldots,m_q$ and $q = 1,2,\ldots,s$ as listed in Table 5.

We iteratively improve the position of *Reference point*, $RP_i = (X_i^{RP}, Y_i^{RP})$ approaching the proximity of the true position of a sensor node i. Here, we used RP_i to represent the center of communication range of sensor node i in GA to determine the selection of anchors that has an *Indicators point*, IP_i closest to RP_i. Multiple *Indicators points*, $IP_i = IP_{i,1}, IP_{i,2}, \ldots, IP_{i,s}$ are calculated from the average of selected anchors of each set $q = 1,2,\ldots,s$. Calculating the *Indicators point* from the anchors according to the sets (which have their RSS similar to each other in a set) can improve the fluctuation of a radius distance.

As shown in Figure 38, we repeatedly update the position of a RP_i to determine the location of a sensor node i. In the first loop of the estimation, an RP_i is located arbitrarily in the WSN environment without any knowledge of the position of the sensor node i. We used GA approach to find the reliable selection of anchors in every set q that has their IP_i close to an RP_i. An RP_i is updated in each loop which improves its position approaches to an area which has a high density of IP_i. IP_i in each set q are calculated respectively in each loop according to the updated position of RP_i. After the selection of anchors, we determine the moving distance of RP_i by evaluating the concentration of the IP_i coordinates based on updated RP_i. An RP_i is updated repeatedly until the number of loops of improvements is satisfied. The location of a sensor node is determined from the average of selected anchors in the end of the loop. In the next section, we present the selection phase and estimation phase in each loop of improvement.

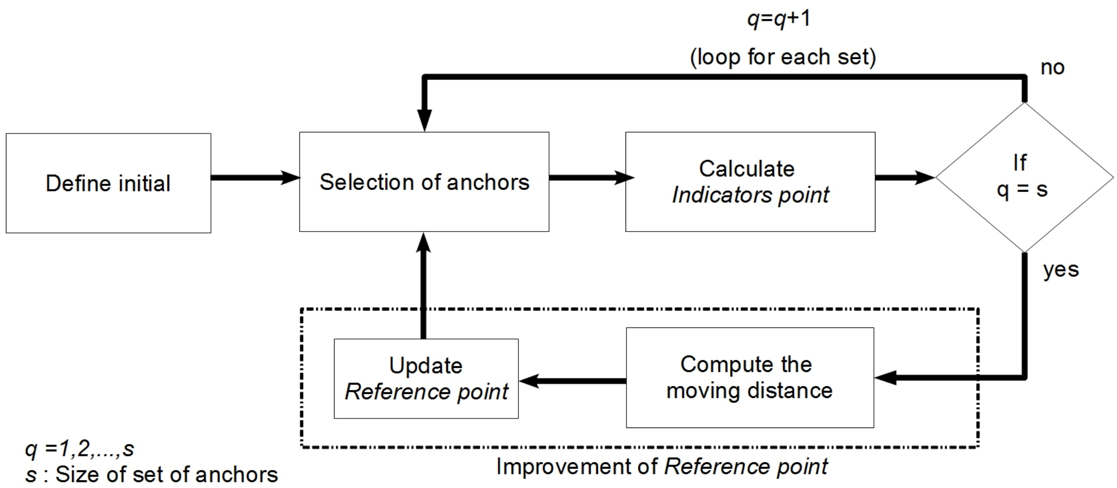


Figure 38: Iteration of GA in each loop to determine global solutions for each range level of RSS

5.2 Selection phase and estimation phase in non-geometric based anchor selection

In this method, the selection phase and estimation phase are performed repeatedly in each loop. In selection phase, multiple selections of anchors are determined for each set q by using GA. The number of selections of anchors provide the multiple of *Indicators points*. We improve a *Reference point* in each loop according to the concentration of multiple *Indicators points* by using optical flow algorithm approach [87]. In the estimation phase, the *Indicators points* determined from each set q in the end of the loops is utilized to determine the location of a sensor node. In the next section, we describe more concretely a selection phase and an estimation phase respectively.

5.2.1 Selection phase

Assuming we have a total of N_q anchors in a set q, we determine all anchors in $A_{k_q,q}$ as an initial population, $P_q = \{A_{1,q}, A_{2,q}, \ldots, A_{N_q,q}\}$. The pseudocode for the GA in determining the selection of anchors is given in Algorithm 3. We determine the average coordinates of anchors in P_q as $IP_{i,q}$, which is computed as:

$$IP_{i,q}^{local} = \left(\frac{\sum_{k_q=1}^{N_q} X_{k_q,q}^{anchor}}{N_q}, \frac{\sum_{k_q=1}^{N_q} Y_{k_q,q}^{anchor}}{N_q}\right) \tag{13}$$

The chromosome representation and the generation process in GA is outlined in Figure 39. Let P_q be the initial population in GA and compute the distance between IP_q^{local}

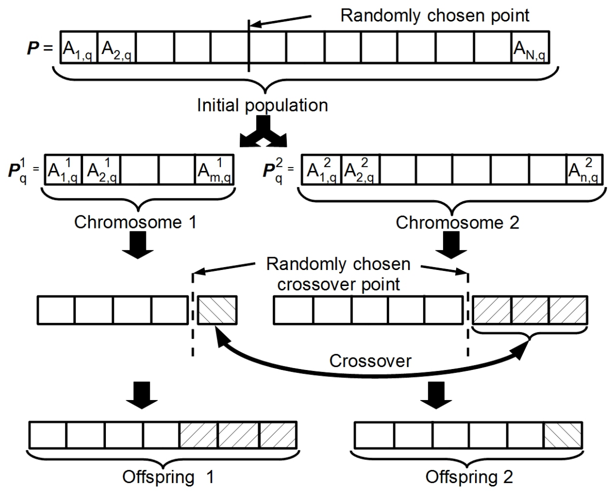


Figure 39: The chromosome representation and generation process in GA

and RP_i as the initial fitness of GA, F_q as:

$$F_q = \sqrt{(X^{RP} - X^{IP_q^{local}})^2 + (Y^{RP} - Y^{IP_q^{local}})^2} \quad (14)$$

where $(X^{IP_q^{local}}, Y^{IP_q^{local}})$ denotes a coordinate *Indicators point* for P_q. We divide P_q into two samples of populations, P_q^1, P_q^2 at randomly chosen points to represent two chromosomes in GA and compute the fitness of each chromosome as $F_q^1$and F_q^2 using the same Equation (14). The global solution is determined from a pair of chromosomes based on the least fitness (i.e., closest distance) by comparing F_q^1 and F_q^2. A chromosome that has better fitness is selected as the global solution, P_q^{global}.

In determining the optimum solution of GA, we find the global solution among local local solutions and updating it to improve global solution toward the optimum. Global solution which is improves its location across iteration of GA and survived until the last iteration of GA is assumed as best solution, which is the best selection of anchors.

5.2.2 Improvement of *Reference point*

In the improvement of *Reference point*, we evaluate the concentration of *Indicators point* calculated from the best selection of anchors of each set. We utilize the employment of direction vector to improve RP_i in each loop. Direction vector is an entity which represents the direction and magnitude of RP_i to improve its location. The idea is to evaluate the concentration of multiple IP_i to configure which direction it should move to improve its location approaching to the true location of a sensor node i.

In order to determine the location of a sensor node i, we exploit RP_i to evaluate the concentration of *Indicators points*. RP_i needs to change and improve its location to find

Algorithm 3 Selection of anchors with GA

$P\_Init \leftarrow P_q = \{A_{1,q}, A_{2,q}, \ldots, A_{m_q,q}\}$
$M \leftarrow rand()$
$IP1\_q \leftarrow Chromosome, P_q^1 = \{A_{1,q}, A_{2,q}, \ldots, A_{M,q}\}$
$IP2\_q \leftarrow Chromosome, P_q^2 = \{A_{M+1,q}, A_{M+2,q}, \ldots, A_{i,m_q}\}$
$F1\_q \leftarrow$ Distance between center of $IP1$ and RP
$F2\_q \leftarrow$ Distance between center of $IP2$ and RP
while $loop < MAXLoopCount$ **do**
    if $F1\_q < F\_global$ **then**
        $P\_Best \leftarrow P_q^1$
        $F\_global \leftarrow F1\_q$
    end if
    if $F2\_q < F\_global$ **then**
        $P\_Best \leftarrow P_q^2$
        $F\_global \leftarrow F2\_q$
    end if
    $crossover()$ // Generation of offspring
    $P_q^1 \leftarrow Offspring1$
    $P_q^2 \leftarrow Offspring2$
    $F1\_q \leftarrow$ Distance between center of $IP1$ and RP after crossover
    $F2\_q \leftarrow$ Distance between center of $IP2$ and RP after crossover
    $loop \leftarrow loop + 1$
end while

a location that has a high density of IP_i coordinates. Direction vector is used as a measurement of the concentration to help RP_i improve its location approaching to the true location of a sensor node. It is important to understand the effect of location of RP_i to the concentration of IP_i.

Figure 40 shows the effect of different positions of *Reference point* to the concentration of *Indicators points* which are determined from selected anchors in each set. Considering the anchors are divided into two sets, set_1 and set_2 according to the RSS value received from a sensor node i, we evaluate the concentration of *Indicators points* by using a distance between two *Indicators points* of both sets, *dist* based on the different positions of *Reference point*, $R1, R2, R3$ and $R4$. In these figures, we select the anchors which have their *Indicators point* closest to a *Reference point* in each set. Here, *Indicators point* is calculated from the average of selected anchors. In Figure 40(a), two anchors located at the bottom of a sensor node i from each set are selected as their *Indicators points* are the closest to $R1$ among other selection of anchors in each set. In Figure 40(b), different selection of anchors (at the right side of sensor node i) are selected according to the position of $R2$. The *dist* values of both cases are not significantly different as the distances between sensor nodes i and both *Reference points*, $R1$ and $R2$ are not significantly different. However, in Figure 40(c), *Indicators points* from each set are located closer to each other. The possibility to find more anchors that have less variation of distance between anchors and $R3$ is high when $R3$ is located closer to the center of circle. Figure 40(d) shows the positions of *Indicators points* from both sets and $R4$ are almost at the same position with sensor node i when $R4$ is located exactly at the same position with sensor node i. This is because of the $R4$ is located at the point of where the variation of distance between $R4$ and all available anchors is minimum.

We compute a direction vector by using the plotted *Indicators points* coordinates $\{IP_{i,1}, IP_{i,2}, \ldots, IP_{i,s}\}$ to improve the position of RP_i iteratively. Initially, RP_i is located arbitrarily in the WSN environment without any knowledge of the position of the sensor node i. As we compute IP_q^{global} based from selected anchors whose have the closest IP_i to RP_i for each set. In order to determine the direction vector to improve RP_i in each loop, we apply optical flow algorithm approach [87] which presents a way of estimating motion from a sequence of images. The optical flow algorithm can be easily applied to estimate the flows of $\{IP_{i,1}, IP_{i,2}, \ldots, IP_{i,s}\}$ to compute the direction vector of moving distance of RP_i to a sensor node i. The computation of optical flow plays a key role in several computer vision applications, including motion detection and segmentation, form interpolation, three-dimensional scene reconstruction, robot navigation and video compression.

In optical flow, gradient-based methods are common techniques of estimating the pattern of apparent motion of objects from the image sequence due to the relative motion

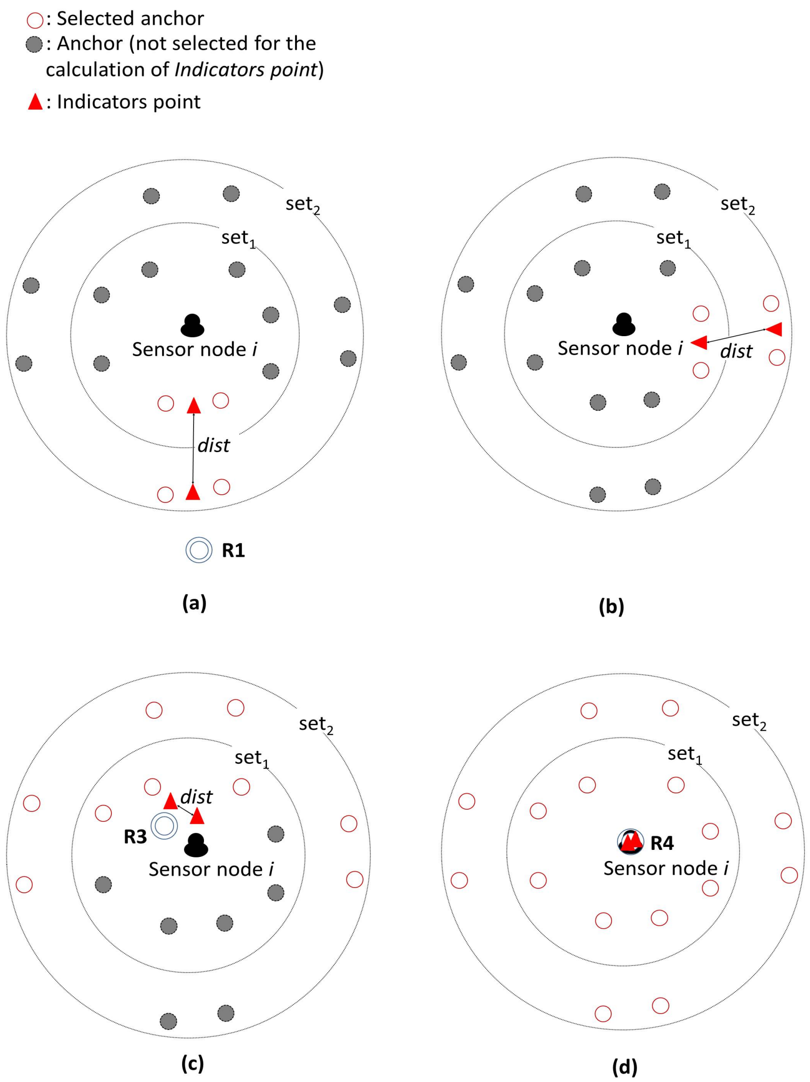


Figure 40: Improvement of T approaching true position of sensor node.

between camera and object. They use spatial (x, y) and time, t partial derivatives to estimate image flows at all positions of the image [87]. An assumption is made in these approaches that the brightness of any parts of the image frames moves. As shown in Figure 41, assuming there are two different images taken at times t and times $t+1$, the total derivatives of brightness are zero as the equation as below:

$$\frac{\partial I}{\partial x}\vec{U} + \frac{\partial I}{\partial y}\vec{V} + \frac{\partial I}{\partial t} = 0 \tag{15}$$

where $I(x, y, t)$ is the image brightness function, $(\vec{U}, \vec{V})$ denotes the optical flow vector.

To apply optical flow algorithm to determine the direction vector of moving distance for RP_i, we consider a square region centered at RP_i that is divided into 3×3 frames as

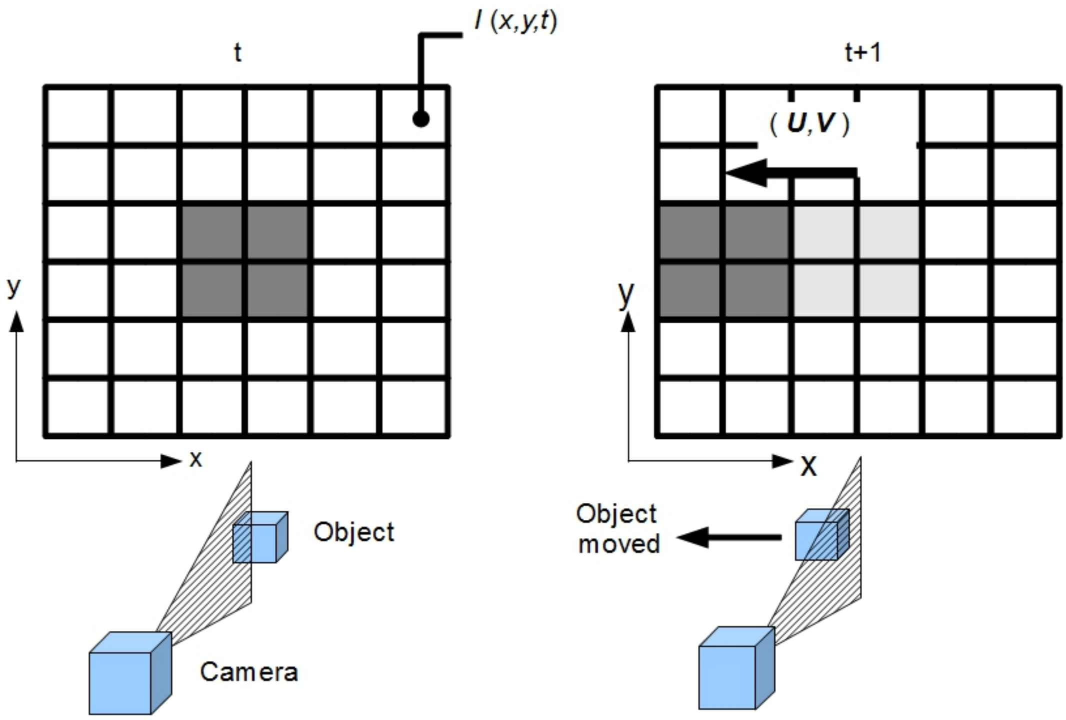


Figure 41: Optical flow from the relative motion between camera and object from two different images taken at times t and $t+1$.

shown in Figure 42. The square region has a length L along each side that initially covers all the *Indicators points* coordinates. We call the square region the Sequence Spatial Density (SSD). Each frame contains a value that indicates the number of $IP_{i,q}$ coordinates.

Let $I_{x,y}$ be the number of $IP_{i,q}$ points in the frame (x,y) where x,y is the indexes of the frames in SSD shown in Figure 42. We determine a direction vector by computing the partial derivatives of SSD as the sum of the differences between two adjacent frames in SSD as:

$$\begin{aligned}
\frac{\partial I}{\partial x} &= (I_{2,1}-I_{1,1})+(I_{3,1}-I_{2,1}) \\
&\quad +(I_{2,2}-I_{1,2})+(I_{3,2}-I_{2,2}) \\
&\quad +(I_{2,3}-I_{1,3})+(I_{3,3}-I_{2,3}) \\
\frac{\partial I}{\partial y} &= (I_{1,2}-I_{1,1})+(I_{1,3}-I_{1,2}) \\
&\quad +(I_{2,2}-I_{2,1})+(I_{2,3}-I_{2,2}) \\
&\quad +(I_{3,2}-I_{3,1})+(I_{3,3}-I_{3,2})
\end{aligned} \tag{16}$$

We compute the partial derivatives of SSD horizontally $\frac{\partial I}{\partial x}$ and vertically $\frac{\partial I}{\partial y}$ to compute the direction vector at each loop of the improvements by using the direction vector

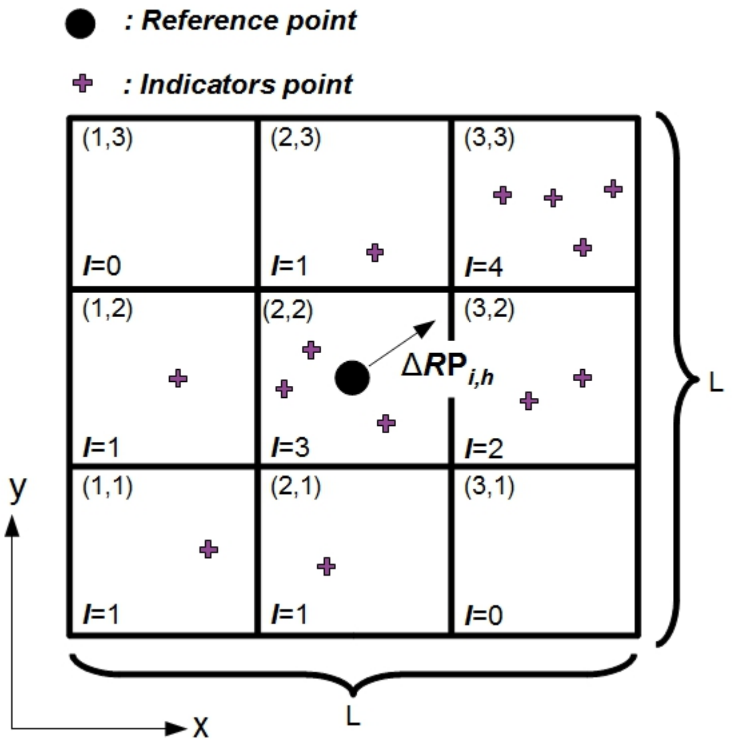


Figure 42: Computation of direction vector

function, $\overrightarrow{DVF}$ as:

$$\overrightarrow{DVF} = (\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}) \tag{17}$$

We improve RP_i by using $\overrightarrow{DVF}$ with length ΔRP_i proportional to the vector's magnitude, $|\overrightarrow{DVF}|$, computed as:

$$|\overrightarrow{DVF}| = \sqrt{(\frac{\partial I}{\partial x})^2 + (\frac{\partial I}{\partial y})^2} \tag{18}$$

$$\Delta RP_{i,h} = \left(\frac{\frac{\partial I}{\partial x}}{|\overrightarrow{DVF}|} \times \nu, \frac{\frac{\partial I}{\partial y}}{|\overrightarrow{DVF}|} \times \nu\right) \tag{19}$$

where ΔRP_i is a magnitude of moving distance of RP_i for a loop. Here, ν denotes a scale factor parameter for the unit vector computed from $\overrightarrow{DVF}$ to determine the length of improvement, ΔRP_i. Given $RP_{i,h}$ is the *Reference point* at h-th loop, we improve the position of $RP_{i,h}$ with direction vector $\Delta RP_{i,h}$ for the next loop of improvement as:

$$RP_{i,h+1} = RP_{i,h} + \Delta RP_{i,h} \tag{20}$$

The improvement of RP_i will also affect the concentration of *Indicators points*. As we can see from Figure 43, Figure 44 and Figure 45, *IP* has improved its position approaching

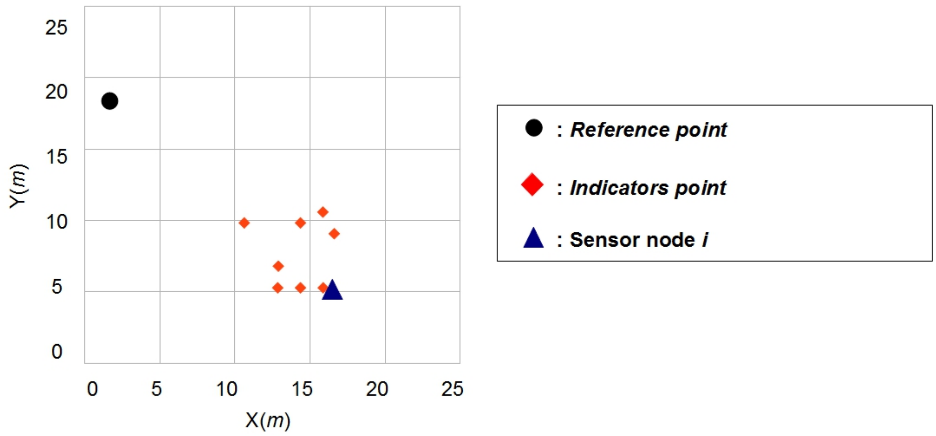


Figure 43: Number of loops=20

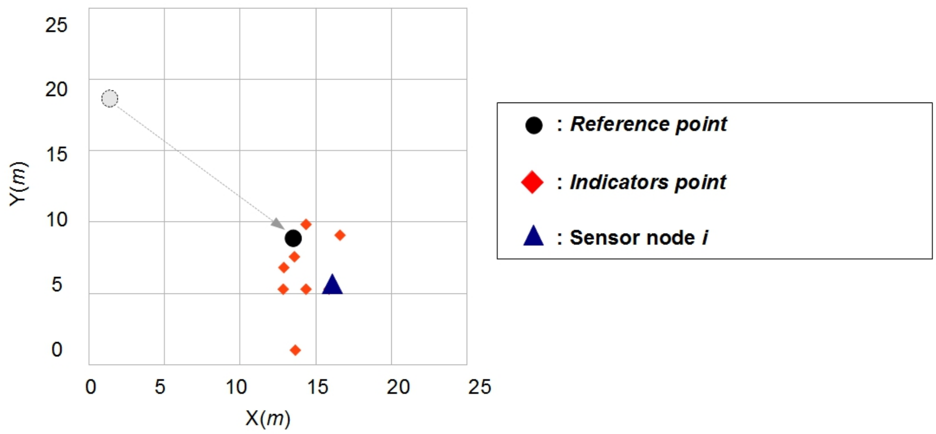


Figure 44: Number of loops=40

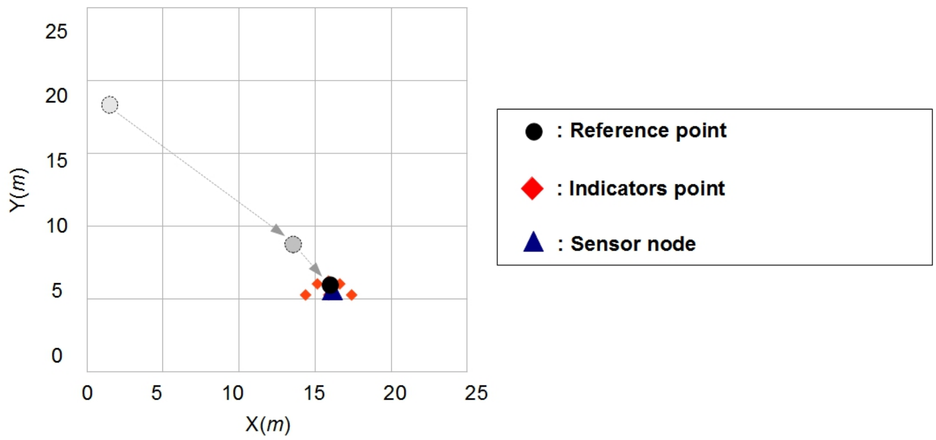


Figure 45: Number of loops=60

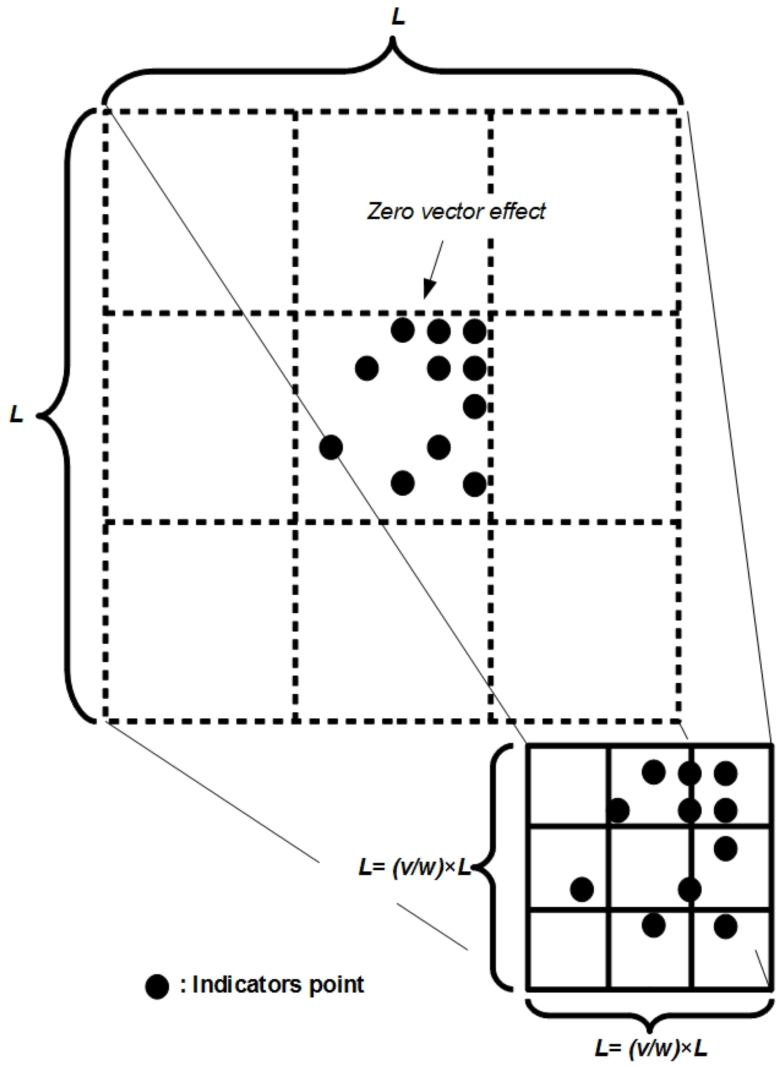


Figure 46: Reduced L length for SSD every m loops of improvement.

the true positions of sensor nodes i at 20, 40, and 60 loops respectively. Figure 43 shows the *Indicators points* determined from the selected anchors of the sets based on RP_i at 20-th loop of the improvement. When RP_i is improved approaching to a sensor node i at 40-th loop of the improvement as shown in Figure 44, *Indicators points* seems to start moving closely to each other due to the existence of more anchors which have less variation of distance to the center of circle. At 60-th loop of the improvement as shown in Figure 45, RP_i has improved its location close to sensor node i which is also the center of circle to all available anchors. The possibility to find the anchors that have their *Indicators point* closer to RP_i is high at this loop. The location of *Indicators points* are concentrating to the center of circle and located close to each other.

A frame that has large number of IP_i provides more weight in direction vector in the improvement of RP_i. The possibility of sensor node i located in the vicinity of a frame is higher, compare with the frames with less number of IP_i. The concentration of IP_i coordinates gives us a direction of where a sensor node i is located relatively from RP_i. The frames, however, can provide us with less accurate of direction vector when most of the IP_i located in mainly in a limited number of frames while the most of the frames do not contain any IP_i. When RP_i improves its location to the vicinity of a true location of sensor node i, the numbers of the IP_i increase due to the increasing of available anchors in the vicinity of a sensor node i. These anchors are located closer to each other, compare to the locations of anchors of where RP_i is located far away from a true location of a sensor node i. It is difficult to determine direction vector from SSD with a larger size of frames because this would allow the less numbers of frames with IP_i.

Figure 46 shows the $L \times L$ size of SSD with the 3×3 frames which is used to determine the direction vector of the improvement of RP_i. To avoid phenomena where improvement was not taking effect because the frames were too large, we reduce the size of SSD by the fraction of v/w every h-th loop of improvement. Here, v/w is a proportion of the reduced size of SSD in each loop. We call these phenomena *zero vector effects*, where the direction vector became zero as all the *Indicators points* are located inside the center frame of SSD. If none of the center coordinates are located in the frame other than the center frame of the SSD, the direction vector will become zero as they are computed from the sum of the differences between two adjacent frames.

In the next section, we present a simulation experiment to evaluate the performance of our method in selecting the anchors based on dynamic *Reference point*. The effect of the reduction of SSD size, number of loops and effect of *DoI* to the localization error are evaluated in this experiment to demonstrate the performance of the localization.

5.3 Simulation experiment

In this section, we conduct a simulation experiment to evaluate the performance of this method to localize the sensor nodes in WSN. We evaluate the numbers of loops to have the estimated location of sensor nodes improved their position approaching to the true locations of sensor nodes. This experiment also evaluates the performance of *Reference point* to improve its location in different *DoI* wireless signal propagation model [66] as used in Chapter 4. The RSS measurement was a value from our degree of irregularities (*DoI*) extended log-distance path loss in Equation (4).

As applied in the simulation experiment in Section 4, we use the extended log-distance radio propagation model as shows in Equation (12) to simulate path loss values which are used as RSS in this simulation. The simulated RSS according distance is shown in Figure 32 where the path loss values are varied significantly due to the effect of $rand()$ in order to simulate path loss model by using $DoI = 0.4$, rather than increasing smoothly through distance as demonstrated in a model with $DoI = 0$. The parameter settings that are used

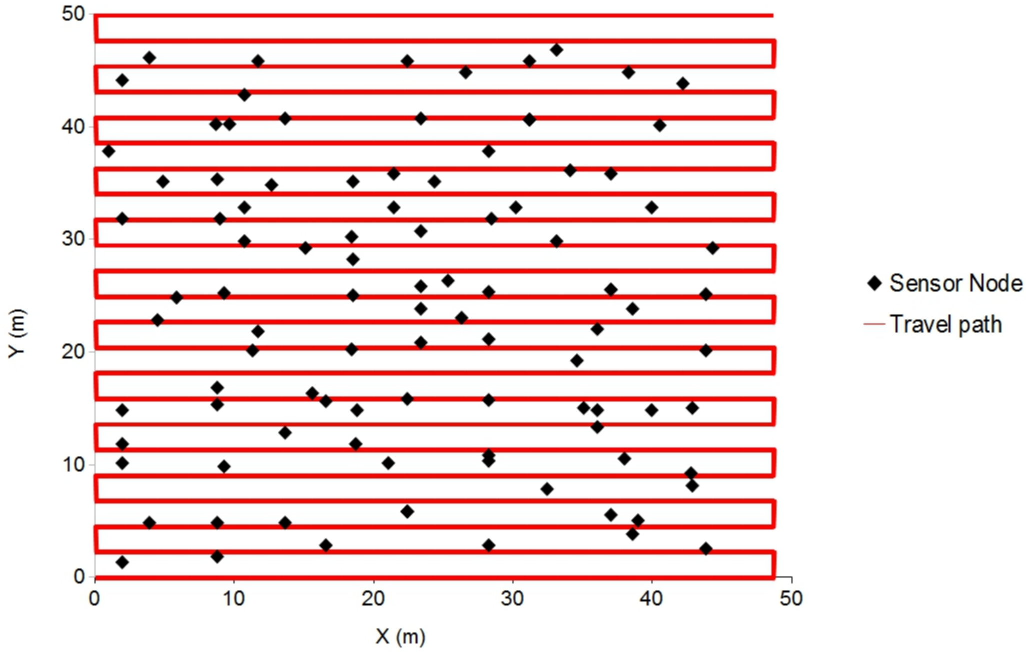


Figure 47: Deployment of sensor nodes

in Chapter 4 as shown in Table 4 are also employed in this experiment.

The remaining part of this section presents the simulation setup and the results we obtained from evaluating performance.

5.3.1 Simulation setup

We implemented our method in a custom C simulator, where we randomly deployed 100 of sensor nodes with one mobile receiver traveling in a 50m×50m square region, as seen in Figure 47. The mobile receiver and sensor nodes had the same communication range of 10m.

A mobile receiver traveled in a sensory boundary field and received signals from sensor nodes within their communication range at each interval of time unit t. All positions of sensor nodes i were estimated by our proposed method as the coordinates of RP_i at the end number of loops. RP_i coordinates are arbitrarily deployed within the sensory boundary field for each sensor node. We deployed the RP_i for all sensor node i in the first loop of improvement at the center of the sensory boundary field as an initial coordinate of RP_i. The SSD frames were used to compute the moving distance of RP_i in which the initial value of L was 50m where all center coordinates were included in the coverage area of SSD for each IP. Table 6 shows the parameters setup that applied in this simulation.

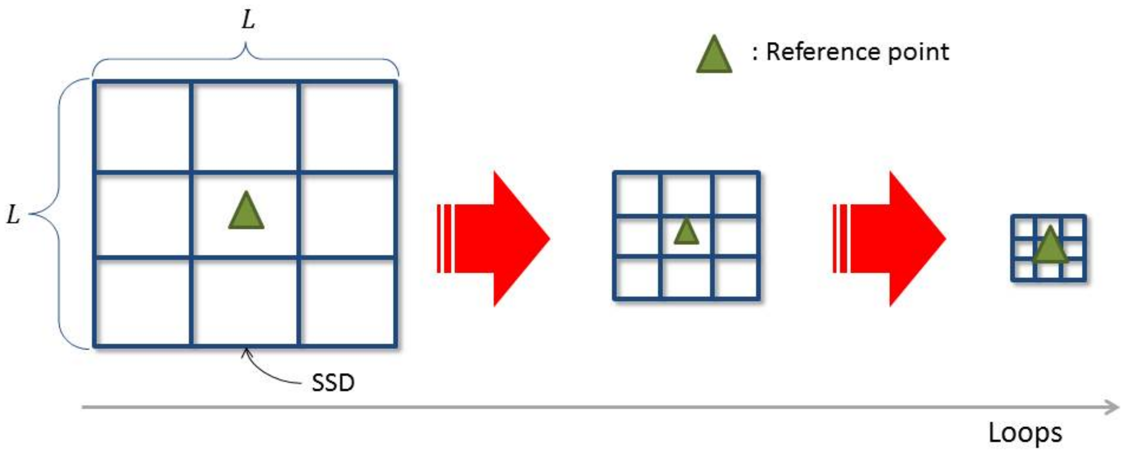


Figure 48: Reduction of L with proportion $v/w = 1/4$

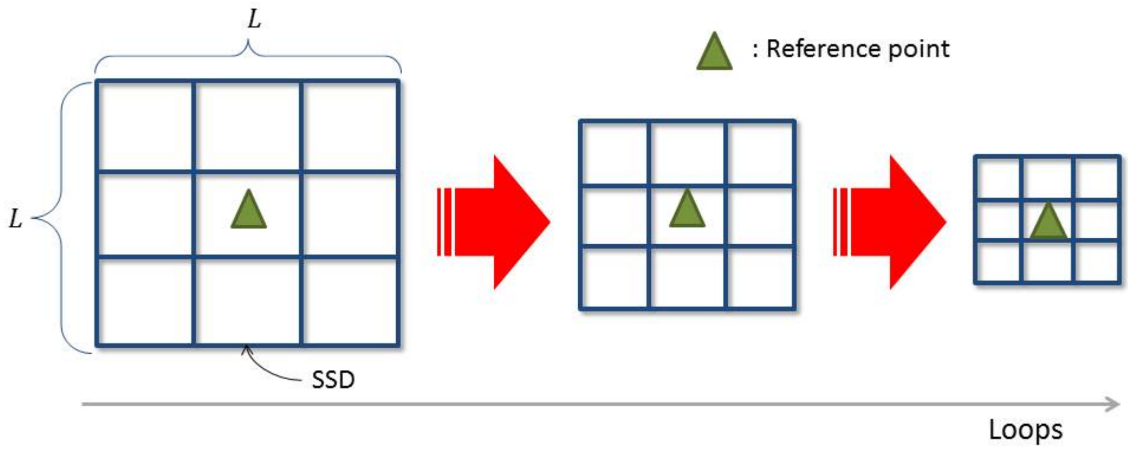


Figure 49: Reduction of L with proportion $v/w = 3/4$

We defined the criterion in our method for the localization error as the difference between *Reference point* and the true location of a sensor node in a loop of improvement, h. Localization error indicated the degree of efficiency in the location estimation that this method could achieve.

5.3.2 Results

In this experiment, we compared the cumulative distribution function (CDF) of loops for the number of sensor nodes that had their localization error reduced below 2m with two different values of parameters v and w, $v/w = 1/4$ and $v/w = 3/4$, when parameter L was reduced by the fraction of v/w through the loops of improvement as shown in Figure 48 and Figure 49 for each value respectively. These figures show that the reduction from $v/w = 1/4$ is faster than the reduction from $v/w = 3/4$. As shown in Figure 50, less

Table 6: Simulation setup

Parameters setup	Value
Size of sensor field	50m×50m
Radius of wireless communication range	10m
Scale factor parameter for the unit vector, ν	70m per number of cycles
Initial size of SSD, $L \times L$	50m×50m
Proportion of reduction of L in each iteration, v/w	$1/4$ and $3/4$

than 71% of *Reference point* coordinates had their localization error reduced below 2m approaching the true location of sensor nodes when the number of loops reached 35 where parameter L was reduced by the fraction of $v/w = 1/4$. However, the percentages were larger where parameters L was reduced by the fraction of $v/w = 3/4$, as seen in Figure 51. In this case, the percentage of *Reference point* that had their localization error reduced below 2m was more than 80% when the number of loops reached 80.

The size of the square region of sequence spatial density (SSD) has an impact on computing the direction vector to improve *Reference points*. A larger SSD will increase the number of *Indicators points* coordinates included in SSD that increases the total value of differences between the number of *Indicators points* coordinates between two adjacent frames. However, if L is reduced too much between the two cycles of improvement, the number of average coordinates that are included in SSD will decrease. The decreased number of *Indicators points* coordinates in SSD will increase the possibility of *zero vector effects* that take place when the center coordinates are only located in the center frame of SSD. As we can see from Figure 50, the *zero vector effects* took place when the number of loops reached 35 and many of the average coordinates were excluded from SSD because the value of parameter L was reduced too much when $v/w = 1/4$ compared to the improvement in Figure 51 where the *Reference points* coordinates were continuously improved when $v/w = 3/4$ until the last number of loops.

We also compared the required number of loops to improve the *Reference points* in different numbers of anchors. We fixed two values of localization error as a threshold in this evaluation scenario to assess how many loops were needed for the *Reference points* to improve their positions below these two thresholds (i.e., $2m$ and $5m$). The average

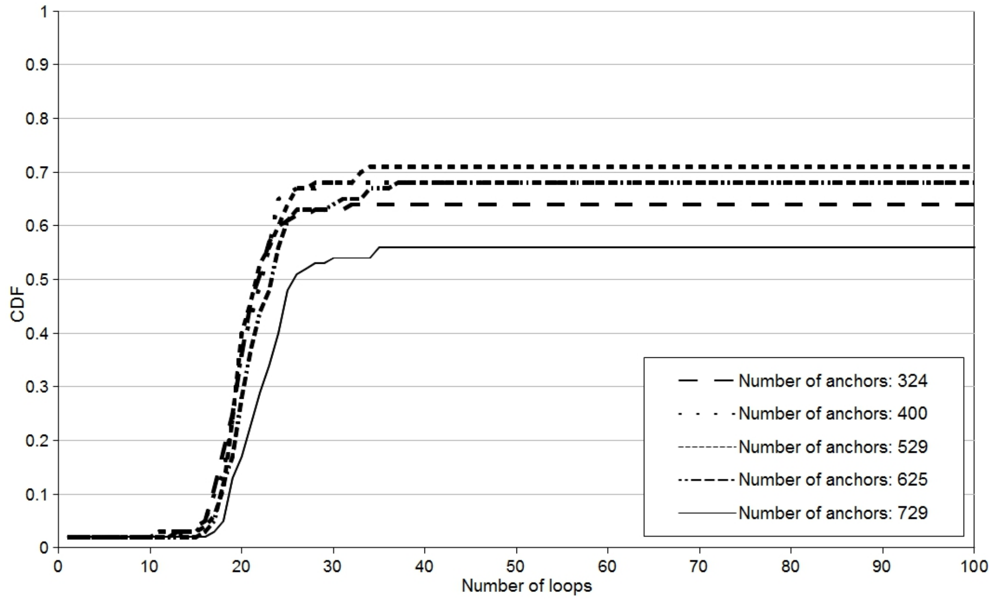


Figure 50: Cumulative distribution of number of loops for number of sensor nodes that had their localization error reduced below 2m when parameters L was reduced by fraction of $v/w = 1/4$.

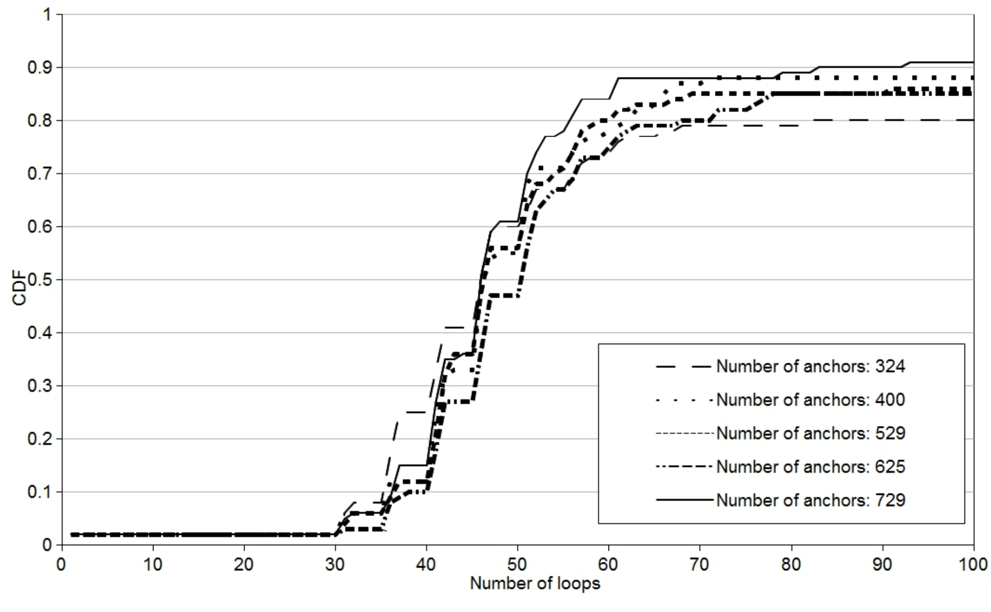


Figure 51: Cumulative distribution of number of loops for number of sensor nodes that had localization error reduced below 2m when parameters L was reduced by fraction of $v/w = 3/4$.

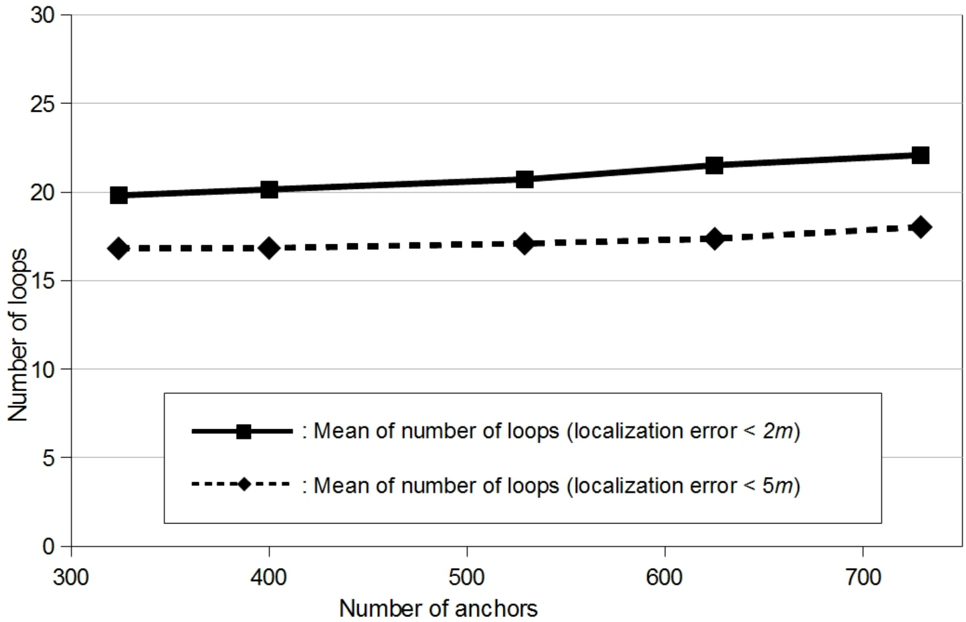


Figure 52: Effect of localization error on number of cycles when parameters L was reduced by fraction of $v/w = 1/4$.

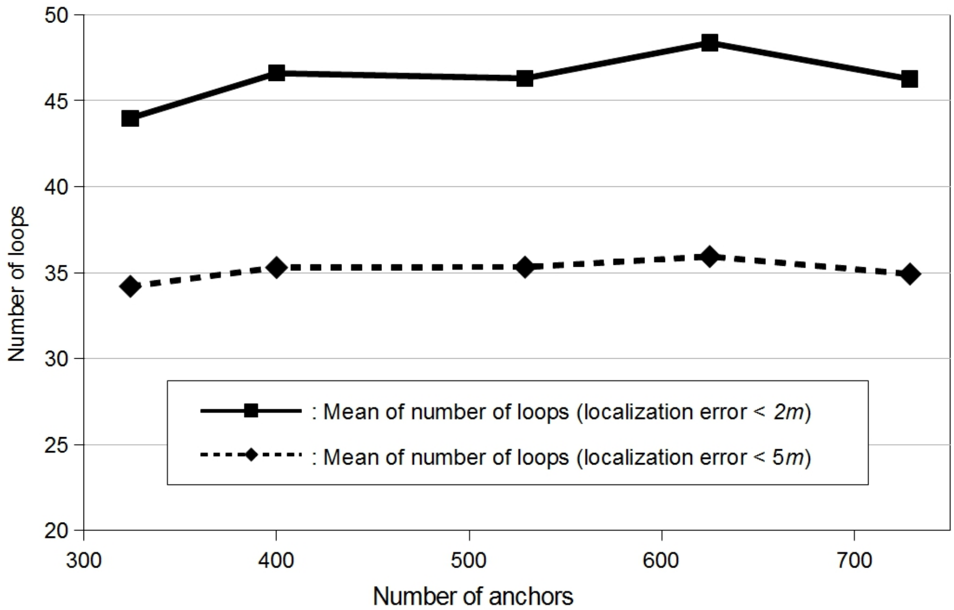


Figure 53: Effect of localization error on number of cycles when parameters L was reduced by fraction of $v/w = 3/4$.

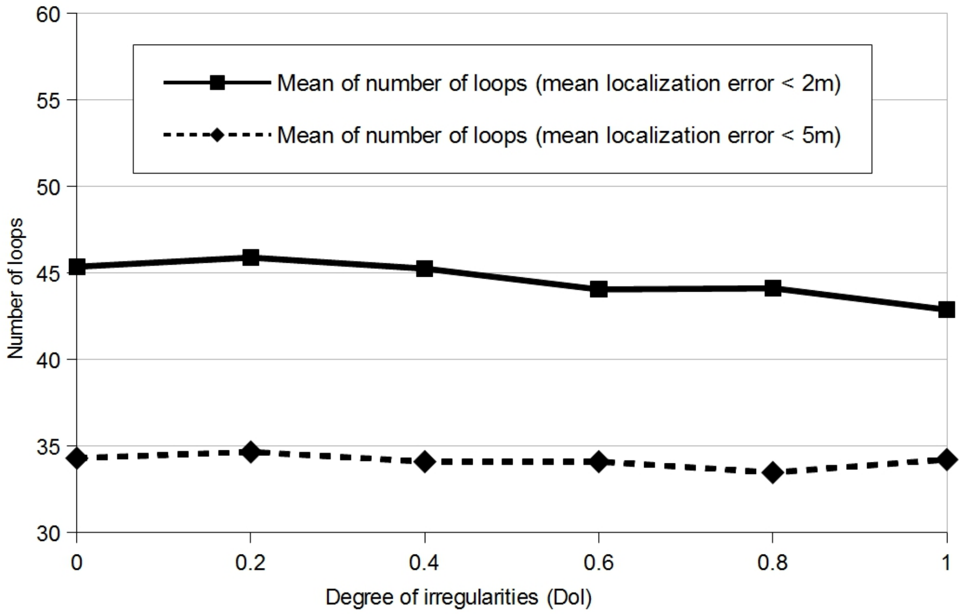


Figure 54: Effect of DoI on number of loops.

number of loops for each *Reference point* was used to represent how many loops were required for each number of anchors. As shown in Figures 52 and 53, the numbers of loops were almost equal in all numbers of anchors under both conditions. However, the parameter of v/w affected the number of loops that reduced the localization error of *Reference points*. The *Reference points* required less than 21 loops $(2m)$ and 17 loops (5m) for each threshold in which parameters L was reduced by the fraction of $v/w = 1/4$, as seen in Figure 52. However, the *IP*s required greater numbers of loops to reduce their localization error below 2m and 5m, as seen in Figure 53. They needed 46 loops for the former and 35 loops averagely for the latter in which parameters L was reduced by the fraction of $v/w = 3/4$.

SSD reduced by a large fraction of v/w yielded a small difference in the number of *Indicators points* coordinates in the frames in SSD between loops compared to the condition in which SSD was reduced by a small fraction of v/w. The small fraction of v/w enabled SSD to reduce its size by a larger L, which created large differences in the number of *Indicators points* in each frame as the average coordinates that were located separate from one another. These will increase the values of the moving distance that improved the position of *Reference points* in fewer numbers of loops.

We also compared what impact DoI had on a localization error in the estimated location of a sensor node in various locations. The mean localization error was not entirely different for all *DoI* values, as seen in Figure 54. In this method, we only used RSS to observe the proximity of anchors rather than exact distance measurement between sensor nodes and anchors. Therefore, as shown in this figure, the irregularities in RSS (different value of *DoI*) did not have a huge impact on localization error in any sensor nodes on average as they did not directly use the RSS values as a metric to estimate the position of sensor nodes. The mean number of loops under both conditions where the threshold of localization error was set to $2m$ and $5m$ corresponded to about 45 and 34.

5.4 Conclusion

We proposed a proximity-based localization that employs the selection of anchors based on dynamic *Reference point* in determining the location of a sensor node. We used the genetic algorithm approach for selecting the anchors in order to determine the location of a sensor node. We used a GA to iteratively find the best selection of anchors that have the closest *Indicators points* to *Reference points*. We improved the positions of *Reference points* by measuring the direction vector from the concentration of *Indicators points* in the vicinity of *Reference points* by using optical flow approach. The anchors in our proposed algorithm were divided into sets based on RSS measurement level to reduce the variation of radial distance between anchors and center of circle in each set. We evaluated our method based on a variety of metrics that proved that it was resistant to the number of anchors that used in the calculations and high DoI environments at a given number of loops while providing low localization error.

The ability to localize sensor nodes without any static reference objects in noisy environments for proximity-based localization can improve the efficiency of localization in large areas. However, determining the location of a sensor node still remains unsolved as we determined the location of a sensor node by continuously improving the *Reference points* approaching the true target nodes until the number of loops is satisfied a boundary (i.e., 100 loops).

Determining suitable values for parameters L was major causes of difficulties in our investigations. We plan to design a method of determining receiver mobility to obtain accurate location estimation by using localization based on proximity techniques. We also plan to apply our method to a real environment by running empirical experiments that focus on accurate proximity-based sensor node localization for mobile localization in the future.

6 Conclusion and future works

This PhD thesis has explored the proximity-based localization that selectively utilize the anchors in Wireless Sensor Networks (WSN) and evaluated their effectiveness through simulation experiments. A mobile receiver which is aware of its location (anchor) is used to travel and collect the messages from static sensor nodes with unknown locations in WSN environment. We have proposed a method to select reliable selection of anchors to perform the localization. Received Signal Strength (RSS) measurement is employed to indicate the relation between anchor and its neighboring sensor nodes. We used the location of anchors that are located in the vicinity of a sensor node to perform localization of a sensor node. We proposed the method of selecting the anchors to retrieve the reliable selection of anchors, instead of using all available anchors that located within the communication range of a sensor node. The use of selected anchors has achieved a good performance of proximity-based localization efficiency.

6.1 Conclusion

In selecting the anchors for proximity-based localization, we evaluate the distance between the location of average of selected anchors and *Reference point* in noisy environments. We used the *Indicators point* as a metric to measure whether the selected anchors have less variety of their distance to the *Reference point* or not. We select the anchors based on two types of *Reference point*, static *Reference point* and dynamic *Reference point*. We have proposed the proximity based localization method that utilize the selection of anchors based on static *Reference point*. We assume a mobile receiver travels in a connection of straight lines. Each line contains two anchors located at the edges of a line. *Indicators point* is calculated from the average of selected anchors at the lines. Each line contains the footprints which are the locations of mobile receiver located between two anchors at each interval time unit. *Reference point* is calculated using the average of three footprints which have largest RSS. We select the anchors, which have smallest distance between *Reference point* and *Indicators point* based on the genetic algorithm approach. Here, the distance is converted from RSS measurement by using fuzzy logic approach. The estimated location of a sensor node is calculated from the average of points, each of which is located at the shortest perpendicular distance to a line between a pair of selected anchors. The feature of this method is to provide the ability to distinguish an estimated position based on *Indicators point* by comparing the distances of both estimated position and *Indicators point* to *Reference point*. As for the results of simulation experiment, we demonstrated that we are able to distinguish 89% of estimated position of sensor nodes, which have improved their mean localization error for about 53% compared to the estimated position of sensor nodes determined from all anchors.

We also proposed the proximity based localization method that utilize the selection of anchors based on dynamic *Reference point*. Unlike the method that used static *Reference point*, This method utilized the locations of mobile receiver at each interval time unit as anchors. Anchors are divided into multiple sets based on their RSS measurement. Multiple *Indicators points* are calculated from the average of selected anchors of each set. The concentration of multiple *Indicators points* gives us indication about the true location of a sensor node. Initially, *Reference point* is determined randomly at a known location. In determining the location of a sensor node, *Reference point* is improved iteratively approaches to an area which has a high density of *Indicators points* by using optical flow approach. The feature of this method is to provide the ability for a sensor node to determine its location by using anchors selectively without using any static reference coordinates or objects. As for the results of simulation experiment, we have demonstrated 80% of sensor nodes have improved their *Reference points* below 2m of distance between *Reference points* and true position of sensor nodes. The results of the experiments in this PhD thesis indicate that our proposed method can improve the efficiency of average-based localization.

6.2 Limitations and future works

The limitation of our proposed methods is the time complexity of GA. Suppose that GA has an order of $t(size)$ complexity, time complexity $O(t(size))$ is the time taken to compute the problem of selecting the best selection of anchors from the *size* of population, where *size* is a total number of anchors in a population. In selecting the anchors by using GA, numerous times across all anchors in the population in numerous iterations of GA is performed to find the best selection of anchors. The increase of the size of the population will in turn increase the problem size for the GA, which will affect the time complexity of these methods. A larger population size means larger computing time or resource is needed for the GA to complete its computation. It is necessary for our methods of the selection of anchors to perform efficiently in real time in order to consistently produce efficient results without using up too much computing and time resource.

Other limitation on estimating a sensor node by using the selected anchors is the requirement of fixed number of loops in the improvement of *Reference point*. The ability to indicate whether the selection of anchors is reliable or not by using iteratively improved *Reference point* provides the improvement in localization efficiency in a highly dynamic environment. However, determining the exact estimation of sensor node still remains unsolved as we determined the location of sensor nodes by using a fixed number of loops in the improvement of *Reference point*. Determining suitable values for the parameters in SSD were major causes of difficulties in our investigations.

For further research, we suggest to perform analysis study about the time complexity of GA for the selection of anchors. Analysis of time complexity can provides the ability to predict the effect of total number of anchors in the selection of anchors by using GA. It is useful for analyzing and optimizing the real time efficiency of our proposed methods. We also plan to investigate the characteristic of *Reference point* to provide self-determine indication about the reliability of selected anchors without using any fixed number of loops. Based on the *Indicators point* provided by the information of anchors, *Reference point* will be able to predict the requirement of number of loops to estimate the exact location of a sensor node.

Based on the these studies, we plan to design a method of determining the mobility of mobile receiver to obtain high-accurate location estimation based on the prediction of time complexity and self-determine indication of selection of anchors from *Reference point*. Improvement in mobility of mobile receiver could provide more anchors which are reliable to estimate the location of a sensor node. A mobile receiver could provide a better anchor placement in order to determine the reliable selection of anchors. We suggest to deploy our methods in real environments for investigating the performance by using comparative analysis with that obtain in the simulation experiments.

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