Indoor Positioning Methods Based on Pre-Observation of RSSI for Office Environment

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Preface

Indoor positioning system is a system to evaluate the position of a terminal, based on the terminal's beacon signal and sensor information held by people. In this doctoral dissertation, the goal is to develop a positioning method for indoor positioning system subjected to office enviroment. Office enviroment means a room with obstruction such as metal partition and furniture, and people or objects that are a element that effect mulipath in relatively small indoor environment.

There are two application conceivable with a viewpoint of a worker and manager for positioning in a office environment. In a worker's viewpoint, positioning can be utilized as information such as working log and progress report. In a manager's viewpoint, such as observation of worker behavior, presentation of context-aware information, and automatic control of electronics depending on position that can be considered as a application.

Previous research do not offer enough position information solution such as method using adjacent information like radio wave TOA(Time of Arrival) and infrared light for LOS(Light-of-Sight) assumed environment. On the other hand, considering the application examples, position detection based on item that need active contact such as RF-ID and magnetic card are insufficient. Concerning the problem of privacy, method based on using image processing on surveillance camera is not realistic.From the view of this, position system using RSSI(Received Signal Strength Indicator) is though to be promising.

This dissertation will have a composition of the following with the approach to this problem and result of the verification experiment against this problem.

In the first chapter, the proposed approach in prior research will be listed and classified regarding indoor positioning system. Moreover, the required condition of the position system under office environment will be defined and the positioning method to fulfill this condition will be discussed. While showing the whole picture of the indoor positioning system based on prior measurement especially about RSSI, the stand point and the problem to work on this dissertation are revealed.

In the second chapter, the specific of the RSSI depending on the sight such as cover and metal partition in office environment based on the measurement experiment in continuous space of RSSI in actual environment are revealed. Moreover, this chapter shows the capability of reproducing the specifics of the dependence to this sight by modeling the details of electromagnetic character of covers and metal partitions in office environment and by electromagnetic field simulation. Since there is a need for enormous memory space, know-how of modeling electromagnetic character, and parallel computation for this calculation, we ran the calculation on a super computer with the help of Professor Omiya's laboratory.

In the third chapter, method to utilize the estimation of the position information of RSSI data in continuous space is proposed. Also, represented the RSSI specific depending on sight by nonparametric function of broken line approximation, then modeled the noise component less than 4 [dBm] with normal random number using the knowledge from the measurement experiment in chapter two. The proposal method use this as a likelihood function for particular filter. We carried out a measurement experiment based on the proposal method in office environment including multipath such as over of metal walls, furnitures in the room, and the measurer. Creating a evaluation data by moving around the domain of prior measurement area using a Zigbee end device by a person holding the positioning target, we found that there was an average of 2.4m of error with the accuracy of positioning.

In the fourth chapter, a technology for high performance positioning by using fingerprinting-based method without RSSI data in continuous space is discuessed. Method to optimize layout of fingerprints and routers dynamically will be proposed. This chapter formularizes a layout problem as a problem which optimizes RMS of positioning error by using variables, layout of fingerprints and routers. Then, this chapter succeeds decrease several fingerprints unnecessary. Moreover, this shows an influence of user's distribution of test data on the result of the optimization. Namely, necessity of dynamic selection of fingerprints and routers is revealed.

In the fifth chapter, method to estimate an affection of crowd pattern in the field on RSSI will be proposed.

In the sixth chapter, this dissertation is summerized.

Chapter 1

Overview of Indoor Positioning Technologies

1.1 Introduction

Indoor positioning system is a system to evaluate the position of a terminal, based on the terminal's beacon signal and sensor information held by people.

Indoor positioning systems are important, thus these are studied by many researchers in various contexts. At a viewpoint of Context-aware and Location-aware [Chen 00, Schilit 94], position information is a important information for estimating the user in an environment. [Gu 09] evaluated the performance of indoor positining systems as location aware service in context of Personal Networks (PNs). PNs are designed to meet the users needs and interconnect users' devices equipped with different communications technologies in various places to form one network. This paper descrives, users in PNs are able to receive services as the following scenarioes. 1) Fitness Center Scenario, 2) Conference Scenario. [Woo 11] proposed a system to measure the position information of the head mount beacon attached to the head of the tunnel worker's. This system is for saftey management of tunnel workers since there is a need to manage the detail of work logs and records of entarnce and exit. [Hllerer 99] proposed a system to direct immersive augmented reality by showing navigation information to the user's head mount display corresponding to the users position. [Mulloni 09] conducted a proving test of a navigation at a academic meeting venue depending on position information. [Tesoriero 08] proposed a system to recommend displayed items at a museum depending on position information. [Hosokawa 05] proposed a positioning system without the need of user's to posses a terminal. From this, daily soft identification is actualized by measurement performed in the background.For example, in a situation where a user sit in front of a television and the television show a program that is suitable for the user.

In this dissertation, the goal is to develop a positioning method for indoor positioning system subjected to office enviroment. Office enviroment means a room with obstruction such as metal partition and furniture, and people or objects that are a element that effect mulipath in relatively small indoor environment.

This chapter organizes traditional approaches and problems to be solved on indoor positioning systems. Especially, this chapter describes algorithms for range-based positioning and fingerprinting-based positioning, which are major examples of indoor positioning method based on RSSI (Received Signal Strength Indicator). Moreover, this chapter generalize an indoor positioning system based on RSSI and reveals a problem to be solved on this system.

1.2 Categories of indoor positioning systems

Several types of wireless technologies are used for indoor location. Fig. 1.3 depicts a rough outline of the current wireless-based positioning systems, which is a modied version of [Vossiek 03]. It is beyond the scope of this paper to provide a complete overview of systems available till now.

1.2.1 Position

In this section, the way to classify the represention of a position which is the goal of positioning will be summarized.

From this difference, the required accuracy of the argroism differs greatly.

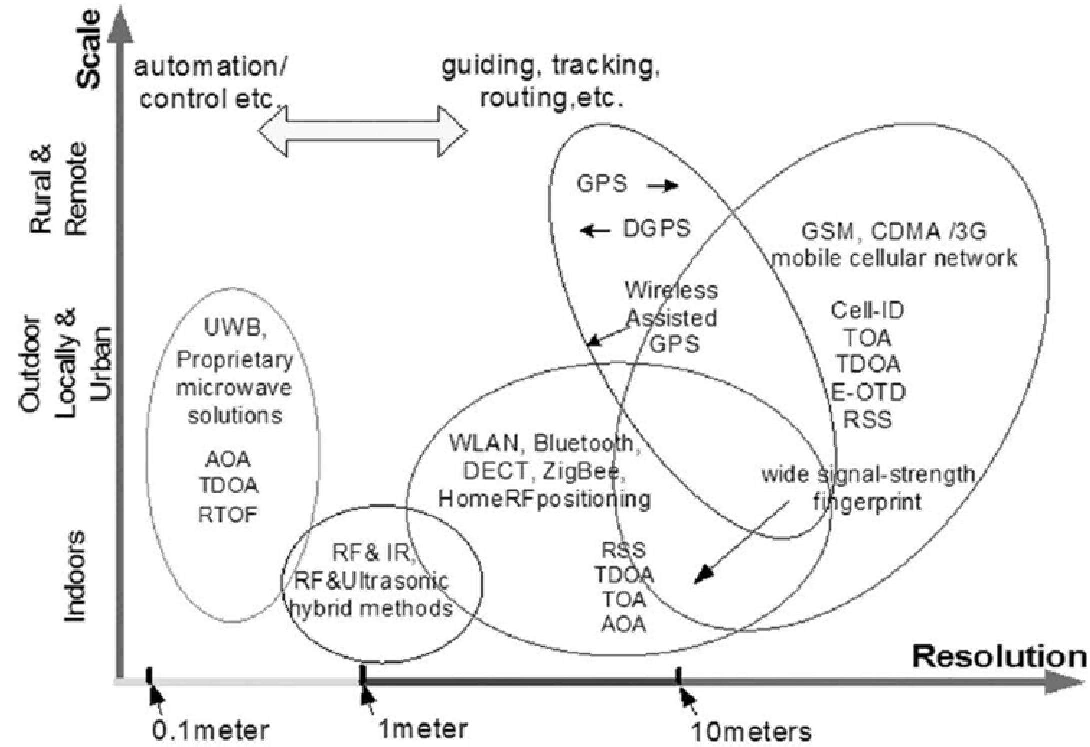

Figure 1.1: Outline of current wireless-based positioning systems.

Absolute

Absolute Position is a position vector $\boldsymbol{x} \in \boldsymbol{X}_{absolute}$ determined by the normal coordination on a map.

$\boldsymbol{x} \in \boldsymbol{X}$ is a subset of a m dimentional real number vector space.

This position information is very easy to visualize and many positoning system use this.

Relative

A relative position relation.

This can be used to analyze users psychological distance at party venues.

Proximity

Proximity stands for the neigboring relation between standard terminals.

Set of position informations $\boldsymbol{X}_{proximity}$ is represented as a subset of discrete space $\mathbb{Z}$.

Neigboring relation between a tag of an active RFID is commonly used. Also, this is used as advertisement for application use such as showing a introduction video when the cutomer comes near a shop or sending a direct mail right when the customer enters a shop. [Tesoriero 08] proposed a system pushes a guidance infomation of an exhibit using proximity.

When considering absolute position as a base, it can be assosiated by the picture below.

$$f : \boldsymbol{X}_{absolute} \rightarrow \boldsymbol{X}_{proximity} \tag{1.1}$$

In this case, when area of potioning space is defined as S, if the resolution of adjacent information $S/|\boldsymbol{X}_{proximity}|$ is small enough, accuracy is not much needed with position information.

Global position

Absoulte position assosiated with world coordinate is global position. If the normal coordinate is percise, the absolute position can be assosiated one-to-one with this.

Sequence of positions

Sequence of position refers to a series of postion informations.

Sequence of postion is given as a mapping of the below when the set of possible position information is defined as $\boldsymbol{X}$ at the time of $t \in T$.

$$\tilde{\boldsymbol{X}} : T \rightarrow \boldsymbol{X} \tag{1.2}$$

t is at times discrete time $t \in \mathbb{N}$, and at other times a continuous time $t \in mathbbR$.

Additionary with information estimated in the past, in the case of using this method, it is effective to use the estimation method usind prior information.

Positions of crowd and density

Method for estimating groups of postion all together. In some cases this becomes numbers of histogramsand in other cases becomes a porbability density function.

1.2.2 Location technologies

Triangulation

Triangulation is a positioning method based on triangular surveying.

When measuring the distance from its own position $\boldsymbol{x}$ to three or more observation point, we cosider distance vector as $\boldsymbol{d}$.

Relation between the measurement of the sensor and the distance is premise to this method. There are 3 ways depending on the variety of sensors and the measurement method differs in each.

time of arrival (TOA): Method using the arrival time of the sensor as distance. This is the same method as the GLobal Positioning System(GPS). When using a sensor with a speed of light such as radio wave, error occurs from the error of arrival time leading to a error in distance. Therefore, time synchronization between measurement of an accurate time and the time of the sensor is necassary. To reduce the load of time synchronization, there is a method call TDOA which adds a observation point as a that corrects the shifted time measured at this point.

received signal strength indiator (RSSI): Triangulation method using RSSI. Estimating the distance by utilizing the property of the RSSI attenuation in prportion to the inverse square. Regarding the property of the distance of RSSI in actual enviroment, details will be discussed later in the paper using experiment data.

angle of arrival (AOA): Triangulation method using arrival angle. Used as a positioning system at optical systems such as infarared light distance sensor module.

Considering that each method of triangulation is based on distance, wraparound on a wall is a weak feature.

Fingerprinting

Fingerprinting is a location technology based on advanced measurment.

When postion set of space is defined as $\boldsymbol{X}$, we consider several representative points $\boldsymbol{x}_i \in \boldsymbol{X}$. We take a sample of observation values $\boldsymbol{Y}(\boldsymbol{x}_i)$ with the sensor at these's points in advance. These points of sampling are called fingerprint. Method of estimating position information using the set of fingerprint $F = \{\langle x_i, Y(x_i)\rangle\}$ is called fingerprinting.

Depending on the sensor method, there are such as fingerprinting based on TDOA and fingerprinting based on RSSI.

Both method have sufficient numbers of sample.Furthremore, this will perform effictivly under the condition of completely covering the space and the measurment data possesing reproducibility.

On the other hand, in the case of the data having no reproducibility because of many noise in the enviroment, or not enough measurement data, there will not be any difference between the fingerprints, which will not perform effectivly. For that reason, many measurement datas will be needed which generally cost high making this method difficult.

Proximity

Proximity is a binary information whether a target devices is near by beacons and base stations or far from them. Proximity-based positioning is a method which localize a rough area with proximity. In old technologies, an example of proximity is to localize a nearest base station of mobile phone. Recently, iPhone 5 is loaded with a new beacon system, which is called "iBeacon". iBeacon can be localize a smart phone with proximity of BLE (BlueTooth Low Energy) and it is used practically. The most typical device of iBeacon is Estimote Beacons [1] and is attracted by O2O engineers.

[1] estimote.com

1.2.3 System architecture

Three types of achitecture can be assumed for the system architecture.

Self-positioning architecture

This is a mechanism to calculate position information with the computer inside the terminal using only the information from the user's terminal internal sensor. This has a advantege of needing not to use any cost to setting up an infrastructure, since there is no need to use infrastructure to measure the enviroment.

There is a method called pedestrian dead reckoning(PDR) which use accelerometer. There is a filltering mechanism examined to reduce errors in sensors, since there can be an accumulation of errors with only the use of internal sensors.

Infrastructure positioning architecture

Method of measuring by using the computer on the enviroment side based on the information given by the external sensor.

This needs a set up of infrastructure in advance. The function of the terminal can be minimized.

Since the infrustructure side can give informatino, this method cab be easily used in O2O systems such as recommendation services and watching systems.

Self-oriented infrastructure-assisted architecture

Fundamentally, this is a mechanism using the information of external sensor to correct the error made by the measurment based on the internal sensor of the computer of the terminal.

There is a need to set up infrastracture, but fundamentally, in the case where the accuracy of internal sensor is enough, the equipment can be simplified.

1.2.4 Wireless technologies

Infrared (IR) Positioning Systems

Infrared positioning systems is a method which detects a human as a binary information by using a sensor fixed on the ceilings. It it unnecessary for a user to have a target devices because these methods are infrastracture architectre. These methods are high-accuracy but it is need to increase number of sensors for application to broad area. And then, it is difficult for them to personalize because of no device users have.

In the paper [Hosokawa 05] et al., a person is identified by "fingerprint" detection at entrance. Then, the person is tracked by using IR information and bayesian estimation without mobile devices.

Ultra-sound Positioning Systems

Method of estimating position using ultrasonic waves. There is a way of estimation absolute position and detecting proximity according to TOA. Since the reachable distance is relativly short, this postitioning is available in small space.

Radio Frequency (RF) Positioning Systems

Regarding the RF system, various types of information can be used for positioning such as Received Signal Strength Indicator (RSSI), Angle of Arrival (AOA), Time of Arrival (TOA).

Out of the above, RSSI is relativly simple to use. In gernal RF systems, since the API is offered on the software side, measurement of field indensity is standardized as specification of protocol. Also considering that such as wireless LAN(Wi-Fi) and BlueTooth are already established as a infrastructure of communication use, there is a big advantage of cases of needing to not add new infrastuctures. On the otherhand, since any of the RSSI, AOA, TOA can be effected by multipath, a suitable measurment is necessary.

Magnetic Positioning Systems

Method for detecting proximity relation of induced current using electromagnetic induction.

This has an advantage of the terminal side not requiring battery and electricity consumption being extremly small. On the otherhand there is a disadvantege of this failing to work if the distance is not close.

Vision-based Positioning Systems

Method using image processing with a camera. There is a problem where image prcocessing needs relativly large computer power and also a problem concerning privacy by surveillance camera. Recently, they proposed methods based on not only two-dimension image but also based on 3D point crowd by using Microsoft Kinect and OpenNI.

Audible Sound Positioning Systems

Method for positioning based on the emmition of a signal with a frequency of audiable sound in an enviroment with a speaker.

Since a common microphone can be used, a portable terminal without an additional function can be used for this method.

Shopkick [2] is famous as an O2O application example by using audible sound proximity.

1.3 Related works on indoor positioning method using RF system

1.3.1 Cellular-based

We apply this at low cost because most users have cellphones. The lack of base stations lowers positioning accuracy (50-200 meters [Liu 07]), however.

[2] http://www.shopkick.com/

1.3.2 Wi-Fi-based

The number of mobile computers with wireless LAN modules is increasing, so positioning using Wi-Fi technology, e.g., RADAR [Bahl 00], [Seshadri 05, Evennou 06, Zaruba 07], is attracting increasing attention. Wi-Fi based technology requires costly access points.

Wi-Fi technology in practical use includes Ekahau[3], AirLocation[4], and PlaceEngine[5]. AirLocation localizes targets at 1-3 meter accuracy in indoor space based on the Time Difference Of Arrival (TDOA), but cannot ensure positioning accuracy in all indoor environments.

PlaceEngine, localization used by laptops, has access points already included, so cost for introduction is minimized, but accuracy is not always sufficient to meet close indoor service demands because not all indoor environments have wireless access points.

1.3.3 ZigBee-based

ZigBee, an IEEE802.15.4 communication protocol, features low electricity consumption, low transmission power of 1 mW, and a narrow bandwidth. ZigBee also features energy detection scanning radio strength to enrich routing quality, so it does not require that devices for observing RSSI be expanded.

An RSSI-based approach requires standard RSSI data over indoor environments calculated using ray tracing [Zaruba 07] or Finite-Difference Time Domain (FDTD) simulation [Yee 66, Taflove 05]. Simulation for precisely modeling indoor environments and calculating approximate data is extremely expensive, however, and calculated approximate data and real data are not equal even if progressing highly precisely.

ZigBee easily obtains RSSI data, so we propose using standard RSSI data. Standard data using mobile device positioning is considered promising. We propose using

[3]Ekahau, http://www.ekahau.com/
[4]HITACHI, http://www.hitachi.co.jp/wirelessinfo/index.html
[5]Koozyt, http://www.placeengine.com/

preobservedRSSI for ZigBee localization and demonstrate that this localization is viable for navigation in real indoor environments.

1.4 Indoor positioning system based on RSSI observation

1.4.1 Overview of general indoor positioning system

This section illustrates an overview of general indoor positioning system using RF system, especially a positioning system based on RSSI observation. Fig. 1.2 is a diagram of the overview. It is essential for a RSSI based positioning system to observation a RSSI in advance, this phase is called "pre-observation", so this model has a phase of pre-observation. Using this data, RSSI-based method localize a target position in online phase.

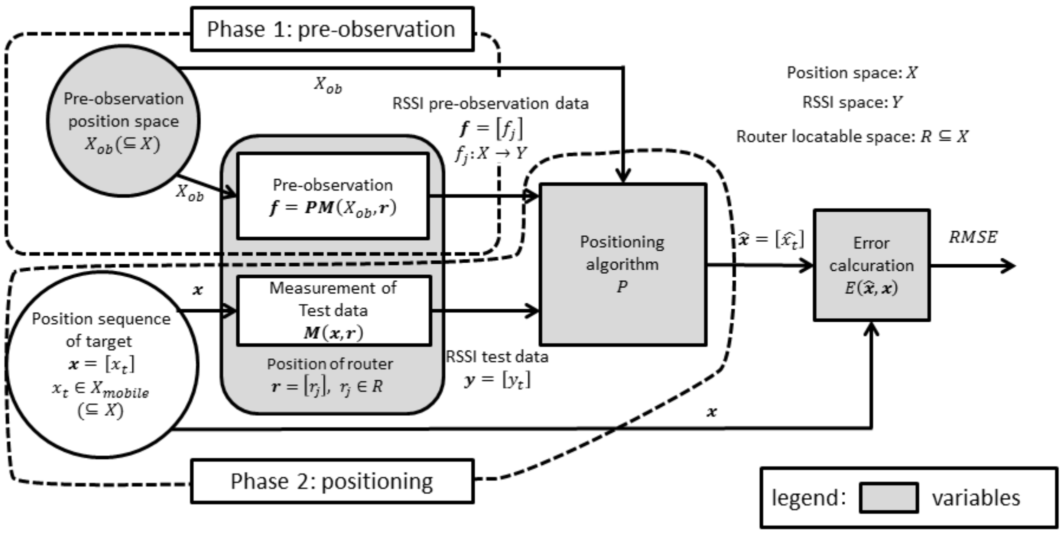

Figure 1.2: Overview of general indoor positioning system.

There are two kinds of the ways to detect a position using RSSI observation. First is range-based positioning and another is fingerprinting-based positioning.

1.4.2 Range-based positioning

Range-based positioning method is a method approximates a relationship between r and RSSI, where r is distance of a beacon from a router, as a parametric function $f(r)$.

The folloning equation is $f(r)$ used by [Bahl 00].

$$f(r) = a + 10b \log_{10}(r) \tag{1.3}$$

where a and b are arbitrary constants. These constants are estimated from pre-measurement data. a means RSSI value measured at 1 meter. b is means a coefficient of a decay curve.

[Kim 12] and [Lim 10] proposed a method to estimate two parameters a, b for range-based positioning without pre-observation. [Kim 12] describes a method to estimate parameters by calculating SVD matrix composed of RSSI between each nodes. [Lim 10] calibrates these parameters using Self-RSS measured by reference node besides routers. [Zemek 08] proposed a method to correct these parameters while measuring based on measured RSSI value without estimating parameters.

[Sheng 05] use maximum likelihood estimation method instead of a simple trilateration.

[Patwari 03-1] proposed a method to calculate error of estimation of range-based positioning depending on the Cramer-Rao lower bounds.

Since range-based positioning is a method on the presupposition of an environment with ideal radio wave, there is no application example of range-based positioning with environment containing office environment(including cover by metal partitions, multi-path).

1.4.3 Fingerprinting

Fingerprinting is a method to evaluate position by comparing the RSSI vector observed during positioning by sampling RSSI vector on space in advance. Generally, since the need of prior measurement, the cost for the measurement is higher compared to range-based positioning, but the accuracy is better on the other hand.

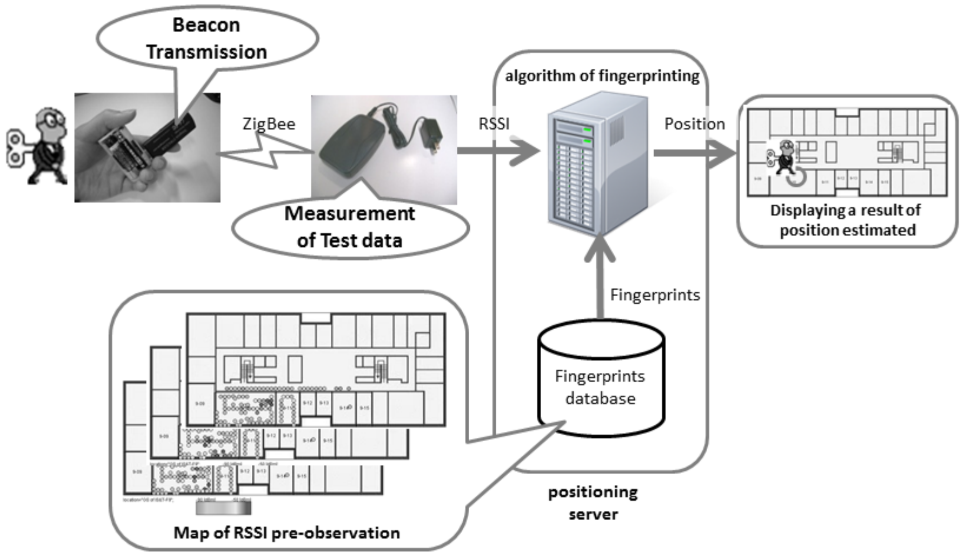

Figure 1.3: Overview of fingerprinting.

There are many methods to decide position using fingerprint. Typical examples are [Bahl 00] which use k-NN (Nearest Neighbors) and [Seshadri 05] which use Baysian Filter. [Yim 08] proposed a method which combines k-NN method with particle filters and use INS (Inertial Navigation System) to calculate predictive distribution. [Swangmuang 08] is a fingerprinting method based on Wi-Fi. This research aim to improve accuracy using proximity graphs of fingerprint on RSS space. In this research, a method to estimate the accuracy of Nearest neighbor using fingerprint is proposed. From using the estimated model, the calculation performance have improved by a selection of "good" fingerprint and reduction of fingerprints. [Giorgetti 09] is a method to position using only one antenna. This method estimate position from estimating the solid angle of direction of the receiver and RSSI by arranging a directional receiver in a regular dodecahedron position and individually measuring the RSSI of each transmitter. [Lloret 09] proposed a method which decrease the cost of prior measurement while maintaining the positioning accuracy by mixing range-based positioning and fingerprinting. [Widyawan 07] is a method which calculates prior measurement value of fingerprint based on ray tracing and Motif model. [Zaruba 07] is a method which estimate measured value using ray tracing. [King 06] is a method which consider direction in measuring fingerprint.

1.4.4 Problems to be solved

Factors of positioning error are the following three points in the office environment which this dissertation aims to.

1. multipath phasing effect
2. shield by metal partition
3. reflection and absorption by human

Range-based method is known as a method which can perform 1.0-2.0 meters accuracy, however, the methodis appricable to only 1. condition. Range-based methods are difficult to apply 2. and 3. conditions.

On the other hands, fingerprinting-based methods are applicable to the 1. and 2. environments. Because, the methods need no assumption but reproducibility of RSSI. However, fingerprint-based methods are less accurate than range-based methods because fingerprint-based methods depend on a resolution of sampling. Moreover, no methods which are appricable to 3. condition has proposed till.

So, this dissertation approaches the following three agendas.

1. to extend a range-based method to apply 2. condition.
2. to improve an accuracy of a fingerprinting-based method in 1. and 2. conditions.
3. to develop an estimation of accuracy of indoor positioning system in 3. condition.

This dissertation disscusses agenda 1. in Chapter 2 and 3, agenda 2. in Chapter 4, and agenda 3. in Chapter 5.

1.5 Conclusion

This chapter, the proposed approach in prior research will be listed and classified regarding indoor positioning system. Moreover, the required condition of the position system under office environment will be defined and the positioning method to fulfill this condition will be discussed. While showing the whole picture of the indoor positioning system based on prior measurement especially about RSSI, the stand point and the problem to be solved are revealed.

Chapter 2

Comparison of RSSI between Office Environment and Simulation by FDTD

2.1 Introduction

It is important to estimate an approximate function of RSSI observaions for a range-based positioning method. [Bahl 00] and [Patwari 03-1] use the following $f(r)$, which is a simple parametric function.

$$f(r) = a + 10b\log_{10}(r) \tag{2.1}$$

Otherwise, RSSI observation is generally affected by multipath and NLOS in an office environment, where is a target of this dissertation. Both [Bahl 00] and [Patwari 03-1] aims a corridor, which is LOS environment, and an spacious room. Thus, no range-based positioning method aims an office environment.

The things which affect RSSI observations are the following three factors:

1. Shields by a metal furniture and a metal fixtures.

2. Multipath effects from the surrounding things and walls.

Figure 2.1: Example of an office environment, where is aimed by this dissertation

3. Absorption and reflection by men in the room.

Rayleigh's distribution is used in multipath environment and Motif model is used in NLOS environment. However, no simple model is used in office environments because of complexity of the environment. Thus, it is not clear that a relationship between distance and RSSI observation in office environments. Then, this chapter investigate the relationship in detail by measuring RSSI observations in continuously. Moreever, this chapter measures several sequence of RSSI observations and reveal an accord between these sequences. Finally, we try to reproduce the real sequence of RSSI observations by using FDTD method [Yee 66, Taflove 05] to reveal a dependency of the feature of RSSI observations on the structure of office environment.

2.2 System implementation

First, this section describes a way to measure RSSI. This section designed a measurement system by using ZigBee modules.

ZigBee is a specification for a suite of high level communication protocols used to create personal area networks built from small, low-power digital radios. ZigBee is based on an IEEE 802.15 standard. ZigBee also have the function of energy detection, which scans radio-strength, to enrich the quality of routing, and then doesn't need expansion of the devices to measure RSSI.

Thus, this chapter used a ZigBee module as beacons and routers. This chapter used ETRX2USB made by Telegesis, which is shown by Fig. 2.2. This module can communicate with personal computer via serial communication of USB2.0.

Figure 2.2: ZigBee node, ETRX2USB.

RSSI observations are measured according to the following instructions.

1. A beacon broadcasts ZigBee packets at regular intervals.

2. A router fixed in a wall receives these packets and measures RSSI observation. The router sends RSSI observations to a beacon via ZigBee.

3. The beacon collects their RSSI observations and transmit thier RSSI observations to notebook computer via serial communication.

4. The notebook computer restores their RSSI observations.

2.2.1 Measuring machine

A beacon was fixed on a measuring machine, which is shown by Fig. 2.3, and was moved at the height of 0.43 [m], which is on the supposition that a user holds the

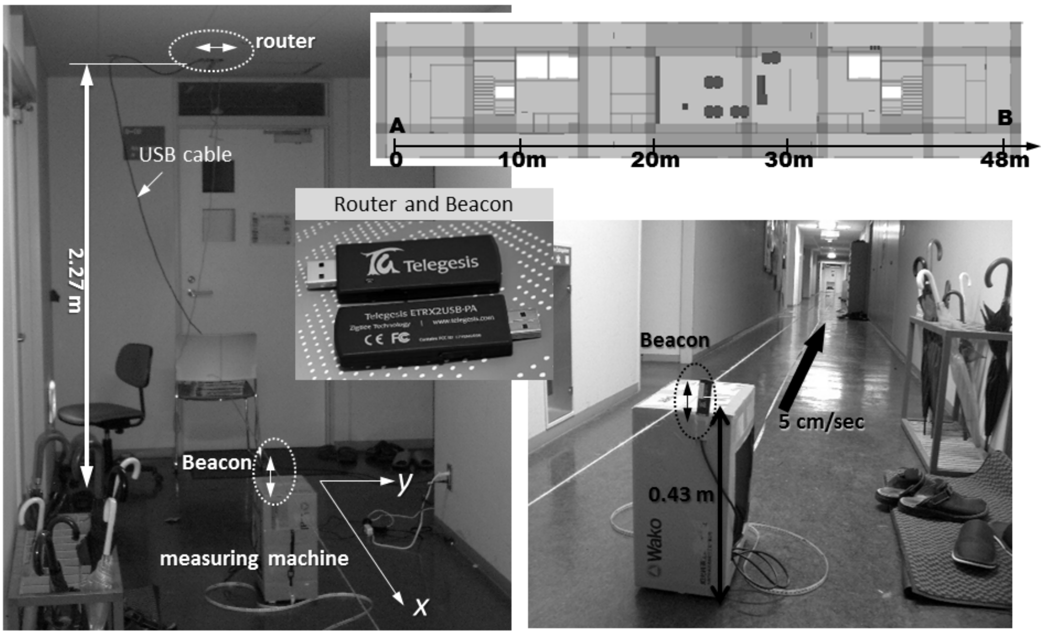

Figure 2.3: Mobile node.

beacon at this height. A base part of the measuring machine was made of corrugated cardboard.

The beacon was ordered to transmit multicast packets, which requests a router to measure RSSI of these packets, at regular intervals. The transmission power of these packets is fixed to 0 [dBm]. Although the transmission power is supposed to be off 0 [dBm] by a physical factor, this chapter doesn't consider that.

We set the transmission intervals at which the beacon can multicast packets safely, which is 1.0 [sec] intervals. Because a ZigBee module cannot multicast packets at short intervals.

Now, we need to relate a measurement RSSI data with a position where the beacon has transmitted the data. Then, this chapter limited the beacon's position to a line and moved a measurement machine at a constant speed (5cm per seconds).

The router was fixed on the ceiling and it was supplied electric power to via a USB cable. The router was installed a program which measures RSSI observations and sends back to the beacon.

2.2.2 Test environment

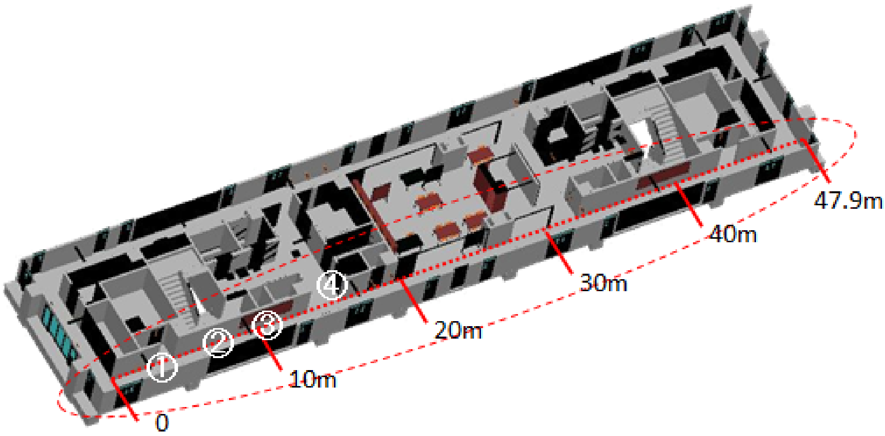

Figure 2.4: A model of test environment.

The author conducted a measurement in a laboratory floor (Fig. 2.4). The wall of this floor is composed of gypsum board, metal board, concrete, etc. and then is not flat. So, this environment is complicated multipath and is NLOS (Non Light-of-Sight) environment.

A interference from wireless LAN and an absorption of radio waves by people traffic are considered the other factors in affecting radio-environment. This floor has some laboratories where wireless LAN is deployed. Zigbee uses the ISM band, which is also used by Wireless LAN, and then ZigBee is affected by wireless LAN.

A notebooks in the measuring machine (Fig. 2.3) for recording RSSI observations has some communication modules for wireless LAN or Bluetooth. However, these modules was disconnected during these measurements in case wireless LAN or Bluetooth affects the RSSI observations.

Then, we conducted these experiments in midnight to avoid an absorption of people.

2.2.3 Model of FDTD simulation

This chapter shows the capability of reproducing the specifics of the dependence to this sight by modeling the details of electromagnetic character of covers and metal partitions in office environment and by electromagnetic field simulation, which is called FDTD simulation. Since there is a need for enormous memory space, know-how of modeling electromagnetic character, and parallel computation for this calculation, we ran the calculation on a super computer with the help of Professor Omiya's laboratory. The model in Fig. 2.5, 2.6, 2.7 was created by them.

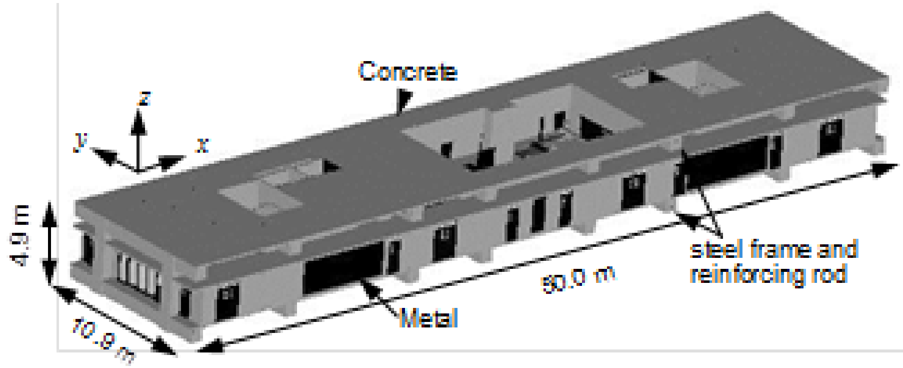

Figure 2.5: Model of Calculation for FDTD simulation (general view).

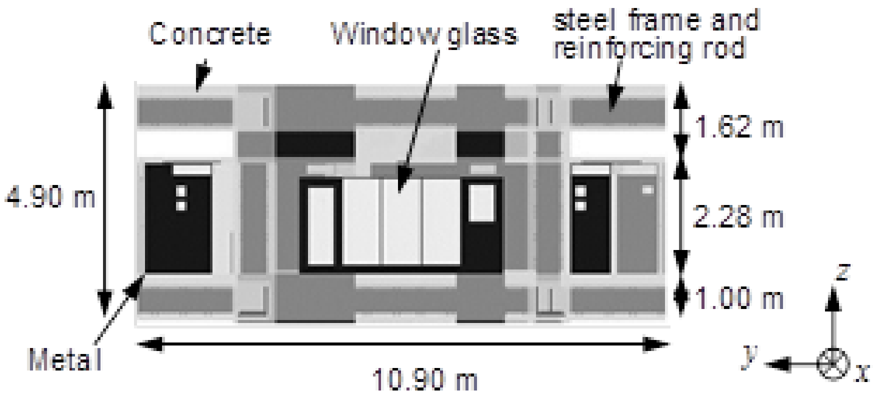

Figure 2.6: Model of Calculation for FDTD simulation (side view).

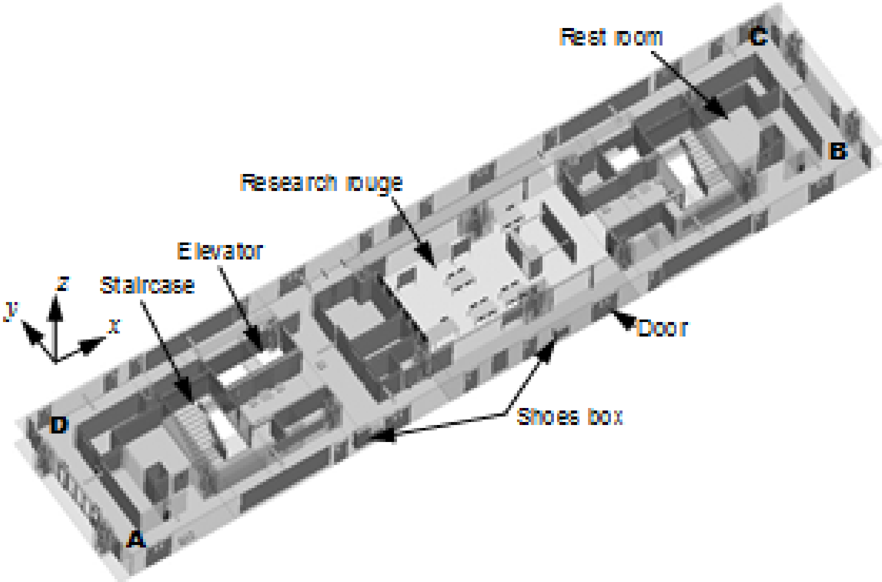

Figure 2.7: Model of Calculation for FDTD simulation (inner structure).

2.3 Experimental

2.3.1 Result of measurement

Fig. 2.8 ploted out the first sequence of RSSI observations. Horizontal axis means a walk from starting point to a location where mobile node has been transmitting. Vertical axis means a RSSI observation. And then, the author calculated an approximate of the sequence and overlay multiple graphs. The approximate functions are third moving average and 11-th moving average.

Fig. 2.9 ploted out the three sequence of RSSI observations. This graph shows three approximate functions of the sequences have a number of corresponding peaks.

2.3.2 Result of FDTD simulation

We conducted FDTD simulation and the result is here 2.10. This chart overlays two graphs, which are a sequence of real observations and a sequence simulated by using FDTD. These two graphs are very similar, especially from 5 meters to 12 meters.

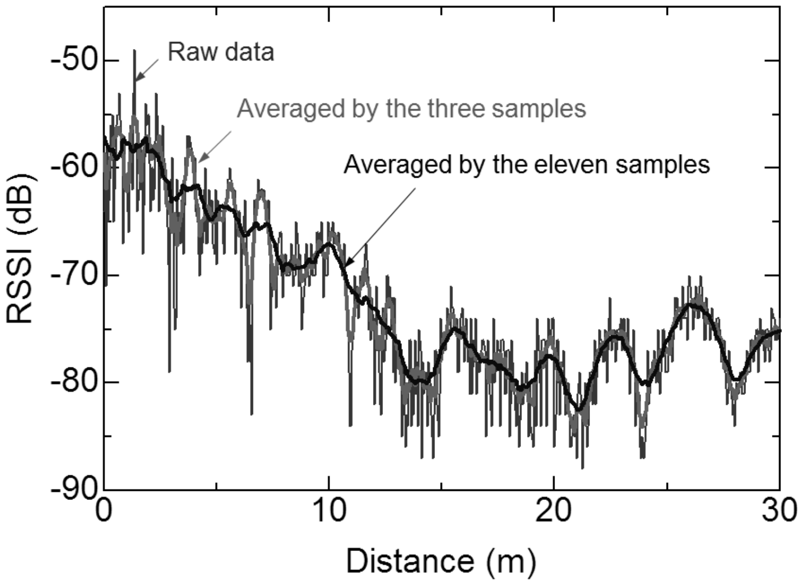

Figure 2.8: A relationship between distance and RSSI.

2.4 Conclusion

This chapter describes the specific of the RSSI depending on the sight such as cover and metal partition in office environment based on the measurement experiment in continuous space of RSSI in actual environment are revealed. Moreover, this chapter shows the capability of reproducing the specifics of the dependence to this sight by modeling the details of electromagnetic character of covers and metal partitions in office environment and by electromagnetic field simulation. Since there is a need for enormous memory space, know-how of modeling electromagnetic character, and parallel computation for this calculation, we ran the calculation on a super computer with the help of Professor Omiya's laboratory.

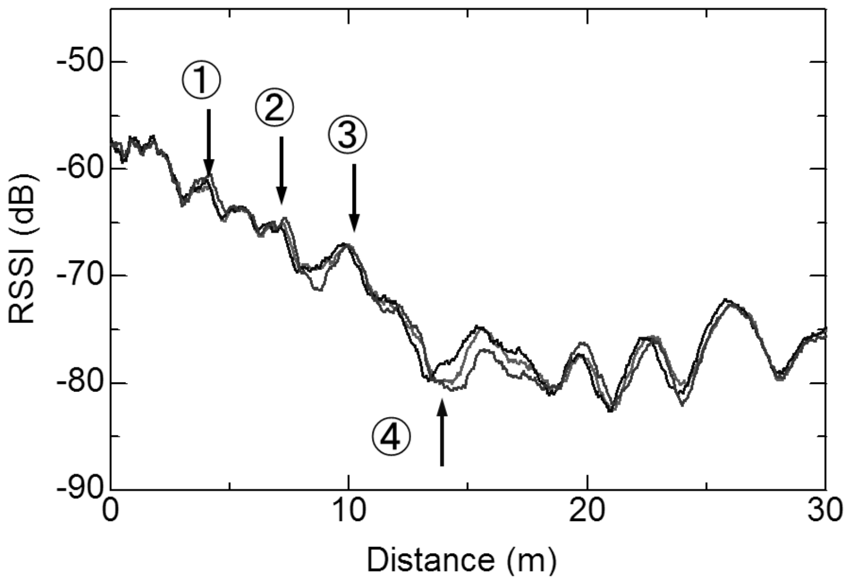

Figure 2.9: Reproducibility of the relationships between distance and RSSI.

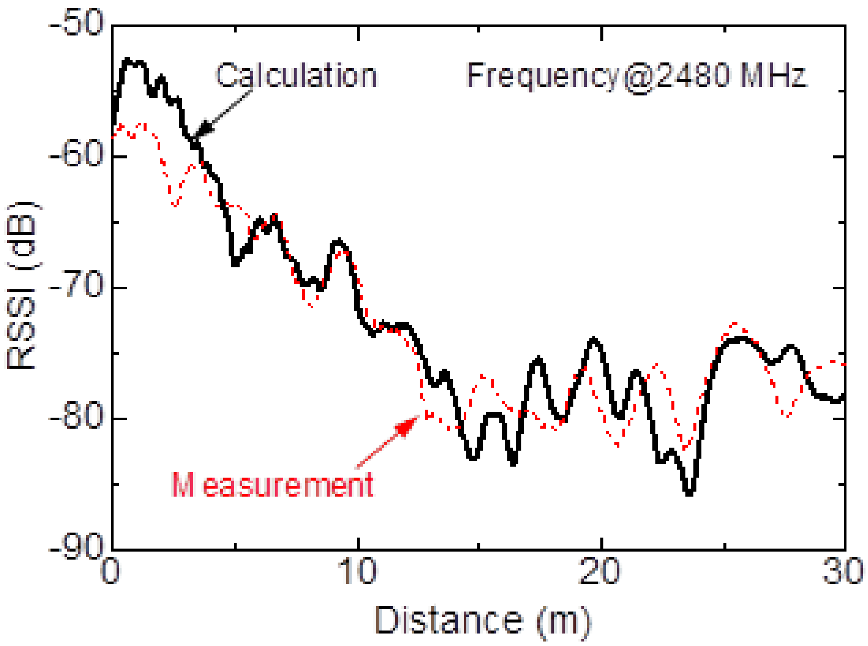

Figure 2.10: Comparison of RSSI between measured and simulated.

Chapter 3

An Indoor Positioning Method Based on Pre-Observation of RSSI in Continuous Space

3.1 Introduction

This chapter proposes an indoor positioning method on the assumption of continuous pre-observations or FDTD simulation such as the second chapter. The proposed method is an enhanced range-based positioning. There is no range-based positioning for office environment.

This chapter proposes a method that approximates a relationship between distance and RSSI observation as a piecewise linear function. The function has no inverse function, therefore a RSSI observation correspond with two or more different positions. Moreever, this chapter proposes to apply particle filter to the case.

3.2 Positioning

We assume that some sensor nodes for RSSI observation are located in indoors environments and others are installed in mobile terminals carried, like cellphones, by users (mobile nodes). We attempted the accurate localization by the fusion of RSSI data measured by these fixed nodes.

In our proposal, we conducts the following transactions:

1. A mobile node regularly sends packets requesting a fixed node to measure RSSI to neighboring fixed nodes.

2. The fixed node receives packets sent by the mobile node andmeasures RSSI of this packet (ZigBee communication).

3. The fixed node forwards measured RSSI to positioning servers via an Ethernet.

4. The positioning server collects RSSI data and the positioning server determines a mobile node location.

5. The positioning server stores the mobile node location in a database.

6. A mobile computer accesses the positioning server via the Internet, displays a positioning result.

These transactions enable mobile terminals to obtain their locations and to regularly display them. Navigation services can use these locations. We have implemented both the mobile node and the fixed node with ZigBee. ETRX2USB (Telegesis, Fig. 3.1, left) is used as a mobile node wireless-module that communicates with a computer via serial communication.

The ETRX2 EAP-E Ethernet Access Point (Telegesis, Fig. 3.1, right) is used as the fixed node, which works as a gateway of Ethernet and as a ZigBee node. These devices are used when the fixed node should send measured data to the server for managing indoor locations.

3.3 Calculating location

The sections that follow calculate mobile node positioning using RSSI data observed by fixed nodes.

Figure 3.1: ZigBee modules: ETRX2USB (left), ETRX2 EAP-E (right).

We calculated mobile sensor location by checking continuously observed RSSI against preobserved standard RSSI data, i.e., a map of a mobile sensor's location generally two- or three-dimensional of an RSSI value that a fixed node may observe when the mobile node transmits a packet.

Section 3.3.1 discusses general particle filter and RSSI use. Section 3.3.2 discusses proposed standard data models.

3.3.1 Particle filter

The particle filter [Doucet 01] statistically estimates state vector $x(t)$ from a series of observed data vectors $\{y(t)\}$ to a general state space model represented sequentially as follows:

$$x(t) = f(x(t-1)) + \eta(t) \tag{3.1}$$

$$y(t) = g(x(t)) + \epsilon(t) \tag{3.2}$$

$\eta(t)$ is system noise and $\epsilon(t)$ observation noise. Assuming $x(t)$ is a mobile node location at time t and $y(t)$ is a RSSI vector observed by fixed nodes at time t, we apply particle filter to positioning assuming that the mobile node location follows the Markov process.

The particle filter estimates its probabilistic density $p(x(t))$, not $x(t)$ itself. $p(x(t))$ is approximately represented by a mass of particles, each particle having state $x_i(t)$ and weight $w_i(t)$.

The probabilistic density of state x becomes high if highly weighted particles crowd around x, but low if particles do not crowd around x or if only low-weighted particles surround x.

The particle filter calculates the estimated state $x(t)$ from state $x_i(t)$ and weight $w_i(t)$ of individual particles.

$$x(t) = \sum_{i=0}^{N} w_i(t) x_i(t) \tag{3.3}$$

The particle filter concept resembles maximum likelihood estimation concept [Sheng 05]. Maximum likelihood estimation uses only observed series $\{y(t)\}$, but the particle filter uses processing characteristics (Eq. (3.1) and $\{y(t)\}$ as prior knowledge, so the particle filter cannot estimate well without properly designing likelihood function $L(x|y)$ for state x when y is observed and without a propermodel for prospecting state $x(t+1)$ when state $x(t)$ is at time t.

We designed $L(x|y)$ based on preobservation (in Section 3.3.2). Eq. (3.4), a simple random walk, is used as processing model Eq. (3.1).

$$x(t) = x(t-1) + \eta(t) \tag{3.4}$$

$\eta(t)$ is system noise at time t in Eq. (3.2), $\eta \sim N(\cdot; 0, \sigma_\eta^2)$ and σ_η^2 is a parameter meaning a variation system noise. The particle filter algorithm is as follows:

1. Make a particle distribution. If no prior knowledge is given, distribute particles uniformly. Weight wi of each particles is initialized by 1.

2. Repeat the following three steps:

   (a) Move each particle by Eq. (3.1).

   (b) Measure $y(t)$ and calculate weight $w_i(t)$ of each particle, moved in the first step, using the following equation:

$$w_i(t) \leftarrow w_i(t) \times L(x_i|y) \tag{3.5}$$

$L(x|y)$ is calculated by checking the Eq. (3.2).

(c) Choose particles by a probability proportional to the weight $w_i(t)$ and leave the particles to next step. (This procedure is called Resampling.) Weight $w_i \leftarrow 1$.

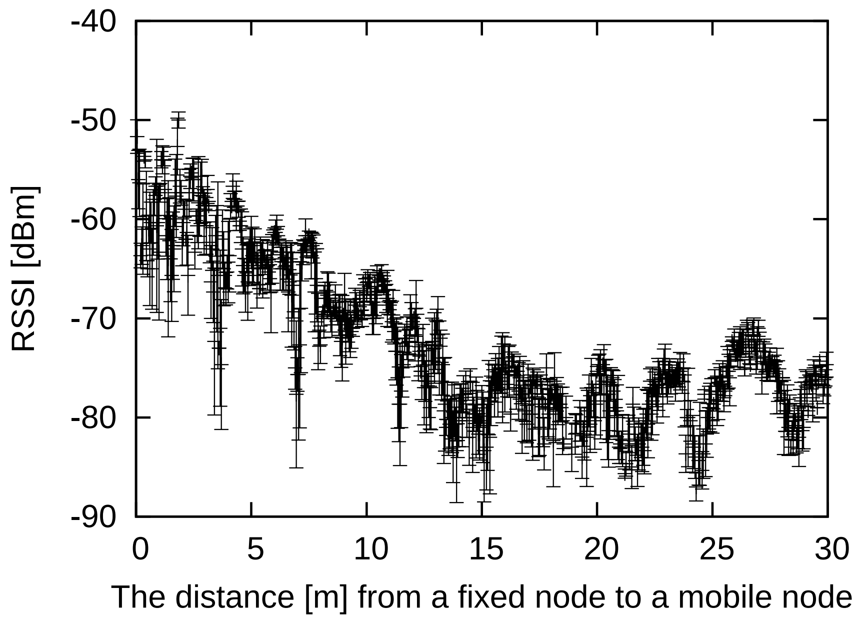

Figure 3.2: RSSI vs. direct distance, observed in a laboratory corridor.

3.3.2 Polyline approximation for standard data

Fig. 3.2 shows the relationship between RSSI [dBm] and direct distance r [m] from fixed to mobile nodes, measured in a laboratory corridor. (Fig. 3.2 is the mean and the variation of three experiments.)

Distance r and RSSI have an inverse effect between them, but strong and weak parts also exist assumed to be site-specific the gradual change appears to have reproduction. Specifically, 10 dBm fluctuations are laid over the graph of Fig. 3.2. The fluctuations are caused by multipath effect.

The gradually changing trend is represented by function $g(x)$ dependent on mobile node location x. Themultipath effect is represented by noise ϵ. We use $g(x)$ with polyline approximation and with a probable variant generated by normal distribution, called polyline approximation.

Likelihood function L(x—y) to x is as follows when y is observed:

$$L(x|y) = N(y|g(x), \sigma_\epsilon^2(x)) \tag{3.6}$$

$N(x|\mu, \sigma^2)$ is a normal distribution function. μ is its mean and σ^2 its variation. $\sigma_\epsilon^2(t)$ is variation in observation noise.

3.3.3 Evaluation of our proposal

We evaluated these trials with two indicators presented by [Liu 07]:

Accuracy

We used the first indicator representing positioning accuracy, meaning positioning error, i.e., the difference between the real and estimated location. Positioning error of each trial is shown by RootMean Squared Error (RMSE), as follows:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=0}^{T-1} \|x(t) - \hat{x}(t)\|^2} \tag{3.7}$$

T is time for each trial, $x(t)$ the real location of a mobile node at time t, and $\hat{x}(t)$ the location of the mobile node estimated by particle filter at t.

Precision

We used distance error Cumulative Distribution Functions (CDF) as the second indicator, meaning precision. CDF is represented as probability distribution $P[X]$ that distance error x is smaller than or equal to X. One system has a location precision of 90 percent within 2.3 meters. The distance error CDF of 2.3 meters is 0.9.

3.4 Experimental

In principle, gradual variation in RSSI is replicable and localization is done by checking observed data against preobserved data. In principle, this localizes nodes accurately unless no change occurs in the environment. How much will the accuracy of localization for a single mobile node become using our previous proposal?

We preobserved the real environment using the measuring machine shown below (experiment 0). We then make standard data for localization in Section 3.2 from preobservation data. We then localize test data observed by the mobile node carried by user @ (experiment 2) with preceding standard data.

We then determined the capability of our proposal making observation intervals longer.

3.4.1 Test environment

We conducted experiments on the laboratory floor (Fig. 3.3). The wall consists of gypsum board, metal board, concrete, etc.

The room contains furniture and partitions. A radio signal is interrupted, so the environment causes a complex multipath and makes a Non light-Of-Sight (NLOS) environment.

The interference from a wireless LAN and absorption of radio waves by a crowd of people are considered other factors adversely affecting the radio environment. This floor has laboratories using wireless LAN. ZigBee uses the ISM band, also used by the wireless LAN and Bluetooth, adversely affecting ZigBee communication. Although the PC for recording observed data in the mobile measuring machine of Fig. 3.4 has communicationmodules for wireless LAN or Bluetooth, these functions were disconnected during the experiment in case wireless LAN or Bluetooth adversely affected the radio environment. The environment has unrelated ISM devices, such

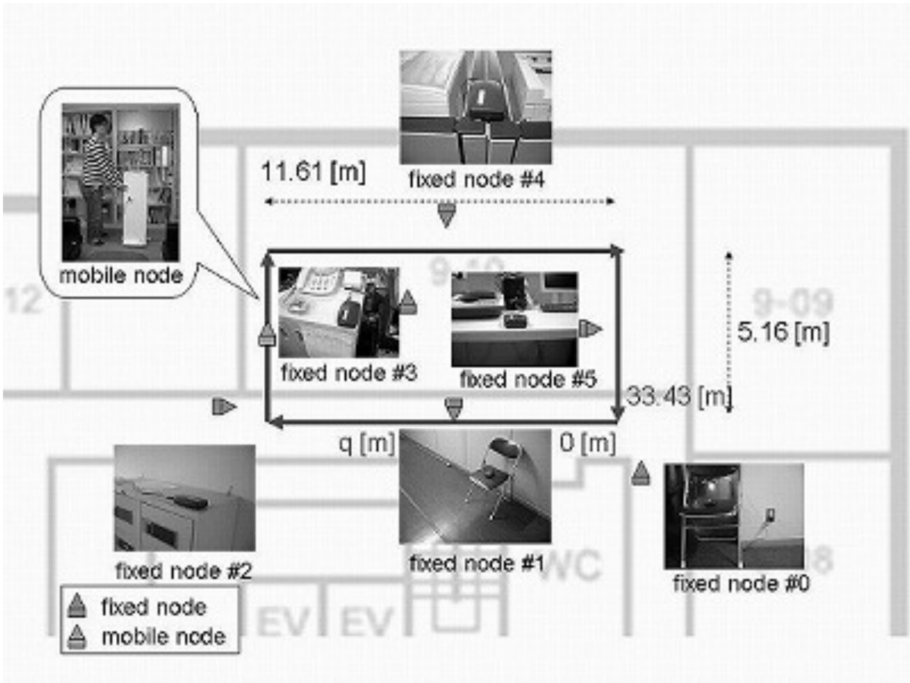

Figure 3.3: Laboratory floor.

as cellular phones, than do not interfere in ZigBee communication, but may interfere in ZigBee RSSI, because RSSI involves radiowave strength surrounding the receiving node when the ZigBee packet is received. The impact of nonrelated ISM band devices on ZigBee RSSI may be larger than their impact on Wi-Fi RSSI because the ZigBee radiowave is weaker than that of Wi-Fi, but time constraints prevent dealing with this matter here.

To minimize the effect of absorption by a crowd of people, we conducted experiments late at night to minimize interference from outside sources.

3.4.2 Measuring machine for standard data

Observation data must correspond precisely with the location where it is observed to determine the precise relationship between location and RSSI measured by an approximation model. We thus limited a mobile node to a track where we could measure it and relate the transmission location precisely to its observed data.

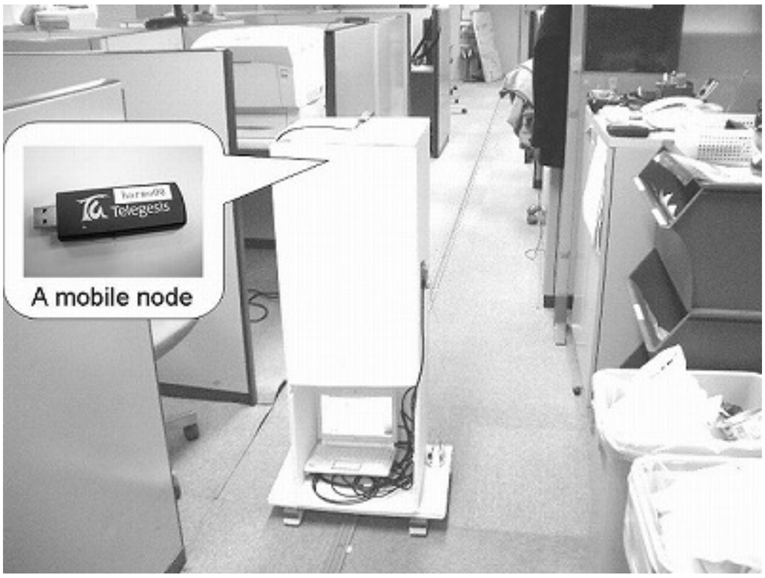

Figure 3.4: Measuring machine for preobservation.

The experimental setup ensured the relationship between the transmission location and RSSI observed. The mobile node was fixed on a measuring machine (Fig. 3.4) at 1.0 m, at which it was assumed that a user walked with a mobile terminal. The measuring machine base was made of polystyrene considering radio wave characteristics. We set rails on the laboratory floor to enable the measuring machine on the mobile node to move only along these rails. Next, we had a mobile node autotransmit packets at regular 2.0 s intervals and moved a mobile node at a constant speed (Fig. 3.4). We determined transmission time from the approximate location where the mobile node transmitted.

The transmission location had to be revised, however, because users could not walk at an exactly constant speed, so we set triggers on measurement rails at 0.43 meter intervals. These switching triggers under the measuringmachine (Fig. 3.6) are pressed when the measuring machine passed over the every triggers, so it is easily guaranteed at 0.43 meter interval that the relationship between the transmission location and the RSSI is correctly observed. In this interval, we revised a location with linear transformation assuming that a measuring machine walks at a constant speed. Packed transmission is fixed at 0 dBm in the program. Although transmission

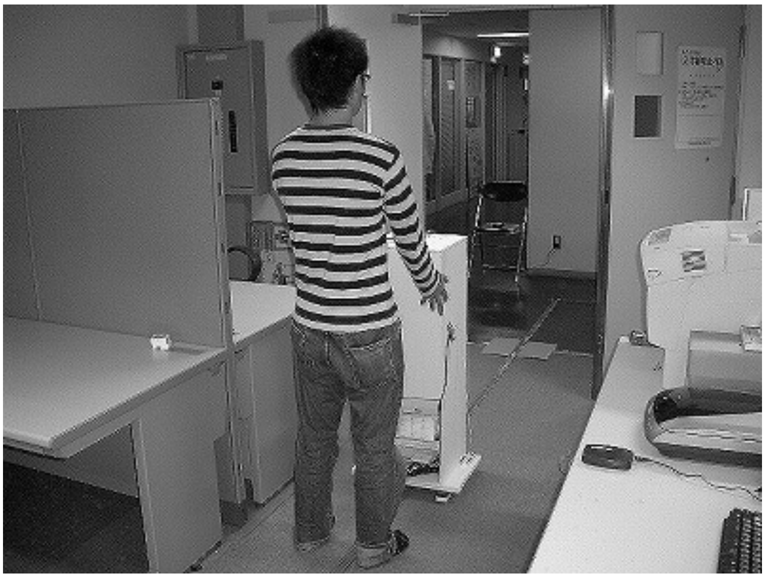

Figure 3.5: Measuring machine pushed by a lab technician.

power is supposed to be off 0 dBm by a physical factor, this is not considered here. Fixed nodes were set at the five points shown in Fig. 3.3 three in the laboratory and the other two in the corridor. Each fixed node faced in the direction shown by Fig. 3.3 and is designated fixed node 1, etc. All were supplied with electricity. Fixed nodes were installed in the program measuring RSSI of sent packets and returning measured RSSI. Measurement rails were throughout the laboratory and the corridor (Fig. 3.3). The direction of the measuring machine was clockwise (Fig. 3.3). Walking speed was 0.15 m/s but differed with the experiment. The mobile node was observed at 0.3 m intervals as the measurement packet was transmitted at 2.0 s intervals.

3.4.3 Pre-observation

Fig. 3.7 plots the first 5 RSSI data observed by fixed node 4. The horizontal axis is the walk [m] from the starting point to the location where a mobile node has transmitted a packet, and the vertical axis RSSI observed then. We include an approximation function, a line graph, in Fig. 3.7. Each part of the approximation function is 0.86 meters long. Fig. 3.7 shows that RSSI peaks at a point near fixed

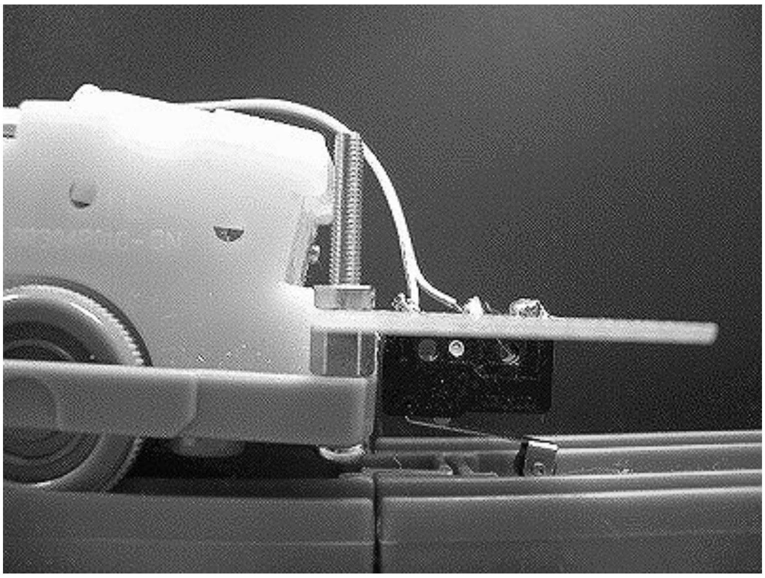

Figure 3.6: Switch under a measuring machine and a trigger on a measurement rail.

node 4 (22.38 meter walk) and that RSSI declines as the distance between mobile and fixed nodes increases. RSSI does not simply decline and drop down somewhere. RSSI observed after 22.38 meters, for example, is smaller than RSSI observed before 22.38 meters. This effect is supposed to be caused by a person standing between fixed and mobile nodes, and interrupting the light of sight between them.

3.4.4 Test data

Test data was measured by a person carrying a mobile node (Fig. 3.8) at a height of 1.0 meter.

In this experiment, an observation interval was set to 20 s, which is determined by preliminary examination as a safe-sending interval. The measurement data was collected in the server computer via Ethernet from fixed nodes (Telegesis EAP-E). This experiment is conducted 10 times.

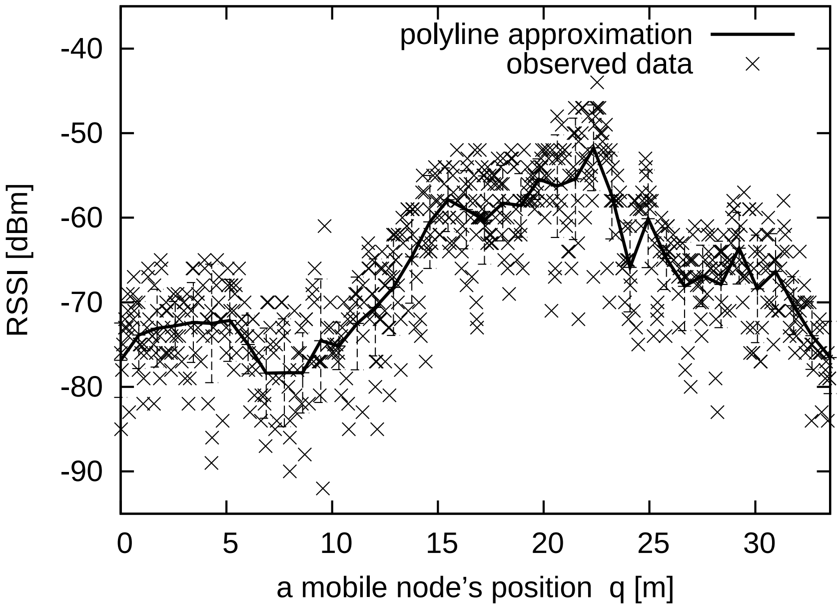

Figure 3.7: RSSI data on mobile node transmission positioning, observed by fixed node 4.

3.4.5 Experiment 1: particle filter to test data

This section conducted the particle filter to 10 preobservation data by the preceding section. Table 3.1 shows this experiments parameter set.

Table 3.1: Experiment 1 parameter.

name of parameters	value
number of particles	1000
positioning interval	0.02 sec
resampling interval	0.10 sec
σ_η	1.0
number of test data	10
number of partitions for polyline approx.	38
partition length for polyline approx.	0.86 meter

Experimental results are shown in Figs. 3.9-3.11.

Figure 3.8: User carrying mobile node in experiment 1 for test data measurement.

3.4.6 Experiment 2: observation intervals

In determining the localization results changing the RSSI observation rate, we changed the observation rate in simulation with part of the test data measured in Section 5.4 using the 7 parameters shown in Table 3.2.

Table 3.2: Experiment 2 parameter.

name of parameters	value
observation rate [times/sec]	0.5, 1, 2.5, 5, 10, 25, 50

Experimental results are shown in Fig. 3.12.

3.5 Discussion

Experiment 1 involved localization of only one mobile node, giving an ideal interval and localizing a mobile node with average 2.48 meter accuracy.

What happens when the number of mobile nodes is large? The number of packets for localization is proportional to the number of mobile nodes, so increasing mobile nodes adds to the ZigBee channel traffic load.

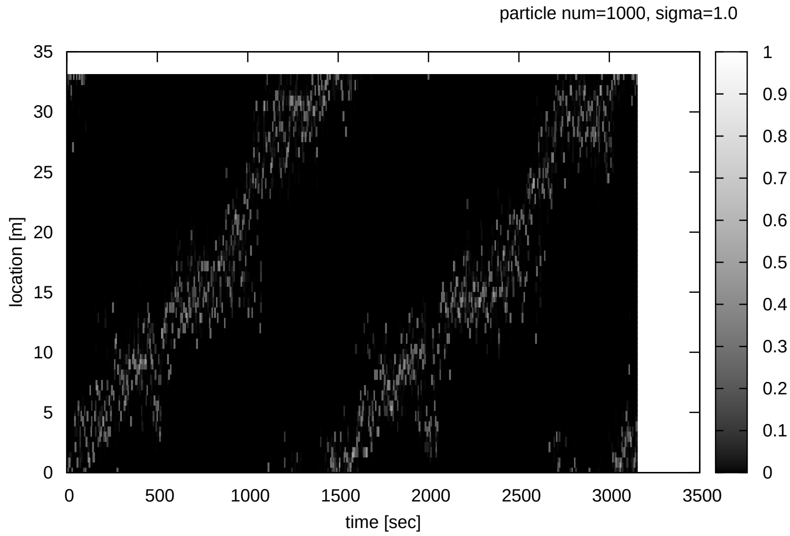

Figure 3.9: Experiment 1: particle distribution by time step in one trial.

Preliminarily, a mobile node sends a message to a fixed node with 50 packets/s, so packet rate r packets/s with which n mobile nodes sends a fixed node is r = 50 n , r = 5.0 packets/s when n = 10, and r = 2.5 packets/sec when n = 20.

Experiment 2 conducted localization controlling the observation rate corresponding to these numbers, so average error is 2.340.19 meters at a rate corresponding to 10 nodes, and average error is 2.480.36 meters at a rate corresponding to 20 nodes. Under these conditions, localization is conducted within an accuracy of 3.0 meters, even taking 1 into consideration accurate enough for positioning many mobile nodes.

3.6 Conclusions

We have proposed RSSI approximation by polyline for indoor positioning system using ZigBee RSSI, and conducted RSSI observation in real indoor space affected by multipaths and NLOS. We calculated mobile node positioning for a user carrying the mobile node. We showed that mean localization error is 2.48 meters using our proposal. In experiments controlling the RSSI observation interval, we showed the

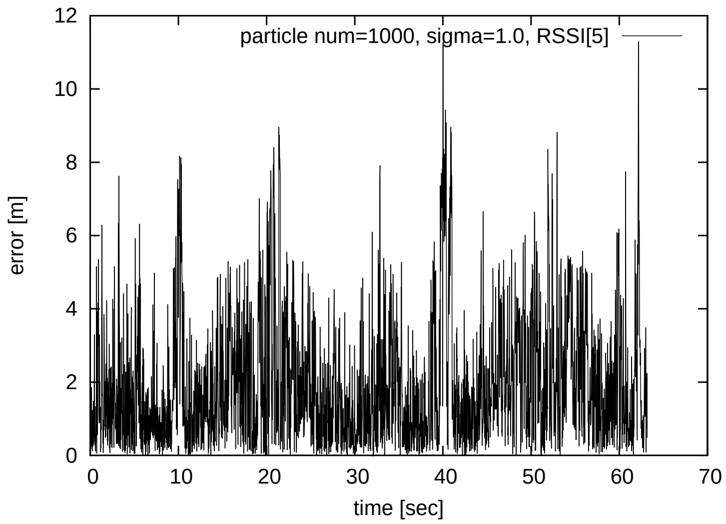

Figure 3.10: Experiment 1: estimated positioning error by time step in one trial.

relationship between observation intervals and positioning accuracy. Although we must choose a low packet rate when users are increasing and the channel is loaded, our proposal conducts localization with sufficient accuracy.

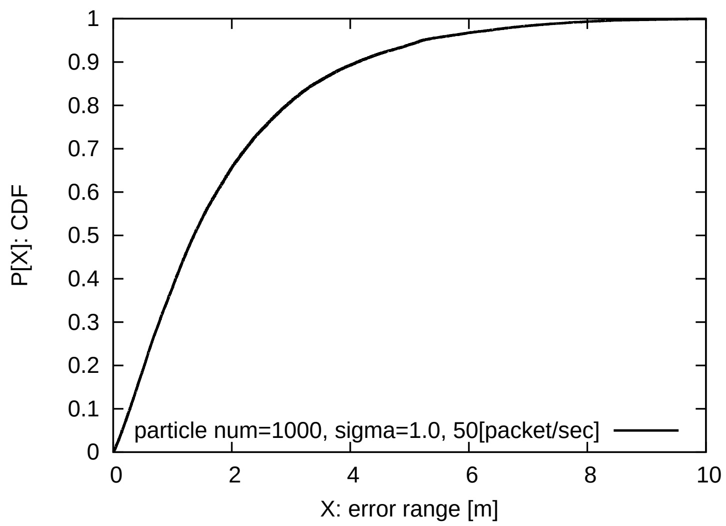

Figure 3.11: Cumulative probability for positioning error in X.

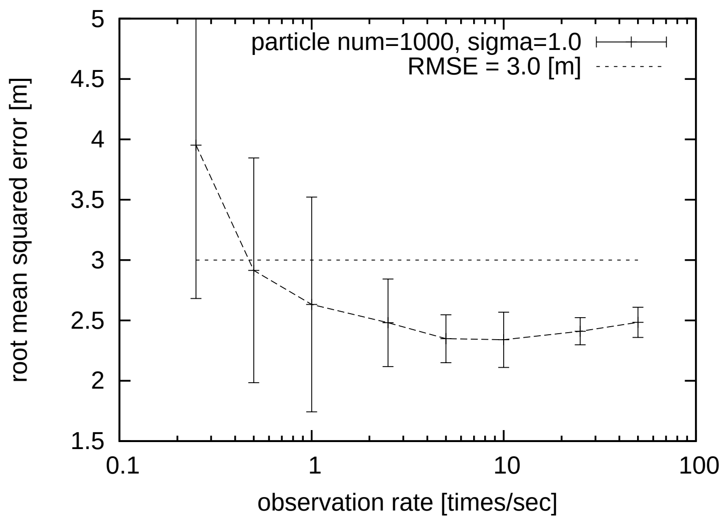

Figure 3.12: RSSI observation transmission vs. positioning accuracy (RMSE).

Chapter 4

Optimization of Indoor Positioning Method Based on Sampling of Fingerprints

4.1 Introduction

This chapter try to develop a methodology for improving an accuracy of fingerprinting-based indoor positioning.

In fingerprinting-based method, an enviroment of the positioning system changes if an spot to measure changes. An optimal arrangement of fingerprints and routers changes if the enviroment changes. Concerning the arrangment of the router, there is a need to think about the physical limitations such as power and cable.

However, how much the arragement of fingerprint and router have impact on the accuracy of measurement is not known enough.

This chapter discusses the way to optimize a positioning accurary by changing a layout of fingerprints and routers. First, this chapter tests a positioning accuracy by using a fingerprinting-based method of prior research [Evennou 06] in real office environment. Then, the method to optimize the layout of fingerprints and routers will be proposed. Finally, an examination will be conducted for a performance evaluation on the optimization.

4.1.1 Related works

Regarding the arrangment of the router, according to Patwari's research [Patwari 03-1], the accuracy of the triangulation can be improved by deleting the information of the router far away of the current possition.

Regarding the arrangment of the fingerprint, according to Kaemarungsi, et al's paper [Kaemarungsi 04], there is a tendency of performance improving when the number is large. Swangmuang, et al. [Swangmuang 08] proposed a way to reduce the number of fingerprints.

This method reduces the number of fingerprints depending on the created Voronoi diagram's domain area size from a disatnce of RSSI space. From this result, there was a case where the accuracy nearly did not change when the number of fingerprints were decreased.

As understood from this, there is a need of a design guidelie for the arrangment of fingerprint and router. This does not mean the more fingerprints and routers are placed, the more the performance is improved meaning that the way to appropriatly select this is not clear.

4.2 Fingerprinting

This section describes a fingerprinting-based method, especially k-Nearest Neighbors (k-NN) based particle filter, which has been proposed in [Evennou 06].

4.2.1 Definition of fingerprinting

Fingerprinting is a positioning method based on RSSI pre-observation. This section explains it in detail.

4.2.2 Variables

A location of a user at a discrete time:$t \in \{0, 1, 2, ...\}$ is described as $x_t \in \boldsymbol{X}$, A RSSI data measured by a ZigBee router node $i \in \{1, 2, 3, ..., M\}$ is described as $y_t^i \in \boldsymbol{Y}$

and a RSSI vector measured at time t is described as $\boldsymbol{y}_t = [y_t^1, y_t^2, y_t^3, ..., y_t^M]$, where $\boldsymbol{X}$ is a set which means scope of a user location and $\boldsymbol{X} \subseteq \mathbb{R}^2$. $\boldsymbol{Y}$ is a union of $\acute{\boldsymbol{Y}} \subset \mathbb{R}^M$ and a set $\{\perp\}$ ($\perp$ is a sinbol which means "in this time, RSSI was not observed".)

When a discrete time is t, a real time $T \in \mathbb{R}$ and a sampling time is Δt, their relation is $T = \Delta t \times t$.

The purpose of the localization algorithm is to decide a location estimation $\hat{x}_t$ at time t using $\boldsymbol{y}_t$.

4.2.3 k-Nearest Neighbors

k-Nearest Neighbors is a method which select the nearest k fingerprints by observed $\boldsymbol{y}_t$ and decide a location estimation by weighted averaging of thier fingerprints. [Bahl 00, Evennou 06] k-Nearest Neighbors uses an M-euclidian distance as the distance between fingerprints and uses inverse of distance as thier weights.

When a location of n-th fingerprint is X_n $(1 \leq n \leq N)$, its RSSI value is $\boldsymbol{Y}_n$ and an observed RSSI is $\boldsymbol{y}_t$, The distance between one fingerprint $\boldsymbol{Y}_n$ and the observed $\boldsymbol{y}_t$ is follows:

$$d(\boldsymbol{Y}_n, \boldsymbol{y}_t) = \sqrt{\sum_{i=1}^{M} (Y_n^i - y_t^i)^2} \tag{4.1}$$

Also, when k-Neighbors is $\boldsymbol{N}_k$, the estimation $\hat{x}$ is described as following equation:

$$\hat{x} = \frac{\sum_{n \in \boldsymbol{N}_k} (1/d(\boldsymbol{Y}_n, \boldsymbol{y}_t)) \cdot X_n}{\sum_{n \in \boldsymbol{N}_k} (1/d(\boldsymbol{Y}_n, \boldsymbol{y}_t))} \tag{4.2}$$

, where k is a given variable.

4.2.4 Particle filter

Particle filter was proposed by Kitagawa et al. in 1987. [Kitagawa 87] A user location x_t can be decided by particle filter [Doucet 01] in condition that x_t and a RSSI vector $\boldsymbol{y}_t$ follows the next two suppositions:

- x_t depends on x_{t-1} and is decided probabilistically. [Markov Processing]
- $\boldsymbol{y}_t$ depends on x_t and is decided probabilistically.

Particle filter estimates a distribution of x_t on supposition.

A distribution of x_t is discribed by a set of candidates of estimated location, which calls "particles" $\{p^k\}$, where k is $(1 \leq k \leq K)$. A particle p^k has a location x^k and its weight w^k. The location of the user is decided by the following equation:

$$\hat{x} = \frac{1}{W} \sum_k w^k x^k \tag{4.3}$$

, where W is the follows

$$W = \sum_k w^k \tag{4.4}$$

4.2.5 Algorithms of particle filter

The algorithms of particle filter is the followings.

1. Generate the particles $\{p^0\}$ at $t = 0$ randomly.

   $$x^k \leftarrow x \sim p(\boldsymbol{X})$$

   $$w^k \leftarrow 1$$

   , where $p(\boldsymbol{X})$ is an uniform distribution in $\boldsymbol{X}$.

2. Repeat the following processes from $t = 0$ to $t = t_{fin}$.(t_{fin} is a finishing time)

   (a) each k $(1 \leq k \leq K)$

      i. Update the x^k following a prediction equation (Eq. (4.5)).

      ii. Calcurate a likelihood $L(x^k, \boldsymbol{y}_t)$ of particle k from RSSI vector $\boldsymbol{y}_t$ observed at time t and multiply the weight of each particle by L.

      $$w^k \leftarrow w^k \times L(x^k, \boldsymbol{y}_t)$$

iii. Decide an estimation location based on Eq. (4.3).

(b) Carry out the following processes when a variance of $\{w^k\}$ falls below a threshold.

i. Calcurate W followed by Eq.(4.4).

ii. Extract the particle left next step by probability $\frac{w^k}{W}$.

iii. Each k $(1 \leq k \leq K)$

$$w^k \leftarrow 1$$

(c) $t \leftarrow t + 1$

4.2.6 Prediction

This study suppose a target location x_t is following a simple random walk and uses the following equation as prediction.

$$x_t = x_{t-1} + \eta_t \tag{4.5}$$

, whereη_t is random variable generated by $\eta_t \sim \mathcal{N}(\cdot|0, \sigma_\eta^2)$. $\mathcal{N}(\cdot|0, \sigma_\eta^2)$ is a normal distribution that an average is 0 and a variance is σ_η^2.

4.2.7 Likelihood function

Next, this section shows the likelihood function based on fingerprint used by [Evennou 06].

$$L(x, \boldsymbol{y}) = \frac{1}{\sqrt{2\pi}\sigma_\epsilon} \exp\left[-\frac{\parallel x - X_{\boldsymbol{y}} \parallel^2}{2\sigma_\epsilon^2}\right] \tag{4.6}$$

, where $X_{\boldsymbol{y}}$ is a result of k-NN based localization when a RSSI vector $\boldsymbol{y}$ is observed. This function is a normal distribution centering the result of k-NN localization, where σ_ϵ^2 is a given variable.

4.3 Performance Tests

This section researched the performance of ZigBee particle filter to indoor localization.

First, this study measured a RSSI using a measurement unit and made a fingerprint data. Then, this study performed two simulations and one real data tracking with particle filter. Finally, this paper assumed a real application and demonstrated an all day tracking.

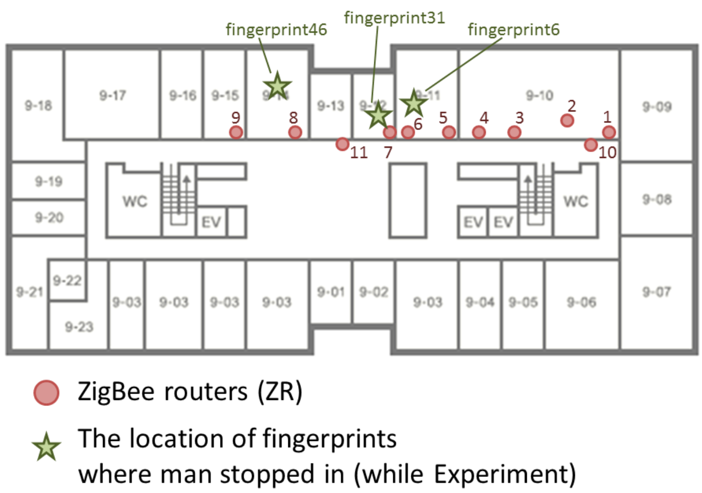

Figure 4.1: Test environment (the laboratory floor)

4.3.1 System components and router setting

9 ZigBee routers (ZR: Telegesis ETRX2 ethernet access point) were deployed in this floor (Fig. 4.1) All ZR connects to a server machine via ethernet.

ZigBee end device (ZED: Telegesis ETRX2USB), which is moving with someone, sends a packet to ZRs at a regular interval (100ms). ZR installed in indoor space can receive this packet and measures its RSSI. ZR hops Measured RSSI to the server machine via ethernet. The server machine receives the RSSI data and calculates the location of the ZED.

Figure 4.2: ZigBee routers; ZR 1 is right in 9-10, ZR 8 is right in 9-14

Figure 4.3: Measurement unit for measuring fingerprints

4.3.2 Measurement of fingerprints

This study measured the fingerprints using measurement unit (Fig. 4.3). A measurement is 50 data. (100ms * 5sec) One measurement is performed at each 86 locations. Each fingerprint was given by avaraging the measurement.

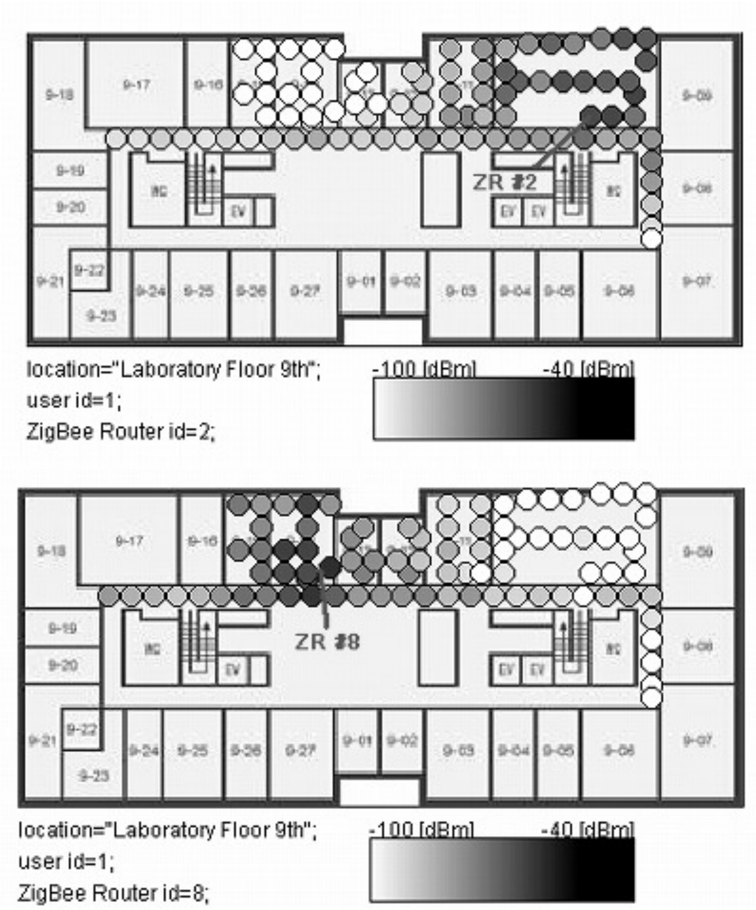

Figure 4.4: Pre-measured fingerprints in laboratory floor on ZR 2 and ZR 8

4.3.3 Experiment 1: simple positioning test on the sampling points

Testdata 1: simulation under noiseless situation

First, this experiment shows a localization error of particle filter to a testdata, which is composed of a fingerprint measured in section 4.3.2. This experiment made the following 88 testdata.

Testdata i ($\{i = 0, 1, 2, ..., 88\}$):

FOR $t = 0$ to 100 every 0.1 [meter] $\{y_i(t) := \bar{y}_i\}$

Parameters of a particle filter is Table. 4.1 in this experiment. Left of Fig. 4.5

Table 4.1: Parameter set for particle filter.

name of parameters	value
Number of particles	1000
Interval of localization	0.1 [sec]
Initial σ_η	1.0
Initial σ_ϵ	4.0
Number of fingerprints	86
Number of neighbors averaged (k)	9
Resampling threshold	10^{-20}

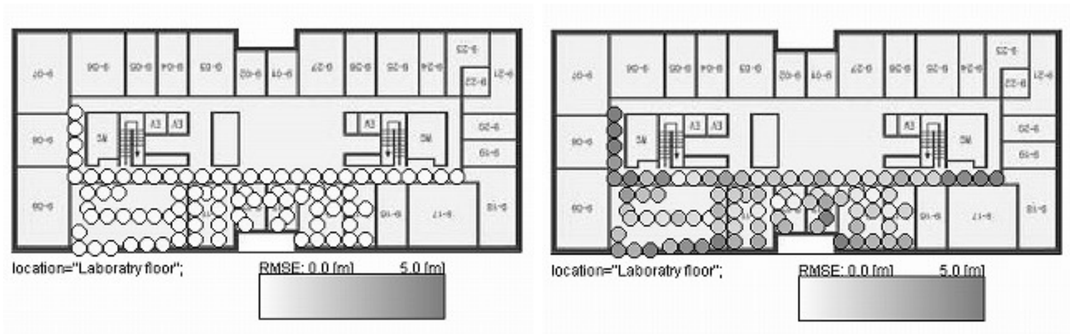

Figure 4.5: RMSE on each point where fingerprint is measured: left is noiseless data, right is noisy data(+-2[dBm])

shows each of 88 results of this experiment.

Testdata 2: simulation under noisy situation

Fingerprint data in Section. 4.3.2 has a dispersion of a range due to some of reasons, then this experiment add a noise of a normal distribution to the 88 fingerprints. This experiment made the following 88 testdata.

Testdata i ($\{i = 0, 1, 2, ..., 88\}$):

FOR $t = 0$ to 100 every 0.1

$\{y_i(t) := \bar{y}_i + \eta_t, \eta_t \sim \mathcal{N}(0, 2.0^2)\}$

Parameters of a particle filter is same of Section 4.3.3 in this experiment. Right of Fig. 4.5 shows each of 88 results of this experiment.

Testdata 3: real measurement data

This experiment used a testdata, which is composed of a RSSI measured by a end device which is carried. A result of this experiment is compared with the results of the simulation (testdata 1 and testdata 2).

I was carrying a ZigBee end device and measuring with timing. (Fig. 4.6 (photo), 4.7 (result of localization)) A pathway in this experiment is the followings.

1. rest on fingerprint 3 for 20 seconds.
2. move from fingerprint 3 to fingerprint 31 at 20 seconds.
3. rest on fingerprint 31 for 20 seconds.
4. move from fingerprint 31 to fingerprint 46 at 20 seconds.
5. rest on fingerprint 46 for 20 seconds.
6. move from fingerprint 46 to fingerprint 31 at 20 seconds.
7. rest on fingerprint 31 for 20 seconds.
8. move from fingerprint 31 to fingerprint 3 at 20 seconds.
9. repeat from 1 to 8 twice, and then execute 1.

Localization error was calculated as follows.

- fingerprint 3: RMSE of three data of "1."
- fingerprint 31: RMSE of three data of "3." and three data of "7."
- fingerprint 46: RMSE of three data of "5."

Result of particle filter in this experiment is Fig. 4.7.

Figure 4.6: A carried ZED node for measurement of test data 3 in experiment 1

Table 4.2: Performance of particle filter on three fingerprints.

RMSE [m]	noiseless simulation	noisy simulation +-2[dBm]	real measured data
fingerprint 3	0.206	1.989	1.693
fingerprint 31	0.219	1.405	0.957
fingerprint 46	0.186	1.388	3.498

4.3.4 Experiment 2: tracking test with one day measurement

This section demonstrates a performance of a localization in real application. This experiment had a person in the laboratory carrying an end device (Fig. 4.8) and measured RSSI all the day.

After that, we heard his actions in that day by questionnaire. The part of his actions are the followings.

1. started the measurement at 10:41.
2. worked in 9-12, basically.
3. visited point A at 11:36.

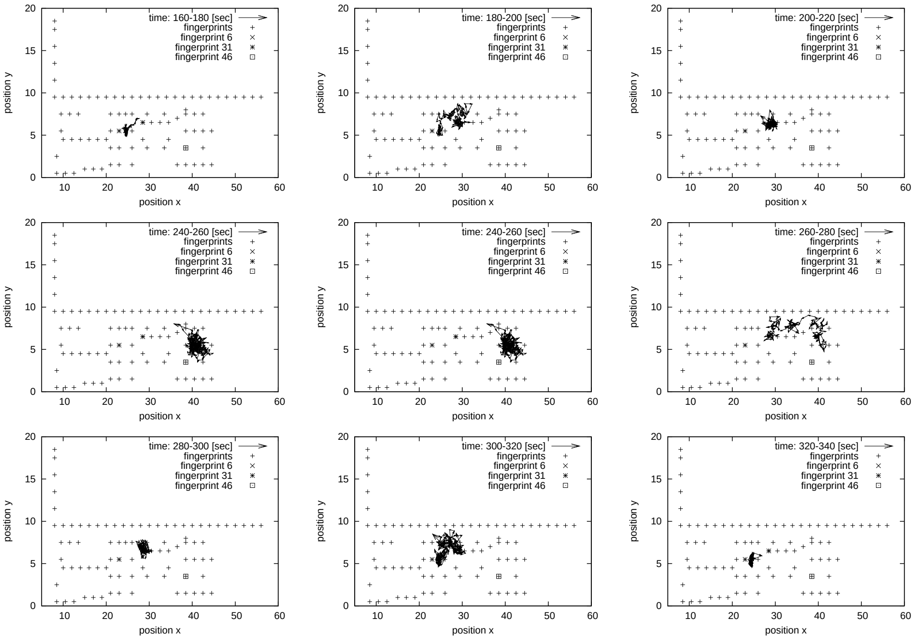

Figure 4.7: Results of localization in experiment (t=160-340msec)

4. had a meeting in 9-11 from 13:31 for a while.

5. had a meeting in 9-14 from 19:40 to 20:10.

6. finished the measurement at 20:14.

Except this, he was almost always working in 9-12.

The result of testdata 1 shows the fingerprints of this experiment can be distinguished unless it is in noisy situation.

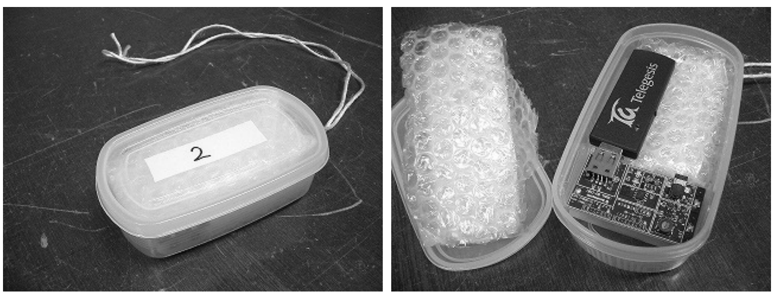

Figure 4.8: A carried ZED node for measurement in experiment 2

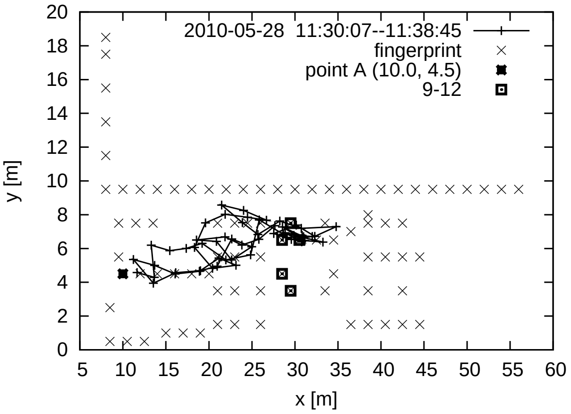

Figure 4.9: Result of all day tracking (experiment 2) from 11:30:07 to 11:38:45

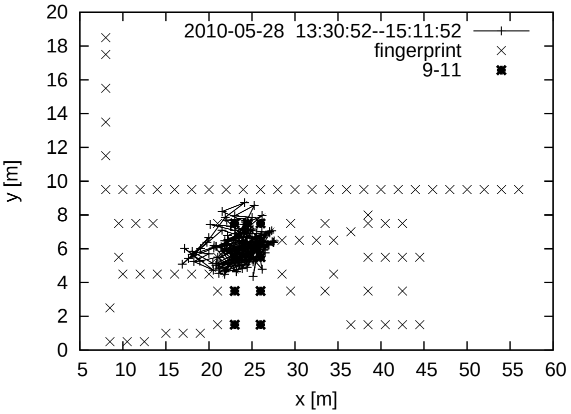

Figure 4.10: Result of all day tracking (experiment 2) from 13:30:52 to 15:11:52

However, a real situation is noisy. Then, the result of testdata 2 simulates the localization error in noisy situation. There exist some fingerprints whose localization error is smaller than 2.0 meters, whereas there exist some fingerprints whose localization error is larger than 5.0 meters in noisy situation. Localization error of fingerprint 3, 31 and 46 is at least smaller than 2.0 meters in this situation.

Whereas the result of testdata 2 shows the localization error in "simulated situation" which considers observation error (as normal noise), the result of testdata 3 shows that in "real situation". The localization error are smaller than 2.0 meters in both fingerprint 3 and fingerprint 31, where each of fingerprints can be distinguished

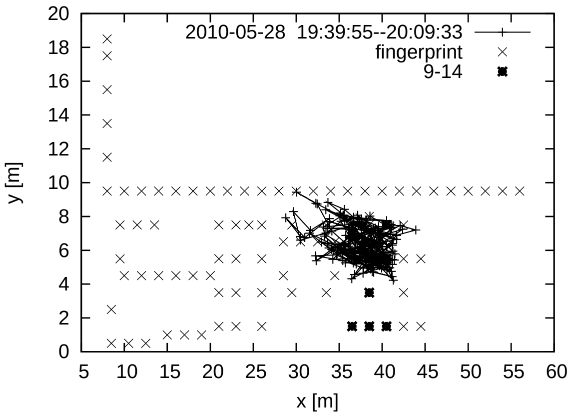

Figure 4.11: Result of all day tracking (experiment 2) from 19:39:55 to 20:09:33

in even a real situation. On the other hand, a localization error of fingerprint 46 is larger than 2.0 meters. Therefore, the RSSI is affected by some reasons (such as a experiment person), the impact of which is harder than that of the normal noise in this situation.

Then, in the result of experiment 2, Fig. 4.9 can point out a person, who has end device, has been visiting the point-A then. Also, 4.10 and 4.11 can correctly guess the person has been around 9-12 and 9-14 then. Therefore, this method can localize a moving target with an area levels localizarion.

4.4 Solution of layout optimization

4.4.1 Flow of searching fingerprints and routers layout

This section discusses about the former discovery method of fingerprints and routers layout.

In formal discovery methods, it is essential to repeat the following instractions.

1. locate (relocate) routers in real environment
2. measurement (re-measurement) of fingerprints
3. measurement (re-measurement) of test data

4. positioning trial and error estimation

Then,the set of placeable fingerprint location is defined as $F_{locatable}$, and the set of placeable router location is defined as $R_{locatable}$, the relocation and re-measurement number $O(2^{|F_{locatable}|+|R_{locatable}|})$ becomes in exponential order.

4.4.2 Improved flow of layout optimization

Since we pointed out a problem of the number of re-measurement in the precending section, we made an assumption as the following in order to reduce the number of re-measurment and realistically search.

First, there is a limitation of the arrangment of fingerprint and router and the search is carried out with the arrangment decieded in advance. That is, $|F| = |F_{locatable}|$, $|R_{locatable}|$.

In the case of router, this assumption can be understood from the physical limitation by the power receptacle. In the case of fingerprint, considering the movable physical location for humans the assumption can be thought appropriate.

In view of this, this chapter proposed the following flow. First, router and fingerprint is placed at all the placeble position and measured in advance with this arrangment. Next, modification is made on the measurment of the test case. Normally, there should be a measurement on the test case corresponding to each fingerprints and routers layout. However, since measurment is needed everyime for the test case, this becomes a bottle neck in this method. This time, seeing that only the order relation of the error of the fingerprints and routers layout is important, the accracy does not have to strictly match with the real enviroment. Therefore, spurious test case based on measered fingerprints value is substituted for the test case. Specifically, in regard to the vector value of each measured fingerprints, the model of RSSI measurements affected by crowd behavior obtained on Chapter 5 which is deformed is used as test case. That is, when i-th fingerprint of RSSI vector is defined as $\boldsymbol{Y}_i = [Y_{i1}, Y_{i2}, ..., Y_{ij}, ..., Y_{iM}]$, we correct the RSSI vector value $\boldsymbol{Y'}_i = [Y'_{i1}, Y'_{i2}, ..., Y'_{ij}, ..., Y'_{iM}]$ effected by crowd behavior as the following.

$$Y'_{ij} = Y_{ij} + \epsilon \tag{4.7}$$

Where, ϵ is normal noize, is created by ϵ $N(\cdot|\mu, \sigma^2)$. μ is bias and σ^2 is variance modeled by Chapter 5. Test case $\boldsymbol{T}$ is lined up created as following.

$$\boldsymbol{T} = [\boldsymbol{Y'}_1, \boldsymbol{Y'}_2, ..., \boldsymbol{Y'}_K] \tag{4.8}$$

K is the number $|F|$ of fingerprints.

There is a concern whether the order relation between the accuracy of the measurment obatined here with the test case and the accuracy of the measurment using real measurment test case is kept. There is a need to discuss this and is a interesting assumption.

This concern will be discussed at the last experiment by using an actuall measured test case.

4.4.3 Formulization of optimization problem

Evaluate function and constraints of layout optimization problem are formulized by the following equations.

$$\begin{array}{ll} \min_{f,r} & RMSE(\boldsymbol{T}, fingerprinting(\boldsymbol{F}(f,r), \boldsymbol{I}(f,r))) \\ s.t. & f \in 2^F \\ & r \in 2^R \end{array} \tag{4.9}$$

Here, $\boldsymbol{T}$ is the correct data, $\boldsymbol{F}(f, r)$ is a set of fingerprint with the value of corresponding section deleted by f, r, $\boldsymbol{I}(f, r)$ is a test case with the value of correspoinding section deleted by f, r.

4.4.4 Genetic algorithm

Here, the optimization problem in the above will be solved using Genetic Algorithm (GA).

Gene is defined as *gene* and the size if $|F| + |R|$ and each has the value of $\{0, 1\}$. Interpretation of the value is as below.

$$gene[i] = \begin{cases} \begin{cases} 1 & (\text{using } \ i-th \ \text{ fingerprint}) \\ 0 & otherwise \end{cases} & (0 <= i <= |F|) \\ \begin{cases} 1 & (\text{using } \ (i-|F|)-th \ \text{ router}) \\ 0 & otherwise \end{cases} & (|F| <= i <= |F| + |R|) \end{cases} \tag{4.10}$$

This chapter uses a simple method for GA. Namely, this chapter uses a combination of elite-selection and roulet-selection for selection, one-point crossover and simple mutation.

Regarding the parameters of GA, the adequete value in the following was used considering the variou experiment held in advance.

Table 4.3: Parameters of genetic algorithm.

name of parameters	value
Generations	1000
Number of genes	200
Length of gene	162 (=143+19)
Probability of elite selection	0.1
Probability of cross over	0.3
Probability of mutation	0.15

Table 4.4: Parameters of k-nearest neighbors.

name of parameters	value
Number of neighbors (k)	4
Number of test data trials	100

4.4.5 Result

This section shows four results of genetic algorithm.

This section has observed a pre-measurement data in a test environment as Fig. 4.12. 144 fingerprints and 19 routers was located in the environment as the figure.

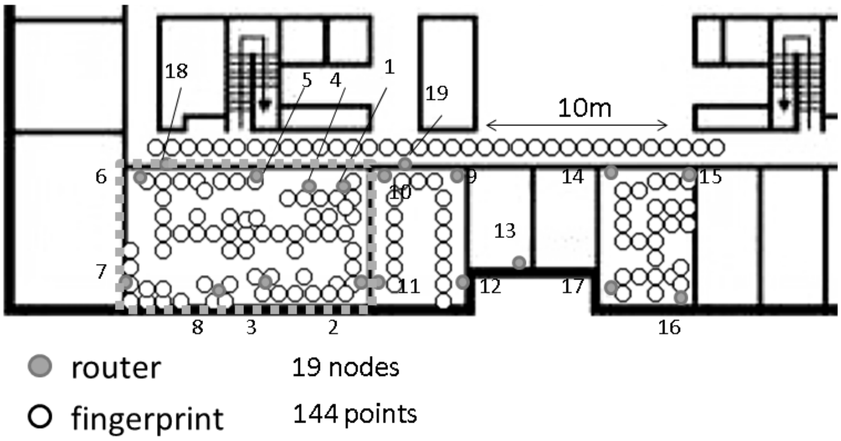

Figure 4.12: A test environment for fingerprints and routers optimization.

This section applies a genetic algorithm to the following two patterns as a mobility assumption of users and compares two results of them.

1. Users can move all office areas. (whole testdata)
2. Users can move only a room enclosed by a broken line. (testdata in single room)

Initial gene was given by the following two patterns.

1. All initial values of genes are "1". (all 1 start)
2. All initial values of genes are given in a random manner. (random start)

As a result, both results are similar after 1000 steps.

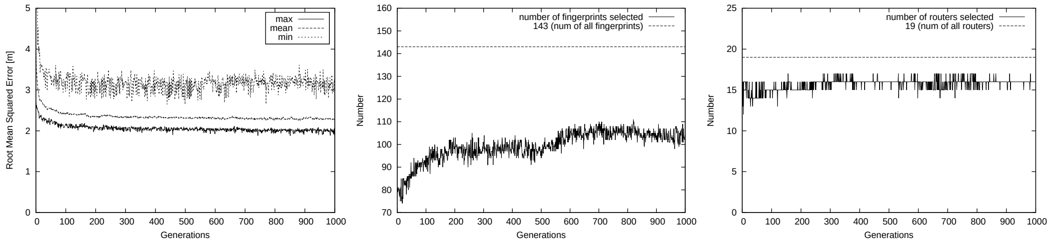

Figure 4.13: Learning curves of GA. Random start and using Whole testdata. (left: generation vs. error, center: generation vs. number of selected fingerprints, right: generation vs. number of selected routers)

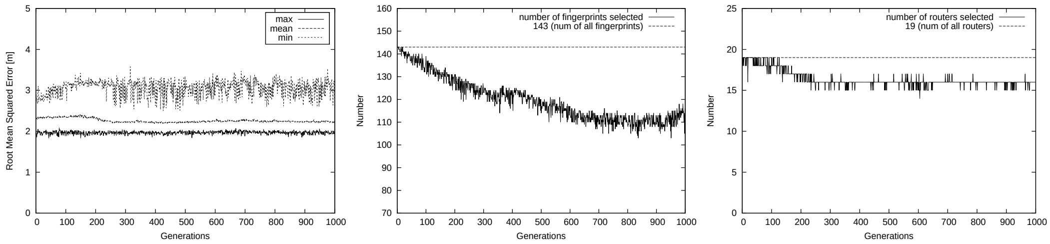

Figure 4.14: Learning curves of GA. All 1 start and using Whole testdata. (left: generation vs. error, center: generation vs. number of selected fingerprints, right: generation vs. number of selected routers)

We carried out an experiment using all the fingerprint as test case. Then used GA on the result and selected the best individual according to the evaluation value and selected fingerprints and routers. Figure 4.17 shows this.

On the other hand, we used the test case of using only fingerprint of one room and used GA on the result and selected the best individual according to the evaluation value and selected fingerprints and routers. Figure 4.18 shows this.

From this result, compared with Figure 4.17, the way of selecting fingerprint and router tend to differ.

For example, routers of room 9-10 which were not selected in Figure 4.17 were seleted in all of Figure 4.18.

On the other hand, routers of room 9-14 which were all selected in Figure 4.17 were only selected of one out of 4 in Figure 4.18. This shows that the test case using

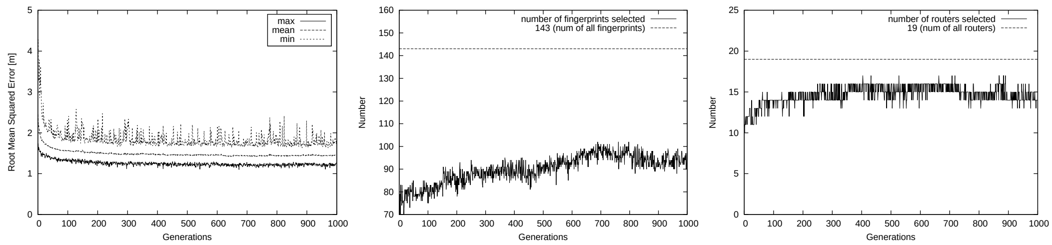

Figure 4.15: Learning curves of GA. Random start and using testdata in single room. (left: generation vs. error, center: generation vs. number of selected fingerprints, right: generation vs. number of selected routers)

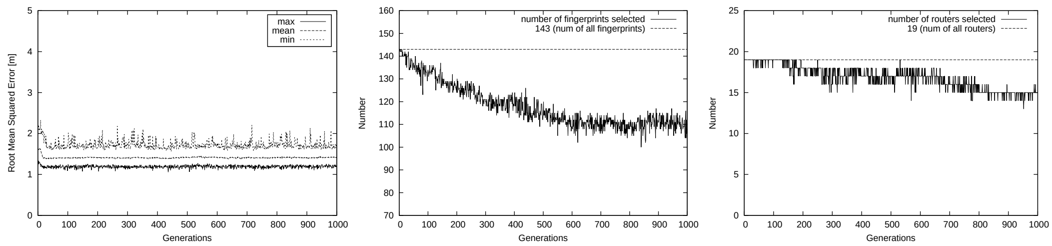

Figure 4.16: Learning curves of GA. All 1 start and using testdata in single room. (left: generation vs. error, center: generation vs. number of selected fingerprints, right: generation vs. number of selected routers)

the surrouding of the domain are favorably selected.

As well as regarding fingerprints, it can be seen that the trend differs in two cases.

What's interesting is that, when only room 9-10 was used, the 12 fingerprints of a far room such as room 9-14 were continuously selected. From this, fingerprints and routers which are far away do not neccasary mean it is not needed.

4.5 Discussion

Analyzed how much contirbution is made by the fingerprints and routers excluded by the selection of GA.

From this result, we found out that fingerprints and routers not-selected by GA

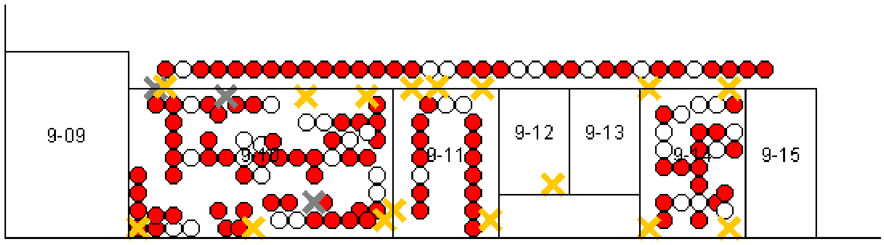

Figure 4.17: Result of GA using whole testdata. Selected fingerprints and routers. After 1000 generations.

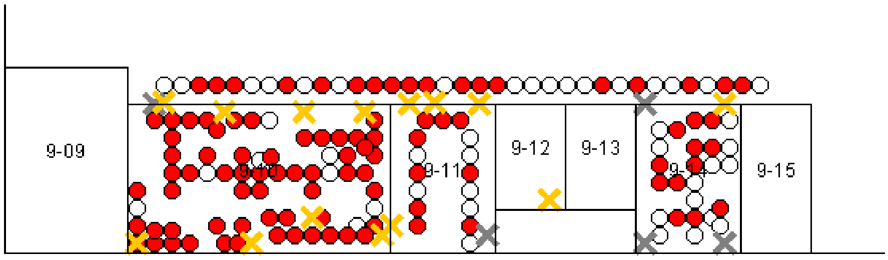

Figure 4.18: Result of GA using testdata in single room. Selected fingerprints and routers. After 1000 generations.

has a detoration of accuracy or has barely no effect compared to fingerprints and routers selected by GA.

Moreover, from the comparative experiment against the deviation of test case of experiments, we found that the selection does not always depend on the distance from the test case.

It was found that not always did the room with the most distance become reduced primarily.

Fingerprints and routers of room 9-14 were continuously selecetd and had nearly the same accuracy improvment contribution compared with fingerprints and router using other test cases with a closer positions especially in the case of room 9-10.

Regardless that there is a tendancy by location, to correctly select fingerprints and routers which give severe effect on the accuracy of positioning, there is a need not noly to select from location but also analyzation is essential based on pre-measurement data such as our research.

4.6 Conclusion

In this chapter, an optimization problem is formularized to minimizes RMSE of a positioning system by using two variables (layout of fingerprints and routers). The author proposed an optimizing method based on GA. Moreover, the author proposed a method to optimize layout of fingerprints and routers dinamically.

Chapter 5

Effects of Crowd Behavior on Performance of Fingerprinting Based Indoor Positioning System

5.1 Introduction

Recently, advancement of urbanization in many parts of the world and global population is increasing, various crowd phenomena has been remarkable in public space. Crowd phenomena often contains a lot of matter in terms of public institution and transportation use, crowd related disaster, and so on [Helbing 07]. Change point of view, finding difference between daily sight and extraordinary scene in public space has a lot of value. Because of above, crowd behavior analysis and detection have received attention from social and technical research [Zhan 08]. A lot of method have been proposed about crowd analysis and detection. S.Saxena et al. proposed a method of crowd behavior recognition using video [Saxena 08]. J.Cui et al. suggested laser-based detection and tracking of people, they overcome tracking errors [Cui 07].

And now, to acquire crowd analysis, detection or behavior information, not only contracted view-point such as one of the room in the building structure but also wide vision such as whole building structure is required as well. However, using camera, video or laser range finder enable us to get a lot of information about crowd, but unit cost is high, so detecting and tracking of crowd in large space is not realistic using their method. Additionally, crowd detection and analysis method using camera or video have a privacy issue, it can't be applied to public infrastructure.

Consequently, we suggest a method for solving the above problems. To describe the detail, we use the ZigBee's RSSI data from its electromagnetic wave, analysis it and attempt to acquire crowd behavior from the macro view-point.

In order to do above this, this paper shows about what crowd behavior is like in indoor space, metering experiment to find out whether ZigBee's RSSI fluctuate by crowd behavior in indoor space and the possibility of estimation of crowd behavior.

5.2 Relationship between crowd behavior and RSSI

This section is described about ZigBee's overview and influence on ZigBee's RSSI from crowd behavior. ZigBee is the standard of wireless sensor network as IEEE802.15.4 for controlling of instrumentation and it is expected to use for home automation system, indoor positioning system, and so on, so many studies focus on this technology actively [Sugano 06, Grossmann 07]. ZigBee is disadvantageous in slow data transmission rate, while it gives an advantage on low cost. ZigBee is also use a frequency band of 2.4GHz, so it is manageable because of unnecessary license for using electromagnetic wave.

It is already known that ZigBee's RSSI using frequency band of 2.4GHz is influenced by human body [Youssef 07, Nakatsuka 08]. Here, we show Fig. 5.1 which indicates RSSI difference between existing a crowd and no existence of it.

This figure is the graph with RSSI on the y-axis and time on the x-axis. This figure shows the result of the fluctuating data, that is, ZigBee's RSSI hardly changes in no existence of crowd, but in dynamic environment with crowd it fluctuates wildly. This different would be caused that difference of electromagnetic wave absorption rate on the human body, rate of screening electromagnetic wave path with crowd and environment change from dynamic crowd. Basically, an indoor space tends to be a multi-path environment. Multi-path is defined as the electromagnetic wave path

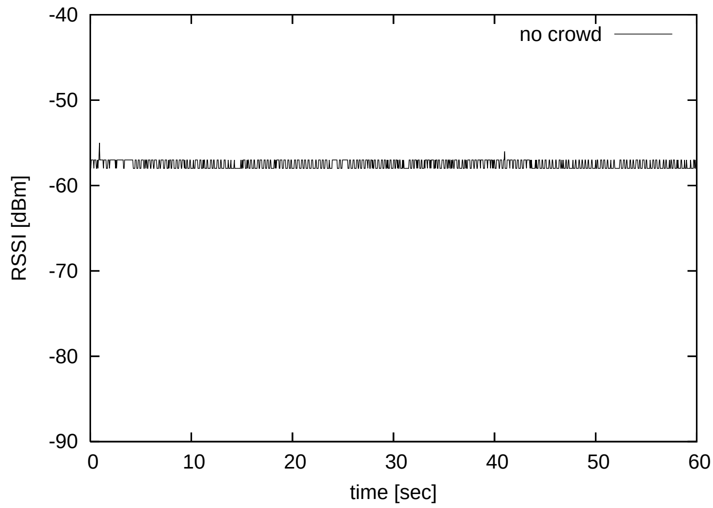

Figure 5.1: Time-series data from ZigBees RSSI without crowd.

produced by direct wave mixing with indirect wave such as reflected wave, diffracted wave, transparent wave and etc. In such as ratio wave environment, environmental changes have an influence on ZigBee's RSSI in that. That is to say, RSSI would fluctuated by pattern of crowd behavior. In light of the above discussion, we define the pattern of crowd behavior in indoor space.

5.3 Evaluation flow of indoor positioning system affected by crowd behavior

An affection of RSSI and RSSI-based positioning by crowd behavior has not been clear. And then, it is difficult to evaluate the affection in real crowds, and this evaluation has not reproductivity besides.

This chapter would like to develop a estimation method of positioning accuracy precisely while using a virtual environment in crowds.

Therefore, this chapter proposed the following simulation model (Fig. 5.3).

This method constructs a test data artificially based on pre-designed affection

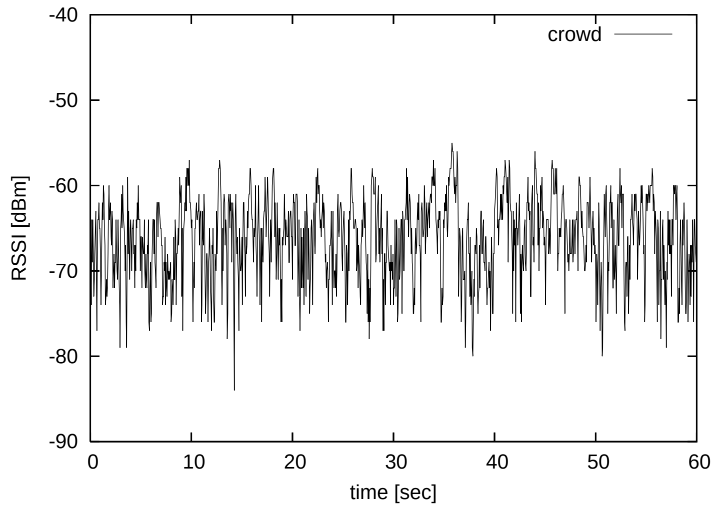

Figure 5.2: Time-series data from ZigBees RSSI with crowd.

model.

In the following sections, crowd behavior patterns will be categorized as parameters for measurements of our proposal.

5.4 Definition of crowd behavior patterns

We discuss in what it is like crowd behavior in indoor space in this section. Crowd behavior has a lot of natures, such as static or dynamic, high flow or low flow, constant direction or various directions and so on [Polus 83]. As main measures that separate crowd behavior, we define the density, the velocity and the disorder.

5.4.1 Density

A population density is defined as head-count per unit area. M is a limit of the population density in general indoor spaces. It is known that $1/M$ is smaller than 0.5 [Polus 83]

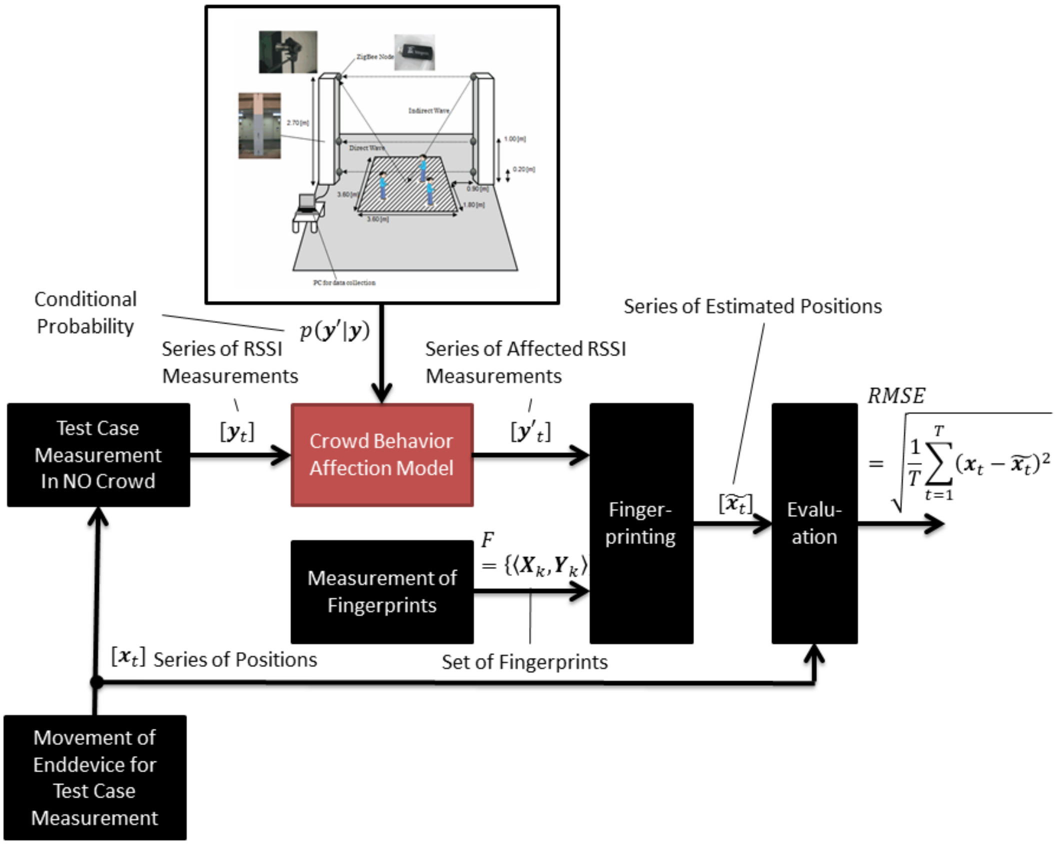

Figure 5.3: A diagram of a simulation model on crowdbehavior affection.

5.4.2 Velocity

Some of crowd phenomena include flowable pedestrian. Here, we define velocity as separation of crowd behavior instrumentally. If the velocity equals 0[m/s], this indicates static environment. We think of the maximum of velocity as value of 1.2[m/s], which is velocity close to brisk walking pace, so we consider the range of the velocity of 0[m/s] to 1.2[m/s] in this study.

5.4.3 Disorder

Dynamic crowd behavior move various direction which is one or two flow like single-aisle or three or more flow like open space. Where we express the degree above described as the disorder and we define that the disorder indicates considerable variation of collective behavior. We also define that the disorder is described by the velocity vector distribution. From above definition, the uniform distribution leads to that the disorder is more higher, by contrast the biased distribution leads to that the disorder is more lower under the velocity constant condition. In addition, no distribution equals static environment.

From the above, we define a pattern of the crowd behavior in indoor space, specifically we split the density into five patterns (1, 2, 4, 8, 16[head] per 3.6   3.6[m2] as experimental area), the velocity into three patterns (0, 0.7, 1.1[m/s]) and the disorder into three patterns (0, low, high) because of making an experiment more effectively. Here pattern of the disorder which its level is high is shown by 5.2, and which is low. As above, we can split crowd behavior in indoor space to 25 patterns if disorder's degree of 0 is equivalent to velocity's' value of 0[m/s] and treat characteristic of crowd behavior as feature amount of it.

5.5 Experimental

We make an experiment of measuring ZigBee's RSSI on the assumption that the crowd behavior patterns from the above for all practical purpose under actual indoor environment. This section shows what to use equipment, how to make a choice experimental environment and how to measure this experiment.

5.5.1 Instruments

As conducting the experiment, because of superiority of general-purpose properties and user-friendliness on the point of USB standard, compact size and ease of setting, we choice a wireless communication device of Telegesis LTD for ZigBee modules named ETRX2USB. This device enables us to access it and to configure advanced setting using serial communication. In what follows, we describe ETRX2USB as ZigBee terminal.

About the object ZigBee terminal fixed on, we made the pillar of Styrofoam and polystyrene foam on ground that these materials are easy on the wallet, are easily-worked and have the nature which these permeability of the electromagnetic wave is nearly equal to that of air. That is, this pillar will be less affect to the electromagnetic wave.

The structure of communication is composed of three pair, that is, six ZigBee terminals. About the pair of the ZigBee terminals, the one is a part of sender, the other is a part of receiver and each terminal communicates with one-to-one. In the experiment, the terminal communication method is a relatively-stable unicast communication because if that is multicast communication, overhead traffic will increase by getting back response such as ACK and communication will become unstable from the congestion by shortening communication interval. In addition, it is more desirable that acquisition data of ZigBee's is precise per each pattern of crowd behavior. So we set 50[msec] as the communication interval excluding the congestion and the communication delay by the results of preliminary experiments.

On the other hand, ZigBee standards use a frequency band of 2.4 GHz, so its communication quality is possible to drop with interference because wireless LAN, Bluetooth and so on also use it. More over, the frequency bandwidth of ZigBee standards is more narrow than that of wireless LAN. As increasing communication under the same channel assignment, it is possible that the ZigBee terminals cannot communicate with each other. With this in mind, we setup its channel with each pair to circumvent the effect of dropping communication quality from the results of preliminary experiments.

5.5.2 Environment

As actual environment, we measure the ZigBee's RSSI in the lounge of 9th floor, building of Information Science and Technology, Hokkaido University (Fig. 5.4).

This environment has the open ceiling structure and the ceiling of height is twice as high.

In this environment, we fixed the ZigBee terminals on the heights of 0.2[m/s], 1.0[m/s] and 2.7[m/s]. Especially, 2.7[m/s] high is one of the common ceiling as

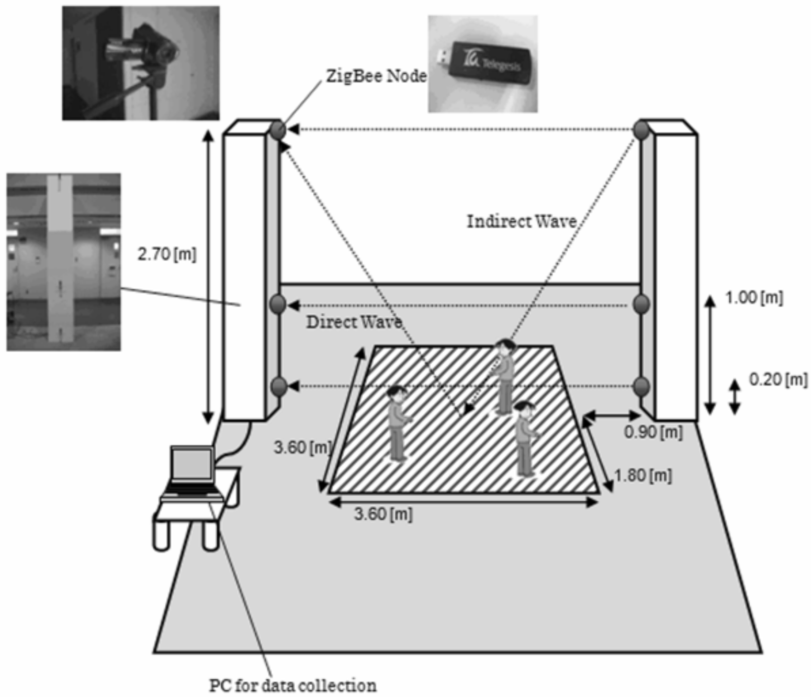

Figure 5.4: Measurement environment to evaluate a crowd affection.

architectural attribution, so we adopt it from some height of ceiling.

Here, we have an assumption that data of ZigBee's RSSI is different each height of the ZigBee's' terminal attached to the pillar. About the communication with the ZigBee's pairs of 0.2[m/s] and 1.0[m/s] high, it would appear that the direct wave and the indirect wave are interrupted by the crowd behavior. Meanwhile, about its of 2.7[m/s] high, it would appear that only indirect wave is interrupted by the crowd behavior. Each ZigBee terminal, that is the ZigBee pair, attached in same height communication with each other exclusively by separating their network from other.

All ZigBee terminals are connected through the USB cables because of reducing influence of electromagnetic wave from computer to collect the data. The ZigBee terminals attached to the right pillar are connected to a power source and to the left pillar are connected to the computer. The left-sided terminals forward packets to the right-sided terminals, while the rightsided terminals measure the RSSI between the left-sided and the right-sided, and send the buck packets with the RSSI data to the left-sided.

To analyze the crowd behavior itself, we track the appearance of the experiment with the digital camcorder.

5.5.3 How to measure

To get things start, we describe the point of innovation to get what one wants the crowd behavior each feature amount.

About the velocity, 0.7[m/s] and 1.1[m/s], we assume that the length of stride of pedestrian equals 60[cm] approximately and we aim to become that the collaborators walk at an ideal speed to use the electronic metronome from the computer.

About the disorder, it's' considered that the disorder which we want to obtain is achievable to comply with walking such as Fig.regular or Fig.irregular. Consequently, we aim to become that the ideal disorder can be obtained by pasting the vinyl tape along a walking route in experimental area and by guided on the collaborators to walking along a pasted vinyl tape. Nonetheless by the configure of the above description, it will become that the feature amount of the velocities and the disorders cause the differences between real data and ideal one. There we verify and hove correct for these feature amounts to extract these real data from the video files provided by the digital camcorder using a tracking algorithm with a computer vision program. For improving detection of tracking, the collaborators wear a white coat and a red cap. Additionally, in this experiment, we peg the measurement time at 3[min] per pattern of the crowd behavior.

5.5.4 Result of measurement

On the basis of these configurations, we measure the data of ZigBee's RSSI with 25 patterns of the crowd behavior. The data of it about terminals attached to 1.0[m] high, the horizontal axis is the density per experimental area and the vertical axis is the velocity and the disorder degree. Here, the result of computer vision program appears that 0.7[m/s] is altered 0.5[m/s] and 1.1[m/s] is altered 0.7[m/s] approximately about the velocity.

This figure indicates that static environment has hardly a lot of ups and downs, whereas dynamic environment undergoes significant RSSI fluctuation against time. Perhaps this result suggests the possibility that screening of electromagnetic wave propagation path from the crowd behavior causes the shift of multi-path environment and human body absorbs electromagnetic wave. This figure also indicate that increasing in the crowd density more fluctuates the RSSI data than decreasing in it. It would appear that the rate of screening of electromagnetic wave propagation path is likely to increase and the variance of multi-path environment severe changes according to increasing in crowd density, so this kind of outcome would is produced. Additionally, the more increasing in the crowd density, the more increasing in the amplitude. This change can be the average of robustness of electromagnetic wave path runs down with increasing the crowd density.

As just described, in some pattern of the crowd behavior, there is a characteristic wave form of the ZigBee's RSSI, so it is expected that it is possible to estimate the crowd behavior using the ZigBee's RSSI. To move discussion forward, we describe analytical method to extract feature amount of the crowd behavior in each pattern in next section.

5.5.5 Result of positioning

As a result, this chapter showed bias value is not large in crowds. Then, variance is a constant value in all cases in which a population density is larger than 0.3 [m^2], this chapter also revealed. Therefore, we can regard a probability of RSSI in crowds as the following model.

1. Bias of RSSI time step equals to zero.
2. Variance of RSSI time step equals to 25.0 [$(\mathrm{dBm})^2$].

This chapter conducted a positioning test to test data in these situations. Concretely, this chaper generate a test data by adding a normal noise to a pre-observation

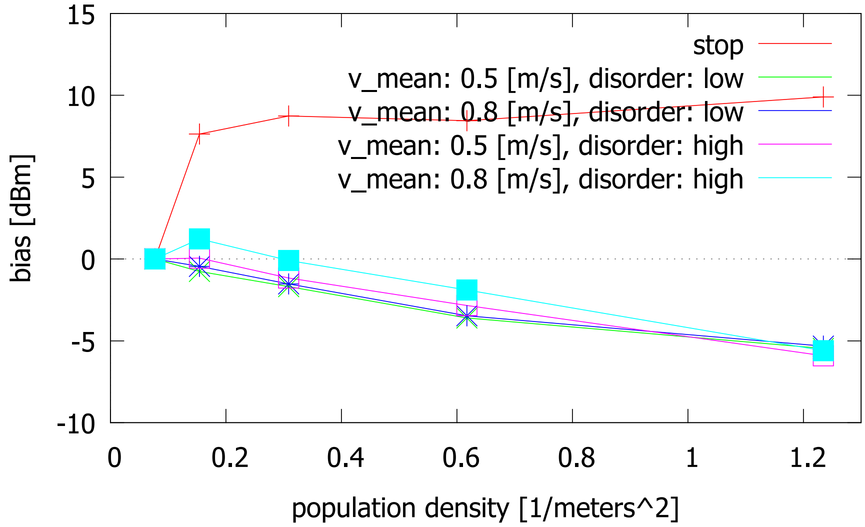

Figure 5.5: Affection of population density on RSSI bias in direct wave.

data in no crowd. Next, positioning simulations are conducted to the test data by using particle filter estimation. Then, the normal noise was 0 of mean and 25 [$(\text{dBm})^2$] of variance from those results.

This chapter demonstrated a positioning trial to a test data (Fig. 5.9). RMSE of the trials to the test data was 1.38 meters average and this fits within a tolerance. In this manner, this chapter proposed an method which estimates a positioning error by using a simulated test data based on a detailed measurement of RSSI in a real field.

5.6 Discussion

In the 25 patterns of the crowd behavior, this chapter suggested a data analysis method which is the time series analysis and the frequency analysis to set the crowd behavior apart from the ZigBee's RSSI data. This chapter made a choice the calculation of the RSSI's average, the variance and the median as the time series analysis and the discrete Fourier analysis as the frequency analysis. The radar charts which these method plotted (Fig. 5.10).

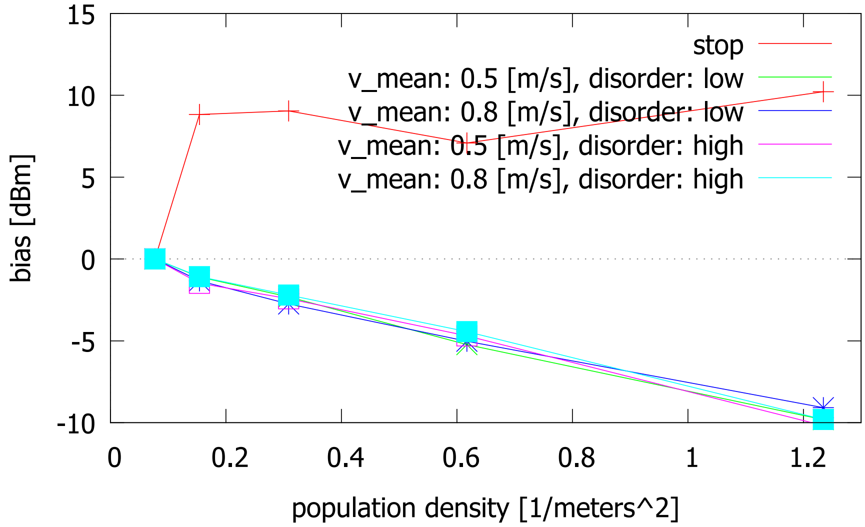

Figure 5.6: Affection of population density on RSSI bias in reflection wave.

About these figures, the horizontal axis stands for the crowd density per the experimental area and the vertical axis stands for the velocity and the disorder. Regarding radar chart, "ave" stands for the average, "var" stands for the variance, "med" stands for the median and "f1" to "f5" stands for the value of averaging Fourier spectrum per 300 of the frequencies to enhance repeatability. The RSSI data of the ZigBee terminal is attached to 1.0[m] high. Also that is attached to 2.7[m] high.

There is the evident that the variance in case of the static environment is extremely low, while the dynamic environment have the high variance relative to the static it. This is attributed to the fact that the multi-path environment and the electromagnetic wave path varies continuously according to the moving crowd. The more increasing crowd density, the more change the value of average gradually. It would appear that the rate of screening electromagnetic wave path which is robustness lead to this result. Furthermore, as growing velocity, the tendency has been to increase f1 and f2. This result is expected to guide by the reason which the RSSI data of the pattern with high velocity contains various frequency component and the electromagnetic wave path is very unstable. Though we cannot extract feature

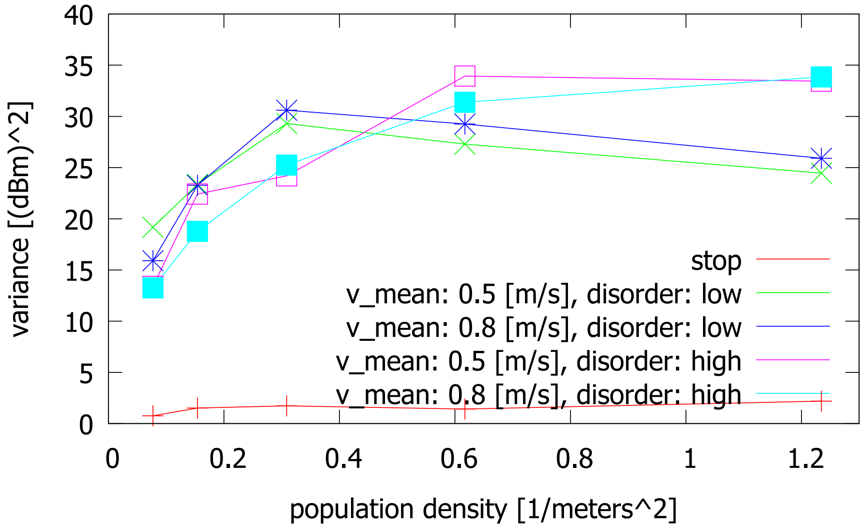

Figure 5.7: Affection of population density on RSSI variance in direct wave.

of the disorder, so we need to other method to extract it.

By contrast with the changing average and median with the changes in the crowd density, but the value of f1 to f5 gradually increase by the transition of the pattern toward lower right all in all graph. However, this result is not always true linearly-increasing completely, so we need to think a method of getting feature and make an experiment of varied patterns.

5.7 Conclusion

This chapter proposed the ZigBee's RSSI measuring method using each pattern of the crowd behavior to acquire the information of the crowd behavior from macro view-point. We also showed the crowd behavior of feature amount is divided into three features, that is the density, the velocity and the defined patterns of the crowd behavior. Furthermore, we measured the ZigBee's RSSI with these patterns and analyzed data from it using both the time series analysis and the frequency analysis.

Our results of measuring RSSI shows that we are able to check the fluctuated

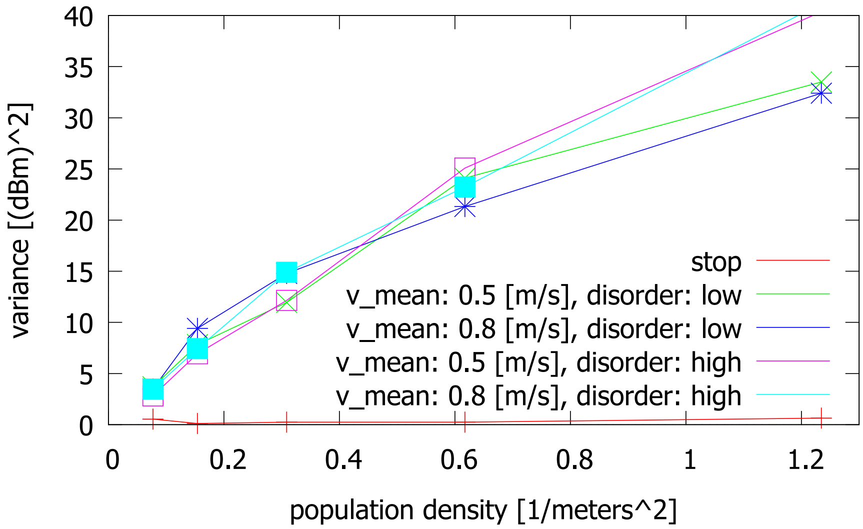

Figure 5.8: Affection of population density on RSSI variance in reflection wave.

data of RSSI from the differing pattern of the crowd behavior. To analyze this data, the average data from the terminals of 1.0[m] high and the Fourier spectrum from the terminals of 2.7[m] high increase according to growing to the large feature amount. The analyzed data indicates the obvious result with the variance from difference between the static and the dynamic. However, the disorder isnft extracted by the method we conducted. Moreover, it is thought to exist that many applicable methods of analysis of the data from this experiment, so we do a search these methods.

As feature work, we try to estimate crowd behavior to split status of indoor space to several patterns and to consider estimation of crowd behavior with extend ZigBee terminals throughout indoor space on the basis of these results.

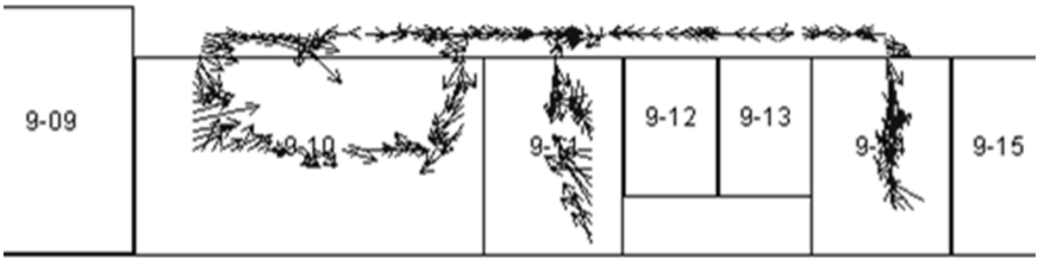

Figure 5.9: A positioning trial using a test data made by the proposed method.

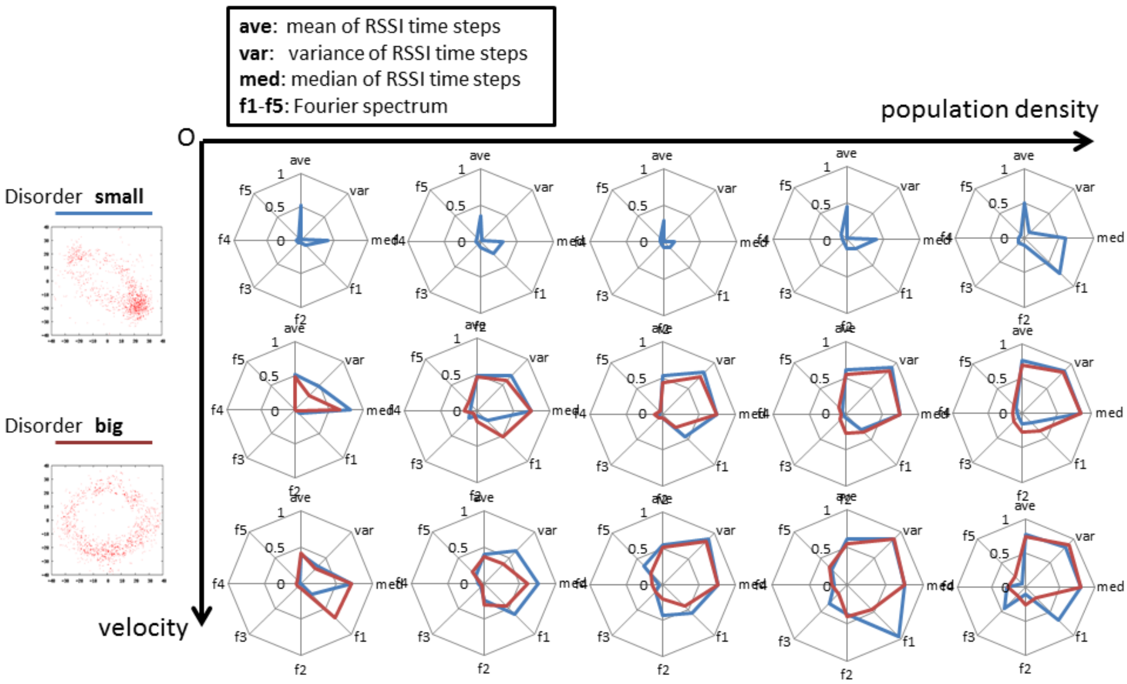

Figure 5.10: A radar charts to analyze a crowd behavior affection on RSSI measurements.

Chapter 6

Summary

The main purpose of this study is to develop a positioning method for indoor positioning system subjected to office enviroment. For this purpose, several discussions and considerations were described as following chapter.

In the first chapter, the proposed approach in prior research was listed and classified regarding indoor positioning system. Moreover, the required condition of the position system under office environment was defined and the positioning method to fulfill this condition will be discussed. While showing the whole picture of the indoor positioning system based on prior measurement especially about RSSI, the stand point and the problem to work on this dissertation were revealed.

In the second chapter, the specific of the RSSI depending on the location such as cover and metal partition in office environment based on the measurement experiment in continuous space of RSSI in actual environment were revealed. Moreover, this chapter shows the capability of reproducing the specifics of the dependence to this location by modeling the details of electromagnetic character of covers and metal partitions in office environment and by electromagnetic field simulation. Since there is a need for enormous memory space, know-how of modeling electromagnetic character, and parallel computation for this calculation, we ran the calculation on a super computer with the help of Professor Ohmiya's laboratory.

In the third chapter, method to utilize the estimation of the position information of RSSI date in continuous space was proposed. Also, represented the RSSI specific depending on the location by nonparametric function of broken line approximation, then modeled the noise component less than 4 [dBm] with normal random number using the knowledge from the measurement experiment in chapter two. The proposal method use this as a likelihood function for particular filter. We carried out a measurement experiment based on the proposal method in office environment including multipath such as over of metal walls, furnitures in the room, and the measurer. Creating a evaluation data by moving around the domain of prior measurement area using a Zigbee end device by a person holding the positioning target, we found that there was an average of 2.4m of error with the accuracy of positioning.

In the fourth chapter, method to optimize layout of fingerprints and routers dinamically was proposed.

In the fifth chapter, method to estimate an affection of crowd pattern in the field on RSSI was proposed.

From these results, by proposing a new method of extending the former prior measurement type of indoor positioning system, knowledge concerning the following three points were obtained in this doctoral dissertation. Proposed a method to evaluate position based on prior measurement in continuous space and revealed that there position can be measured with 2.4m of error in office environment. Proposed a method to optimize the arrangement of fingerprints and routers dynamically depending on the users positional distribution. We revealed that the positioning accuracy could be improved by using this method. Investigated how much impact people gave to RSSI using various dynamic models which were not certainly clear using former methods, and revealed the effect this gave to the positioning method based on RSSI. The above are the validity of this research.

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