Smart Home Platform for Human Care Based on Healthcare as a Service

2021, September

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Abstract

The aging of society has received considerable attention as a social problem. It is very important to provide monitoring and health support services to ensure the quality of life of the elderly. In the context of the ever-expanding demand for nursing services, we should pay attention to a severe shortage of professional caregivers. The research and development of smart home can greatly reduce the workload of caregivers. Internet of Everything (IoE) including the Internet of things (IoT) known as an advanced paradigm to connect physical and virtual things for enhanced services, has been introduced for developing smart homes, but measurement data are only used for simple safety confirmations, such as human localization and fall detection. On the other hand, Healthcare as a Service (HaaS) has been used in recent years, and it is expected to build a bridge from the data measured by smart home to the healthcare services such as health promotion support and health management. Furthermore, the initial implementation and operating costs of smart home often become high, and it is difficult for elderly people to customize the selection and layout of the devices, to update the parameters of smart home, and to choose a suitable healthcare service.

In this thesis, to solve the above problems, I design a platform for realizing smart home based on HaaS. First, I put forward the concept of HaaS for smart home. I propose a low-cost, easy-to-use, and human-centric care platform based on HaaS and Informationally Structured Space (ISS). The proposed smart home platform can freely manage three main compatible components of measurement layer, analysis layer, and service layer. To maintain compatibility, we propose a general preprocessing scheme to meet the needs of behavior measurement with environmental sensor data. Furthermore, I design an initial set-up method based on human behavior analysis without direct human customization and re-learning in a variety of different scenarios to realize the easy implementation. Next, I develop a HaaS-based service integration system to realize human-friendly operations. Finally, I discuss the effectiveness of the proposed system through various types of experiments on healthcare services.

The thesis consists of six chapters.

Chapter 1 discusses the background and related research. The research purposes and goals are also clearly explained in this chapter.

Chapter 2 presents the survey of current smart home research. Through the analysis of core concepts such as IoT, IoE, HaaS, and ISS, which are inseparable from smart home, we clarify the research and development goals of this thesis. I clarify the definition of HaaS to meet the needs of healthcare for the elderly, and propose the smart home platform based on HaaS to solve the practical problems discussed in Chapter 1. In order to clarify the design guidelines, I discuss the monitoring system platform defined by three layers: the measurement layer, analysis layer, and service layer. Then I define the function and structure of each layer. The measurement layer is used for obtaining sensor data and perform basic processing; the analysis layer is used for user behavior analysis; the service layer is used for providing services through service robots and smart devices.

Chapter 3 explains the physical structure of the human-centric wireless sensor network system in the measurement layer from the perspective of sensor selection and measurement. First, we discuss a selection method of sensors based on the actual needs of users. Furthermore, I explain the problems and challenges faced by non-contact environmental sensor systems. Next, in view of the characteristics of human activities and the integration of multiple sensors, I propose human behavior estimation by using a spiking neural network to effectively process sensor data from multiple different information sources and accurately distinguish human activities from indoor non-human-activity noise. The experimental results show that the proposed method can measure human activities using different kinds of sensors. Furthermore, the comparison results with conventional methods show that the proposed method achieves a similar or higher accuracy in performance.

Chapter 4 designs an easy implementation method according to the users personalized information without additional processes such as customization and re-learning by a human operator. From the viewpoint of ISS, I first develop a monitoring system composed of servers, sensors, and smart devices for users to enter their personalized information in advance. Next, I design a fuzzy inference-based spiking neural network using the user's personalized information linked with a pre-designed knowledge-based system. Experimental results show that the system can adapt to different usage environments and maintain high accuracy without additional learning.

Chapter 5 explains a human-centric approach to provide personalized services. From the viewpoint of HaaS, I design a cloud-based healthcare system for smart home. First, I clarify the functions and characteristics of a service robot in human-centric healthcare. Next, I explain the data structure and information flow in the overall system including sensors and service robots. Furthermore, I develop a scenario editor to realize the easy design of healthcare services. The scenario editor can integrate three processing levels for healthcare services according to (1) the types of sensors connected to the network in the data level, (2) measurement results of environmental states and human activities in the information level, and (3) interactive scenarios with a service robot in the knowledge level. In experiments, I set up a smart home including multiple sensors, multiple network protocols, and multiple robots. The experimental results show that the service robot can select a suitable scenario and provide personalized healthy living advice according to the state of daily activities. Moreover, the system can provide healthcare services to users while maintaining its stability, even if the number of sensor nodes is increased or decreased.

Chapter 6 concludes the thesis and explains the future research directions. The thesis discusses the methodology for constructing a HaaS smart home platform including human activities and behaviors monitoring from different points of view.

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Chapter 1

Introduction

1.1 Background

In recent years, the aging of the population has become a severe social problem. Advanced countries such as Japan and Germany are facing aging populations. By 2025, one in three citizens will be over 65, according to the Japanese government (Fig. 1.1) [1]. The ratio of the elderly population to the male population is 14.6%, and that of the female population is 22.6%, which means that there will be about 2.3 million male and 4.7 million female elderly.

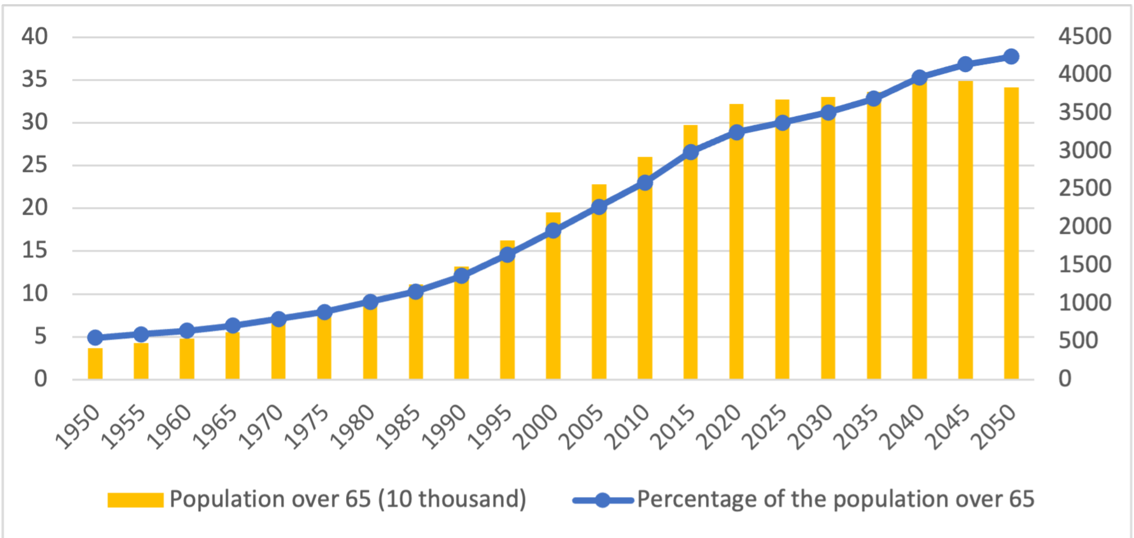

Figure 1.1: *The trend of older adults living alone*

The problem of isolated death due to the increase in the number of elderly people living alone is becoming a major social problem. According to the results of a survey conducted by the Tokyo Metropolitan Government, 4968 isolated deaths happened on aged 65 and over in Tokyo in 2013, but in 2016 it was 5219, and the number increased to 6089 in 2019. According to a survey of men and women living alone aged 65 and over nationwide, 76.3% of the elderly living alone said they would like to live alone as they are though they may have children or other relatives to rely on [2].

In order to deal with the care problem of the elderly living alone, various types of sensor networks have been applied to elderly monitoring. Devices that need to be wear by the elderly [3] and the devices that need to be placed in the field of vision of the elderly [4] may cause both physical and psychological loads on the elderly [5]. Furthermore, when sudden cardiac arrest, falls or other anomaly happens to elderly, the elderly monitoring system should notify it to their caregivers who may not stay with the elderly.

1.2 Literature Review of Smart Home

How to provide timely health support for such a large number of elderly people living alone has become a social problem.

One solution can be a smart home for elderly. Smart homes aim to promote independence among the elderly in their own home by acting as both an assisted living device and monitoring system [6]. Smart homes should be able to provide services to elderly including personal hygience and care, physical activity, social engagement, leisure, health and safety(Fig. 1.2). Through a combination of hardware, such as sensors and smart devices, and software, the elderly can conduct their daily activities with minimal assistance from others. Only if the system detects emergencies or anomalies, help from caregivers is needed.

The smart home is not a recent invention. It has gained popularity in the form of a concept among consumers and industry experts. The smart home concept began with the invention of the remote control, introduced by Nikola Tesla in 1898.

The industrial revolution of the early 1900s brought the first household appliances, and the 1920s saw the invention of vacuum cleaners, clothes dryers, toasters and a host of other household appliances. These were not ”smart” appliances, but their introduction changed the lives of people in the 20th century.

In the 1930s, inventors turned their attention to home automation technology, but it wasn’t until 1966, when the first intelligent automation system, the Echo IV, was developed, that the idea came to fruition. The device allowed consumers to create calculated shopping lists, control home temperatures, and turn appliances on and off. The Kitchen Computer was created in 1969. It could automatically create recipes, but the device was not commercially successful because of its price.

In 1991, a concept called ”Gerontechnology” was born. This term combines gerontology

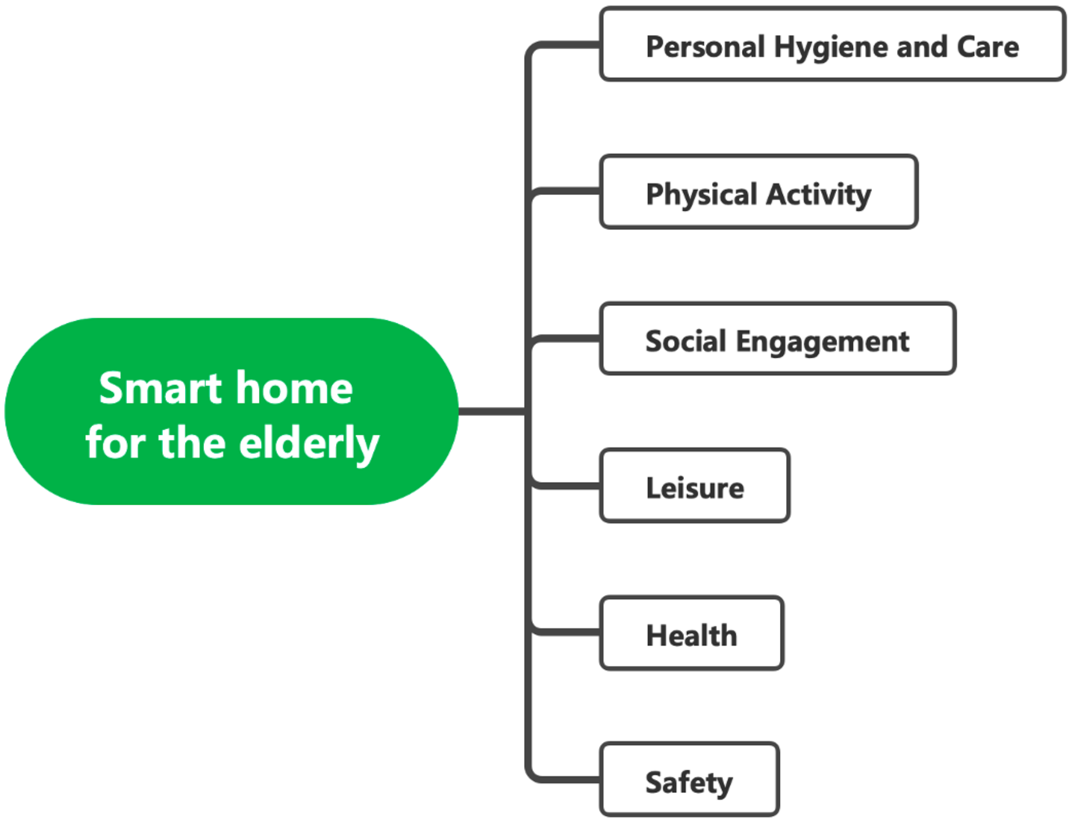

Figure 1.2: *Smart home for the elderly*

and technology and aims to make life easier for the elderly through technological means. This directly influenced the approach to the development of today's smart homes for elderly.

The early 2000s were characterized by the rapid spread of smart home technology. Different technologies emerged and were slowly integrated into the home. Products such as home networking and home robots were introduced and gradually became less expensive, and smart homes began to become an affordable option for consumers. At the same time, the rapid development of the Internet of Things (IoT) and cloud technologies provide technical possibilities for the emergence of remote care systems [7] [8].

In summary, smart home can be seen as the integration of the development of IoE, domestic robot, and Gerontechnology(Fig. 1.3).

1.2.1 Wireless Sensor Networks

A Wireless Sensor Network (WSN) consists of innumerable, randomly positioned sensor nodes, which organize themselves into a co-operative network performing the three simple functions of communications, computations and sensing. Research and investigations in the

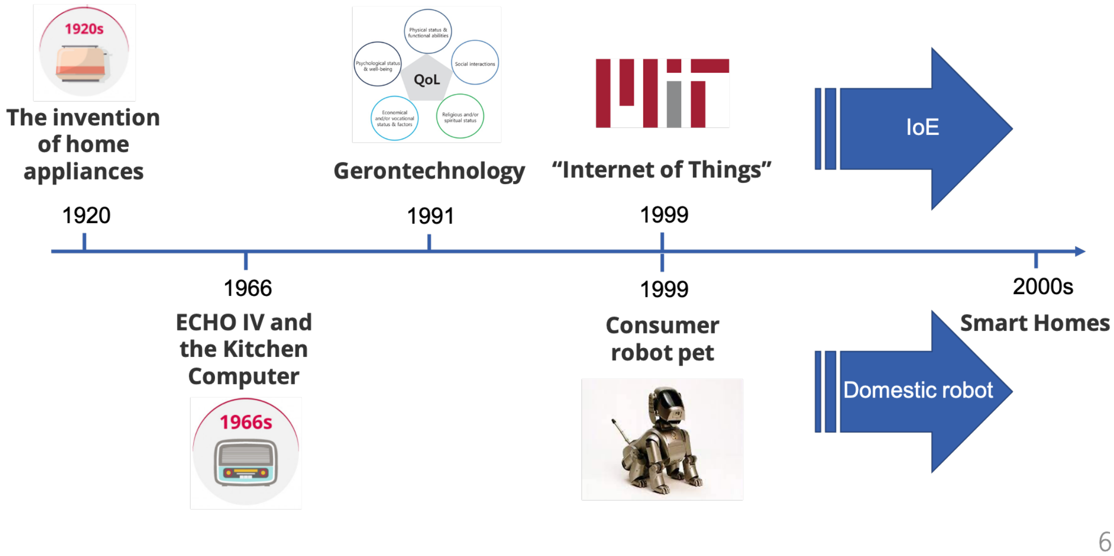

Figure 1.3: *Technology of smart homes*

area of WSN has become an extensive explorative area during the last decade, especially due to the challenges offered, Healthcare monitoring being one of them [9].

Wireless Sensor Network (WSN) is a collection of power-conscious wireless sensors that are spatially distributed and forms an autonomous system that is independent of pre-existing infrastructure. In order to record and monitor conditions in various locations, a co-operative system is formed. This system uses dedicated transducers with communication infrastructure exclusively for this purpose. The applications of WSN includes data-intensive task performance like seismic monitoring, habitat monitoring, terrain surveillance and so on as well as gathering of information. Proactive computing is largely dependent on sensor networks. In this technology, computers can anticipate human necessities like healthcare and act on their behalf if required. The combination of proactive computing and sensor network technologies has a life-changing potential and to improve the quality of living by providing a healthy lifestyle. It also improves the efficiency and awareness, enhances safety and productivity at a social scale [10].

The importance of wireless sensor networks(WSN) in health monitoring is constantly increasing [11].

1.2.2 Cloud Computing

Cloud computing is the delivery of different services through the Internet. These resources include tools and applications like data storage, servers, databases, networking, and software [12].

Rather than keeping files on a proprietary hard drive or local storage device, cloud-based storage makes it possible to save them to a remote database. As long as an electronic device has access to the web, it has access to the data and the software programs to run it.

Cloud computing is a popular option for people and businesses for a number of reasons including cost savings, increased productivity, speed and efficiency, performance, and security.

Cloud computing is not a single piece of technology like a microchip or a cellphone. Rather, it's a system primarily comprised of three services: software-as-a-service (SaaS), infrastructure-as-a-service (IaaS), and platform-as-a-service (PaaS) (Table. 1.1) [13].

Table 1.1: *Three types of cloud computing*

SaaS	SaaS involves the licenses of a software application to customers. Licenses are typically provided through a pay-as-you-go model or on-demand. This type of system can be found in Microsoft Office's 365 [14].
IaaS	IaaS involves a method for delivering everything from operating systems to servers and storage through IP-based connectivity as part of an on-demand service. Clients can avoid the need to purchase software or servers, and instead procure these resources in an outsourced, on-demand service. Popular examples of the IaaS system include IBM Cloud and Microsoft Azure [15] [14].
PaaS	PaaS is considered the most complex of the three layers of cloud-based computing. PaaS shares some similarities with SaaS, the primary difference being that instead of delivering software online, it is actually a platform for creating software that is delivered via the Internet. This model includes platforms like Salesforce.com [16] and Heroku [17].

1.3 The current development of smart home

Today's smart home has already been commercialized (Fig. 1.4). The current mainstream trends of smart home include:

- Temperature, humidity, light intensity, carbon dioxide monitoring
- Microclimate closed-loop control
- Professional aquarium system

- Elderly home care system
- Visual management uses touchscreen panel
- Multiple operating modes and parameter set
- Fully automatic system
- Data collection for big data

The elderly care system is one of the major markets But until now, most smart home products only realize remote control.

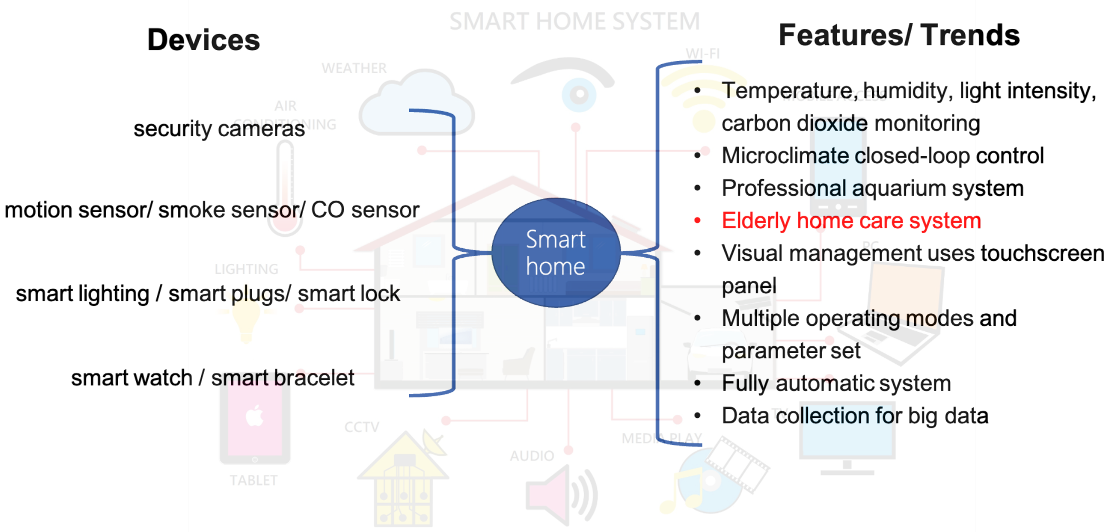

Figure 1.4: *Smart home nowadays*

At the same time, smart home for elderly is still an important research direction in academia. Recently, many researchers are working on smart homes that can protect the QoL of the elderly [18–40].

Table. 1.2 shows a few examples of typical studies: A.N. Aicha [41] used motion sensors, door sensors, and pressure mats to achieve unwanted person detection; J. Yu [42] used temperature and humidity, pressure sensors, and electric meters to achieve behavior estimation and continuous monitoring; R. Sokullu [44] used environmental sensors to achieve anomaly detection; and H.M. Do [42] used human sensors and RGB-D camera implemented position tracking, activity monitoring, and fall detection. In addition, H.M. Do uses a robotic partner as an interface to communicate with humans.

All of these studies have yielded good results in their respective research questions. But unfortunately, in most of the research, measurement data are only used for simple safety

Table 1.2: *Related research of smart home*

Researcher	Year	Sensors	Robot partner	Function
A.N. Aicha [41]	2016	Motion sensor Door sensor Pressure mat	No	Detection of unwanted personnel
H.M. Do [42]	2017	Body sensor RGB-D camera	Yes	Position tracking Activity monitoring Fall detection
J. Yu [43]	2019	Temperature and humidity Pressure sensor Electricity meter	No	Behavior estimation Continuous monitoring
R. Sokullu [44]	2020	Environmental sensors	No	Abnormal detection

confirmations, such as human location and fall detection [45]. How to increase the overall quality of life with the monitoring results and How to provide more comprehensive healthcare services in smart home are still follow-up questions that researchers must face.

1.4 Future Trends

Internet of Everything (IoE) including the Internet of things (IoT) known as an advanced paradigm to connect physical and virtual things for enhanced services, has been introduced for developing smart homes, but measurement data are only used for simple safety confirmations, such as human localization and fall detection. On the other hand, Healthcare as a Service (HaaS) has been used in recent years, and it is expected to build a bridge from the data measured by smart home to the healthcare services such as health promotion support and health management. Furthermore, the initial implementation and operating costs of smart home often become high, and it is difficult for elderly people to customize the selection and layout of the devices, to update the parameters of smart home, and to choose a suitable healthcare service.

1.5 Goal of This Thesis

In this thesis, to solve the above problems, I design a platform for realizing smart home based on HaaS. First, I put forward the concept of HaaS for smart home. I propose a low-cost, easy-to-use, and human-centric care platform based on HaaS and Informationally Structured

Space (ISS). The proposed smart home platform can freely manage three main compatible components of measurement layer, analysis layer, and service layer. To maintain compatibility, we propose a general preprocessing scheme to meet the needs of behavior measurement with environmental sensor data. Furthermore, I design an initial set-up method based on human behavior analysis without direct human customization and re-learning in a variety of different scenarios to realize the easy implementation. Next, I develop a HaaS-based service integration system to realize human-friendly operations. Finally, I discuss the effectiveness of the proposed system through various types of experiments on healthcare services.

1.6 Thesis Structure

The thesis consists of six chapters as shown in Fig. 1.5.

Chapter 1 discusses the background and related research. The research purposes and goals are also clearly explained in this chapter.

Chapter 2 presents the survey of current smart home research. Through the analysis of core concepts such as IoT, IoE, HaaS, and ISS, which are inseparable from smart home, we clarify the research and development goals of this thesis. I clarify the definition of HaaS to meet the needs of healthcare for the elderly, and propose the smart home platform based on HaaS to solve the practical problems discussed in Chapter 1. In order to clarify the design guidelines, I discuss the monitoring system platform defined by three layers: the measurement layer, analysis layer, and service layer. Then I define the function and structure of each layer. The measurement layer is used for obtaining sensor data and perform basic processing; the analysis layer is used for user behavior analysis; the service layer is used for providing services through service robots and smart devices.

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Chapter 5 explains a human-centric approach to provide personalized services. From the viewpoint of HaaS, I design a cloud-based healthcare system for smart home. First, I clarify the functions and characteristics of a service robot in human-centric healthcare. Next, I explain the data structure and information flow in the overall system including sensors and service robots. Furthermore, I develop a scenario editor to realize the easy design of healthcare services. The scenario editor can integrate three processing levels for healthcare services according to (1) the types of sensors connected to the network in the data level, (2) measurement results of environmental states and human activities in the information level, and (3) interactive scenarios with a service robot in the knowledge level. In experiments, I set up a smart home including multiple sensors, multiple network protocols, and multiple robots. The experimental results show that the service robot can select a suitable scenario and provide personalized healthy living advice according to the state of daily activities. Moreover, the system can provide healthcare services to users while maintaining its stability, even if the number of sensor nodes is increased or decreased.

Chapter 6 concludes the thesis and explains the future research directions. The thesis discusses the methodology for constructing a HaaS smart home platform including human activities and behaviors monitoring from different points of view.

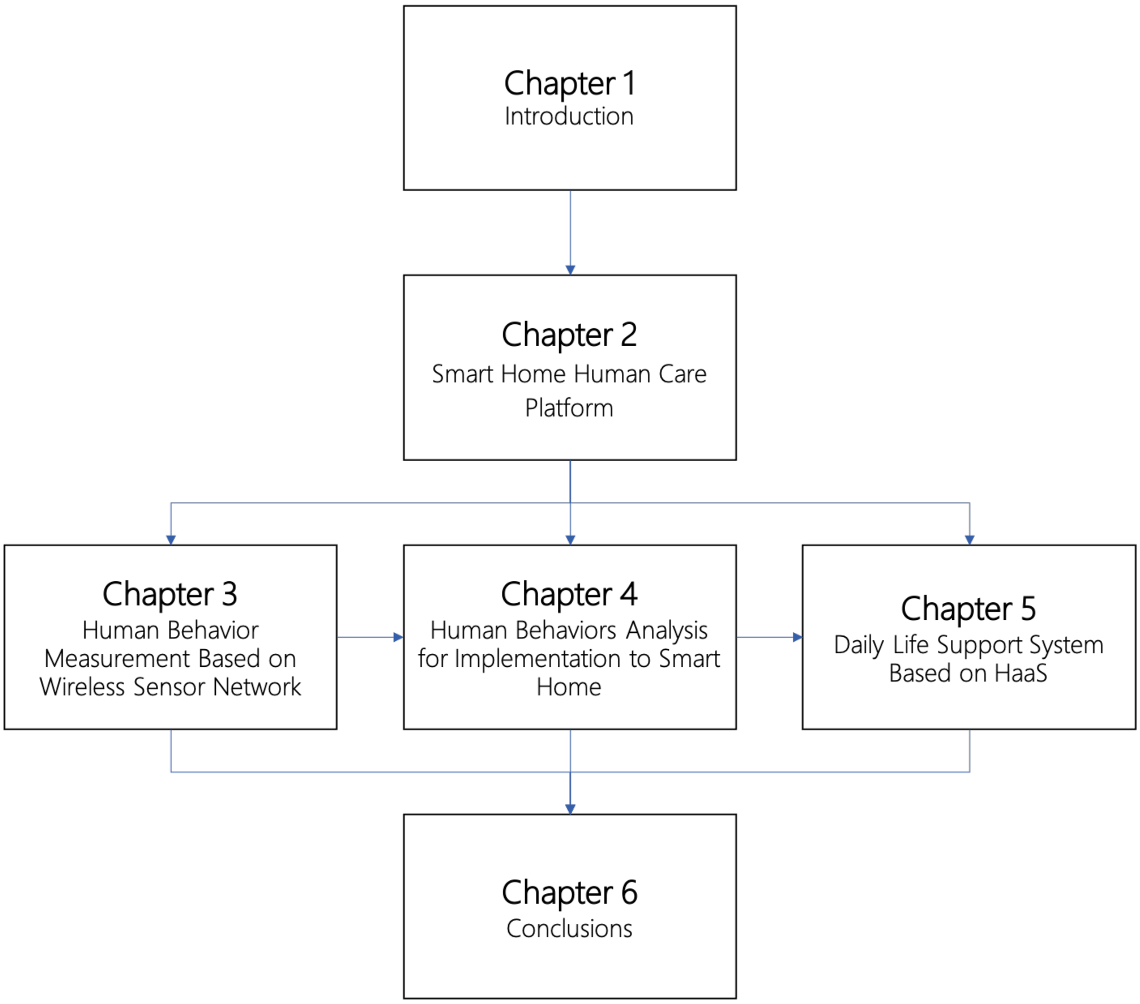


Figure 1.5: *The structure of the thesis*

Chapter 2

Smart Home Human Care Platform

2.1 Introduction

Currently, advanced countries such as Japan and Germany are facing the problem of population aging. According to the Japanese government report, in 2025, one third citizens will be over 65 years old, which means there will be about 2.3 million male and 4.7 million female elders at that time [46] .

More serious is the number of elder aged 65 or more who lives alone tends to increase in both men and women. According to the "Survey Results on the Economy and Living Environment of the Elderly in 2016" of the Cabinet Office, as can be seen in Fig.2.1, in 1980, about 880,000 elderly(15.5%) lived alone. But in 2010, the number increase in 4.80 million (31.4%).

Elderly living alone is considered to be a big problem due to the deterioration of dementia and lonely death, which refers to a Japanese phenomenon of people dying alone and remaining undiscovered for a long period of time [47]. According to the survey results conducted by the Bureau of Social Welfare and Public Health, Tokyo Metropolitan Government, trends in the number of lonely deaths of elderly people aged 65 and over in Tokyo 23 wards increased to almost 2 times, from 1,441 in the year 2003 to 2,727 in the year 2012. We must admit that lonely death has become an inevitable serious social problem.

Elderly people are increasing, but caregivers are always in an inadequate state. As a result, the quality of nursing care falls and the confirmation of the safety of the elderly becomes insufficient. In the event of an accident requiring a prompt response, there is a possibility that the correspondence may be delayed. Especially in the case of elderly living alone, it is extremely difficult to grasp the situation.

When we are concerned about the care of the elderly, we find that a bathroom is a high-

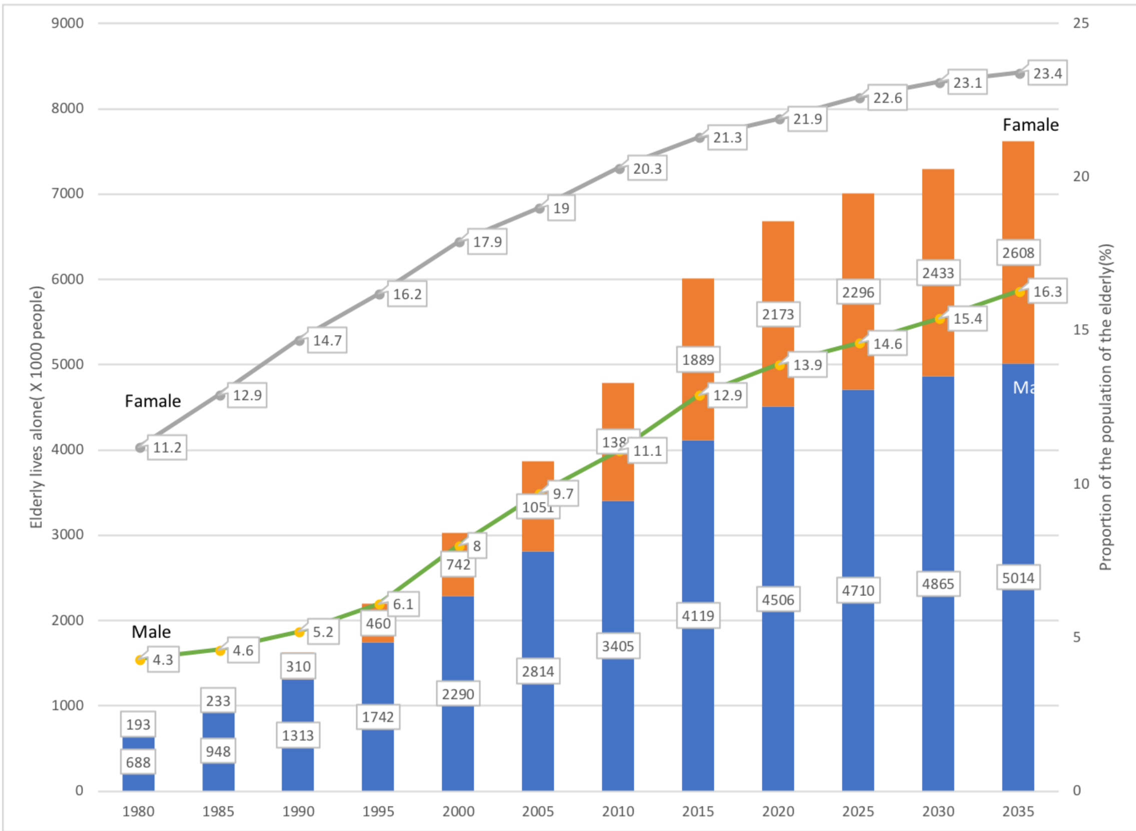


Figure 2.1: *The trend of elderly living alone*

risk place for the elderly. 80%-90% of the sudden deaths in the bathroom occur in the elderly [48]. Moreover, once an elderly person falls down in the bathtub or faints while bathing, it will be difficult to reach the phone or other methods to call someone else for help.

2.2 Smart Home

A smart home is a residence equipped with smart technologies aimed at providing tailored services for users. Smart technologies make it possible to monitor, control and support residents, which can enhance the quality life and promote independent living [49] [50].

In this study, the elderly who can be active are referred to as “healthy elderly” and the period during which they can maintain a healthy state is defined as “healthy life expectancy”. Consider a methodology for extending life expectancy. As healthy elderly people, elderly people who have new values and strong lifelong active intentions are called “active seniors”, and elderly people who are intelligent, smart, and enjoy their old age are called “smart seniors”. In order to extend healthy life expectancy, it is important to support health promotion for physical health and support for connecting people for mental health. Therefore, in order to build a community that values human dignity, we have considered a methodology for synergistically improving the QOL and quality of community (QoC) of people living in the area. Kubota Laboratory has adopted the concept of Computational Systems Care based on this broad meaning of care. We have made a proposal (Fig. 2.2). In general, community research often focuses on ”connection” itself, but it will be necessary to consider social and existential identities. Social identity is about awareness of what kind of social group you belong to, and tends to lead to a sense of superiority or inferiority as a relative presence in the community. Existential identities, on the other hand, are self-contained as to what kind of personality and values you consider yourself to be. Computational system care aims to help older people build confidence in their social and existential identities through natural communication. It is difficult to infer how older people perceive their social and existential identities, but to some extent they can be inferred from the personal content of smart devices, between humans and robots. It will be easier to build a mutual cognitive environment.

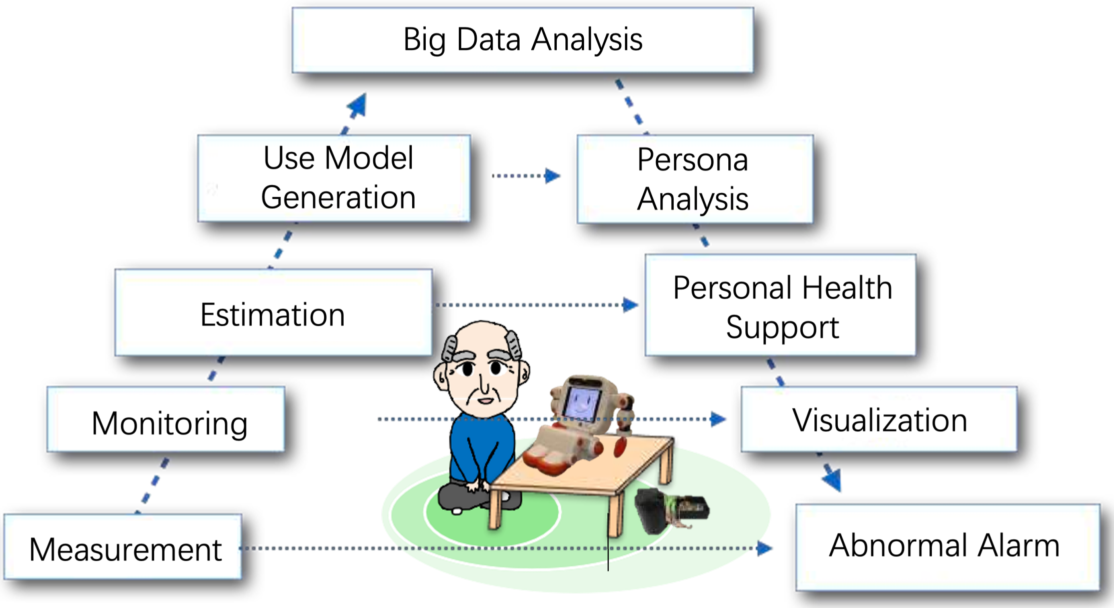


Figure 2.2: *Conceptual diagram of computational system care*

Computational system care systematizes watching by clarifying the relationship between functions from a systematic point of view and clarifying the methodology from a computational point of view. In Fig. 2.2, bottom-up measurement, monitoring, feature extraction, and user model generation are performed from the lower left, and top-down, user classification based on persona analysis, information recommendation, daily monitoring, and anomaly detection. , Gives a hierarchical structure. Data mining and learning are the main methodologies for measurement and feature extraction, and reasoning, prediction, exploration, and optimization are the main methodologies for persona analysis and information recommendation. Lifestyle modeling is important for daily monitoring, and if the modeled lifestyle can be referred to, it will be easier to detect anomalies.

As an attempt to extend the healthy life expectancy of healthy elderly people, by maintaining the function of the locomotorium by walking etc., motivation and motivation for going out, and by performing gymnastics such as radio calisthenics and arm raising exercises. A method of maintaining physical strength and range of motion of joints is generally used. As a national initiative, national health promotion measures have been developed several times. Health promotion is based on the awareness that each and every citizen "protects his or her own health". In the National Health Promotion Campaign (Health Japan 21) in the 21st century, the number of deaths in the middle of life is reduced and healthy life expectancy is reduced. The purpose is to improve stretching and QOL. However, in these methods, it is important for the elderly to continue exercising, and it is necessary to improve their motivation for exercising. In order to motivate, it is first necessary to think about what kind of person you want to be, and persona analysis is often used. Cooper defines "persona" as "not a real human being, but a substitute for a real human being in the design process."

By performing persona analysis, the image of the person to whom the service is provided becomes clear. Next, by using the scenario method, a specific scene can be assumed, a series of specific exchanges (service flow) can be considered, and the advantages and disadvantages of the service can be examined. Fig. 2.3 lists the persona images that take health promotion support into consideration. The flow of arrows in this figure is described in order to think about what kind of person you want to be.

External promotion

Level		Needs
1	Pay no attention to one's health	Consciousness
2	Aware of the impact of health	Knowledge
3	Recognized the importance of a healthy life	Reason
4	Expect for a healthy lifestyle	Method
5	Try a suitable healthy lifestyle	Target
6	Maintain a healthy lifestyle	Support
7	Hope to get expert advice on keep a healthy life	Pursuit

Self-promotion

Figure 2.3: *Health promotion support and persona image*

In fact, in order to improve motivation for things, it is indispensable to perceive and evaluate the actions taken by the person. In addition, it is thought that the quality and motivation of the action will be improved by making a plan for the next action based on the evaluation. However, there are also problems such as difficulty in observing one's own actions objectively and quantitatively, and difficulty in evaluation and planning due to lack of specialized knowledge. Therefore, in many cases, it is necessary to receive assistance from a specialized instructor or therapist, but it is difficult for the elderly living alone to perform it regularly at home when the population of the elderly is large compared to the number of specialists. The current situation is.

With the advent of domestic robots, it is expected to introduce health promotion support that combines robot technology and biometric technology, and Kubota Laboratory uses robot partners to maintain and improve the health of the elderly. I have provided support. In these support, the robot partner is used as if it were an instructor, and by selecting gymnastics according to the physical condition, physical ability, and motivation of the elderly, the health condition of the elderly is efficiently improved. Self-efficacy that seems to be "I can do it" is important for maintaining and improving physical and mental health, and intrinsic motivation based on this self-efficacy makes it possible to continue daily health promotion. Therefore, Kubota Laboratory has proposed a method of presenting gymnastics that improves the self-efficacy of the elderly by using self-efficacy as an index showing motivation for gymnastics.

Against this background, in this study, we will measure the behavior of the elderly from various perspectives, such as measuring the amount of activity using a micro-vibration sensor and measuring exercise, in order to realize health promotion support for the elderly. We will examine the methodology for this and conduct preliminary experiments.

2.2.1 Internet of Things and Wireless Sensor Networks

Smart devices or objects, capable of communication and computation, ranging from simple sensor nodes to home appliances and sophisticated smart phones are present everywhere around us. The heterogeneous network composing of such objects comes under the umbrella of a concept with a fast growing popularity, referred to as Internet of Things (IoT) [33, 51–53].

IoT-centric concepts like augmented reality, high-resolution video streaming, self-driven cars, smart environment, e-health care [54–57]. The basic logic of IoT [58] [59] is to embed sensors in the things in people's daily lives, and enable things to communicate with each other through wireless sensor networks (WSN) [60] and radio frequency identification (RFID) [61] [62]. Through the communication between things, we have entered a new era of technology. The development of multiple technologies has enabled the realization and development of the concept of IoT. Allows us to use network technology to achieve communication between any type of things at any place and at any time [63]. The things in IoT are uniquely addressed through IP address and they are physical in natures where they can integrate with the network [64]. Sensors in the Internet of Things can perceive the physical environment and report data remotely via the Internet. The Internet of Things can use intelligent decision-making methods to make responses and decisions based on the collected data [65].

A number of monitoring and functional assessment systems for elderly care have been developed recently [66]. These systems can be categorized into two types by technical approach. One approach is using an instrument to get the elderlys physiological signals, such as wearable devices [67], measurement sensors [68] [69], and even RFID tags [3]. Another approach is sensing the environmental changes, and estimate human behavior indirectly [4]. The former one is more accurate in general, but may not be acceptable to the elderly. Healthy elderly may also be reluctant to wear such instrument due to safety and privacy concerns. For such reasons, to avoid discomfort and disbelief of elderly, we adopt environmental sensors to monitor and estimate the behavior of the elderly.

Table 2.1: *Sensors used in monitoring system (living room)*

Motion	Accelero-meter	Camera	Vibration Sensor
Walking	+	+++	+++
Sitting	+++	+	+
Exercise	+	+++	++
Sleeping	+++	+	+
Falling down	+	+++	+++

Table.2.1 and Table.2.2, analyzed the availability of three sensors commonly used in the monitoring system for different scenarios. More plus signs indicate that human behavior characteristics are more easily captured by the sensor, and it is less difficult to develop the estimation algorithm. We hope to find a sensor can be used in as many scenarios as possible. It is improper to install camera in the bathroom. The utilization of accelerometer is also limited as it is hard to be installed everywhere reached by person. For all such consideration, vibration sensor is decided to use the in this study.

Some studies had proved that vibration data can be used to analyze the state of human activities indoors. For example, Jeong [70] used vibration sensors to determine the pace

Table 2.2: *Sensors used in monitoring system (bathroom)*

Motion	Accelero-meter	Camera	Vibration Sensor
Bathing	+	-	+++
Falling down	+	-	++
Heat shock	+++	-	++
Get in/out	+++	-	+++

and direction of people walking. Li [71] proposed a novel indoor footstep localization using vibration sensors. In terms of the form of equipment, the vibration sensors used in smart homes can be divided into two categories: smart floor tiles/mats [72] and vibration sensor nodes [73]. The former needs to be laid in the room in advance, which is more common in the integrated smart home for monitor the user's location. The latter is relatively flexible and can be installed or disassembled as needed.

Compared with the visual signal that can obtain two-dimensional or even three-dimensional data, the data of the vibration sensor was one-dimensional and not intuitive enough. However, as a vibration wave, its properties were similar to sound waves or radio waves, and we could learn some methods to deal with the latter. Fehske had combined neural networks with spectral correlation for signal classification [74]. Off-line prepossessing was used to extract signal features, to reducing on-line computation of neural networks. Muda [75] used mel frequency cepstral coefficient (MFCC) and dynamic time warping (DTW) techniques for voice recognition, that contained triangular overlapping window and discrete cosine transform in the pre-processing.

2.2.2 Healthcare as a Service

Unlike the traditional smart home, I propose the concept of Healthcare as a service in this study. This is not the first time this concept has emerged. But before that, most of the relevant research focused on hospital scenarios [76] and did not take smart homes into account. The development of cloud computing allows us to look at services from another perspective. With the help of cloud computing, companies no longer sell products, but become service providers:

Specifically, the Internet of Things and sensor networks enable the collection of user information. The terminals placed in the user's home are responsible for completing user behavior analysis.

In such a model, users have the right to freely choose whether to use, and which service content to use, while operators can customize the direction of their services according to their own products.

2.2.3 Informationally Structured Space

From an information resource perspective, accessibility in information resources and the environment is critical to both person and the systems that serve them. Therefore, we want to design the system as a structured platform to collect, store, transform, and provide information. This environment is called the Informationally Structured Space (ISS) [77] (Fig.2.4). Technically, an elderly health care system can include information technology (IT), network technology (NT), robot technology (RT), etc. [78].

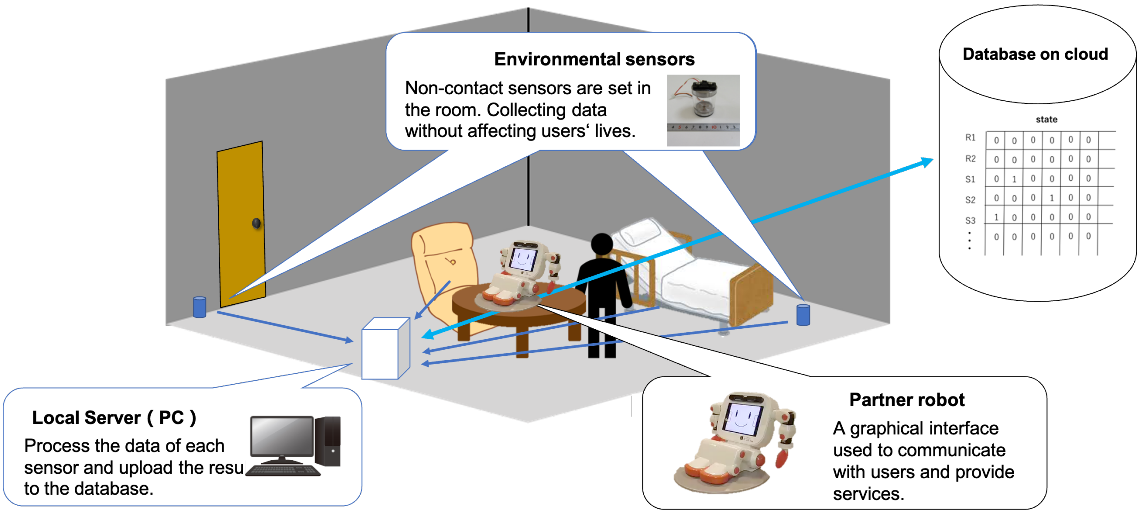


Figure 2.4: *The concept of informationally structured space*

The network of the system collects information from various sensors and sends them to the server using wireless communication methods [79] such as Bluetooth, Wi-Fi, and Zigbee. The server processes the sensor data, turn into estimated human behavior and sends it to the partner robot and the caregivers smart phone (Fig.2.5) [80] [81]. Based on the received information, the robot will give advice to the elderly. For example, the robot will remind the elderly drinking water if the room temperature and humidity are high. Once an abnormal situation found and nobody around, the system will alert the caregivers at the first time.

In addition to the necessary database features, the information structure space has the following properties.

1. Information Sharing Attributes: All data is independent of the type of sensor, robot, and development environment.

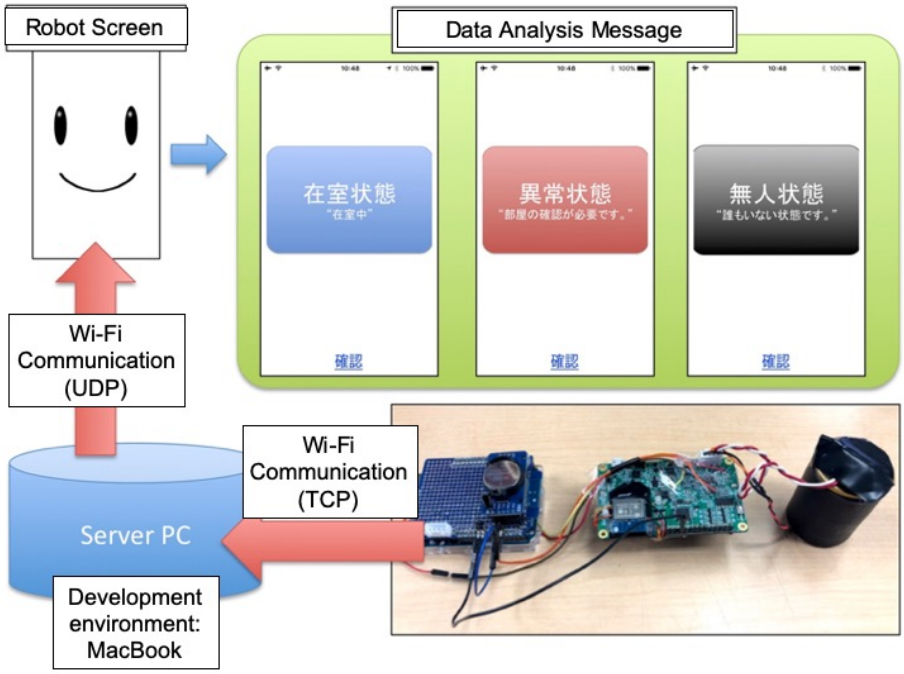


Figure 2.5: *A simple behavior monitoring system including sensors, server and robot*

2. Information interpretability: All data is interpretable between robots and people.

3. Information reversibility: Measurement data is the reciprocal between digital data and symbolic representation.

4. Standardization and Modularity: In the default state, in order to provide a unified default service, the data should be stored in a standardized form and kept modular for all server equipment and programs to call (Fig.2.6).

5. Adaptability and Maintainability: The format and content of information storage should meet the individual needs of users and be determined according to the physical and transmission environment.

2.3 Smart Home Human Care Platform

It is expected that the system will not only be able to store sensor data, but also analyze and interpret it for delivery to caregivers in a resolvable manner. For example, the system should not only record changes in body temperature in the elderly, but also infer the possibility of illness in the elderly through changes in body temperature.

Fig.2.7 shows the concepts of the elderly care system based on the idea of ISS. In my work, I mainly focus on the measurement and monitoring part.

The network of the system collects information from various sensors and sends them to

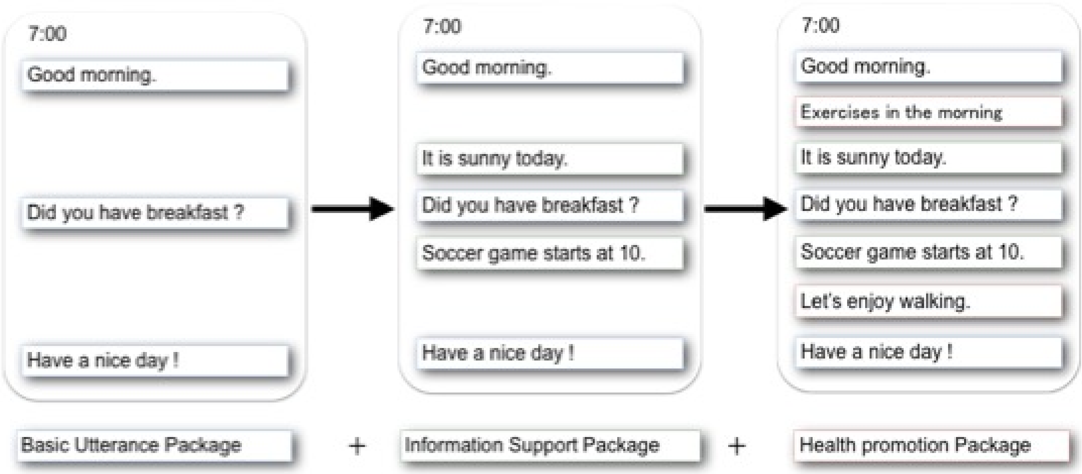


Figure 2.6: *Organized service packages of ISS*

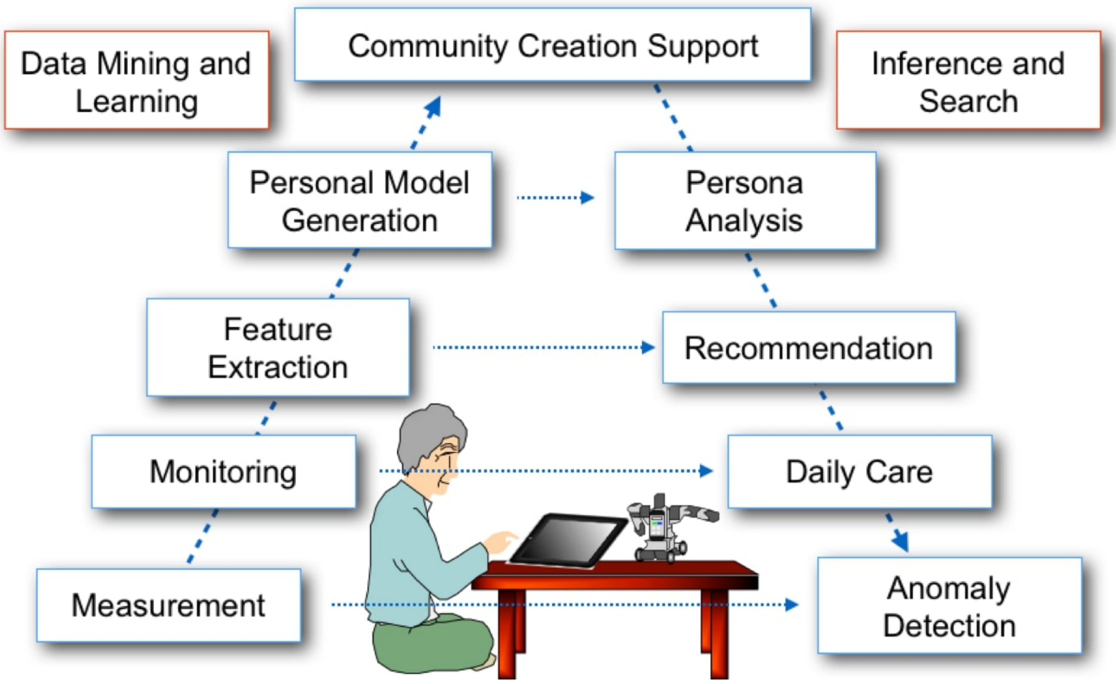


Figure 2.7: *Hierarchical structure from behavior monitoring to daily care*

the server using wireless communication methods [79] [82] such as Bluetooth, Wi-Fi, and Zig-bee. The server processes the sensor information into estimated human behavior and sends it to the partner robot and the guardians mobile phone [80] [81]. According to the situation, the robot can give tips to the elderly (such as reminding the elderly to drink water if the temperature and humidity are high in the house), and once the elderly is in an abnormal situation, if nobody has noticed the situation, the system can send alarm to the caregivers in the first time.

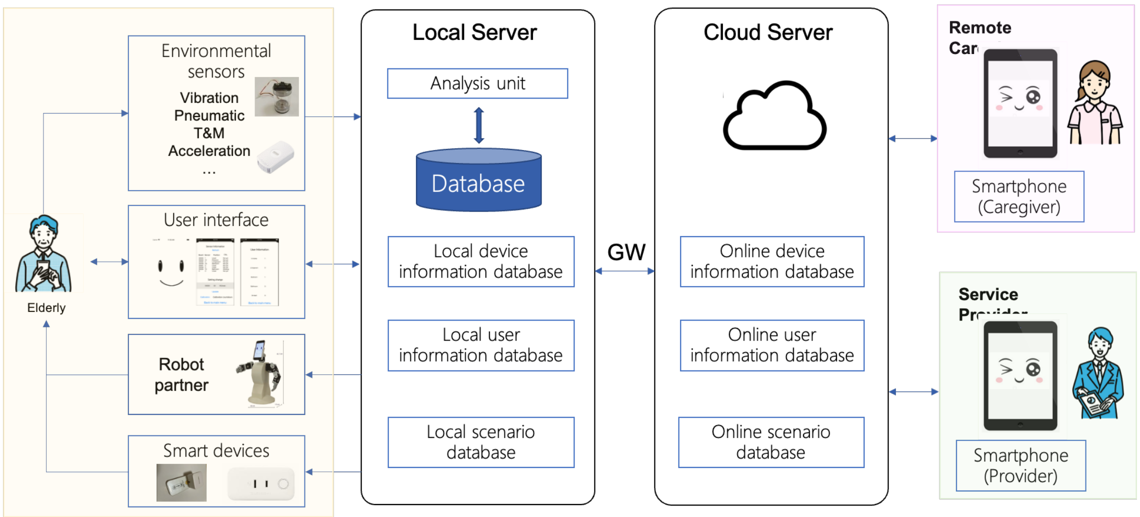


Figure 2.8: *Component of SHHCP*

Fig. 2.8 shows the components of a complete smart home human care platform (SHHCP). SHHCP contains two parts: local and remote.

local-part includes environmental sensors for measurement user's activity data; user interface used to display the current state of the user, the operating state of the system, and to set basic information; A robot partner that is used to communicate with users in language and actually undertake the function of daily life support; A series of smart appliances and smart switches that can be remotely controlled via API. These devices directly serve the users daily life and are connected to the local server. The local server undertakes the work of data analysis, and all measured data are processed on the local server. At the same time, the local server is connected to the cloud server through the gateway, which can upload user information in real time and update the service content from the cloud service. Remote caregivers and service providers can access the cloud server, obtain the operating status of the system, and modify and customize services.

SHHCP can also provide Real-time monitoring and abnormal detection services. Above this, one of the goals of SHHCP is to improve the QoL of healthy elderly through promote a healthy daily-life rhythm [83] (Fig. 2.9. Fig. 2.10 shows the main functions of SHHCP.

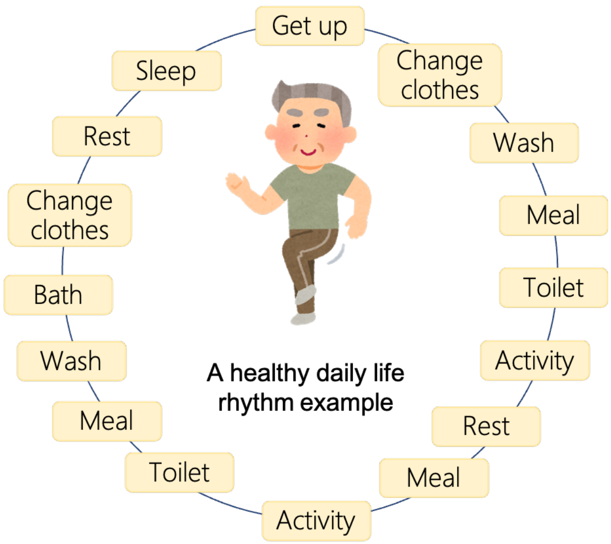


Figure 2.9: *A healthy daily life rhythm example*

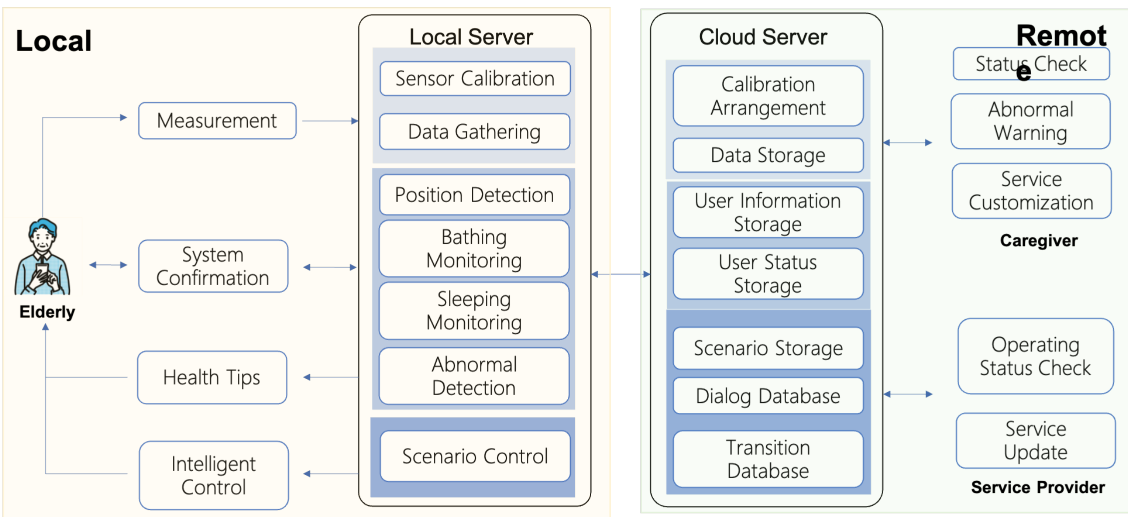


Figure 2.10: *Function of SHHCP*

Through the health tips system, the SHHCP can provide the elderly with daily life, physical, and mental healthcare support services.

External promotion

Level		Needs
1	Pay no attention to one's health	Consciousness
2	Aware of the impact of health	Knowledge
3	Recognized the importance of a healthy life	Reason
4	Expect for a healthy lifestyle	Method
5	Try a suitable healthy lifestyle	Target
6	Maintain a healthy lifestyle	Support
7	Hope to get expert advice on keep a healthy life	Pursuit

Self-promotion

Figure 2.11: *Different healthcare tips in different health promotion status*

According to different health promotion status, the system divides users into seven levels (Fig. 2.11). Through pre-settings and subsequent corrections during the conversation, the system can determine the user's current health promotion status and give appropriate healthcare tips based on its specific situation.

In order to achieve the above functions, I divide SHHCP into three layers according to the division of labor: measurement layer; analysis layer; service layer

2.3.1 Measurement Layer

Table.2.3 shows some of the application scenarios we have implemented. We divided the scene into three area: the bathroom, the living room, and the bed. For the bathroom, we want to monitor the bathing time of the elderly and whether the elderly may lose consciousness due to heat shock. In the living room, we pay attention to whether the elderly may fall and whether the amount of activities is sufficient for the elderly during the day. In bed, we want to know the sleep time of the elderly and also the quality of sleep.

Some functions require two or more sensors to complete together, which has higher requirements for multi-sensor cooperation.

Table 2.3: *Main detection target of the system*

Detection Area	Detection Tagert	Sensor Number
Bathroom	Bathing time	2
	Disappointment	1
Livingroom	Location determine	2+
	Activity detection	2+
	Fall detection	2+
Bed	Sleeping time	1
	Fall detection	2

2.3.2 Analyze Layer

From the viewpoint of ISS, I first develop a monitoring system that includes servers, sensors, and smart devices for users to enter their personalized information in advance. Next, I design a fuzzy inference-based spiking neural network, by using the user's personalized information and the pre-designed knowledge-based system. Experimental results show the system can adapt to changing use environments and maintain high accuracy without additional learning.

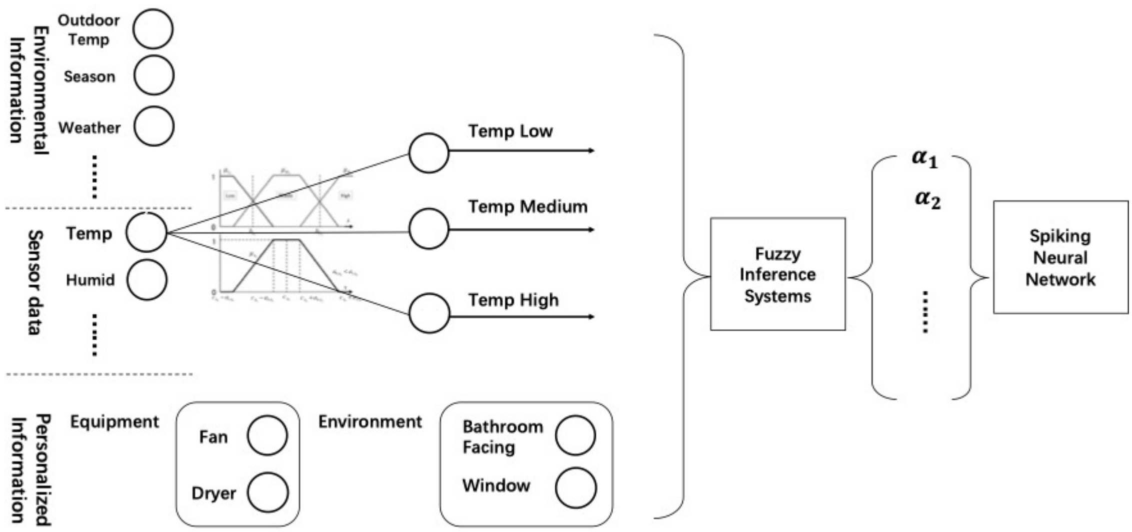


Figure 2.12: *With the help of environmental information, sensor data, and personalized information, the sensitivity of each input can be finer adjusted.*

2.3.3 Service Layer

The main purpose of the service layer (Fig. 2.13) is to connect the measurement result with the actual service. As mentioned earlier, the core goal is to improve the QoL of the elderly through the daily life support system.

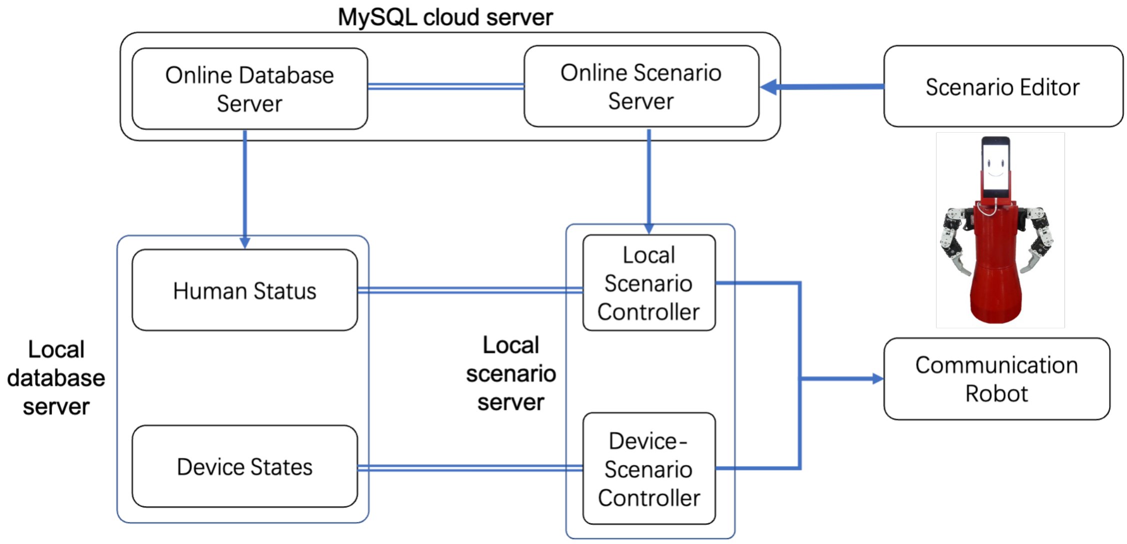


Figure 2.13: *The structure of the service layer*

In service layer, the user status and device state are sent to the local scenario server. In local scenario server, there is a scenario controller, which directly controls the conversation content of the robot partner.

At the same time, the local server is connected to the cloud server, current system states are reported to cloud in real time.

Through the scenario editor, caregivers, therapists, and service providers can create, edit, and customize specific service content for elderly care without technical barriers.

2.3.4 Research Topic

Fig. 2.14 shows the overview of this thesis.

The core proposal is smart home platform for human care based on HaaS, which contains three main components: environmental sensors, cloud service and robot partner. For each part, I put forward specific research topics, and give solutions in Chapter 3 to 5.

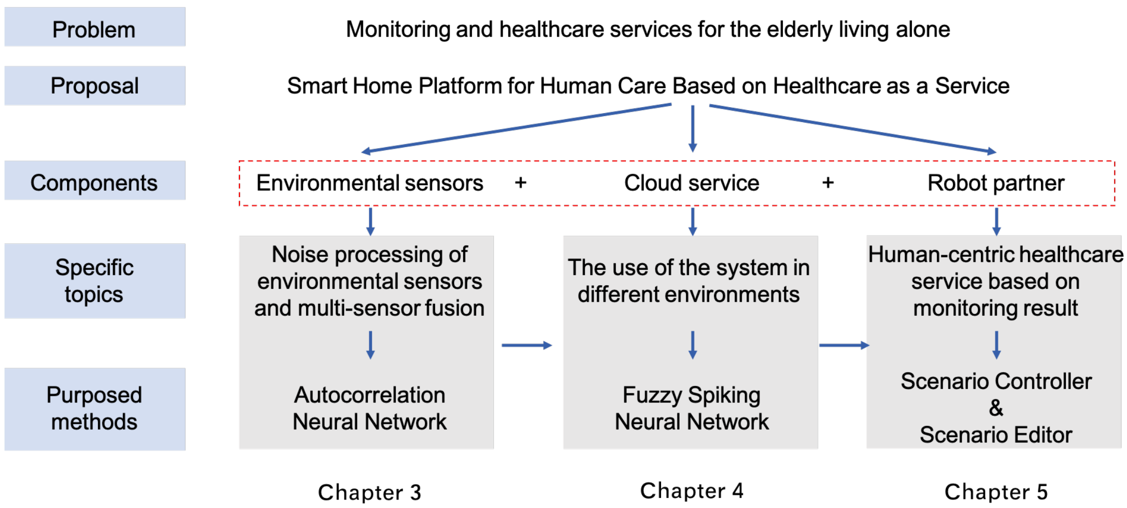


Figure 2.14: *Overview of research topics*

Chapter 3

Human Behavior Measurement Based on Wireless Sensor Network

3.1 Introduction

Chapter 3 explains the physical structure of the human-centric IoT system from the perspective of sensor selection and measurement. First, we discuss a selection method of sensors based on the actual needs of users. Furthermore, we explain the problems and challenges faced by non-contact environmental sensor systems. Next, given the characteristics of human activities and the integration of multiple sensors, I propose human behavior estimation using a spiking neural network, which could effectively process sensor data from multiple different information sources, and accurately distinguish human activities from indoor non-human-activity noise. The experimental results show that the proposed method can measure human activities using different kinds of sensors.

For the sensor we choose, we will give a series of experiments and provide specific algorithms to realize the measurement and monitoring functions.

3.2 Environmental Sensors

Not all types of sensors are suitable for the smart home scenario. Traditional vision-based sensors can give good results in monitoring the location and status of people [84], but have very big privacy issues.

From a HaaS perspective, we need to consider both the needs of the user, and the needs of the service provider. Specifically, elderly want sensors that are non-wearable and do not violate their privacy; service providers want sensors that are stable and easy to install. On top

Table 3.1: *Sensor devices for behavior monitoring*

		Sensor Devices		
		Sensor Tag	Vibration Sensor	T&H Sensor
Mounting Position		Door	Floor	Wall
Changing Room	Face Washing	+	+	++
	Changing	+	++	+
	Fall Down	+	+++	+
	Open Door	+++	+++	+
Mounting Position		Bathtub	Bathtub	Bathtub
Bath Room (Shower)	Bathing	+	++	+++
	Fall Down	+	+++	+
	Open Door	+++	++	++
Bath Room (Bathtub)	Bathing	++	+	+++
	Fall Down	+	+++	+
	Drowning	+	++	++

of that, low cost and low power consumption are the common expectations of both parties.

One of the most important targets is to detect falls and drowning of older individuals in the bathroom. Table. 3.1 (The number of + indicates the fitness of the sensor and the corresponding environment) also shows the sensor devices for behavior monitoring in a bathroom. Firstly, we will discuss how to measure the state of older individuals and their surrounding environment. Older individuals need to avoid heat shock, which can be caused by the temperature difference between the bathroom and outside when a person moves in or out. However, we wont be able to use image sensors in the bathroom for privacy reasons. Therefore, we will use only sensor network devices to measure environmental data such as temperature, humidity, illumination, vibration, and acceleration.

All sensors in the system can upload information in real-time. But we found that not all sensor data can reflect human activities in real-time. For example, when the user moves into the room, the vibration sensor faithfully records the vibration on the ground, reflecting human activity in real-time. On the other hand, when the user turns on the bathroom faucet, the humidity will rise. But the room's humidity will not reach extreme value immediately when the user turns on the tap.

Therefore, according to the data type of the sensor, we further divide the sensors into short-term behavior estimation sensors and meddle-term behavior estimation sensors.

3.2.1 Short-term Behavior Estimation Sensors

Short-term behavior estimation sensors refer to sensors with a data frequency of 1 Hz and above. Through the real-time data reported by these sensors, the system can determine the user's current location and status in seconds. Considering that dangerous monitoring is also an important function of the system, we always hope to be alerted when the user is in danger, so I use short-term behavior estimation sensors as the main sensors of the system.

3.2.1.1 Ultra-sensitive Vibration Sensors

NEW SENSOR Incorporated (NSI) developed the sensor we used in this research to provide support for watching over the elderly at home. A lithium battery powers the device, and battery replacement was not necessary for about half a year. The specific specifications are described in Table.3.2 below. Also, the vibration sensor is shown in Fig.3.1. The previous type of vibration sensor in the "safe sensor system" used ultrasonic signal to measure the change of wave of liquid, and NSI developed a new type of vibration sensor by laser measurement in order to improve the performance. In this way, it is possible to achieve high sensitivity while being inexpensive to produce. In addition, since the vibration is measured by placing the sensor on the floor where the measurement is performed, privacy problems are less likely to occur and the sensors can be installed easily.

Table 3.2: *Specification of Ultra-sensitive Vibration Sensor*

Case size	48mm x 35mm
Operating power supply	3V / 500mAh
Output voltage	-3V to 3V
Sampling frequency	500Hz
Liquid depth	4mm
Filled liquid	Silicone oil

Fig. 3.2 shows the comparison of some sensors that can be used in smart homes. Considering the basic requirements on privacy protection and non-wearing, we mainly choose from various indirect motion detect sensors. The lateral comparison found that the vibration sensor can meet all needs. However, at the same time, the system must admit that indirect data sacrifice the advantage of accuracy, which is the main problem that the research must solve.

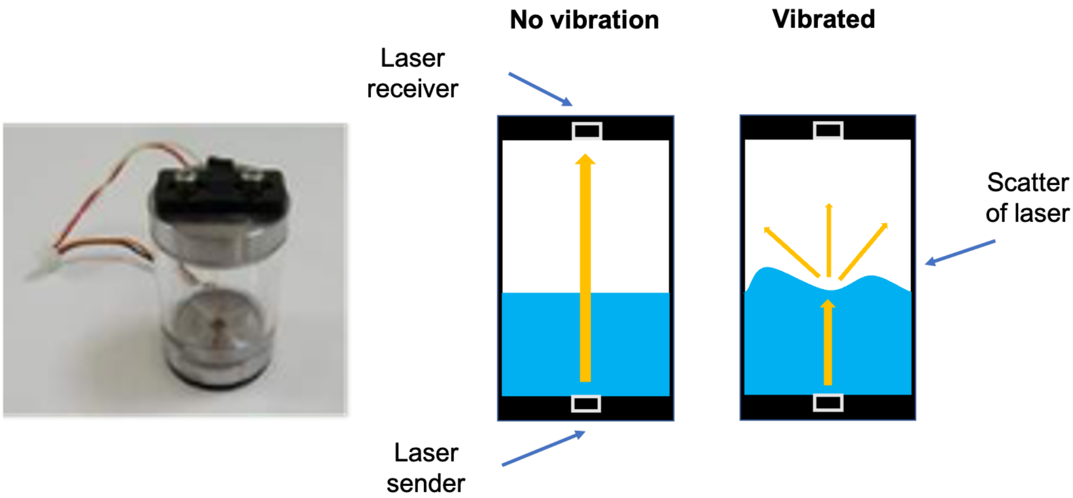


Figure 3.1: *Ultra-sensitive vibration sensor*

	Wearable sensor	Vision sensor	Indirect motion detect sensors			
	Body-sensor	Camera	Doppler radar	Infrared sensor	Vibration mat	Vibration sensor
Ease-to-set	-	+++	+++	+	+	+++
Privacy Protection	-	-	++	++	++	+++
Cheap	-	-	++	+	-	+++
Low-energy	+	-	++	++	+++	++
Imperceptible	-	+	++	+++	++	+++
Statable	+++	+++	++	++	+++	++
Accuracy	+++	+++	++	++	++	+
Multifunction	+++	+++	+	+	+	++

Figure 3.2: *Advantages and disadvantages of vibration sensor*

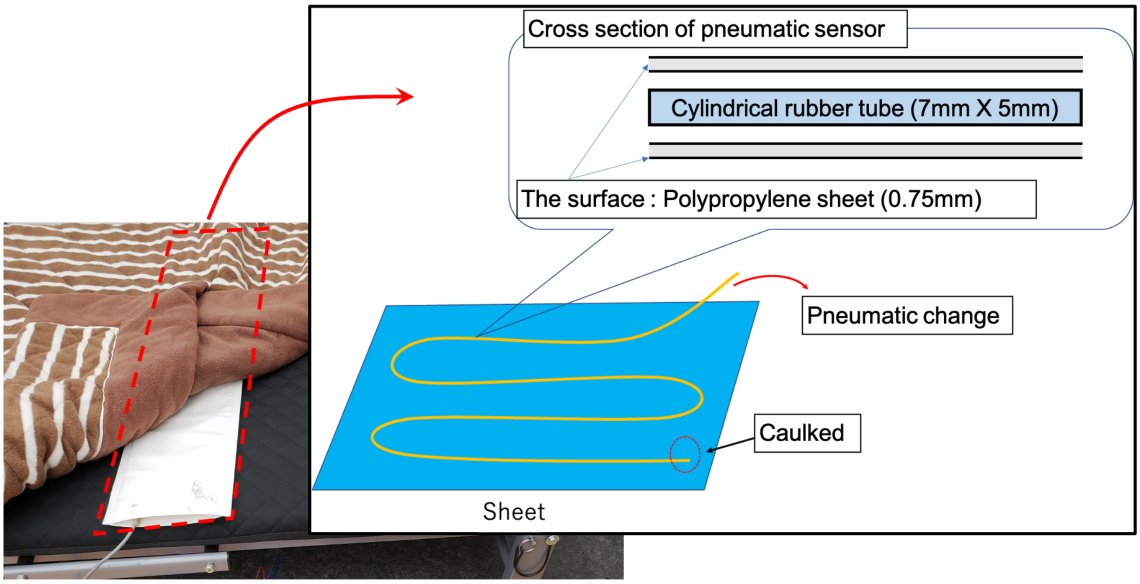


Figure 3.3: *Pneumatic sensor mat*

3.2.1.2 Pneumatic Sensors

As shown in Fig.3.3, this pneumatic sensor had a rubber tube passed through the inside of the seat, and by measuring the change in the air pressure inside this tube, it is possible to measure the vibration. Like the vibration sensor, this pneumatic sensor had a relatively simple structure. It could be manufactured at a low cost, and the measured data is unlikely to cause privacy problems.

3.2.2 Middle-term Behavior Estimation Sensors

The data frequency of a middle-term behavior estimation sensor is usually from 1 to tens of data per minute, and its data usually has a certain hysteresis. Although the real-time performance is relatively poor compared to short-term sensors, sensors such as temperature and humidity are also important data sources in this system, which can assist the system in judging user status.

3.2.2.1 Temperature and Humidity Sensors

When choosing a sensor to be installed in the bathroom, the following factors are mainly considered: 1. Battery; 2. Wireless communication function; 3. Suitable for high temperature and high humidity environment; good waterproof performance, no risk of leakage.

Considering the difficulty of the experiment and other reasons, we chose a sensor that can simultaneously obtain temperature and humidity: MM-BLEBC2(Fig.3.4).

Sensor	Temperature	Humidity
Range	-40 to 70°C	0 to 100%RH
Error	±0.5°C (0 to 50°C)	±2.5%RH (0 to 90%RH)
The smallest unit	0.05°C	0.05%RH

Figure 3.4: *Temperature and humidity sensor(MM-BLEBC2) used in the experiment*

3.3 Behavior Estimation With Real-time Response Sensors

3.3.1 Pro-precessing

3.3.1.1 Low-pass Filter (LFP)

A low-pass filter is a filter that passes signals with a frequency lower than a selected cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. The exact frequency response of the filter depends on the filter design. The filter is sometimes called a high-cut filter, or treble-cut filter in audio applications. A low-pass filter is the complement of a high-pass filter.

In optics, high-pass and low-pass may have different meanings, depending on whether referring to frequency or wavelength of light, since these variables are inversely related. High-pass frequency filters would act as low-pass wavelength filters, and vice versa. For this reason it is a good practice to refer to wavelength filters as short-pass and long-pass to avoid confusion, which would correspond to high-pass and low-pass frequencies.

Low-pass filters exist in many different forms, including electronic circuits such as a hiss filter used in audio, anti-aliasing filters for conditioning signals prior to analog-to-digital conversion, digital filters for smoothing sets of data, acoustic barriers, blurring of images, etc. The moving average operation used in fields such as finance is a particular kind of low-pass filter and can be analyzed with the same signal processing techniques as are used for other low-pass filters. Low-pass filters provide a smoother form of a signal, removing the short-term fluctuations and leaving the longer-term trend.

Filter designers will often use the low-pass form as a prototype filter. That is a filter with unity bandwidth and impedance. The desired filter is obtained from the prototype by scaling for the desired bandwidth and impedance and transforming into the desired band form (low-pass, high-pass, band-pass, or band-stop).

$$v_{in}(t) - v_{out}(t) = Ri(t) \tag{3.1}$$

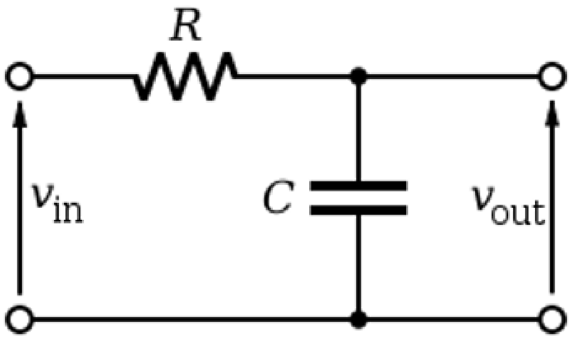


Figure 3.5: *Low-pass Filter*

$$Q_c(t) = Cv_{out}(t) \tag{3.2}$$

$$i(t) = \frac{dQ_c}{dt} \tag{3.3}$$

Here, Q is the charge accumulated in the capacitor at time t. Based on these three equations

$$v_{in}(t) - v_{out}(t) = RC\frac{dv_{out}}{dt} \tag{3.4}$$

This equation can be discretized. For simplicity, let's assume that input and output samples are taken at equal intervals at dT time intervals. The sample of v_{in} is represented by $(x_1, x_2, x_3 ... x_n)$, and v_{out} is represented by the sequence $(y_1, y_2, y_3 ... y_n)$.

$$x_i - y_i = RC\frac{(y_i - y_{i-1})}{\Delta_T} \tag{3.5}$$

And by rearranging the terms,

$$y_i = x_i\frac{\Delta_T}{RC + \Delta_T} + y_{i-1}\frac{\Delta_T}{RC + \Delta_T} \tag{3.6}$$

That is, the discrete-time implementation of a simple RC lowpass filter is an exponentially weighted moving average.

$$y_i = \alpha x_i + (1 - \alpha)y_i \tag{3.7}$$

where

$$\alpha = \frac{\Delta_T}{RC + \Delta_T} \tag{3.8}$$

The filter recurrence relationship provides a way to determine the output sample in terms of the input sample and the preceding output.

The following pseudocode algorithm simulates the effect of an LPF on a series of digital samples.

Pseudocode:

```
// Return RC low-pass filter output samples, given input samples, // time interval dt, and time constant RC function lowpass(real[0..n] x, real dt, real RC) var real[0..n] y var real  := dt / (RC + dt) y[0] :=  * x[0] for i from 1 to n y[i] :=  * x[i] + (1-) * y[i-1] return y
```

The loop that calculates each of the n outputs can be refactored into the equivalent:

```
for i from 1 to n y[i] := y[i-1] +  * (x[i] - y[i-1])
```

3.3.1.2 Weighted Root Mean Square

I use weighted root mean square (WRMS) for further pre-processing. Since that the waveform at time t is affected by the previous action, we calculate RMS (δ_t) using the data y_i at time $(t, t-1, ...t-99)$.

$$\sigma_t = \sqrt{\frac{\sum_{i=0}^{n} w_i \delta_i^2}{n \sum_{i=0}^{n} w_i}} \tag{3.9}$$

3.3.2 Autocorrelation Neural Network

A neural network for processing real-time data with less computational complexity is Time Delay Neural Network (TDNN) [85]. TDNN is is a multilayer Artificial Neural Network (ANN) architecture whose purpose is to classify patterns with shift-invariance. Shift-invariant classification means that the classifier does not require explicit segmentation prior to classification. For the classification of a temporal pattern (such as speech), the TDNN thus avoids having to determine the beginning and end points of sounds before classifying them [86].

TDNN were often used to analyze sound waves [87], and the vibration waves in our study and sound waves had similar properties. TDNN used signals with a time window as the input, which is very suitable for vibration data with large fluctuations. It is hard to figure out the features of a single data, but the data over a period of time would have some particular features. TDNN need less storage space and less processing unit than deep learning, and can be written into a sensor substrate with small memory. Since less computing power was required, running TDNN consumed very little electric power. So, we believed TDNN was appropriate for real-time behavior estimation using vibration sensors.

However, in experiment we found that, when the signal-noise ratio was low or person was far away from the sensors, TDNN was challenged to make correct estimations.

To solve the problem, we considered to find a new method which can identify human actions and environmental noise, while preserving the advantages of TDNN.

For the raw data pre-processing, we used the low-pass filter (LPF) and weighted root mean square (WRMS) (Fig. 3.6). The 40 Hz LPF filtered out the environmental noise preliminarily. For a real sequence of vibration data y, since the waveform at time t is considered to be affected by the previous action, we calculate WRMS (σ_t) to process the data further using y_i ($i = t, t-1, ...t-n$), where n is the time window, as follows:

$$\delta_i = y_i - \bar{y} \tag{3.10}$$

$$w_i = e^{-k\left(\frac{n}{2}-i\right)^2} \tag{3.11}$$

$$\sigma_t = \sqrt{\frac{\sum_{i=0}^{n} w_i \delta_i^2}{n\sum_{i=0}^{n} w_i}} \tag{3.12}$$

where $\bar{y}$ is the average of y_i ($i = t, t-1, ...t-n$) and k is a control variable, which represents the attenuation degree of vibration.

In actual research and experiments, we improved the vibration sensor so that real-time 250Hz data can be obtained. So we set $n = 250$ so that every σ_t would be calculated from 1 second vibration data, and after several trials, we experimentally set $k = 0.01$.

The reason to calculate the weighted average over time had two considerations:

1. any specific vibration data was affected by the previous time point rather than isolated;

2. when multiple sensors used, we were challenged by the consistency of the internal clock in each sensor. The weighted average could reduce the impact of time synchronization on subsequent algorithms.

A lot of activities of person in the room could cause vibrations. Walking was a typical one. Our experiments showed that the vibrations caused by walking had an considerable periodicity.

$$\mathrm{AC}_\tau = \frac{1}{N_{AC}} \sum_{t=0}^{N_{AC}-1} \sigma_t \sigma_{t-\tau} \tag{3.13}$$

We calculated the autocorrelation coefficients of the vibration data of walking. Preliminary test results were shown in Fig.3.7. The horizontal axis represents the time of the time-series data, and the vertical axis represents the autocorrelation AC_τ. τ was set from 0 to 2 second and also in discrete time steps. The time step was set to 0.04s so N_{AC} (whole number of terms) in formula (3.13) was 50. Scale of gray in the figure showed the correlation. The

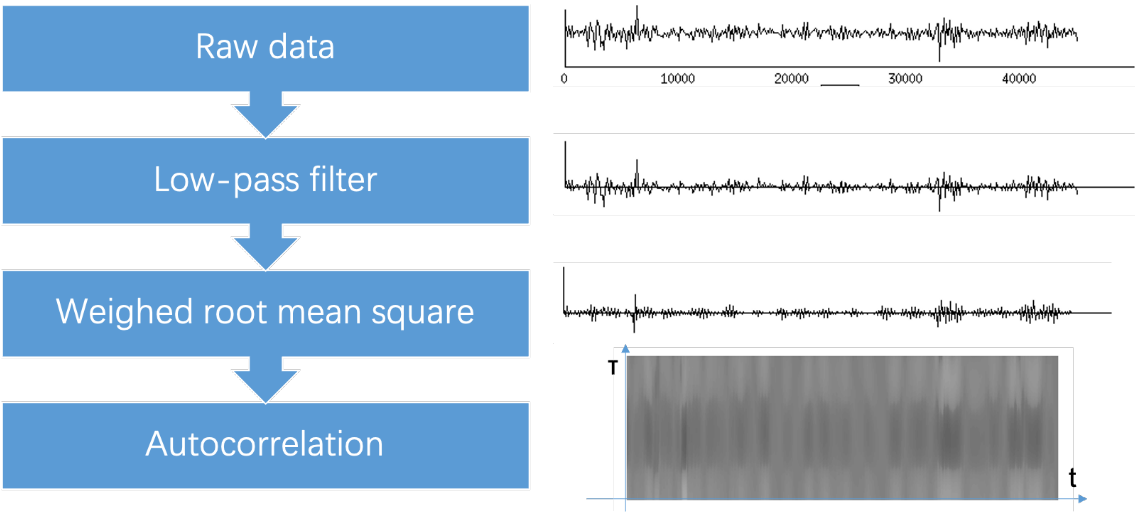


Figure 3.6: *Pre-process of sensor data*

contract ranges from black at the lowest to white at the highest.

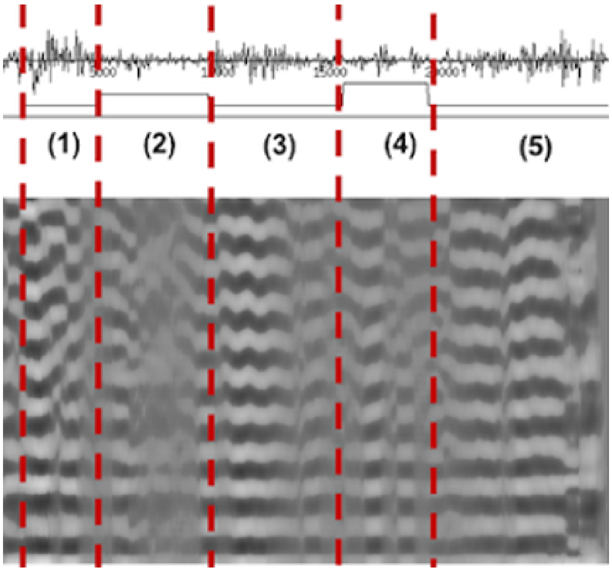


Figure 3.7: *Preliminary test results: raw data(up) and autocorrelation(bottom) of siting (2)(4) and walking (1)(3)(5)*

When participant walked in the room (1, 3 & 5 in Fig.3.7), the autocorrelation graph presented an obvious black-and-white periodic change. When the participant sat quietly in a chair, although environmental noise existed, the autocorrelation graph was always gray, showed no apparent correlation. By using the same method, we tested the autocorrelation graphs of participant keeping quiet in a bathtub, and received similar findings. The period change was mainly from participants breathing and heart-beat.

Above preliminarily experiments proofed that we could identify the vibration of some periodic human behavior from environmental noise by using autocorrelation. We believed that, compared to the traditional TDNN, using autocorrelation as the input of neural networks can retain more features of human behavior (Fig. 4).

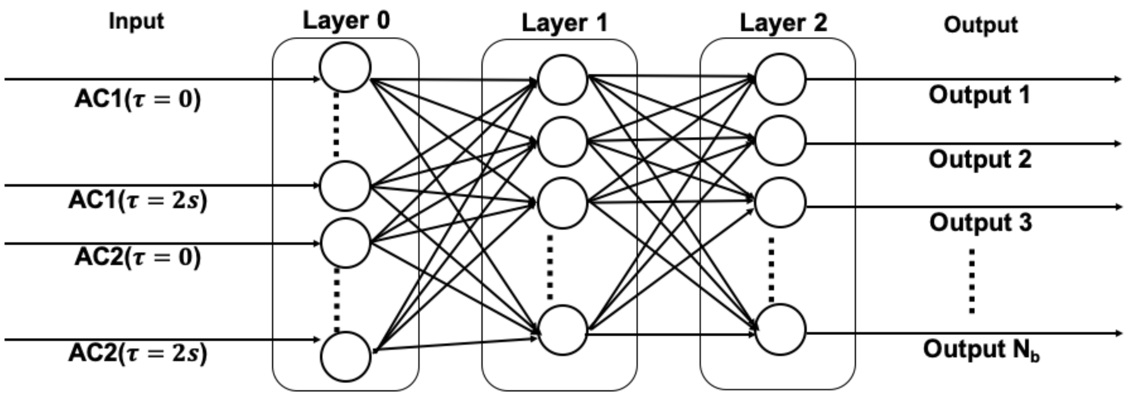


Figure 3.8: *The structure of proposed method for multi-sensor*

The proposed ANN is composed to into three layers: input layer, hidden layer, and output layer (Fig. 3.8). For each t, the autocorrelation coefficient of the noise-reduced data of each sensor from $\tau = 0$ to 2 seconds will be used as inputs (Layer 0). For the sake of low power consumption and real-time processing, we used one hidden layer (Layer 1) which contained 100 neurons fully connected with input layer and output layer. The number of neurons in the output layer is determined by the specific scenario. As shown in Layer 2, there were N_b outputs. The output neuron with the highest value would determine the final estimation results. If the output value of all output neurons were lower than a certain threshold, the output will be set to “Unknown, indicating the system could not determine the current state.

We used back-propagation to train the network. Data was collected from the participants home. We installed four sensors, two in the bathroom and two in the living room. During the period of data collecting, the participant maintained normal habits for his daily behaviors, and recorded all the activities by hand. By this way, we collected ten sets of 250Hz data for each scene, nine were used for training and one was used for evaluation.

When the vibration sensor installed at the entrance and the vibration sensor installed in the room react continuously, a person enters the room, and the subsequent processing starts.

After the monitoring system confirms a human entry, the time-series measurement data is modified by the root mean square(RMS). The time window is set to 2 to 3 seconds. The points that exceed the preset threshold are extracted as the vibration generation points. After performing noise removal and data molding by moving average and RMS on the data of the vibration generation location obtained in this way, the number of steps and the falls is measured by using the autocorrelation function [88] as shown in Equation(3.14).

$$R(\tau) = \frac{1}{R(0)} \sum_{i=1}^{N} v_i \cdot v_{i+\tau} \tag{3.14}$$

where N represents the total number of data, and v_i represents the i-th data. t represents the lag of the autocorrelation coefficient, and t is discretized as the same step length as the data.

We use autocorrelation function (ACF) instead of Fast Fourier transform (FFT) because ACF could be implemented at even lower computational cost. Moreover, ACF can easily extract the periodic characteristics of the time-series data, and it has been widely used in similar data analysis based on vibration signals [89] [90]. If periodicity is found in the ACF result, it can be assumed that this is due to a walking in this monitoring. For example. interval peak could be found from the ACF out during a person walking normally(Fig.3.9(left)). The number of steps is calculated based on the walking frequency calculated from this peak interval. If the ACF result does not show periodicity(Fig.3.9(right)), it is recorded and reported as a fall if the following conditions is met:

(1) Very large vibration is detected.

(2) No vibration is detected by any sensor for a certain period after (1).

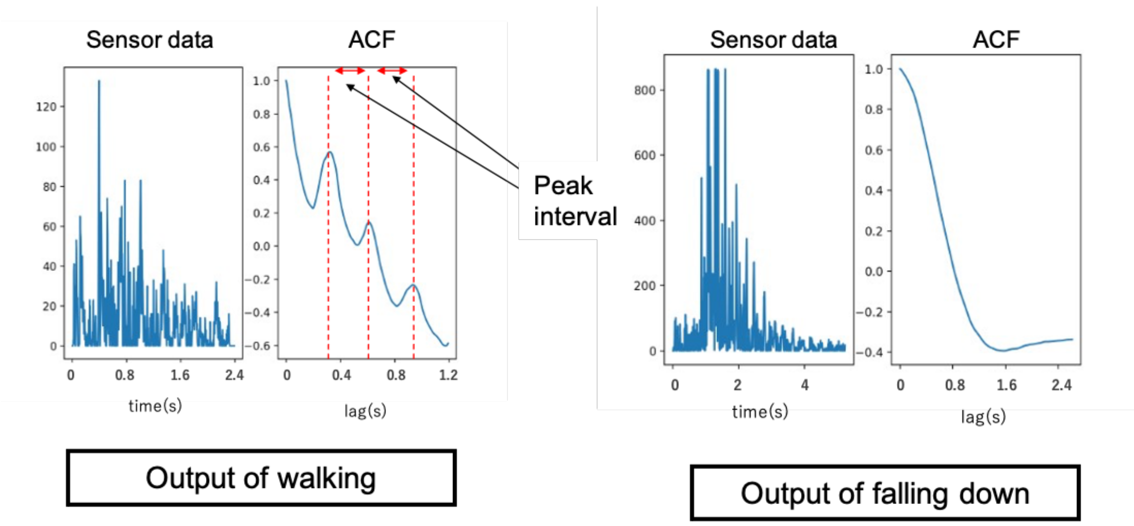
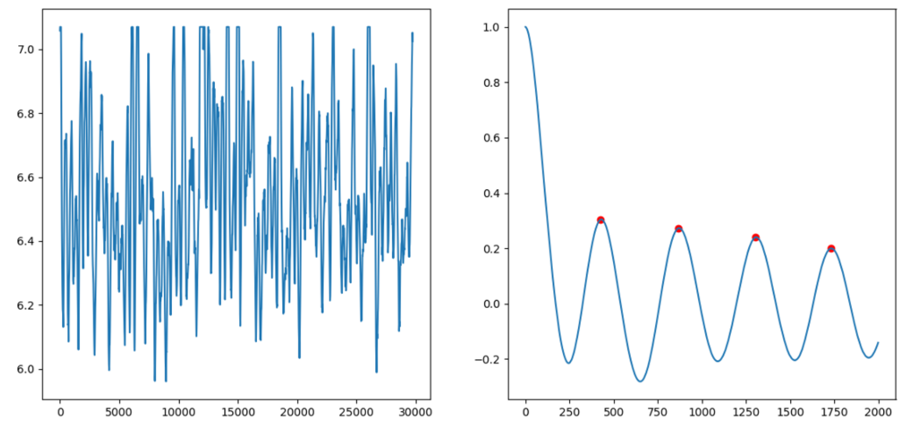


Figure 3.9: *vibration data and ACF output of walking(left) and falling down(right)*

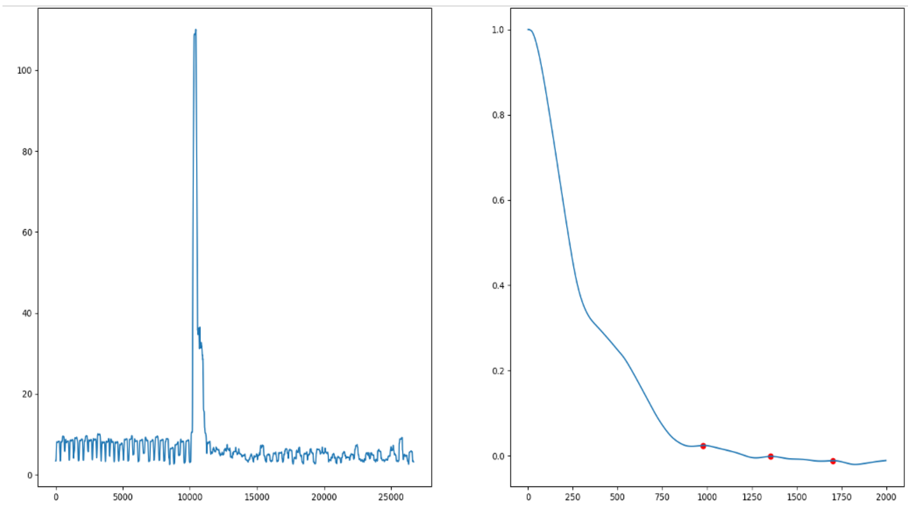
According to Hagiwara [91], the Physical Activity Scale for the Elderly(PASE) score was significantly correlated with walking steps. Accurately identifying the elderly walking and calculating the walking step will help us grasp the activity of the elderly.

3.3.2.1 Heartbeat detection using pneumatic sensor

The heartbeat is calculated by using ACF after removing noise using RMS from the sensor data. When the obtained data becomes abnormal, the caregiver is notified that something abnormal has occurred during sleep.



Result without noise



Result with noise

Figure 3.10: *Example of the result of performing a series of processing on data(Left: result after MA and RMS; Right: output of ACF*

This method works well in the absence of strong external activities. As shown in Fig.3.10(upper), the black dot reflects the peak of human heartbeat. But the noise caused by body movements such as turning over is extremely large with respect to the heartbeat to be measured this time, and it is difficult to measure the heartbeat when the body is moving significantly(Fig.3.10(lower)).

Therefore, we added body movement removal between preprocessing and ACF(Fig.3.11(left)).

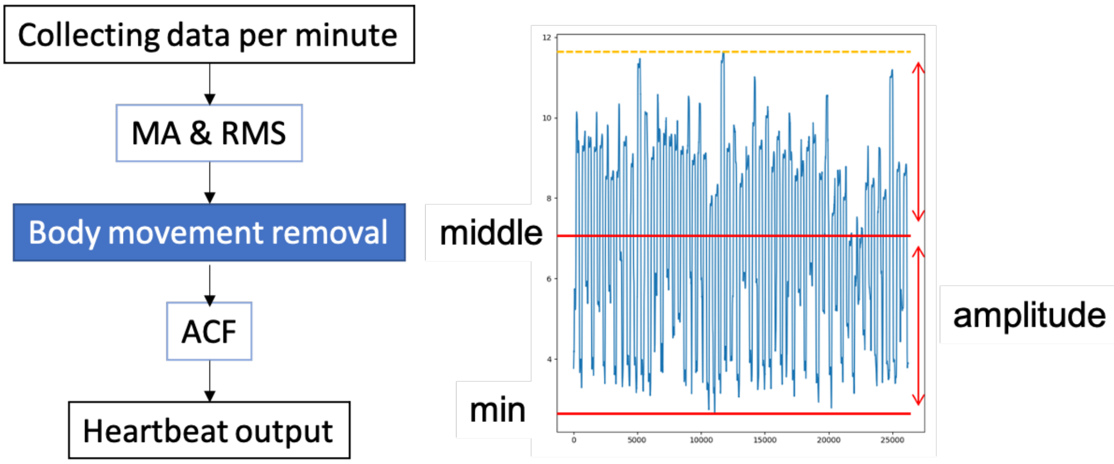


Figure 3.11: *The process of calculating heartbeat from pneumatic data*

This time, assuming that the amplitude does not fluctuate within the data divided every minute, the amplitude(v_a) is calculated from the medium(v_m) and minimum values of the data, and then the body movement is removed by Equation(3.15).

$$v_i^{'} = min(v_i, (v_a + v_m)) \tag{3.15}$$

where v_i means the vibration data of time step i and $v_i^{'}$ is the output after removing body movement noise.

In addition, if the situation in which a large amount of data judged to be physical movement is included for several minutes continues for several minutes, it is considered that the physical condition of the elderly may have changed suddenly, and the caregiver is notified. Was decided to be performed.

3.3.2.2 Activity level detection using vibration sensor

The vibration sensor numerically represents the activity of the elderly in the room. Therefore, it is considered that the integration of vibration data can be expressed numerically by the amount of activity of the elderly for a certain period of time. Then, it is considered that the daily decline of physical strength can be estimated from the hourly unit or the sum of the daily activity amount. If you get stuck in the daytime, give instructions to do gymnastics. The following preliminary experiments were conducted to verify the above viewpoint.

A vibration sensor was placed in the bedroom and data was collected for 30 minutes. During this time, the experimenter was free to move around the room, exercising for about 3 minutes in 7 and 23 minutes. Experimental data is shown in Fig. 3.12.

The experimental results of integration are shown in Fig. 3.13 and Fig. 3.14.

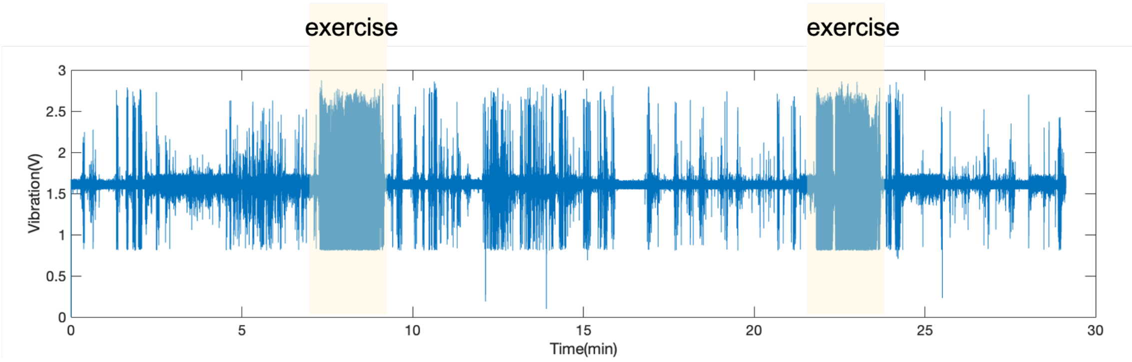


Figure 3.12: *Vibration measurement of daily life for 30 minutes*

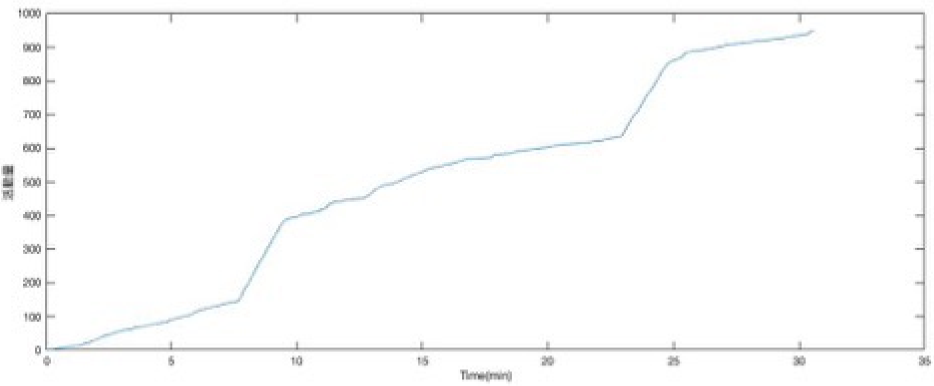


Figure 3.13: *30 minutes of activity (cumulative)*

When the experimenter exercises, the amount of activity accumulates faster.

Fig. 3.14 shows the amount of exercise every 5 minutes as a vertical bar graph. The values of 5-10 minutes and 20-25 minutes are relatively large, which can be seen to be consistent with the time of the experimenter's two exercises.

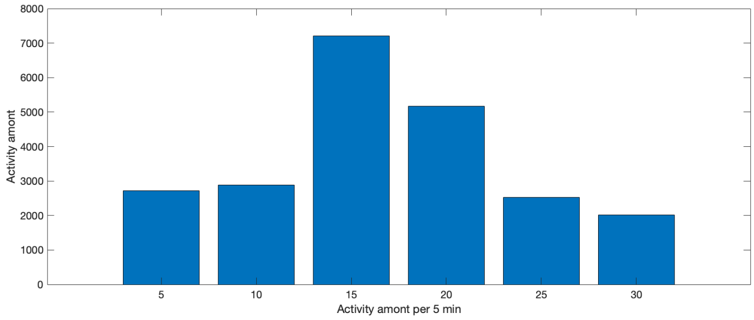


Figure 3.14: *30 minutes of activity (every 5 minutes)*

Therefore, it can be concluded that the momentum can be reflected by integration.

However, between 0-5 minutes and 25-30 minutes, the experimenter did not exercise. Theoretically, the momentum during these two periods should have been zero. Since the above algorithm uses the result of simply integrating the vibration data as it is, environmental noise inevitably affected the result. As shown in Fig. 3.12, there was no movement of the experimenter between 0-5 minutes and 25-30 minutes, but there was vibration due to environmental noise.

In previous studies, we have implemented a system that uses multiple sensors at the same time, and using the data from multiple sensors, it has become possible to collaborate to determine what the user is in which room and what they are doing. Therefore, consider modifying the method of calculating momentum using two sensors.

In real life, various living sounds may affect the sensor. The noise received by the sensor is considered to be basically the same. Based on the above points, the following algorithm is proposed.

For example, if there are two sensors (A and B) in an adjacent room and one of the sensors A detects human activity:

$$M = M_A - M_B \tag{3.16}$$

M represents the momentum, and $M_A$and M_B represent the momentum calculated from the vibration data of the sensor A and the sensor B, respectively. However,

$$M_i = \int_i \hat{W}_i, i = AorB \tag{3.17}$$

W_i represents the LPF-processed vibration data of the sensor i, respectively. In other words, the momentum calculated from a person's room is subtracted from the calculated momentum from an unmanned room. In this way, the influence of environmental noise can be reduced to some extent.

To test the above idea, the following experiment was carried out.

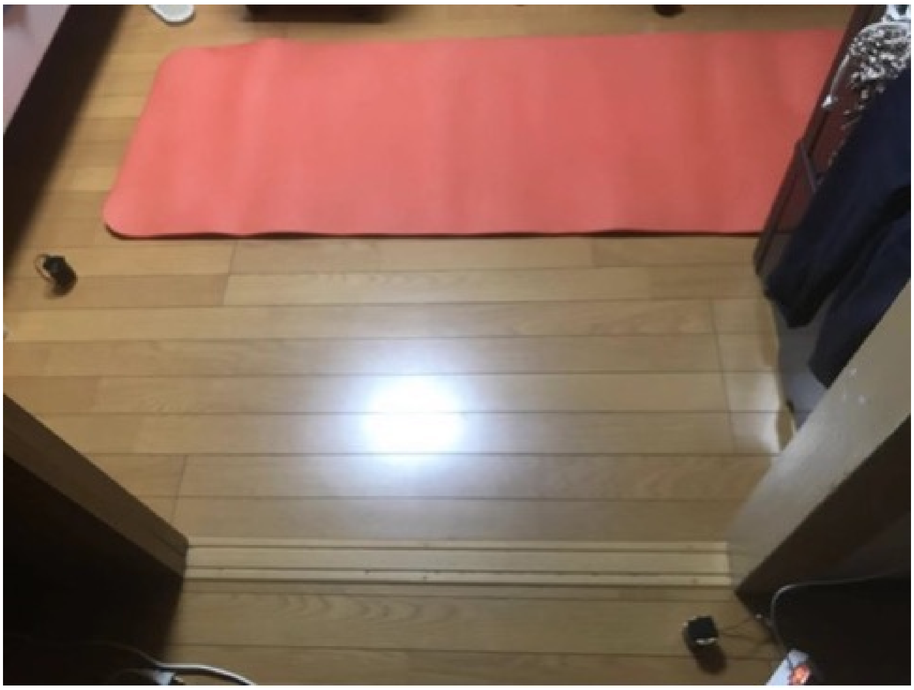


Figure 3.15: *Experimental environment*

As shown in Fig. 3.15, the two sensors were located inside and outside the room. There was one yoga mat in the room. The experimenter exercised on a yoga mat for 10-20 minutes. 20 minutes of data from the two sensors were recorded separately.

During the experiment, the sliding door between the two rooms was closed.

Fig. 3.16 and Fig. 3.17 show the raw data and preprocessed data of the two sensors, respectively. It can be seen that the amplitude of vibration is larger in 10 to 20 minutes. This is consistent with the fact that the experimenter exercised during this period. At the same time, it can be seen that the ambient noise is small, but not zero, which affects the calculation of momentum.

Fig. 3.12 shows the momentum for 30 minutes calculated by simple integration. It can be seen that the maximum momentum for 5 minutes is 7,000, and the momentum when there is no activity is about 2000 to 3000. In other words, even without exercising, the value of momentum is about half that of high-density exercise, which is clearly contrary to common sense.

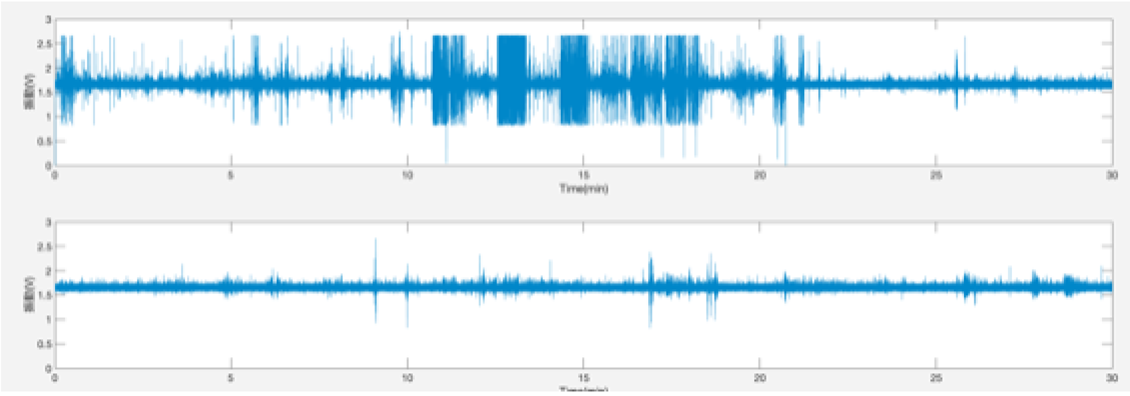


Figure 3.16: *Experimental results (raw data) (top: in the room, bottom: outdoors)*

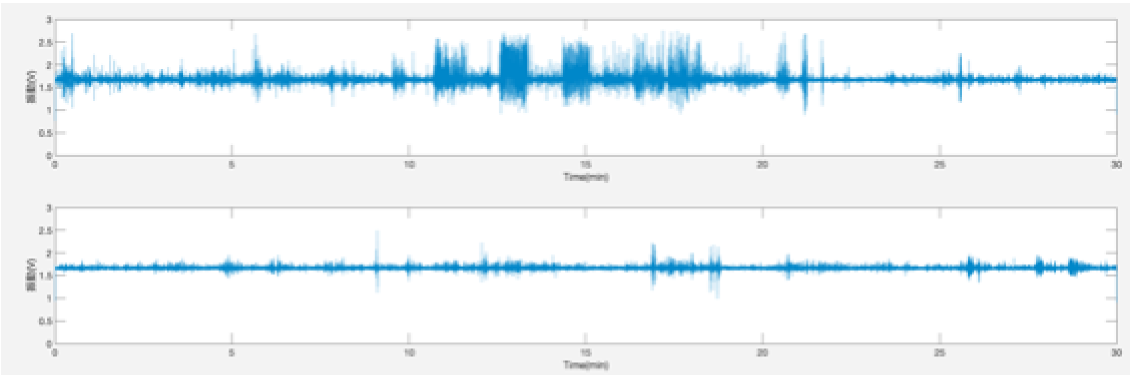


Figure 3.17: *Experimental results (with LPF) (top: inside the room, bottom: outside)*

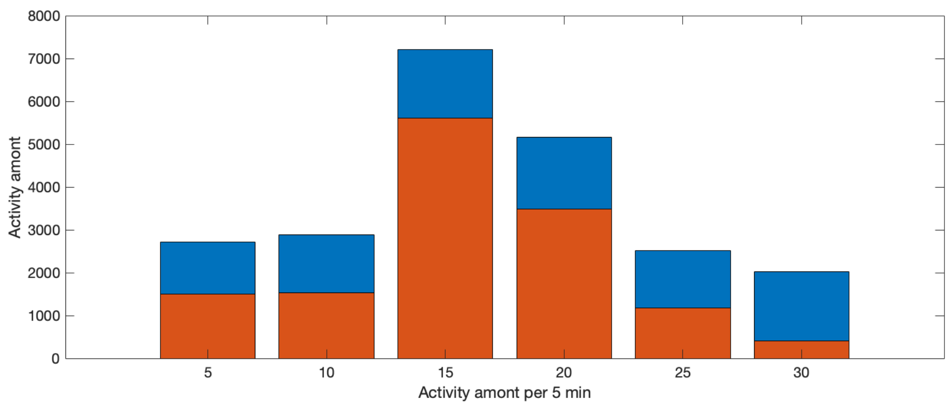


Figure 3.18: *Momentum for 30 minutes (blue: conventional method, orange: proposed method this time)*

Fig. 3.18 shows the results after using the new method. It can be seen that the momentum for 30 minutes was reduced and the part affected by the environmental noise was removed. According to the new calculation method, it can reach 5000 or more when the amount of exercise is high, and when there is not much activity, the amount of exercise is only about 1000, which is more consistent with the fact.

3.3.2.3 Synthesized behavior estimation algorithm based on the multiple sensors

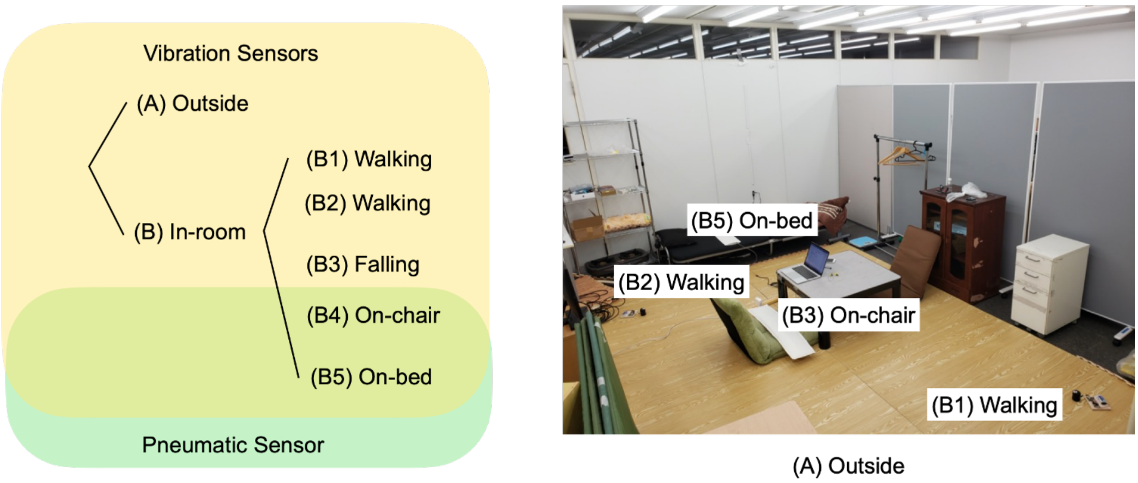


Figure 3.19: *Left: Vibration sensors are used as global sensors to identify most of the activities; pneumatic sensor are used as local sensors to identify the position and actions of people in a quiet state. Right: A room with multiple sensors. The detectable activity is marked around the corresponding sensors.*

As an extension of the above two methods, we proposed the following method for behavior estimation using the multiple sensors as Fig.3.19.

Fig.3.20 showed an example with two vibration sensors($k=1,2$) and one pneumatic sensor($k=3$). The raw data from each sensor would be firstly send to preprocessing layer, which processed sensor data separately by MA and RMS. The second layer is the ACF layer. $x_{k,j} = ACF(k,j)$ where j is the separated time delay from 1 to constant n. The final estimation result(s) is determined by the following formula.

$$y_i = \sum_{j=1}^{n} \sum_{k=1}^{m} w_{k,j,i} x_{k,j} \tag{3.18}$$

$$s \leftarrow arg \max_i f(y_i) \tag{3.19}$$

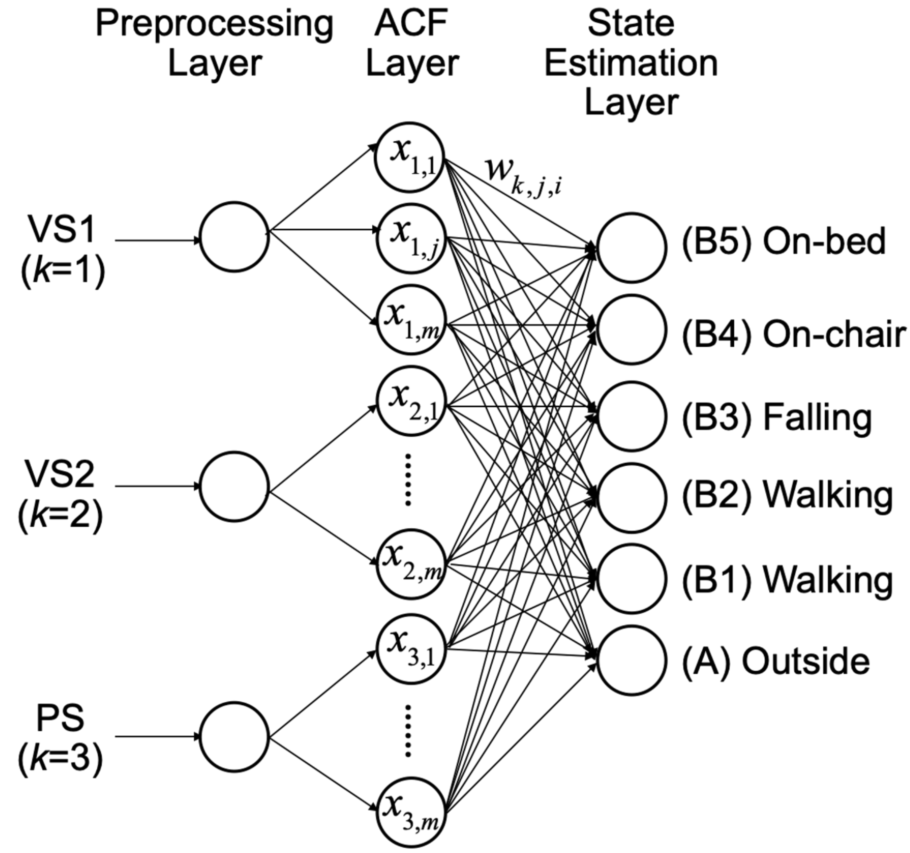
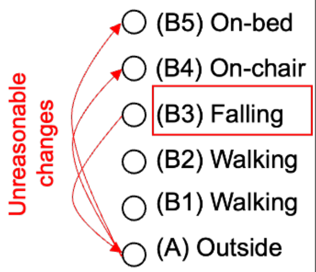


Figure 3.20: *Synthesized behavior estimation algorithm based on the multiple sensors*

$$f(y) = \begin{cases} tanh(y) & when\ sensors\ are\ activated \\ 1 - tanh(y) & otherwise(Outside) \end{cases} \tag{3.20}$$

Since this is a time-series system, we have added an attenuation function $f(y)$ to reduce the influence of inactive sensors on the system results. $w_{k,j,i}$ is a weight parameter between $ACF(k, j)$ and i-th human state. All the $w_{k,j,i}$ are initialized based on experience.



		result of t+1					
		(A) Outside	(B1) Walking	(B2) Walking	(B3) Falling	(B4) On-chair	(B5) On-bed
result of t	(A) Outside	-			Error	Error	Error
	(B1) Walking		-		Anomaly		
	(B2) Walking			-	Anomaly		
	(B3) Falling	Error			-	Error	Error
	(B4) On-chair	Error			Anomaly	-	Error
	(B5) On-bed	Error			Anomaly	Error	-

Figure 3.21: *Using the transition matrix, we marked anomaly and unreasonable changes.*

Sometimes, result may transmit unreasonable as Fig.3.21(Left). If an unreasonable change in action occurs, it might be due to a malfunction of the sensor network, or it might be an unexpected situation in the elderly. Referring to the method of state transition diagram, we drew a table and identified all unreasonable changes ("Error" in Fig.3.21). When "Error" detected, the system would send a reminder, and the caregiver could check the situation.

3.3.3 Experiments

We would mainly observe the accuracy, precision and sensitivity defined by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.21}$$

$$Precision = \frac{TP}{TP + FP} \tag{3.22}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3.23}$$

3.3.3.1 Behavior Estimation Using Vibration Sensors in Bathroom

Three participants joined the experiment: One male in his 20s, one female in her 20s, and one male in his 60s and experiments are carried out in the homes of each participant. In the bathroom of the two young participants homes, the bathtubs were separate from the bathroom floor, while the bathtub in the elderlys home was integrated with the floor. All the bathtubs were made of plastic. two young participants homes had wooden floor while the elderlys home had floor sheet on the concrete ground.

Figure 3.22: *The position of the vibration sensors setting in and out of the bathroom*

For the bathroom scene, we placed two sensors, one was close to bathroom door and one was on the edge of the bathtub (Fig. 3.22). Participant were required to take bath regularly. To simulate unconsciousness of the participant, we asked participant remain still in the bathtub and lean against the side of the bathtub. Even though, vibration was still generated due to participants heartbeats and tiny body moves. We believed the scenario of the elderly losing consciousness in the bathtub could be simulated to the greatest extent in this way.

We repeated experiments ten times for each participant. One set of raw data and pre-processed data was showed in 3.23 and Fig. 3.24 respectively. The participant took a shower before going to bath in the bathtub. He kept still for a while during the bathing, and then acted back to normal. It was proved that vibration still could be detected even the person stay still in the bathtub. Although "taking shower" and "keeping still" are somewhat similar in waveform, our preliminarily experiment showed the later one performed more regularly causing by the periodic heat beat.

For the bathroom scene, our proposed ANN had three outputs, namely "Staying outside", "Bathing" (included both taking shower outside bathtub and taking bath in bathtub), and "Keeping still". If none of outputs reached the threshold, we classified the result as "Unknown". In such way, as shown in Fig.3.25 (with parentheses), the system gave four estimation results.

Fig.3.26 and Table.3.3 showed the results of estimation. In the table, the data was shown in seconds, and gray cell showed the correctly estimation results. The average accuracy of

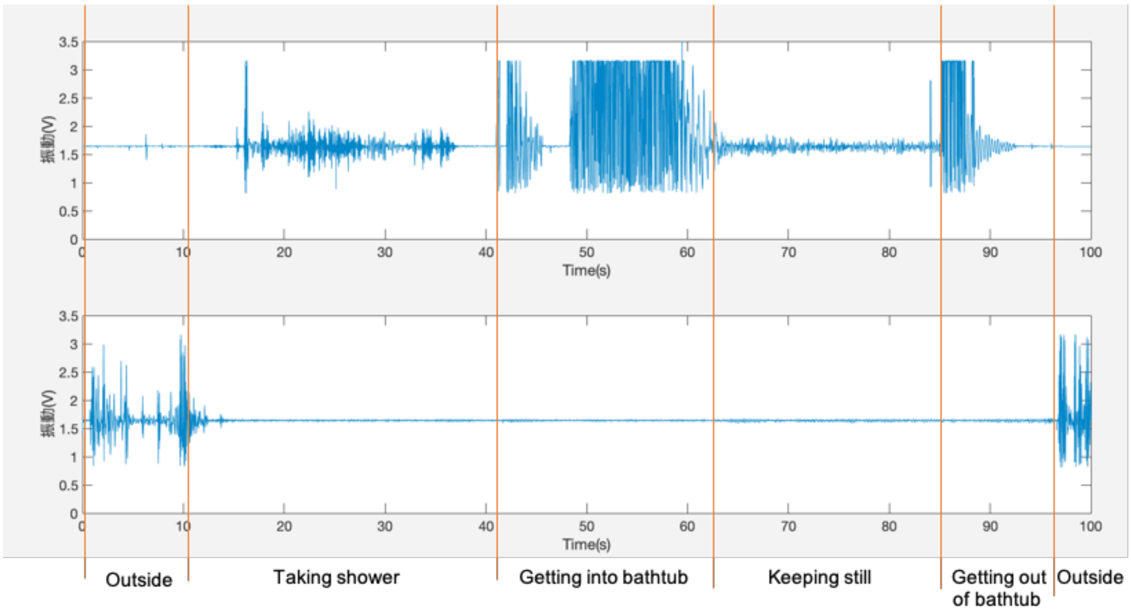


Figure 3.23: *The raw vibration data from the sensors(Upper: bathtub; Lower: outside)*

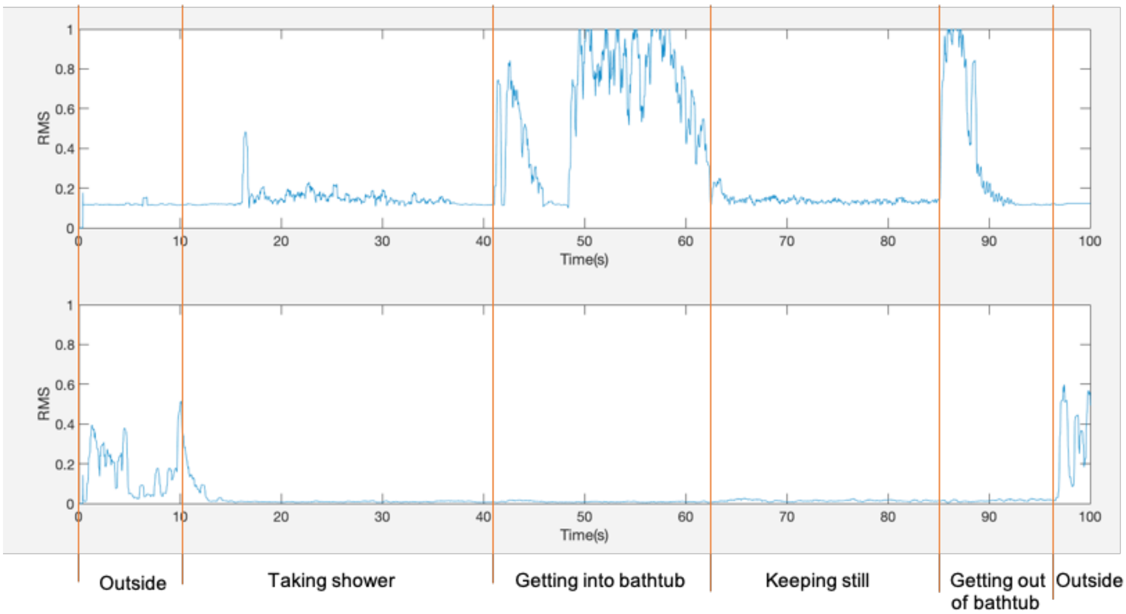


Figure 3.24: *The pre-processed data from the sensors(Upper: bathtub; Lower: outside)*

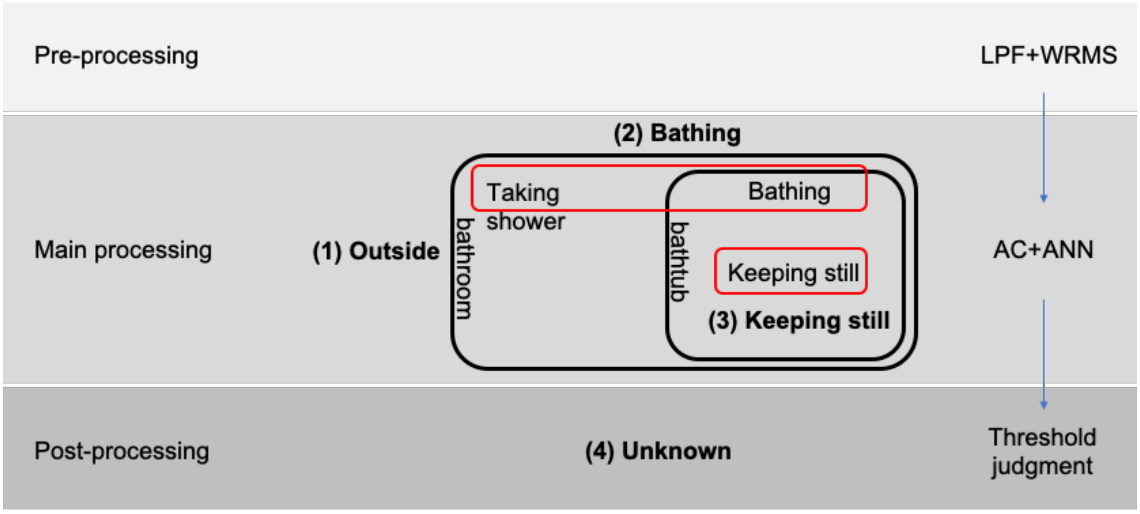


Figure 3.25: *Four estimation results of bathroom scene and their relationship with human behavior*

TDNN was 71.9%. In comparison with this, accuracy of the proposed method achieved 84.7%. When the participant was out of the bathtub, the sensor could hardly detect the vibration of participants movements as the floor was separated from the bathtub. This reduced the accuracy of identifying person taking shower or not. Some of the vibration was misidentified as “Keeping still”.

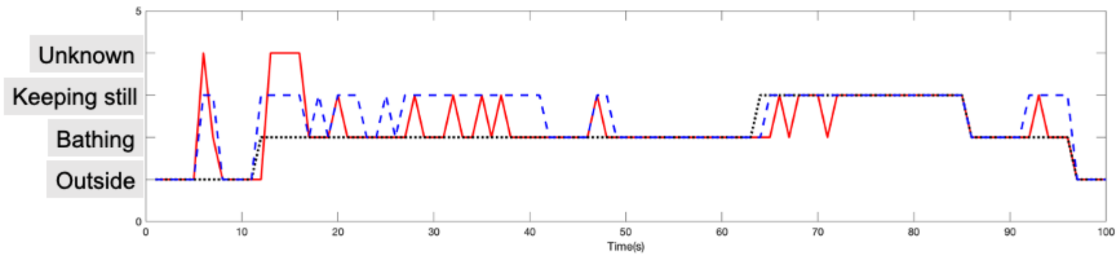


Figure 3.26: *Estimation result of bathroom scene(Black dotted line: Ground truth, Red line: The proposed method, Blue dashed line: TDNN)*

Considering the usage of the system was for monitoring elderlys danger, we mainly focused on the estimation results of “Keeping still”. The Keeping still precision rate of the proposed method was 82.9% while traditional TDNN got 97.3%. This did not mean that proposed method was worse, because we should also focus on the sensitivity rate. The Keeping still sensitivity rate of TDNN was just 48.3%, which meant TDNN would give numbers of alarm that did not represent real abnormalities. In contrast, the proposed method’s sensitivity rate was 69.6%, much better than TDNN.

Table 3.3: *Confusion matrix of bathroom experimental results(unit: second)*

		Ground truth		
		Staying outside	Bathing	Keeping still
Estimation (TDNN)	Staying outside	401	21	0
	Bathing	0	1020	21
	Keeping still	53	752	753
	Unknown	0	0	0
Estimation (Proposed method)	Staying outside	391	17	0
	Bathing	12	1658	103
	Keeping still	1	222	511
	Unknown	42	63	2

3.3.3.2 Behavior Estimation Using Vibration Sensors in Living room

In our earlier studies [92], we had completed the falling detection using vibration sensors and achieved satisfied results. We understood elderly stay in rooms for most of time, and lack of physical exercise. For the living room scene, we needed to approximately locate the elderly first, and detect he/she had enough activity.

We placed two sensors in two adjacent rooms, a bedroom and a living room (Fig.3.27). The participant walked from the bedroom to the living room, took a rest on the chair first, then took some physical exercises (radio calisthenics), and returned to the bedroom at the end.

For the living room scene, our proposed ANN had four outputs, namely “Stay in bedroom”, “Stay in living room”, “Exercising”, and “Sitting on chair”. If none of outputs reached the threshold, we classified the result as “Unknown”. In such way, the system gave five estimation results.

Similarly, we repeated experiments ten times. Fig.3.28 and Fig.3.29 showed data from one set of experiment. It can be noticed that neither sensor could detect any perceptible vibration when participant sitting on the chair.

Fig.3.30 and Table.3.4 showed the results of estimation. In the table, the data was shown in seconds, and gray cell showed the correctly estimation results.. The average accuracy of traditional TDNN was 66.0%. In comparison, accuracy of the proposed method achieved 81.0%. Both methods could recognize the position of person. When person sat on the chair quietly, although there was almost no vibration detected, both methods could recognize that after training. For other reasons might lead to no vibration, we would analyze in our future study.

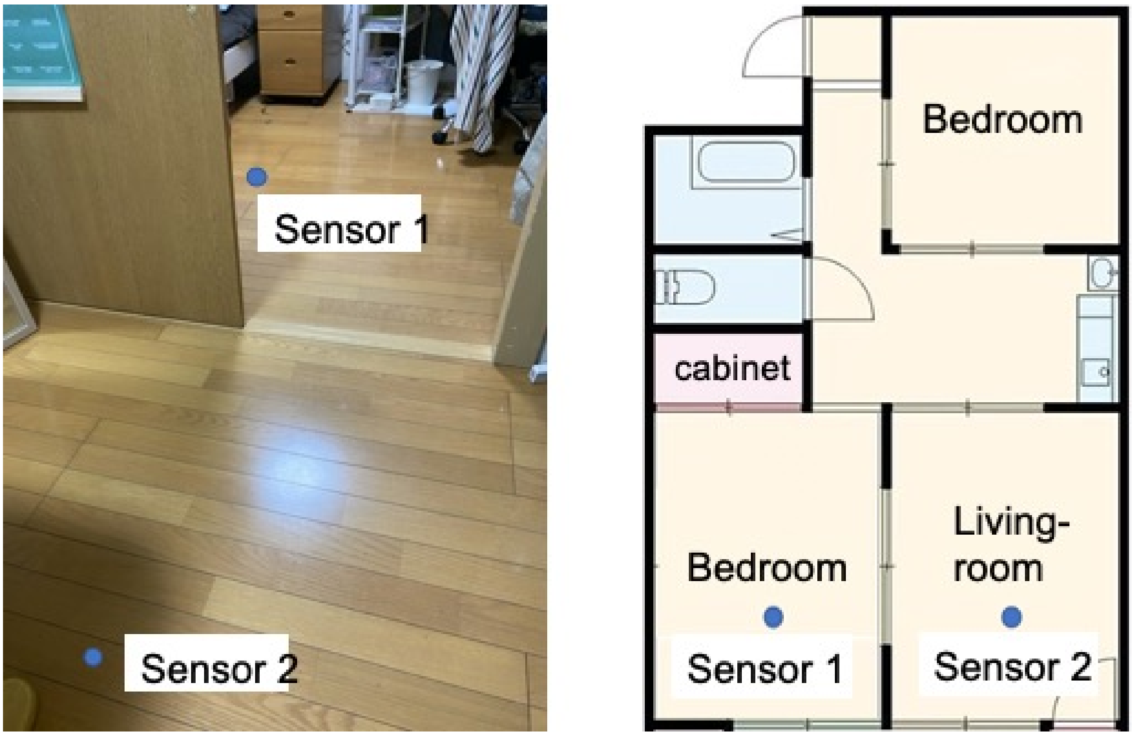


Figure 3.27: *The setting position of the vibration sensors(left) and the layout of the rooms(right)*

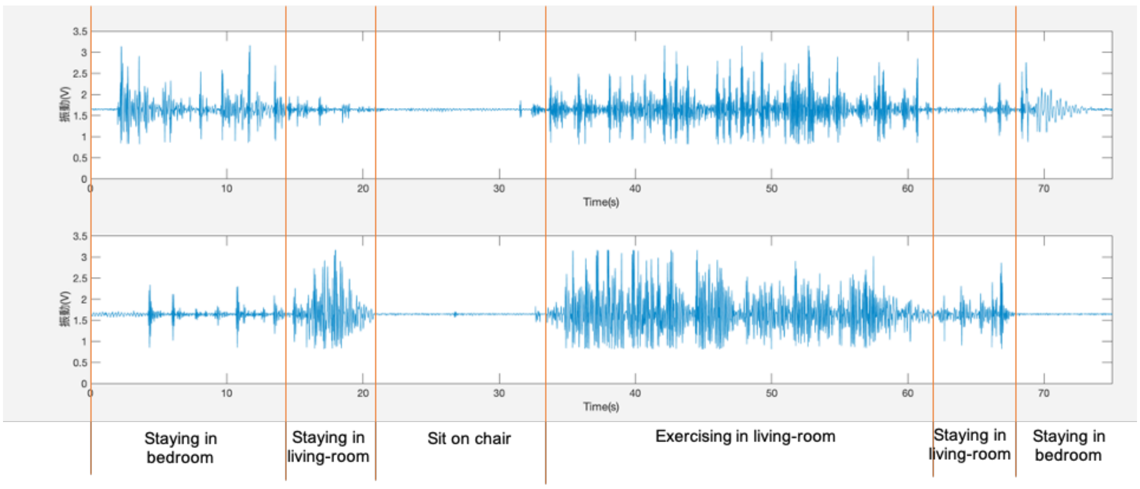


Figure 3.28: *The raw vibration data from the sensors(Upper: bedroom; Lower: living room)*

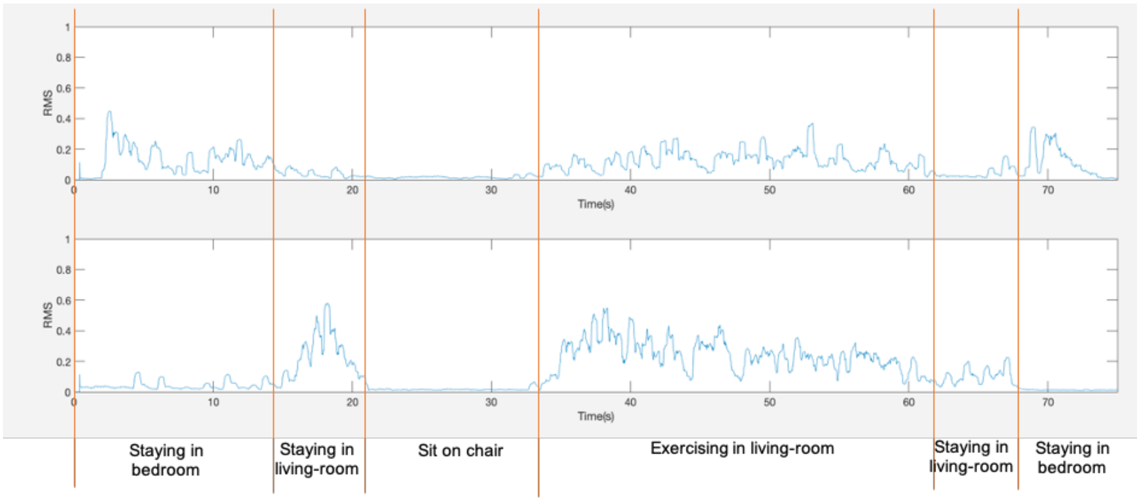


Figure 3.29: *The pre-processed data from the sensors(Upper: bedroom; Lower: living room)*

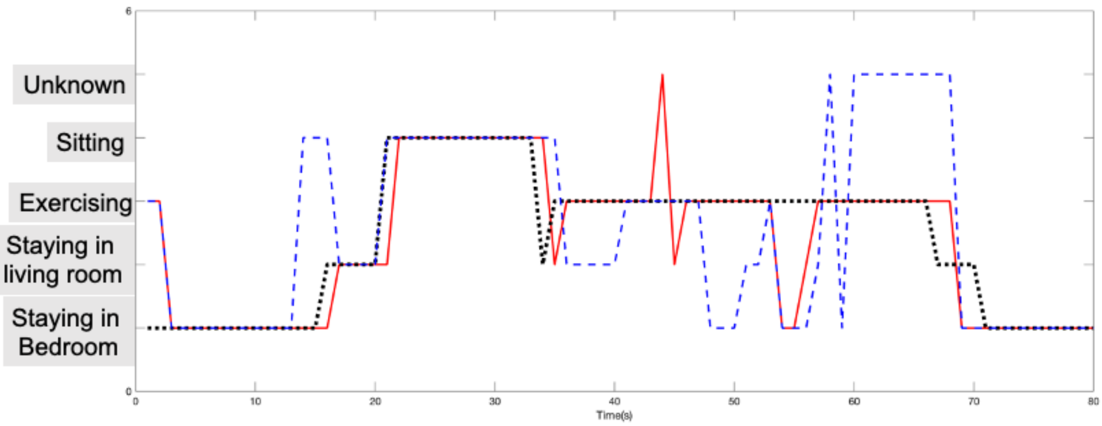


Figure 3.30: *Estimation result of living room scene (Black dotted line: Ground truth, Red line: The proposed method, Blue dashed line: TDNN)*

Table 3.4: *Confusion matrix of living room experimental results(unit: second)*

		Ground truth			
		Bedroom	Living room	Exercising	Sitting
Estimation (TDNN)	Bedroom	586	53	35	0
	Living room	0	141	156	4
	Exercising	78	0	285	16
	Sitting	31	33	23	401
	Unknown	7	63	233	0
Estimation (Proposed method)	Bedroom	611	45	5	0
	Living room	1	173	48	21
	Exercising	52	63	462	30
	Sitting	2	44	1	491
	Unknown	0	33	62	0

When we focused on the problem of activity recognition, the "Exercising" precision rate of the proposed method was 80.1%, much better than TDNN which could only reach 38.9%. When person exercised continuously in the room, the waveform of the vibration sensor actually presented a strong uncertainty. This seriously interfered the performance of traditional TDNN. In contrast, the proposed method took into account the inter-relationship in continuous vibration data and remained the characteristic of person's periodicity activities by using autocorrelation, which led us a much better result. Also, we noticed that the results of propose method were more stable, and in line with human behavior patterns.

3.3.3.3 Experiment around Bed

Compared to young people, older people may spend more time in bed a day, and the length of this time largely reflects the mental and physical health of the elderly. So in this experiment we focus on this.

First we tried to place the sensor on the ground next to the bed, but the attenuation caused by the vibration transmitted from the bed to the ground caused us to be unable to get valid data. Considering that the bed used by many people does not have a platform for the sensor, we use tape to fix the sensor to the bed leg to ensure that the sensor is parallel to the ground.

The experimenter was required to active freely near the bed. While sitting on the bed, the experimenter could read a book and drink water. Then the experimenter lay on the bed and simulated the turn over during light sleep and the quietness during deep sleep. Fig.3.31 and Fig.3.32 show the raw data and the data after pre-processing of one experiment.

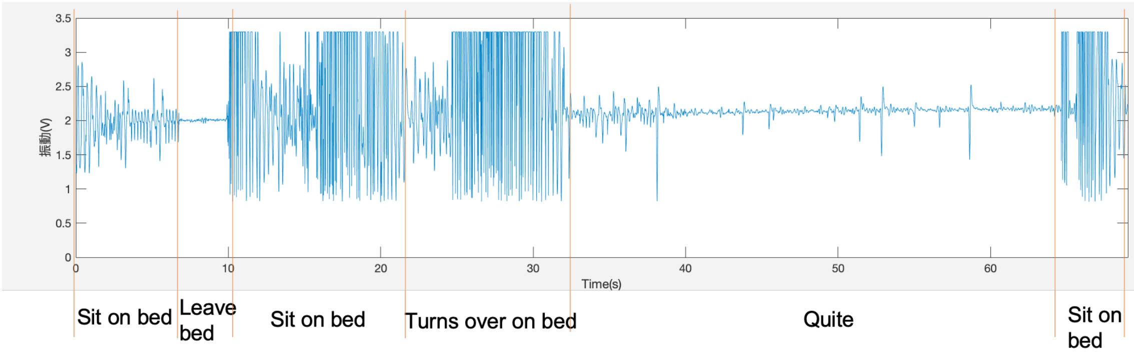


Figure 3.31: *The raw vibration data from the sensor on bed*

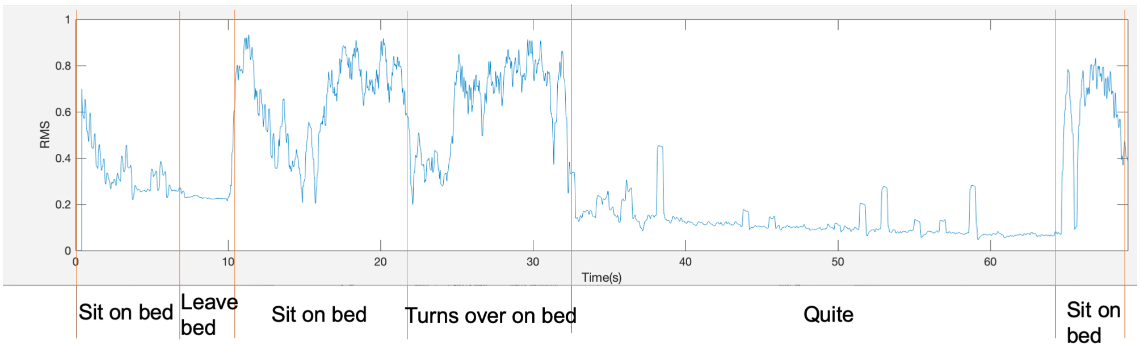


Figure 3.32: *The pro-processed data from the sensor on bed*

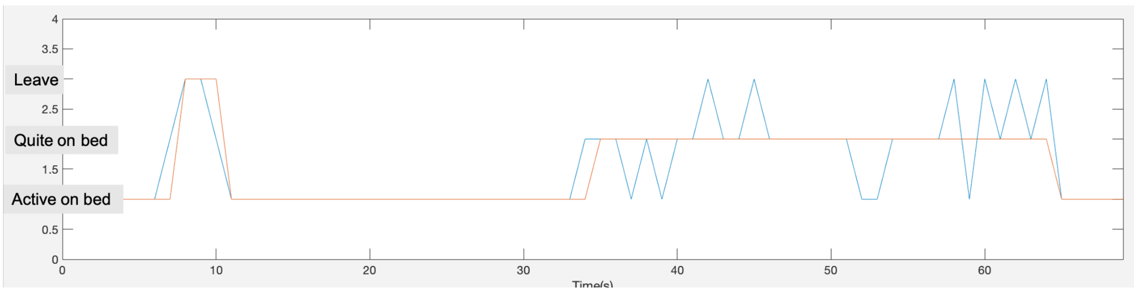


Figure 3.33: *The estimation around bed(orange: teacher data; blue: estimated result)*

Table 3.5: *Comparison Table(bed)*

		Ground truth		
		Active	Stay quite	Leave
Estimation	Active	4851	376	0
	Stay quite	475	5301	97
	Leave	0	0	1456

Fig.3.33 and Table.3.5 shows the results of estimation. In the experiments we found that it is difficult to distinguish between ordinary activities of the experimenter on the bed and turn over with a single sensor. Therefore, we currently divide behaviors into three categories: leaving the bed, moving on the bed, and resting on the bed (this mainly refers to the quiet state of the user in deep sleep). Based on this classification, our accuracy reached 92.4%.

3.3.3.4 Behavior Estimation Using Vibration and Pneumatic Sensors in Bedroom

Figure 3.34: *Settlement of vibration sensor and pneumatic sensor*

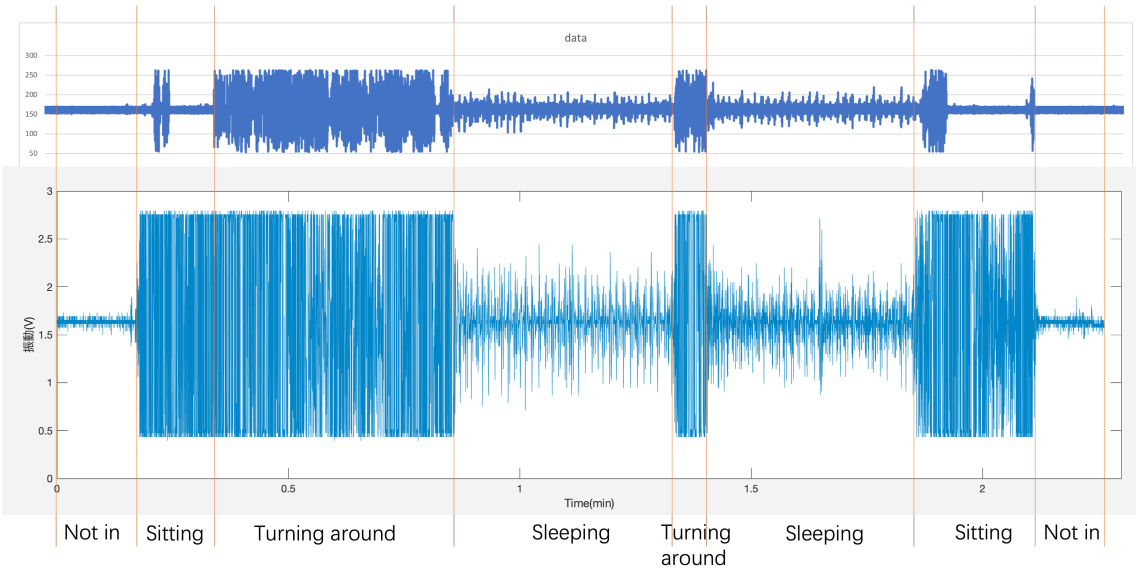


Figure 3.35: *A set of sensor row data of activities around bed*

Through individual analysis, it was found that it was difficult for any sensor to fully estimate the user's activity in bed.

In consideration of this situation, in order to perform more accurate motion analysis, the estimation result of the vibration sensor is improved by supplementing the result of the mattress sensor. When presuming that the vibration sensor is "present", the result of the mattress sensor is used to distinguish between "sitting" and "going back to sleep". How is the result at this time shown:

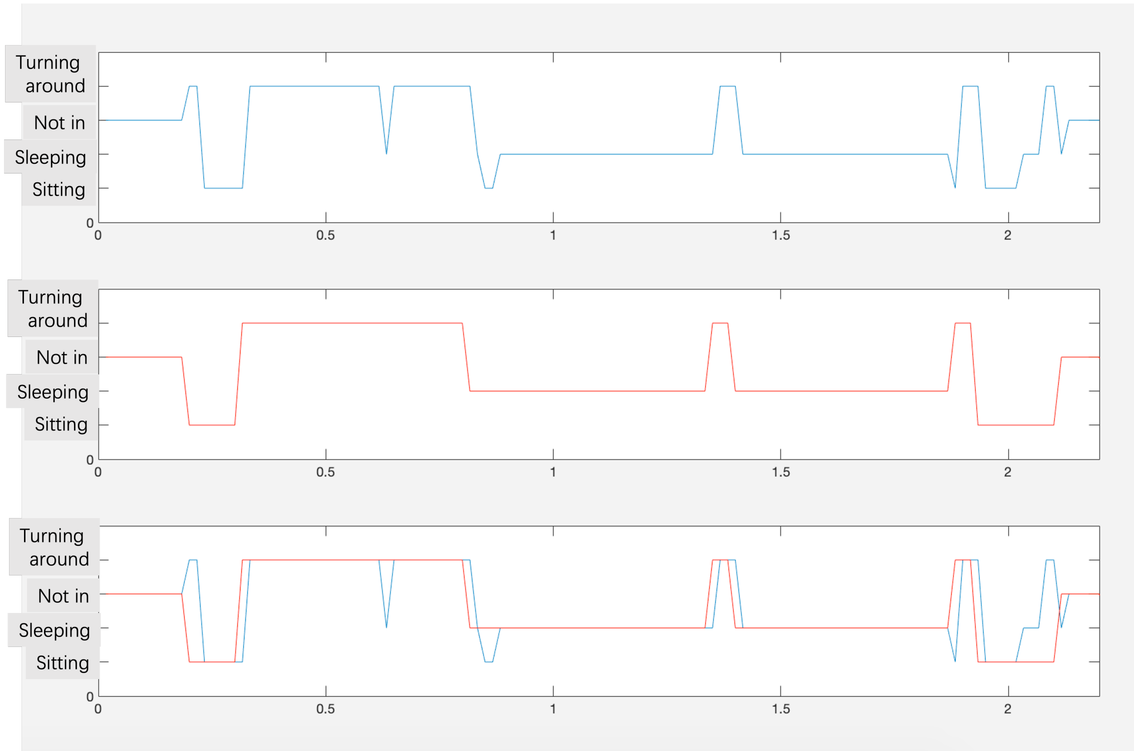


Figure 3.36: *Experimental result of activities around bed*

Table 3.6: *Experimental result of activities around bed*

		Ground truth			
		Sit	Sleeping	Not in	Turning around
Estimation	Sitting	10	2	0	2
	Sleeping	3	57	1	2
	Not in	0	0	16	0
	Turning around	5	2	0	31

3.4 Behavior Estimation Using Delayed Response Sensors

3.4.1 Spiking Neural Network

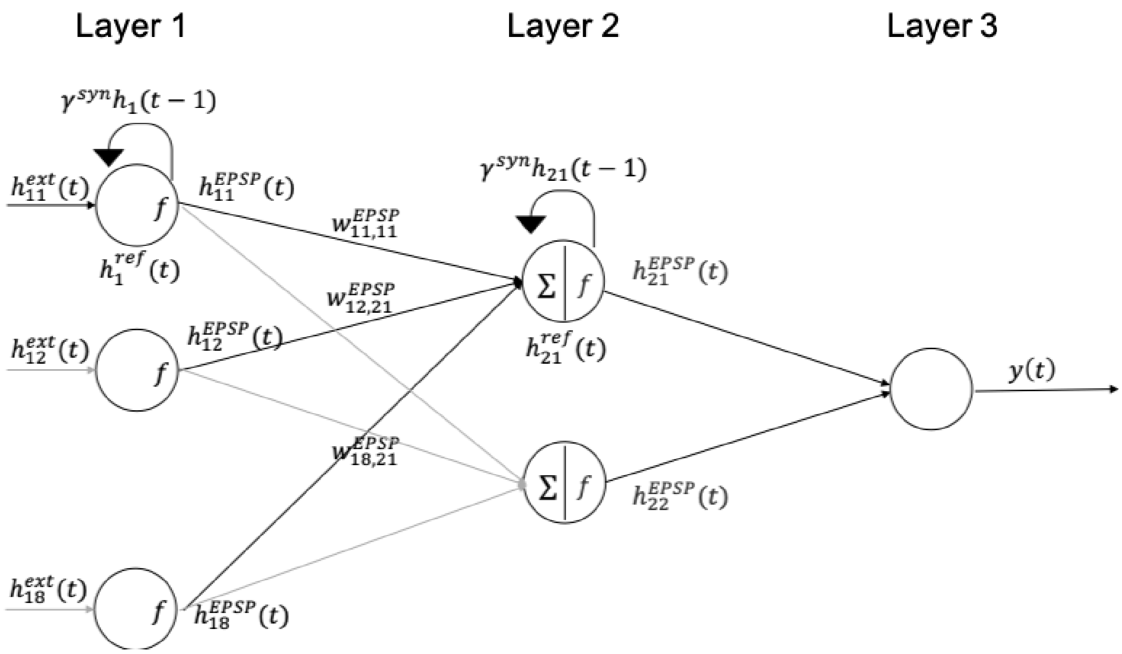


Figure 3.37: *Structure of Fuzzy Spiking Neural Network for behavior estimation*

In the SNN, A pulse will be outputted when the internal potential of the i_{th} neuron becomes higher than a predefined threshold (q_i). The internal state ($h_i(t)$) of i_{th} neuron at time t and the output pulse ($p_i(t)$) are defined as follows:

$$h_i(t) = tanh(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)) \tag{3.24}$$

$$p_i(t) = \begin{cases} 1 & if\ h_i(t) \geqslant q_i \\ 0 & otherwise \end{cases} \tag{3.25}$$

To avoid too frequent pulse output, we use hyperbolic tangent to precess $h_i(t)$. $h_i^{ext}(t)$ is the input to the i_{th} neuron from the external environment which is weighted temperature and humidity sensor data. $h_i^{ref}(t)$ indicates the refractoriness factor of the neuron. $h_i^{syn}(t)$ including the output pulses from the other neurons is calculated as:

$$h_i^{syn}(t) = \gamma^{syn} \cdot h_i(t-1) + \sum_{j=1}^{N} w_{j,i} \cdot h_j^{PSP}(t) \tag{3.26}$$

Here, $w_{j,i}$ is the parameter of a weight coefficient from neuron j_{th} to neuron i_{th}, which is the training target. $h_j^{PSP}(t)$ is the pre-synaptic potential (PSP) approximately transmitted from the j_{th} neuron at time t; N is the total neuron number.

Furthermore, $h_i^{ref}(t)$ is subtracted from the refractoriness value in the following,

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & if\ p_i(t-1) = 1 \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & otherwise \end{cases} \tag{3.27}$$

Here γ^{ref} is a discount rate and $R > 0$. The presynaptic spike output is transmitted to the connected neuron according to PSP with the weight connection. The PSP is calculated as follows:

$$h_i^{PSP}(t) = \begin{cases} 1 & if\ p_i(t) = 1 \\ \gamma^{PSP} \cdot h_i^{PSP}(t-1) & otherwise \end{cases} \tag{3.28}$$

where γ^{PSP} is the discount rate ($0 < \gamma^{PSP} < 1.0$). Therefore, the postsynaptic action potential is excitatory if the weight parameter, $w_(j,i)$is positive. If the condition $h_j^{PSP}(t-1) < h_i^{PSP}(t)$ and $h_j^{PSP}(t-1) > \varepsilon$ (ε is a constant used to control the learning conditions to prevent $w_{j,i}$ from converge to 0.) are satisfied, the weight parameter is trained based on the temporal Hebbian learning rule as follows:

$$w_{j,i} \leftarrow tanh(\gamma^{wgt} \cdot w_{j,i} + \xi^{wgt} \cdot h_j^{PSP}(t-1) \cdot h_i^{PSP}(t)) \tag{3.29}$$

where γ^{wgt} is a discount rate and ξ^{wgt} is a learning rate.

3.4.1.1 State Transition Diagram

In previous studies and experiments, we found that the system can detect whether someone is taking bath in the bathroom, but there is a significant time delay between real time of start/end of the bathing and the estimated time. This time delay is caused by the nature of FSNN. FSNN focuses on the amount of change accumulated over time, not instantaneous changes, so this kind of time delay is unavoidable.

But considering our goal: to grasp the living conditions of the elderly, and to know whether the elderly are in danger for the first time, we want to decrease the time delay as much as possible. In the further study, we will consider using the estimated result to to determine the potential heat shock or drowning. For example, the system may focus on long bathing times. This may mean a potential risk. But time delay may cause the system to be unable to accurately determine.

Therefore, we consider using the state transition diagram to post-process the data in order to improve the the system. A state transition diagram is a digraph whose nodes are states and whose directed arcs are transitions labeled by event names [93], can be expressed as a potential link between several events. Fig.3.38 shows the state transition diagram of some possible behavior of elderly around bathroom.

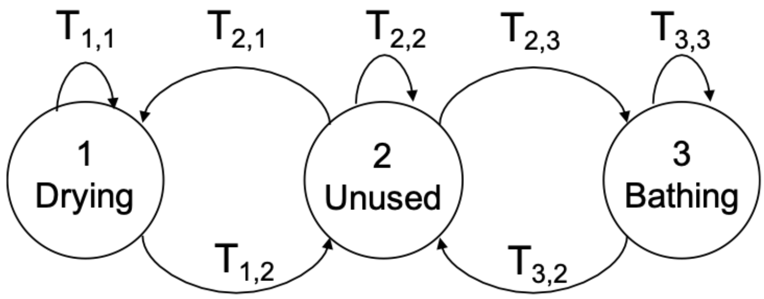


Figure 3.38: *State transition diagram of behavior around bathroom*

There is no link between dehumidifying the bathroom and bathing. In other words, when the system estimates that the person is taking a bath, the estimated state at the next time step is likely to be a continuous bath or finish bath, but it is doubtful to be dehumidifying the bathroom.

Based on this point of view, we added a post-processing to Layer 3: If the current state is bathing, the threshold of unused is adjusted to one-half of the normal state.

3.4.2 Experiment

3.4.2.1 Behavior Estimation Using Temperature and Humidity Sensors in Bathroom

Our experimental subjects are four different families in Japan, using the modular bathroom with a door separate the bathroom and the changing room which makes temperature and humidity differences between the two rooms. The layout for the bathroom and changing room of one family with four members is shown in Fig.3.39. In general, every family member takes a bath every day, ranging from 5-23 minutes. And we found that some families have the habit of using a shower head to clean the bathroom. This puts higher demands on the accuracy of our algorithm. When the humidity in the bathroom is significantly increased, the system needs to change the temperature to determine whether the current situation is bathing or cleaning the bathroom.

We asked the experimenter to place a temperature and humidity sensor in each of the bathroom and changing room. The sensors are mounted on the wall of the bathroom and changing room 50 cm from the ceiling. The sensor will always record temperature and humidity for a period of one week. At the same time, a smartphone with this special APP

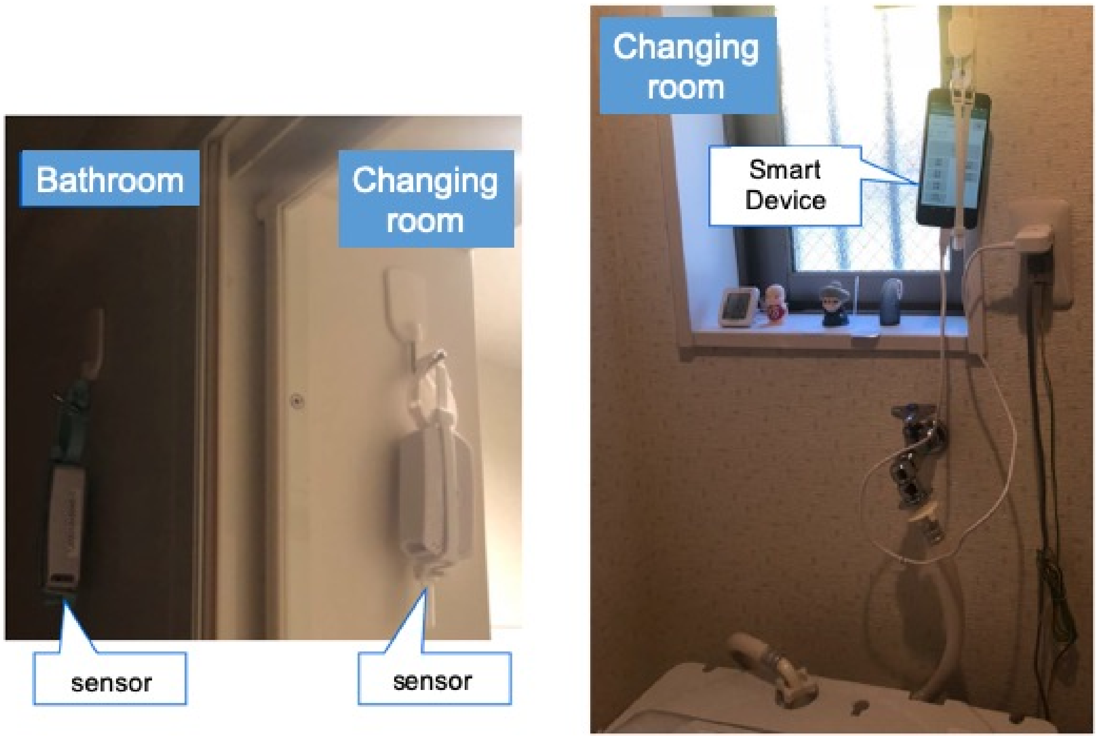


Figure 3.39: *Experimental environment(Two sensors and one smart-phone for recording daily life behavior)*

pre-installed in the Changing room can be used as a teacher data by simply clicking on the mobile phone when the family members perform any behavior in the bathroom and the changing room. For example, when a member enters the bathroom for a bath, he will click on the APP ”bath” button on APP. Also, he will click the ”finish bath” button after the bath. In this way, we can get more accurate teacher data for family members in the bathroom.

In this experiment, we focus on three indicators: precision, sensitivity, and average time delay between estimated result and the true time when finishing bathing.

TIME	BA_T	BA_H
0:10:54	20.51	60.78
0:11:04	20.51	60.76
0:11:15	20.51	60.76
0:11:49	20.51	60.78
0:12:05	20.51	60.77
0:12:09	20.51	60.77
0:12:21	20.5	60.78
0:12:38	20.5	60.77
0:12:41	20.5	60.77
0:12:49	20.51	60.77
0:13:29	20.5	60.79
0:13:56	20.5	60.79
0:14:00	20.5	60.79
0:14:26	20.51	60.75
0:14:34	20.5	60.77
0:14:41	20.5	60.77
0:15:24	20.54	60.71
0:15:35	20.51	60.75
0:15:36	20.51	60.75
0:15:52	20.5	60.75

TIME	BA_T	BA_H
0:11:00	20.51	60.78
0:11:15	20.51	60.76
0:11:30	20.51	60.76
0:11:45	20.51	60.76
0:12:00	20.51	60.78
0:12:15	20.51	60.77
0:12:30	20.5	60.78
0:12:45	20.5	60.77
0:13:00	20.51	60.77
0:13:15	20.51	60.77
0:13:30	20.5	60.79
0:13:45	20.5	60.79
0:14:00	20.5	60.79
0:14:15	20.5	60.79
0:14:30	20.51	60.75
0:14:45	20.5	60.77
0:15:00	20.5	60.77
0:15:15	20.5	60.77
0:15:30	20.54	60.71
0:15:45	20.51	60.75

Figure 3.40: *One set of temperature and humidity data(left: raw data; right: pre-processed data)*

As shown in the Fig.1-1, unlike the vibration sensor and pneumatic sensor, the data volume of the temperature and humidity sensor is very small, only 3 to 5 data per minute. Through preprocessing, we unify the data to 4 per min. Fortunately, the temperature and humidity changes are continuous and stable, so we can still perform behavior estimation under this amount of data.

As can be seen from the Table.3.7 , the use of the mobile migration map as post-processing increase the precision but on the other hand, the sensitivity decreased. Since we want to minimize the time delay, we think that precision is a more important indicator for this problem. In fact, the system’s time delay was indeed shortened from 4.5 minutes to 1.7 minutes. Since

Table 3.7: *Experimental result*

State Transition Diagram		×		○	
		Estimation			
		T	F	T	F
Teacher data	T	307	81	273	115
	F	139	10912	75	10976
precision		0.69		0.78	
sensitivity		0.79		0.70	
Time Delay(m)		4.51		1.72	

our system is currently updated once a minute, we can say that this result is very satisfactory.

Table 3.8: *Performance comparison of the three algorithms in behavior estimation using temperature and humidity sensors*

	ANN	TDNN	SNN
Average accuracy	0.76	0.93	0.97
Average precision	0.44	0.48	0.59
Average sensitivity	0.28	0.73	0.81
Average time delay		3.43 min	1.72 min

Table 1-1 shows the performance comparison of the three algorithms in behavior estimation using temperature and humidity sensors. The performance of simple Artificial Neural Networks is very bad. This is consistent with our speculation. ANN only pays attention to the current input, and the change of temperature and humidity is continuous and there is a time lag. TDNN performs better. It also pays attention to continuous input in the past period of time, but according to experimental results, its average time delay is longer.

Fig.3.41 captures a part of the real-time data experiment. In this data, we can see that two family members have bathed on this day. According to the spiking situation and the estimation result, the system judges the start time of the bath accurately, but there is a time delay for the end time. However, when we use the state transition diagram to help post-processing, this delay is greatly shortened, more accurately reflecting the real situation.

3.5 Discussion

In this chapter, I clarified the selection criteria for sensors used in smart homes, and classified the sensors as real-time response sensors and delayed response sensors. In view of the different characteristics of the two types of sensors, I respectively give algorithms for behavior estimation. ACNN is suitable for processing data containing people's periodic activities,

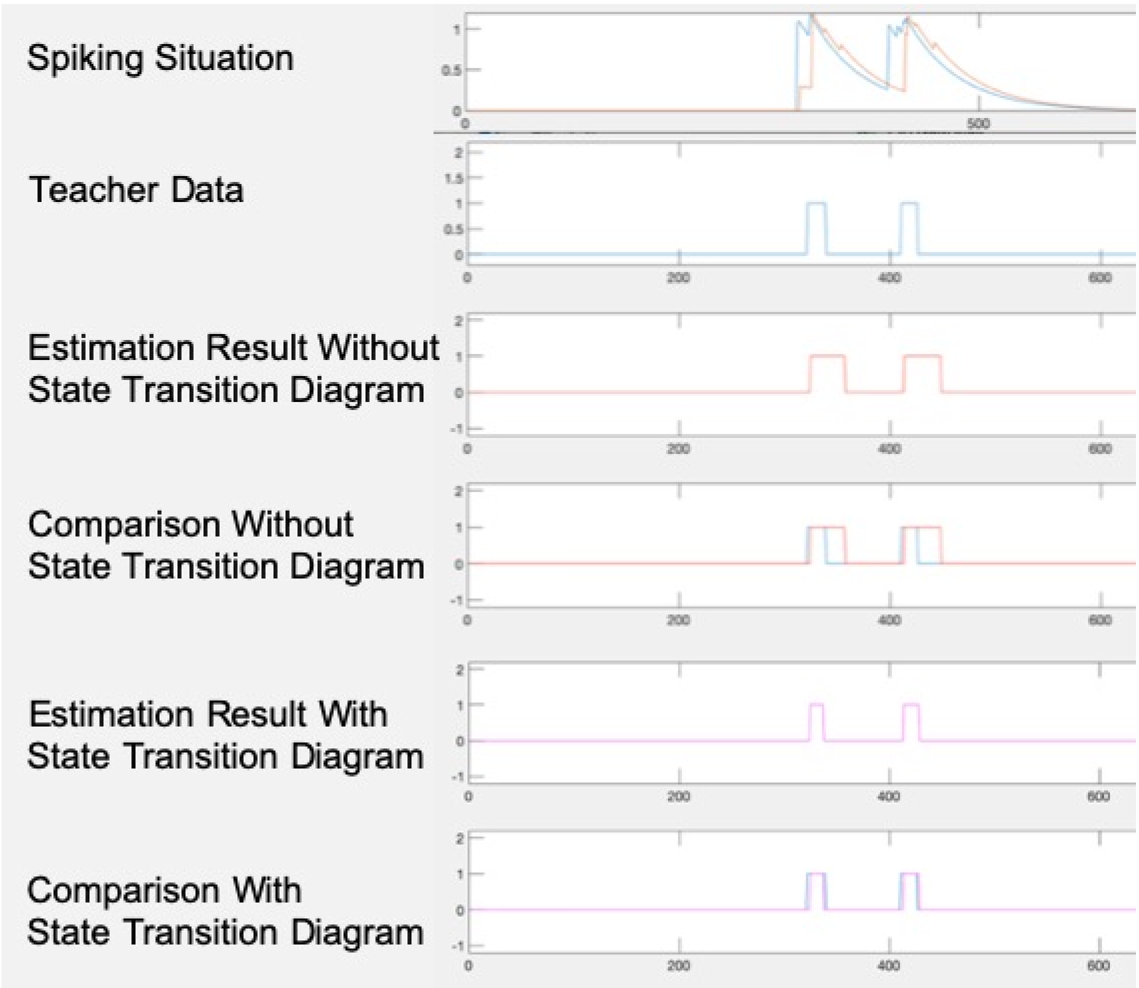


Figure 3.41: *Time delay becomes shorter when using state transition diagram*

while SNN has a good effect on processing sensor data with delay. Through experiments, I have proved the usability of the above algorithm.

Through experiments, I showed how the system responds when the user is in an abnormal state. The system can send status information to caregivers in real time.

Through the post-processing of the data, the system can not only get the user's current state, but also obtain the user's daily exercise volume, sleep heartbeat and other physiological information. These information can better help the system to judge the user's health status, and these data will be used to provide a more targeted system tips system.

It should be noted that at the processing level, I choose different NNs to achieve behavior estimation. This leaves a hidden danger on the system. The performance of NNs depends on training data and it is difficult to collect user data in actual use.

In the next chapter, I will try to solve this problem.

Chapter 4

Human Behaviors Analysis for Implementation to Smart Home

4.1 Introduction

Chapter 4 designs an easy implementation method according to the users personalized information without extra cost such as customization and re-learning by a human operator. From the viewpoint of ISS, I first develop a monitoring system that includes servers, sensors, and smart devices for users to enter their personalized information in advance. Next, I design a fuzzy inference-based spiking neural network, by using the user's personalized information and the pre-designed knowledge-based system. Experimental results show the system can adapt to changing use environments and maintain high accuracy without additional learning.

4.2 Neural network adjustment based on analyze layer

Through the research in the previous chapter, SHHCP already has full-featured NNs for behavior estimation, but the performance of NNs depends on training data and it is difficult to collect user data in actual use.

We can ask users or service providers to perform simple initialization settings when installing the equipment. But the data required to train neural networks is huge, and it is difficult for us to require users to record their actions in life like professionals. The activities of people in the family are very complicated, and it is difficult to use unsupervised learning to modify. Similarly, it is impossible for us to require users to adjust the parameters in the neural network by themselves.

In spite of the above difficulties, we can indeed ask the user to input the basic information of the actual use environment, such as the orientation of the room, floor information, and the floor material.

Based on the above logic, in this chapter we have designed a set of methods to adjust the performance of neural networks through environmental information. Through environmental information, the neural network can be adjusted at a level that users can perceive and understand (Fig. 4.1).

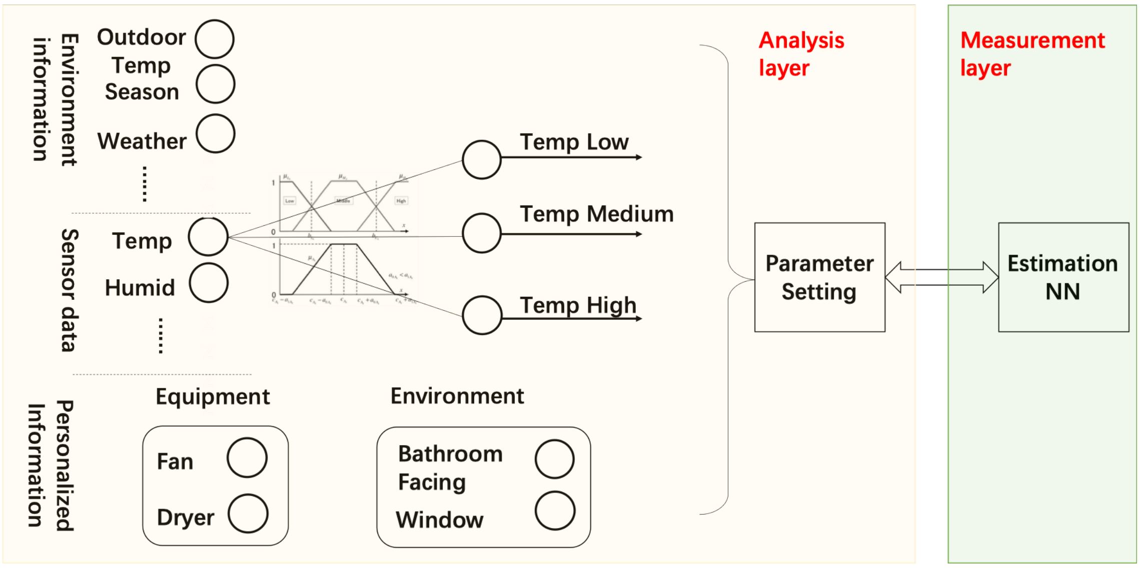


Figure 4.1: *Through environmental information, the neural network can be adjusted at a level that users can perceive and understand*

4.2.1 User Interface

For the different environments of different families, the system is difficult to distinguish in advance, and this information obviously involves the user's personal privacy. So I plan to give users the ability to set their own home environment.

Fig. 4.2 shows the interface APP we used in SHHCP. The main interface is a anthropomorphic smiling face. According to our research, a design with a human form will make the elderly feel more cordial. By clicking the left and right eyes of the smiley face, you can enter the interface for viewing system status and viewing user status. And by clicking on the mouth of the smiling face, you can enter the personalized environment setting interface. In this interface, users only need to press a few buttons to quickly set home information.

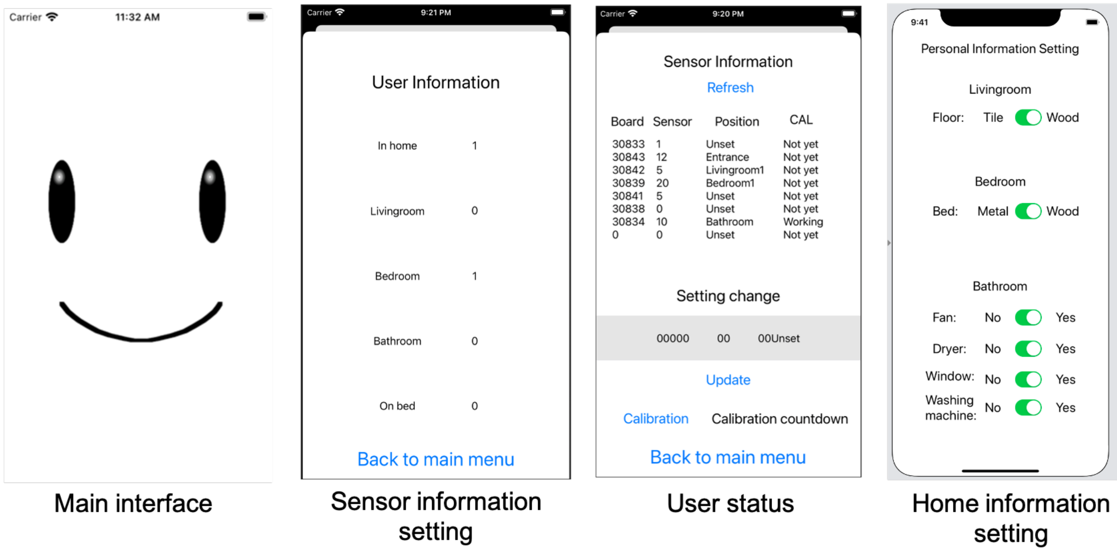


Figure 4.2: *User interface for SHHCP*

4.2.2 Fuzzy Inference-based SNN for Hyper-parameters Customize

In our tests, I found that the environment of different households has a great impact on sensor data. But it is very difficult to retrain neural network for each family. So I added fuzzy inference system as the preprocessing.

Fuzzy computing is the methodologies related to fuzzy theory and fuzzy information processing. Although computers have high accuracy and high-speed calculation capability, it is difficult to deal with situations and data containing complex fuzziness. Human can flexibly deal with these situations. In order to quantitatively express and process human subjective judgment and fuzziness, Lot Zadeh proposed the fuzzy set theory in 1965. Since then, until the 1980s fuzzy system was an active research field. Then, the research in fuzzy systems experienced a dark age in the 1980s, but it was reborn by Japanese researchers in the late 1980s. Today, it is a very active research field again with many successful applications, especially in control systems.

Fuzzy inference system is the actual process of mapping from a given input to output using fuzzy logic. In Aliustaoglu's research [94], a two-stage fuzzy model was developed to monitor tool wear condition by a sensor fusion model. Bergasa [95] use fuzzy-logic in their driver vigilance computation system for its well-known linguistic concept modeling ability.

In our system, the confidence of each sensor is different under different environmental conditions. For example, when bathing, the humidity of the bathroom may reach 100%, at which point I must increase the sensitivity to humidity to catch small changes in humidity. For this I use fuzzy inference systems to adjust the weight of all data (Layer 1 in Fig.4.5).

In simple terms, I classify the input into three dimensions of ”High”, ”Middle”, and ”Low”. Since ambiguity exists in the sensor value itself, I convert the sensor value from 0 to 1 by using the following fuzzy membership function. Then, the data after preprocessing will be sent to SNN(Fig.4.3).

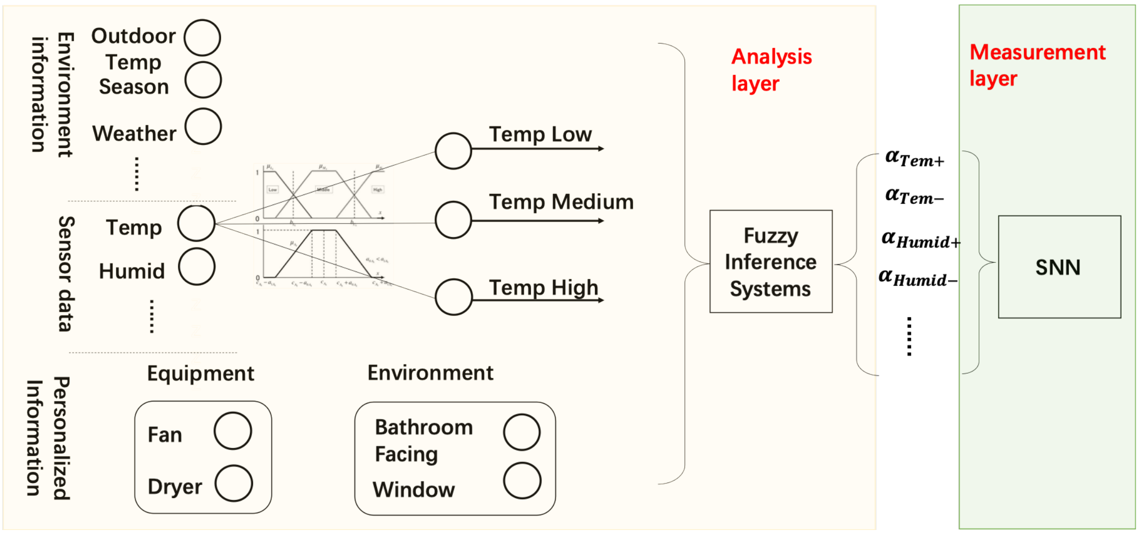


Figure 4.3: *Through environmental information, sensor data, and personalized information, the hyper-parameter of SNN can be adjusted*

For example, to solve the above humidity problem, I built two basic rule sets.

Fuzzy rule set 1:

$$\begin{array}{lcl} IF & Humid = Low & THEN \mu_{Humid} = 1.0 \\ IF & Humid = Medium & THEN \mu_{Humid} = 4.0 \\ IF & Humid = High & THEN \mu_{Humid} = 9.0 \end{array}$$

It can be seen that in rule set 1, when the humidity is high, the sensitivity of the input of humidity to SNN(μ_{Humid}) is correspondingly increased, which gives us the opportunity to capture small changes in humidity around 100%.

Fuzzy rule set 2:

$$\begin{array}{lcl} IF & Humid = Low & THEN \mu_{Temp} = 1.0 \\ IF & Humid = Medium & THEN \mu_{Temp} = 2.0 \\ IF & Humid = High & THEN \mu_{Temp} = 3.0 \end{array}$$

In rule set 2, I consider that the humidity data is less reliable when the humidity is high so that I need to increase the sensitivity of other sensors to prevent missing important changes.

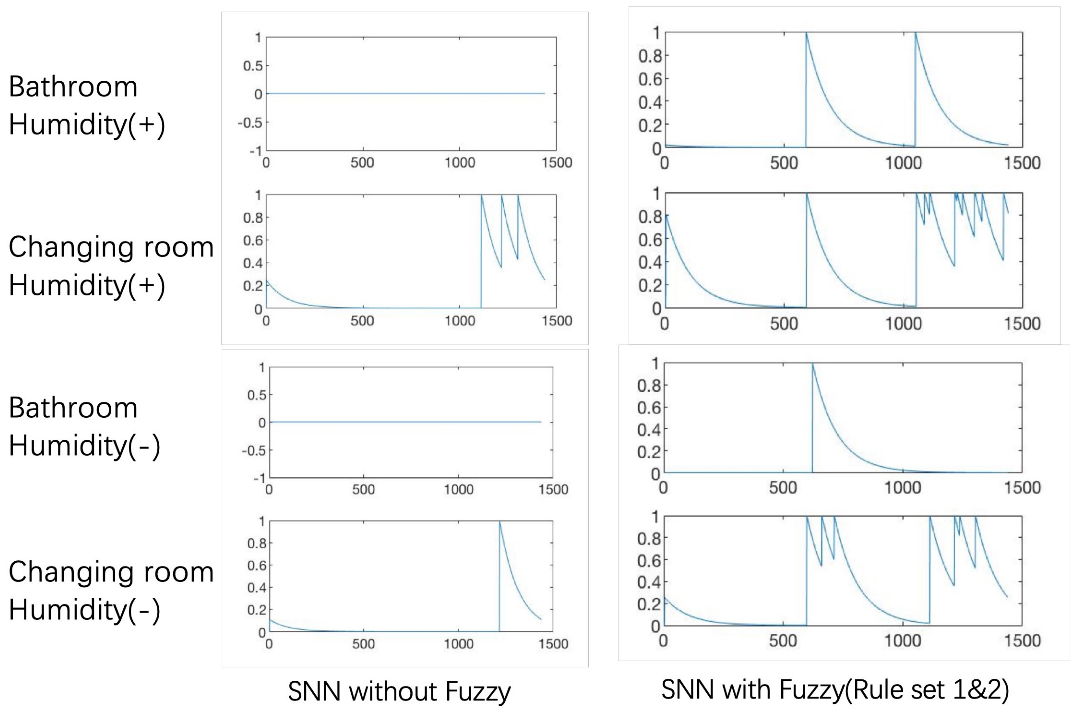


Figure 4.4: *Spiking of the input neurons.*
Left: traditional SNN; Right: FSNN (rule set 1)

I selected the humidity information for a certain day, during which the family took bath twice. When I enter this set of data into the SNN, intuitive, I hope to see two sets of spiking. In Fig.4.4, I can see the difference between traditional SNN (all the sensitivity μ are set in the same value) and FSNN with fuzzy rule set 1. The four figures on the left show the spike situation under traditional SNN. It can be seen that the humidity of the bathroom does not make any spiking, which means that this set of data cannot be used for learning or estimation. On the other hand, from the right group (using the fuzzy rule set 1), I can clearly see two sets of spiking. According to the comparison with the teacher data, they correspond to the family's bathing time.

Further, besides the basic rules, I can add more rules. According to the idea of ISS, behavior estimation is not only the work of sensors and arithmetic units, but also other data in the system to coordinate work. For example, with the information of season and the weather, I can estimate the approximate indoor temperature which can be useful for the estimation system. By using environmental information, sensor data, and personalized information (input by the user), I can make the system suitable for the family.

In this way, based on the idea of information integration of ISS, I have designed a series of basic rules and personalization rules, so the system will be able to personalize the SNN input based on the environmental information, sensor data, and personalized information.

As shown in Fig.4.5, behavior estimation algorithm is divided into four steps: First, the sensor network collects temperature and humidity information and sends it to the server in real time over Wi-Fi. In the server, I use fuzzy inference to pre-process the data, and each set of sensor data is divided into "increasing amount of change" and "decreasing amount of change", which ensures that all data input to the spiking neural network(SNN) is positive. Through the SNN, the estimated scores of various behaviors are calculated, and the behavior with the highest score is determined as the current state.

4.3 Experiment

Our experimental goal is to detect people's activities in the bathroom. Through the physical sensor data and FSNN, the system will be able to determine whether the person is taking a bath and how long it has been. When the bathing time exceeds the normal value, the system will give a warning.

In our pre-experiment, I tried to use a variety of environmental data including temperature, humidity, illumination, sound, indoor and outdoor pressure. However, having more data does not mean better results. For example, illumination is heavily affected by sunlight, which makes it difficult to believe. In addition, considering that this system will be used in elderly

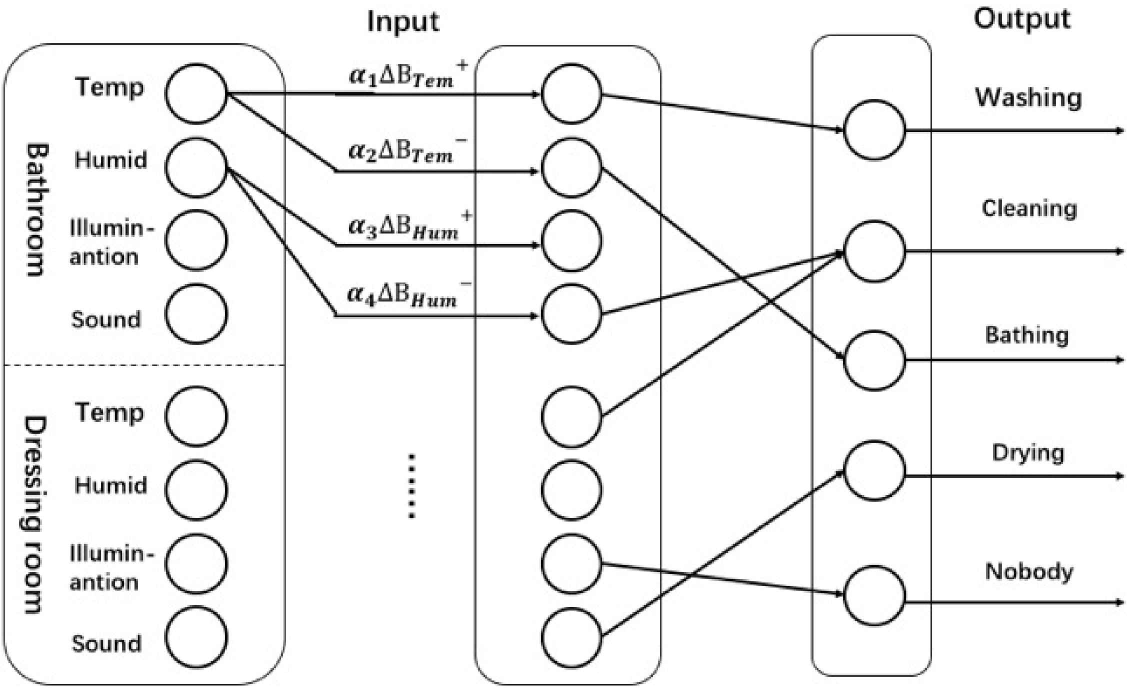


Figure 4.5: *Structure of behavior estimation algorithm*

health care systems, this requires us not to increase costs without restrictions. I must choose as few sensors as possible to achieve the best possible results. In the end, I found that only temperature and humidity is good enough.

4.3.1 Behavior Estimation Using Temperature and Humidity Sensors in Bathroom for Different Environmental Conditions

For example, in the pre-experiment, I chose two families with very close bathroom conditions(Table.4.1). They all have typical Japanese modular bathroom with fan and window without a dryer. In the changing room, house A has heating and house B has a fan. In order to control the variables, I did the experiment in autumn so that no heating was used during that time. I can compare the effects of the exhaust fan and make a set of fuzzy rules.

After several attempts, the rule set of the fan is as following (I need to note that this rule will be used in conjunction with rule set 1 but not replace it.).

Fuzzy rule set 2:

$$IF \quad Humid = Low \quad THEN \mu_{Humid} = 1.0$$
$$IF \quad Humid = Medium \quad THEN \mu_{Humid} = 1.0$$
$$IF \quad Humid = High \quad THEN \mu_{Humid} = 0.8$$

Table 4.1: *Equipment of two family's bathroom for comparison experiments.*

Equipment		House A	House B
Bath Room	Dryer	×	×
	Fan	○	○
	Window	○	○
Changing Room	Fan	×	○
	Heating	○	×
	Washing machine	○	○

This rule means that sensitivity of the input of humidity is the same as the base rule when the humidity is low or medium, but when the humidity is high, the sensitivity will be slightly lower than the house without fan (still higher than when the humidity is low or medium). This is intuitive. When a fan is used in a bathroom or in a changing room, the humidity will decrease faster, so there is no need to set the sensitivity in a too high level.

Table 4.2: *The result of the pre-experiment of fuzzy rule set 2*

House	A		B	
Use of rule set 2	○	×	○	×
True Positive	79	88	25	25
False Negative	29	20	4	4
False Positive	58	60	25	48
True Negative	1075	1073	1387	1364
Accuracy	0.93	0.94	0.98	0.96
Precision	0.58	0.59	**0.50**	0.34
Sensitivity	0.73	**0.81**	0.86	0.86

In Table.4.2, I can see if the rule set on the fan is optimized as I wish. For house A without a fan in changing room, when I do not use this rule, its predicted sensitivity is higher. On the other side, For house B with a fan, when I use this rule, its precision is higher, which means it less misreported.

4.3.2 Behavior Estimation Using Vibration Sensors in Living room for Different Environmental Conditions

This time, a preliminary experiment was conducted using two different beds. The two beds are made of metal (Fig. 4.6 left) and wood (Fig. 4.6 right), respectively. During the experiment, the sensor was attached to the bed leg with paper tape to keep it 20 cm away from the ground and perpendicular to the ground (Fig. 4.7). For reference, another sensor was placed on the floor next to the bed.

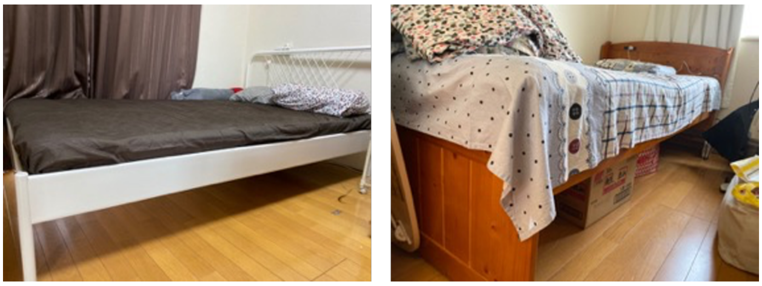


Figure 4.6: *Metal bed (left) and wood bed (right)*

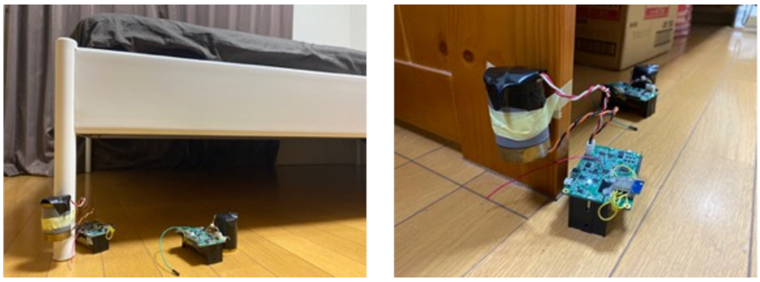


Figure 4.7: *One vibration sensor is set on the wooden floor and the other one is set on the feet of the bed (left: metal bed; right: wood bed*

Since the placement position, purpose of use, and measurement target of the two sensors are different, the sensitivity of the sensors was adjusted to two different states. Specifically, the sensor on the bed was set with higher sensitivity because I wanted to capture even the user's small movements and heartbeat. On the other hand, the ground sensor was set to a relatively low sensitivity. If the sensitivity is too high, the effect of noise will increase and the accuracy will worsen.

The experimental data are shown below:

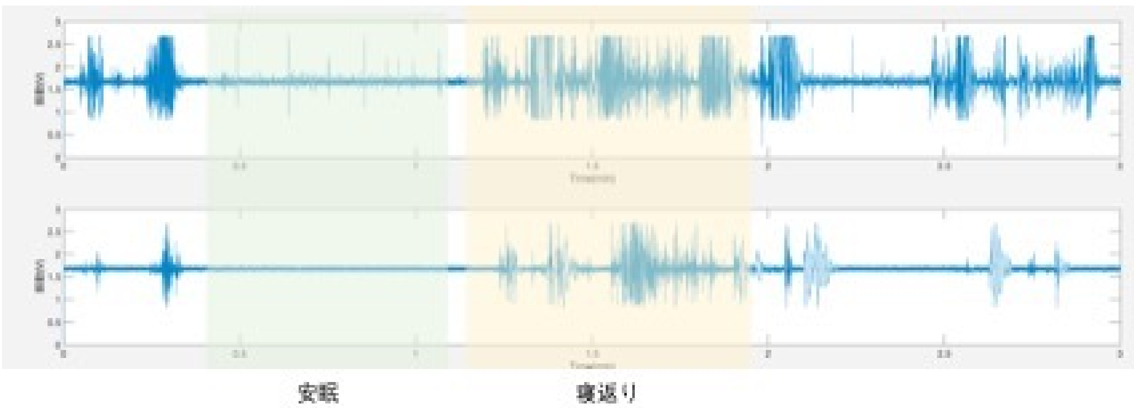


Figure 4.8: *Raw vibration sensor data of sleeping monitoring on metal bed (upper: bed; lower: ground)*

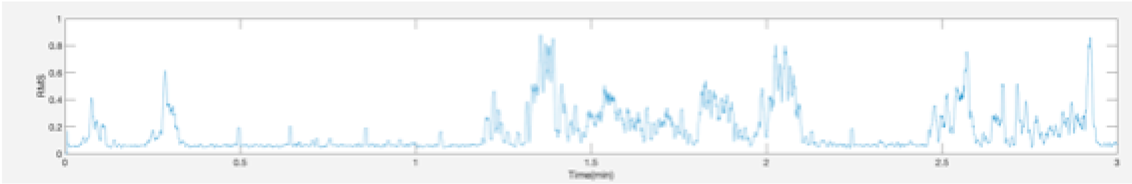


Figure 4.9: *vibration sensor data of sleeping monitoring on metal bed with pre-processing (upper: bed; lower: ground)*

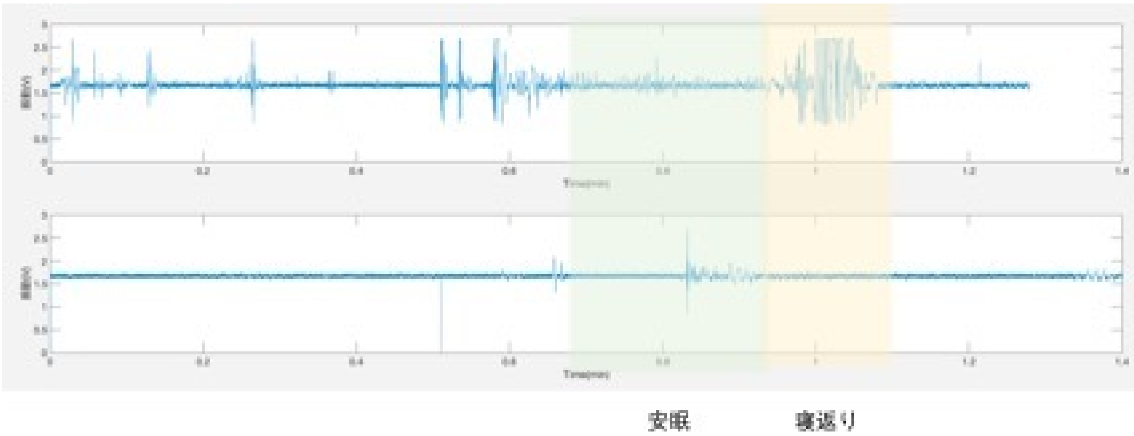


Figure 4.10: *Row vibration sensor data of sleeping monitoring on wood bed (upper: bed; lower: ground)*

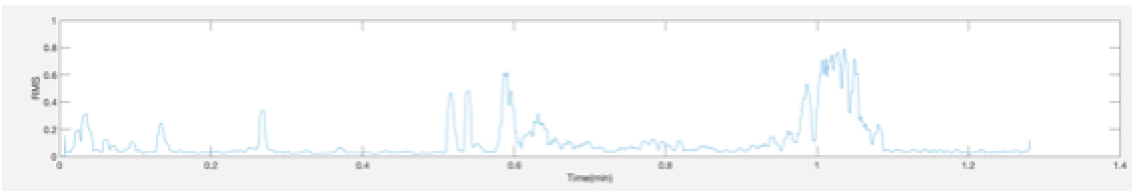


Figure 4.11: *vibration sensor data of sleeping monitoring on wood bed with pre-processing (upper: bed; lower: ground)*

It can be clearly seen that the vibration of the metal bed is more obvious (Fig. 4.8, Fig. 4.9), while the vibration amplitude of the wooden bed is smaller when a person is on the bed (Fig. 4.10, Fig. 4.11). This vibration is also reflected in the value of the sensor near the bed.

In the previous experiment, the NN was trained on a metal bed. In order to make this NN can be used on a wooden bed, I added the following rule:

$$IF \quad Bed = Wood \quad THEN \mu_{Vibration} = 1.5 \tag{4.1}$$

Table 4.3: *Experimental result of hyper-parameter adjustment on bed scenario*

Training data	Test data	hyper-parameter adjustment rule	Accuracy	Precision
Metal bed	Metal bed	Not use	0.92	0.91
Metal bed	Wood bed	Not use	0.55	0.65
Metal bed	Metal bed	Use	0.71	0.75

The Table. 4.3 shows the results of the experiment under different conditions with or without rules. Among them, precision refers to the precision that recognizes the turning over of the person in bed. It can be seen that the NN trained for metal beds performs best when actually used on metal beds, with an accuracy of over 0.9. When the same NN is used in a wooden bed, the performance is poor. However, when I introduced the hyper-parameter adjustment rule, its performance improved significantly.

4.4 Discussion and Conclusions

I designed an elderly health care system using an environment sensor network. Based on the traditional SNN, I introduced the fuzzy interface system and designed a series of fuzzy rule sets to pre-process the sensor data. In the experiment, by analyzing the sensors installed in the bathroom and the changing room, I achieved a 97% average accuracy and 78% average sensitivity that shows our system is effective.

Due to the huge difference in home environment, it is impossible to apply all smart home with only one NN. The ideal situation is to get more data and build a few typical homes and use the Fuzzy Inference System to fine-tune the input.

In addition to user data, wide area environmental information like seasons and weather may also interfere with the results. If there are more training sets, this information can also be designed as a fuzzy rule set to improve the accuracy of the system.

Chapter 5

Daily Life Support System Based on HaaS

5.1 Introduction

This chapter explains a human-centric approach to provide personalized services. From the viewpoint of HaaS, I design a cloud-based healthcare system for smart home. First, I clarify the functions and characteristics of a service robot in human-centric healthcare. Next, I explain the data structure and information flow in the overall system including sensors and service robots. Furthermore, I develop a scenario editor to realize the easy design of healthcare services. The scenario editor can integrate three processing levels for healthcare services according to (1) the types of sensors connected to the network in the data level, (2) measurement results of environmental states and human activities in the information level, and (3) interactive scenarios with a service robot in the knowledge level. In experiments, I set up a smart home including multiple sensors, multiple network protocols, and multiple robots. The experimental results show that the service robot can select a suitable scenario and provide personalized healthy living advice according to the state of daily activities. Moreover, the system can provide healthcare services to users while maintaining its stability, even if the number of sensor nodes is increased or decreased.

5.2 Service Integration in Smart Home

This section explains a structured platform that can collect, store, transform, and provide information. This environment is called the Informationally Structured Space(ISS) [77]. The network of the system contains information from various sensors. It sends them to the server using wireless communication methods [79] such as Bluetooth, Wi-Fi, ZigBee, and Sub-1 GHz wireless communication solutions. The ISS server estimates human states from the measurement data and sends the estimation results to the partner robot to communicate with the elderly and caregivers' smartphones [80] [81].

5.2.1 Modular System

A modular system means that the equipment in the systemespecially the sensor nodescan be freely increased, decreased, and adjusted according to user needs. As shown in the Fig. 5.1, according to the actual needs of the user, he can customize his own smart home.

The system needs to flexibly adjust the available services according to the devices connected to the network.

Case	Vibration sensor	Robot partner	Sensor Tag	Camera	Apple Watch	Behavior estimation	Position-ing	Identif-ying	Physical condition	Watch over	Monitor-ing
1	○					○	△	△	○	×	○
2	○	○				○	△	△	○	△	○
3	○	○	○			○	○	△	○	△	○
4	○	○			○	○	○	○	◎	○	○
5	○	○	○	○		◎	◎	○	○	○	◎
6	○	○	○	○	○	◎	◎	○	◎	○	◎

Figure 5.1: *Users can choose the type of sensors and smart devices to use*

5.2.2 Human Interface

5.2.2.1 Smart Phone Interface

Our system can be personalized by the user. Naturally, we thought of using a smart phone APP as a graphical interface to allow users to set up and view information. Since our design is geared towards the elderly, we must consider the age-appropriate design. Simply put, the interface of a smart phone should be simple, clear, and user-friendly.

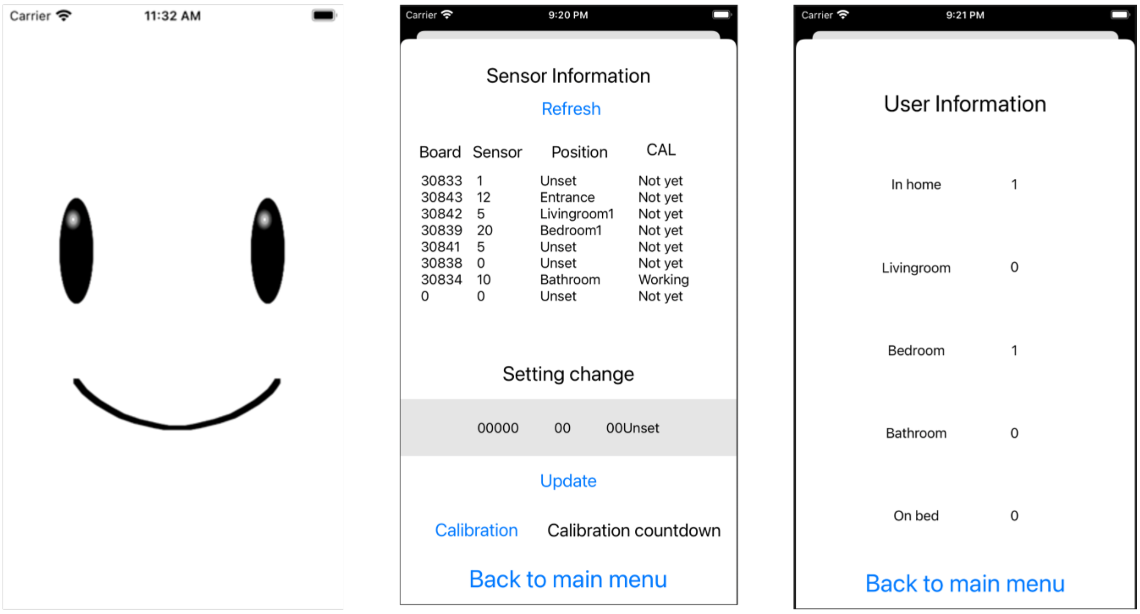


Figure 5.2: *smartphoneUI*

Figure 5.3: *Smartphone app for elderly monitoring system*

Next, we show how to refer to the data on the smartphone app to check the results measured by this monitoring system. An example of the developed smartphone application is shown in Fig. 5.3. This app can display the status up to now of the elderly living alone. The current state of the elderly acquired from the server and displayed on the screen is updated every five minutes. In Fig. 5.3 (right), a graph of the heart rate is output as an example. The graph of this measurement result is displayed only when the system can calculate the heart rate and the number of steps.

5.2.2.2 Robot Partner

Recently, the demand to robot partners has been increasing to realize natural communication with people in interactive services. In fact, various types of robot partners have been developed to support human daily life based on human-robot interactions [96]. For example, robot concierges have been applied to information service and guide in science museums according to the predesigned scenarios. Furthermore, as a rapid progress of information technology and network technology, partner robots can be easily inter-connected each other. Multi-robot communication has been used in educational scenes, e.g., team teaching and remote education [97].

Furthermore, multi-robot partners have been used in interactive information support system to activate shopping streets and local communities [98] [99]. The information service is done according to predesigned query-based simple utterance contents. Another potential application is a multi-robot theater to realize the information service and guide to visitors in shopping streets, airports and stations. However, the utterance contents look like a static story teller, even if there are many robots in such a theater. The main problem is in the flexibility of scenarios. The theater that creates a story together with others performed in an unplanned or unscripted way, is called Improvisation (Improv, in short) [100]. Originally, improvisational theater has been used to enjoy a drama-like entertainment created spontaneously by the performers. However, it is difficult to prepare the rough scenario for multi-robot improvisation theater.

In this study - a smart home scenario for the elderly - robot partners are used to communicate directly with the elderly. Considering that the elderly do not prefer metal, human-sized robots, I used robots that are placed on a tabletop in my study. To meet various requirements, a smart device-based robot system [101] names “iPhonoid”(Fig. 5.4) is used to reduce construction costs. iPhonoid consists of iOS devices, robot bodies, micro controllers, and servo motors [102]. iOS devices equip a variety of sensors such as gyroscopes, accelerometers, illuminate sensors, touch interfaces, compasses, two cameras, and microphones. These sensors are sufficient for the robot partner to interact with the elderly.

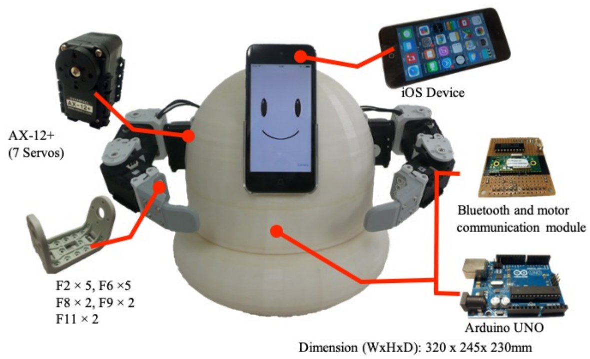


Figure 5.4: *Construction and individual components of iPhonoid*

The benefits of using robots in the smart home are numerous. Traditional smart homes are only able to passively acquire user status, but there is no way to actively communicate with the user to understand their current situation and needs. Robots, on the other hand, are a good interface for interaction [103]. Compared to smartphones or smart tablets, robots have anthropomorphic features that make them more accessible to the elderly.

A simple application example: after the robot knows that the elderly are out of abnormal state, they can confirm the current status to the elderly through the screen and the microphone. If the robot gets a response that requires help or gets not responded for a while, the robot can inform the caregiver.

5.3 Healthcare Tips System Based on HaaS

In previous research, we have implemented a smart home monitoring system including sensors, server, and user terminals. In order to control the communication content of the robot in real time, we have added a local server for controlling the robot on the previous system.

We subdivide the cloud server into online information database and online scenario database. The former contains all the information from sensors, networks, and smart devices, as well as the current state of the user derived from the above information. The latter includes all pre-set communication scenarios.

Correspondingly, the local server is also divided into an information server and a scenario server, which are connected to the two parts of the cloud server through Wi-Fi. The device states module records the operating conditions of all the devices in the current system. Depending on the connection and operating conditions, the services that the system

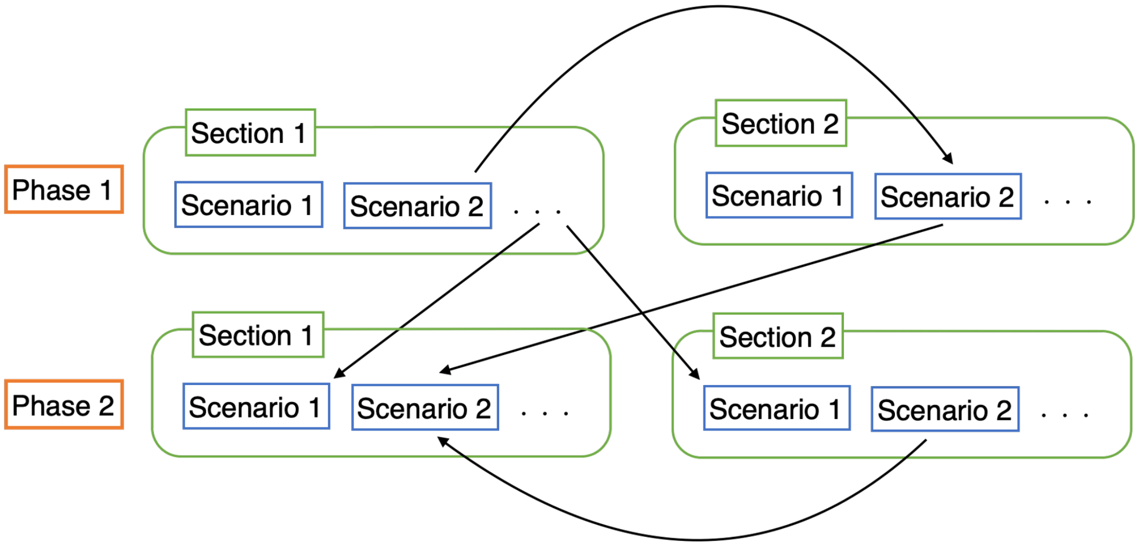


Figure 5.5: *The structure of cloud-based robot communication system*

can provide will change through device-scenario controller. The Local scenario controller directly controls the communication content of the robot. According to the current situation, the system will decide what kind of service (such as exercise amount management) to provide to determine the Phase. Each Phase contains several Sections corresponding to different situations under this service (such as insufficient exercise amount reminder, exercise amount reports, etc.), each Section contains several specific scenarios, which include the specific communication dialog, expressions and postures (if necessary) of the robot .

According to the different services provided, each scenario has its own independent Phase_ID, Section_ID, Scenario_ID. The system can skip section and scenarios, and can go back to previous scenario. The next section is transited to the next according to the conditions, e.g., voice recognition and users interaction.

5.3.1 Cloud Service

As shown in the Fig.5.8, from the data level, the system is divided into three parts: sensor network, cloud server, and user interface.

5.3.1.1 Data Structure

There are many types of equipment in the system, and the possible output of each type of equipment is completely different. We need a unified, interpretable, and flexible data structure to ensure the unity of states in robots, sensors, and servers.

The scenario transition system can integrate three processing levels for healthcare ser-

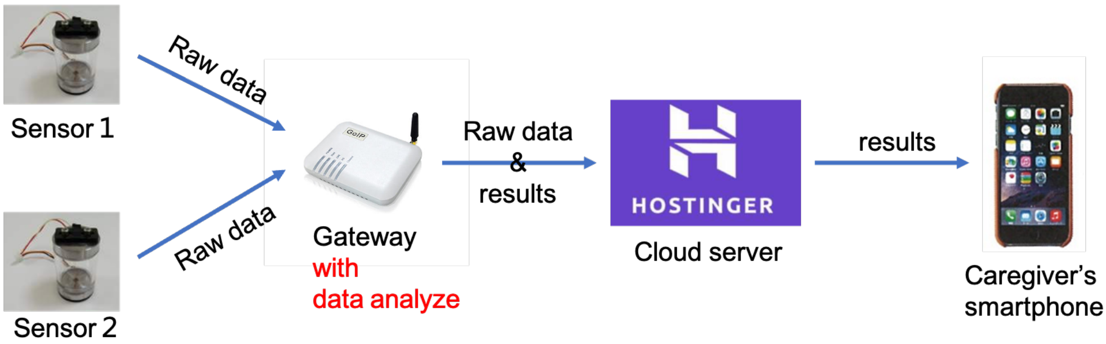


Figure 5.6: *cloud-based smart home*

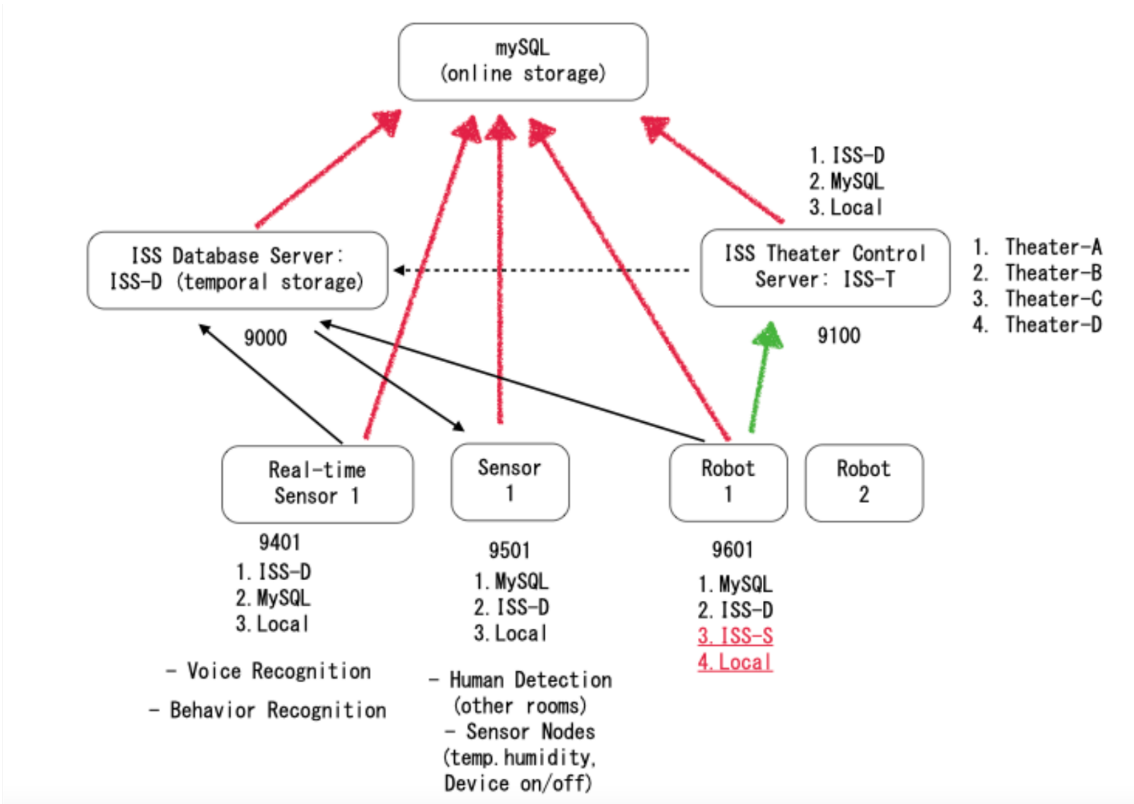


Figure 5.7: *Smart home system structure including Cloud mySQL server, local server and device nodes*

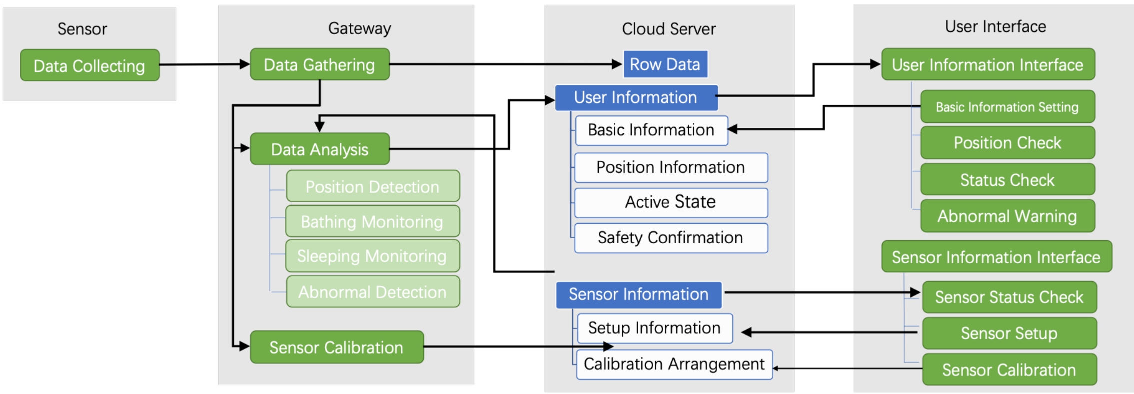


Figure 5.8: *Data trans flow*

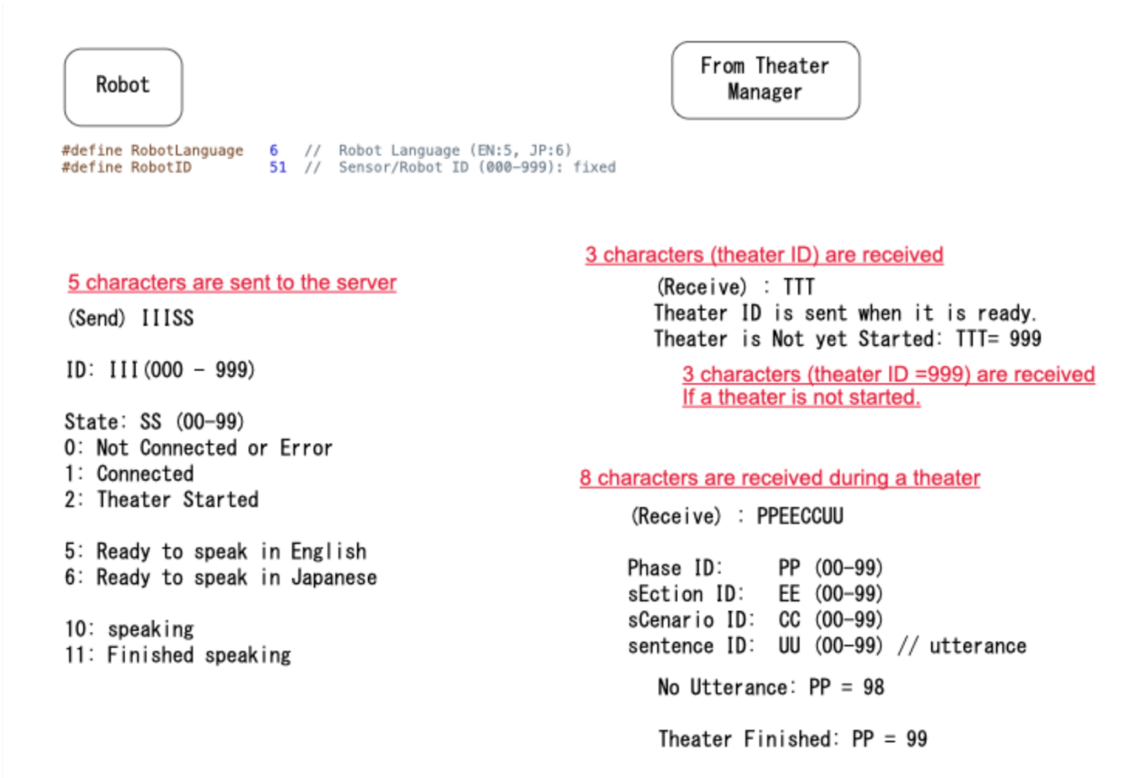


Figure 5.9: *Data Structure*

vices according to (1) the types of sensors connected to the network in the data level, (2) measurement results of environmental states and human activities in the information level, and (3) interactive scenarios with a service robot in the knowledge level.

- Data level

First of all, we must consider that in different households, the types and quantities of connected sensors and smart devices are different. However, it is obviously unrealistic to independently develop a set of robot communication scenarios for each situation. The Device-scenario controller is designed to solve the above problems.

The enabled state of all scenarios is set as shown in the Table. 5.1

Table 5.1: *Mode of a scenario*

Mode	Explanation
0	OFF
1	Full mode
2	Basic mode

When the user chooses not to enable a certain function, or the device does not meet the enabling conditions, the mode is set to 0. The scenario controller will not select dialogue from the scenario with mode=0. When the function is enabled, mode is set to 1. The scenario controller will select the dialogue normally. In particular, some services require specific sensors or smart devices to provide complete services. When the corresponding device is unavailable, the mode will be set to 2. In basic mode, the system will use other sensors and environmental information to provide the same service as well as possible.

Here I show two examples:

```
if mat_sensor.state == 0 or 99 then
    sleep_management.mode = 0;
else
    sleep_management.mode = 1;
end
```

When the mat sensor used to measure the sleep status of the elderly cannot be used, the sleep management function is disabled; when the sensor tag placed in the medicine cabinet to monitor whether the elderly take medicine on time cannot be used, the medical remind function becomes the basic mode: only remind the elderly to take medicines according to the time.

```
if sensortag_medicine_cabinet.state == 0 or 99 then
    medical_remind.mode = 2;
else
    medical_remind.mode = 1;
end
```

It should be noted that only when the conditions are not met at all, the system will close the corresponding service.

- Information level

In order to improve the ease of use and interpretability of the system, all sensor information is not simply stored on the server in the form of raw data, but also includes storage based on events and status. For example, the humidity sensor in the room can report the current humidity in real time, but this value is meaningless to the user. Since a dwelling is considered to be healthy at a humidity of 40 - 60%, we divide the humidity into 1 (too low), 2 (comfortable) and 3 (too high). In this way, we can design new scenarios not based on values, but based on events and states.

- Knowledge level

Merely displaying the current state of the user on the user interface cannot be called a service. Only when the system makes full use of these data, and provides the information that users need through communication and other forms based on existing knowledge, is the complete form of the service. The focus of scenario control at the knowledge level lies in the flexible use of this information.

According to the guidance of medical institutions for the healthy life of the elderly [104], as well as the sensors we can currently use, we have listed some of the health tips functions that can be provided (Fig. 5.10). We divide healthcare service for the elderly into three aspects: daily life healthcare, physical healthcare, and psychological healthcare.

5.4 Scenario Editor for Robot Partner

The previous section introduced the healthcare tips system in detail, but this is only an essential service.

On the one hand, service providers may need to add or modify service content based on their own hardware characteristics. On the other hand, users and their caregivers may wish to

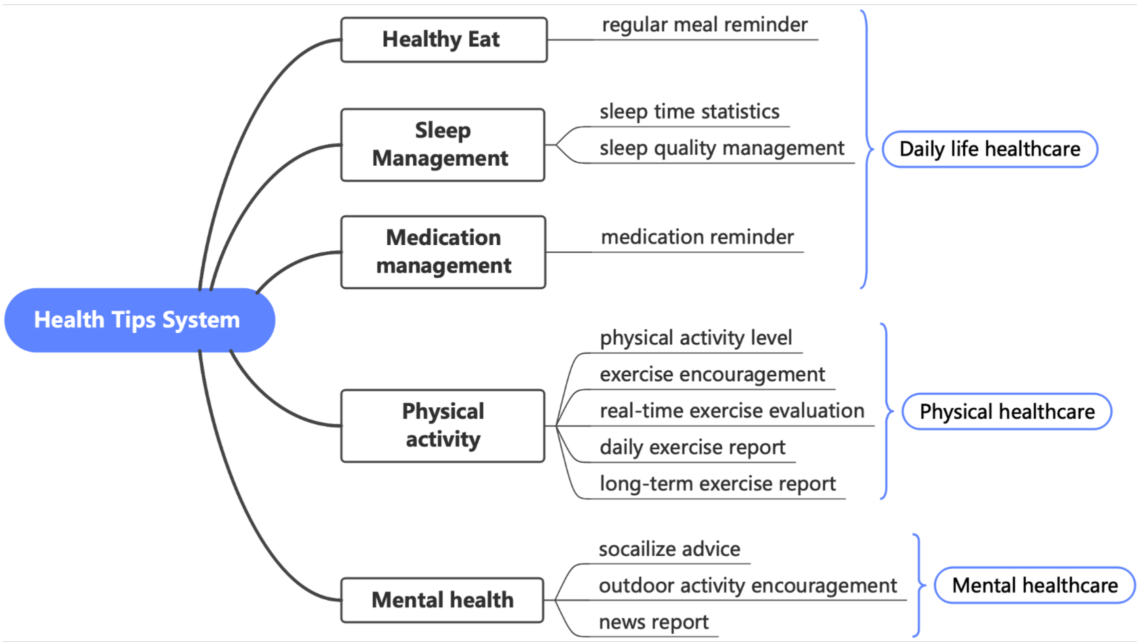


Figure 5.10: *Functions of healthcare tips system*

customize services based on the characteristics of their families. In addition, we very much hope that professional medical staff can participate in the design of specific service functions.

The common feature of the above three groups of people is: they lack professional robotics and IoT knowledge. Therefore, I develop a human-friendly scenario editor for users unfamiliar with robot technology (RT) and information and communication technology (ICT). The upper right of Fig. 5.11 shows the scenario editor linking with the cloud database. Specifically, the scenario editor is divided into two parts: the dialog editor and the transition editor, respectively connected to the dialog database and the transition database on the cloud server.

We designed the robot user interface to make it easy for people who are unfamiliar with robots to operate the robot in a friendly and intuitive manner. In addition, content can be created and managed by downloading content from a database in the cloud and editing it via the iPad, making it possible to create content anywhere with an iPad that can connect to the Internet. Fig. 5.12 shows the screens of the scenario editor.

5.5 Experiment

In this part, I will demonstrate the functions of the health service system including robots, smart devices used as user interfaces, and sensors through several different experiments.

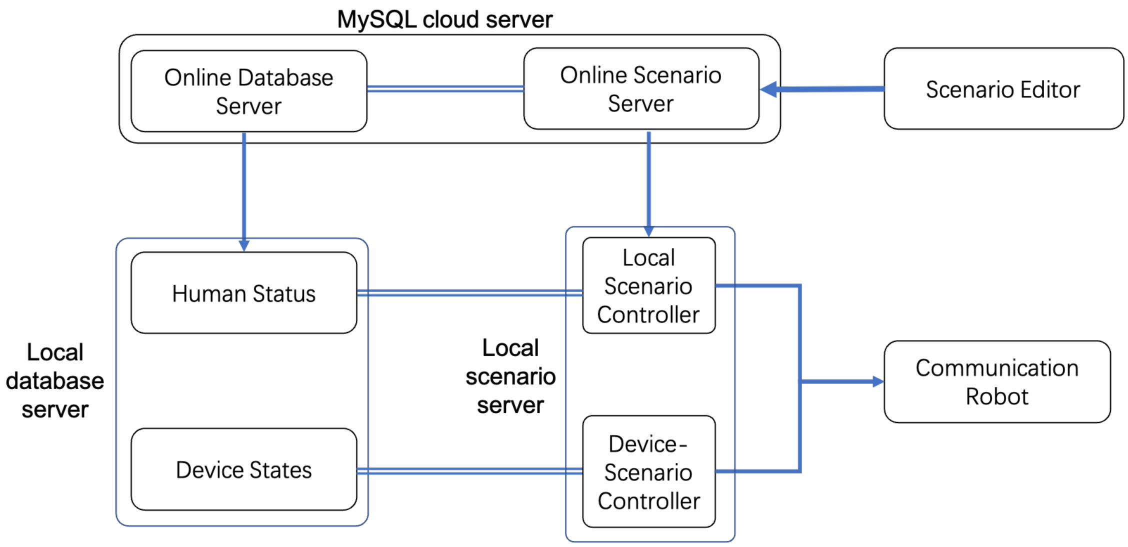


Figure 5.11: *The structure of cloud-based robot communication system*

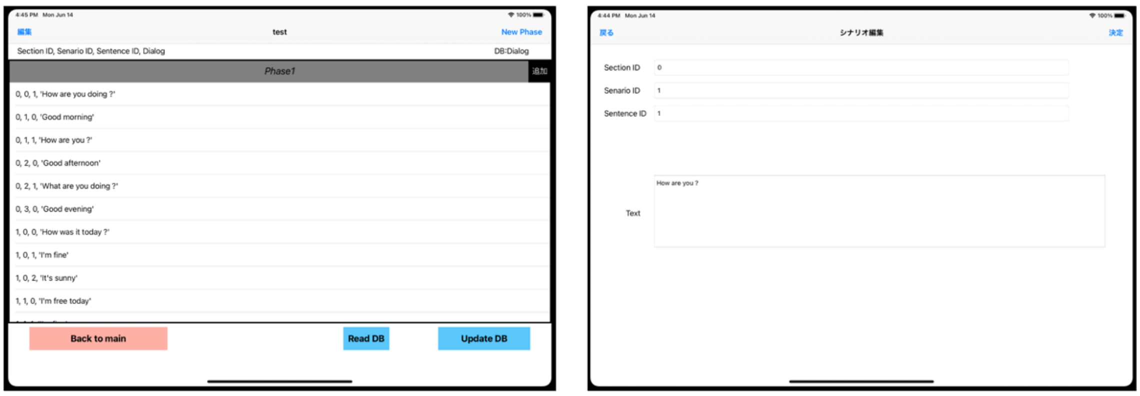


Figure 5.12: *Screen of scenario editor (Left: dialog list interface; Right: dialog editing interface)*

5.5.1 Experiment of Abnormal Alarm Status Confirmation with Robot-sensor Collaboration

I demonstrated the entire system. I allowed the experimenter to act freely in the room and obtained the sensor information, as shown in the Fig. 5.13. Based on the sensor data, the system made inferences and obtained results (lower part of Fig.5.13), which were then uploaded to the cloud server.

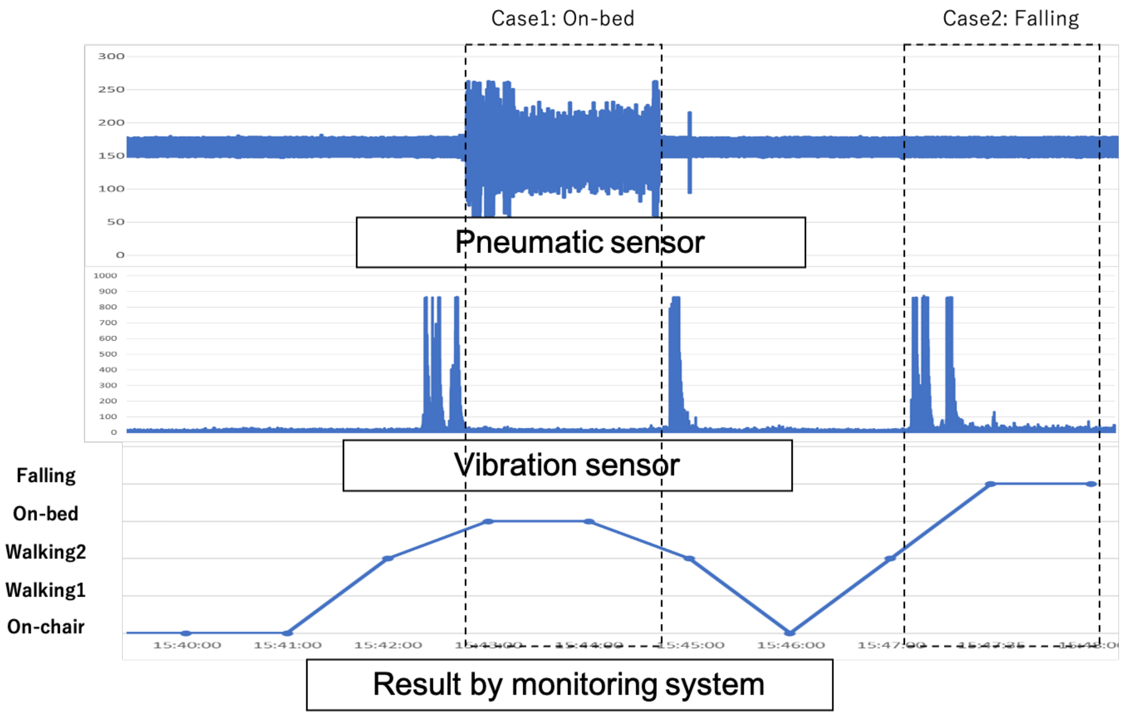


Figure 5.13: *Vibration sensor data (upper), pneumatic sensor data (middle) and estimation result (lower) of the demonstration*

The cloud server would delivers the results to the smartphone app in real time (Fig. 5.14). As a special case, if the system determines the elderly person to be in an abnormal state, the letters on the app would be underlined (lower part of Fig. 5.14). It should be noted that under normal circumstances, the system updated the current status every five minutes, and this information was displayed on the app for the first time when a fall occurred.

5.5.2 Experiment of Status Confirmation with Robot-sensor Collaboration

In this section, we will use a demonstration of users or service providers create new function through the scenario editor.

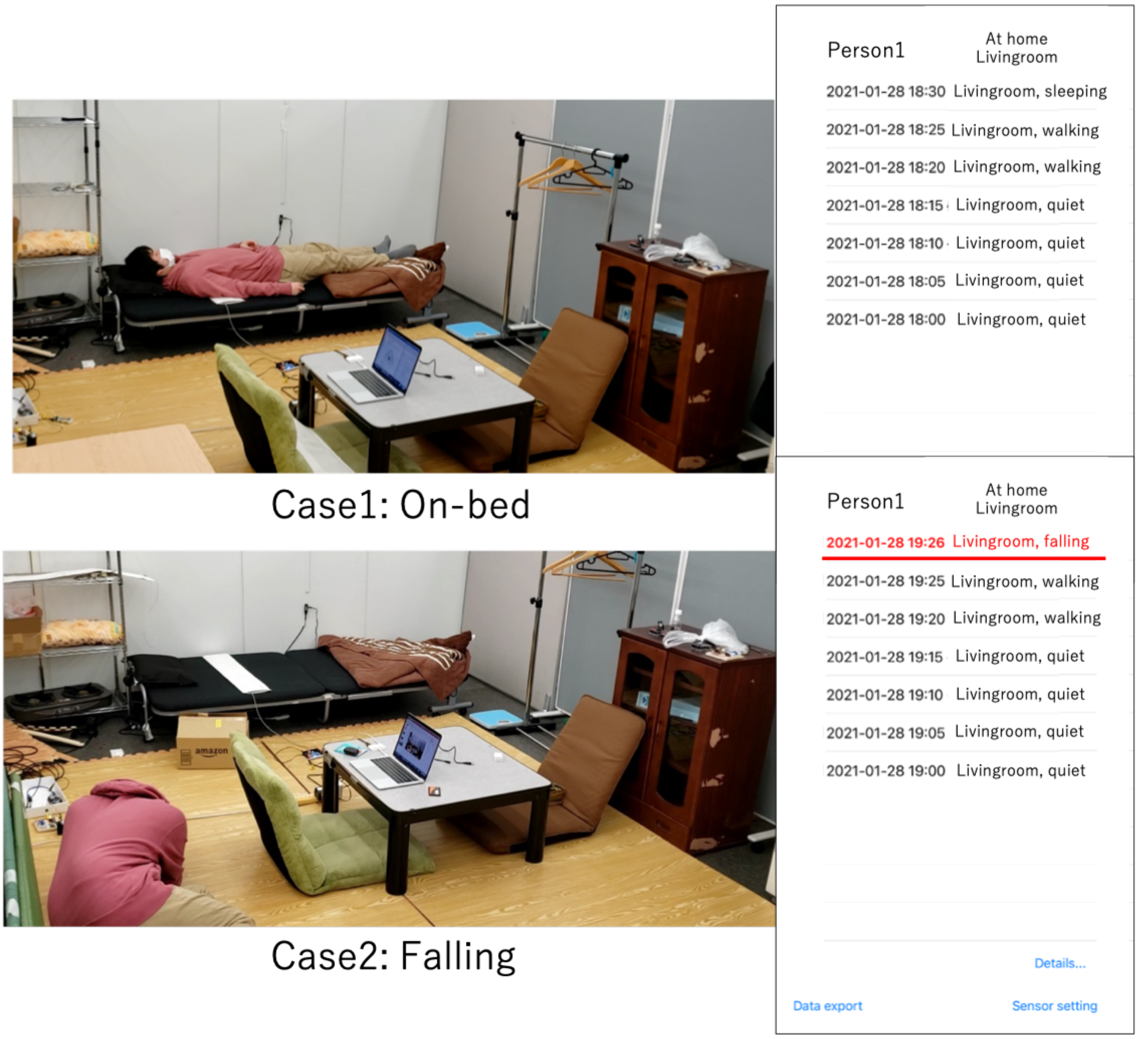


Figure 5.14: *Real-time status of a person in the room can be viewed from the app.*

We chose to use a set of vibration sensors. This kind of vibration sensor can monitor the movement of people in the room in real time and alert the caregiver when the elderly person falls (Fig. 5.15) [105]. However, in most cases, the elderly people have the ability to recover on their own after a fall, so alarms are not always necessary. Therefore, we create a status confirmation function through the scenario editor to improve the accuracy of the fall detection.

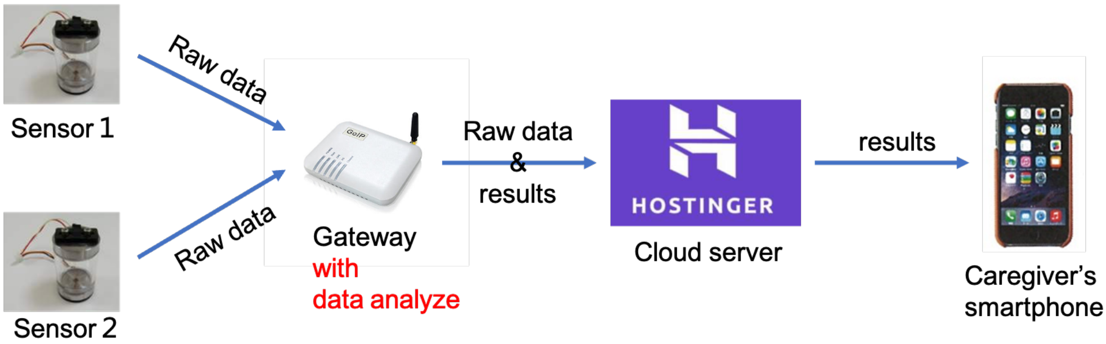


Figure 5.15: *A basic fall detection function based on vibration sensor*

When we use robot partners, we can perform a second confirmation to further ensure that the user's status is correctly grasped, and seek help according to actual needs (Fig. 5.16). When the system determines that someone may have fallen, the robot will confirm by voice. If a voice response is received, or the vibration sensor detects human activity again, the system will not alarm. If there is no response for a period of time, the system will contact the caregiver for help.

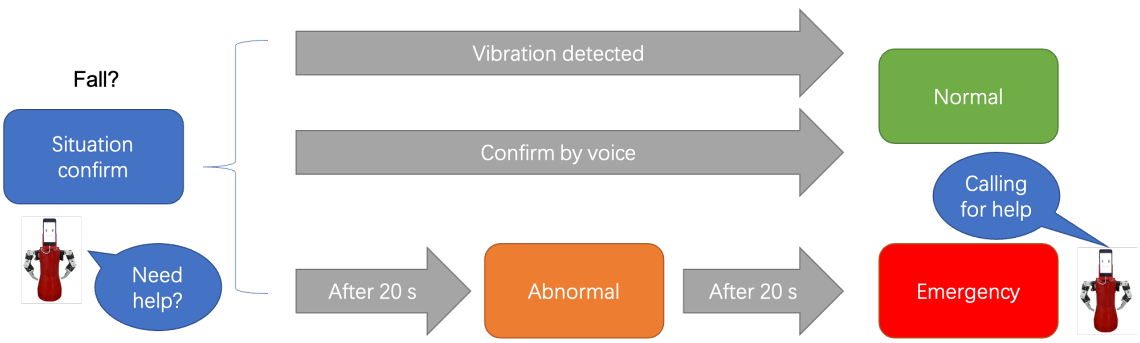


Figure 5.16: *A robot fall confirmation system demonstration*

Table. 5.2 shows some of the dialogs that may be used in situation confirmation service. and the sentence number includes Phase_ID, Section_ID, Scenario_ID. The scenario in this service is simple, so all dialogs are in the same section. Through the scenario editor, we can easily modify the content of the dialog.

Table 5.2: *Dialog for fall confirmation system*

ID	Dialog
(0,0,0)	I heard a loud noise, are you okay?
(0,1,0)	I'm glad you are okay.
(0,1,1)	Please let me know if you need help.
(0,2,0)	Are you falling down? need any help?
(0,3,0)	I can not hear you. I will call for help.

Table. 5.3 shows the sensors that this service needs to call. The number in parentheses after the sensor represents the sensor number. All information from wireless sensors are numbered 0-99; messages from the system are numbered 100-199; the results from voice recognition are recorded in 200-299. NEW SENSOR Incorporated (NSI) has developed the sensor we use in this study. Under our training, the current vibration sensor can obtain data such as the person's position, current action, and walk steps. For convenience, irrelevant state is not shown in the table. For speech recognition, we use the Speech framework of Swift under the iOS platform. And we have prepared a dictionary of synonyms. Words with the same meaning as Yes will also be detected, and the status of "Voice recognition: Yes" will be changed to TRUE.

Table 5.3: *Some sensors and their states used in the fall confirmation system. The number in parentheses after the sensor represents the sensor number; the number in parentheses after the status represents the status number. These two sets of numbers are used in the scenario editor*

Information	State 1	State 2
Vibration (70)	Active (1)	Fall (2)
Voice recognition: Yes (200)	TURE (1)	FALSE (2)
Timer (100)	$>$ 20 s (1)	$>$ 40 s (2)

When we have prepared all the dialogs and planned which sensors to use in this service, we can start to make the transition table for the status confirmation service. In Table. 5.4, we show the transition rules in logical language. And Fig. 5.17 shows the transition rule set actually used to control this process on the iPad APP.

When we upload the dialog and transition to the cloud server by just clicking "Update" on the iPad), and ensure that all the sensors that need to be used in this service are correctly connected to the network, this service can be used.

Fig. 5.18 shows the actual operation of the system after the "Status Confirmation Service" is installed. When the participant fell from the bed to the floor, the robot confirmed it. Since no feedback was received within 40 seconds, the robot sent an alert to the caregiver's mobile phone.

Table 5.4: *Transition table for fall confirmation system*

Dialog Old	Dialog Next	Situation
NULL	(0,0,0)	vibration = fall
(0,0,0)	(0,1,0)	vibration = active or voice recognition = yes
(0,1,0)	(0,1,1)	//
(0,1,1)	(0,2,0)	timer $>$ 20 s
(0,2,0)	(0,3,0)	timer $>$ 40 s

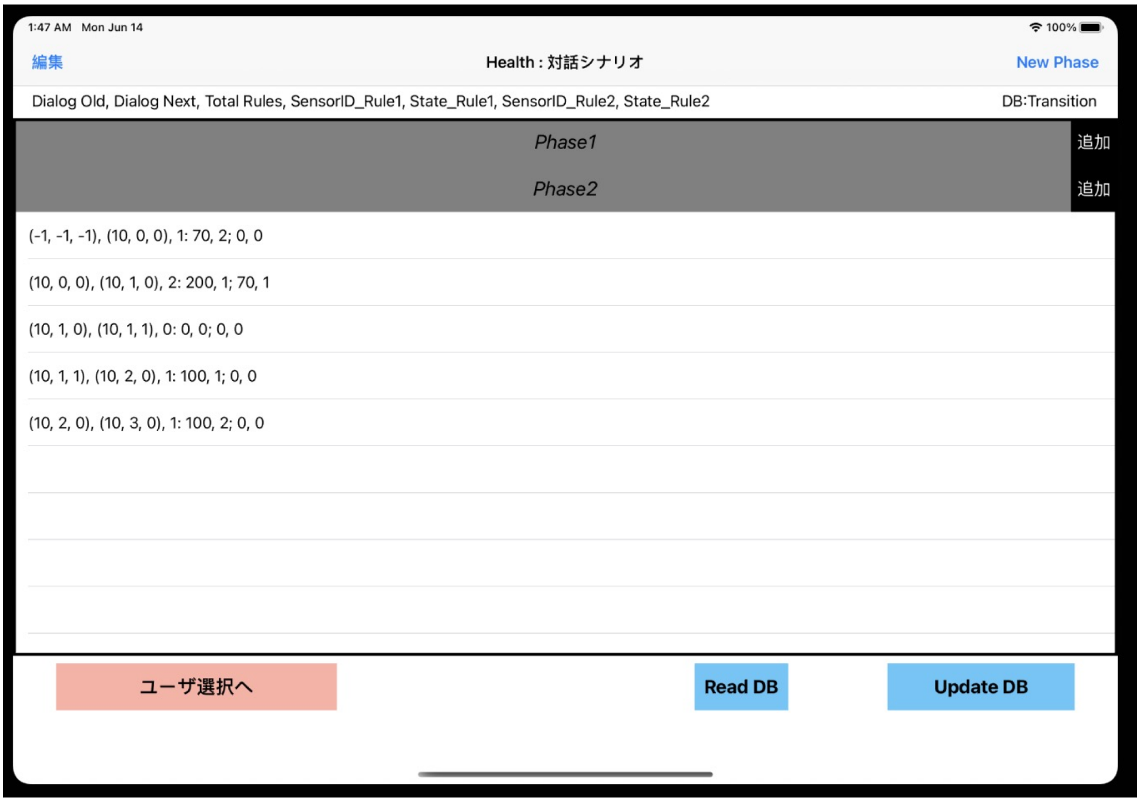


Figure 5.17: *All transitions can be check and edit on the scenario editor APP*

Figure 5.18: *The robot can correctly issue an fall alarm based on sensor information*

5.5.3 Experiment of Scenario Editor

In this experiment, we will demonstrate the usability of the system. Specifically, in this experiment, a participant (20s Female) unfamiliar with robot technology (RT) and information and communication technology (ICT) joins and uses the scenario editor on the iPad to create a healthcare function.

After 30 minutes of learning, the participants initially mastered the usage of the scenario editor and decided to create a function to encourage users to exercise. Fig. 5.19 shows the specific content and branches of this function in the form of a logical block diagram. When the system finds that the user has not been out until the afternoon, it will recommend physical activities suitable for the user according to the weather of the day, the user's physical condition, and the user's wishes. This diagram was not drawn by the participant, and there is no need to draw a similar block diagram when actually creating it.

Fig. 5.20 and Fig. 5.21 show the two database completed by the participant. It took 1 hour and 50 minutes to complete this function.

Table. 5.5 shows three different scenarios, the system can change the content of the dialogue according to the specific situation.

The specific dialogue content of case 1:

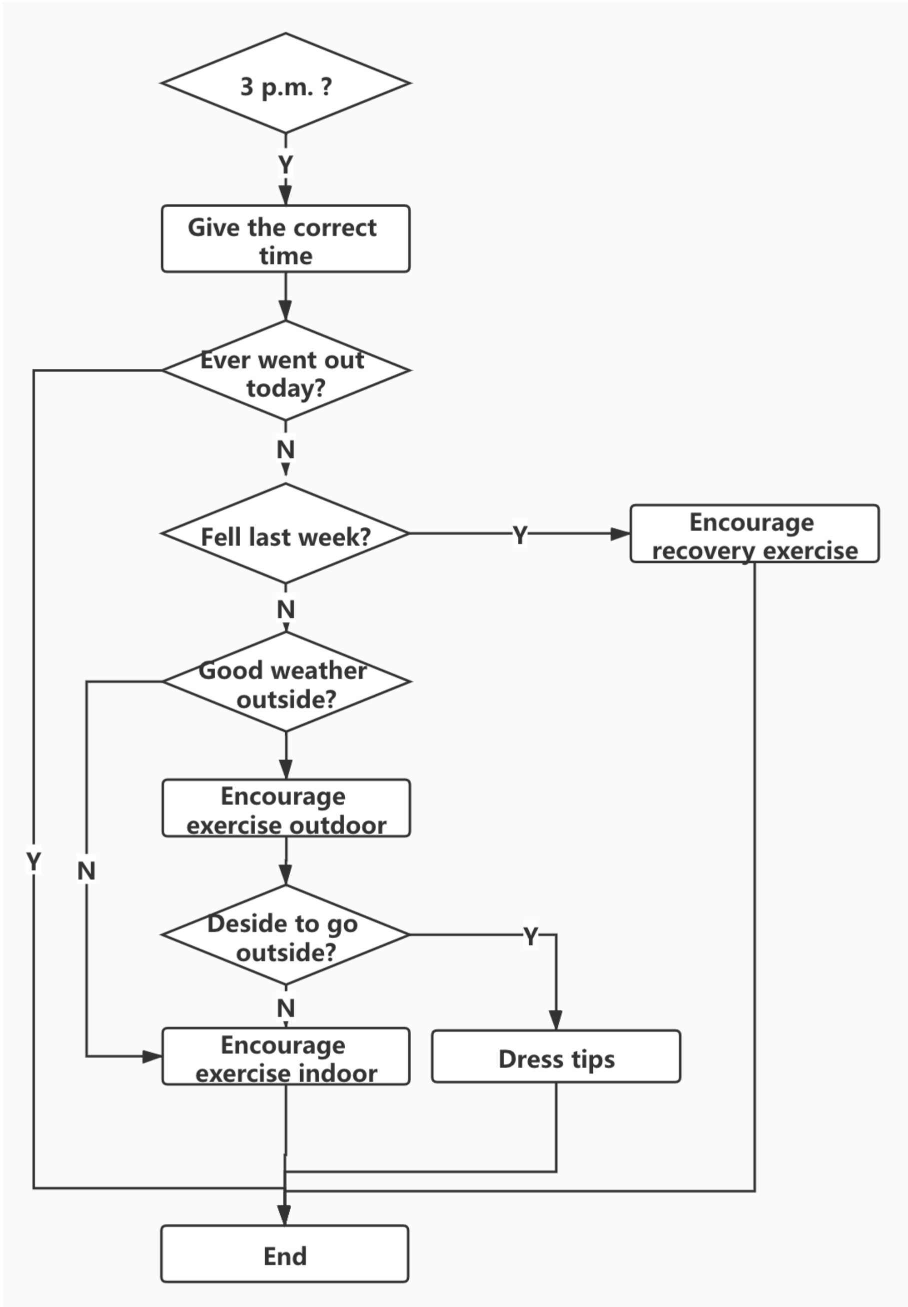


Figure 5.19: *Physical activity encouragement service created by the participant*

Table 5.5: *Encouragement of activities in three different situations*

Case1		**Case2**		**Case3**	
Leave home	no	Leave home	no	Leave home	no
Fell last week	> 0	Fell last week	0	Fell last week	0
		Weather outside	bad	Weather outside	good
		Air conditioner	on	Sleep status	bad

PhaID	SecID	ScenaID	SenID	Device_ID	Content
50	0	0	0	71	Good afternoon! It is 3 o'clock.
50	0	1	0	71	Do you want to turn on the lights?
50	0	2	0	71	OK. Lights on.
50	0	3	0	71	OK. You can ask me to do that whenever you want.
51	0	0	0	71	Hi, good afternoon!
51	0	1	0	71	I find you haven't gone out of the house whole da...
51	2	0	0	71	Would you like to take a walk?
51	1	0	0	71	Would you like to do some exercise at home?
51	1	1	0	71	Great! Exercise is good for you!
51	1	1	1	71	OK. Here I recommend some simple exercises you can...
51	1	1	2	71	These exercises are for seniors to improve stren...
51	3	0	0	71	Okay, it's fine. But sitting for too long is not g...
51	3	0	1	71	You may stand up and stretch yourself.
10	1	1	0	71	OK. Let's take a walk!
10	1	1	1	71	I just check the temperture outside. You should be...
52	2	0	0	71	OK.You can ask me to do that whenever you want to ...
1	0	0	0	71	Is there anything else that I can help you?
1	0	1	1	71	OK. Have a good day!
1	0	1	2	71	Got it. Call me when you want
30	0	0	0	71	Your air conditioner is on.
30	0	0	1	71	I suggest you turn it off when you do the exercise...
30	0	0	2	71	OK. I will turn it off.
18	0	0	0	71	You fall once last week. I don't recommend you to ...
18	0	0	1	71	It's good to just get up and have a radio gymnasti...
18	1	0	0	71	You seem didn't have a good sleep yesterday.

Figure 5.20: *Dialogue database created by the participant*

PhaID_Old	SecID_Old	ScenaID_Old	PhaID_Next	SecID_Next	ScenaID_Next	Total_Rules	Item_Rule1	Value_Rule1	Item_Rule2	Value_Rule2
0	0	0	51	0	0	1	time	15	0	0
51	0	0	51	0	1	1	leave house	0	0	0
0	0	0	51	0	0	1	time	15	0	0
51	0	0	51	0	1	1	leave house	0	0	0
51	0	1	18	0	0	1	fall time last week	1	0	0
18	0	0	0	0	0	0	0	0	0	0
51	0	1	51	2	0	2	fall time last week	0	weather	1
51	0	1	51	1	0	2	fall time last week	0	weather	2
51	2	0	10	1	1	1	voice: YES	1	0	0
51	2	0	51	1	0	1	voice: NO	1	0	0
51	1	0	51	1	1	1	voice: YES	1	0	0
51	1	0	1	0	1	1	voice: NO	1	0	0
51	1	1	30	0	0	1	air conditioner	1	0	0
30	0	0	0	0	0	0	0	0	0	0
1	0	1	18	1	0	1	sleeping status	3	0	0
18	1	0	0	0	0	0	0	0	0	0

Figure 5.21: *Transition database created by the participant*

Robot:	Hi, good afternoon!
Human:	Hi, good afternoon!
Robot:	I find you haven't gone out of the house whole day.
Human:	It is a busy day.
Robot:	You fall once last week. I don't recommend you exercise vigorously. But it's good to just get up and have a radio gymnastics.
Human:	Thank you for you advise.

In this case, the system detects that the user's exercise is insufficient, but at the same time, according to the user information that the system has, it recognizes that the user was injured in the last week, so the system chooses to give milder exercise suggestions.

The specific dialogue content of case 2:

Robot:	Hi, good afternoon!
Human:	Hi, how are you!
Robot:	I find you haven't gone out of the house whole day.
Human:	Yes, you are right.
Robot:	Would you like to do some exercise at home?
Human:	Id love to! Any advice?
Robot:	Great! Exercise is good for you! Here I recommend some simple exercises you can do at home. These exercises are for seniors to improve strength and balance.
Human:	Thank you.
Robot:	Your air conditioner is on. I suggest you turn it off when you do the exercise.
Human:	Can you turn it off?
Robot:	OK. I will turn it off. (Turn off the air conditioner)

In this case, the system detects that the user is not exercising enough, and after checking the weather, it is found that it is not suitable for outdoor sports, so it is recommended that the user perform broadcast gymnastics. It also gives suggestions on suitable gymnastics types. Furthermore, the system finds that the temperature in the room is low, so it is recommended that the user turn off the air conditioner before exercising. After obtaining the user's consent, the system controls the smart switch via API to turn off the air conditioner.

The specific dialogue content of case 3:

Robot:	Hi, good afternoon!
Human:	Hi!
Robot:	I find you haven't gone out of the house whole day.
Human:	Yes.
Robot:	Do you want to go outside?
Human:	No.
Robot:	Would you like to do some exercise at home?
Human:	No, I dont think so.
Robot:	You seem didn't have a good sleep yesterday. Maybe you can exercise a little to help improve the quality of sleep.
Human:	Maybe you are right.

In this case, the system detects that the user is not exercising enough and gives suggestions for outdoor sports. Through voice recognition, a reply was received that the user did not want to go out, and the system instead suggested that the user exercise at home. After the user refused again, the system called the user's physiological information and found that the user's sleep quality was poor, so it gave a suggestion that "appropriate exercise helps sleep."

5.6 Discussion

After the experiment, participants gave a report on the experience with the scenario editor:

Positive:

- From the perspective of caregiver, the scenario editor can meet the needs for service customization.
- The scenario editor provides a wealth of preset scenes, which can cater for the physical and spiritual needs of the elderly.
- By using the scenario editor, caregiver's sense of participation is improved, and the regret of not being able to be with the elderly is greatly reduced.
- No technical difficulties were encountered during use.

Negative:

- The interface of the APP should be more friendly and easy to use.
- The corpus should be more complete and richer. No manual input needs will be great.
- It is difficult for the elderly themselves to customize services.

Based on the above evaluation, it can be concluded that the scenario editor does allow a better definitive service function without technical staff. But its operation must be further simplified. Although it is natural to number the dialogs or sensors in the system, it is equally difficult to understand for the average person, who would like to see a literal representation rather than a number with no real meaning.

5.7 Improvement and Future Work

n order to make the system simpler for the average person to use, and to allow users to use it under different platforms. I further developed a Python-based scenario editor shown in Fig. 5.22. In this version, the user no longer has to memorize the sensor numbers, but can select them from a drop-down menu as lower in Fig. 5.22.

In the future I will continue to improve this work and communicate with actual health care workers for further experiments.

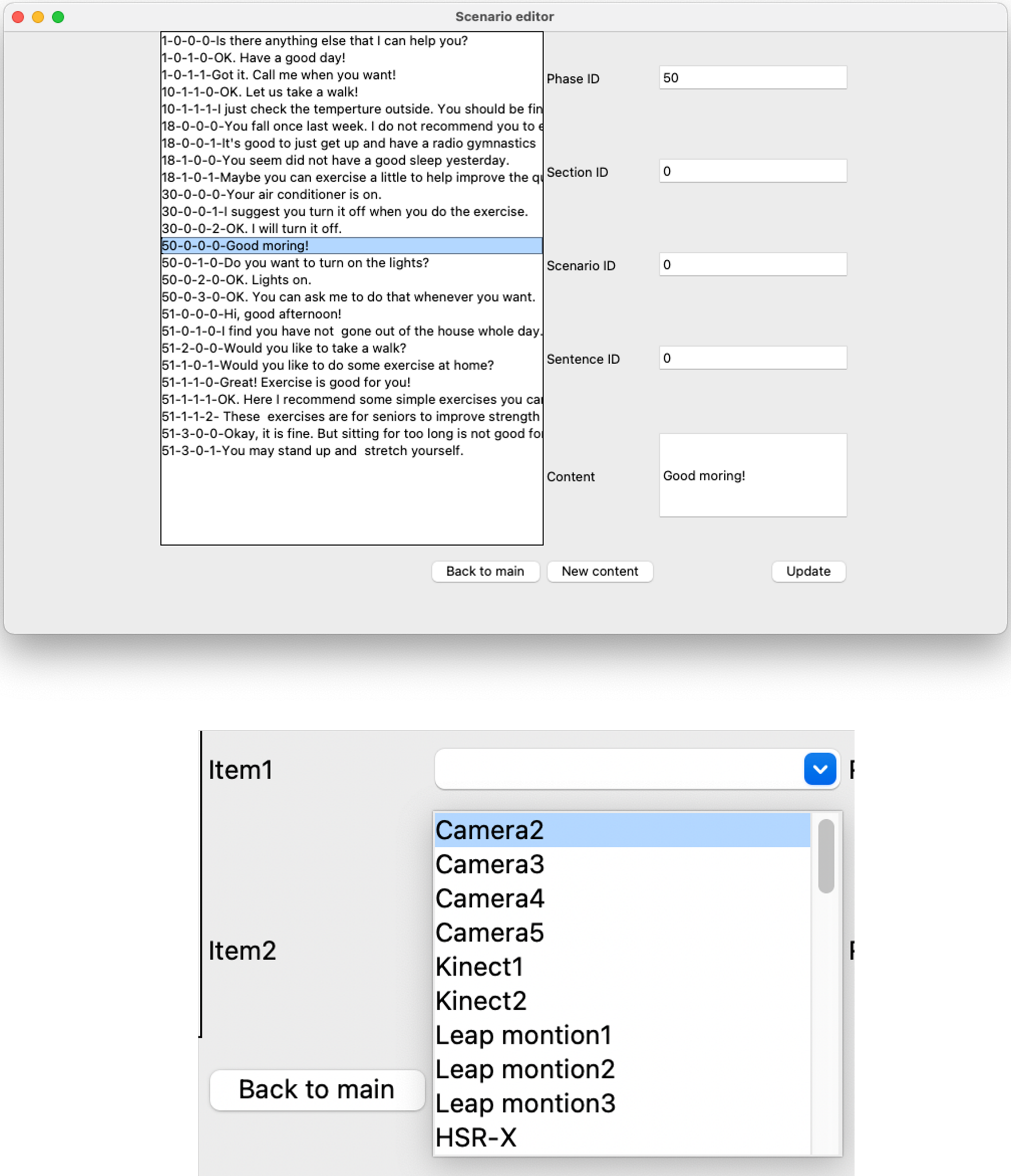


Figure 5.22: *Scenario editor(Python version)*

Chapter 6

Conclusions

6.1 Concluding Remarks

In this article, I clarified the research goals of this thesis based on the development status and expected functions of smart home. I clarified the characteristics of a healthcare system that was convenient for the elderly:

1. Considering the privacy of the elderly who use the system and not giving a burden.
2. The introduction cost should not prevents the spread of the system.
3. Easy to operate for both elderly and caregivers.

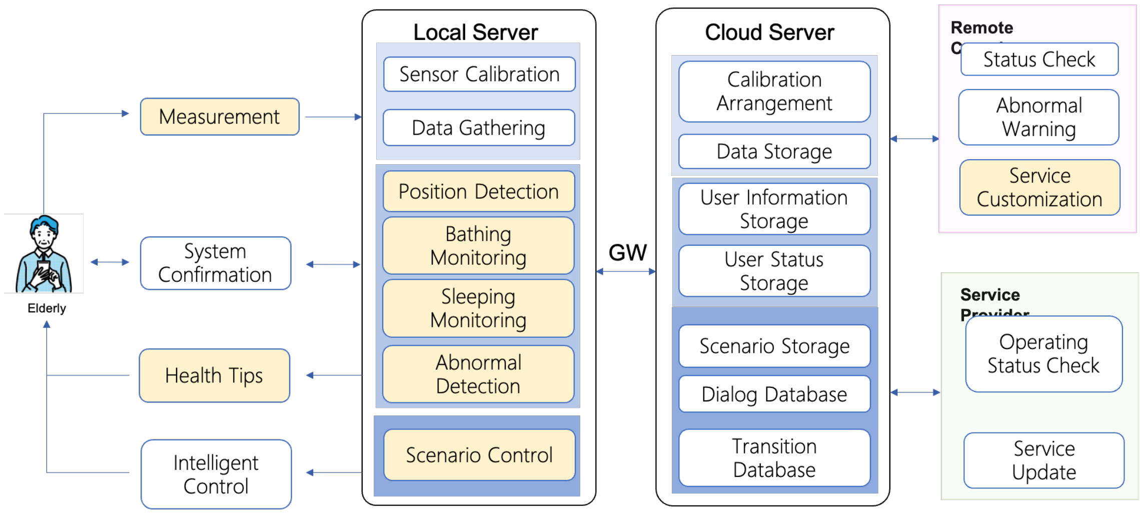


Figure 6.1: *main research and development in SHHCP*

Based on the above point of view, I proposed SHHCP (Fig. 6.1) and completed the design and development of several main modules. To clarify the design guidelines, I discuss the healthcare system platform defined by three layers: the measurement layer, the analysis layer, and the service layer. Next, I define the function and structure of each layer. The measurement layer is used for obtaining sensor data and perform basic processing; the analysis layer is used for user behavior analysis, and the service layer is used for providing services through service robots and smart devices.

(1) In the measurement layer, the sensors used for indoor behavior estimation were classified into short-term behavior estimation sensors and medium-term behavior estimation sensors, and sensors for smart homes were systematized. I proposed an autocorrelation neural network for short-term behavior estimation. Next, in order to perform medium-term behavior estimation, I proposed a methodology for multi-sensor fusion that complementarily integrates multiple different sensors using a spiking neural network. Through experiments on bathrooms, living rooms, bedrooms, etc., it was shown that monitoring and behavior estimation can be performed efficiently.

(2) In the analysis layer, I proposed a method of personalizing by reflecting the user's life log and living environment information. First, construct a fuzzy inference system for environmental adaptation based on data obtained in various living environments, and relearn the behavior estimation system in the measurement layer by performing fuzzy inference in the analysis layer from the experimental results. It was shown that it can be adapted to various environments and different users.

(3) In the service layer, I built a smart home platform using a local scenario controller that cooperates with a cloud server in real time. Experiments using various scenarios have shown that health care content is selected according to the measurement results of various devices connected to the user's current state, and that health care services can be provided through smart devices and robot partners. In addition, in order to reduce the technical difficulty related to customization, I constructed a scenario content editor using a smart device, and from the experimental results, I showed that the healthcare service can be easily edited.

6.2 Future Works

In order to better complete the SHHCP, my future work is divided into short-term and long-term parts.

Short-term future works:

(1) Field experiment of the platform in the home of the elderly living alone. Covid-19 seriously delayed this part of the work. I plan to restart field experiments after the epidemic is under control.

(2) After obtaining more data through (1), I will further complete the construction of fuzzy rule sets. I hope to be able to build several standard home models.

(3) I will further improve the scenario editor and improve its ease of use. And invite more participants to conduct functional tests.

(4) I plan to seek cooperate with medical professionals to complete a more scientific health tips system.

Long-term future works:

(1) In the long run, one of the goals of this research is to reduce the cost of smart home. This enables smart homes to better serve the elderly, and allows more families with insufficient funds to use smart home care systems.

(2) On the other hand, I hope to lower the threshold for medical workers to join in the development of smart home functions. Only when professional medical personnel are willing and able to join the work, can we design a more targeted and scientific healthcare support system. I wish to facilitate in-depth cooperation between the medical field and enterprises, which is the core of HaaS.

[84] [56] [57] [54] [49] [50] [55] [106] [53] [66] [107] [45] [83]

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