NAIST-IS-DD1461001

Doctoral Dissertation

Study on Sensing Technology for Resident's Behavior Awareness in Home

Yukitoshi Kashimoto

February 2, 2017

Graduate School of Information Science
Nara Institute of Science and Technology

A Doctoral Dissertation
submitted to Graduate School of Information Science,
Nara Institute of Science and Technology
in partial fulfillment of the requirements for the degree of
Doctor of ENGINEERING

Yukitoshi Kashimoto

Thesis Committee:

Professor Keiichi Yasumoto	(Supervisor)
Professor Minoru Okada	(Co-supervisor)
Associate Professor Yukata Arakawa	(Co-supervisor)
Assistant Professor Hirohiko Suwa	(Co-supervisor)
Assistant Professor Manato Fujimoto	(Co-supervisor)

Study on Sensing Technology for Resident's Behavior Awareness in Home*

Yukitoshi Kashimoto

Abstract

Thanks to the continuous advancements of ubiquitous computing technologies, Resident's Behavior Awareness (RBA) with sensors in home is attracting more attention. To realize the wide spread use of RBA, it needs to fulfill the following requirements: (i) Adoption of diffusive devices and (ii) Accurate recognition of context. However, few applications are realized, because they usually cannot fulfill these requirements. Thus, the objective of this study is to develop sensing technologies for improved RBA, and to expand applicability of them.

To realize RBA applications, we need to develop techniques to estimate the following two types of information: Location and Activity. 1) In order to track the location of resident, we need to develop indoor positioning system. 2) In order to estimate the activity of resident, we need to develop an activity recognition system.

The indoor positioning system includes the floor plan creation tool, as well as the system itself. The indoor positioning system enables the resident's behavior awareness application to recognize the surrounding environment of the user. First, we work on the development of floor plan creation tool. In this study, we utilize the prevailed device: smartphone, and develop an easy-to-use measurement method: the user completes a lap along all of the walls in a single room, and the tool estimates the accurate shape and size of this room. To realize an accurate measurement, we attach an ultrasonic distance measurement sensor to the phone and develop a technique to handle the noise effects from the object

*Doctoral Dissertation, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-DD1461001, February 2, 2017.

such as bookshelf attached to wall. The evaluation result showed that the we created the accurate floor plan. Through the experiments, we confirmed that we created an accurate floor plan creation tool with diffusive devices that is essential to RBA.

Second, we work on the development of indoor positioning system that adopts diffusive sensors and achieves accurate positioning of the user. In this study, we work on the development of a vibration type estimation technique towards indoor positioning system. The proposed system estimates the position of a user by distinguishing the vibrations that occur when the user interacts with furniture. To design the diffusive and low-cost system, we utilize an easy-to-conceal and low-cost piezo sensor attached on the floor in a home. To improve the recognition accuracy, we use Mel Frequency Cepstrum Coefficient (MFCC) feature to estimate various vibration types. Through evaluation, the system estimated the vibration type with F-measure: 93.9%. Through experiments, we confirmed our fundamental indoor positioning technique works with diffusive devices that is essential to RBA.

The activity recognition system in a home enables resident's behavior awareness applications through recognizing the activity state of the user. However, there is no system that is privacy-aware and utilizes diffusive sensors and performs accurate activity recognition. In this study, we develop an activity recognition system to track resident's behavior at home. The system is making efficient use of Passive Infra-Red (PIR) door sensors installed in a home. To design the diffusive and low-cost system, we adopt a device-free and low-cost energy-harvesting PIR sensor. To improve the recognition performance of the PIR sensor's dead zone, we utilize machine learning and supplemental techniques. The evaluation results showed that the system estimated the user's activity with F-measure: 68.6%. Through experiments, we confirmed our fundamental activity recognition system works with diffusive devices that is essential to RBA.

Keywords:

indoor positioning, floorplan creation, particle filter, activity recognition

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background and motivation

First, we will introduce Context-Aware Computing and after, we describe Resident's Behavior Awareness and motivations. The relationship between Context-Aware Computing and Resident's Behavior Awareness is depicted in Figure 1.

1.1.1 Context-Aware Computing

Thanks to the advancements in the development of ubiquitous computing, there is a strong research interest in realizing Context-Aware computing. The term: "Context-Aware Computing" is initially defined by Schilit et al. in 1994[1]. According to the article, Context-Aware Computing is a technology to sense the surrounding environment and find the meaning of objects in it, which is similar to the process in human's brain. In other words, through this technology, the computer estimates the user's context by sensing the following: "What or Who," "When," "Where," "What does he/she or it do?". With the information, we can develop various kinds of applications.

Up until now, there are various kinds of Context-Aware Computing applications in practical use as well as in the research domain.

First examples are health care applications which are broken down below: There are many research studies which work on healthcare[2, 3, 4, 5, 6, 7, 8, 9, 10, 11]. For example, in [3], authors propose an smartphone application that tracks the user's health status by utilizing wearable sensors and locations, and reports them to the care-advisor. Based on the report, the advisor supports the user to improve his/her health. On the other hand, there are many commercial applications such as Google Fit[1], Fitbit[2], Up by Jawbone[3], Flu near you[4], and

[1]Google Fit: `https://play.google.com/store/apps/details?id=com.google.android.apps.fitness`

[2]Fit bit: `https://www.fitbit.com/jp`

[3]Up by Jawbone: `https://jawbone.com`

[4]Flu near you: `https://flunearyou.org/`

Runkeeper[5]. One example is the life log application such as Moves[6]. In Moves, the smartphone application records the sensor data from the accelerometer, GPS, and so on. After activities the application analyzes the stored data, and estimates the user's activity such as "Where and when did the user run?". After this process, it generates activity report for him. The report helps the user to spend his or her life in a healthier way, for example to lose weight.

Other examples are the social networking applications installed in a smartphone. There are many studies which work on this domain[12, 13, 14, 15, 16]. For example in [15], they propose an smartphone Instant Messenger (IM) application: Hubbub which automatically extracts the relationship between users from interactions in IM. Based on the relationship, the IM automatically sends the messages that encourage the user's conversation. In addition, there are many applications in practical use such as Facebook[7], Twitter[8], Linkedin[9], Foursquare[10], and Pokemon Go[11]. These applications estimate the location in the real world as well as in the social network domain. Based on the estimated relationship, they recommend the user to exchange contact information with each other.

1.1.2 Resident's Behavior Awareness (RBA)

Nowadays, Context-Aware Computing specifically inside buildings is attracting attention. Here, we define it as Resident's Behavior Awareness (RBA). As its name suggests, RBA is a technology to estimate the user's context inside a building by utilizing sensors.

RBA enables various kinds of applications such as Energy saving appliance control and concierge service in a smarthome[12], and the elderly monitoring system in nursing home. In "Energy saving appliance control in smarthome," the system reduces the power consumption by considering the location of the user within a

[5] Runkeeper: `https://runkeeper.com/`
[6] Moves: `https://moves-app.com/`
[7] Facebook: `https://www.facebook.com/`
[8] Twitter: `https://twitter.com/`
[9] Linkedin: `https://www.linkedin.com/`
[10] Foursquare: `https://foursquare.com/`
[11] Pokemon Go: `http://www.pokemongo.com/`
[12] Smarthome is a house in which there are many sensors attached to the ceiling, wall, or floor to track the residents .

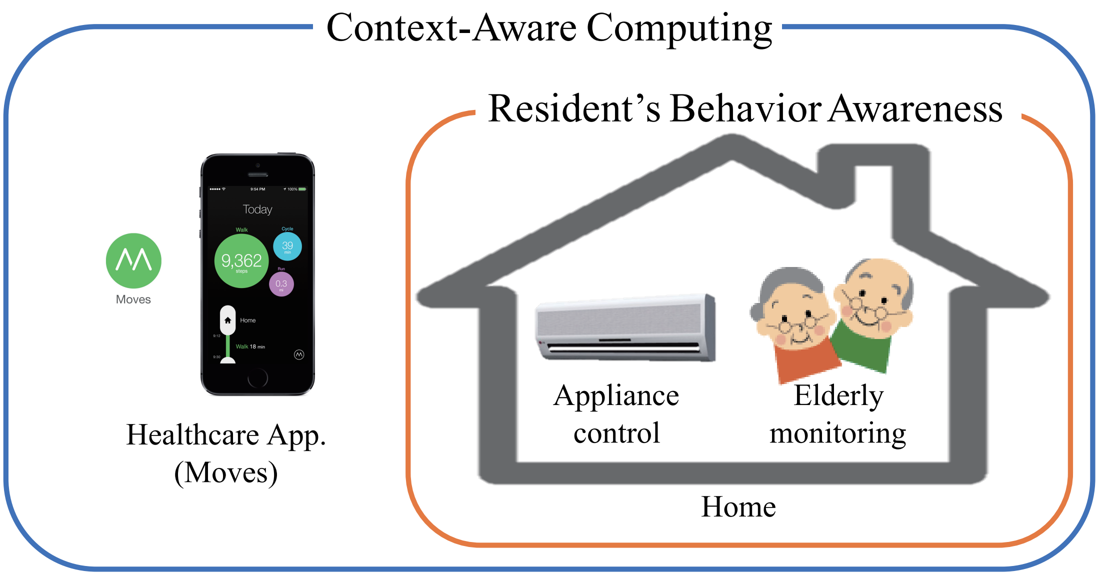

Figure 1. Context-Aware Computing and Resident's Behavior Awareness

smarthome. For example, when the user leaves a room without turning off an airconditioner, the system automatically recognizes the absense of a person and powers the airconditioner off. In "concierge service in smarthome," the system provides the user with life supporting services in a smarthome. For example, we assume that the user has a habit of going bed after taking a bath and the system learns the life pattern of the user. In "Elderly monitoring system," the system monitors the senior citizen that lives his daily life apart from his/her family. When the user starts taking a bath, the concierge system turns on the air-conditioner and changes the lighting in the bedroom. For example, we assume that the activity pattern of the user changes, since he/she begins being suffered from dementia. Then, the system detects it and notifies it to his/her family.

In these applications, the system senses the user's behavior: "What or Who," "When," "Where," "What does he/she or it do?". Based on the acquired information, the system estimates the user's context: "How much calorie did the user take or consume?," "What kind of activity did the senior citizen perform?," and "What kind of concierge service does the user prefer to?". Then, the system provides the service on the context. While there are many Context-Aware Computing applications, there are small number of RBA applications in practical use.

In some research fields, there are RBA applications proposed. One example is the home-concierge robot by NEC[13]. This robot recognizes the user's context by utilizing camera, infrared sensor, and so on and provide services such as babysitter and elderly monitoring. However, the practical use of the robot is limited to some experimental objective.

1.1.3 Motivation

As we have surveyed in the former section, there are many Context-Aware Computing Applications. On the other hand, there are few RBA applications into practice. Through the literature review[17][18], we find that the state-of-the-art RBA applications are hard to be widely used, since they are too performance-centric and demands expensive devices. However, Referring to the widespread use of low-cost IoT devices these days[19], we strongly believe that we are able to develop techniques that accelerates the diffusion of RBA applications. Then, finally we decided to work on the development of fundamental technology to realize RBA system.

1.2 Classification of RBA

There is various taxonomy for Context-Aware Computing[20]. In this thesis, by referring the document, we categorize RBA in the following two view points: "Classification by information flow (Classification A)" and "Classification by information characteristic (Classification B)".

1.2.1 Classification by information flow (Classification A)

Our laboratory originally categorizes the ubiquitous computing system in terms of information flow by referring Cyber-Physical System[21] as depicted in Figure 2. In accordance with this manner, RBA can be divided into three types.

[13]NEC childcare robot PaPeRo: `http://www.nec.co.jp/press/en/0503/1601.html`

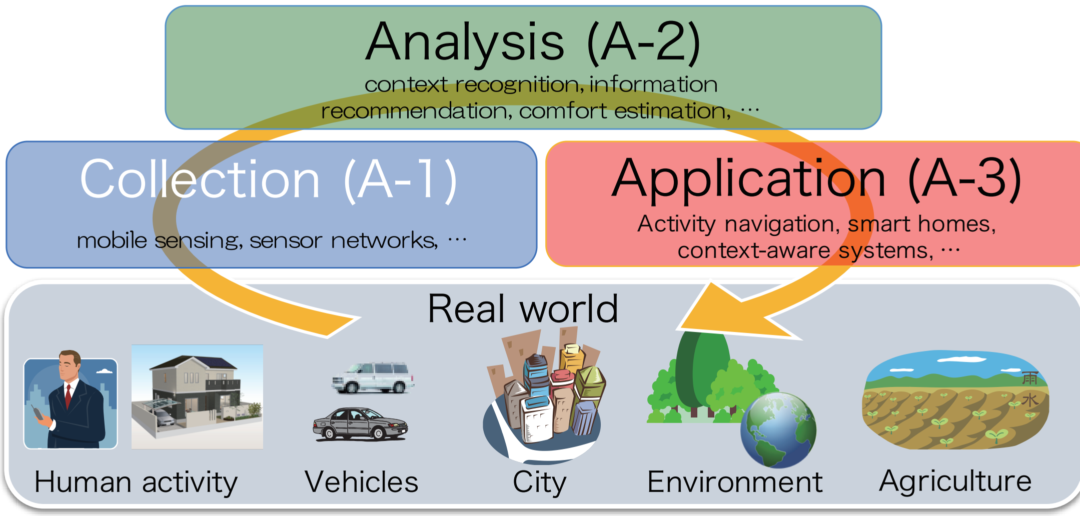

Figure 2. Information flow in Cyber-Physical System
(From Ubi-lab's document)

Data collection from real world (A-1)

"Data collection from real world" focuses on gathering the information of human/object by utilizing sensors. In addition, the well-designed sensor network conveys the data to the computers.

Context estimation by analyzing collected data (A-2)

In "Context estimation by analyzing collected data," the computer processes the collected data from A-1 and recognizes the user's context such as "What or Who," "When," "Where," "What does he/she or it do?". In addition, it estimates physical, psychological and health status, futuristic activity of the user.

Context-aware service application (A-3)

"Context-aware service application" realizes the services such as health care, elderly monitoring, and home-concierge robot. These applications works on the context estimated in A-2.

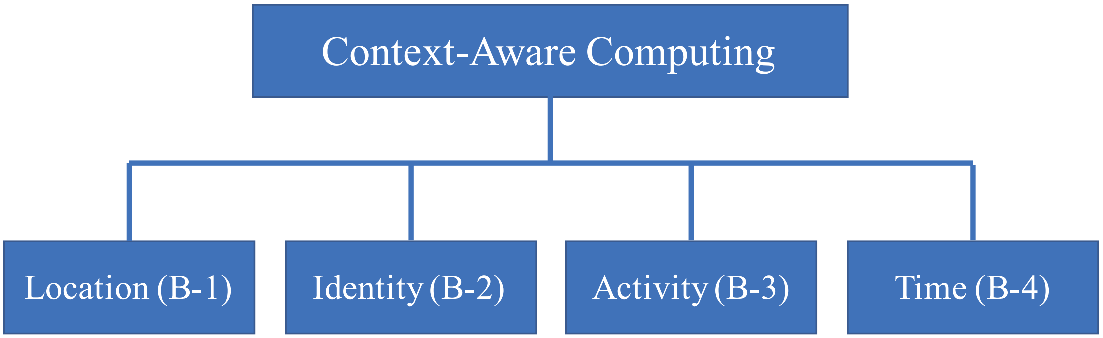

Figure 3. Information characteristics in Context-Aware Computing

1.2.2 Classification by information characteristics (Classification B)

Dey et al. defines the categories of context for Context-Aware Computing in terms of the most likely pieces of context (information characteristic) that will be useful in the applications[20] as depicted in Figure 3. Based on the information characteristics, RBA can be divided into four types.

Location: Where (B-1)

Location of the user or object is the important information to recognize the context. Same as Subject, to track the user or object easily, we can utilize mobile device to it. However, to alleviate the installation cost, we need to estimate the location without tag.

Identity: What or Who (B-2)

Identity: "What or who behaves" is the key information to recognize the context. There are mainly two approaches for this. First approach is that the user or object carries a mobile tag which transmits identification (ID) code. Based on ID, the system easily distinguishes them. However, assuming the home environment, carrying the tag becomes burden on the user. There are two reasons for this. First reason is that most user prefer to take off those devices when he/she spends in home. Second reason is that attaching those tag to all objects in home raises the installation cost. Therefore, the system needs to distinguish the user or object without attaching tag.

Activity: What does he/she or it do? (B-3)

Activity of the user or object is the important information to recognize the context. Same as Subject, we can utilize mobile device to it. However, to alleviate the installation cost, we need to estimate the activity without tag.

Time: When (B-4)

Time information is also the key information to recognize the context. To track time information, the system always keeps on synchronizing to an accurate clock that is provided through Internet.

1.3 Requirements for RBA

Our motivation is to realize the RBA application. To take the adaptation into building, the device must be diffusive one. Furthermore, the performance of Context-Awareness must be accurate. Thus, RBA needs to accomplish the following requirements.

Requirement 1: Adoption of diffusive device

Requirement 2: Accurate recognition of the context

To achieve Requirement 1, our target RBA system utilizes diffusive devices. The diffusive devices, which are easy to be deployed in building, are low-cost and easy to be used. To achieve Requirement 2, our target system utilizes machine learning and signal processing technique.

1.4 Scope and research goal

In the previous sections, we described several challenges and defined the requirements to realize the RBA system. As we have discussed in 1.1.3, the current RBA are too performance-centric and utilizes expensive devices, which cannot fulfill the requirements . For example, the RBA system such as the indoor positioning or activity recognition system by utilizing camera has been gradually realized. However, those information systems can be applied to limited applications.

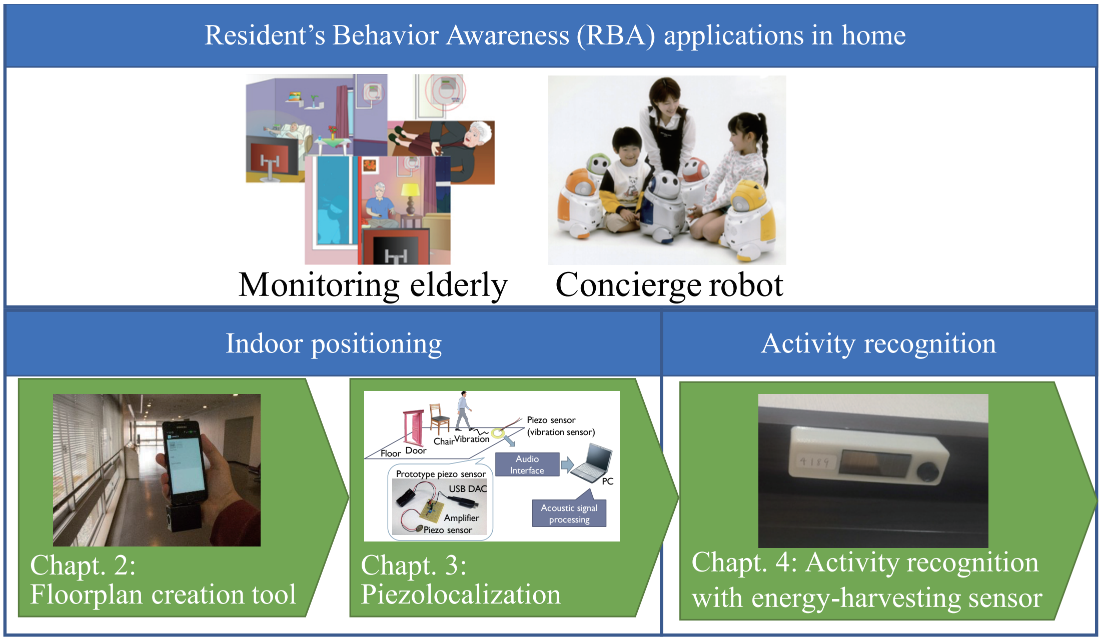

Figure 4. Requirement in developing RBA applications

Objective of our research is to address the development of a few fundamental systems for RBA that fulfills both requirements. Specifically, we tackle the development of new devices, which is relevant to (A-1), and data processing system, which is relevant to (A-2), to realize RBA. Since Application domain (A-3) must be realized after matured A-1 and A-2, we strongly believe that we need to establish the basis of A-1 and A-2.

In terms of "Information characteristics (Classification B)," we need to tackle "Location (B-1)" and "Activity (B-3)". This is because these two domains are essential but more challenging than other two: "Identity (B-2)," and "Time (B-4)". For "Identity (B-2)," we consider that we can estimate it after obtaining "Location (B-1)" and "Activity (B-3)" by utilizing the user's habits affecting these two. For example, in home, we can track the user based on the moving pattern and activities, i.e. if a father tends to take a bath every morning, we can easily estimate a user who stays in the bathroom to be him. For "Time (B-4)," we can easily track it just by recording the clock connected to Internet. Therefore, we focus on B-1 and B-3.

In this study, we aim to develop three fundamental systems/techniques as depicted in Figure 4. The first one is the floor plan creation tool. The second one is the indoor positioning system. The other one is the activity recognition system of the resident in home. Based on the previous discussion and requirement, we focus on three specific systems: “Floor size and shape estimation tool by utilizing a smartphone attached with an ultrasonic distance measurement sensor,” “Indoor positioning system by utilizing a piezo sensor attached to floor,” and “Activity recognition technique by utilizing energy-harvesting PIR sensor”.

Floor plan creation tool

In “Floor size and shape estimation tool by utilizing a smartphone attached with an ultrasonic distance measurement sensor,” our objective is to realize the low-cost (diffusive) and accurate floor plan creation tool. Floor plan is the key information to realize RBA, since it enables the system to recognize the location of the user. Based on the location of the user, the system recognizes the context of the user. For example, if the user exists in kitchen, the system can estimate that the user performs cooking. We focus on the development of the first prototype of the proposed tool and achieve the fundamental floor plan creation performance for RBA.

Indoor positioning system by utilizing piezo sensor

In “Indoor positioning system by utilizing a piezo sensor attached to floor,” our objective is to realize the low-cost, tag-free (diffusive), and accurate indoor positioning system. Same as the floor plan creation tool, the indoor positioning system is also the key information to realize RBA, since it enables the system to estimate the location of the user. We focus on the development of the first prototype of the indoor positioning hardware and technique to estimate the floor vibration type.

Activity recognition by utilizing energy-harvesting sensors

In “Activity recognition technique by utilizing energy-harvesting sensors,” our objective is to realize the low-cost (diffusive), tag-free, and accurate activity recognition in smart home. Activity of the user is the significant information to estimate the user's context. We focus on the development of the first system and establishment of fundamental technique to realize the activity recognition in smarthome by utilizing the machine learning.

1.5 Contributions

Thus far, we have overviewed the current Context-Aware Computing and focused on the RBA domain that is especially developing field in it. And more, we classified RBA in terms of information flow and its characteristic. Then, we focused on the development of three fundamental system to realize RBA. The contributions of each system are as follows:

In "Floor size and shape estimation tool by utilizing a smartphone attached with an ultrasonic distance measurement sensor," our major contribution is that we have realized the simple and low-cost room measurement tool that estimates the size and shape of the room accurately. Specifically, we achieve the following contributions.

- Simple room measurement method
- Development of low-cost room measurement tool
- Accurate room measurement technique

In "Indoor positioning system by utilizing a piezo sensor attached to floor," we show the feasibility of the accurate indoor positioning system by utilizing a diffusive piezo sensor attached on floor. Specifically, we achieve the following contributions:

- Piezo-sensor-based indoor positioning hardware
- Vibration estimation technique by utilizing machine learning and MFCC feature

In "Activity recognition technique by utilizing energy-harvesting PIR sensor," we show the feasibility of the accurate activity recognition system by utilizing PIR and door sensors. Specifically, we achieve the following contributions:

- Development of tag-free activity recognition system by utilizing energy-harvesting sensors
- Activity recognition by utilizing machine learning
- Supplemental technique for dead-zone of PIR sensor

1.6 Outline of thesis

This thesis consists of five chapters.

In chapter 2 of this thesis, we describe our work on the indoor positioning system that includes the floor plan creation tool as well as the system itself. The indoor positioning system enables the resident's behavior awareness application to recognize the surrounding environment of the user. First problem is that there is no floor plan creation tool that adopts diffusive sensors and achieve accurate floor plan creation. Then, we present a room measurement tool which utilizes a smartphone equipped with an ultrasonic sensor gadget. By utilizing this tool, an ordinary user can measure the size and shape of a room and create a floor plan with small effort. In the measurement, the user completes a lap along the walls of all rooms. Then, the tool estimates the accurate shape and size of the room. It leverages the inertial sensors, embedded in the smartphone, to track the user in the walking path. Moreover, the ultrasonic sensor in the gadget measures the distance between the path and walls. There are three main challenges to achieve optimized performance. The first challenge is the stride length estimation for indoor environment. To realize this, we estimate the stride length of the user walking toward the wall by utilizing an ultrasonic sensor and accelerometer. The second challenge is consideration of adjacent objects, such as bookshelves, that deteriorate the accuracy in spatial layout estimation. To cope with this problem, we use a mixed Gaussian filter. The last challenge is that the narrow room, such as corridors, leads to the low accuracy, since the error of the estimated stride length affects the estimation. To cope with this problem, we implement two ultrasonic sensors in the reverse direction, and measure the distance between walls directly. The results from experiments show the considerable improvement in shape and size estimation accuracy.

The chapter 3 of this thesis describe our next problem is that there is no indoor positioning system that adopts diffusive sensors and achieve accurate estimation of the user's position. Then, we introduce a technique to estimate the vibration type estimation toward the realization of indoor positioning system in building by utilizing piezo sensor attached to floor. The indoor positioning system has to fulfill the following four requirements: Req 1: high accuracy; Req 2: low installation cost; Req 3: small burden on the user. There are several studies which work on the indoor positioning system. Some studies[22][23] estimate the position of the user by utilizing the inertial sensors in the smart phone. Accelerometer and gyroscope in the smart phone estimate the walked path of the user. However, the accumulated error from these inertial sensors makes the positioning system inaccurate. In some experimental installations, they use an indoor positioning system which adopts ultrasonic sensor[14][15]. A user holds an ultrasonic transmitter. There are ultrasonic receivers which are attached on the ceiling of the room. Based on the Time Difference of Arrival (TDoA) of the ultrasonic wave between the transmitter and the receivers, the system estimates the position of the user. However, the system requires high installation cost, since we have to attach many receivers on the ceiling. Moreover, the user always has to carry the transmitter. That becomes burden on the user. There is an indoor localization system which utilizes camera[24]. This system estimates the position of the user based on image processing. However, capturing the posture of the user infringes his privacy. In summary, these previous works do not satisfy the all requirements. The other one is a technique to create the floor plan of the building.

In the chapter 4, we describe the activity recognition system in home that enables the resident's behavior awareness applications to recognize the state of the user. However, there is no system that utilizes low-privacy and diffusive sensors and performs accurate activity recognition. Specifically, the current living activity recognition system has the following problems remain: (i)privacy exposure due to utilization of cameras and microphones; (ii) high deployment and maintenance costs due to many sensors used; (iii) burden to force the user to carry the device and (iv) wire installation to supply power and communication

[14]ActiveBat: `http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/`
[15]Cricket Indoor Location System: `http://cricket.csail.mit.edu/`

between sensor node and server; (v) few recognizable activities; (vi) low recognition accuracy. Then, we propose an in-home living activity recognition method to solve all the problems. To solve the problems (i)–(iv), our method utilizes only energy harvesting PIR and door sensors with a home server for data collection and processing. The energy harvesting sensor has a solar cell to drive the sensor and wireless communication modules. To solve the problems (v) and (vi), we have tackled the following challenges: (a) determining appropriate features for training samples; and (b) determining the best machine learning algorithm to achieve high recognition accuracy; (c) complementing the dead zone of PIR sensor semipermanently. We have conducted experiments with the sensor by five subjects living in a home for 2–3 days each. As a result, the proposed method has achieved F-measure: 62.8% on average.

Chapter 5 summarizes this thesis, with discussion about the contributions, limitations and feasible future work.

2 Floor size and shape estimation tool by utilizing a smartphone attached with an ultrasonic distance measurement sensor

2.1 Introduction

The resident's behavior awareness applications can offer various services to the user such as the home appliance control and concierge robot. These applications recognizes the surrounding environment of the user by utilizing the indoor floor plan. For example, the home appliance control system recognizes that the user stays in kitchen for long time, which means that user cooks, and then adjusts the temperature of air-conditioner so that the user feels comfortable. To create the floor plan, we need to develop an floor plan creation tool.

In order to develop the floor plan creation tool for the resident's behavior awareness, we believe that an easy-to-use measuring tool is important. The floor plan creation workflow consists of (i) Step 1. Room measurement to measure each room and (ii) Adjustment for connection between rooms to format the floor plan as illustrated in Fig.5. We focus on the realization of Step (i). There are many measurement tools which we can assume to use for this purpose. One of the famous tools is the electro-optical distance measuring instrument for land survey. This tool measures the distance between two points by utilizing the Time of Flight

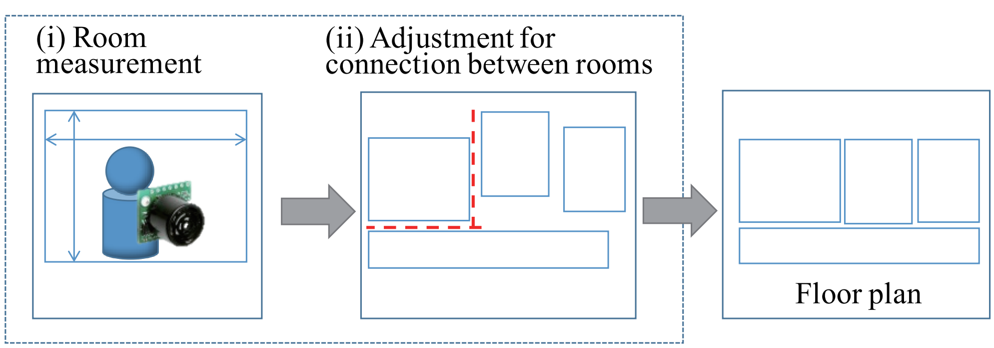

Figure 5. Steps for creating a floor plan

(ToF) of the laser wave. Second familiar tool is the stereo camera, Kinect[16], Laser Imaging Detection and Ranging (LIDAR)[17] which can be connected to a laptop. These tools measure the size of the room by the image processing. Another expanding approach is the utilization of the inertial sensors such as the accelerometer and gyroscope in the smartphone[25]. Some users install an ad-hoc application to their smartphones and walk in the building. By collecting the walked paths which are estimated from those inertial sensors, the application estimates the size of the room. Then, we employ the smartphone based approach, since it has the advantages of the usability and low installation cost for the volunteer users to measure many buildings. In this chapter, we add the ultrasonic distance measurement gadget to the smartphone so that the tool measures the distance between the walked path and wall. When the user measures the size of a room, the user makes a lap along the wall. After that, the tool estimates the accurate shape and size of the room. This tool leverages the inertial sensors implemented in the smartphone to track the walking path of the user. Moreover, the ultrasonic sensor in the gadget measures the distance between the path and walls.

2.2 Related research

Many research studies on the room measurement have been reported. In this section, we discuss them in terms of the accuracy and the amount of work effort for the measurement.

2.2.1 Rough floor plan creation with the inertial sensor in the smartphone

CrowdInside[25] and Hallway[26] are the state-of-the-art approach, which utilizes the inertial sensors (e.g. accelerometer and gyroscope) in the smartphone. First, they estimate the location of the user by utilizing the indoor localization techniques. Next, they extract the position of the user when he is close to the walls. Finally, they connect points to shape a convex hull and estimate the size and

[16]Kinect, Microsoft: `http://www.xbox.com/kinect`
[17]LiDAR, Hokuyo-Denki: `https://www.hokuyo-aut.jp/02sensor/`

shape of the room. However, the accumulated error of the inertial sensors is the challenge for these approaches. In CrowdInside, they utilize GPS to modify the error. Nevertheless, in some buildings (e.g. reinforced concrete buildings), GPS is not available. On the other hand, Hallway utilizes the WiFi fingerprint to modify the error. Nevertheless, the construction of WiFi fingerprint is a laborious work for the ordinary user. Moreover, in some rooms, they do not suppose that objects attached to the wall prevent the user from walking along the wall.

2.2.2 Structure extraction of the facility from the walking path of users

There is a study that works on the structure extraction of the facility[27]. It utilizes the inertial sensors in the smartphone. First, it collects the walking paths of the user. Second, it finds the common parts (e.g. a path in a corridor) from them. Finally, it combines those parts and constructs the building structure (e.g. the connection between rooms). However, the structure extraction techniques are not sufficient to estimate the room shape and size.

2.2.3 Image processing with the depth sensor and camera

Google Tango project[18], Structure[19], and Spike[20] have been working on the 3D modeling of buildings in the recent years. First, they attach the depth sensor to the smartphone. Second, the camera in the smartphone captures the surface of walls, floors, and the ceilings. The depth sensor measures the distance between the smartphone and all the surfaces. Finally, they construct the model of the building by image processing techniques. However, the 3D structure model is a complex data for the indoor navigation. Even though the required model is simple 2D floor plan, the users have to measure the room in 3D scan manner and create the 3D model of the room. Those works become burdens on the user. Moreover, it is not cost-effective and needs large battery amounts and processing power.

[18]Google Tango Project: `https://www.google.com/atap/projecttango/`
[19]Structure: `http://structure.io/`
[20]Spike: `http://www.ikegps.com/spike`

Table 1. Comparison between the distance measurement sensors

Sensor type	Weight	Price	Battery consumption	Connectivity[22]
Laser rangefinder	heavy	Costly	Heavy	Poor
Kinect	heavy	Costly	Heavy	Poor
Ultrasonic sensor	Light	Low cost	Small consumption	Good

2.2.4 Summary for related research

There are several studies[26][27] and an application which generate the floor plans utilizing inertial sensors in the smartphone. Some studies[26][27], collect users' trajectories and find the common paths among them by utilizing Pedestrian Dead Reckoning (PDR). Finally, they generate the floor plan from the walking path of the user. However, more than 20 paths must be collected to compensate the low accuracy of PDR, and it is tedious and time-consuming. This work imposes a strain on the ordinary user. RoomScan[21], an iPhone application, is a tool to measure the shape and size of rooms. The user touches each wall in the room and walks along the walls with the smartphone. Simultaneously, the application estimates the shape and size of the room by utilizing PDR. However, RoomScan can measure rooms where four walls are directly touched by the user and some rooms without accessible walls, e.g., a stairwell cannot be measured. Moreover, the user fails to measure the spatial layer of the room, while obstacles and objects in the room prevent the walking task. Thus, we have to develop complementary techniques for the smartphone based approach.

In order to cope with the above-mentioned problems, we propose to add a distance measurement sensor for the smartphone. There is different types of sensors for this purpose, such as a laser rangefinder, Kinect, and an ultrasonic sensor. Table 1 shows the comparison between the sensors. However, the laser rangefinder and Kinect have heavy battery consumption and are neither light nor cost-effective for the ordinary user. To make matters worse, these sensors require the laptop computer to process the complex data and makes the connectivity to the smartphone difficult. On the other hand, the ultrasonic sensor is light

[21] RoomScan: `http://locometric.com/`

and low cost and works with the small amount of energy consumption. Also, the ultrasonic sensor has good connectivity to the smartphone, since it outputs the distance data which requires small processing resource. Thus, we employ the ultrasonic sensor.

2.3 How to measure the room

2.3.1 Requirements and policy for the room measurement

We suppose that the volunteer users measure rooms. Therefore, the measurement tool must be low cost and easy-to-use. Also, the measured size of the room must be accurate. Thus, we define the requirement for this tool as follows:

Requirement 1: low cost device

Requirement 2: an accurate measurement

Requirement 3: small effort to measure the room

To achieve Requirement 1, we utilize the inertial sensors in the smartphone and an ultrasonic sensor gadget. However, as we have discussed in Sect. 2.2, we cannot accurately measure the room just with the inertial sensor in the smartphone. Thus, we develop a low-cost ultrasonic sensor gadget and attach it to the smartphone. The ultrasonic sensor measures the distance between walking path of the user and walls. Additionally, we develop an algorithm to eliminate the effect from adjacent objects next to the wall so that we achieve Requirement 2. To achieve Requirement 3, the user walks along walls of the room. The tool achieves the estimation of the shape and size of the room for a single measurement.

2.3.2 Assumption for the floor and room

We suppose the following conditions:

- Rooms are separated by walls.
- Shape of the room is rectangular.
- The whole wall is not covered with obstacles.

We categorize the rooms into two groups. First, rooms that are separated by walls, such as rooms in office buildings. Second, rooms that are not separated, such as open spaces in shopping malls. In general, we can say that the indoor navigation works efficiently in the first one. Thus, our target rooms is the first category. As the second assumption, we suppose that the shape of the room is rectangular. In addition, we suppose that the room does not have opened windows and sunk part such as bay window. As the third assumption, we suppose that the whole wall is not covered with obstacles. We assume it, since the obstacles that cover the whole wall prevent an ultrasonic wave from reaching the wall.

In addition, it is considered that there is an accumulated error after the measurement. However our preliminary experiment shows that the accumulated error is negligible. This is because the accumulated error becomes small if the total walk distance is small. (e.g. We observed 0.3[m] error against the 44[m] walking distance.) Moreover, we use the gyroscope to estimate the change of moving direction. It is the other factor for this small-accumulated error. As a result, we modify the start and end point of the measurement, the red circles, to the cross point of the walking path, the green circle, as described in Figure 6.

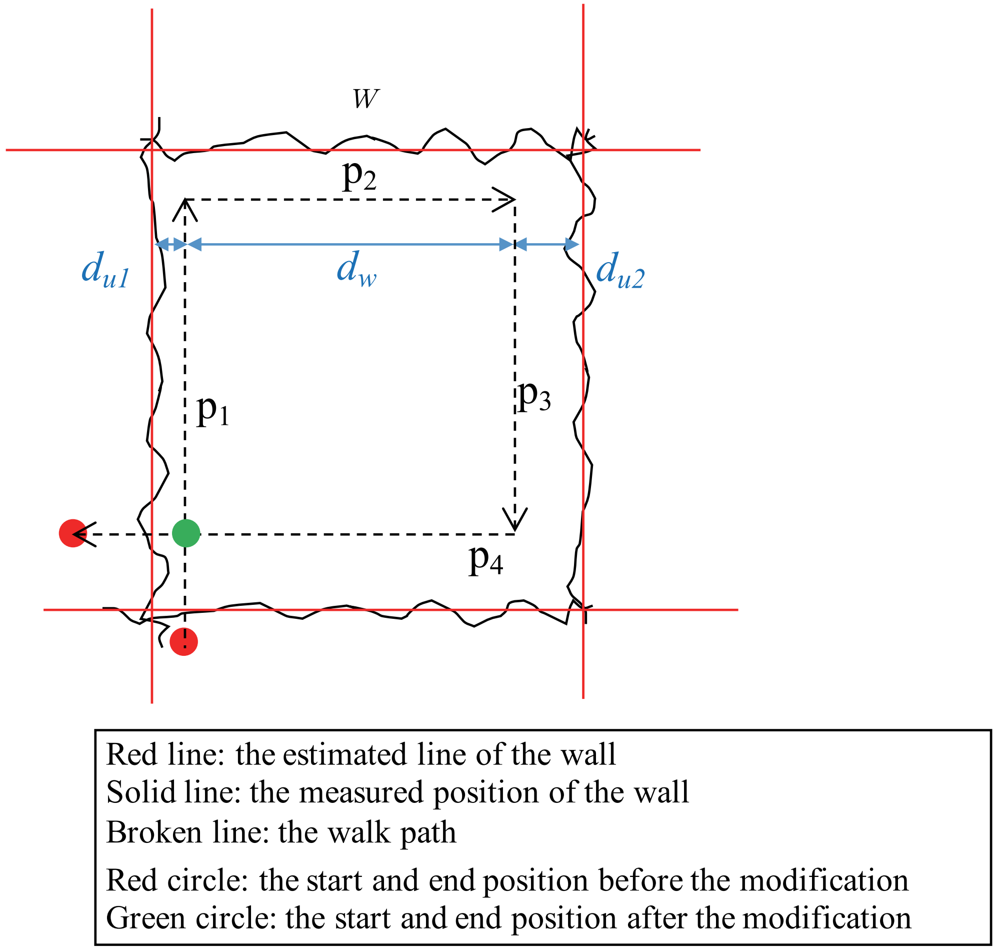

Figure 6. The room size/shape estimation

2.3.3 Problem definition and basic idea for the solution

We measure the room shape and size in two steps.

In the first (Step1), the user walks along walls and make a lap in a room. The user holds the smartphone attached with an ultrasonic sensor gadget. Next, the user walks along the walls of the room and makes a lap in it. At the same time, the inertial sensors (accelerometer and gyroscope) estimate the walking path of the user by utilizing the PDR technique. The ultrasonic sensor measures the distance between the path and walls. We use PDR algorithm described in[28][29][30]. We also use the gyroscope to estimate the change of moving direction. (i.e. if the accumulated angle from the gyroscope exceeds 90, the tool estimates that the user changes the walking path to perpendicular direction). In order to improve the performance of PDR, we have to measure the stride length of the user accurately (Challenge A). The stride length of the user varies according to the environment around him. To handle this problem, we measure the stride length by utilizing an ultrasonic sensor when he walks toward the wall.

In the second (Step2), the tool estimates the shape and size of the room. We measure the distance between walls, combining the distance from walking path and ultrasonic sensor. We estimate the distance by equation (2) as illustrated in Figure 6.

$$w = d_w + d_{u1} + d_{u2} \tag{1}$$

Here, d_w denotes the distance calculated from the walking path. d_{u1} and d_{u2} denote the distance measured by ultrasonic sensors in $p1$ and $p2$, respectively. We calculate d_w from the product of the number of steps and the average stride length measured in Step 1. In order to improve the performance of the room size estimation, we have to tackle two more challenges. One is that the narrow room, such as corridors, leads to the low accuracy (Challenge B). To cope with this problem, we use two ultrasonic sensors, installed in the reverse direction, and measure the distance between walls directly. The other is that objects, such as bookshelves, attached on the wall deteriorate the room shape estimation accuracy (Challenge C). We formulate this problem as a number estimation problem of the mixed Gaussian distribution and solve it by utilizing Bayesian Information Criteria (BIC) and Expectation-Maximization (EM) algorithm.

2.4 Three room measurement methods

We describe the solution for three challenge which we have mentioned in Section 2.3.3 as follows:

Challenge A: Stride length estimation

Challenge B: The shape and size estimation for a narrow room

Challenge C: Eliminating influence of objects adjacent to walls

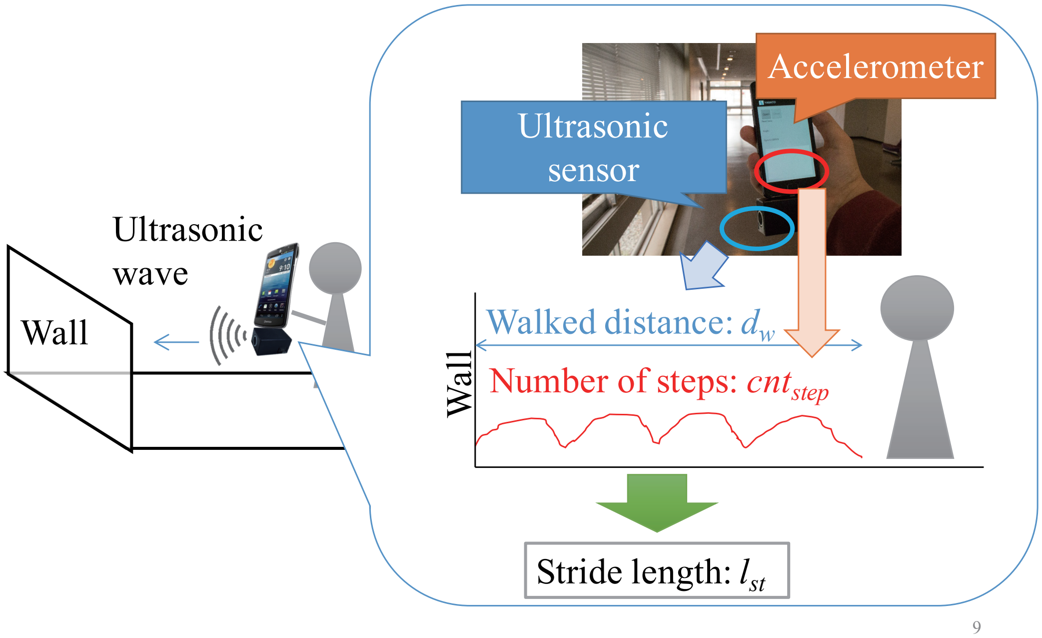

Figure 7. The distance between the user and the wall

Solution for Challenge A: Stride length estimation

In order to realize the precise room measurement, we need to measure the stride length accurately. Unfortunately, the accurate stride length estimation is difficult in the indoor environment (Challenge A).

There are many techniques[23][24][25] to estimate the stride length by utilizing the correlation between the height of the user and his stride length (We call these methods as "height correlation method"). In those techniques, they have found the correlation between them from the experiment and generated the regression formula such as (2).

[23]Soleus: determing your stride: https://cdn.shopify.com/s/files/1/0196/4616/files/determingyourstride.pdf

[24]Oregon Scientific SE900 User ' s manual: http://www.manualguru.com/oregon-scientific/se900/users-manual/page-3

[25]How to Determine Stride Length for an Elliptical Machine: http://bodytrainersreviews.com/how-to-determine-stride-length-for-an-elliptical-machine

$$l_{st} = 0.415 * h \quad (2)$$

Here, l_{st} denotes the stride length of the user. h is the height of the user. However, several articles[31][26] have reported that these techniques are not enough to estimate the stride length accurately, since there is a weak correlation between them. Thus, we cannot adopt this technique to estimate the stride length.

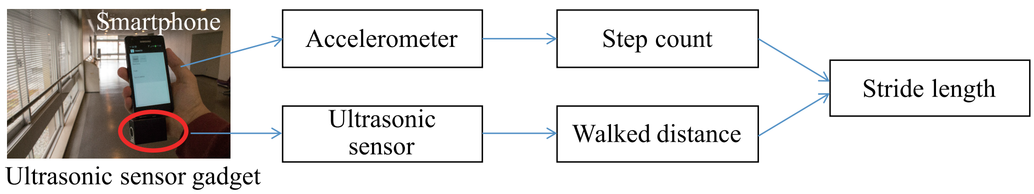

Figure 8. The workflow for the stride length estimation

Also, we can estimate the stride length in outdoor environment by utilizing the accelerometer and Global Positioning System (GPS)[32][33] in the smartphone. In these studies, they calculate the stride length from the walked distance measured by GPS and the number of steps estimated from the accelerometer. However, we cannot use these techniques for the room measurement. There are two reasons for this. First, we cannot use GPS in the building, since the radio wave from the GPS satellite is blocked by the building. Second, even if we try to use the stride length estimated outside, we cannot use that length in the building. This is because Öberg et al. reported that there is a difference between outdoor and indoor stride length[34]. Thus, we have to develop a new technique to estimate the stride length for indoor environment.

In order to cope with this challenge, we estimate the stride length of the user by utilizing the ultrasonic sensor and the accelerometer implemented in the smartphone. Figure 7 illustrates the situation of the stride length estimation. Figure 8 illustrates the workflow of the stride length estimation. First, with the

[26] Using the ADXL202 in Pedometer and Personal Navigation Applications: `http://www.analog.com/media/en/technical-documentation/application-notes/513772624AN602.pdf`

ultrasonic sensor, we measure the walked distance, when the user walks toward the wall. Simultaneously, with the accelerometer, we calculate the number of walking steps. Second, we calculate the stride length based on the walked distance and the number of walking steps as described in (3).

$$l_{sl} = d_w / cnt_{step} \tag{3}$$

We denote that l_{sl} is the stride length of the user. d_w is the walked length of the user. cnt_{step} is the walking steps of the user. Figure 9 illustrates the sensor data output of the ultrasonic sensor and the accelerometer.

Solution for Challenge B: Shape and size estimation for a narrow room

We can measure the size and shape of most rooms by the technique described in Section 2.5.2. Since the error of the estimated stride length affects the estimation, we fail to accurately estimate the short wall length in narrow rooms, such as corridors (Challenge B).

We have conducted a pilot experiment to observe the effect of the short wall to the user. We asked three users to walk along the walls and make a lap in a corridor which has 22 [m]×2.0 [m] size for five times. We observed their behavior especially when they walk along the short wall, i.e. 2.0 [m] wall. As a result, we confirmed that they cannot walk along that wall with keeping the constant stride length.

In order to cope with this problem, we use two ultrasonic sensors in the gadget and measure the distance between walls. Figure 10 illustrates the measurement diagram of the narrow room. First, the user holds the smartphone with the ultrasonic sensor gadget. Second, the user moves from one side of the corridor to the other side. Then, two ultrasonic sensors measure the short side of the room. Simultaneously, the inertial sensors measure the long side of the room. We switch them based on the error code from the ultrasonic sensor. The ultrasonic sensor, which we have selected, outputs the error code when the distance between the sensor and an object exceeds 4.5m. If the number of sensors without error is one, we adopt the technique described in Section 2.3. On the other hand, if the number is two, we adopt the technique using two ultrasonic sensors.

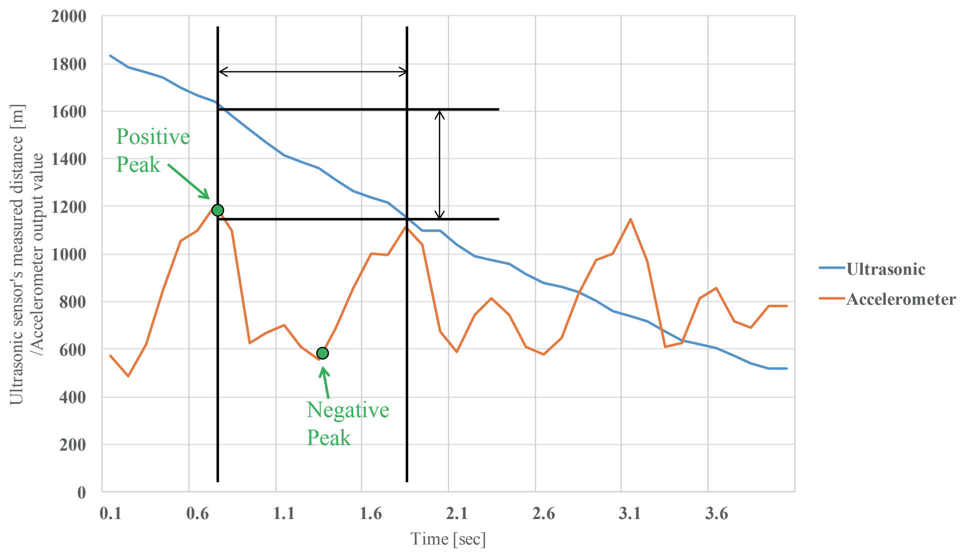

Figure 9. The output from the ultrasonic sensor and the accelerometer when the user walks toward the wall

Solution for Challenge C: Eliminating influence of objects adjacent to walls

Objects adjacent to the wall affect the room shape and size estimation (Challenge C). Figure 11 illustrates this problem. The user walks along the wall and keeps the distance d_0 between the walking path and the wall. When the user walks near the object, the distance is d_1. This change causes the mixed Gaussian distribution and disturbs the accurate estimation. To cope with this problem, we adopt Bayesian Information Criteria (BIC) and Expectation-Maximization (EM) algorithm. The processing flow is described as follows:

Step 1: Estimation for the number of Gaussian distributions utilizing BIC

Step 2: Estimation for the mean value for each Gaussian distribution

Step 3: Estimation the maximum mean value μ_{max}

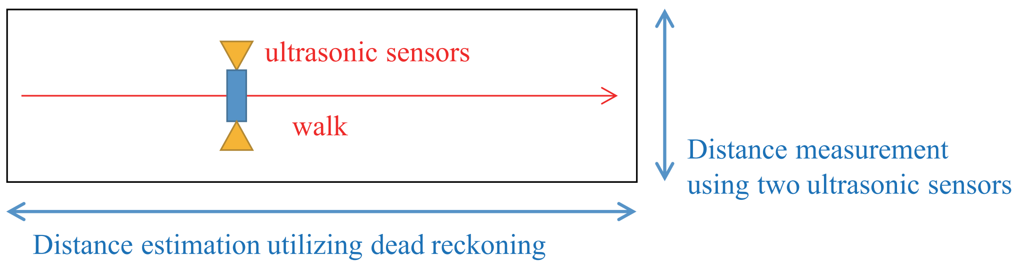

Figure 10. The measurement for the narrow room

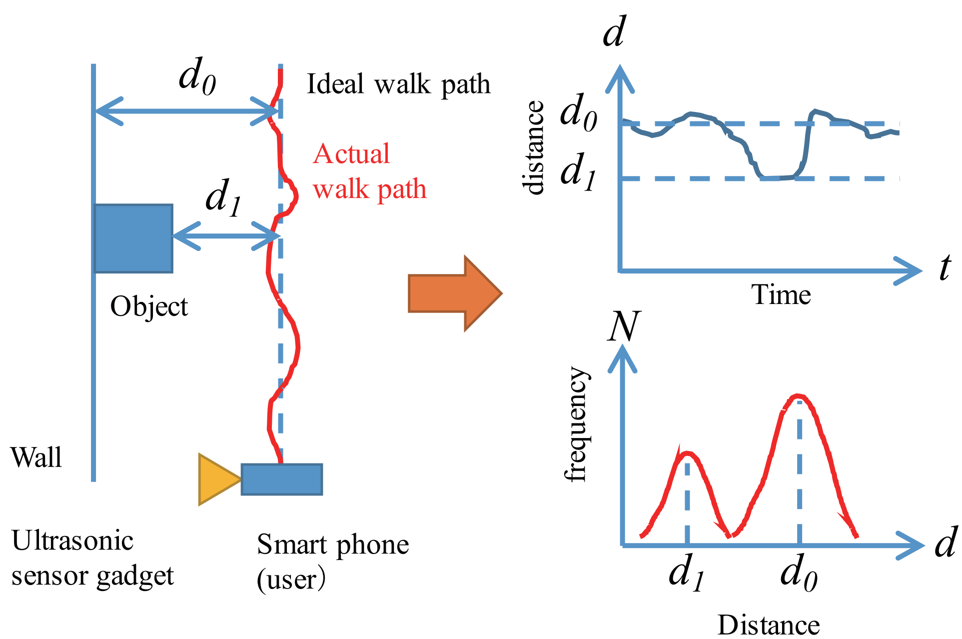

Figure 11. The mixed Gaussian distribution from walls and obstacles

In Step 1, we estimate the number of Gaussian distributions using BIC. We use BIC definition in (4)

$$BIC = 2 \times (Logarithmic\text{-}likelihood) \tag{4}$$

In Figure 11, we can estimate the number of Gaussian distributions as two.

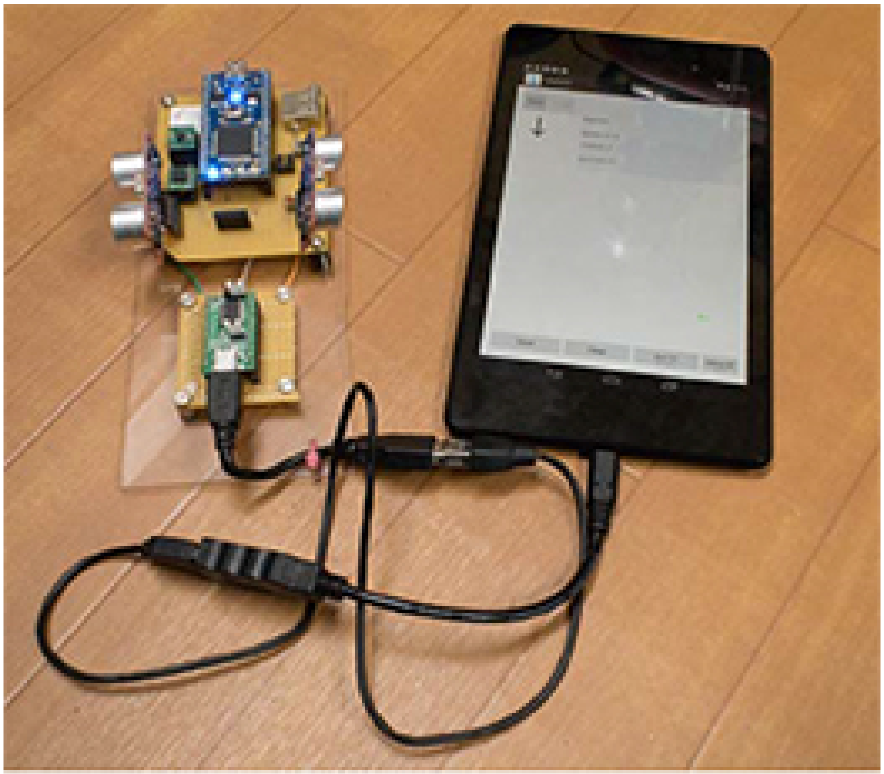

Figure 12. The prototype device

In Step 2, we estimate the mean value for each Gaussian distribution. In Figure 11, we can estimate mean values as $\mu_0 = d_0$ and $\mu_1 = d_1$.

In Step 3, we estimate the distance between the walking path and the wall, extracting the maximum mean value. In Figure 11, we can estimate it as $\mu_{max} = \mu_0 = d_0$.

We assume that the room does not have the wall which has sunk part.

2.5 Implementation

2.5.1 Prototype device

We have implemented a prototype of an ultrasonic sensor gadget shown in Figure 12. The gadget consists of mbed, a microcontroller, and two ultrasonic sensors. The size of the device is 80mm × 180mm × 40mm. It weighs less than 120g.

mbed (Micro-Processing Unit)[27] sends the distance data to Android smartphone application via an USB cable. Android application processes the data from the sensor gadget, accelerometer, and gyroscope and generates the measured shape and size on the display.

Figure 13 shows the design of the ultrasonic sensor gadget. The ultrasonic sensor gadget consists of three components, which are ultrasonic sensors, Micro Processing Unit (MPU), and USB connector. We implement two ultrasonic sensors in the reverse direction with each other and perpendicular direction to the walking path. The ultrasonic sensor gadget communicates with the measurement application in the smartphone via USB connector. First, the smartphone application written in Android Java emits the start signal for the measurement. Second, the MPU generates the ultrasonic wave from the transmitter and measures the Round Trip Time (RTT) of it. Based on RTT, the MPU calculates the distance between the walk path and the wall by equation (5).

$$d = (331.5 + 0.6t) \times RTT \div 2 \tag{5}$$

We denote that d is the distance between the path and the wall. t is the Celsius temperature and the sampling rate is 10 Hz.

We conducted a preliminary experiment to evaluate the accuracy of the distance measurement. We compared the measured distance between the ultrasonic sensor and the laser range finder, when the user stands at 0.5[m], 1[m], 2[m], and 4[m] from a wall. We use Leica DISTO D210, a laser range finder. Table 2 shows the result. The result proves that the prototype device measures the distance within 0.2[m] errors. We consider that the proposed tool has the sufficient basic performance to create the floor plan, since it achieved the competitive performance to the laser range finder. In addition, we found that there is a proportional correlation between the error and the distance from the wall, suggesting that the posture of the user strongly affects it.

2.5.2 Conceptual design of the practical room measurement tool

Figure 14 illustrates the conceptual design of the room measurement tool. The conceptual design adopts an ultrasonic sensor gadget smaller than the proto-

[27]NXP semiconductors, mbed LPC1768: `http://mbed.org/nxp/lpc1768/`

Table 2. The measurement result of the prototype device and laser range finder

Distance	Prototype device	Laser range finder
0.5m	0.5m	0.5m
1m	1.1m	1.3m
2m	1.9m	2.0m
4m	4.2m	4.2m

type. Also, all components are implemented in the connector for the smartphone. Thanks to these features, the user is able to carry this gadget to anywhere he wants and measure the room with small effort.

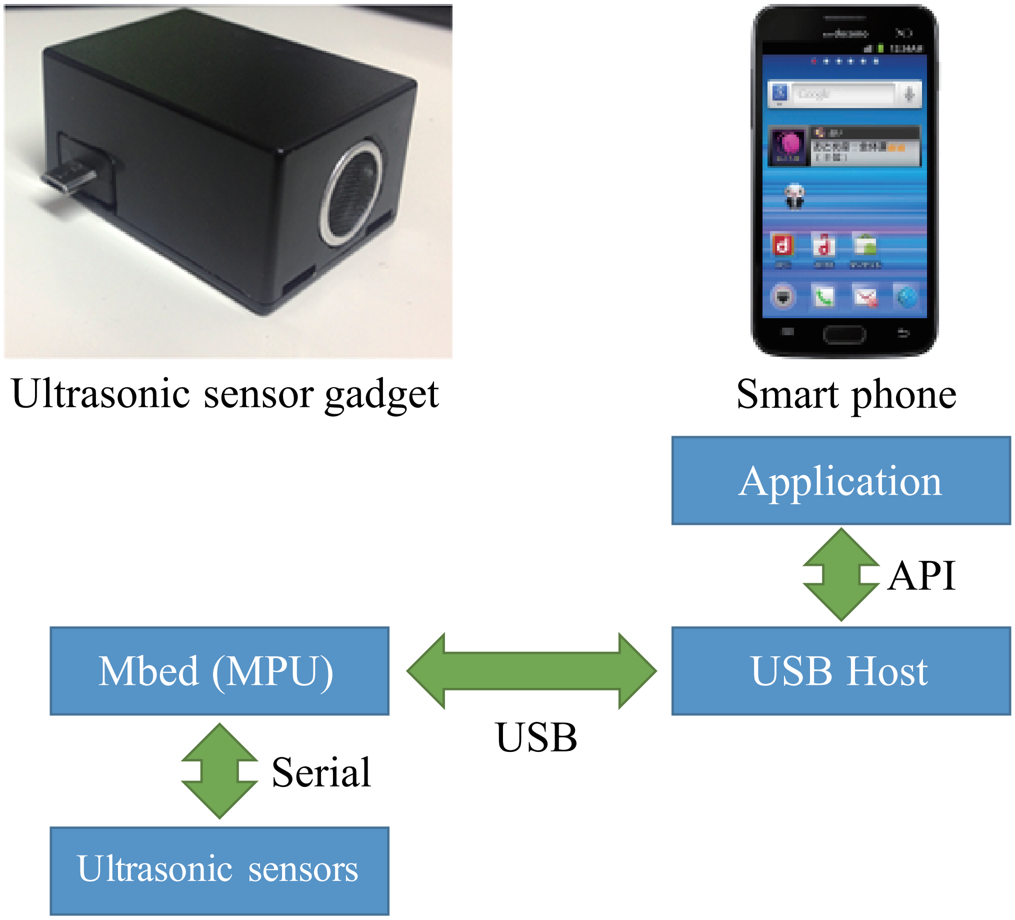

Figure 13. The system architecture of the ultrasonic sensor gadget

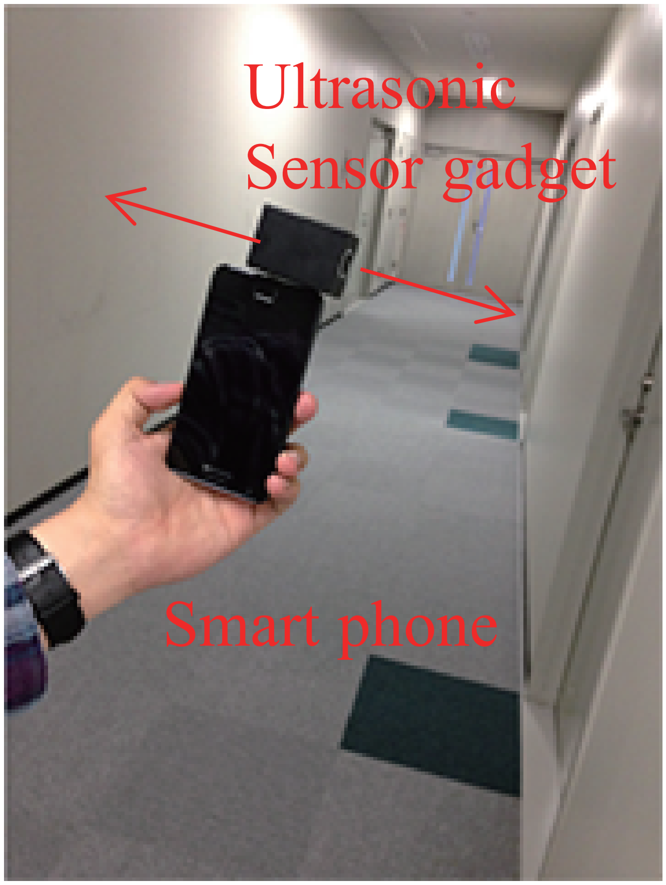

Figure 14. The usage of the proposed system

2.5.3 Real-time feedback view

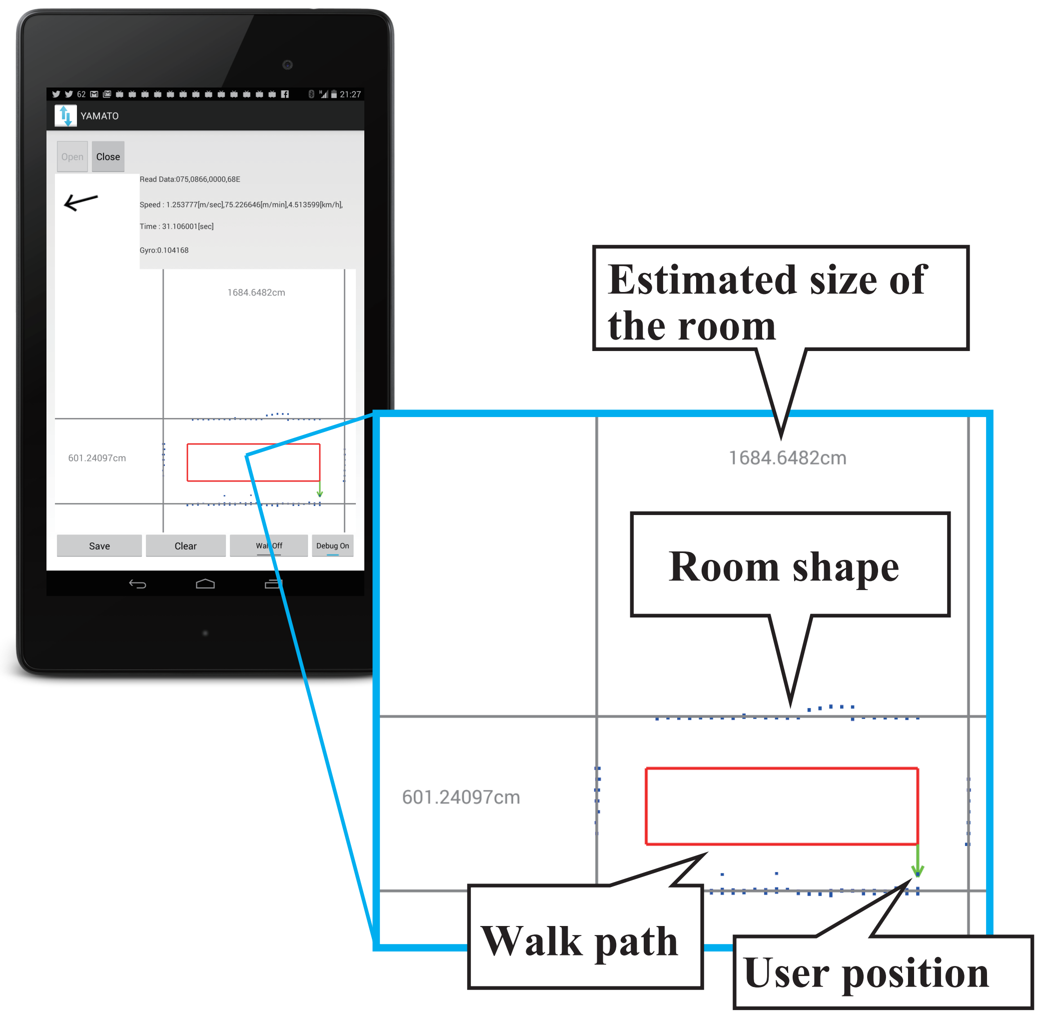

Figure 15. The interface for real-time feedback to the user

We implement a real-time feedback view for the user, to suppress the unnecessary measurement. When the user conducts the measurement, the tool shows the estimated room shape on the application simultaneously. Figure 15 shows the feedback view. When the user notices that he makes a mistake, he can stop it and measure it from the beginning.

Figure 16. The evaluation environment

2.6 Evaluation

We conducted three experiments to evaluate the proposed tool.

2.6.1 Stride length estimation

Evaluation method

We conducted an experiment to evaluate if the technique described in Section 2.4 can measure the stride length precisely. We also instituted the other experiment to figure out the performance of the proposed method to the multiple users with different heights. We conducted these two experiments in the corridor of the author's university depicted in Figure 16. In order to evaluate the performance, we set up the special walking pattern described in the following scenario.

1. The user holds the smartphone attached with the ultrasonic sensor gadget.
2. The user directs the ultrasonic sensor at the wall.
3. The user walks toward the wall from about 4m away from it.
4. The user stops in front of the wall.
5. The user makes "U-turn" in front of the wall and starts walking toward the other side of the corridor.
6. The user stops walking until the point under about 4m from the other side of the corridor.

We measure the stride length in (3)–(4). Also, we calculate the walked distance of the user by equation (6).

$$d_c = d_{u1} + d_w + d_{u2} \tag{6}$$

Here, d_c denotes the length of the corridor. d_{u1} denotes the distance between the point the user stops in the step (2) and the wall. d_w denotes the walked distance of the user with the technique which we measured in (3). d_{u2} denotes the distance between the point the user stops in the step (4) and the wall. In other words, we calculate that distance by utilizing the technique described in Section 2.4. In this experiment, we calculated the distance from (8).

$$d_w = l_{sl} \times cnt_{move} \tag{7}$$

Here l_{sl} is the stride length of the user. cnt_{move} is the number of steps of the user.

In order to evaluate the effect of the height difference between users, we asked three users (170cm, 180cm, and 200cm) to participate in the experiment. We conducted the evaluation five times for each user.

Table 3. The evaluation result to measure the length of the corridor

	User1	User2	User3
Soleus (Stride-height correlation)	30.4m(10.4m)	29.1m(9.1m)	26.6m(6.6m)
Proposed method	19.7m	20.0m	19.8m

Table 4. The comparison of physical profile between participants

	User1	User2	User3
Height	1.7m	1.8m	2.0m
Number of steps (average)	38	35	27
Soleus (Stride-height correlation)	0.77m	0.81m	0.89m
Stride length (Proposed method)	0.49m	0.55m	0.69m

Also, we measured the length of the corridor by utilizing "height correlation method" described in Soleus and compared the performance.

Result and discussion

Table 3 shows the measured length and the error of the corridor by utilizing each technique. We calculated the result from the average of five times experiment. Also, Table 4 shows the height, average number of steps, stride length of each user.

From the evaluation result, we discovered that the proposed method accurately measures the length of the corridor. On the other hand, the corridor length 30m with "height correlation method". There are two reasons for this result. First, there is a weak correlation between the stride length and the height. Second, these two correlation models are formulated from the experiments outdoor. Therefore, we confirmed that we cannot apply these models for indoor environments.

2.6.2 Shape and size estimation for a narrow room

Evaluation method

We conducted an experiment in two rooms, Room D and Room F. Room D has a 3.0[m] width wall. Room F has a 2.6[m] width wall. The user walked along the wall, keeping along the line that is drawn 1[m] away from the wall. Then, we collected the position of the user from inertial sensors and the distance from the ultrasonic sensor gadget. Next, we measured the length of the wall using the two ultrasonic sensors. After that, we measured it by a single ultrasonic sensor. Finally, we compared them.

Result and discussion

Table 7 shows the result. Two ultrasonic sensors method measured the length with less than 5.0% error, while the single one measured it with more than 10% error. We discovered that the proposed method accurately measures the size of two narrow rooms. Also, we found that the proposed method works more accurately in Room F than Room D, since the stride length estimation error affects more in the narrow room.

Figure 17. The experimental environment (Left picture: Student room, Right picture: Corridor)

2.6.3 Eliminating the error due to the objects attached on the wall

Evaluation method

In the first experiment, the user walked along the wall on the straight line, which is drawn 1[m] away from the wall while holding the smartphone with the prototype. We conducted this experiment with two walls. One is the wall in the office (Student room). 70 % of the wall is covered by bookshelves. The other is the wall in a corridor (Corridor). The wall is not covered with any objects. Then, we collected the position of the user from inertial sensors and the distance from the ultrasonic sensor gadget. Next, we measured the distance between the user and the wall by using the proposed method. On the other hand, we measured the distance by using the simple average. Finally, we compared two distances. In the second experiment, we examined the relationship between the measured distance and the cover rate of objects. Moreover, we changed the cover rate of the bookshelves in Student room between 0% and 100%, and then we compared the distance by two methods, similarly to the first experiment.

Result and discussion

Table 5 and 6 show the result of the accuracy in the experiments. The "Simple average" is the distance estimation between the user and the wall with the simple average. The "Proposed method" is the distance with the proposed technique. Table 5 shows that both methods, the proposed method and the simple average, achieve accurate distance estimation. We have confirmed that the proposed method works accurately in the normal condition, i.e. no objects adjacent to the wall. Table 6 shows that the proposed method measures the distance as 95[cm], while the simple average measures it as 78[cm].

Figure 18 shows the position of the wall and objects in the office. The red line shows the position of the wall. The dashed red line shows the bookshelf. The blue dots show positions of the wall and objects which the proposed tool has captured. The user walked along the line, i.e. $y = 0$. Also, Figure 20 shows the distribution of the distance between the user and the wall in Student room. There are two Gaussian distributions. The one whose average value is $\mu_1 = 55[cm]$ is made up from bookshelves. The other one whose average value is $\mu_2 = 95[cm]$ is made up

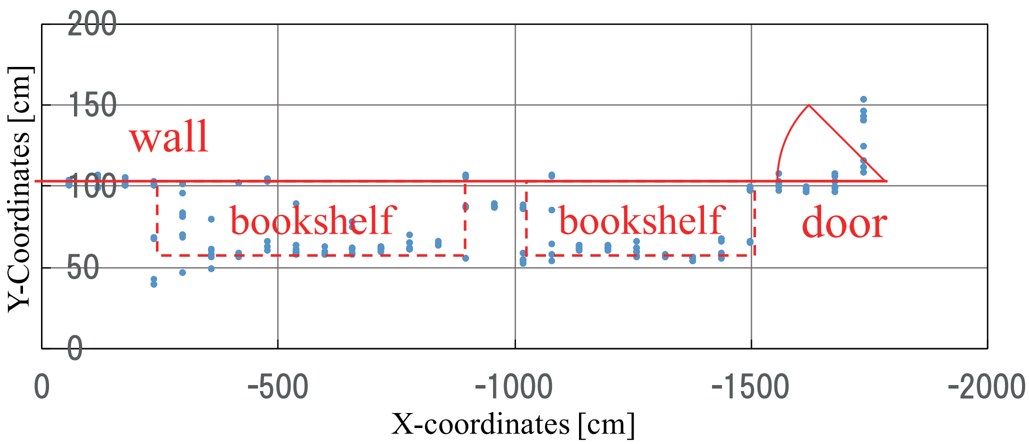

Figure 18. The position of walls and objects in the office

from the wall. As a result, we found that the proposed method eliminates the influence of objects adjacent to the wall.

Figure 22 shows the relationship between the measured distance and the cover rate of objects. The vertical axis shows the measured distance, while the horizontal axis shows the cover rate. We found that the proposed method works correctly up to 80%. We also discover that the proposed method fails to divide the mixed Gaussian distributions over 80% cover rate. This is because two Gaussian distributions are merged when over 80% of the wall is covered.

Table 5. The experiment result for the corridor wall

	Distance	Error
Simple average	105cm	5.0%
Proposed method	105cm	5.0%

Table 6. The experiment result for the student room wall

	Distance	Error
Simple average	78cm	22%
Proposed method	95cm	5.0%

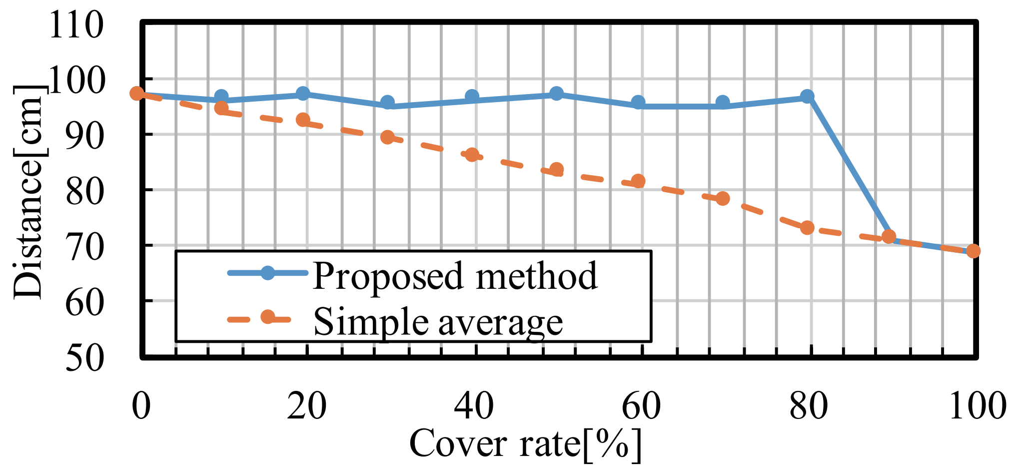

Figure 19. The relationship between the wall coverage and the measured distance

Table 7. The result for the corridor wall

Room	Length	Single ultrasonic sensor	Two ultrasonic sensors
D	3.0m	3.6m (Error: 16%)	2.9m (Error: 4.7%)
F	2.6m	3.1m (Error: 21%)	2.7m (Error: 5.0%)

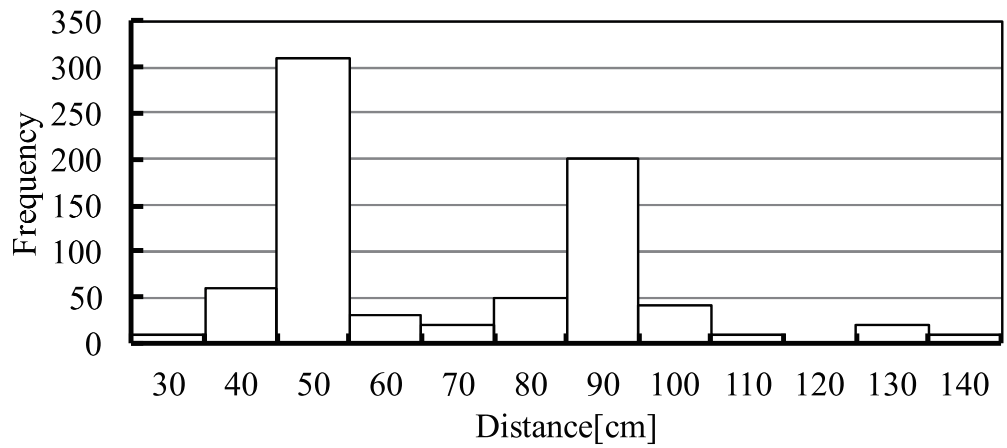

Figure 20. The frequency distribution of the distance between the wall and the user

Table 8. The measurement time for each room

Room	A	B	C	D	E	F	G
Manual measurement [s]	82.4	47.1	50.3	59.1	45.1	119.1	165.1
Proposed tool [s]	36.9	30.2	21.1	31.2	30.1	62.2	73.4

2.6.4 Evaluation for floor plan

Evaluation method

In order to evaluate the usability of the proposed room measurement tool, we created a floor plan of a building and measure the time for the work. First, the user walked along the wall. Then, we collected the position of the user from inertial sensors and the distance from the ultrasonic sensor gadget. Next, we created a floor plan by utilizing the proposed method. Here, we attached one room to the other manually. We compared the size of the measured rooms and the real ones. Also, we compared the measurement time for each room.

Result and discussion

Figure 21 illustrates the floor plan we created. The solid line denotes the real shape of the room. The dashed line denotes the shape using the proposed method. In addition, Table 9 shows the true, estimated, error, and predicted error length of each room. The left part of the table shows the result of East-West direction. The right part of the table shows that of North-South direction. From these results, we strongly believe that our prototype achieves the accurate room shape and size estimation. In addition, Table 8 shows the measurement time for each room. From this table, we have confirmed that the measurement time is short enough for the volunteer user to use this tool with small effort.

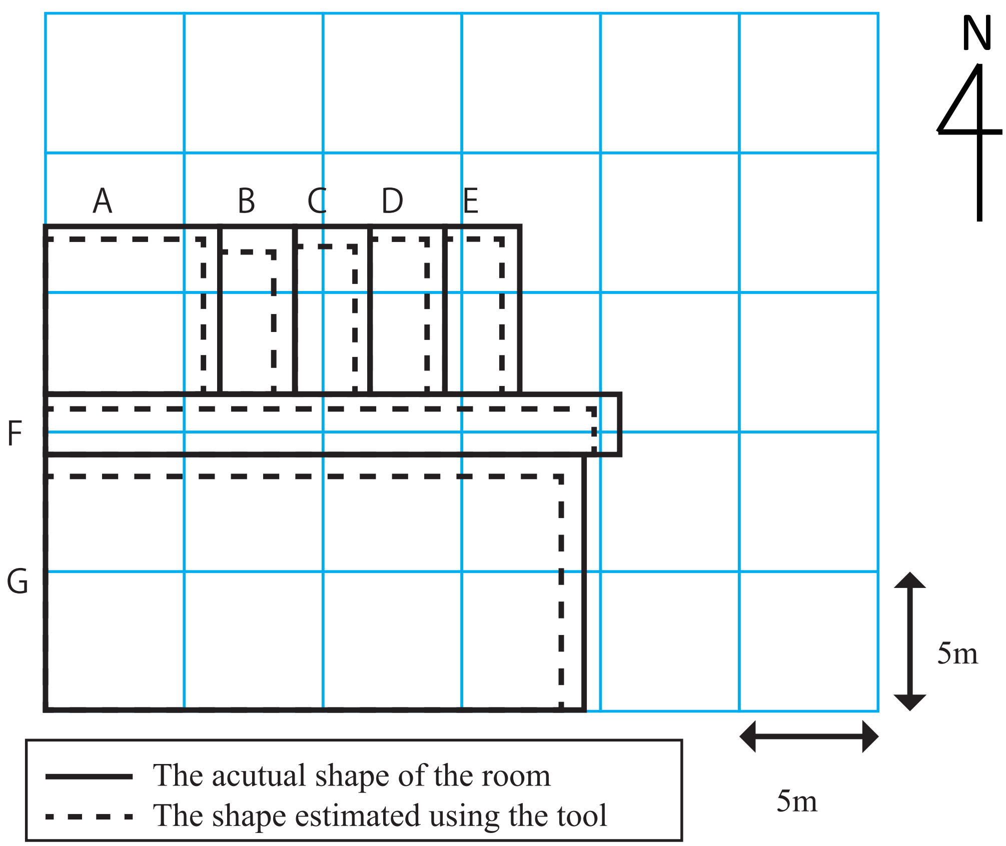

Figure 21. The created floor plan

Table 9. True, estimated, error, predicted error length of each room

	East-West				North-South			
	True	Estimated	Error	Predicted error	True	Estimated	Error	Predicted error
A	6.3m	6.4m	0.1m	1.3m	5.9m	6.0m	0.1m	1.2m
B	3.0m	3.3m	0.3m	1.0m	6.4m	6.3m	0.1m	1.3m
C	3.0m	2.7m	0.3m	1.0m	5.9m	4.8m	0.9m	1.2m
D	3.0m	2.9m	0.1m	1.0m	6.4m	6.8m	0.4m	1.3m
E	3.0m	3.3m	0.3m	1.0m	5.9m	6.3m	0.4m	1.2m
F	22m	23m	1.0m	3.0m	2.6m	2.7m	0.1m	0.9m
G	19.1m	21m	1.9m	2.6m	11m	10m	1.0m	1.8m

2.7 Discussion

We have realized a room measurement tool composed of a smartphone with an attached ultrasonic sensor. Through experimental evaluations, we confirmed that the proposed tool satisfies the requirements presented in Section 2.3: easy-to-use, low-cost, and accurate.

To evaluate whether operating our proposed tool was easy enough, we asked users to complete a lap along a wall. We interviewed some users whether using our proposed tool is simpler than the measurement-based method. Most of them answered responded that using our proposed tool was easier than the measurement-based method because it required less time to use.

To reduce costs, we simply attached an ultrasonic sensor to a smartphon. Smartphones are ubiquitous nowadays and have negligible cost. The ultrasonic sensor costs less than other sensors, i.e. the ultrasonic sensor costs just \$20, while the laser rangefinder and Kinect cost \$100 and \$2,450 respectively. We believe that adding external device will not be a burden on the user, since there is situation in society to prompt it as we mentioned in "1. Introduction".

To achieve accurate measurements, we proposed three techniques: stride length estimation, shape and size estimation of narrow rooms, and eliminating the influence of objects adjacent to the wall. The evaluation results showed that our proposed techniques achieved more accurate measurements.

For stride length estimation, our proposed method measured a corridor more accurately than the height-stride-length-correlation method. For the 20 m corridor, our proposed method estimated the length as 19.8 m, while the height-stride-length-correlation method estimated it as 28.7m. On the other hand, the corridor length 30m with the height-stride-length-correlation. There are two reasons for this result. First, there is a weak correlation between the stride length and height. Second, these correlation models are obtained from outdoor environments. Therefore, we confirmed that we cannot apply this model for indoor environments. As a result, we conclude that the proposed stride-length-estimation was essential to realize an accurate floor plan creation tool.

For the shape and size estimation of narrow rooms, we found that our proposed method accurately measured the size of two narrow rooms. Also, we found that our proposed method worked more accurately in Room F than Room D, because the stride length estimation affects narrower rooms more. In terms of eliminating the influence of objects adjacent to walls, our proposed method estimated the distance between the walked path and the wall more accurately than the simple average method. The 1-m distance between the walked path and wall was estimated as 97cm by our proposed method, while the simple average estimated it as 78cm.

As we presented in Section 2.4, objects adjacent to the wall influences the accuracy of measurements. Our proposed method analyzed the accumulated data and estimated an accurate distance. On the other hand, the simple average method suffered from objects, such as the 40 cm-wide bookshelf. Furthermore, we explored the limits of our proposed method in terms of how much cover rate of the object to the wall it can eliminate. We evaluated it using a simulation where we changed the length of the wall for the data obtained from previous measurements. Then, we applied the proposed method and measured whether it can measure the distance accurately. Figure 22 shows the relationship between the measured distance and the cover rate of objects. The vertical axis shows the measured distance, while the horizontal axis shows the cover rate. We found that the proposed method works correctly up to 80%. We also discover that the proposed method fails to divide the mixed Gaussian distributions over an 80% cover rate. This is because the two Gaussian distributions are merged when over 80% of the wall is covered.

In addition, we consider that the proposed method is hard to eliminate the object adjacent to wall that has the thickness less than 20 [cm]. This is because the preliminary experiment to measure the accuracy of the ultrasonic distance measurement sensor shows that the tool has the error up to 20 [cm].

In the experiment to create a floor plan of a building, we conducted the experiment on room types with enough to evaluate the basic performance of our proposed tool. We discuss the error in terms of the error model. The error model of the proposed tool is the summation of the error from the ultrasonic sensor, DR, and user's posture.

$$(Error) = (Ultrasonic - sensor) + (DR) + (User's - posture) \tag{8}$$

From the preliminary experiment in Section 2.5.1, the error of the ultrasonic distance sensor is 20 [cm]. Evaluation result showed that the accumulated error of DR and the effect from the user's posture are 30 [cm] and 50 [cm] respectively. Therefore, the total error is calculated as 1 [m]. On the other hand, the evaluation result showed that we estimated the size and shape of the room under 1 [m] error.

In addition, we discuss whether the accuracy is enough to realize RBA with some case studies. First, we discuss the elderly monitoring system. We consider that the accuracy is enough to realize the system, since the system recognizes which room the senior citizen stays in. We interviewed the owner of a nursing home. He says that the staff in the nursing home monitors which room the senior citizen stays in and estimates his/her physical or mental status. Second, we discuss the home-concierge robot. We consider that the home-concierge demands the floor plan in the following two objectives. First objective is that the floor plan enables the robot to recognize which room the user stays in. For this objective, the performance of the proposed tool is sufficient, since the robot can recognize which room the user stays in. Second objective is that the robot utilizes the created floor plan to move in the house. For this objective, the created floor plan is not sufficient, since it does not show the accurate area in which the robot can move. That is, the robot also requires the position of obstacles. To cope with this problem, the robot also needs to be equipped with the obstacle detection and record the position of it to the created floor plan.

On the other hand, assuming realistic use-cases, our experimental room set still does not cover all room types. Thus for future work, we will consider how to account for a larger variety of rooms.

Moreover, we can assume to utilize the proposed tool and create the floor plan for the researches described in Chapter 2 and 3. However, we did not create it, since we have already had the floor plan that is precisely created when it built.

2.8 Conclusion

In this research, we proposed the room measurement tool that utilizes the smartphone attached with an ultrasonic sensor gadget. There are three challenges to realize the measurement tool. The first challenge is that we have to develop a technique to measure the stride length in the building. To solve this problem, we calculated the stride length from the ultrasonic sensor and the accelerometer. The second challenge is that objects, such as bookshelves, attached on the wall

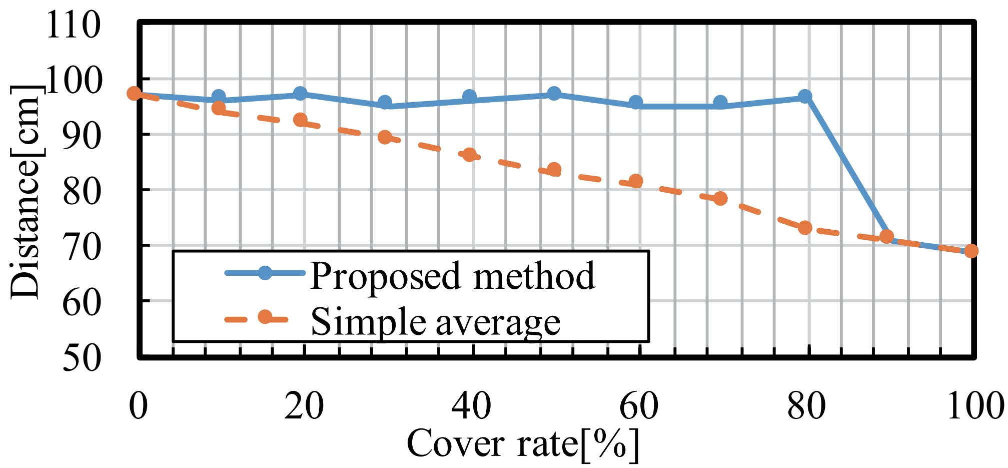

Figure 22. The relationship between the wall cover rate and the measured distance

deteriorate the room shape estimation accuracy. To solve this problem, we used a mixed Gaussian filter. The third problem is that the narrow room, such as corridors, leads to the low accuracy. To cope with this problem, we used two ultrasonic sensors, implemented in the reverse direction, and measure the distance between walls directly. The evaluation experiments showed that the proposed tool can measure more accurate shape and size estimation than the existing methods.

3 Indoor positioning system by utilizing a piezo sensor attached to floor

3.1 Introduction

The resident's behavior awareness applications can offer various services to the user such as the home appliance control and concierge robot. These applications recognizes the surrounding environment of the user by utilizing the indoor positioning system. For example, the home concierge robot recognizes the position of the user by utilizing this technique and approaches to him/her. Thus, we need to develop an indoor positioning system that utilizes the diffusive sensor.

In this chapter, we present a piezo sensor-based indoor positioning system which estimates the position of the user by utilizing the piezo component attached on the floor. Our system fulfills the requirements as follows: First, assuming that the positions of all furniture are known in advance, our system accurately estimates the position of the user from the vibration type of furniture in the home (Req 1). Second, our system suppresses the installation cost by utilizing the low cost piezo component (Req 2). Third, our system does not require the user to carry any mobile device (Req 3). Finally, our system does not capture any privacy-related information such as the image of the user (Req 4).

In order to realize the proposed positioning system, we have tackled two challenges. First challenge is the development of an indoor positioning technique. We can assume that we estimate the position of the user from several piezo sensors by utilizing that technique. Although we have to acquire the velocity of the vibration wave which travels on the floor, we cannot calculate that velocity. Thus, we have developed a new technique which estimates the position of the user from the type of the vibration. Second challenge is the selection of the feature vector to estimate the vibration type accurately. We have selected Mel-Frequency Cepstrum Coefficients (MFCC), Fast Fourier Transform (FFT), and Envelope shape features from preliminary experiments.

3.2 Related work

Many research studies on the indoor positioning system have been reported. In this section, we divide them into two groups: "Wearable sensor approaches" and "Device free approaches".

3.2.1 Wearable sensor approaches

Wearable sensor approaches estimate the position of the user by utilizing mobile devices such as a smart phone, smart watches and so on.

There are several studies of indoor positioning which utilizes the Pedestrian Dead Reckoning (PDR)[22][23]. In those studies, they estimate the position of the user by utilizing the inertial sensors, such as accelerometer and gyroscope, in the smartphone. However, the accumulated error of the sensors is the challenge. In order to cope with this problem, some studies adopt correction techniques. In [35], for instance, they adopt the ultrasonic landmark to correct the error.

Meanwhile, Active Bat[28] utilizes the ultrasonic wave to estimate the position of the user. They estimate the position of the user by utilizing TDoA technique. They attach the ultrasonic receivers on the ceiling. Also, the user carries a ultrasonic transmitter. Thus, TDoA technique estimates the position of the user. However, the ultrasonic positioning system costs more than €3,000. The installation cost is the burden on the user. In addition, the wearable device approaches force the user to carry the mobile device.

3.2.2 Device free approaches

Device free approaches estimate the position of the user by utilizing the sensor attached to the wall or floor in the building. Thus, those approaches realize the indoor positioning system without forcing the user to carry any mobile device.

There are several studies which estimate the position of the user by utilizing the stereo cameras[36][37][38][39]. They install several stereo cameras in the room. Based on the image processing of the cameras, they estimate the position of the user. However, in order to realize the indoor localization for every room, the installation of many stereo cameras is required and the cost becomes a burden to

[28] ActiveBat: `http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/`

Table 10. Comparison between the related researches and the proposed system

	Accuracy	Cost	Dev-free	Privacy
PDR[22]	-	$\surd$	-	$\surd$
Active Bat	$\surd$	-	-	$\surd$
Camera[36]	$\surd$	-	$\surd$	-
Radio wave[44]	$\surd$	-	$\surd$	-
Piezo (proposed)	$\surd$	$\surd$	$\surd$	$\surd$

the user. Moreover, the stereo camera always captures the posture of the user. This intrudes on the user's privacy.

There are several studies which estimate the position of the user by utilizing the transmission of the radio wave[40][41][42][43]. Pilot[44] is a device-free positioning system from the channel state of Wireless Local Area Network (WLAN). However, it requires the installation of several Access Points (APs). Also, the complex site survey of the radio wave is required to use the system. Thus, the installation cost becomes the burden on the ordinary user.

3.2.3 Comparison between the related researches and proposed system

Table 10 shows the comparison between the related researches and the proposed system. First row shows the requirements for the indoor positioning system we assume. Accuracy, Cost, Dev-free and Radio wave correspond to requirements 1 to 4 respectively. The related researches cannot fulfill all the requirements. Meanwhile, the proposed system (Piezo) achieves the requirements.

3.3 Piezo indoor positioning system

3.3.1 Requirements and policies

In order to realize the indoor positioning system, we have to fulfill the following requirements.

Requirement 1: Accurate indoor localization

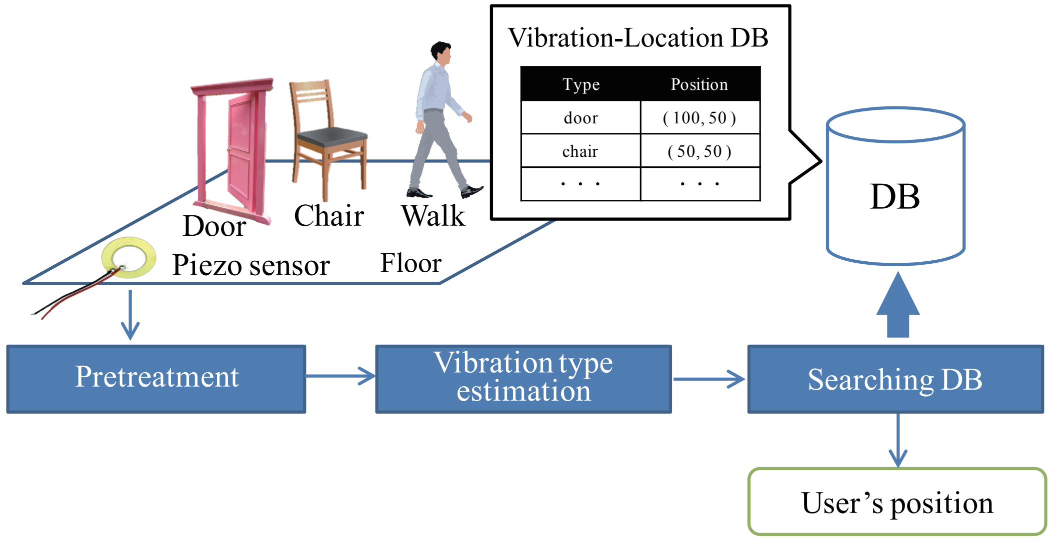

Figure 23. System overview

Requirement 2: Low installation cost

Requirement 3: Device free

Requirement 4: Low privacy concern

To achieve Requirement 1, we develop vibration type estimation technique for indoor positioning in stead of TDoA. To achieve Requirement 2, we select the piezo component as the sensor, since the sensor costs less than other sensors[29]. To achieve Requirements 3 and 4, we attach the piezo sensor on the floor. Thus, the user does not have to carry any mobile device. Moreover, the piezo sensor attached on the floor captures information relating to residents' privacy, which we have confirmed through a preliminary experiment.

3.3.2 System overview

Figure 23 illustrates the system of the piezo sensor-based indoor positioning system. Single piezo component is attached on the floor and captures vibration

[29] Piezo Element: https://www.sparkfun.com/products/10293

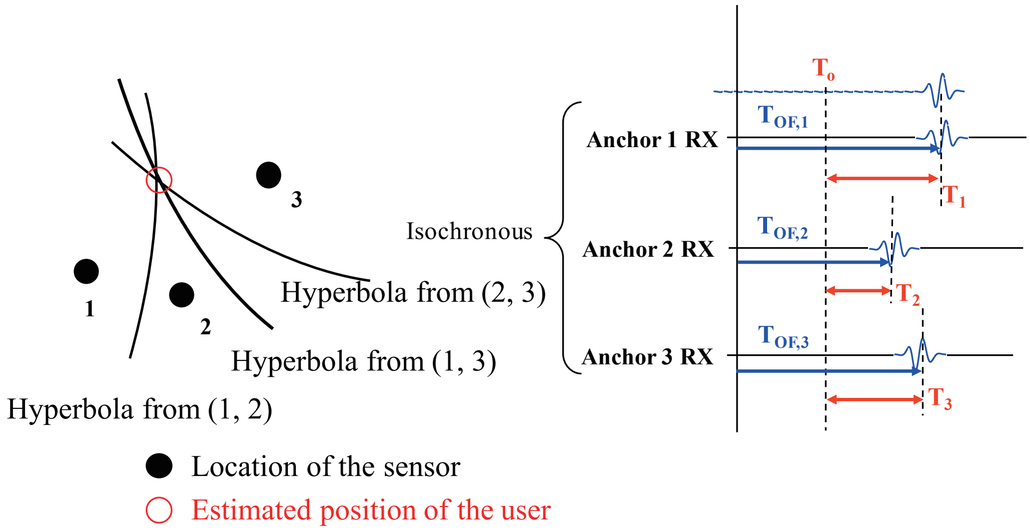

Figure 24. TDoA approach problem

which is generated from the user and furniture. The system estimates the position of the user in three steps. In the first step: “Pretreatment”, the system processes the captured sound in order to reduce the effect from noise. Also, the captured signal is divided into each time-window. In the second step: “Vibration type estimation”, the system estimates the vibration type by utilizing the classifier. In the final step: “Searching DB”, the system queries the database to obtain the location data. The database stores the location which corresponds to the estimated vibration.

3.3.3 Challenges and solutions

Vibration type estimation rather than TDoA

When we develop a piezo sensor-based indoor positioning system, we can assume that we put three piezo sensors on the floor and estimate the position of the user by utilizing TDoA technique. However, TDoA technique cannot estimate the position of the user from the vibration which travels on the floor, since we cannot calculate the velocity of the vibration. Figure 24 illustrates the estimation of the object's position by utilizing TDoA. First, TDoA technique measures the time difference of arrival: T_{12}, T_{13}, and T_{23} of the vibrations between sensors. Second, in order to draw hyperbolic curves, TDoA technique calculates the Difference of Distance (DoD) from the following equation $DoD_{12} = vT_{12}$. In order to estimate DoD, we have to calculate the velocity of the vibration: v accurately. In general, we can calculate the velocity of the vibration which travels through solid body from the following equations:

$$C_L = \sqrt{\frac{E}{\rho} \cdot \frac{1-\mu}{(1+\mu)(1-2\mu)}}$$

$$C_T = \sqrt{\frac{G}{\rho}}$$

Here, C_L denotes the velocity of longitudinal wave in solid body. E denotes the elastic modules. ρ denotes Young's modules. μ denotes Poisson's ratio. C_T denotes the velocity of transverse wave in solid body.

ρ is the density specific to each material. However, the floor is composed of several substances. Thus, we cannot calculate the velocity.

Moreover, even if we assume that we estimate the velocity of the vibration, we cannot adopt TDoA technique due to high installation cost. Since TDoA technique demands several instrumentation devices with the clocks which are synchronized accurately, and are often expensive, adoption of these devices does not fulfill Requirement 2: Low installation cost.

In order to cope with this problem, we estimate the position of the user from the type of vibration. The idea of this technique is that, when we capture the vibration from specific furniture, we can estimate that the user exists around that furniture. Figure 25 illustrates the waveform of vibrations which are captured from a hinged door, a chair, the footsteps of a user. The vibration waveform of the hinged door is captured when a user opens the door. That of a chair is captured when a user stands up from it. There is a difference between the vibrations. First, we should make a database which includes the correlation between the position of each furniture and the vibration type. After that, we can estimate the position of the user.

Feature vector selection

In order to generate a classifier which estimates the vibration type, there are many options for feature vectors. We empirically select three feature vectors: MFCC, FFT and Envelope shape.

Mel-Frequency Cepstrum Coefficients (MFCC) is one of the feature vectors which are frequently used for sound processing[45]. MFCC represents the power spectrum of a signal, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency.

Fast Fourier Transform (FFT) feature is one of the feature vectors which are normally used for signal processing[46]. FFT is the power spectrum of a signal, based on a Fourier transform of it.

Envelope shape is one of the feature vectors which represents the shape of the wave[47]. Figure 26 illustrates the methodology to generate the envelope shape.

3.3.4 Classifier generation

In order to estimate the vibration type, we generate a classifier that learns the training data set including the vibration data and the activity type. There are many options for the classifier. We have selected Logistic regression[30] which is implemented in scikit-learn[31] as the classifier.

3.3.5 Prototype implementation

We have developed the first prototype of the piezo sensor module for it as illustrated in Figure 27. The module consists of the piezo sensor and the amplifier circuit. The total cost of the module is less than €10, which is low cost. The vibration is recorded through USB Audio interface and processed in a laptop with Python[32].

[30] Logistic Regression classifier: `http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html`

[31] Scikit learn: `http://scikit-learn.org/`

[32] Python: https://www.python.org/

3.4 Evaluation

We conducted an experiment to evaluate the proposed vibration type estimation technique. Figure 28 shows the floor map of our smart home testbed. The total cost of the module is less than €10, which is considered low cost. We attached the piezo sensor on the floor close to the slide door as illustrated in the Figure 28.

3.4.1 Recording of vibrations

In order to conduct the evaluations, we collected the vibrations in the smart home. We asked one participant to perform five activities which are likely to occur in the living room: "step", "open door", "close door", "stand up", and "sit down". We collected ten vibrations for each action.

We put labels (activity types) to the vibrations and made a dataset by recording the experiment with a video camera.

3.4.2 Evaluation protocol

We conducted two experiments to evaluate the proposed methods.

In the first experiment, we distinguish the vibration type with the dataset. Since we collected ten vibrations for each action, we conducted the evaluation with Leave-one-out method. Prior to the experiment, we divided the dataset in ten groups. Each group has every vibration type including "step", "open door", "close door", "stand up", and "sit down". Fig 29 illustrates the procedure used in the experiment. First, we processed the vibration data to reduce the effect from the noise. Second, we extracted MFCC feature from each vibration. Third, we divided the dataset into test dataset and the training dataset. Forth, we generated a classifier using Logistic regression from the training dataset. Finally, we estimated the type of each vibration in the test set by utilizing the classifier.

In the second experiment, we evaluated the performance difference of the feature vectors between MFCC, FFT, and Envelope shape.

Table 11. Confusion matrix with MFCC

True \ Predicted	a	b	c	d	e
a=Step	10	0	0	0	0
b=Open door	0	10	0	0	0
c=Close door	0	3	7	0	0
d=Stand up	0	0	0	10	0
e=Sit down	0	0	0	0	10

3.4.3 Result and discussion

Table 11 shows the confusion matrix of the evaluation. Each row shows the name of the activities and each column shows the estimated activities. Table 12 shows the precision, recall, and F-measure of each activity. We calculate the F-measure from the following equation.

$$\text{F-value} = \frac{2\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}}$$

The evaluation result indicates that the proposed classifier with MFCC has achieved the average F-measure: 89%. For each vibration, the proposed method correctly classifies "step", "stand up", and "sit down". On the other hand, the method confuses "open door" with "close door". It is assumed that this misclassification comes from the little MFCC feature difference between these two vibrations.

Table 12 also shows the comparison of feature vectors between MFCC, FFT, and Envelope shape. Each row shows the name of the activities and each column shows F-measure with each feature vector. The Evaluation result shows that MFCC is the best feature vector between these three. However, for distinguishing between "open door" and "close door", Envelope shape is better than MFCC. Thus, we have confirmed that there is a possibility that we can improve the performance by generating a new classifier which combines MFCC and Envelope shape feature vectors.

3.5 Discussion

Here, we discuss whether the accuracy is enough to realize RBA with some case studies. First, we discuss the elderly monitoring system. We consider that the accuracy is enough to realize the system, since the system recognizes which room the senior citizen stays in. We interviewed the owner of a nursing home. He says that the staff in the nursing home monitors which room the senior citizen stays in and estimates his/her physical or mental status. Second, we discuss the home-concierge robot. We consider that the home-concierge demands the indoor positioning in the following two objectives. First objective is that the indoor positioning enables the robot to recognize which room the user stays in. For this objective, the performance of the proposed tool is sufficient, since the robot can recognize which room the user stays in. Second objective is that the robot utilizes the indoor positioning to move in the house. For this objective, the proposed indoor positioning is not sufficient, since it does not show the accurate position in which the robot can move. Therefore, for this objective, the robot needs to utilize the sonar sensor to detect

3.6 Conclusion

We present a piezo sensor-based indoor positioning system which estimates the position of the user by utilizing the piezo component attached on the floor. In order to realize the proposed positioning system, we have tackled two challenges. First challenge is that we have to develop an indoor positioning system which does not utilizes TDoA techniques. In order to cope with this challenge, we have developed a new method which estimates the position of the user from the type of the vibration. Second challenge is that we have to select an appropriate feature to estimate the vibration type accurately. We have selected MFCC feature through comparison evaluation with FFT and Envelop shape. We have implemented the proposed system in the smart home which belongs to the authors' university. As a result, we have confirmed that our system estimates the type with F-measure: 93.9%.

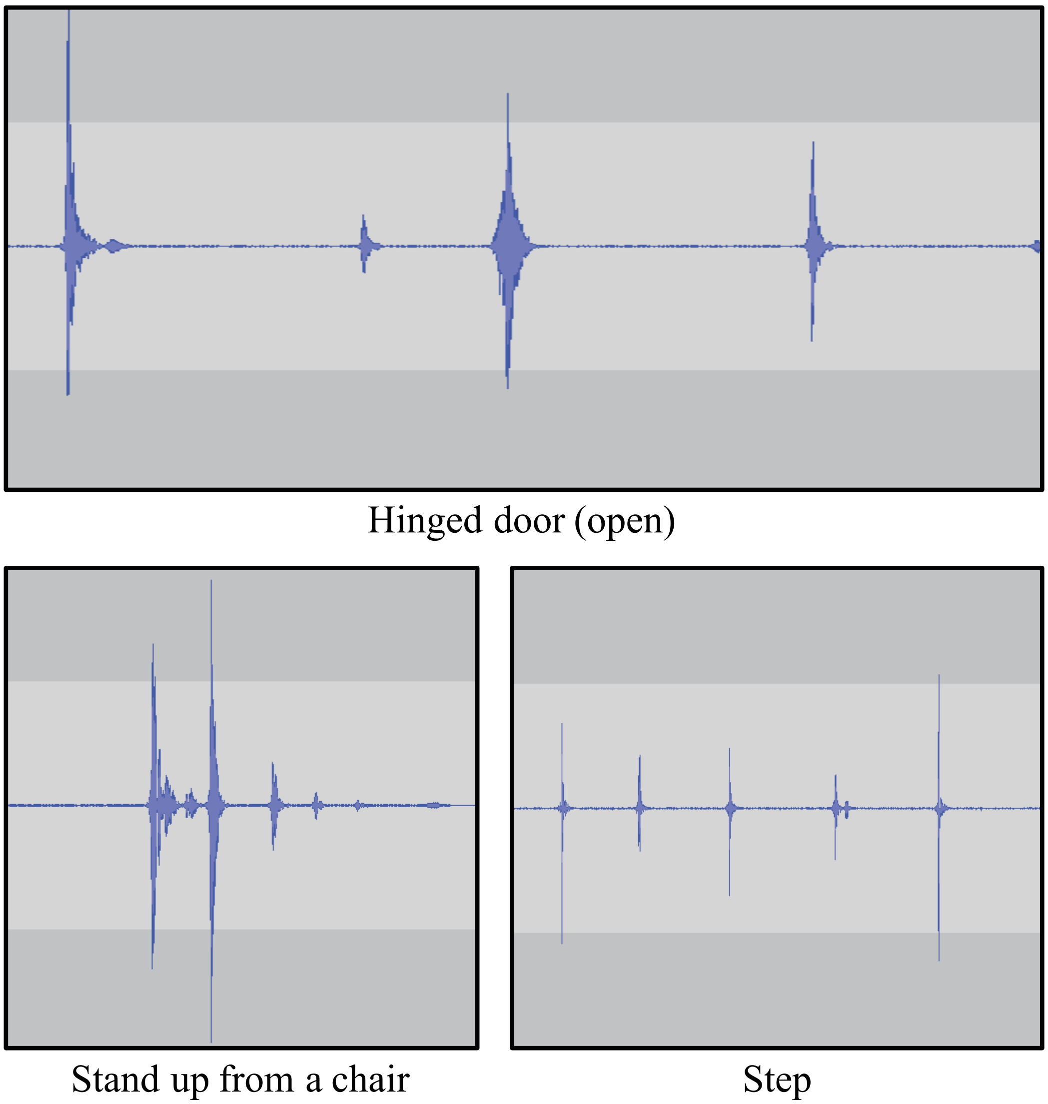

Figure 25. Wave form of the vibrations

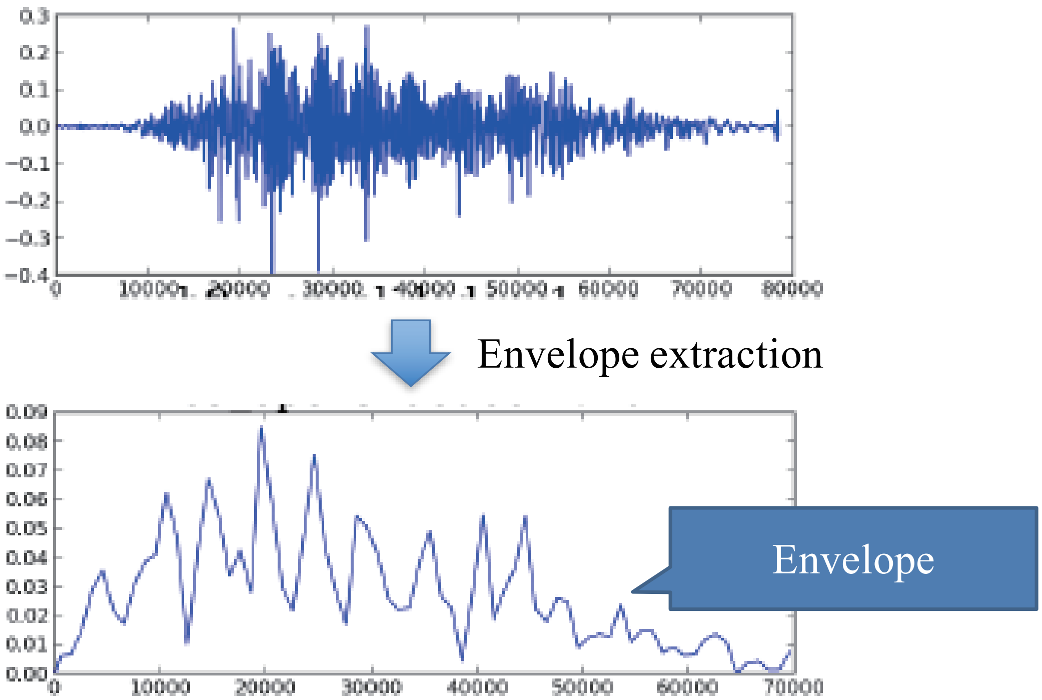

Figure 26. Envelope shape extraction

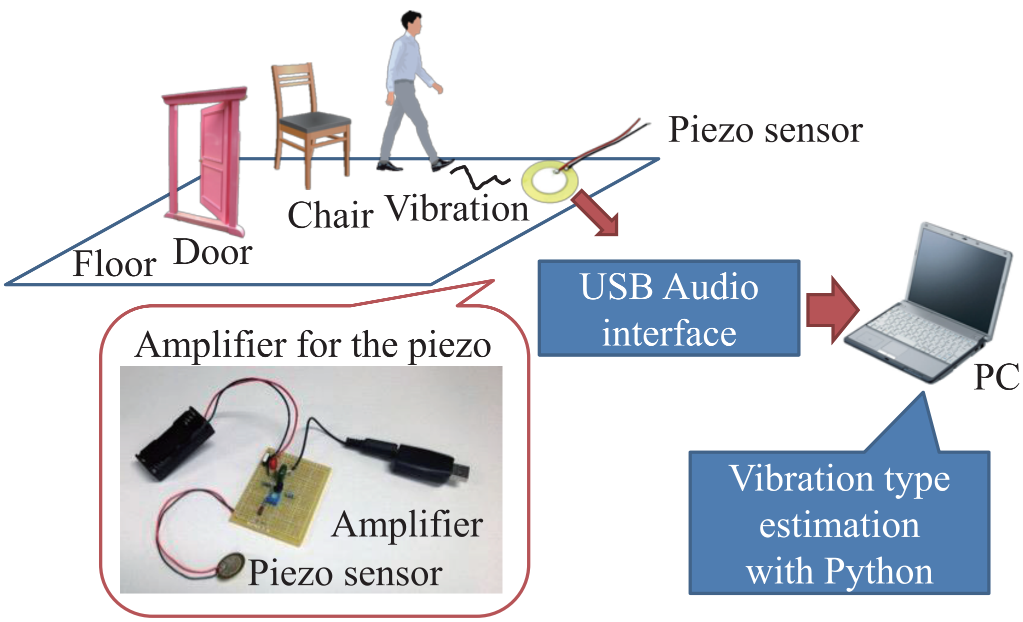

Figure 27. Implementation of the piezo sensor

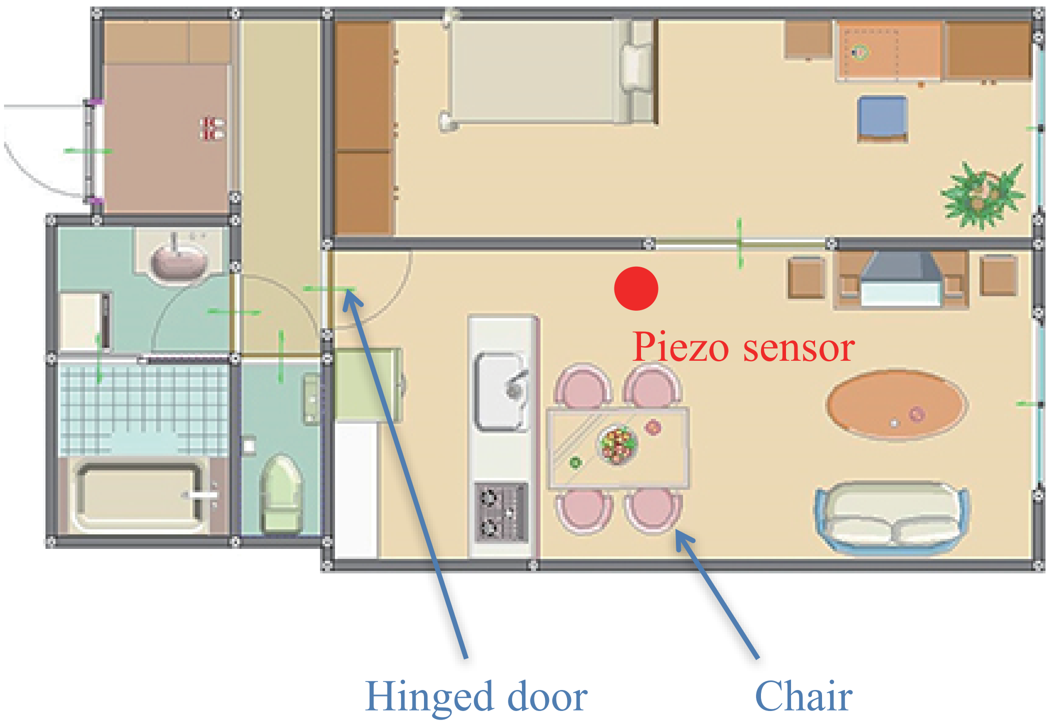

Figure 28. Sketch map of the smart home and the location of piezo sensor and furniture

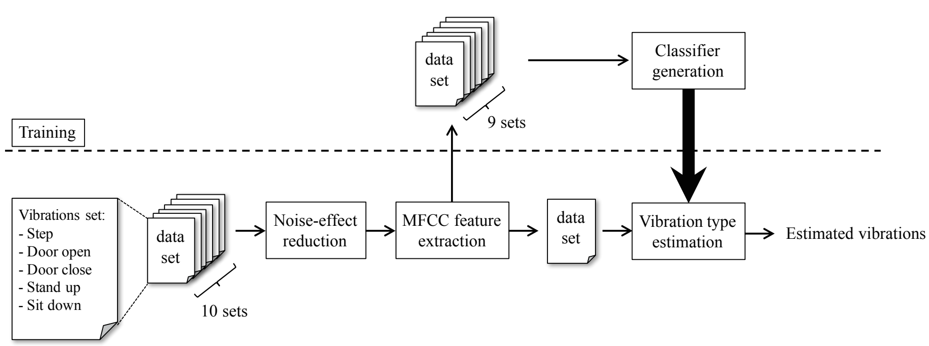

Figure 29. Evaluation procedure

Table 12. Comparison between MFCC, FFT, and Envelope shape

		MFCC	FFT	Envelope
Step	Precision	100%	100%	100%
	Recall	100%	10.0%	66.7%
	F-measure	100%	18.0%	80.0%
Open door	Precision	100%	33.0%	100%
	Recall	76.9%	80.0%	83.3%
	F-measure	86.9%	47.0%	90.9%
Close door	Precision	70.0%	38.0%	80.0%
	Recall	100 %	30.0%	100%
	F-measure	82.4%	33.0%	88.9%
Stand up	Precision	100%	25.0%	20.0%
	Recall	100%	20.0%	100.0%
	F-measure	100%	22.0%	33.3%
Sit down	Precision	100%	60.0%	90.0%
	Recall	100%	55.0%	69.2%
	F-measure	100%	57.0%	78.3%
Average	Precision	94.0%	51.0%	78.0%
	Recall	95.4%	39.0%	83.8%
	F-measure	93.9%	36.0%	74.3%

4 Activity recognition technique by utilizing energy-harvesting PIR sensor

4.1 Introduction

The resident's behavior awareness applications can offer various services to the user such as the home appliance control and concierge robot. These applications recognizes the user's status by utilizing the activity recognition system. For example, the home concierge robot recognizes that the user works on his business hard, and then prepare the bath so that he/she take rest after working. Thus, we need to develop an activity recognition system that utilizes the diffusive sensor.

The survey[48] reported that real-time utilization of IoT data streams is highly anticipated an the real-time activity recognition in home is one of the main applications. Accordingly, there are many studies which work on the activity recognition in the smarthome. There are activity recognition techniques which utilize cameras[49][50]. They estimate the activities of the user based on the image processing. However, in order to realize the recognition in the smarthome, we have to set up several cameras, which breeds the installation cost problem. Moreover, the camera intrudes the user's privacy.

There are different approaches of activity recognition which utilize the wearable devices such as the smartphone[51]. In these studies, they estimate the activities by utilizing the accelerometer and gyro sensors in the device. Nevertheless, they have succeeded in the recognition of simple activities just as "walk" and "run". Thus, they cannot estimate the daily living activities in the smarthome such as "sleeping". Moreover, the wearable device requires the battery replacement, which becomes burden on the user. To summarize, the previous studies leave the following challenges: (i) privacy intrusion from cameras, (ii) small number of activities that are recognized (iii) low accuracy of recognition (iv) high installation and operation cost, (v) burden on the user to wear the device, and (vi) wire installation for power supply and data collection.

In this chapter, we develop an activity recognition system by utilizing energy harvesting Passive Infra-Red (PIR) and door sensors. The energy harvesting

PIR and door sensors have the solar panel and Supercapacitor[33] inside. Under the sunlight or bulb light, the energy generated from solar panel operates the sensor and wireless communication module while charging Supercapacitor. In the night without any light, the charged Supercapacitor keeps the unit running. The cost of the energy harvesting PIR and door sensors is much smaller than that of the ultrasonic positioning sensor. The energy harvesting sensor unit does not demand the battery replacement, since the power supply depends on the solar panel and Supercapacitor. Moreover, the sensor unit conveys the captured data to a home server via wireless sensor network, which does not demand wire installation. The PIR, which detects the user from the infrared emitted from his skin, and door sensors realize the device free[34] activity recognition. Thus, the proposed system solves the challenges (i)–(vi).

4.2 Related work

Many research studies on the activity recognition in the smarthome have been reported. In this section, we divide them into two groups: "Activity recognition by utilizing wearable sensors" and "Activity recognition by utilizing cameras".

4.2.1 Activity recognition by utilizing wearable sensors

Activity recognition methods that use wearable accelerometers have already achieved accuracies greater than 90% for simple actions such as walking, sitting, running and sleeping[52]. However, using wearable accelerometers to recognize abstract or complex activities has not yet been proposed. The method of Bao et al.[53] can recognize 20 activities, such as watching TV, cleaning, and working, using five wearable accelerometers. However, the burden on users is heavy because it requires a user to wear five sensors. Maekawa et al.[51] focused on the magnetic field generated by home appliances when used, and proposed a method of recognizing the living activities, such as watching TV, shaving, the operation of the mobile phone, brushing of teeth and cleaning, using a wearable magnetic sensor.

[33] How does a Supercapacitor work?: `http://batteryuniversity.com/learn/article/whats_the_role_of_the_supercapacitor`

[34] "Device free" means that user does not need to wear any device.

However, their approach is limited to activities associated with the operation appliances.

4.2.2 Activity recognition by utilizing cameras

Brdiczka et al.[54] proposed a technique for recognizing living activities inside a smart home. Their study used an ambient sound sensor and a 3D video tracking sensor, and achieved recognition rates ranging from 70% to 90% for both individual activities, such as working and naps, and activities performed by more than one person, such as conversations and games. However, their method requires a specific camera and microphone and places the residents at risk to privacy exposure. In addition, the recognition accuracy of their method is not enough as many other activities are left unrecognized.

Kasteren et al.[55] designed a system for recognizing living activities such as eating, watching TV, going out, using the toilet, taking showers, doing the laundry, and changing clothes in a smart home embedded with door sensors, pressure-sensitive mats, float sensor, and temperature sensor. The recognition accuracy of their system ranges from 49% to 98%. It can recognize many activities, but it has a high initial costs and low recognition accuracy depending on the type of activities.

Chen et al.[56] designed a system for recognizing complex living activities such as making coffee, cooking pasta, watching TV, taking a bath, and washing hands in a smart home embedding contact, motion, tilt and pressure sensors. Their system achieved a recognition accuracy greater than 90%. However, this method requires many sensors and overall system cost will be high.

4.2.3 Approach of Energy Harvesting PIR and door sensor-based activity recognition

In order to study the challenges in the previous researches, we aim to develop an activity recognition system by utilizing PIR and sensors. Our system achieves low installation and operation cost, reduces user's burden because the user does not need to wear any device, and has less impact on the intrusion of the user's privacy.

4.3 Energy Harvesting PIR and door sensors based Activity Recognition

4.3.1 Requirements and Basic Policy

As we already addressed in Sect. 4.1, the following requirements must be satisfied in activity recognition in homes.

(1) Abstract and various types of living activities are recognized.

(2) Low-cost and a small number of sensors are used.

(3) Low privacy exposure of the residents is realized.

(4) Tag-free activity recognition

Basic steps to solve these requirements are described as follows. To satisfy requirement (1), we target the eight daily living activities such as “cooking” and “taking a meal” to cover the basic activities in the home. The following subsection contains the definitions of living activities and the types of sensor data collected.

4.3.2 Definition of living activity

We describe the target living activities in this section. According to the Statistic Bureau, Ministry of Internal Affairs and Communications in 2011, the main activities within one day is classified into the 20 types shown in Figure 30. The activities are classified as primary activities (i.e., physiologically necessary activities such as sleeping and eating), secondary activities (i.e., mandatory activities in social life such as working and housework), and tertiary activities (i.e. activities in during times that can be used freely). In addition, a detailed classification method with 6 large classifications, 22 middle classifications, and 90 small classifications of activities within one day are also defined. We refer to these definitions in our study, and we extracted eight activities as targets of our living activity recognition method: “Eat”, “Bathroom activity”, “Sleep”, “Cook”, “Clean-up”, “Living room activity”, “Work and Study with PC”, and “Go out”.

Primary activity
- Sleeping
- Personal errands
- Meal

Secondary activity
- Commuting to office or school
- Work for income
- Schoolwork
  (The learning activities related to classes of school)
- Housework
- Nursing
- Childcare
- Shopping

Tertiary activity
- Movement (except commuting)
- TV, Radio, Newspaper, Magazine
- Rest, Relaxation
- Learning, Self–development, Training (except schoolwork)
- Hobby, Recreation
- Sports
- Volunteer activities
- Companionship, Association
- Seeing a doctor, Recuperation

Figure 30. Examples of living activity classification

4.3.3 Collection of sensor data

In this subsection, we describe the sensors used in our study. Data is collected by a person living in the smart home shown in Figure 31 (Experimental housing facilities of 1 bed room and 1 living room with kitchen built in the Nara Institute of Science and Technology). In the smart home, power meters, ambient sensors (i.e. temperature, humidity, illumination, human sensors embedded in different places), ultrasonic positioning sensor, door sensors, faucet sensors have been already deployed. In the proposed method, we additionally installed 11 PIR, which includes nine directional PIR sensors, and eight door sensors whose power is supplied from the energy harvesting module. The captured sensor data is stored in a server via EnOcean [35] protocol based wireless sensor network.

[35] EnOcean https://www.enocean.com

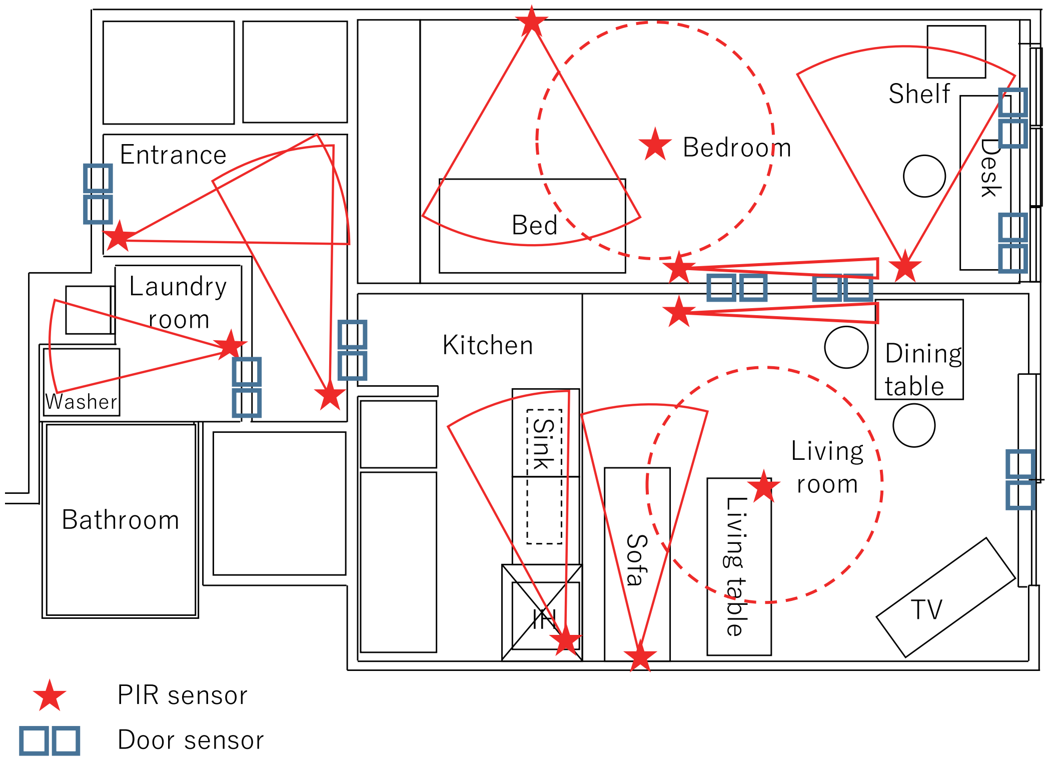

Figure 31. Floor plan and the position of sensors

Figure 32 shows the energy harvesting PIR sensor. Figure 33 shows the energy harvesting door sensor. The PIR sensor outputs 1/0 corresponding to the existence of the user. Each sensor has EnOcean network transmitter and conveys the captured data to a home server with a EnOcean network interface via EnOcean communication protocol, when the PIR sensor detects the user's motion or the door sensor detects the door's open/close. The server stores the received data with the timestamp into the database. The sensor unit operates from the energy that is generated from the solar panel under sunlight or bulb light. Simultaneously, the unit charges Supercapacitor. In the night without any light, the charged Supercapacitor keeps the unit running. Both sensors are provided from Rohm Co., Ltd.

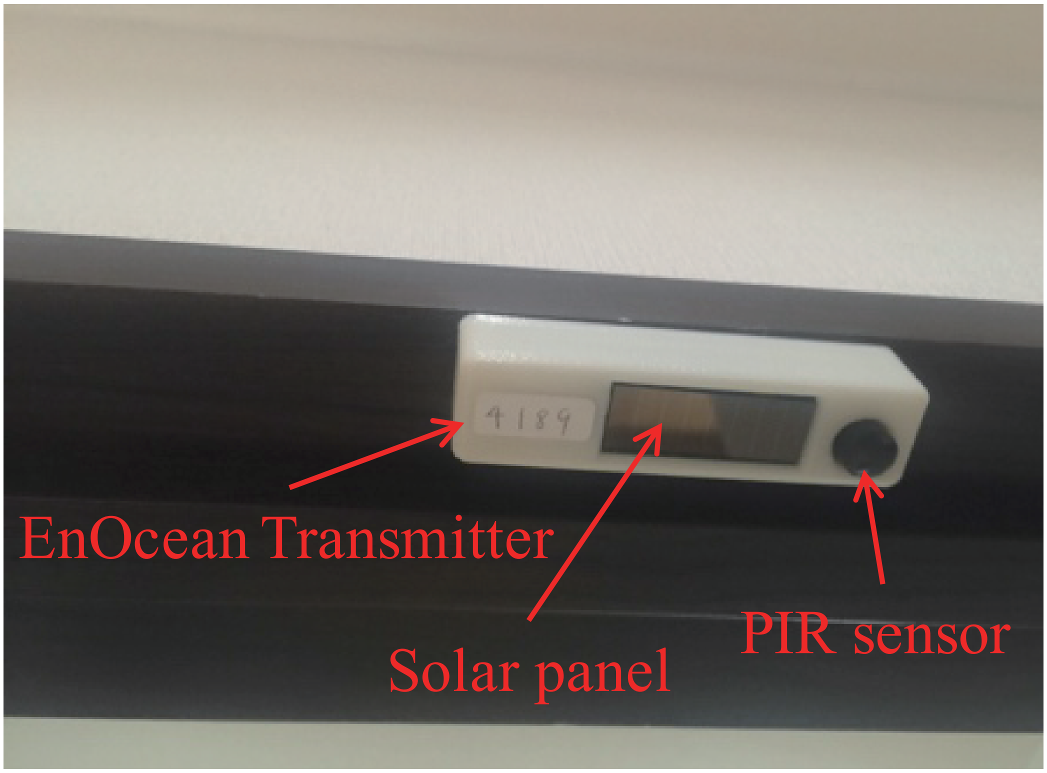

Figure 32. Energy harvesting PIR sensor

4.3.4 Activity recognition technique

In this section, we describe our method for recognizing living activities. The proposed method recognizes the daily living activities by machine learning. The process of applying machine learning is composed of the following three steps. (1) Acquisition of training data to be used for learning, (2) extraction of the feature values of the training data acquired, (3) construction of a recognition model for living activities. In the following subsection, we describe the details of these steps.

Acquisition of Training Data

For machine learning, the system needs the training data which have the correspondence between the living activity labels and the sensor data in advance. We have developed a living activity labeling tool to easily obtain the training data.

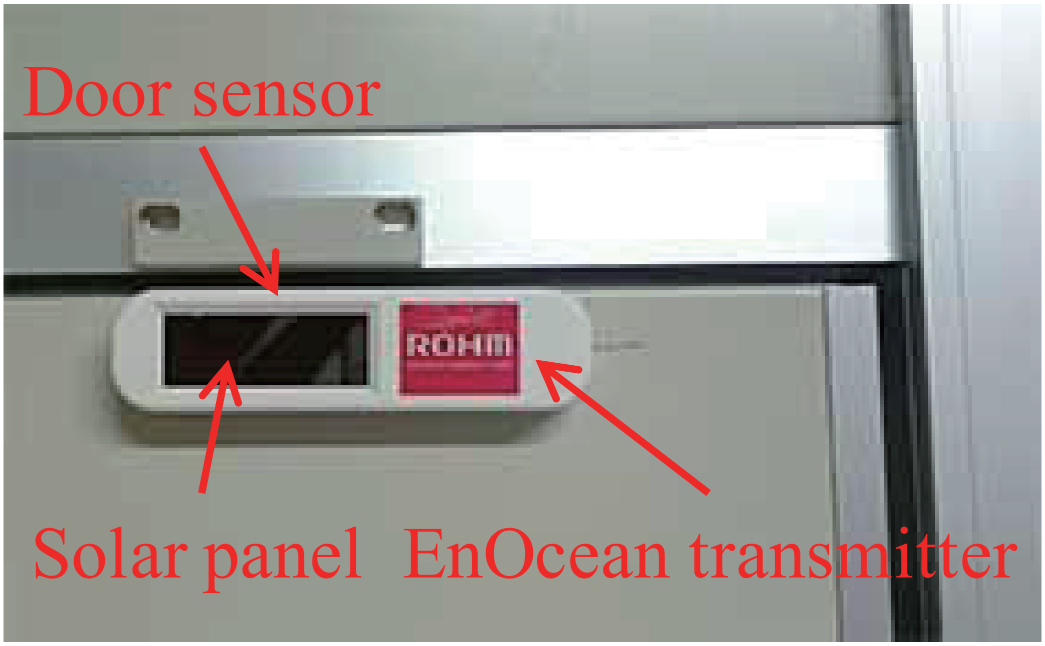

Figure 33. Energy harvesting door sensor

This tool supports the labeling of living activity and visualizing of multiple heterogeneous sensing data collected in a smart home. This tool extracts the data for arbitrary time interval from the accumulated sensor data, and shows graph of various types of sensor data (Power consumption of each home appliance, temperature and humidity of each room, etc.). Furthermore, it integrates a function of synchronously displaying the corresponding video recorded as ground truth, and we can use the labeling function which links arbitrary time interval of sensor data to a specific activity with easy user operation: (1) select the sensor button associated with the action, (2) select a time interval by dragging on the graph, and (3) select the corresponding label of the living activity.

Extraction of Feature Value

Feature value is a data that is effective to identify the activities. In the proposed method, we get the feature value from the sensor data of the time interval which is labeled by the living activity labeling tool, as follows. First, we collect data set for living activities, then, divide each data by a fixed time interval (window)

Time	PIR1	PIR2
0:00:00	1	0
0:00:10	0	0
0:00:20	0	0
0:00:30	1	0
0:00:40	0	1

Time	PIR1	PIR2
0:00:00	1	0
0:00:10	1	0
0:00:20	1	0
0:00:30	1	0
0:00:40	0	1

Figure 34. complement for the dead zone of PIR sensor

into samples, and calculate the feature value for each sample which is required by machine learning. We set 10 seconds to time window when dividing each data, since 10 second interval achieved the best recognition accuracy in the preliminary experiment with various lengths of time windows. As the feature value, we use the OR product of PIR and door sensors in each time window. In other words, if the sensor reacts at least one time in the time window, we regarded the time window as the reacted one.

Furthermore, we have developed a supplemental technique for the PIR sensor, since the sensor has the following challenge: when the user exists close to the sensor without moving, the sensor cannot detect the user. Figure 34 illustrates this technique. If there is no PIR sensor reacting, we hold the latest PIR sensor output until any sensor responds.

Construction of Living Activity Recognition Model

We construct a machine learning model using feature values of sensor data labeled by the developed labeling tool as training data. We use Weka which has various classifiers to generate the recognition model. In the proposed method, we empirically employ Random Forest classifier which is one of the popular pattern recognition algorithms.

4.4 Evaluation method

To evaluate the performance of the proposed method, we collected data of daily living activities in the smart home described in Figure 31. Below, we describe an overview of experiments and results of evaluation.

The experiment targeted to recognize eight activities which occur frequently in a home: "Eat", "Bathroom activity", "Sleep", "Cook", "Clean-up", "Living room activity", "Work and Study with PC", and "Go out". Five subjects (Two male subjects in 30s, two male subjects in 20s, and a female subject in 20s) lived in the smart home for two-three days each. We collected the data for 14 days in total. In Figure 31, locations of the appliances and furniture that were used for the activities are shown. The TV is located in the area marked "TV" and the participant watched TV while sitting on the sofa, "SF". The participant cooked using the IH heater, "IH". Meals were taken on the dining table, "TB". Finally, dishwashing was done in the sink, "SK".

After collecting the data, we labeled the sensor data according to activity type using the living activity labeling tool. The recorded video was used as ground truth. We constructed a machine learning model from the extracted features of PIR and door sensors by utilizing Random Forest. We used 19 features extracted from the 10 second time window. For the machine learning model, we generated three models: one model generated from both the PIR and door sensors, another from only the PIR sensor, the other from only the door sensor. We evaluated the proposed method by means of Leave-one-day-out cross validation, i.e. the one-day data of 14 days is used for the test data, while the other data is used for the training data. And, we change the date used for the test data. Furthermore, we compared the proposed method with Ueda's technique[57]. In Ueda's technique, the subject wears the ultrasonic sensor transmitter. Based on the position from the ultrasonic positioning system, we estimated the subject's activity by utilizing Random Forest.

Table 13. Evaluation result of PIR and door sensors

Activity	Precision	Recall	F-measure
Go out	74.5%	84.9%	72.5%
Living	58.2%	65.6%	58.4%
Work and study	23.9%	16.5%	18.2%
Cook	75.9%	85.2%	79.3%
Eat	18.4%	79.5%	10.3%
Bathroom	95.3%	91.1%	92.6%
Sleep	61.2%	62.8%	59.5%
Clean up	27.5%	14.0%	17.1%
AVerage	65.8%	64.0%	62.8%

Table 14. Comparison between PIR&door, PIR, and door

Evaluation item	PIR&door	PIR	door
Precision	65.8%	66.2%	29.3%
Recall	64.0%	67.1%	31.1%
F-measure	62.8%	61.2%	24.9%

4.5 Evaluation result

Table 16 shows the confusion matrix for “Evaluation for four activities”. Each row in the confusion matrix describes the activity which the user performs in the evaluation. Each column describes the predicted activity. Table 13 shows the Precision, Recall, and F-Measure for each activity. Precision is the ratio of retrieved instances that are relevant. Recall is the ratio of relevant instances that are retrieved. We obtained F-Measure from the following equation.

$$\text{F-Measure} = \frac{2\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}}$$

Table 13 shows the proposed method achieved F-measure; 65.8%. For each activity, “Bathroom activity” has the highest F-measure: 92.6%, while “Eat” has

Table 15. Comparison with Ueda's method

Evaluation item	Proposed	Ueda[57]
Precision	65.8%	76.9%
Recall	64.0%	70.1%
F-value	62.8%	70.2%

the lowest value: 10.3%. It is found that the activity that has the strong correlation with the specific position has the higher F-measure. For example, when the subject performs "Bathroom activity", he basically stays in the bathroom, which breeds the highest score. On the other hand, when the subject performs "Eat", he sits on either chair or sofa, which breeds the lowest score. Moreover, when the user has a meal while sitting on the sofa, we cannot distinguish the activity between "Eat" and "Living activity" which includes "watching TV".

Table 14 shows the average precision, recall, and F-measure of PIR&door, PIR, and door models. With the comparison with the F-measure, PIR&door model has the highest F-measure. And, single PIR and door models followed it. The evaluation result indicates that we can estimate the subject's activity just by utilizing only PIR sensor model to some extent. However, only door sensor model cannot estimate the subject's activity very accurately, since we cannot distinguish between "Living Activity" and "Cook".

Table 15 shows the comparison with Ueda's method. The evaluation result shows that our proposed method has the F-measure comparable to Ueda's. Moreover, our proposed method does not force the user to wear the ultrasonic sensor, which means that the proposed method is better than Ueda's.

Table 16. Confusion matrix of PIR and door sensors

	Go out	Living	Work and study	Cook	Eat	Bathroom	Sleep	Clean up
Go out	41	0	0	0	0	0	0	0
Living	0	459	186	3	7	0	0	0
Work and study	9	168	526	100	129	3	0	0
Cook	1	2	0	238	0	0	0	0
Eat	1	68	31	8	4	0	0	0
Bathroom	2	0	0	0	0	210	5	0
Sleep	0	0	0	0	0	0	5	0
Clean	2	2	1	6	3	3	1	5

4.6 Discussion

Here, we discuss whether the accuracy is enough to realize RBA with some case studies. First, we discuss the elderly monitoring system. We consider that the accuracy is enough to realize the system, since the system recognizes which room the senior citizen stays in accurately through the evaluation. We interviewed the owner of a nursing home. He says that the staff in the nursing home records the activities which we estimated through the evaluation and estimates his/her physical or mental status. Second, we discuss the home-concierge robot. We consider that the home-concierge can provide the service based on the estimated activity.

4.7 Conclusion

In this research, we proposed an in-home living activity recognition technique in the smart home. To suppress the privacy invasion and introduction cost, the proposed method estimated the user's activity by utilizing the energy harvesting PIR and door sensors. We generated the classifier to estimate the activities: "Eat", "Bathroom activity", "Sleep", "Cook", "Clean-up", "Living room activity", "Work and Study with PC", and "Go out" by utilizing Random Forest. Evaluation result showed that we recognized the user's activities with F-measure: 62.8%.

5 Conclusion

In this thesis, we studied the resident's behavior awareness. The objective of the study was the feasibility study on the fundamental systems and technique that are essential to realize the resident's behavior awareness applications.

In Chapter 2, we proposed the room measurement tool that utilizes the smartphone attached with an ultrasonic sensor gadget. There are three challenges to realize the measurement tool. The first challenge is that we have to develop a technique to measure the stride length in the building. To solve this problem, we calculated the stride length from the ultrasonic sensor and the accelerometer. The second challenge is that objects, such as bookshelves, attached on the wall deteriorate the room shape estimation accuracy. To solve this problem, we used a mixed Gaussian filter. The third problem is that the narrow room, such as corridors, leads to the low accuracy. To cope with this problem, we used two ultrasonic sensors, implemented in the reverse direction, and measure the distance between walls directly. The evaluation experiments showed that the proposed tool can measure more accurate shape and size estimation than the existing methods. Thus, we proved the potential and developed the fundamental technique of the target tool. In this thesis, the proposed floor plan creation tool considered that the shape of room is rectangular. However, in real condition, there are some shapes other than rectangular. Future work includes the shape and size estimation for rooms with other shapes. Moreover, we are going to work on the automatic floor plan creation based on the estimation for the contiguity between rooms.

In Chapter 3, we studied a piezo sensor-based indoor positioning system which estimates the position of the user by utilizing the piezo component attached on the floor. In order to realize the proposed positioning system, we tackled two challenges. First challenge was that we have to develop an indoor positioning system which does not utilizes TDoA techniques. In order to cope with this challenge, we developed a new method which estimates the position of the user from the type of the vibration. Second challenge was that we have to select an appropriate feature to estimate the vibration type accurately. We selected MFCC feature through comparison evaluation with FFT and Envelop shape.

We implemented the proposed system in the smart home which belongs to the authors' university. As a result, we confirmed that our system estimates the type with F-measure: 93.9%. Thus, we proved the potential and developed the fundamental technique of the target system. Future work includes the position estimation during walking. In order to realize the estimation, we believe that we should develop two techniques. First technique is the step count. The evaluation result indicates that we can estimate "step" vibration. By counting the number of "step" vibration, we can calculate the step count. Second technique is the estimation of the moving direction. We think that We can estimate the moving direction of the user by attaching several piezo sensors. Thus, we are going to develop a technique to estimate the position of the user while walking by combining these two techniques.

In Chapter 4, we proposed an in-home living activity recognition technique in the smart home. To suppress the privacy invasion and introduction cost, the proposed method estimated the user's activity by utilizing the energy harvesting PIR and door sensors. We generated the classifier to estimate the activities: "Eat", "Bathroom activity", "Sleep", "Cook", "Clean-up", "Living room activity", "Work and Study with PC", and "Go out" by utilizing Random Forest. Evaluation result showed that we recognized the user's activities with F-measure: 62.8%. Thus, we proved the potential and developed the fundamental technique of the target system. Future work includes minimization of the number of sensors to reduce the installation cost. In order to realize this, we count on the estimation of the removed sensors' reaction by utilizing the user's life pattern that breeds the time series pattern of the sensors. Moreover, we plan to utilize the log of the watt meter attached to the home appliances, which also indicates the user's life pattern. Furthermore, we plan to develop a technique to recognize the activities when there are multiple residents. Finally, we are going to deploy the system into an ordinary house and conduct the adaptability to the real environment.

After solving the remaining challenges described in each research, we plan to work on the propagation of RBA system as well as developing RBA applications.

Acknowledgements

Five years ago, that was my first encounter with Professor Keiichi Yasumoto, who is the leading researcher in ubiquitous computing and distributed system and led me to NAIST. With a short discussion with him, I've realized that he has the many view points and profound insight for the domains as well as instructing students. In addition, he has the gentle attitude toward every person and gives chances to students. That is why I had decided to study under his leadership. At first, I was a stranger around the domains and did not have skills on paper writing and presentation. However, to improve my skills, he held many seminars on ubiquitous computing, distributed system, and paper writing. The experience through that becomes the basis of my engineering knowledge and skill today. In addition, he taught me strictly when I was lazy. He supported me when I was in struggle to something. That his humanity made my core as a researcher which has Doctoral degree. Therefore, recalling my memory with him, I cannot thank him too much. But, here I would like to show my best appreciation and be eternally grateful to him.

I would also like to thank the members of my thesis committee, my co-supervisor Professor Minoru Okada, Associate Professor Yutaka Arakawa, and Assistant Professors Hirohiko Suwa and Manato Fujimoto. Their work in reviewing my thesis and their insightful comments and suggestions helped me to improve my thesis's overall quality.

Professor Minoru Okada provided me with gentle but helpful comments to improve my research. His comments especially in terms of signal processing trained me to look my research from different point of view as well as raised the quality of it. In addition, he gave me a part-time job chance to work in Synthesis, an embedded and FPGA engineering company. Through that experience, I obtained skills for developing engineering products. I truly appreciate him for above-mentioned experience.

Associate professor Yutaka Arakawa was in charge of my thesis committee. His instruction was truly helpful to improve my research in terms of not only research view points but also commercial engineering ones. I strongly believe that the instruction from him helps me in KDDI research career. In addition, he also provides me with many chances to work or conduct research with the commercial companies. Through the experience, I could learn the discussion skills for collaboration researches as well as obtaining engineering ones, which is hard to be experienced in an ordinary laboratory. Furthermore, he taught me the entertainment to become a premier member of airline company through research work. Here, I would like to show my best appreciation to him.

Assistant professor Hirohiko Suwa was in charge of my thesis committee. His instruction was truly helpful to improve my research in terms of not only engineering view points but also social infomatics. Here, I would like to appreciate his instruction.

Assistant professor Manato Fujimoto was in charge of my thesis committee. His instruction from indoor positioning and radio wave engineering was truly helpful to improve my research. And more, I thank that he instructed me strictly as in carrot and stick, sometimes giving me not so funny jokes. Here, I would like to appreciate his instruction.

Many of my fellow students have graduated in the time since I joined NAIST. My thanks extended to all current and former members of Ubi lab. Friendship with them made my five years in NAIST much more meaningful.

In addition, I would thank to Ryo-chan to start getting along with me, and give me many knowledge on architecture in Finland.

Finally, I owe my deepest gratitude to my parents, Takashi Kashimoto and Yumi Kashimoto who raised me for 27 years and looked after me by today.

References

[1] Bill N. Schilit, Norman. Adams, and Roy. Want. Context-Aware Computing Applications. In *1994 First Workshop on Mobile Computing Systems and Applications*, pages 85–90. IEEE, 12 1994.

[2] Abu Saleh Mohammad Mosa, Illhoi Yoo, and Lincoln Sheets. A Systematic Review of Healthcare Applications for Smartphones. *BMC Medical Informatics and Decision Making*, 12(1):67, 12 2012.

[3] Maged Boulos, Steve Wheeler, Carlos Tavares, and Ray Jones. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX. *BioMedical Engineering OnLine*, 10(1):24, 2011.

[4] Kimberly B. Lee, Jesus Aaron Ramirez, Rebeccah Collins, John Bucheit, Kakotan Sanogo, and Michael P. Stevens. Antimicrobial stewardship practices in Virginia. *American Journal of Infection Control*, 12 2016.

[5] Laurie J. Conway and Shanina C. Knighton. Journal club: Social media as an antimicrobial stewardship tool. *American Journal of Infection Control*, 45(3):293–294, 3 2017.

[6] Yasuaki Tagashira, Mikihiro Horiuchi, Yasuharu Tokuda, Brian S. Heist, Masanori Higuchi, and Hitoshi Honda. Antimicrobial stewardship for carbapenem use at a Japanese tertiary care center: An interrupted time series analysis on the impact of infectious disease consultation, prospective audit, and feedback. *American Journal of Infection Control*, 44(6):708–710, 6 2016.

[7] J. Daniel Markley, Amy Pakyz, Shaina Bernard, Kimberly Lee, Nital Appelbaum, Gonzalo Bearman, and Michael P. Stevens. A survey to optimize the design of an antimicrobial stewardship smartphone app at an academic medical center. *American Journal of Infection Control*, 45(3):317–320, 3 2017.

[8] Christine Bui, Elizabeth Zhu, Monica A. Donnelley, Machelle D. Wilson, Margaret Morita, Stuart H. Cohen, and Jennifer Brown. Antimicrobial stew-

ardship programs that target only high-cost, broad-spectrum antimicrobials miss opportunities to reduce Clostridium difficile infections. *American Journal of Infection Control*, 44(12):1684–1686, 12 2016.

[9] Mary Lou Manning, Jeanne Pfeiffer, and Elaine L. Larson. Combating antibiotic resistance: The role of nursing in antibiotic stewardship. *American Journal of Infection Control*, 44(12):1454–1457, 12 2016.

[10] Sharon Mickan, Helen Atherton, Nia Wyn Roberts, Carl Heneghan, and Julie K Tilson. Use of handheld computers in clinical practice: a systematic review. *BMC Medical Informatics and Decision Making*, 14(1):56, 12 2014.

[11] Abu Saleh Mohammad Mosa, Illhoi Yoo, and Lincoln Sheets. A Systematic Review of Healthcare Applications for Smartphones. *BMC Medical Informatics and Decision Making*, 12(1):67, 12 2012.

[12] Seungwoo Choi, Hayeon Jeong, Minsam Ko, and Uichin Lee. LockDoll. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems - CHI EA '16*, pages 1165–1172, New York, New York, USA, 2016. ACM Press.

[13] Xavier Benavides, Judith Amores, and Pattie Maes. TagMe. In *Proceedings of the extended abstracts of the 32nd annual ACM conference on Human factors in computing systems - CHI EA '14*, pages 2197–2202, New York, New York, USA, 2014. ACM Press.

[14] Anand Ranganathan, Roy H. Campbell, Arathi Ravi, and Anupama Mahajan. ConChat: a context-aware chat program. *IEEE Pervasive Computing*, 1(3):51–57, 7 2002.

[15] Ellen Isaacs, Alan Walendowski, and Dipti Ranganthan. Hubbub. In *Proceedings of the SIGCHI conference on Human factors in computing systems Changing our world, changing ourselves - CHI '02*, page 179, New York, New York, USA, 2002. ACM Press.

[16] Anupriya Ankolekar, Gabor Szabo, Yarun Luon, Bernardo A. Huberman, Dennis Wilkinson, and Fang Wu. Friendlee. In *Proceedings of the 11th*

International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '09, page 1, New York, New York, USA, 2009. ACM Press.

[17] Chris. Johnson, Paul. Montague, Chris. Steketee, Association for Computing Machinery., and Australian Computer Society. *Proceedings of the Australasian Information Security Workshop Conference on ACSW Frontiers 2003 : volume 21, 2003 : Adelaide, Australia*. Australian Computer Society, 2003.

[18] Charith Perera, Arkady Zaslavsky, Peter Christen, and Dimitrios Georgakopoulos. Context Aware Computing for The Internet of Things: A Survey. *IEEE Communications Surveys & Tutorials*, 16(1):414–454, 21 2014.

[19] Li Da Xu, Wu He, and Shancang Li. Internet of Things in Industries: A Survey. *IEEE Transactions on Industrial Informatics*, 10(4):2233–2243, 11 2014.

[20] Gregory D. Abowd, Anind K. Dey, Peter J. Brown, Nigel Davies, Mark Smith, and Pete Steggles. Towards a Better Understanding of Context and Context-Awareness. pages 304–307. Springer Berlin Heidelberg, 1999.

[21] NIST Cyber Physical Systems Public Working Group. *Framework for Cyber-Physical System*. 2016.

[22] Azkario Rizky Pratama and Risanuri Hidayat. Smartphone-based Pedestrian Dead Reckoning as an indoor positioning system. In *2012 International Conference on System Engineering and Technology (ICSET)*, pages 1–6. IEEE, 9 2012.

[23] Deepak Pai, Inguva Sasi, Phani Shekhar Mantripragada, Mudit Malpani, and Nitin Aggarwal. Padati: A Robust Pedestrian Dead Reckoning System on Smartphones. In *2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications*, pages 2000–2007. IEEE, 6 2012.

[24] Ching-Sheng Wang and Chien-Liang Chen. RFID-based and Kinect-based indoor positioning system. In *2014 4th International Conference on Wireless Communications, Vehicular Technology, Information Theory and Aerospace & Electronic Systems (VITAE)*, pages 1–4. IEEE, 5 2014.

[25] Moustafa Alzantot and Moustafa Youssef. CrowdInside. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems - SIGSPATIAL '12*, page 99, New York, New York, USA, 11 2012. ACM Press.

[26] Yifei Jiang, Yun Xiang, Xin Pan, Kun Li, Qin Lv, Robert P Dick, Li Shang, and Michael Hannigan. Hallway Based Automatic Indoor Floorplan Construction Using Room Fingerprints. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '13, pages 315–324, New York, NY, USA, 2013. ACM.

[27] Hyojeong Shin, Yohan Chon, and Hojung Cha. Unsupervised Construction of an Indoor Floor Plan Using a Smartphone. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 42(6):889–898, 2012.

[28] Nadir Castaneda and Sylvie Lamy-Perbal. An improved shoe-mounted inertial navigation system. In *2010 International Conference on Indoor Positioning and Indoor Navigation*, pages 1–6. IEEE, 9 2010.

[29] Bernhard Krach and Patrick Roberston. Cascaded estimation architecture for integration of foot-mounted inertial sensors. In *2008 IEEE/ION Position, Location and Navigation Symposium*, pages 112–119. IEEE, 2008.

[30] Ken Fyfe Ross Stirling, Jussi Collin. An Innovative ShoeMounted Pedestrian Navigation System. In *In Proceedings of European Navigation Conference GNSS 2003*, 2003.

[31] Kyle Aidan McCormick. *Identifying Trackways Using Step Length: Behavioral Inferences from Jaguar Cave, Tennessee*. PhD thesis, California State University, Chico, 2010.

[32] Ladetto and Quentin. On foot navigation: continuous step calibration using both complementary recursive prediction and adaptive Kalman filtering. In *Proceedings of ION GPS*, volume 2000, pages 1735–1740, 2000.

[33] Dae-Ki Cho, Min Min Mun, Uichin Uichin Lee, William J. Kaiser, and Mario Gerla. AutoGait: A mobile platform that accurately estimates the distance walked. In *2010 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 116–124. IEEE, 3 2010.

[34] Tommy Oberg, Alek Karsznia, and Kurt Oberg. Basic gait parameters: reference data for normal subjects, 10-79 years of age. *Journal of rehabilitation research and development*, 30(2):210–23, 1993.

[35] Carl Fischer, Kavitha Muthukrishnan, Mike Hazas, and Hans Gellersen. Ultrasound-aided pedestrian dead reckoning for indoor navigation. In *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments - MELT '08*, page 31, New York, New York, USA, 9 2008. ACM Press.

[36] John Krumm, Steve Harris, Brian Meyers, Barry Brumitt, Michael Hale, and Shafer Shafer. Multi-camera multi-person tracking for EasyLiving. In *Proceedings Third IEEE International Workshop on Visual Surveillance*, pages 3–10. IEEE Comput. Soc, 2000.

[37] Neal Checka, Kevin Wilson, Vibhav Rangarajan, and Trevor Darrell. A Probabilistic Framework for Multi-modal Multi-Person Tracking. In *2003 Conference on Computer Vision and Pattern Recognition Workshop*, volume 9, pages 100–100. IEEE, 6 2003.

[38] François Fleuret, Jérôme Berclaz, Richard Lengagne, and Pascal Fua. Multicamera people tracking with a probabilistic occupancy map. *IEEE transactions on pattern analysis and machine intelligence*, 30(2):267–82, 2 2008.

[39] Kyle Heath and Leonidas Guibas. Multi-person tracking from sparse 3D trajectories in a camera sensor network. In *2008 Second ACM/IEEE International Conference on Distributed Smart Cameras*, pages 1–9. IEEE, 9 2008.

[40] Chenren Xu, Bernhard Firner, Robert S. Moore, Yanyong Zhang, Wade Trappe, Richard Howard, Feixiong Zhang, and Ning An. SCPL: indoor device-free multi-subject counting and localization using radio signal strength, 2013.

[41] Brad Mager, Philip Lundrigan, and Neal Patwari. Fingerprint-Based Device-Free Localization Performance in Changing Environments. *IEEE Journal on Selected Areas in Communications*, 33(11):2429–2438, 11 2015.

[42] Neal Patwari and Joey Wilson. RF Sensor Networks for Device-Free Localization: Measurements, Models, and Algorithms. *Proceedings of the IEEE*, 98(11):1961–1973, 11 2010.

[43] Stefano Savazzi, Monica Nicoli, Francesca Carminati, and Michele Riva. A Bayesian Approach to Device-Free Localization: Modeling and Experimental Assessment. *IEEE Journal of Selected Topics in Signal Processing*, 8(1):16–29, 2 2014.

[44] Jiang Xiao, Kaishun Wu, Youwen Yi, Lu Wang, and Lionel M. Ni. Pilot: Passive Device-Free Indoor Localization Using Channel State Information. In *2013 IEEE 33rd International Conference on Distributed Computing Systems*, pages 236–245. IEEE, 7 2013.

[45] Henrik V. Sorensen, Douglas L. Jones, Michael T. Heideman, and C. Sidney Burrus. Real-valued fast Fourier transform algorithms. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 35(6):849–863, 6 1987.

[46] Douglas O ’ Shaughnessy. Invited paper: Automatic speech recognition: History, methods and challenges. *Pattern Recognition*, 41(10):2965–2979, 10 2008.

[47] George Tzanetakis and Perry Cook. Musical genre classification of audio signals. *IEEE Transactions on Speech and Audio Processing*, 10(5):293–302, 7 2002.

[48] Keiichi Yasumoto, Hirozumi Yamaguchi, and Hiroshi Shigeno. Survey of Real-time Processing Technologies of IoT Data Streams. *Journal of Information Processing (JIP)*, 57(2), 2016.

[49] Jesse Hoey and James J Little. Value-directed human behavior analysis from video using partially observable Markov decision processes. *IEEE transactions on pattern analysis and machine intelligence*, 29(7):1118–32, 7 2007.

[50] Loren Fiore, Duc Fehr, Robot Bodor, Andrew Drenner, Guruprasad Somasundaram, and Nikolaos Papanikolopoulos. Multi-Camera Human Activity Monitoring. *Journal of Intelligent and Robotic Systems*, 52(1):5–43, 1 2008.

[51] Kenji Mase. Activity and location recognition using wearable sensors. *IEEE Pervasive Computing*, 1(3):24–32, 7 2002.

[52] Oscar D. Lara and Miguel A. Labrador. A Survey on Human Activity Recognition using Wearable Sensors. *IEEE Communications Surveys & Tutorials*, 15(3):1192–1209, 23 2013.

[53] Ling Bao and Stephen S Intille. Pervasive Computing: Second International Conference, PERVASIVE 2004, Linz/Vienna, Austria, April 21-23, 2004. Proceedings. chapter Activity R, pages 1–17. Springer Berlin Heidelberg, Berlin, Heidelberg, 2004.

[54] Oliver Brdiczka, Matthieu Langet, JÉrÔme Maisonnasse, and James L. Crowley. Detecting Human Behavior Models From Multimodal Observation in a Smart Home. *IEEE Transactions on Automation Science and Engineering*, 6(4):588–597, 10 2009.

[55] Tim L. van Kasteren, Gwenn Englebienne, and Ben. J. A. Kröse. An activity monitoring system for elderly care using generative and discriminative models. *Personal and Ubiquitous Computing*, 14(6):489–498, 2 2010.

[56] Liming Chen, Chris D. Nugent, and Hui Wang. A Knowledge-Driven Approach to Activity Recognition in Smart Homes. *IEEE Transactions on Knowledge and Data Engineering*, 24(6):961–974, 6 2012.

[57] Kenki Ueda, Morihiko Tamai, and Keiichi Yasumoto. A method for recognizing living activities in homes using positioning sensor and power meters. In *2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, pages 354–359. IEEE, 3 2015.

Publication List

Journal Papers

1. Kashimoto, Y., Arakawa, Y., Yasumoto, K.: "Room measurement tool combining ultrasonic sensor and inertial sensor in smartphone for simple floor plan creation", International Journal of Ad Hoc and Ubiquitous Computing, 2017 (accepted), (Corresponding to Chapter 2)

2. Kashimoto, Y., Hata, K., Nakagawa, E., Suwa, H., Fujimoto, M., Aarakawa, Y., Shigezumi, T., Komiya, K., Konishi, K., Yasumoto, K.: "A Living Activity Recognition System Based on Power Consumption of Appliances and Energy Harvesting PIR and Door Sensors", Journal of Information Processing (JIP), Special issue of "Network and Distributed Processing", (Mar. 2017), (Corresponding to Chapter 4)

International Conference

1. Kashimoto, Y., Fujimoto, M., Suwa, H., Arakawa, Y., and Yasumoto, K.: "Floor vibration type estimation with piezo sensor toward indoor positioning system", 7th International Conference on Indoor Positioning and Indoor Navigation (IPIN 2016), (Oct. 2016), (Corresponding to Chapter 3)

2. Kashimoto, Y., Yasumoto, K.; "YAMATO: A Wearable Floor Map Generation System", Poster Session, SenSys 2013 (Nov. 2013), (Corresponding to Chapter 2)

3. Kashimoto, Y., M., Aarakawa, K., Yasumoto, K.: "A floor plan creation tool utilizing a smartphone with an ultrasonic sensor", 13th IEEE Consumer Communications and Networking Conference. (CCNC 2016), (Jan. 2016), (Corresponding to Chapter 2)

4. Kashimoto, Y., Hata, K., Suwa, H., Fujimoto, M., Arakawa, Y., Shigezumi T., Komiya, K., Konishi, K., and Yasumoto, K.: "In-smarthome Activity Recognition with Energy Harvesting PIR and Door Sensors", 1st Interna-

tional Workshop on Information Flow of Things (IFoT 2016), (Nov. 2016), (Corresponding to Chapter 4)

Other Publications

Journal Paper

1. Firouzian, A., Kashimoto, Y., Yamamoto, G., Keranen, N., Asghar, N., Pulli, P.: "Evaluation of Near-Eye LED Indicators on Glasses for Simple and Smart Navigation in Daily Life", Springer Special Issue in eHealth360 °, pp. 17-22, 2016.

International Conference

1. Kashimoto, Y., Fujiwara, M., Fujimoto, M., Suwa, H., Arakawa, Y., Yasumoto, K.: ALPAS: Analog-PIR-sensor-based Activity Recognition System in Smarthome, The 31st IEEE International Conference on Advanced Information Networking and Applications (AINA 2017), (Mar. 2017)

2. Kashimoto, Y., Morita, T., Fujimoto, M., Arakawa, Y., Suwa, H., Yasumoto, K.: Sensing Activities and Locations of Senior Citizens toward Automatic Daycare Report Generation, The 31st IEEE International Conference on Advanced Information Networking and Applications (AINA 2017), (Mar. 2017)

3. Kashimoto, Y., Morita, T., Fujimoto, M., Arakawa, Y., Suwa, H., and Yasumoto, K.: "Implementation and Evaluation of Daycare Report Generation System based on BLE Tag", The International Conference on Mobile and Ubiquitous Multimedia 2016 (MUM 2016), (Dec. 2016)

4. Firouzian, A., Kashimoto, Y., Yamamoto, G., Keranen, N., Asghar, Z., and Pulli, P.: "Near-Eye LED Indicators on Glasses for Simple and Smart Navigation in Daily Life", EAI International Conference on IoT and Big Data Technologies for HealthCare 2016 (IoTCare 2016), Jun 15-16, 2016

5. Komai K., Fujimoto, M., Arakawa, A., Suwa, H., Kashimoto, Y. and Yasumoto, K.: "Elderly Person Monitoring in Day Care Center using Bluetooth Low Energy",10th International Symposium on Medical Information and Communication Technology (ISMICT ' 16), Mar 13-20, 2016

6. Kashimoto, Y., Firouzian A., Asghar, Z., Yamamoto, G., Pulli P.: "Twinkle Megane: Near-Eye LED Indicators on Glasses in Tele-Guidance for Elderly", FIRST WORKSHOP ON PERVASIVE TECHNOLOGIES AND CARE SYSTEMS FOR SUSTAINABLE AGING-IN-PLACE (PASTA 2016), Mar 14-18, 2016

7. Komai, K., Fujimoto, M., Arakawa, Y., Suwa, H., Kashimoto, Y., Yasumoto, K.: "Beacon-Based Multi-Person Activity Monitoring System for Day Care Center", FIRST WORKSHOP ON PERVASIVE TECHNOLOGIES AND CARE SYSTEMS FOR SUSTAINABLE AGING-IN-PLACE (PASTA 2016), Mar 14-18, 2016

8. Kanaoka, R., Kashimoto, Y., Arakawa, Y., Tobe, Y., and Yasumoto, K.: "A Cumulative Error Compensation Model of Dead Reckoning Toward A High Accuracy Indoor Positioning System," 2015 JSME-IIP/ASME-ISPS Joint Conference on Micromechatronics for Information and Precision Equipment (MIPE 2015) June 14–17, 2015.

9. Kashimoto, Y., Ogura, K., Yamamoto, S., Yasumoto, K., Ito, M.: "Saving Energy in Smart Homes with Minimal Comfort Level Reduction",Workshop Proc. of IEEE PerCom 2013, pp. 372-376 (Mar. 2013)(WiP paper).