Doctor of Philosophy

Extraction and Measurement of Living Alone Elderly's Daily Activity Routines for Healthcare using Non-intrusive Sensing

February 2019

Department of Architecture & Architectural Engineering
The Graduate School
Seoul National University

Bogyeong Lee

Abstract

Extraction and Measurement of Living Alone Elderly's Daily Activity Routines for Healthcare using Non-intrusive Sensing

Bogyeong Lee
Department of Architecture & Architectural Engineering
The Graduate School
Seoul National University

The growth in the number of single-member households is a critical issue worldwide, especially among the elderly. For those living alone, who may be unaware of their health status or routines that could improve their health, a continuous healthcare monitoring system could provide valuable feedback. Assessing the performance adequacy of activities of daily living (ADL) can serve as a measure of an individual's health status; previous research has focused on determining a person's daily activities and extracting the most frequently performed behavioral patterns using camera recordings or wearable sensing techniques.

However, the existing methods used to detect and extract common patterns of an occupant's activities in the home fail to address the spatio-temporal dimensions of human activities simultaneously and guarantee from privacy concerns. Though it is important to assess the ADL routines of the elderly for early diagnosis of the geriatric disorders, it has rarely investigated to develop methods for assessing the variability of ADL routine, which can present the occupant's health status.

This research proposes a model for detecting the ADL and a method to extract the ADL routine from a cumulative spatio-temporal log by using the non-intrusive sensing techniques (i.e., a tomographic motion detection system). Also, a method to quantify and assess the variability of ADL routines is developed, which provides a basis for detecting abrupt of gradual change of an occupant's ADL routines the result from a mental disorder.

The findings and extracted routines from the experiment collecting 60 days of spatio-temporal log of the elder subject demonstrate the capacity of the proposed approach to extract the ADL routine and reveal the variability of the ADL routine in terms of quantified the irregularity and the abnormality.

This research can offer valuable information for home-automated healthcare applications by enabling the assessment of the variability of ADL routines. In addition, the results of this research show a possibility of extracting and assessing the living alone elderly's ADL routine using coarse-grained data (i.e., the spatio-temporal log) with little infringement of personal

privacy. The achievements of this research contribute to a part of the welfare of the elderly living alone by improving their quality of daily life and providing a warning for the high variability of the ADL routines which is recommended seeing a doctor for an early diagnosis of geriatric disorders.

Keywords: Activities of Daily Living (ADL); Multiple Sequence Alignment (MSA); Routine Variability; Non-intrusive Sensing; Geriatrics; Smart-home

Student Number: 2014-30186

Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Research Background

The rapid increase of single-person households, especially the elderly living alone, is a critical issue worldwide because those elderly who live alone may be unaware of and have difficulty coping with their health issues. A degenerative mental disease such as dementia is a major cognitive geriatric disorder requiring long-term treatment, and it is expected to increase social cost for treatments with aging trends. To reduce the social cost for geriatric disease, an effort should be made to early diagnosis of cognitive disorders.

This leads to an increasing demand for automated health monitoring systems using sensor-based techniques, such as recording video or collecting physiological data using wearable sensors. However, these techniques raise privacy concerns due to collecting excessive personal data. Although the existing intrusive sensing approach has the advantages of detecting a short-term activity presented as a posture (e.g., walking, sitting, running etc.) of the occupant easily, it is difficult to detect activities with behavioral contexts such as the relations between the consecutive activities. Also, the disadvantages are significant to the elderly for wearing additional devices,

such as causing discomfort or inconvenience which reduce the quality of life (Lee et al. 2015; Zhang et al. 2016; Galinina et al. 2018). It is necessary to develop a method to extract and monitor the ADL even the occupant does not wear the additional devices.

Being able to track and analyze the Activities of Daily Living (ADL) routines in less intrusive manners (e.g., tracking occupancy patterns in home using motion sensors) is considered as an attractive alternative since it is possible to collect data from the occupant's environment, such as the spatio-temporal data of when and where the space is occupied by the occupant, rather than the occupant's physiological data.

ADL refers to activities carried out on a daily basis to maintain a person’s own conditions, such as bathing, dressing, going to the toilet, and eating. The degree of how consistent the elderly perform his/her ADL can act as a measure of health, especially for elderly health (Katz 1963). A rapid or gradual change of ADL routines can indicate a change in physical or mental health (Blankevoort et al., 2010; Urwyler et al., 2017). For applying the theory to the smart-home healthcare, an occupant's ADL routines should be extracted to assess the adequacy of performing the ADL and to monitor the health status of the living alone elderly by using non-intrusive sensing techniques. From the tracking and analyzing the variability of ADL routines,

a cognitive disease such as dementia can be detected at a very early stage where a traditional test cannot determine whether the disease exists or not. When the high variability of ADL routines are detected using non-intrusive approach, it can be informed to the elder of his/her trends of the ADL routine variability and contribute to reducing the social and individual burden by improving the self-healthcare capacity.

1.2 Problem Description

The delayed diagnosis of geriatric cognitive diseases for the elderly living alone can be a cause of increasing the social burden since the cost for long-term treatment is usually required to both the individual and members of society. Improving the quality of the daily life of the elderly living alone and continuing their health status can lead to continuous social participation of the elderly so that it directly affects reducing the social costs of an aging society.

For proactive diagnosis of geriatric cognitive diseases, the ADL routines as variability changes as a non-intrusive approach can be assessed for a long-term stable monitoring. Although the existing intrusive sensing approach can directly sense the physiological status, the ADL variability in terms of spatio-temporal context cannot be detected in a convenient way.

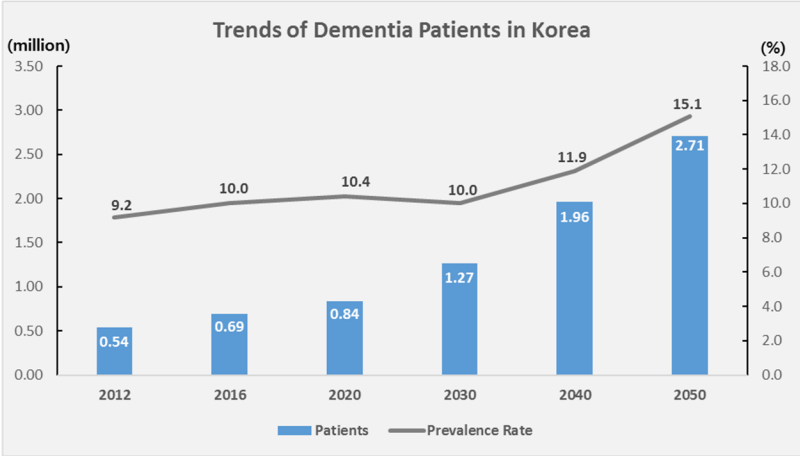


Figure 1.1 Increasing Trends of Geriatric Patients (Demetia) in Korea (adpated from (Kim et al. 2016))

Despite its significance, it is difficult to detect the ADL by using the non-intrusive sensors as accurate as the existing intrusive sensors without manual analysis. In addition, extracting the routines of human activities including the occupant's ADL routines is still quite challenging. Since human activity daily data logs are usually massive and multi-dimensional (i.e. agent performing an activity, location and time an activity occurs, causal relationship among activities, etc.), it is difficult to extract the common patterns quantitatively (Wilson 1998). Data from the routines of human activities should contain the activities' details, such as order, duration, and behavioral context (i.e., causal relationships between situations and activities) (Banovic et al. 2016; Davidoff et al. 2010).

Due the limited information available from the spatio-temporal log, it is difficult to assess the ADL routines as finding whether the occupant has maintained their own patterns of daily living normally. Therefore, it is required to develop metrics, which can show the degree of the change of the ADL routines as a quantitative value using the spatio-temporal log from the non-intrusive sensors to compare and assess the ADL routine variability.

1.3 Research Objectives and Scope

The goal of this research is to investigate the feasibility of assessing the ADL routines of living alone elderly for healthcare using the non-intrusive sensing techniques. To achieve this goal, specific objectives are conducted as follows.

This research introduces and validates the feasibility of a method detecting the ADL by using the cumulative spatio-temporal log from the non-intrusive sensors. As a framework for processing the spatio-temporal log, a model is developed as contextualization for automatically extracting the performed activities by using information of ADL-relevant spaces and instruments.

Based on the detected activities from the spatio-temporal log, this

research proposes an approach to extract a single occupant's ADL routines at home considering spatio-temporal dimensions simultaneously. The Multiple Sequence Alignment (MSA) is used for identifying an occupant's ADL routines at home and examining how the results of MSA can be interpreted in evaluating the adequacy of the ADL.

Finally, the metrics for quantifying and assessing the extracted ADL routine in aspects of the variability is developed, which shows the irregularity and abnormality of the ADL routines.

The ADL detected and extracted through the process of this research are follows the definition of general ADL performed in the residential space, such as bathing, toileting, sleeping, dressing, having and preparing meals, maintaining the status of the space, etc. In addition, the activities, which do not directly influence the health status, such as watching TV, using PC, are included as the ADL being assessed as routines.

The non-intrusive sensors applied in this research is a motion detecting system which can sense and record the time and locations of motion.

1.4 Dissertation Outline

To address the difficulties of assessing the ADL routines as a measure of health status by using the non-intrusive sensing techniques, this research aims to develop an approach to extract and assess the ADL routines. Figure 1.2 describes the process of this research to achieve the research objectives introduced above. The dissertation begins with the introduction describing the importance and necessity of continuous monitoring of the health status from the increase of the elderly living alone as research background. After explaining the challenging issues of non-intrusive sensing for extracting and assessing the ADL routines in aspects of methodologies, the ultimate goal and specified objectives are introduced.

In Chapter 2, several theories and concepts referred in this research and previous research efforts related to this research are explained and analyzed the limitations to overcome and differentiation from the existing research.

In detail, the definition of ADL and the importance of tracking and analyzing the adequacy of ADL are explained as a necessity of this research. Introducing the concept of the variability of human activity, the variability of the ADL routines addressed in this research is explained in terms of representing the health status. The non-intrusive sensing techniques which

are one of the biggest challenges of this research is explained and the reason why this techniques should be applied as an alternative for smart-home healthcare. After describing each definition and relations between the spatio-temporal log and the ADL, related methodologies applied to this research are introduced for extracting the ADL routines and quantifying and assessing the ADL routine variability.

In Chapter 3, the activity contextualization process from the spatio-temporal log introduced in chapter 2 is applied to detect the ADL by using the non-intrusive motion sensors. The results of the test experiment are described showing the total process from how to install the sensors in experimental space to analyzing the findings and implications.

In Chapter 4, the method to extract the ADL routines from the detected daily ADL based on chapter 3 is introduced the MSA comprehensively applied the two types of alignment. The process and results of the experiment for extracting the ADL routines of the subject are described and it is explained the advantages of applying the MSA from the validations comparing with existing methods to extract the common pattern.

In Chapter 5, the concepts required to quantify and assess the extracted the ADL routines are defined and the metrics reflecting the concepts are

developed. For using the spatio-temporal log as a quantitative value, the method of finding an activity from the sequential information of extracted activities are explained with example cases. To assess the ADL routines in terms of variability, the process is described how to calculate the irregularity of ADL during a certain period as a cluster analysis and how to find abnormal activities from the categories defined as spatio-temporal context disassociation cases of activities. From the collected data of conducted experiments, the validities of developed metrics are addressed by comparing the results of the two experimental subjects, which can reflect the differences in the variability of the ADL.

In Chapter 6, the research and experiments' implications conducted in previous chapters are described as discussion. The expected applications from the results of this research are presented in aspects of construction and healthcare.

In Chapter 7 as conclusions, the research results which can contribute to the body of knowledge in the field of construction as a designing for smart-space are described. This dissertation ends with explaining limitations this research has not overcome and future research plan for addressing them.

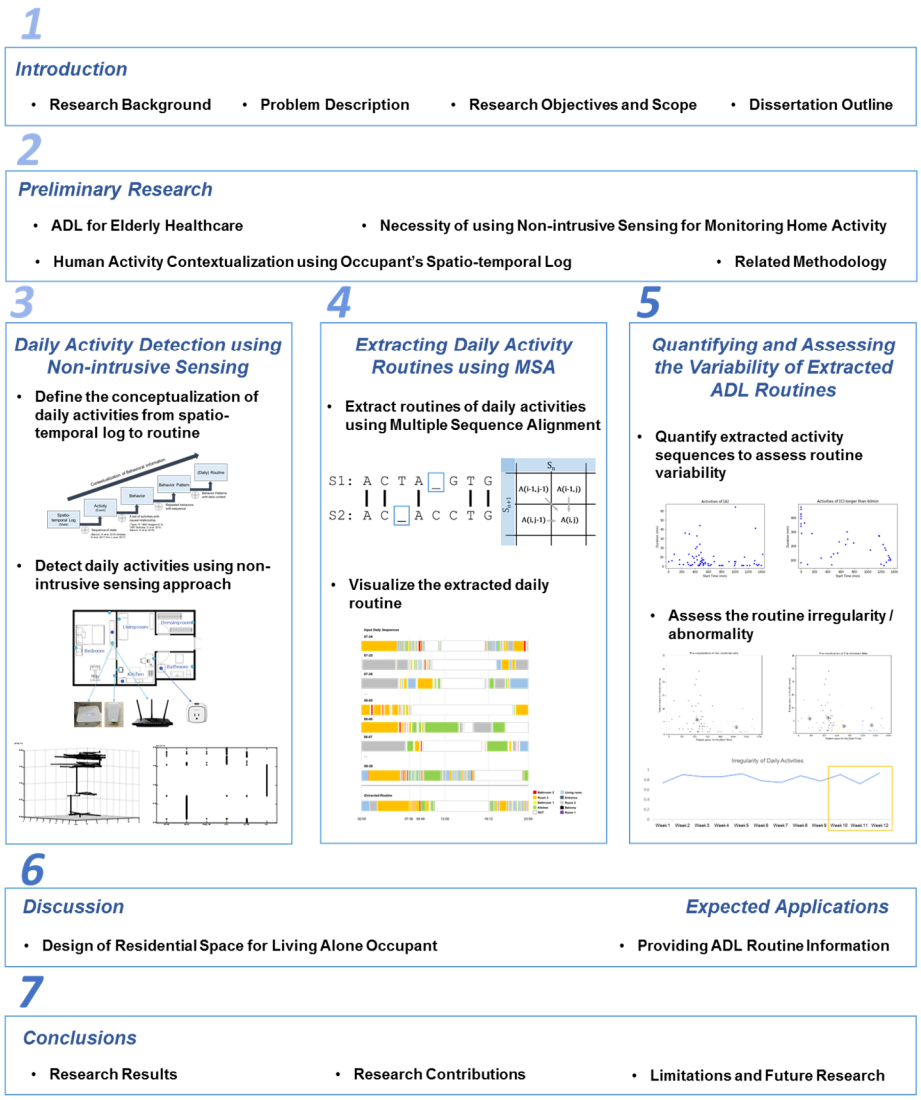


Figure 1.2 Dissertation Outline

Chapter 2. Preliminary Research

This chapter identifies why tracking and analyzing the ADL routines of the elderly using non-intrusive sensing approach (e.g., tomographic motion detecting system) is important for elderly healthcare issues. The definition of ADL and the concept of ADL routine variability used in this research is introduced to assess the results in aspects of health. Based on the necessity of using non-intrusive sensing for monitoring the ADL, the existing sensing techniques and their challenging issues are described. After introducing the sensing techniques used in this research, the conceptual relation among the used data (e.g., spatio-temporal log, activity, routine) is addressed for the ADL data analysis. Finally, the relevant methodologies used to extract the ADL routines and assess their variability are introduced in terms of how they applied in the following research.

2.1 Activities of Daily Living (ADL) for Elderly Healthcare

2.1.1 Definitions of ADL

The ADL refers to basic activities to care for oneself and they usually include bathing, toileting, dressing and activities related to eating despite there are various classifications according to the level of performance (Katz

1963; Nouri and Lincoln 1987; Covinsky et al. 2003; Roehrig et al. 2007).

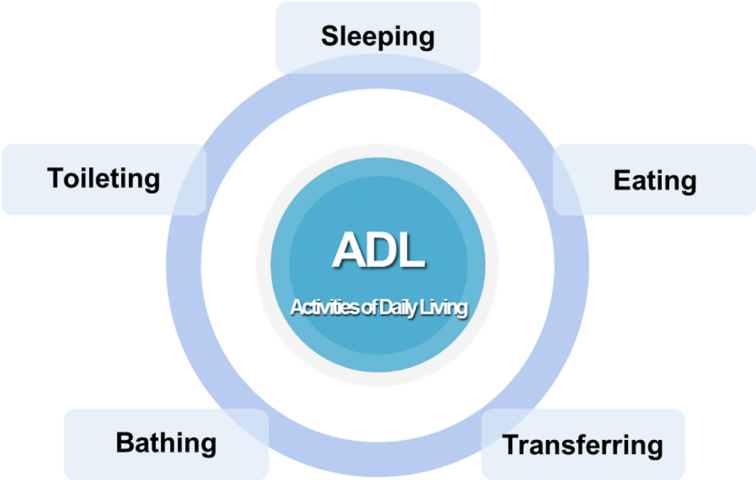


Figure 2.1 Definition of Activities of Daily Livng

In addition to the Figure 2.1, the activities performed using tools are referred to Instrumental Activities of Daily Living (IADL), which includes more complex activities (i.e., financial management, cooking, purchasing, traveling, keeping a home environment, taking medicine, etc.) than the basic ADL (Lawton and Brody 1969; Fillenbaum et al. 1978). Though the IADL also can be included in a wide range of ADL, this research mainly focuses on the basic ADL other than IADL.

2.1.2 The Importance of Tracking and Analyzing the Adequacy of ADL

Since the assessing an ability to perform the ADL can be a measure to diagnose the health status of the elderly, tracking and monitoring the ADL of the elderly raises as an important thing in the health field (Katz 1963). The adequacy of how well the ADL are performed can be defined as three parts; 1) independence, 2) functionality, 3) consistency of ADL (Nouri and Lincoln 1987; Covinsky et al. 2003; Roehrig et al. 2007).

1) The independence of performing ADL

: The healthy elderly should be able to perform ADL independently without any others' supervision or active assistance. It is based on the actual status other than the ability, thus, the patient who has the ability to perform but refuses it is considered he/she does not have independence. The degree of independence is classified according to the level of required assistance (i.e., all ADL can be performed completely independently, only a part of ADL can be performed independently or all ADL performance needs someone's help) (Katz 1963).

2) The functionality of performed ADL

: The ADL should be performed as their original intent in right time and

right place. The poor functionality of ADL presents as an abnormality, which means the disassociation between the activity and its space-time. The disassociation between the activity and its time means the activity is performed at a time other than when it should normally occur (e.g., having a meal in the middle of the night). Another disassociation between the activity and its space means the activity is performed in a space other than where it should normally occur (e.g., sleeping in a kitchen or bathroom).

3) The consistency of performing ADL

: The healthy elderly has his/her own consistent pattern of ADL. The ADL are usually performed repetitively within certain routines except for abnormal events. Especially for the elderly, they spend most of the day in their residential space (i.e., home) and their own ADL performance shows a pattern matches with the characteristics of the individual. Maintaining their own pattern of ADL performance is closely related to the individual's health status.

The ADL pattern includes an order, duration, time and space of performed activities. The order of activities might differ depending on the level of ADL details, for example, someone might always wash his/her hands in the bathroom right after coming back home and change clothes in the dressing room. These three activities performed sequentially can be considered as one of the ADL patterns. How much time takes performing an

activity can also be a measure of pattern consistency. For example, if someone spends 30 minutes in a bathroom for taking a shower and it increases to one or two hours, it can be a signal of pattern change. When the time and space of ADL performance changes, the pattern consistency may be deteriorated. The spatio-temporal context change means that the situation differs from the time and space of the ADL usually performed. The cause of the pattern change can be analyzed to determine whether the abnormal activity occurs or not.

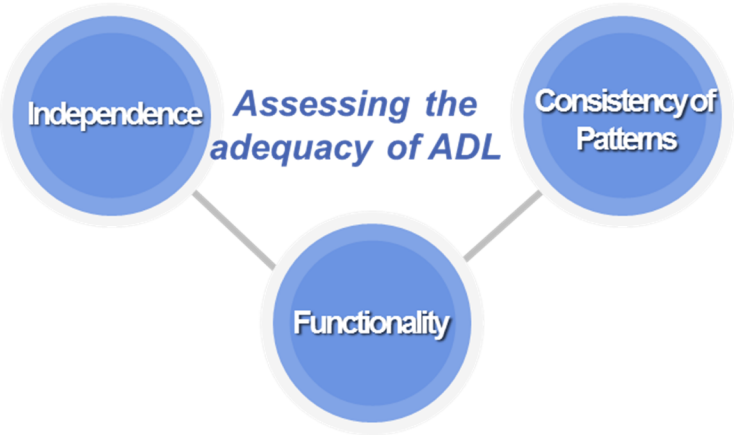


Figure 2.2 Three Parts of Assessing the Adequacy of ADL

In a traditional way, there are two methods to identify the ADL of elderly; 1) direct observation by human effort, 2) questionnaire to the subject or caregiver.

1) Direct observation by human effort

A subject should be observed as day-to-day and collected all his/her daily living information for monitoring ADL performance. A third party engaged with the elderly (i.e., family member, caregiver) can assess the adequacy of ADL performance and take measures such as receiving a diagnosis from a hospital when a certain deterioration is detected. For the case of the elderly who are living alone, a social worker can visit the elderly's house to observe and record the situation at that time. However, it is difficult to grasp the ADL performance completely since the above method only allows temporary observation at the time of visit. To complement this, there is a method to ask directly to the elderly using questionnaire.

2) Questionnaire to the subject or caregiver

Though the most frequently used method is to directly ask the subject whether he/she can perform the ADL independently using questionnaire, it is difficult to grasp the functionality and pattern consistency of ADL performance. There are various questionnaires for assessing the ADL performance and the items in Figure 2.3 is the most frequently used. A weighting is given depending on the types of ADL and the age of the subject so that the results can be quantified. The simple ADL, the IADL which uses the instruments when performing, or complex ADL which requires interactions with the external environment, are classified and used to measure

and score the mental health status of the subject. When the questionnaire gets higher than a certain score, it can be used as a signal of the early stage of the disease related to cognitive impairment, and advanced tests can be conducted to diagnose the disease.

General Activities of Daily Living Scale (GADL)			Score
ADLs Self-care ___/10	1	The patient is able to choose and change clothes (dress and undress) by himself/herself.	
	2	The patient is able to make his/her way to the toilet, undress, clean him/herself properly, and dress again.	
	3	The patient is able to use the shower, soap, and bath sponge properly.	
	4	The patient is able to transfer from his/her bed or chair unaided.	
	5	The patient is able to feed himself/herself with tableware.	
ADLs Domestic ___/8 Cutoff for age > 74 (7/8)	6	The patient is able to do minor household chores.	
	7	The patient is able to use the telephone (make and receive calls).	
	8	The patient is able to prepare his/her own meals.	
	9	The patient is able to do his/her own washing and ironing.	
ADLs Complex /8 Cutoff for age < 74 (6/7) Cutoff for age > 74 (6/7)	10	The patient is able to manage his/her own money or financial matters.	
	11	The patient is able to run simple errands by himself/herself.	
	12	The patient is able to take his/her medication at the correct dose and time by himself/herself.	
	13	The patient is able to go to distant places by himself/herself using some form of transportation.	
Global functioning = ADLs Self-care + ADLs Domestic + ADLs Complex Cutoff for age ≤ 74 (23/24) / Cutoff for age > 74 (23/24)			__/26

Independent (2 points): *performs the activities spontaneously, independently, without help or supervision from other persons or special equipment.* ***Partially dependent (1 point):*** *needs supervision, help, or special equipment to perform the activity safely and correctly.* ***Dependent (0 points):*** *needs constant help or supervision to perform the activity safely and correctly. The cutoffs are based on the distinction between amnestic mild cognitive impairment and mild Alzheimer's disease, and may not be valid for other comparisons. [www.labineurociencia.com].*

Figure 2.3 An Example of Direct Questionnaire (adapted from Paula et al. 2014)

The above methods to collect the ADL-relevant information has the following limitations. In the case of observation using human efforts, the objectivity of the collected information can be compromised due to the subjective judgment of the observer. There is also a clear limit of observation that it can collect only parts of the ADL even the objectivity can be guaranteed unless the observer can monitor the elderly continuously for 24

hours. Another method, using a direct questionnaire also has difficulty to collect accurate information since the answer depends on the subject's memory. In addition, there is a contradict that providing information about his/her own ADL is only possible when the subject's cognitive ability is healthy enough.

To address these issues, an alternative method which does not depend on human observation or memory, and be able to collect and record the ADL-relevant data is required. Using sensors to collect and assess the ADL-relevant data can improve the efficiency of monitoring of the elderly living alone as an alternative.

As the aging progresses, his/her physical and mental functionality may deteriorate and the above three types of ADL adequacy can be damaged. The senile diseases, such as dementia, stroke, other cognitive disorders, or geriatric depression have a high correlation with the lowered functionality and abrupt pattern consistency deterioration of ADL (Covinsky et al. 2003; Andersen et al. 2004; Urwyler et al. 2017). Especially, a gradual change of ADL pattern or performing abnormal activities might occur at the early stage of senile dementia (Ditzler 1991; Blankevoort et al. 2010). It is possible to detect the deterioration of ADL functionality and sudden pattern change and use it as a basis of early diagnosis of geriatric disease by monitoring the ADL regularly. Thus, it is important to monitor and assess the ADL performance

of the elderly on a regular basis to improve the efficiency of elderly healthcare.

2.1.3 Previous Methods for Extracting ADL Routines

Previous research has attempted to apply various pattern-mining techniques to extract patterns of human activities containing behavioral context (i.e. agent performing an activity, location and time an activity occurs, causal relationship among activities, etc.).

Since understanding human routines may improve quality of life (Banovic et al. 2016), identifying the patterns of space-use to predict customers' next locations (Shoval and Isaacson 2007) or regular routines of some groups of people (e.g., commuting activities of a family, pick-ups and drop-offs of drivers, etc.) (Davidoff et al. 2010; Ziebart et al. 2008) is emerging in numerous research fields. For example, utilizing mobile devices or sensors, previous research conducted tracking to find the movement patterns of customers in outdoor spaces (Guo et al., 2006; Lee et al., 2016). The space paths most subjects generally pass by can be identified through clustering all the trajectory coordinates (Qi and Du, 2013; Romero, 2011). Because location provides contextual information about human activities (Roy et al. 2007), using it to extract and predict the most frequent paths is

typical.

While these methods can easily find the order of each location (i.e., path), they also have limitations. It is difficult to extract the contextual meaning of identified routines in terms of temporal dimension (e.g., the start-finish time, duration, daily frequency of activities), which is essential for assessing the adequacy of human activities or ADL routines for elderly healthcare. Furthermore, previous research focused more on human activities performed outdoors (e.g., movement of tourists in attractions, transportation flow of citizens or families) using GPS data rather than home activities. To address these issues, this research proposes an approach to extract a single occupant's ADL routines at home considering spatio-temporal dimensions simultaneously. We use the MSA for identifying an occupant’s ADL routines at home and examining how the results of MSA can be interpreted in evaluating the adequacy of the ADL.

2.1.4 Need for Assessing ADL Routine Variability

To detect the sudden change of ADL routines, it is necessary to define what kinds of pattern change can be relevant to the change of health status. In this research, 'routine variability' includes two concepts of variability; 1)

irregularity and 2) abnormality.

1) Irregularity

The irregularity of routine refers to the state that changing his/her routines inconsistently compared to his/her own pattern. The elderly who have a mental disorder (e.g., cognitive disorders, senile dementia, depression) have a tendency not to maintain the ADL's spatio-temporal patterns (Blankevoort et al. 2010; Urwyler et al. 2017; Aramendi et al. 2018). In the case of the patients, the average duration of each activity is shorter than the duration of the healthy elderly. In other words, it can be inferred when the disease occurs if the moment when the routine irregularity occurs can be detected.

2) Abnormality

The abnormality of routine refers to the state the activities performed in unexpected space at an unexpected time. For example, someone's routine of sleeping occurs in the bathroom (i.e., should be normally bedroom) or he/she does not sleep at the middle of the night as routine, these cases can be identified as an abnormal routine. Detecting abnormal ADL as a routine, it can be used as a basis for the early diagnosis of elderly mental disorders, such as senile dementia (Ditzler 1991; Blankevoort et al. 2010).

To find whether the routine irregularity increases, it is required to derive someone's ADL routine and comparing among the routines of a certain period. Collecting the ADL data and extracting the common pattern from the

collected data is conducted to know when the irregularity increases and how much the degree is. In case of abnormality, the ADL of routines should be assessed in spatio-temporal aspects. The conditions of defining the abnormality in this research are as follows.

1) Time-activity disassociation

In case of an activity occurs when the time the activity usually does not occur (e.g., overnight toileting, wandering (or performing activities other than sleeping at midnight, having meals at other than mealtime, no activity performed until afternoon, etc.).

2) Duration-activity disassociation

In case of an activity continues longer/shorter than the usual duration (e.g., exceptional longer stay in the bathroom, irregular sleep hours, etc.)

3) Frequency-activity disassociation

In case of an activity performed more/less than the usual frequency in a day (e.g., for the number of toileting, having meals, going out in a day, etc.)

To automatically monitor the elderly's ADL performance and assess the trends of variability in long-term, sensor-based techniques which are able to collect the human activity data is required to apply. Various sensors used in various fields are applied to the residential space recently, and it is possible to receive the data through the network among sensors is called smart-home environment.

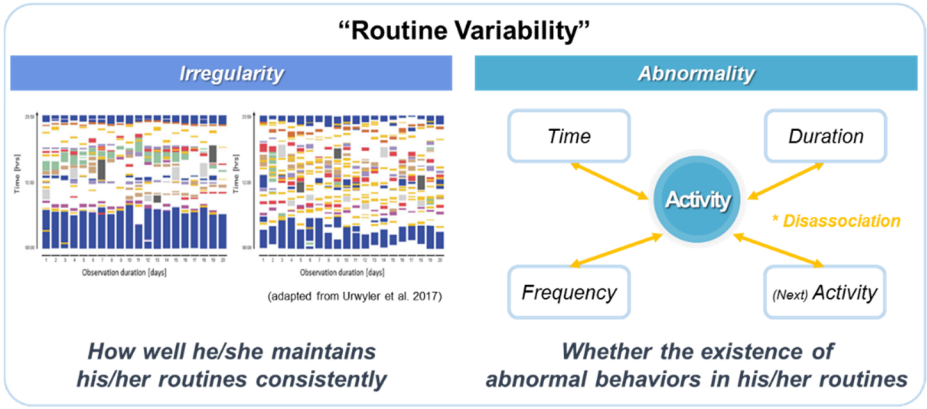


Figure 2.4 Definitions of Routine Variability

2.2 Necessity of using Non-intrusive Sensing for Monitoring Home Activity

2.2.1 Collecting the ADL-relevant Information using Sensing Techniques

The recent sensing techniques in smart-home environment can collect the activity information of the occupants, especially for the elderly healthcare. It is possible to exchange data collected from individual sensors and store the data at the hub system using the network between sensors and the hub as IoT (i.e., Internet of Things) technologies. From the development of these

technologies, a healthcare system using sensors collects and analyzes the occupant's physiological reactions or it is possible to detect physical movement in the residential space as a security system. This approach is more economical and accurate than the existing human efforted method since the collecting and analyzing the data are automatically conducted.

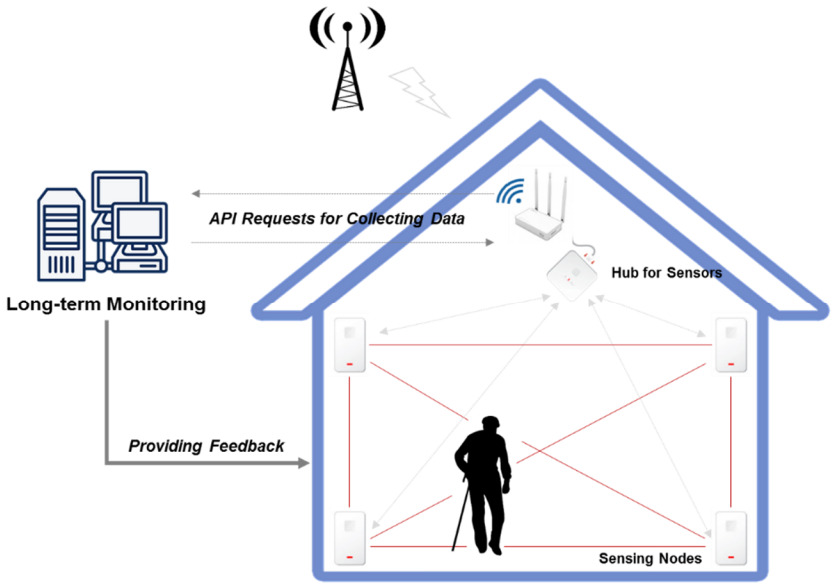


Figure 2.5 Concept of Sensor-based Smart-home Healthcare

Although the dramatic development of sensing techniques and applying the smart-home healthcare system using wearable sensors has increased, there is also negative experience whether the applying the sensors is suitable for the elderly or not (Lee et al. 2015; Galinina et al. 2018). It is difficult for

the elderly to wear the sensors, utilize the specific functions, and deal with malfunctions. In addition, the corresponding sensors should be worn and it might cause some side effects, such as discomfort during daily life. The wearable sensors sometimes raise a greater rejection than the existing human-efforted method. There is another method of collecting data in real time by recording a video from a camera in a residential space and it is usually used to detect an emergency. The camera recording method easily causes a discomfort since the subject might feel the privacy invasion, and is unable to capture the natural status because of conscious of the camera.

2.2.2 Existing Intrusive Sensing Techniques

The intrusive sensing approach is a method of collecting data directly from a target to be sensed and mainly used when collecting human data. It is also called an invasive method, originally derived from energy use analysis and is the opposite concept of non-intrusive method collecting the sensors that can measure the amount of energy usage for each device.

The existing intrusive sensing approach can be classified as two types; 1) Vision-based approach, 2) Contact-based approach.

1) Vision-based approach

: It is a method of collecting image data from a camera recording in a residential space. For short-term monitoring, it can be used to detect an emergency situation and a third party at a distance from the space checks images directly in real time. Otherwise, the long-term monitoring requires a technique to extract the data from the image automatically (e.g., recognizing human posture on the screen and detecting abnormal movement, such as fall.

2) Contact-based approach

: It is a method in which physically direct contact is made between sensors and a subject and mainly used to collect physiological response data from a subject. Thus, it is the most efficient and frequently used method to monitor the elderly's health status in smart-home healthcare system. Due to the improvement of related hardware (i.e., the sensors get smaller even the functions are extended), various wearable sensors are being commercialized which are maximizing the convenience (e.g., attaching to wrist, ankle, or clothes).

Despite the advantages of these intrusive sensing techniques, they have a risk of exposing the individual's biometric information which is more than the needed to extract the ADL routines. In addition, these intrusive sensing techniques can make an elder be conscious of the existence of the sensors and hinder the convenience of daily living in a residential space. It can be lower the accuracy of the detected ADL data and extracted ADL routines.

2.2.3 Need for Non-intrusive Sensing Approach

For detecting the ADL of the elderly, intrusive sensing techniques are being developed focusing on physical movement (i.e., posture change) and vital responses. However, these direct sensing methods have high risks to expose the subject's biometric data when analyzing the individual physiological information. In addition, the subject might be conscious of the existence of sensors since the physical distance between sensors and the subject is close, and it can affect the performance of data collecting. For detecting ADL and ADL patterns rather than gathering as much of the health information as possible, an alternative method is required to collect the necessary data.

There has been research attempts to apply an alternative sensing method to extract an occupant's behavior patterns (Zoha et al. 2012; Chen et al. 2013). As an alternative, non-intrusive sensing is to detect the state of the environment surrounding the subject (i.e., appliance use or space occupied) rather than the subject itself. The concept of this approach is to deduce the condition of the subject through the state of the environment surrounding the subject. This approach is derived from energy use analysis estimating the usage of each individual device through the pattern of the total usage amount.

There are various types of sensors of non-intrusive sensing (e.g., motion detecting sensors, smart plugs). In This research collects the subject's movement data using motion detecting sensors in his/her residential space and extracts ADL-relevant information. The motion sensor can track the subject's spatio-temporal logs without attaching the sensors to subject's body.

2.2.4 Spatio-temporal Log from Motion Detecting System

To collect an elderly's daily activity data non-intrusively, tomographic motion sensors (used Xandem home in this research) are installed at outlets to detect the occupant's movements at home (Banerjee et al. 2014). Because all sensor nodes are connected wirelessly, the tomographic signal is interrupted when a motion is detected, and the system records the spatio-temporal coordinates of the interrupted location.

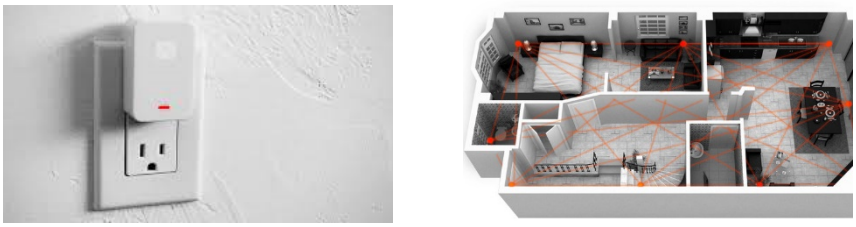


Figure 2.6 Motion Detecting System used in Research (Xandem home)

The spatio-temporal data log consists of the time of collecting data and the location where the occupant is detected. Since the space in this research means the position in the subject's residential space, the coordinates in the two-dimensional plane of x and y-axis will be collected and the coordinates can be measured the relative size of the target residential space. The daily spatio-temporal logs in residential space have a strong relationship with the ADL performed since the normally performed ADL have spatio-temporal context as a right time and right place. This relationship is more detailed described in chapter 3 with the results of an experimental test. Table 2.1 shows the samples of spatio-temporal data log with the location of the occupant detected at regular intervals.

Table 2.1 Examples of the Spatio-temporal Raw Data Log

Timestamp	Coordinates (X)	Coordinates (Y)
2017-09-28 15:00:45	-18.0281	-0.9157
2017-09-28 15:00:50	-15.2376	-1.2379
2017-09-28 15:00:55	-12.1759	2.3875
2017-09-28 15:01:00	-12.9763	2.5794

2.3 Human Activity Contextualization using Occupant's Spatio-temporal Log

2.3.1 Relations of Spatio-temporal Log and ADL Routines

To monitor the occupant's ADL patterns at all times and detect the pattern changes, it is necessary to extract the occupant's ADL pattern in advance. For extracting the ADL patterns, it should be defined how the ADL pattern can be consist the spatio-temporal log which is the unit data used in this research.

Related studies are being conducted in various fields as analyzing the individual's behavior patterns and predicting future behaviors in the marketing area, or improving the quality of life by assessing daily life patterns (Ziebart et al. 2008; Davidoff et al. 2010). In particular, assessing and predicting the occupant's behavior patterns in residential spaces has contributed to improving the quality of residential living with the development of smart-home technology (Roy et al. 2003; Roy et al. 2007; Alirezaie et al. 2017). The concept of spatio-temporal log, activity, behavior, patterns, and routines in the related research is as follows.

1) Spatio-temporal log (State)

: Coarse-grained information in the form of no contextual meaning about the human activities of behaviors, presenting only the state that where a human locates in spatial position when at a specific time

2) Activity (Event)

: Combining relevant states (spatio-temporal log) in order ('spatially relevant' in this research)

3) Behavior

: Combining activities having causal relationships (i.e., Activity A is performed for conducting activity B, and these A and B is defined as behavior C.)

4) Behavior Pattern

: A set of identical behaviors occurred repeatedly (e.g., 'sleeping', or 'driving' pattern)

5) (ADL) Routine

: Repeatedly performed patterns in a certain period ('daily' in this research)

The spatio-temporal data log is the coarse-grained state without behavioral contextual information and represents only the state of a spatial location and temporal log. An activity can be defined as combining these spatio-temporal logs with identical space in temporal order (Banovic et al.

2016; Alirezaie et al. 2017; J. Y. Kim et al. 2017). For example, if someone stays near the washstand of the bathroom at 9 pm for about 10 minutes and after that staying other than the bathroom, these logs can be presented as three activities as follows; 1) Enter the bathroom, 2) Use the washstand, 3) Come out of the bathroom. In this context, a behavior can be defined by identifying causal relationships among relevant activities (Taylor 1950; Hodgson 1997; Brdiczka, et al. 2010; Banovic et al. 2016). This definition presumes that human behavior is regarded as a set of activities with purpose (i.e., intention). As mentioned above example, the causal relationship between the above three activities as follows; enter the bathroom to use the sink, stay near the washstand for about 10 minutes to wash something using the washstand, and come out of the bathroom to end using a bathroom and do the next activity. These relations can be combined as a single behavior, 'wash his/her body'.

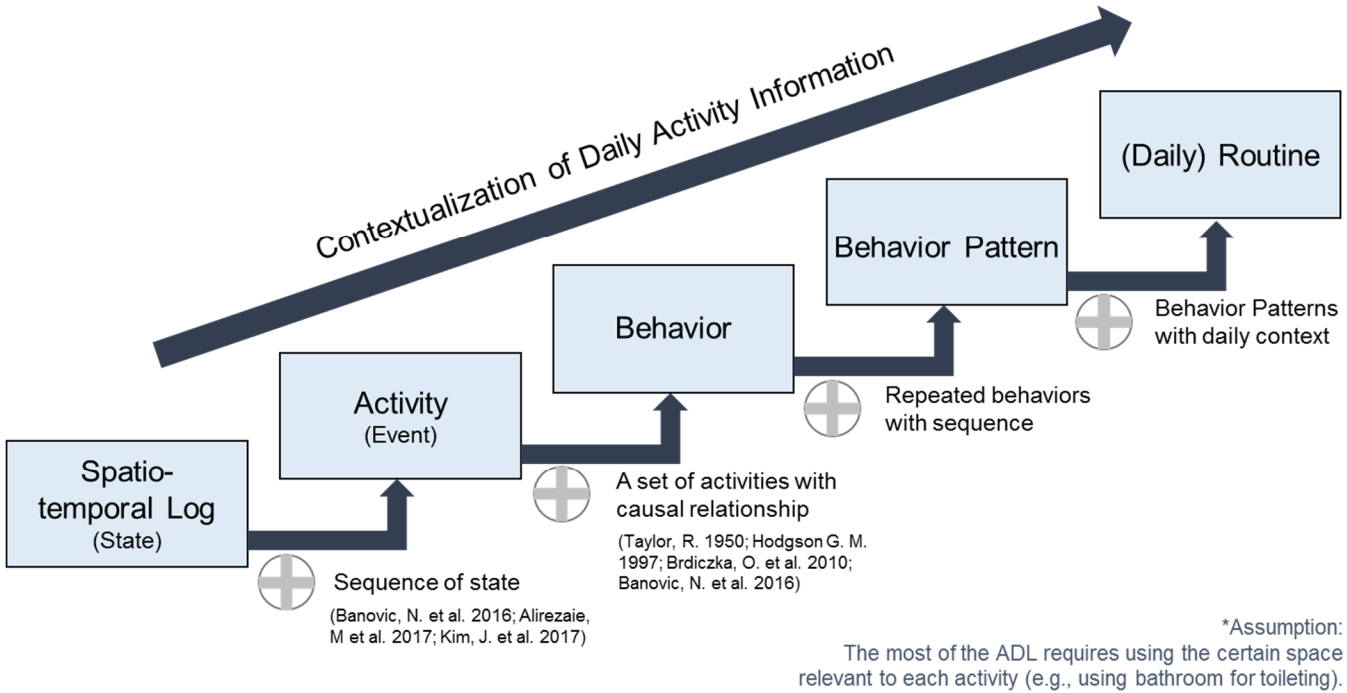


Figure 2.7 The Concept of the Contextualization of Human Behavioral Information

When some of these successive activities (i.e., a behavior) occur repeatedly, the set of activities can be defined as a behavior pattern (e.g., a pattern of taking a shower at night). The ADL routine in this research can be defined as several patterns of home activities when the activities are included in the classification of ADL and repeatedly performed daily.

The concept of ADL routines from spatio-temporal log in this research follows the definitions and assumptions above.

2.3.2 Activity Information from Spatio-temporal Log

In addition to the above definitions, it is possible to grasp the activity patterns of specific time period from visualizing and analyzing the spatial movement path. Visualizing the occupant's spatio-temporal log can contribute to extracting meaningful context of activities and help to understand the end results. The visualized results of spatio-temporal log represent context information of activities in sequence.

The methods to visualize spatio-temporal log can be classified into two types according to the purpose as follows; 1) with respect to time, 2) with respect to space (Andrienko et al. 2003). Since it is easy to derive the path of movement according to time and the order of space use, it validates when

grasping the precedence relations of activities. Thus, in case of with respect to time, this process is applied to grasp and predict the movement path and space utilization pattern of people (Guo et al. 2006; Bach et al. 2014). In case of with respect to space, the purpose of this process is to find the duration and the frequency of staying in each space (Qi and Du 2013; Lee et al. 2016).

For extracting the meaningful context of activities, the above two purposes are reflected in the process of presenting the density (i.e., duration and frequency) of space use for each time frame (Andrienko et al. 2003).

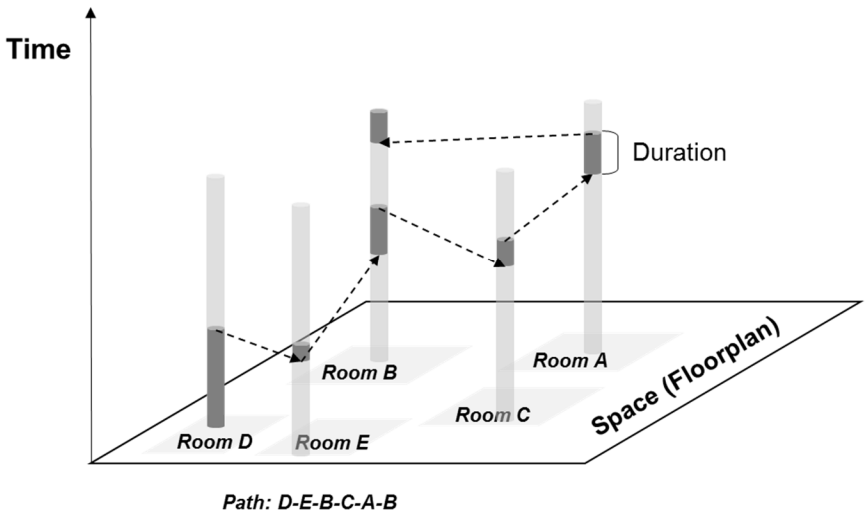


Figure 2.8 Visualization of Space-time Alignment (adpated from Shoval and Isaacson 2007)

Figure 2.8 shows the adapted concept of Hägerstraand (1970) proposed to extract the human movement path, and it represents the duration spent in each space (i.e., room) in sequential order for this research. Apart from it can show the location in a space (i.e., home) on the X-Y plane, it can also represent spatio-temporal attributes by adding a dimension (e.g., adding the width of the cylinder for showing the frequency of each visit in Figure 2.8) (Shoval and Isaacson 2007).

In relevant studies, 'activity map' is developed to visualize the activities performed in sequential order presenting each time when occurred and duration (Roy et al. 2007; Banovic et al. 2016; Urwyler et al. 2017).

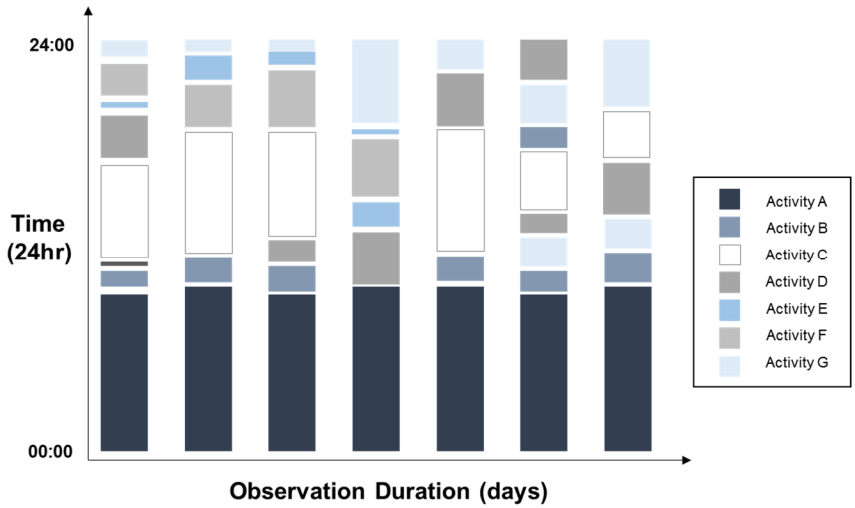


Figure 2.9 The Concept of Activiy Map from Saptio-temporal Log (adapted from Banovic et al. 2016; Urwler et al. 2017)

The purpose of visualizing the activity map is to represent the activities with the highest density, or the time, frequency, duration of each activity at a glance. Despite of the high efficiency of data representing, it also has a limitation in showing the causal relations among various activities or behavioral patterns in a certain period, which are required in this research. In addition, the spatial context or patterns are not reflected in the activity map since previous studies did not extract activities from spatio-temporal log.

Therefore, this research suggests visualized results of the extracted activities' time, location, duration, sequential order, and frequency based on the concept of activity contextualization process and previous activity map.

2.4 Related Methodology

2.4.1 Multiple Sequence Alignment for Human Activity Analysis

Sequence alignment is a major area in bioinformatics for investigating biological sequences, DNA, RNA, and proteins (Abouelhoda and Ghanem 2009). Biological sequence analysis usually has a goal of identifying similarities quantitatively and finding repeated segments among sequences. It is possible to trace a gene's mutation or evolutionary history through sequence alignment analysis. A protein sequence adapted to the current

research is formed from twenty alphabets each representing an amino acid. Due to sequences being represented as alphabets, other research areas besides biologics also have applied the sequence alignment as a data or pattern mining method.

To identify the best match, the technical process gap indel is operated during sequence alignment. Indel means that a gap ("_") instead of a character is inserted or deleted in a sequence to find the best and longest match area (W. C. Wilson 1998; Abouelhoda and Ghanem 2009). A high gap indel allows short-repetitive subsequences to be found by inserting gaps back and forth, which in turn makes the entire length of the aligned sequences much longer. In general, the allowable length of a gap can be defined based on the length of each input sequence and similarity. According to the sequence features and alignment goals, two alignment methods are described below.

(1) Global Alignment

: The global alignment originally from Needleman and Wunsch (1970) is usually applied when the sequences are the same length and are pre-known to be similar (Xia 2007; Abouelhoda and Ghanem 2009). It attempts to align the entire sequence and identify the one optimal alignment. Finding the optimal alignment means that the longest repetitive sequence should be identified when considering the entire sequence. The identified optimal

alignment result considers all input sequences' repetitive range and length at once, so that short subsequences presented irregularly can also be identified if they have rules in long-term. In pairwise alignment (comparing between two sequences), finding the optimal alignment is relevant for finding the highest similarity score (A(i,j)) from the scoring matrix as shown in Equation (1) (Abouelhoda and Ghanem 2009). According to the goal of alignment, the scoring matrix can be adjusted assigning values of match, mismatch, and gap penalty. Due to the calculation complexity of multiple sequences and matrices, BLOSUM (Blocks Substitution Matrix), which is most representative matrix for protein alignment (Henikoff and Henikoff 1992), is usually applied for human activity sequences (Shoval and Isaacson 2007; W. C. Wilson 1998; C. Wilson 2001).

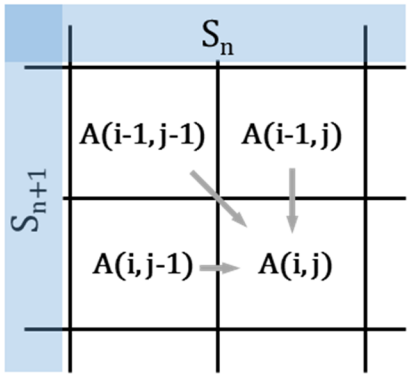


Figure 2.10 Calculation Matrix of Global Alignment (Pairwise)

$$\mathrm{A(i,j)} = max\begin{cases} A(i-1,j-1) + \ \delta(S_1[i],S_2[j]) \\ A(i,j-1) + \ \gamma(S_1[i]) \\ A(i-1,j) + \ \gamma(S_2[j]) \end{cases}$$

where S_n: Given sequences,

A(i, j): the optimal score of aligning $S_1[0 \ldots i]$ to $S_2[0 \ldots j]$, (1)

$$\delta(S_1[i],S_2[j]) = \begin{cases} \sigma \ if \ \ S_1[i] = \ S_2[j] \\ \alpha \ otherwise \end{cases}$$

σ: match score, α: mismatch score, γ: gap penalty

(2) Local Alignment

: Local alignment is appropriate for sequences with different lengths and locally similar regions (divergent or distantly related sequences) (Xia 2007; Abouelhoda and Ghanem 2009). Smith and Waterman (1981) revised the existing global alignment algorithms to align locally related subsequences. The revised calculation does not allow for a negative score in any cell, even when mismatch and gap penalty are negative values (Equation (2)). More than one local alignment over entire sequences can be found with more than one cell of the maximum score.

$$\mathrm{A(i,j)} = max\begin{cases} A(i-1,j-1) + \ \delta(S_1[i],S_2[j]) \\ A(i,j-1) + \ \gamma(S_1[i]) \\ A(i-1,j) + \ \gamma(S_2[j]) \\ 0 \end{cases} \quad (2)$$

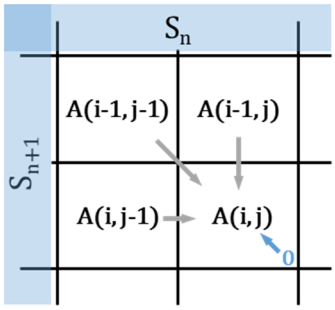


Figure 2.11 Calculation Matrix of Local Alignment (Pairwise)

Sequence alignment method has been widely used in social science research to identify common patterns of some social events (e.g., tourist moving patterns, extracting and comparing routines of vacation and workdays from diary data etc.) (Abbott 1995; Wilson 1998; Abbott and Tsay 2000; Bargeman et al. 2002; Shoval and Isaacson 2007). Since the human activities are inherently performed sequential, sequence alignment is an appropriate approach to consider space-use within a specific time period as a pattern mining technique. Whereas clustering space paths methods are usually based on the probability of the next step, considering only the previous and current location, sequence alignment method can consider the entire sequence at once (Shoval and Isaacson 2007) and find longest optimal repetitive sequences. In this context, it is possible to detect the patterns considering the continuity (order) of the activities. Since short-term activity, such as toileting can be performed sporadically in a day, existing probability-

based approach tends to ignore it when extracting common patterns. However, sequence alignment method can detect hidden patterns using a characteristic of finding short-common subsequences, which is for identifying the patterns of short-term activities.

To apply the sequence analysis from bioinformatics, spatio-temporal data should be processed in a string (characters) sequence. A character of the converted sequences can contain the spatio-temporal information simultaneously (i.e., alphabet presents the space and the number of alphabets present the time [duration]). When a sequence presents activities of a day, daily activities should be presented as multiple sequences and aligned to extract the common patterns of a certain period. To find the common sequences among multiple sequences, pairwise alignment using two methods (i.e., global and local) should be performed for all sequences and aligned as the highest score alignment.

The final output of sequence alignment, the "consensus sequence," presents the identified common patterns among the daily input (multiple) sequences. The Multiple Sequence Alignment (MSA) defines calculation methods for multiple sequences and generally requires computer software because of its complexity. The FASTA (Fast-All) format, a text based format presenting alphabet sequences for FASTA software (Lipman and Pearson

1985), is usually used for MSA applications, since it is easy to implement and recognizes all alphabet sequences.

For extracting and understanding the occupant's daily routine, the consensus sequence should include the daily activities' start-finish time, duration and frequency, but should not be significantly affected by exceptional events which are not commonly occurred (e.g., sleeping late due to a friend's visit). These exceptional events which do not affect the routine are defined as deviations (Banovic et al. 2016). The deviations include uncharacteristic behaviors somewhat different from the routine. Without being affected by deviations, some minor differences should be considered as identical activities. Even a 'staying in the bedroom' occurs at a slightly different time for days, it should be considered as the same 'sleeping' activity, if the duration or start time is similar during the experimental period when extracting the routine. These slight differences that can occur in daily lives can be defined as variations (Banovic et al. 2016). Thus, the variations should be considered as identical activities and deviations should not affect the extracted routines. The MSA can find a common area considering the similarity of the start time (i.e., global alignment), and also considering the similarity of durations even the activity performed at the totally different time (i.e., local alignment). It also can consider the continuity of activities (considering variations as identical) while finding the most commonly

performed activities (eliminating the effect of deviations).

2.4.2 Existing Metrics to Quantify and Assess Human Activity

For extracting routines and assessing the variability of routines, the activity-relevant data should be quantified utilizing the temporal dimensions. The degree of changes in ADL routines should be identified to infer the degree of influence to health status (deterioration). In addition, the routine variability including the irregularity and abnormality can be identified by calculating the distance among the routines or finding routines which have abnormal temporal conditions. From the sequences of activities have qualified dimensions themselves, such as start time, finish time, duration, frequency, and order. For using the quantified value of spatio-temporal log, several existing methods are applied to quantify and measure the variability of the human activities.

1) PP (i.e., Poincare Plot)

The Poincare plot is a measurement method to quantify an inner similarity of a signal or process data which usually formed as a time-series developed by Henri Poincare. The PP is mainly applied to measure heart rate variability (HRV) calculating an interval between two successive R waves

(i.e., RR interval). Considering the PP technique's characteristics measuring the variability between successive data, Urwyler et al. (2017) applied this method to quantify the variability of daily activities.

Figure 2.12 shows the example plot from PP using the ADL data. The ADL of each day is sequentially numbered according to timestamp and the number of ADL of the same timestamp are plotted as ($ADLnumber_{n-1}$, $ADLnumber_n$) where n is an interval.

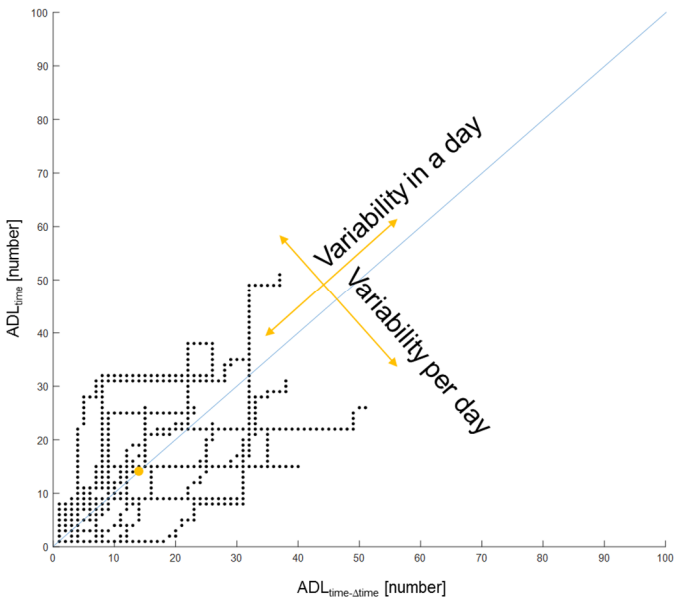


Figure 2.12 Example of PP Applied to ADL Quantification

As shown in the Figure 2.12, the PP technique can present the variability per time interval and the variability of the data itself (as the number of activities performed in a day). Though it is beneficial to find the trend of the variability of ADL, it is limited to find what activities are variably performed and the sequential relations of the activities.

2) Gestalt pattern matching algorithm (so called SequenceMatcher)

As a complement method addressing the above limitations, several quantification metrics to handle the string sequence data are applied to similar research of human activities. Gestalt pattern matching algorithm is a representative metrics to detect match area and quantify the similarity between pairwise string sequences (Ratcliff and Metzener 1988; Aramendi et al. 2018). This metric has advantages of finding the longest contiguous matching subsequence and measuring the similarity as the number of characters identically matched. The algorithm calculated using Python returns a value as follows.

$$\text{Similarity}_{SequenceMatcher} = \frac{2.0 * M}{T}$$

where T: Total number of elements in both sequences,

M: The number of matches

This metric has also a limitation to measuring the ADL variability as shown in case 1 of Figure 2.13. When the identical activities separately performed as shown, the difference between the cases is not reflected in the value of similarity. Since the metric specialize to find 'the longest contiguous' matching area, a relatively shorter matching area can be ignored when calculating the similarity. This characteristic is a clear limitation when calculating the similarity between two daily activity sequences as the short-duration activities which are commonly performed can be ignored.

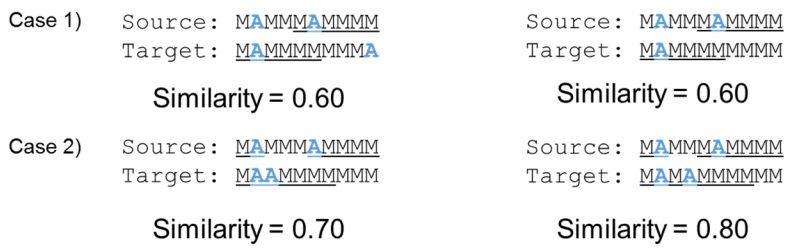


Figure 2.13 Similarity Calculation Example using Gestalt Pattern Matching Algorithm

3) Levenshtein distance

Similar to the Gestalt pattern matching algorithm, Levenshtein distance which is called edit distance can be applied to measure the difference between pairwise sequences. The Levenshtein distance is a string metric for measuring the difference quantitatively between pairwise sequences calculating the minimum number of edits (i.e., insertions, deletions, or

substitutions) required the two sequences make identical, developed by Vladimir Levenshtein (1965).

$$lev_{a,b}(i,j) = \begin{cases} \max(i,j) & if\ \min(i,j) = 0, \\ \min \begin{cases} lev_{a,b}(i-1,j) + 1 \\ lev_{a,b}(i,j-1) + 1 \\ lev_{a,b}(i-1,j-1) + 1_{(a_i \neq b_j)} \end{cases} & otherwise \end{cases}$$

$$Similarity_{Levenshtein} = 1 - \frac{lev_{a,b}(i,j)}{\max(|len(a), len(b)|)}$$

where a, b: Two strings each

However, this metric has a limitation to reflect the differences between the cases whether the characters are consecutive or not. As shown in case 2 of Figure 2.14, the two consecutive characters are not distinguished with the two characters separately occurred. This is another limitation to apply this metric to ADL variability measurement in this research.

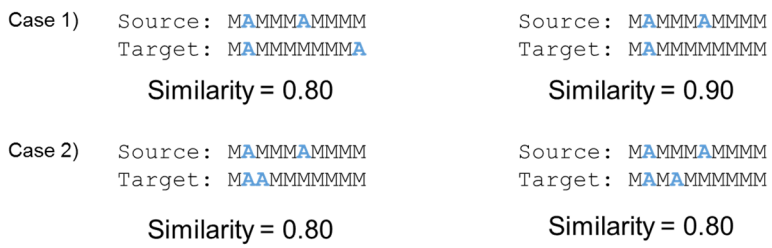


Figure 2.14 Similarity Calculation Example using Levenshtein Distance

4) Plot the start time-duration plot as activity clusters

To address the challenging issues of the previous existing metrics, plotting the collected spatio-temporal log in the axis of temporal dimensions is considered to measure the routine variability. As shown in Figure 2.15 each point is representing an activity (i.e., staying in an identical space) and it includes temporal data, such as each start and end time and duration. From collecting and plotting, these cumulative data can form as some clusters. The start-time and duration can represent the activity's characteristics enough to calculate the variability and this plot is efficient to present repeated values (Lotfi et al. 2012).

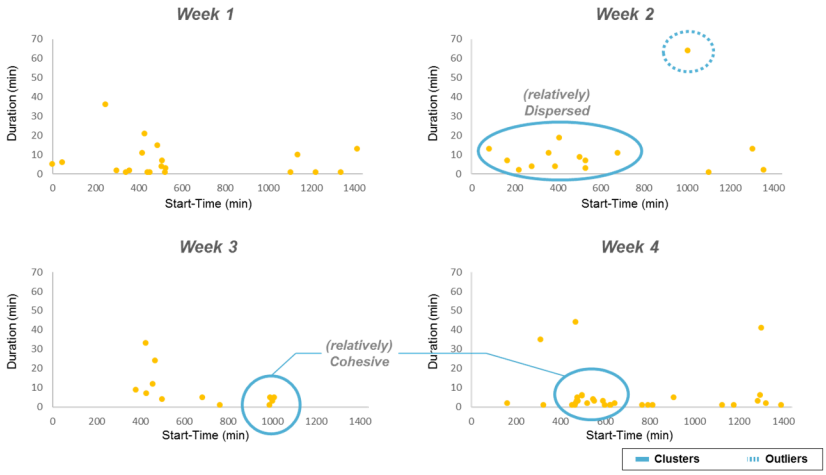


Figure 2.15 Example of Activity Plot Presenting as Clusters

This approach is developed based on the intuitive concept that similar activities would be plotted at a similar space on the coordinate plane since

the activities are performed with similar time and duration.

As shown in Figure 2.15, an activity repetitively performed with similar start-time and duration is presented as a globular cluster and an activity can consist of several clusters according to the temporal aspects. When an sudden irregular activities performed as unexpected deviations, points of these activities might do not belong to any clusters as outliers. By plotting cumulative activities performed in a certain period, the activities irregularly performed are determined to compare to the usual routine. In addition, each point can be assessed whether it belongs to abnormal conditions of activities.

To measure the irregularity of routine, the distance between each point and cluster centroid can be calculated since this distance can show how the points are densely (or sparsely) located. When the activities more regularly performed, the distance between points and centroid are less.

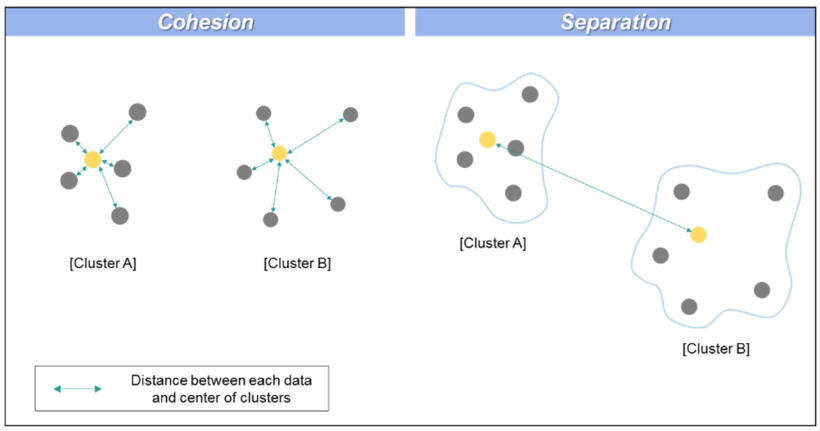


Figure 2.16 Concpets of Cluster Cohesion and Seperation

To find the clusters, outliers and calculate the distance among the points in identical cluster, the degree of cohesion and separation of clusters are measured in the plot. As shown in Figure 2.16, the lower sum of distances in a single cluster means a higher cohesion and the higher sum of distances to all other clusters means a higher separation between clusters. These concepts are applied to measure the routine variability calculating distances in the following chapters.

2.5 Summary

In this chapter, the definitions and importance of monitoring ADL routines of the elderly were described to assess the ADL routine as presenting the elderly's health status. This research based on the theory that the significant change of ADL routine can infer the deterioration of health status for the elderly. The other important concepts proposed in this chapter is 'routine variability' including irregularity and abnormality.

To automatically monitor the elderly's ADL routine and assess the trends of variability in long-term, the sensor-based techniques has recently applied to smart-home environment. From the previous research efforts, this research found the problems of using existing intrusive sensing techniques (i.e., vision-based approach, contact-based approach) for monitoring the ADL in smart-home environment; 1) raising uncomfortable feeling to wear multiple sensors and 2) high possibility of privacy invasion. As an alternative, the necessity of non-intrusive sensing approach using motion-detecting sensors was introduced.

By defining the human activity contextualization process to utilize the spatio-temporal log from motion-detecting sensors, it was proposed how the

spatio-temporal dimensions of data processed to extract and assess the ADL routine.

In addition, the related methodologies were analyzed for extracting the ADL routine using MSA, which is beneficial for finding common patterns of string data. Since the ADL routine variability can reflect the change in a certain period, the previous methodologies to quantify and assess the ADL routine were described. By plotting each activity as a point presenting start-time and duration, the concept of the variability as a cluster cohesion and how to calculate it was introduced in detail.

Chapter 3. Daily Activity Detection using Non-intrusive Sensing

In this chapter, the subject who is living alone's spatio-temporal log is collected and analyzed whether the ADL can be detected actually performed activities from a test experiment of 18 days. Applying the activity contextualization process proposed in chapter 2.3, the activities are detected in time order and the detected results are compared to the performed activities which are recorded by the subject.

3.1 Daily Activity Contextualization Process Design

3.1.1 Developing Conceptual Model Framework

The conceptual framework of the contextualization process suggested in this research includes the process of extracting performed activities from spatio-temporal log. From the initial conditions of space (i.e., floorplan of home), each space can be defined as a plane area and each spatial coordinate can be classified into local space (i.e., room). When the location of instruments in home is set as initial conditions, the classification results have

more detailed spatial state (e.g., refrigerator area in kitchen). In this stage, the occupant's space-time path in home in a certain period can be extracted as shown in Figure 3.1. Based on the definition of activity from spatio-temporal log in chapter 2.3.1, performed activities in a certain period using nearest instruments in each room can be extracted as space use map. When extracting the performed behaviors, the most frequently stayed area in a certain period can be identified with each timestamp as space activity map. The ADL patterns accumulated from a certain period is used for assessing the irregularity and abnormality.

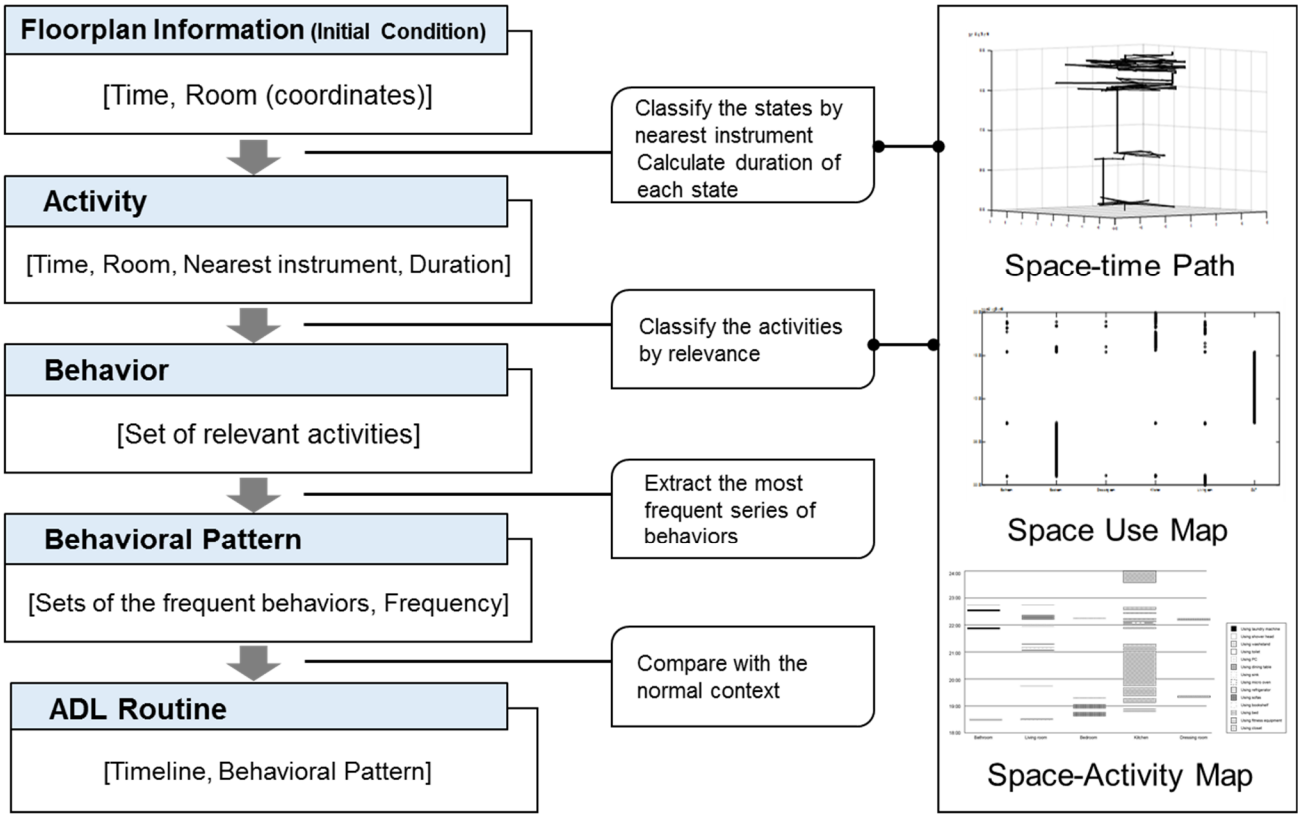


Figure 3.1 Conceptual Framework for Behavioral Contextualization

3.1.2 Extracting Activities from Contextualization Process

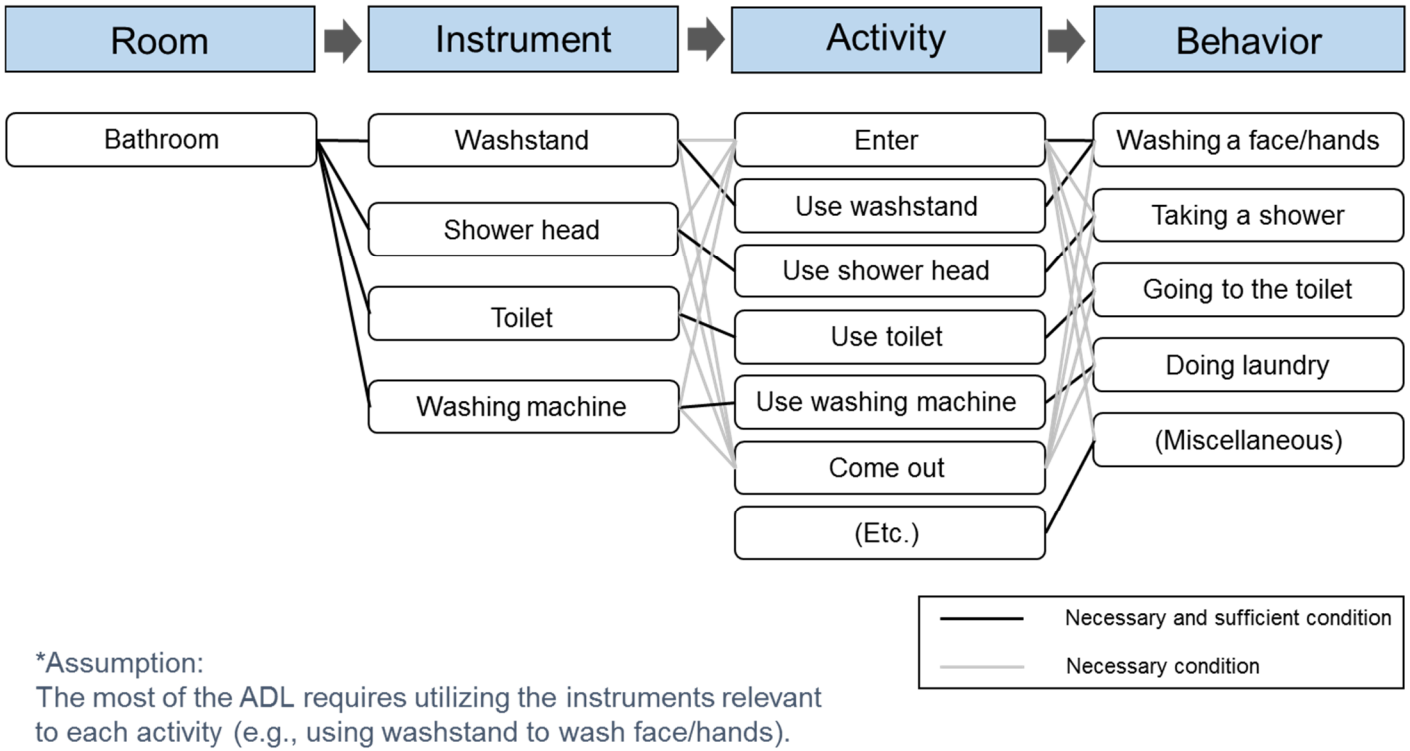
The extracted spatio-temporal log as shown in Table 3.1 includes information on the occupant's location of each timestamp and it represents the 'state' of the occupant. To extract these states as activities, the size of each room and the location of the instruments of each room are set and combined with the duration of each staying. Through this process, it is assumed that the occupant performs an activity using the instrument when he/she stays for a significant duration (i.e., initially more than 5 seconds) at the area of the nearest instrument. This assumption is based on that most of the ADL occurred in a home is performed using the relevant instruments (e.g., sleeping using a bed, having meals using dining table, etc.). The minimum condition of significant duration (5 seconds) can be adjusted according to the occupant's pattern after collecting the data since the duration taken to perform an activity might vary from person to person.

The successive spatio-temporal log in Table 3.1., an activity can be extracted as 'the occupant used the washstand for 10 seconds'. To conduct this process, it is required to classify the types of each instrument in rooms, the instruments representing the activities, and the purposes of each activity as shown in Figure 3.2.

Table 3.1 Examples of the Spatial Contextualization

Timestamp	Coordinates (X,Y)	Room	(Nearest) Instrument
2017-09-28 15:00:45	(-18.0281, -0.9157)	Bathroom	Washstand
2017-09-28 15:00:50	(-15.2376, -1.2379)	Bathroom	Washstand
2017-09-28 15:00:55	(-12.1759, 2.3875)	Bathroom	Washstand
2017-09-28 15:01:00	(-12.9763, 2.5794)	Living room	PC

After extracting the performed activities with each durations using the 'room-instrument-activity relevance map', the daily sequence of most frequently performed activities can be defined as the ADL pattern of the occupant. In addition, the extracted activities can be assessed whether the activities were adequately performed at the expected time and location during the expected duration. To verify the validity of extracted activities, a test experiment of the subject who is living alone is conducted in chapter 3.2.



*Assumption:
The most of the ADL requires utilizing the instruments relevant to each activity (e.g., using washstand to wash face/hands).

Figure 3.2 Examples of Room-Instrument-Activity Relevance Map (Bathroom)

3.2 Test Experiment

In this chapter, the results from an experiment are assessed and visualized to space-activity map to compare them with the subject's self-reported results about actually performed activities.

The results can be presented as 'space-time path' first, plotting all the collected coordinates of two-dimensional space (X-Y) according to each timestamp. The three-dimensional coordinates with temporal dimension added to the spatial coordinates (i.e., (X, Y, Timestamp)) does not include the spatial context, which means each coordinate is not known where it is. After the spatial contextualization from the initial conditions of the subject's home, the coordinates might be changed to the form of (Room, Timestamp). With extracted activities of each room and timestamp, the 'space-activity map' is derived, and it is possible to grasp each activity's order, duration, and frequency in a day at a glance.

3.2.1 Experiment Outline

The experiment was conducted to analyze the validity of the activity detection process using non-intrusive manner as mentioned before, for a subject who is living alone. The subject is a 30-year-old adult worker who

lives alone and goes to work at a certain time during the weekdays. In case of long-term tracking of human activity (i.e., ADL) recognition, relevant previous research (Schwartz et al. 1991; Tapia et al. 2004) has analyzed data from a single subject in terms of the quantitative and qualitative investigation. The experimental space is classified into five ADL-related functional spaces; 1) bedroom, 2) living room, 3) kitchen, 4) dressing room, and 5) toilet. To confirm the feasibility of collecting data in various situation in a home, the subjects were allowed to perform his/her daily tasks the same as usual without any instructions (i.e., rules for this experiment).

Table 3.2 Outline of Test Experiment

Classification	Contents
Type	RC Structure
Area	490 ft^2 (45.5m^2)
Floorplan	
Experimental Date	2017-10-16 (00:00:00) ~ 2017-11.03 (20:36:20)

To collect an occupant's activity data non-intrusively, tomographic motion sensors are installed at outlets to detect the occupant's movements at

home. Because all sensor nodes are connected wirelessly, the tomographic signal is interrupted when a motion is detected, and the system records the spatio-temporal coordinates of the interrupted location. For 18 days, the authors collected the tomographic motion detecting system (Xandem home) (Banerjee et al. 2014) in an experimental space of a living alone office worker's home (Table 3.2). The location of each room and where the nodes are installed is shown in Figure 3.3.

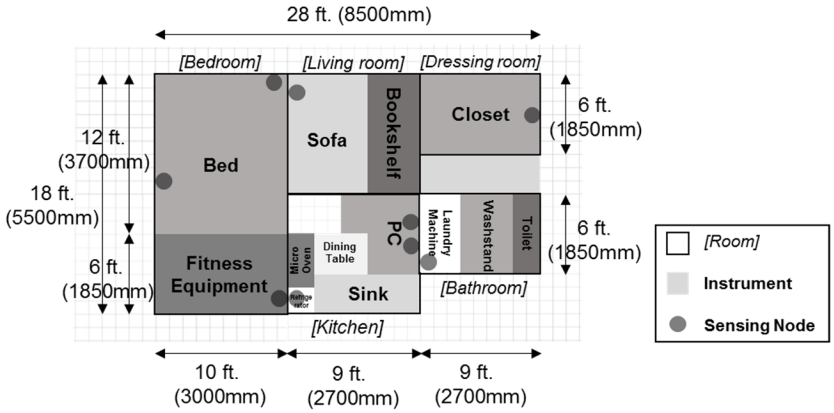


Figure 3.3 Experimental Floorplan (Locations of Rooms, Nodes, and Instruments)

The system collected data logs every five seconds, and spatial coordinates (X-Y) were recorded as zero ((0,0)) when there was no movement in the space. The collected raw data contains [Timestamp, motion detected coordinates (X-Y)]. All (0,0) should be substituted as the location

for last motion detected using the forward fill since the coordinates (0,0) means the subject does not move from the position where the motion is detected.

3.2.2 Detecting Daily Activities using Contextualization Process

Figure 3.4 shows the detected space-time path of the subject in 2017-10-17. The change of the location was not detected from am 8:41:20 to pm 6:30:20 (for 9 hours 49 minutes) and from am 1:11:35 to am 8:30:25 (for 7 hours 18 minutes) since each time was when the subject went out to work and slept in a bedroom.

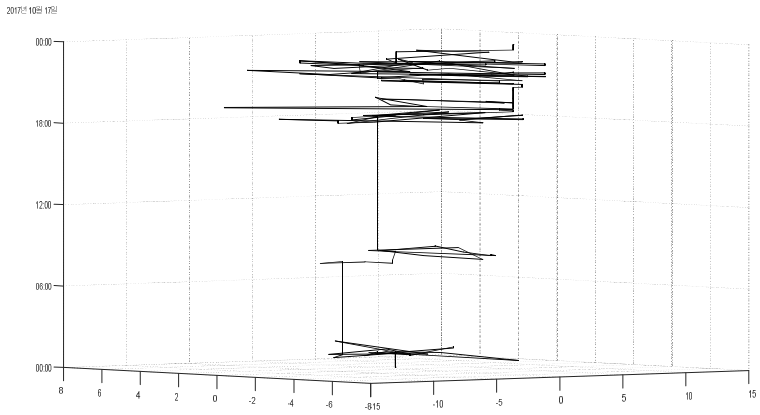


Figure 3.4 Space-time Path of Test Expeiment (2017-10-17)

However, it is difficult to find the information of activities using the above space-time path because the subject moves a lot within home at from pm 6 to am 12. To extract all detected activities through the proposed process, the spatio-temporal log of 2017-10-17 (from pm 6 to am 12, 6 hours) when the subject continuously stayed for the longest time in a home during the 18 days of the experimental period was compared with the actually performed activities.

The experimental space was classified as an initial condition (Figure 3.3) to types of room and each instrument. When the coordinates of each timestamp classified to a room, the space-use map was derived as shown in Figure 3.5. It presents the time, duration, order of each staying, and frequency in each room in a day. According to this results, it is found that the subject usually spent most of his/her time in the kitchen and living room area after returning home from work. Similar to the previous classification, each spatial coordinates was classified to each instrument area in a room and contextualized to extract activities performed.

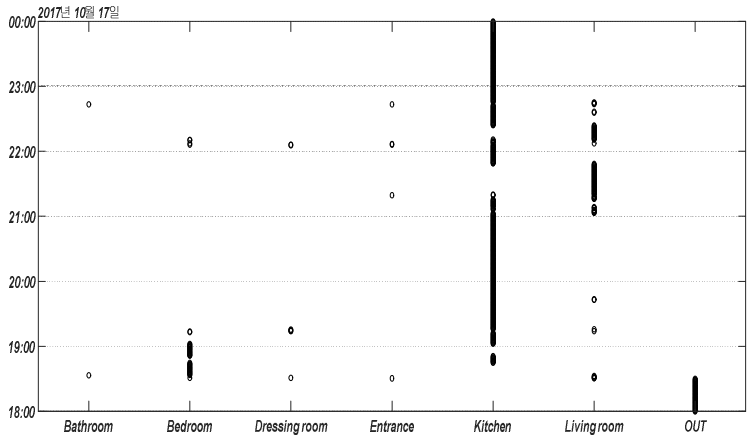


Figure 3.5 Space-use Map of Test Experiment (2017-10-17 18:00 ~ 24:00)

The parts of extracted activities from the location of rooms and instruments are shown in Table 3.3.

Table 3.3 Results of Activity Detection of Test Experiment (2017-10-17 18:00 ~ 24:00)

No	Timestamp	Duration (min)	Detected Activity	Activity Performed
1	2017-10-17 18:30:55 2017-10-17 18:31:10	0.3	Using laundry machine	Washing hands
2	2017-10-17 18:31:15 2017-10-17 18:31:40	0.4	Using bookshelf	Putting down the bags
3	2017-10-17 18:31:45 2017-10-17 18:33:05	1.3	Using sofa	
4	2017-10-17 18:33:10 2017-10-17 18:33:25	0.3	Using shower head	Using toilet
5	2017-10-17 18:33:30 2017-10-17 18:45:05	11.6	Using bed	Changing clothes
6	2017-10-17 18:45:10 2017-10-17 18:45:45	0.6	Using micro oven	-
7	2017-10-17 18:45:50 2017-10-17 18:47:00	1.2	Using PC	
8	2017-10-17 18:47:05 2017-10-17 18:47:45	0.7	Using micro oven	
9	2017-10-17 18:47:50 2017-10-17 18:51:10	3.3	Using dining table	Sitting at the table
10	2017-10-17 18:51:15	11.6	Using bed	Using bed

	2017-10-17 19:02:50			(Watching TV)
11	2017-10-17 19:02:55 2017-10-17 19:03:20	0.4	Using micro oven	Using refrigerator
12	2017-10-17 19:03:25 2017-10-17 19:12:55	9.5	Using PC	Eating dinner (Using PC)
13	2017-10-17 19:13:00 2017-10-17 19:13:55	0.9	Using bed	
14	2017-10-17 19:14:05 2017-10-17 19:15:35	1.5	Using closet	
15	2017-10-17 19:15:50 2017-10-17 19:42:50	27.0	Using PC	
16	2017-10-17 19:43:00 2017-10-17 19:43:20	0.3	Using sofa	Clearing up the rooms
17	2017-10-17 19:43:25 2017-10-17 21:03:00	79.6	Using PC	
18	2017-10-17 21:03:05 2017-10-17 21:06:15	3.2	Using sofa	
19	2017-10-17 21:06:20 2017-10-17 21:07:35	1.3	Using PC	
20	2017-10-17 21:07:40 2017-10-17 21:08:25	0.8	Using bookshelf	
21	2017-10-17 21:08:30 2017-10-17 21:08:45	0.3	Using sofa	
22	2017-10-17 21:08:50 2017-10-17 21:16:00	7.2	Using PC	
23	2017-10-17 21:16:05 2017-10-17 21:19:15	3.2	Using sofa	
24	2017-10-17 21:19:25 2017-10-17 21:19:50	0.4	Using PC	

The result shows that a total 47 activities were detected for 6 hours and about 76% (4 hours 32 minutes) of the total time was spent using ADL-relevant instruments. The three cases of not detected are as the following; 1) in case of the duration at a location is less than 10 seconds, 2) in case of staying a room where not related to any ADL-relevant instruments (e.g., from pm 10:45:25 to pm 10:36:10, 50 minutes 45 seconds), 3) in case of the subject's absence (e.g., from pm 6:00:00 to pm 6:30:20, 30 minuets 20 seconds).

The Figure 3.7 is derived as space-activity map showing the detected activities' time, duration, order, and frequency per each room. To validate the results from the contextualization process (i.e., whether the detected activities were actually performed), the subject recorded what were the activities performed and when did them using self-reported form (Figure 3.6). The subject did not record meaningless activity (e.g., standing still in place taking phone calls, wandering around the room) as a ground truth since they are not relevant to ADL.

Daily Activity Diary

<2017 - __ - __ >

Timestamp	0 – 10 min		11 - 20 min		21 - 30 min		31 - 40 min		41 - 50 min		51 – 60 min		Others
AM 00													
AM 01													
AM 02													
AM 03													
AM 04													
AM 05													
AM 06													
AM07													
AM 08													
AM 09													
AM 10													
AM 11													
PM 12													
PM 01													
PM 02													
PM 03													
PM 04													
PM 05													
PM 06													
PM 07													
PM 08													
PM 09													
PM 10													
PM 11													

* Bedroom: 1, / Bathroom: 2, / Living room: 3, / Sink: 4, / Dining table: 5, / PC: 6, / Refrigerator: 7, / Dressing room: 8

Figure 3.6 Self-reported Form used in Test Experiment

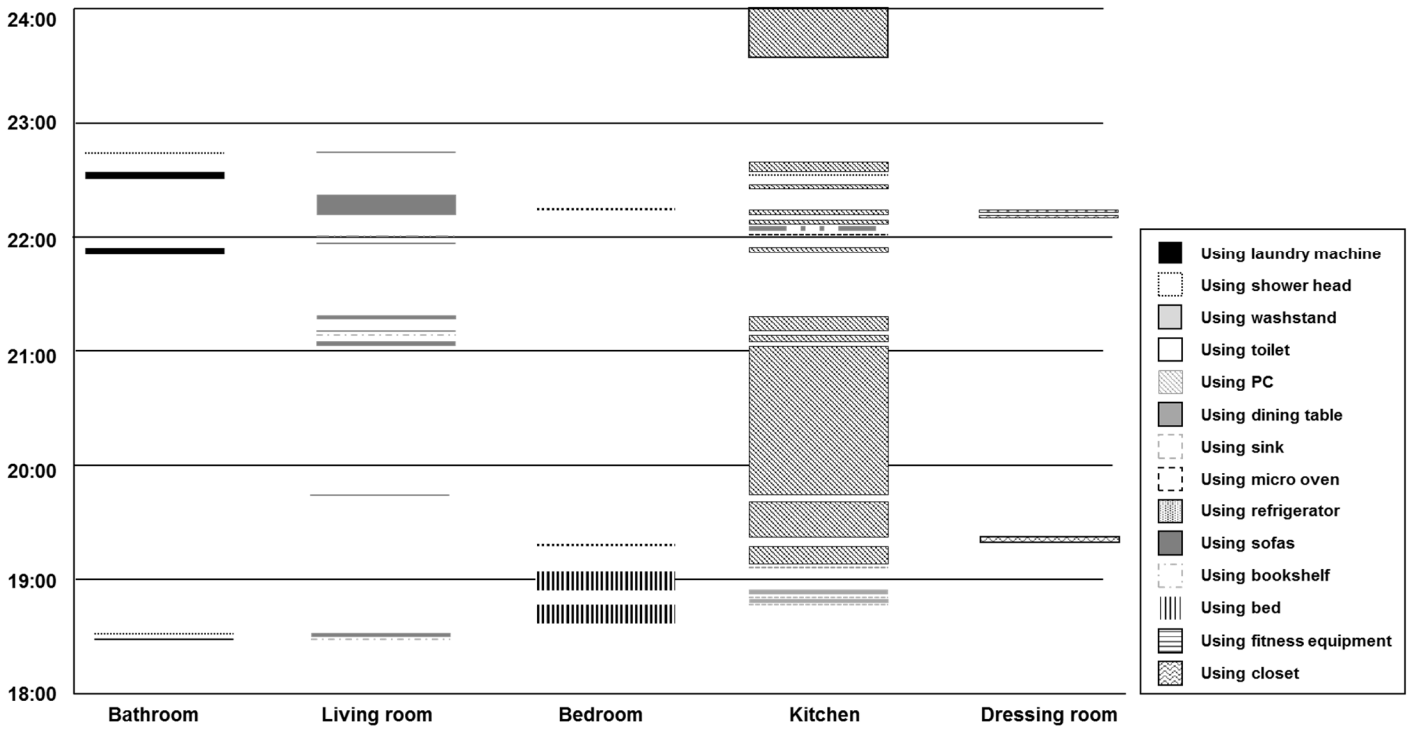


Figure 3.7 Extracted Space-activity Map of Test Experiment (2017-10-17 18:00 ~ 24:00)

3.2.3 Findings and Implications

Table 3.4 shows the reliability test results of applied motion detecting system based on the subject's self-report of data from 2017-10-16 18:40 to 23:59. The applied motion detecting system detected the location where the subject performed an activity relevant to the location with 99% accuracy. Although the results show that the activity performed longer than 5 minutes were detected accurately, it was not detected an activity less than a minute when the subject moved fast.

Table 3.4 Accuracy of Detected Activities from Reliability Test

	B	BA	LI	SI	DT	PC	R	DR
B	4	0	0	0	0	0	0	0
BA	0	3	0	0	0	0	0	0
LI	0	0	17	0	0	0	0	0
SI	0	0	0	1	0	0	0	0
DT	0	0	0	0	6	0	0	0
PC	0	0	0	0	0	32	0	0
R	0	0	0	0	0	1	0	0
DR	0	0	0	0	0	0	0	1
Accuracy = 99%								

(* B = Bedroom, BA = Bathroom, LI = Living room, SI = Sink, DT = Dining table, PC = Personal Computer, R = Refrigerator, DR = Dressing room)

The extracted results and the subject's self-report is analyzed qualitatively and found the below considerations as limitations and implications for follow studies.

1) When a room or an instrument itself represents a definite activity, extracted results have high accuracy of detecting performed activities. For example, using a toilet or a washstand in bathroom refers to an activity clearly such as toileting or washing hands (face), and the detected results of these activities (i.e., spatio-temporal information) are identical with the actual performed activities. However, the cover range of sensing nodes in the bathroom was inaccurate due to the location of the outlet and some errors were occurred in detecting the X- axis of the plane (e.g., the toilet area detected as the shower area and the washstand area detected as washing machine area).

2) The detected activities which duration is less than 5 minutes were mostly not coincided with the performed activities or they were sub-activities for performing other activity of different purposes. For example, the subject reported that he/she spent about 17 minutes (from pm 9:03 to pm 9:20) while wandering around the kitchen and living room, cleaning the rooms. However, the detected results show that the subject used computer or sofa in the living

room during that time and they are totally different with the actually performed activities. Since the proposed contextualization process is based on the instruments in each room, it is not possible to detect the activities which do not use any instruments located in the room.

3) It was also difficult to detect accurately when several instruments were used simultaneously. The subject used the PC having dinner for 30 minutes at pm 7 and the detected result shows that another activity (i.e., having dinner) using PC was not detected. Considering the subject used a refrigerator before using PC at that time, it can be inferred that the activity of that time was related to dinner. However, this inference has limited in assessing activities due to the subjectivity.

4) The activities which use the instruments not close are also difficult to detect using the proposed process. For example, the subject does not have to be closely located to the TV while watching TV so that it is difficult to detect accurately using the process based on the location of instruments. The subject of this test experiment usually watches TV lying in a bed and in this case, it is possible to detect 'using bed' but 'watching TV' cannot be detected.

To overcome the above limitations from the non-intrusive sensing techniques, it is possible to consider a method of personalizing the ADL detection and learning ADL patterns for a single occupant. For example,

'cleaning the rooms' consists of several rooms within a short period of time and these spatio-temporal characteristics can be reflected a activity detecting model. To conduct this, it is required to collect spatio-temporal log for a long-term for a single subject and find each pattern of activities. Despite the above limitations, it was found that the extracted spatio-temporal log from non-intrusive sensing can represent most of the daily activity of the living alone occupant where functionally planned space in this test experiment. Using the proposed process, the single occupant's ADL routines can be extracted in the following chapter.

3.3 Summary

In this chapter, this research conducted a test experiment for the subject who is living alone to confirm the validity of the proposed activity contextualization process. The process could automatically detect performed activities from the collected spatio-temporal log using the location of each room and instruments relevant to ADL. Especially, the ADL using a single instrument could be clearly detected only by collecting spatio-temporal log. From the results of the conducted experiment, it was found that most of ADL can be detected using non-intrusive sensing approach.

Based on the findings of this chapter, the activity contextualization

process would be applied to the case of the elder living alone to extract the ADL routines in a certain period.

Chapter 4. Extracting Daily Activity Routines using Multiple Sequence Alignment (MSA)

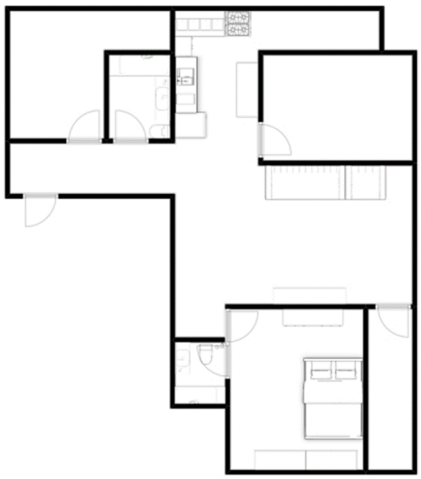
In this chapter, the elderly person who is living alone subject's ADL routines is extracted using MSA (i.e., Multiple Sequence Alignment) with collecting the 60 days of spatio-temporal log from tomographic motion detection system. It is found that MSA methods, mainly used in bioinformatics, are applied to take full advantage of the methods (i.e., processing sequential data and identifying repetitive, hidden rules). The extracted ADL routines considering the activities' spatio-temporal context are evaluated their validity using previously used methods and the subject's self-report, and analyzed results are described.

4.1 Overview of the Data Collection

For 60 days, the spatio-temporal log were collected using the tomographic motion detecting system (Xandem home) (Banerjee et al. 2014) in an experimental space of a living alone elderly's home (Table 4.1). Similar to previous research (Le et al. 2008; Gu et al. 2011) investigating human activity patterns, data from the two subjects (elder subject and office worker subject from chapter 3) are used in an analysis. The subject usually stays at

home, except when going out to the senior community center in the morning or the hospital in the afternoon.

Table 4.1 Outline of Case Experiment

Classification	Contents
Type	RC Structure
Area	1150 ft^2 (106.8m^2)
Floorplan	
Experimental Date	2018-07-23 (14:53:21) ~ 2018-09.21 (16:43:58)

This experiment uses data from 60 days, except 8 days sensed with error. The 8 days when the spatio-temporal logs were not fully collected (17280 logs for a day) due to the system errors were eliminated. A total of 10 sensor nodes were installed to cover the entire area of the experimental space as shown in Figure 4.1. The system collected data logs every five seconds, and

spatial coordinates (X-Y) were recorded as zero ((0,0)) when there was no movement in the space.

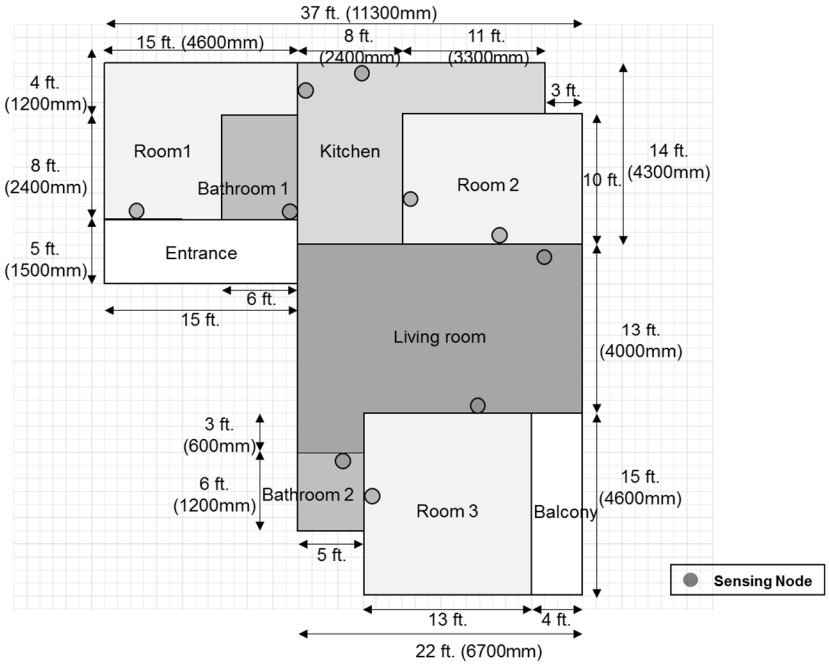


Figure 4.1 Case Floorplan (Locations of Rooms, Sensing Nodes)

4.2 Data Cleansing for Applying Sequence Alignment

The collected raw data contains [Timestamp, motion detected coordinates (X-Y)]. All (0,0) should be substituted as the location for last motion detected using the forward fill. For the next step, the experimental space should be classified by room using the floorplan of the home as an initial value. In this research, the experimental space has a ten-room classification as below.

(A): Bathroom 2	(C): Room 3	(D): Bathroom 1	
(E): Entrance	(F): Balcony	(K): Kitchen	
(L): Living room	(N): OUT	(R): Room 2	(S): Room 1

Each room is represented as a character used in protein sequences. According to the preliminary interview before collecting data, the subject almost uses ‘Bathroom 2’ only and usually uses ‘Room 3’ as a bedroom. The ‘Room 1’ is used as a warehouse and rarely occupied.

```
>07-24
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCARRRRLLLLLLLLLKRRRR
RRRRRRKKRRRRRRRRRRRRRRRKKKKKKRRKRRRKRRRRRRRRRKKKKKKKKCCCCCCCDDDDDDDDDKKK
RRRRRRKKKRRRKKRRRRRRRRRRRRRRRRDKKKKRRLLLLRRRRRRRRKCDCCAAAAAAAAAAAAAAACCC
AAAACCCCCCLLLLLRRRRLLLLLNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNKCCLLRKLLLNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNNN
NNNNNNNNNNNNNNNNNNNRKKKKKKACCRLLRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRKKKKKKKLLL
LLLLLLLLLLLLRRRRRRRRRLKLLLLLLLLLLLLLKKKKKKKKKKKKKKKKKLLLLLLLLLKRCCCCCARL
KRKLLLCCCCCCCCCCCCLCCCCCCCCCCCCCCCCCRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR
RRRRRRRRRRRRRRRRRCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCAAAAAAAAAAAAAKRRRKLLLCCCCRR
```

Figure 4.2 Daily Activity Sequence Presented as 1440 characters for a day in FASTA format (2018-07-24)

Finally, the timestamp-room data log was downsampled for a one-minute interval. This research assumes that intervals less than one-minute are unnecessary for finding ADL relevant activity patterns. When downsampling the data log to the one-minute interval, the most frequent location in which the subject stayed for a minute represents the activity of the minute. Through these data cleansing processes, the 52 days of spatio-temporal sequences (1440 characters for a day) would be presented in the FASTA format shown in Figure 4.2.

4.3 Data Analysis

Due to the computation complexity of aligning multiple sequences, various computer programs for MSA have been developed; Clustal series are those most commonly used (Corpet 1988; Wilson 1998; Wilson 2001; Thompson et al. 2002). This research uses the ClustalG algorithm, eliminated the biological features of other Clustal series and generalized for social science research (Shoval and Isaacson 2007). According to the alignment goal, users can adjust the parameters, especially the gap penalties (gap extension and gap opening) and scoring matrix, which influence the alignment results.

Higher gap penalties decrease the gap size and the sequence tends to keep the original length due to the small amounts of the inserted gap. Lower or no gap size keeps the length of the aligned sequence as the original sequence so that the temporal dimension of the ADL (i.e., duration as a length of consecutive characters) is kept as the original value. The alignment results with higher gap penalties can show the start and finish time of each activity.

Meanwhile, lower gap penalties, which can increase gap size, are more appropriate when input sequences have various lengths. Lower gap penalties allow the large amounts of the inserted gap and find as many common

subsequence areas as possible. The alignment results with lower gap peanlties are more appropriate when input sequences have various lengths.

4.3.1 Alignment with Equivalent Time Frame

To find the most frequent space use patterns during experimental dates, 52 sequences with exactly the same length (1440 characters per day) were selected. All sequences present locations per minute from 00:00 to 23:59 each day. To measure the duration of staying, the length of the consensus sequences should be preserved as 1440 characters. This requires global alignment and an increase in gap penalties to avoid gap indel (assigning gap penalty as [gap extension: 10.0, gap opening: 20.0] which is much higher than default settings). Aligning with the equivalent time frame approach would identify the start-finish time and thus the duration of long-regular staying (e.g., sleeping in bedroom, going out for a while).

4.3.2 Alignment with Contextual Time Frame

The elderly living alone who usually stays at home might have a shorter and irregular routine than a regular worker. For example, the subject in our experiment has a routine of visiting the senior community center once in a

day without specified any particular time. Due to the irregularity of the going out, all other activities at home are also performed at all different time frame, start-finish time of staying and durations. In this context, 'contextual time frame' can be defined as like 'before going out' and 'after coming back', the opposite concept of the equivalent time frame. In these contextual time frame, sequences might have multiple locally common areas and this requires local alignment with allowing a high gap size [gap extension: 0.1, gap opening: 10.0]. Aligning with the contextual time frame approach would identify the order and frequency of each staying. Since the local alignment has a characteristic to find as many common subsequences as possible, the length of the consensus sequences is much longer than the duration of the global alignment result. The sequence length from local alignment differs by the variability (i.e., total length, repetitiveness) of the input sequences.

4.3.3 Identifying Consensus Sequence from Two Alignment Results

The results from the above two alignment methods should be integrated to identify one optimal ‘consensus sequence’. From the result of aligned with the equivalent time frame, the start-finish time and duration of long-regular staying can be obtained due to the characteristic of global alignment finding the longest repetitive area.

The results of the local alignment can be assigned to the remaining area excluding the activities determined from the global alignment result. It considers the repetition rules of short-term home activities. Since local alignment specializes for finding local repetitive subsequences, alignment results are extended to both sides centered the common area and it usually makes the output sequences much longer than input sequences. Therefore, the output sequence from local alignment should be scaled down to the length of the remaining area for coherent daily based analysis. When reducing the length of the sequences from local alignment proportional to the length of the remaining area, the activities less than 30 seconds are eliminated except 'bathroom' activities. Using bathroom during less than 30 seconds is meaningful regardless of the duration while 'kitchen', 'living room' or 'bedroom' during less than 30 seconds consider as meaningless activities, such as wandering or moving to other space. The integrated consensus sequence can be interpreted as the occupant's daily activity routine with temporal information.

4.3.4 Validation of MSA from Comparing with Existing Methods

To determine the validity of the results derived from MSA, the extracted result is compared with the average value of start time. Since it is difficult to

clarify what is the actual routine of ADL, the results should be compared with results from other methods and self-reported results to validate our MSA approach. The start-finish time of long-regular activities, such as sleeping and going out is selected to compare the results because these two activities take a large portion of a day and other short-term activities are sometimes not detectable in other methods.

The mode rule is to find the most frequently staying space within each unit time (i.e., minute) so as the activities at 00:00 is determined as the most frequently staying space at 00:00 within experimental dates. The result from mode rule has not reflected some irregularity and continuity of activities. The average rule is to find the average value of all start-finish time of the activities of all dates. Since the subject's actual daily routine cannot be clearly detected, we check two conditions using the subject's self-reported results whether the extracted consensus sequence is reliable enough to represent the subject's daily routine; 1) The extracted consensus sequence should be not much different from the self-reported results., 2) The extracted consensus sequence should be more specific and stable than average or mode rule.

To determine the reliability of the results, it is identified how much the result affected to start-finish time when the unexpected deviations occurred. Since the deviations are not included in routines, the extracted results should not be influenced by deviations.

4.4 Extracted ADL Routines

4.4.1 Routine Information of Long-Regular Activities (from Global Alignment)

The timetable of long-term space use at home is derived from the global alignment. From the consensus sequence, the start-finish time and duration of long-term activities are obtained as results. The long-term activities of ADL usually include 'sleeping' or 'going out' longer than 60 minutes, and extracting routine information of these activities are important to grasp the subject's ADL routine since they take a large portion of a day. Especially for a sleeping activity, it is a major activity of ADL and knowing the start-finish time and durations of sleeping activity can be used as diagnosing sleep disorders for elderly healthcare. In case of long-regular activities such as sleeping and going out, our experimental case had a few exceptional deviations due to external conditions (i.e., weather, visited by families) and we found that the result from global alignment can effectively ignore them when extracting common routine.

```
>Consensus/1-1440 Percentage Identity Consensus (from ClustalG)
Gap Open: 20.0 / Gap Extension: 10.0
00: LLLLLLLLL LLLLLLLLL LLLLLLLLL LLLLLLLLL LLLLLLLLL LLLLLLLLL
01: LLLLLLLLL LLLLLLRRRR RRRRRRRRRR RRRRRRRRRR RRRRRRRRRR RRRRRRRRRR
02: RRRRRRRRRR RRRRRRRRRR RRRRRRRRCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
03: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
04: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
05: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
06: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
07: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCLLLL LLLLLLCCCC CCCCCCCCCC
08: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCK KKKKKKKKKK KKKKKKKKKK
09: KKKKKKKKKK KKKKKKKKKK KKKKKKKKKK KKKCCCCCCC CCCCCCCCCC CCCCCCCCCC
10: LLCLKKKKKK KKKKKKKKKK KKKKKKNNNN KKNNNNNNNN NNNNNNNNNN NNNNNNNNNN
11: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
12: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
13: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
14: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
15: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
16: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
17: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
18: NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN NNNNNNNNNN
19: NNNNNNNNNN NNNCKKKNNN NNNNNNNNNN NKKKKKKKKK KKKKKKKKKK KKKKKKKKKK
20: KKKKKKKKKK KKKKKKKKKK KKKKKKKCCC CKKKKKKKKK KKKCCKKKKK KKKKKKKKKK
21: KKKKKKKKKK KLLLRRLLRR RRRLCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
22: CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC CCCCCCCCCC
23: CCCCCCCLCC LLLLLLLLLL LCLLLLLLLL LLLLLLCLLL LLLLLLLLLL LLLLLLLLLL
```

Waking up

Going out

Returning home

Sleeping

Figure 4.3 Identified Consensus Sequence from Aligning with Equivalent Time Frame (Global Alignment)

In our experimental case, there are two sections in a day; 1) before going out and 2) after coming back.

1) ‘Sleeping’ Routine from Results

Though the subject usually uses 'Room 3' for bedroom space, sleeping randomly occurred at 'Room 2', 'Room 3', and 'Living room' because of the tropical night during the experiment period. According to the subject’s comment, the subject woke up in the middle of sleep and moved to another room to avoid the heat more often than usual or frequently changed sleeping space each day. Considering these conditions, the sleeping hours can be

derived from where the position the character 'L', 'R' and 'C' do not consecutively appear in the consensus sequence. As shown in Figure 4.3, the start and finish time of sleeping hours are 21:11 and 08:39 each. Since the characters 'L', 'R' and 'C' does not always guarantee the sleeping activity, the result does not mean that the change of characters among 'L', 'R' and 'C' presents the change of sleeping spaces directly. Instead, the sleeping hour sequences show a result of the most frequently and consecutively stayed area considering in each time frame. Thus, when the occupant has a regular pattern of sleeping space, always sleeps in an identical bedroom, the sleeping hours can be detected more precisely.

2) ‘Going Out’ Routine from Results

The going out and returning hours from the community center was more irregular than the sleeping hour so their range are much wider (between 10:26 and 10:32, between 19:13 and 19:31). The consecutive 'N' represents going out and the result shows that the subject usually goes out between 10:26 and 10:32. In case of returning home, where the position the character 'N' does not appear in the sequence is when the subject usually returns home. The subject reported that usually goes out once in a day between 10:00 and 11:00.

According to the previous interview with the subject, the subject performs several activities relevant to ADL except sleeping when “Before going out” and “after coming back”; their durations are 107 minutes (08:39-10:26) and 117 minutes (19:14-21:11) each. The identified duration of

“before going out” (107min) is similar to the average value from input sequences. On the other hand, the duration of “after coming back” (117min) is less than the average value from input sequences, meaning that the results from global alignment can be less influenced by unexpected deviations. The global alignment can be more powerful when finding the start-finish time and duration of activities occurring irregularly, such as the time for returning home. In this research, the maximum duration is selected to include as many at home activities as possible. From determining the timetable of 'sleeping' and 'going out' activities, the other ADL routines performed in home can also be determined as a remaining timetable of a day.

In these two sections, the activities performed in a short time (e.g., bathroom) are mostly ignored, as shown in Figure 4.3. To investigate the activities performed in these sections, input sequences of these timeframes are separately aligned using the local alignment below.

4.4.2 Routine Information of Short-Random Activities (from Local Alignment)

Before going out

```
>Consensus/1-2171 Percentage Identity Consensus (from ClustalG)
Gap Open 1.0 / Gap Extension 0.1
LLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLL
LLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLL
LLLLLLLLLLLLLLLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRRRRRRRRRRRRRLLLLLLLLLLLLL
LLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLRRLLLLLLLLLLLLLLLLLLLLLLL
RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR
RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRLLLRRRRRRRRRRRRRRRRRRRRRRRRRRR
RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCAAAAAACCCCCCCCCCCCCCCCCCCCCCCCCCCKKKKKKKKKKKK
KKKKKKKKKKKKKKKKKKKKKKRCCCCCCCCCCCCCCCRRRRRRRRRRRCCCCCCCCCCCCCCCCCLRRR
RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRKKKRRRAAAAAAAKKKKKAAKKKKK
KKKKKALLLLLKKKKKKKKKRRRRRRRRRRRRRKRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR
RRRRRRRRRRRRRRRRRRRLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLCAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAALLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLNNNNNNNN
NNNNNNNNNNNNNNNNNNNNNNNNLLLLLLLLLLLLLLLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRR
CCCCCCCCCCCCCCCLLLLLLLRRRRLLLLLLLLLLLLLLLLLLLLLLLLKKKKKKKKLLLLLLLLLLKK
LRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCAACCCCCCCCCCCCCCCCCCCCCCCCCACCCAAALAAACCCCCCCCCCCCCCCCCCAAAAACCCCC
CCCCCCCCCCCCCAAAAAAKAAKACCCCCCCCCCCCCCCCCCCAAAALKKKKKCCCCLLLLLLLKKKRRR
RRRRKKKLCCCCCCCCCCCCCCCAAAAAAAAAAAAAAAAAAAACCKKCCCCCCCCCCCCCCACCAAAKKK
KKKKKKKKKKKKKKKKKKCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCLLCCKKKKKKKKKKKKKKKALL
KKKKKKKKKKKKKKLAALLLRRLLLLCCLKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKK
KKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKK
KKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKK
KKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKRRRRRKKKKKKKKKKKKKKKKKKKK
KKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKKAAAAACCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCKKKKKKKKKKKCKKKLLKCLLLCCLCCLLLLLLLLLLLLLCCCLL
ALLLLLLLLLLLLLLLLLLLLLLLLLLKAKKLKKKKKLCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCLLLLLLLLLLLLLLLLLLLLLLLCCAAAAACCCCCCCKKKKKKK
```

Figure 4.4 Parts of Identified Consensus Sequence from Aligning with Contextual Time Frame (Local Alignmet)

From the 52 days of the input sequences, the two-time frames, “before going out” and “after coming back” are separately selected and aligned. The short-term activities of ADL usually include 'using a bathroom for toileting', or 'using a kitchen for having meals' less than 60 minutes, and extracting

routine information of these activities are also important to grasp the subject's ADL routines which are relevant to health status. Using local alignment, it is possible to extract routines of short-term activities that can be performed randomly in a day (e.g., a person randomly uses a bathroom in a day even the frequency of uses are regular.) From the result of local alignment, not only the start-finish time and duration of activities but also the order among activities can be extracted in two home activity timeframe, "before going out" and "after coming back".

As a result of scaled down, bathroom use appears five times between 07:36 and 08:49 within a short interval. According to the subject's comments, the subject usually goes to the bathroom right after waking up in the morning. Due to some ranges of waking up hours (between 07:36 and 08:49), the frequency of bathroom use is overestimated than the real situation. In the night, the subject goes to the bathroom once (22:39) for four minutes. After waking up, the subject uses the kitchen for breakfast and stays 'Room 3' for a while before going out. Again, the subject usually uses the kitchen for dinner after spending the afternoon at the community center. After dinner, the subject stays the 'Room 2', 'Room 3', or watches TV in the living room until he goes to sleep.

As shown in Figure 4.4, short-time activities (e.g., bathroom) are well-

conserved, unlike global alignment, and it was found that local alignment is effective when extracting order and frequency of activities which have various start time or durations.

4.4.3 Extracted ADL Routines from Integrated Consensus Sequences

For an intuitive understanding of the extracted routines, the input and output sequences can be visualized as an activity map (Figure 4.5). The activity map includes spatial dimension by colors and temporal dimension by length (duration) and order (start and finish time).

As shown in Figure 4.5, the subject's daily activity patterns have some exceptional case, when the patterns are far different from usual, such as '2018-08-05'. Though considering all the irregularity, the extracted consensus sequence is well-matched with the daily routine of the subject perceiving his/her own. In the experimental period, the subject reported that he/she wakes up between 6:00 and 8:30, mostly goes out once in a day in the afternoon. The subject comes back at home between 18:00 and 20:00 usually, and goes sleep at between 21:00 and 23:00. These reported patterns are well presented in Figure 4.5 of the extracted consensus sequence. The subject also reported that waking up in the middle of the night and overnight toileting about once in two weeks, and this sparse pattern is not reflected in the

consensus sequence. It implies that overnight toileting of our subject is not frequently occurred to be considered as a routine of the subject. As mentioned above, the subject randomly moved to another room (among 'Room 2', 'Room 3', and 'Living room) in the middle of the sleep due to the tropical night, and it is reflected to the consensus sequence as routine. From the extracted routine, it can be found that the subject experienced some sleep troubles during the experiment period. The subject usually goes to sleep at least after 22:43; if the subject always sleeps at 'Room 3' as usual, sleep disorders could be suspected if any location other than 'Room 3' is found after 22:43. Thus, the abnormal behaviors, such as sleep disorders or frequent overnight toileting can be detected by comparing the extracted routines of regular intervals.

Though these patterns and each durations from the integrated consensus sequence do not clearly fit into the real situation, the identified results can act as a predicted pattern considering historical data. Since it is difficult to define what the actual daily routine is, extracted ADL routines are compared with extracted pattern information from other methods and the subject's self-reported information to verify the reliability.

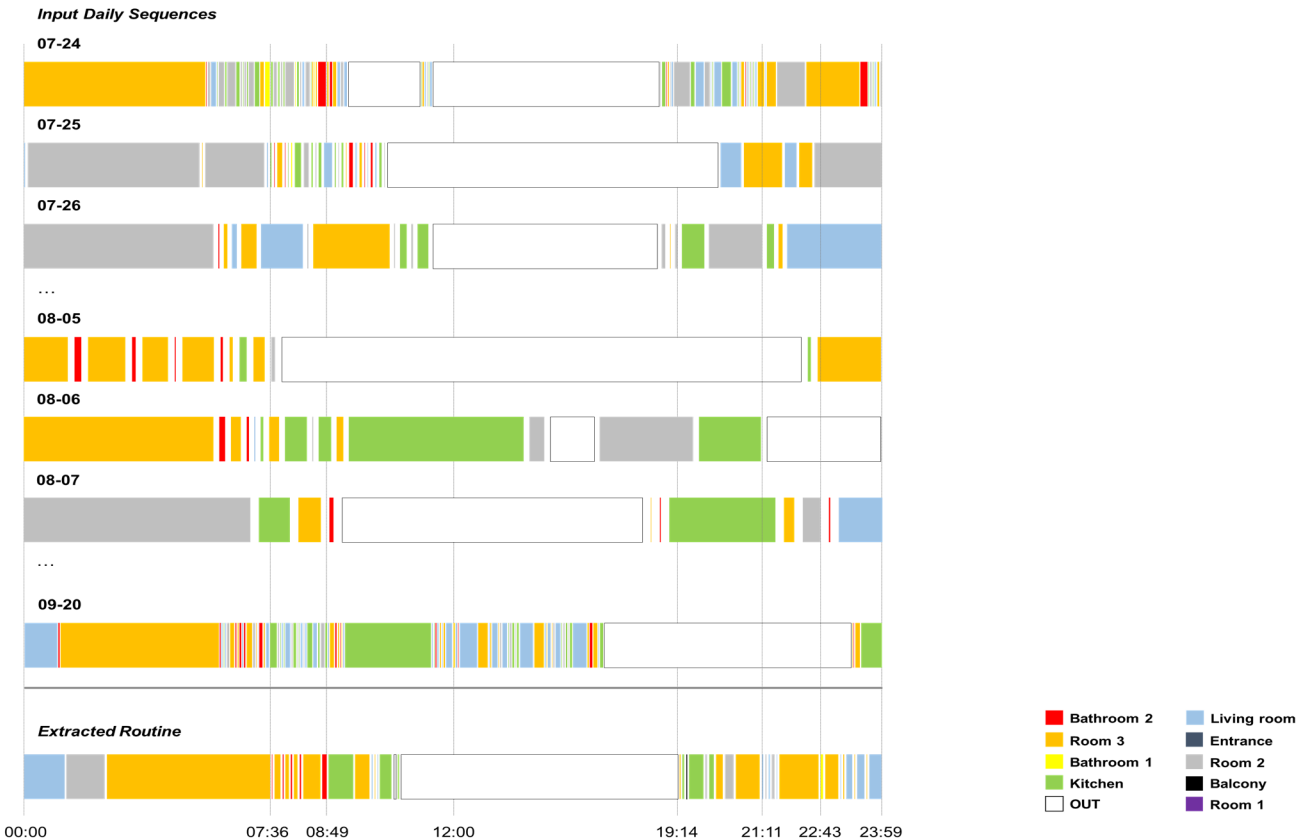


Figure 4.5 Visualized Results of Integrated Sequence from Two Alignment Methods

4.4.4 Validating the Results from MSA

Table 4.2 shows the results from MSA, mode rule, average rule, and the subject's self-report.

The subject reported the start time of each activity as a range due to some daily irregularity. The results from MSA are closely similar and their ranges are narrower than the self-reported results. Though it is difficult to prove that MSA results are more accurate than self-reported results, MSA results are not far different with the actual daily routine when assuming that the subject's report is well reflected the actual daily routine.

In case of results from mode rule and average rule, all values are included the range of self-reported value, except the average value of coming back hours. The average value of the start time of coming back is 16:57 and it is far different with all other results. The average value is strongly influenced by the exceptional schedule, such as the start time of coming back 08:33 at 2018-08-23 or 10:41 at 2018-08-24. In those days, the subject went out early in the morning and came back shortly as unusual. The MSA can consider the common patterns rather than one-day exceptions, extracting more stable results. Also, the MSA result has the advantage of specifying the time range of these activities, which are irregular but necessarily performed.

In case of bedtime, the identified result (between 21:11 and 22:43) can narrow down the range more precisely than just checking each start-finish time (between 18:30 and 23:59) of all dates. The MSA results show more specific and stable results which are not far different from the self-reported results, satisfying the above two conditions.

Table 4.2 Comparing the Result with Mode and Average Rule

	Wake-up	Going out	Coming back	Bedtime
Result	07:36-08:49	10:27-10:33	19:14-19:19	21:11-22:43
Mode Rule	07:00	09:16	19:49	21:17
Average Rule	06:05	09:44	16:57	20:55
Self-reported	6:00-8:30	10:00-11:00	18:00-20:00	21:00-23:00

The MSA has advantages in terms of data processing, such that the spatio-temporal information of a day can be replaced in a string sequence. Using the MSA to identify the spatio-temporal routine is more powerful than just finding the “most frequent value” or “calculate average value of all dates” rule. Even when sequences are not quite regular, MSA can find the possible patterns considering the entire sequences. Though “using a bathroom” usually registers random duration and the subject does not have specific rules to use a sink, the MSA can identify it. It is also possible to identify a pattern that 'using a bathroom' after waking up. Also, a pattern that ‘using a kitchen’ at after waking up in the morning and after coming back home at dinner time

implies that the subject usually uses a kitchen twice a day to have a meal. Especially, short-repetitive sequences appearing randomly (e.g., using a toilet in the bathroom) cannot be detected by the most frequent rule since they are ignored by longer duration activities when extracting common pattern.

The two alignment methods of MSA should be used comprehensively because each method has its own characteristics. With local alignment, an additional modification is required to consider the sequence length as a time dimension, such as scaled down the duration of result. Finding the patterns in short and irregular activity, such as “using a bathroom (A and D),” also can be influenced easily by adjusting the parameters including the gap penalties. Increasing gap penalties (gap extension and gap opening) helps avoid inserting gaps when finding the highest similarity scores for optimal alignment. Decreasing the gap penalty inserts gaps to find short-repetitive subsequences and the consensus sequences can be much longer than input sequences. Thus, the high gap penalty can be selected to preserve the original length of input sequences when using equivalent time frame, and lower gap penalties can be effective in finding short-term repetitive routines. The integrated consensus sequence from two alignments can show how many times the subject wakes up in the middle of the sleep in a day, and it can be used as significant information about an occupant's health or space-use patterns.

4.5 Summary

In this chapter, the ADL routines of the elderly subject who is living alone for 60 days using tomographic motion detecting system was extracted applying MSA and evaluated the validity of extracted routines. It was found that MSA comprehensively using the two alignments (i.e., global alignment, local alignment) has advantages in presenting the spatio-temporal log as a string sequence and using the MSA to extract the routine is useful than other previously used methods.

If the occupant performs the ADL with abnormal patterns frequently enough to be reflected as routine (e.g., waking up at night and performing any activities, using toilet several times at night, using a kitchen in midnight), this ADL relevant information could assist with diagnosing health issues. Thus, the identified activity patterns with temporal aspects can be used to detect the adequacy of each activity (i.e., whether the activity is performed in the right place at the right time). In addition, the extracted routines using the two alignment methods of MSA was found that showing results except for the exceptional deviations. Therefore, the extracted ADL routines can be used as a warning in healthcare when abnormal routines are detected or the routines are significantly changed.

Chapter 5. Quantifying and Assessing the Variability of Extracted ADL Routines

In this chapter, the detected ADL from the previous chapters is quantified as a three-dimensional vector and plotted to measure routine variability. For calculating the irregularity of ADL in 60 days, the activities of each space (i.e., room) are determined as clusters and outliers. By measuring the distance between each point of activity and center in clusters, the irregularity as the ADL routine variability is assessed how regularly the daily activities are performed. In case of abnormality, the performed activities are evaluated how many times the subject performs activities abnormally as counting frequency.

The measured ADL routine variability has assessed the change of value per week and analyzed what the value change means. To validate this approach, the cases which are from the subject who is an office worker and the elder who has relatively irregular pattern are compared that the difference of regularity of ADL routine is actually reflected the results.

5.1 Activity Quantification with Sequential Information

To quantify the collected daily activity sequences from the previous experiment, the consecutive identical characters (i.e., each space presented as a character) should be identified as a single activity with a duration which is the number of consecutive characters. The start-time of each activity (i.e., staying a space) is deduced from the start point of the timestamp from the consecutive characters. The approach of quantifying an activity presented as performed space, start-time, and duration is based on that these three spatio-temporal features can present the characteristics of the activity.

Algorithm **Finding an activity from consecutive characters**

Inputs: daily activity sequences $\boldsymbol{S_i}$
Outputs: activity k vectors in a day $\boldsymbol{A_{ijk}}$ = (ST_{ijk}, DU_{ijk})

1: Label consecutive identical characters as a group
for s_p (p = 0, …, 1339) in $\boldsymbol{S_i}$
label 'X' if s_p == 'X'
p = p + 1
till s_p is not 'X'
return group as a_{ij} (j = activity classification number)

2: Find the frequency of activity 'X' of in day i
count the number of group k for all groups a_{ij}
return k as f_{ij}

3: Find the duration of all activity 'X' of in day i
for all group a_{ij} in $\boldsymbol{S_i}$
count the number of characters d in all groups a_{ijk}
return d as DU_{ijk}

4: Find the start time (position) of all activity 'X' in day i
for all groups a_{ij} in $\boldsymbol{S_i}$
return the first position p of each groups a_{ijk}
return p as ST_{ijk}

5: Eliminate activity vectors according to duration condition
6: Return A_{ijk}

Ex)

* [C] Bedroom

2017-10-20

Space Code	Start time	Duration
1	0	499
1	517	1

2017-10-23

Space Code	Start time	Duration
1	2	1
1	11	487
1	1160	1
1	1187	5
1	1411	23

Figure 5.1 Pseudo Code for Quantifying the Daily Activity Sequences

The characters of each space are converted to integer code for differentiating. The way of quantifying the daily activity sequence is shown in Figure 5.1.

5.2 ADL Variability Analysis

5.2.1 ADL Clusters of Each Space

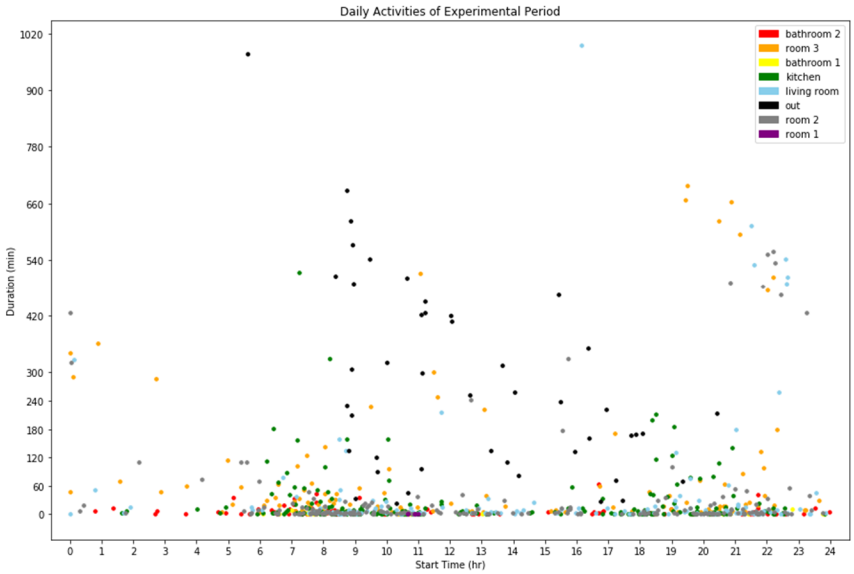


Figure 5.2 Plotted Daily Activities of Experimental Period

The quantified daily activities can be plotted in the plane of (Start-time, Duration) by each space code. The space of the experiment conducted in the

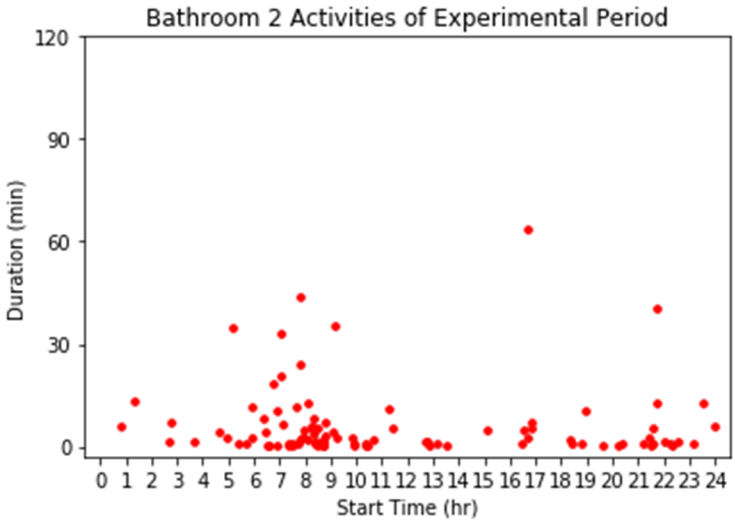
previous chapter has 8 types of rooms including 'not in the home as OUT', and they are classified as integer code from 0 to 7. When plotting all the activities detected in the experimental period, each space code is displayed in different colors to distinguish them as shown in Figure 5.2.

In case of activities which lasted until the day after, the two days of activities are integrated with a single activity which duration is summed with the duration of each day.

As shown in Figure 5.3, each space has different patterns of start-time and duration, most of the activities performed less than 60 minutes. To find the activities regularly performed, the activities presented as a cluster and the activities not belonged to the cluster as outliers should be identified as follows.

1) Determining the number of clusters of each space as temporal patterns

From the collected data, the activities performed at a similar time during similar duration should be identified as a cluster. Though the activities performed at identical space, they might have different characteristics in terms of temporal aspect (i.e. activities performed at a different time or during the different duration). For example, a bedroom can be used to perform not only 'sleeping' but also 'watching TV'. To determine these activities, the points plotted of a single space are evaluated to find how many types of activities are performed during the experimental period.



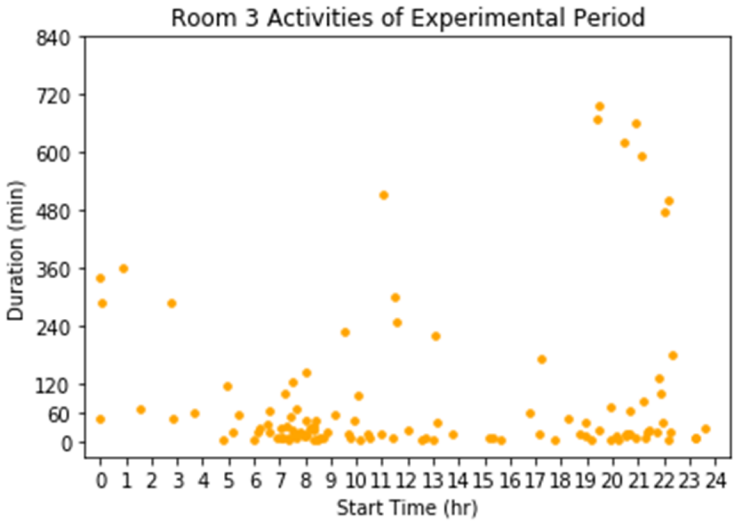
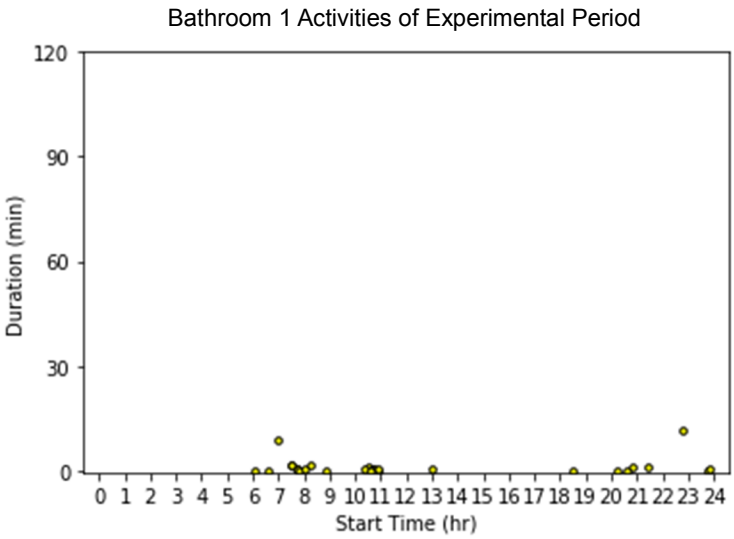


Figure 5.3 Plotted Each Space of Daily Activities of Experimental Period (Above: Bathroom 2, Below: Room 3)



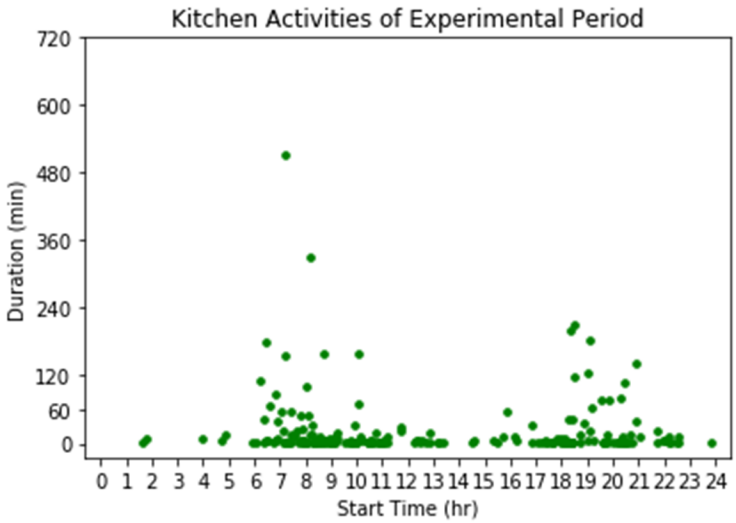
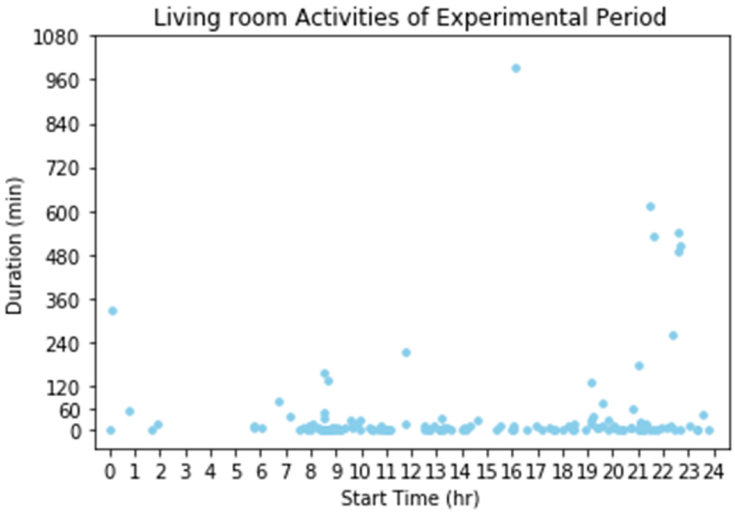


Figure 5.3 Plotted Each Space of Daily Activities of Experimental Period (Above: Bathroom 1, Below: Kitchen)



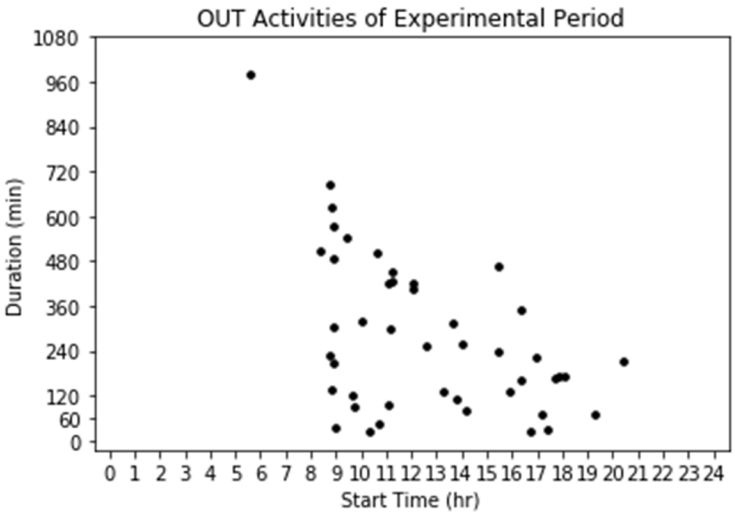
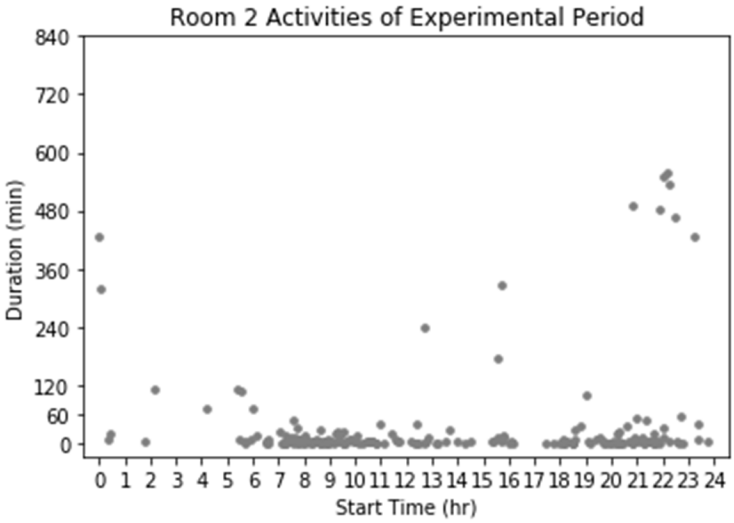


Figure 5.3 Plotted Each Space of Daily Activities of Experimental Period (Above: Living room, Below: Out of space)



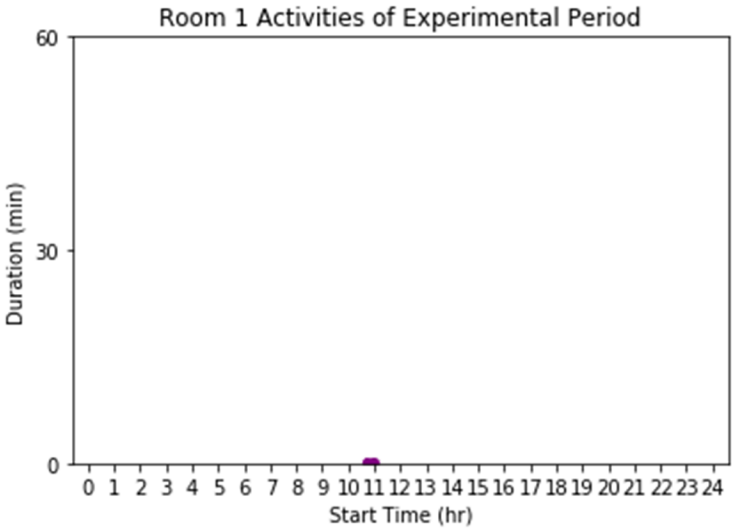


Figure 5.3 Plotted Each Space of Daily Activities of Experimental Period (Above: Room 2, Below: Room 1)

Finding an activity as a cluster, the Silhouette Coefficient can be used to determine how many clusters in the dataset. It is a method to evaluate the clusters' quality from measuring how the data in a cluster is densely located (i.e., cohesion) and how the clusters are separately located (i.e., separation). The value is calculated as follows.

$$S_i = \frac{(b_i - a_i)}{\max(a_i, b_i)}$$

where a_i = distance to its own cluster centroid

b_i = distance to the nearest neighbor cluster centroid

The Silhouette Coefficient ranges from -1 to 1, and the data is well matched to the number of clusters when the value closes to 1. This method is based on the assumption that the evaluating clusters are usually the globular shape with k-means clustering technique.

Since the collected activity data is also based on that similarly performed activities would be plotted around a similar point according to the start-time and duration, the optimal number of clusters of each space is determined by using the Silhouette Coefficient. The optimal number of clusters is defined with comparing the Silhouette Coefficient when the number of clusters (n) which range from 2 to 6, and the n is selected when the Silhouette Coefficient is the largest value as shown in Table 5.1.

In case of activities [N] which present the state when the subject is out from home have a single cluster, and activities [S] are ignored since the data is not enough to make any cluster.

Table 5.1 The Number of Clusters of Each Space from Silhouette Coefficient

	N = 2	N = 3	N = 4	N = 5	N = 6
[A]	0.7503	0.5460	0.5949	0.6026	0.5825
[C]	0.6528	0.6710	0.5842	0.5837	0.5257
[D]	0.8199	0.7733	0.7359	0.7243	0.7143
[K]	0.7366	0.5755	0.4977	0.4728	0.4764
[L]	0.6380	0.6551	0.5605	0.6146	0.5370
[N]			N = 1		
[R]	0.6910	0.5631	0.6032	0.6429	0.5708

2) Defining the outliers as exceptional events (deviations)

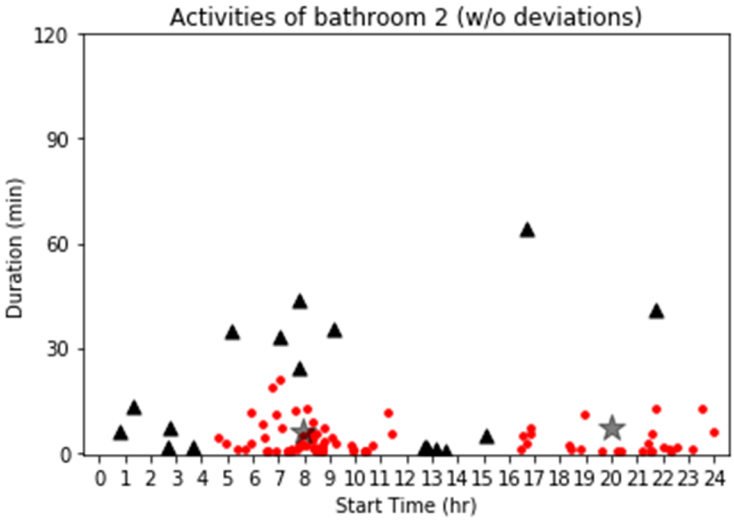
The activities defined as outliers have a meaning of activities which are performed as an unusual pattern. These activities are called as deviations which can occur as unexpected events. To find deviations in a certain period, the Mahalanobis distance which can consider the deviations of each feature (i.e., start-time and duration) is calculated from all activities of each space. Since the activities of each space has their own distribution (e.g., distribution spread over the entire range of start-time) even the same value of deviation of start-time and duration has different meanings to each other.

When determining the threshold to detect an outlier, the collected activity data should be manually evaluated depending on how much freedom would be allowed to deviations. Thus, in case of the subject who is known to have regular ADL routine, the threshold should be strictly limited for determining an activity as an outlier which might be a little out of the distribution of similar activities. On the other hand, in case of the subject who has originally irregular ADL routine, an activity performed a little different start-time or duration would not be strange enough to consider it as an outlier. In this research, the threshold is set as higher than 1.5 times of average of the Mahalanobis distance of each cluster. When an activity performed differently from average more than 1.5 times of the standard deviation, it considers as a deviation from an unexpected event. The determined outliers of each space and activities in clusters are shown in Figure 5.4.

3) Plotting clusters of each space during a period

The clusters of each space without deviations are plotted as different color by week. It is possible to find how much each activity performed during a week is different from the routine presented as a centroid.

The clusters of each space without deviations are plotted as different color by week. It is possible to find how much each activity performed during a week is different from the routine presented as a centroid.



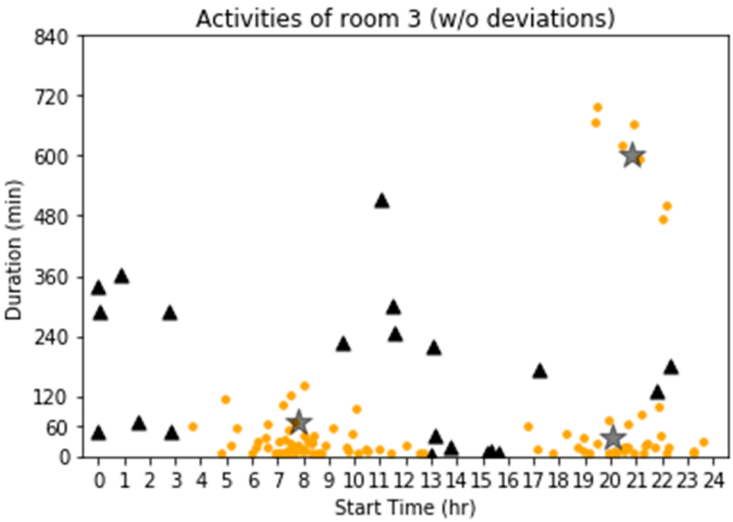
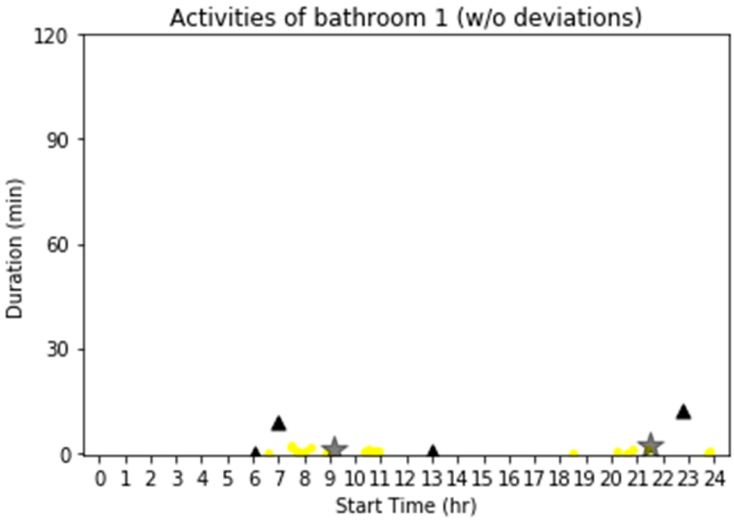


Figure 5.4 Activities of Each Space without Deviations (Above: Bathroom 2, Below: Room 3)



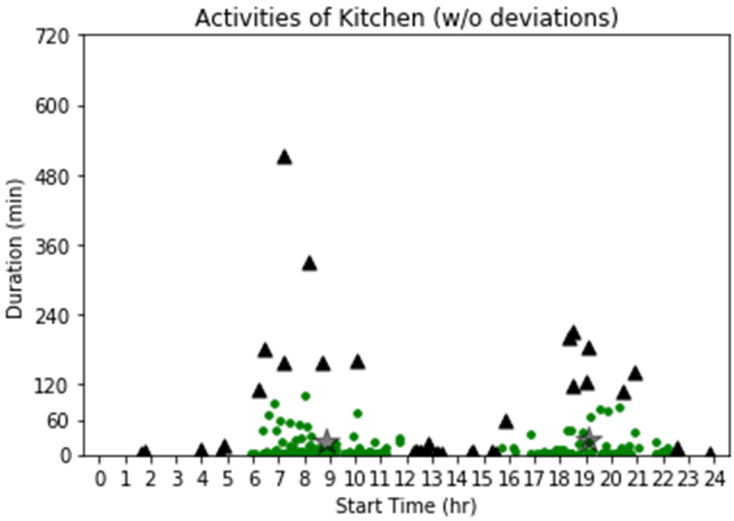
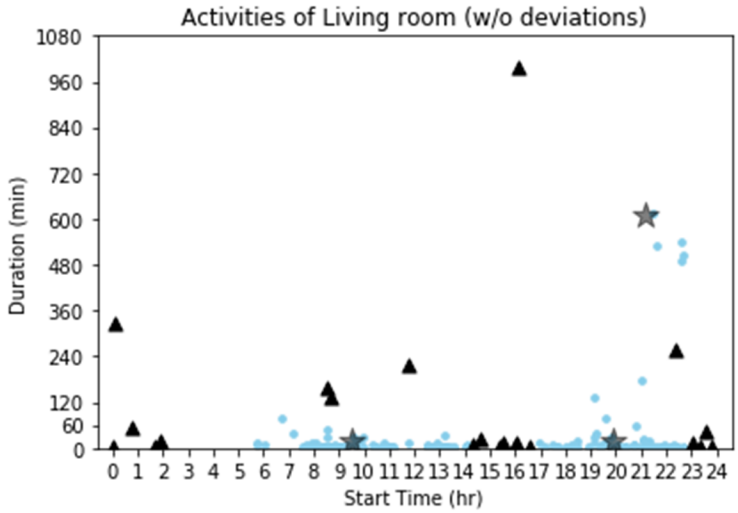


Figure 5.4 Activities of Each Space without Deviations (Above: Bathroom 1, Below: Kitchen)



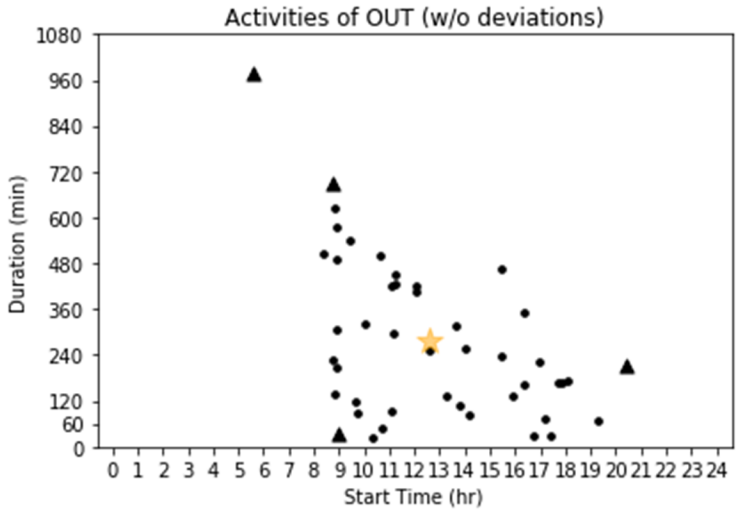


Figure 5.4 Activities of Each Space without Deviations (Above: Living room, Below: Out of space)

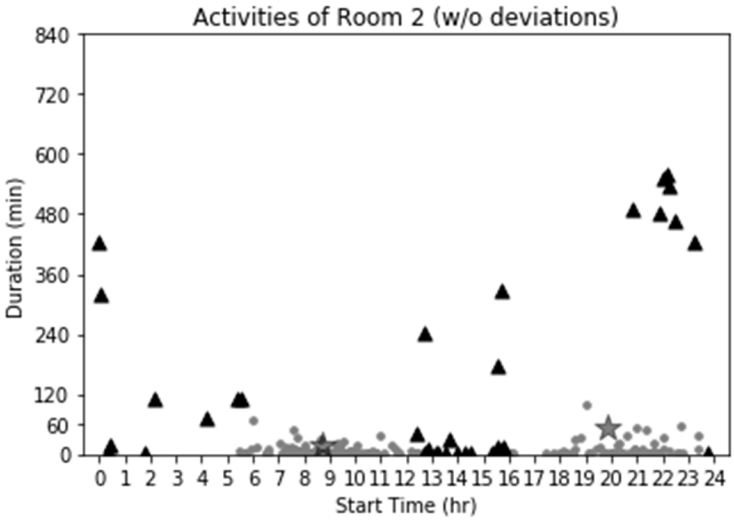


Figure 5.4 Activities of Each Space without Deviations (Room 2)

A case of bathroom activities ([A]) shows two types of routine which performed at about 8 am and 8 pm each with similar duration about 6 minutes. The bathroom activities are usually performed quite randomly when the subject is at a home. Another bathroom activities ([C]) also shows two types of routine which performed at about 9 am and 9 pm each with similar duration about less than 30 seconds. Since the subject in this experiment mostly uses the 'bathroom 2 [A]' for toileting and taking a shower, the frequency and duration are much higher than the 'bathroom 1 [C]' used rarely for toileting.

As mentioned in the previous chapter, the subject in the experiment used a room 3, room 2, and living room for sleeping at night due to the tropical

night during the experimental dates. Based on the results, room 3 and the living room have three types of routine, one in the morning with a duration of less than one hour and the other two types are in the evening. In particular, the evening activities with a duration of about 8 to 9 hours were separated as a cluster and it is possible to infer them as the 'sleeping' activity. The similar activities performed in room 2 [R] were eliminated as deviations despite similar frequency. This is because the activities performed in room 2 [R] other than the sleeping lasted shorter than the activities performed in room 3 and the living room as shown in Figure 5.5. In other words, sleeping in room 2 is considered an exceptional deviation since room 2 had little tendency to stay longer than 1 hour.

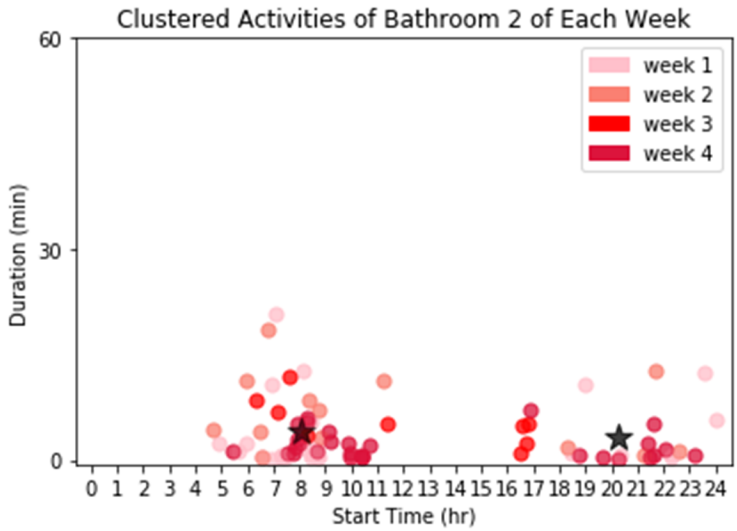
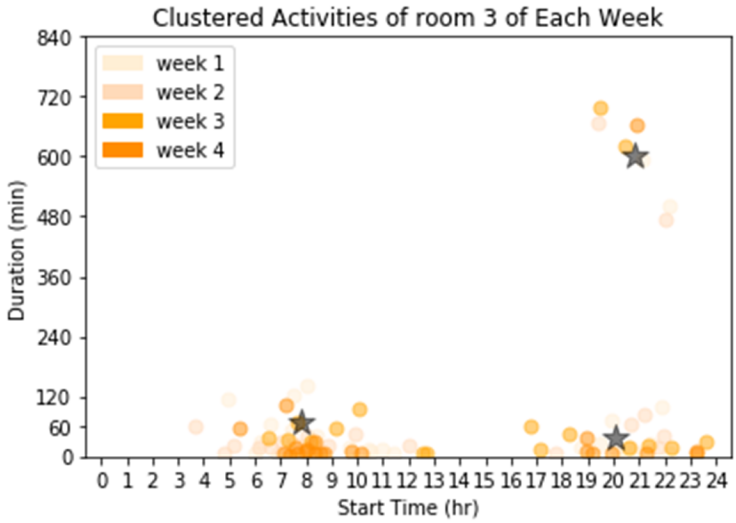


Figure 5.5 Routines of Each Space per Week (Bathroom 2)



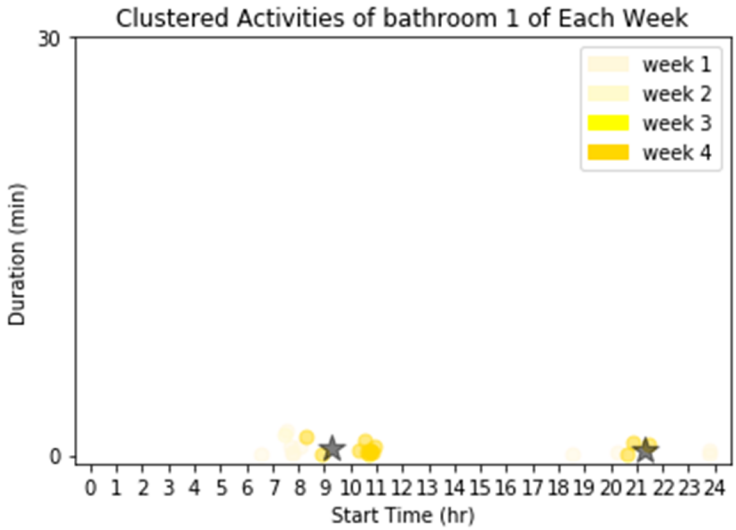
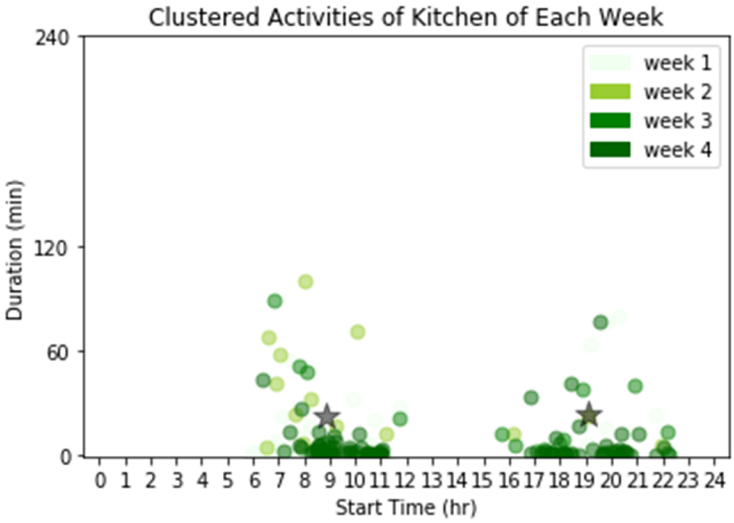


Figure 5.5 Routines of Each Space per Week (Above: Room 3, Below: Bathroom 1)



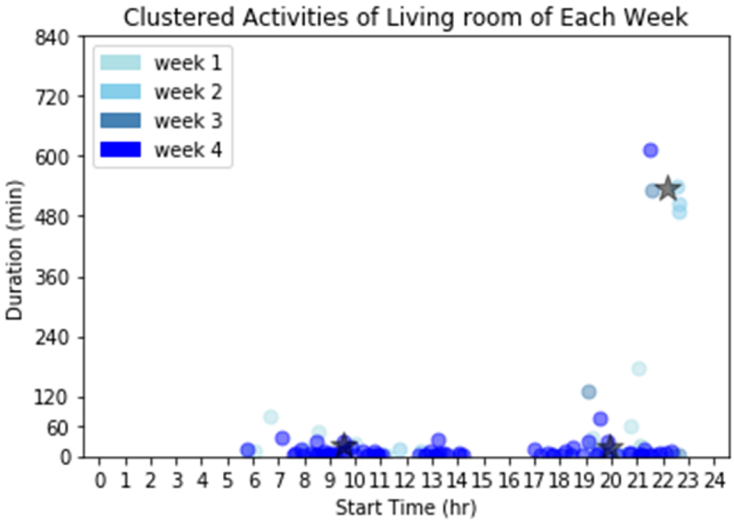
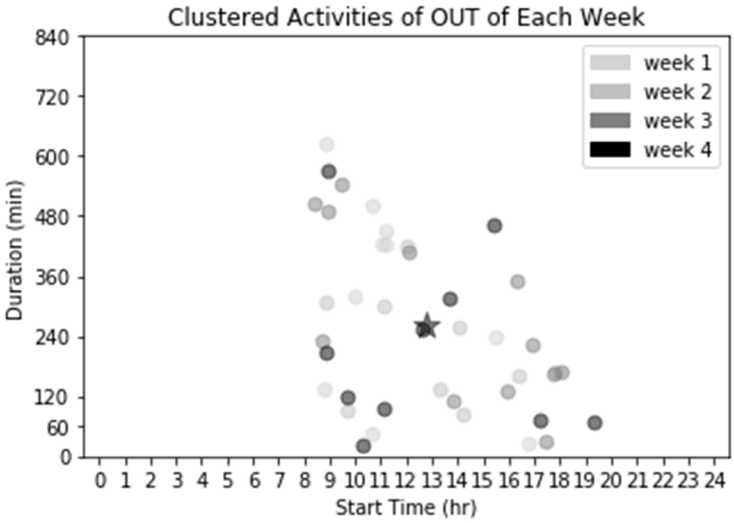


Figure 5.5 Routines of Each Space per Week (Above: Kitchen, Below: Living room)



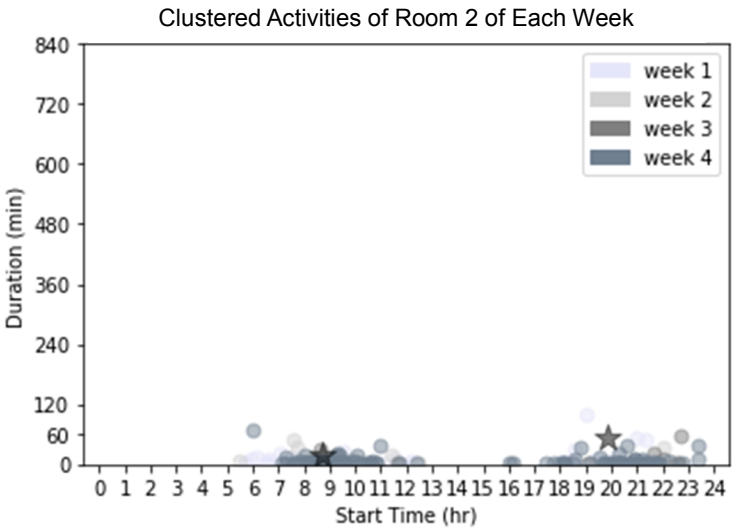


Figure 5.5 Routines of Each Space per Week (Above: Out of space, Below: Room 2)

The 'outing' [N] is one of the most irregularly performed activity not plotted as a cohesive cluster. It reflects the irregularity of the subject which is performed randomly from about 8 am to 6 pm. These irregularities shown in each cluster of each space can be measured as a distance between the activity and the center of the cluster which the activity belonged as follows.

5.2.2 Assessing ADL Irregularity Trends

Based on the collected activity data, it is possible to assess the irregularity trend of activity performance. To apply the concept of distance representing the irregularity, all the data should be transformed as standardization. Since the start-time and duration of data have different scales of unit value, it should be standardized to the 0 of mean and 1 of standard deviation for balancing the impact of value. Then, the each (standardized) Euclidian distance between a data and the center is calculated.

To find when the irregularity of ADL performance increasing or showing gradual change, it is necessary to assess the distance based on the certain short-term period. For example, the average distance of each cluster of each space is summed by week and the irregularity trends can be presented as shown in Figure 5.6.

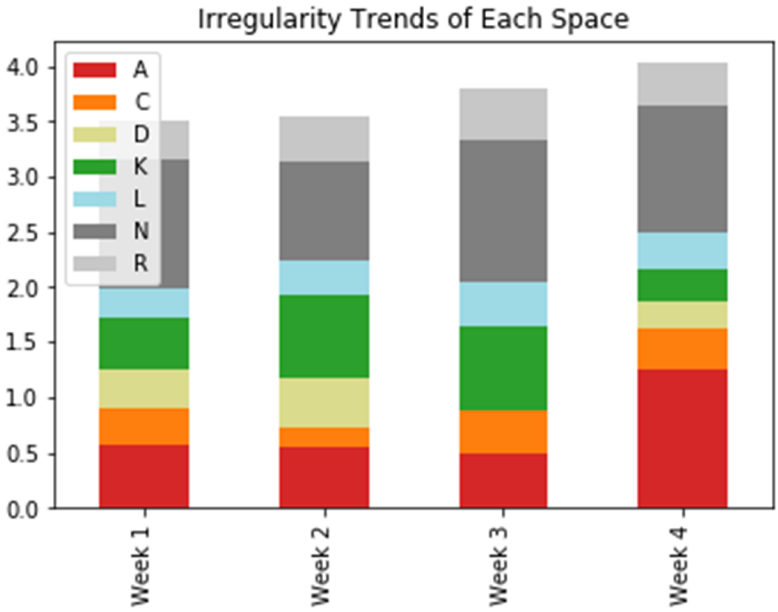


Figure 5.6 Irregularity Trends of Each Space by Week

The aggregated irregularity has continuously increased within the 4 weeks. The plotted as a stacked area is valid for recognizing how many portions of each space contributes to the increase of irregularity. As mentioned before, the outing activity usually takes the largest part of irregularity of all spaces. The activities at the kitchen also take a large parts of the total irregularity and especially increased in week 2 and week 3 when the climate was extremely hot. Though the subject slept at several spaces among room 3, room 2, and living room in this period, the irregularity from these spaces was not as large as the outing or activities in the kitchen. This is because most of the activities other than sleeping were performed quite

regularly. In week 4, the total irregularity is the largest and especially the irregularity of bathroom 2 increased rapidly. It is found that the frequency of using bathroom 2 increased highly since the family of the subject had visited in some days of week 4. Technically, it can be inferred that the visitors might use spaces (kitchen, room 3, room 2, and living room) at a similar time during a similar duration to the subject other than the bathroom.

When assessing the irregularity of an elder, the irregularity of each space can be weighted according to the ADL routines of him/her or a caregiver can give a weighted to the space where is important to the elder's ADL routine.

5.2.3 Assessing the Abnormality Trends

From the definition of routine abnormality mentioned in chapter 2.1.3, the routine abnormality can be assessed with conditions which identifying the spatio-temporal disassociation of each activity. For example, performed activities other than sleeping after midnight can be detected as an abnormal activity. Figure 5.7(a) shows all activities performed in room 3 where usually used as a bedroom, and the shaded area shows abnormal conditions presenting the time-activity and time-duration disassociations. By considering that the subject usually goes to bed at 9 pm to 10 pm, the performed activities shorter than 3 hours at between 12 am and 5 am (i.e., the

time when the subject rarely waked up) can be identified as abnormal activities of time-activity (i.e., sleeping) disassociation. In the subject case, 5 frequency of these abnormal activities are performed in room 3 and this frequency takes about 4% of the total activities performed in room 3. In order to assess the severity of abnormality, the following two approaches can be considered according to the criteria of the subject.

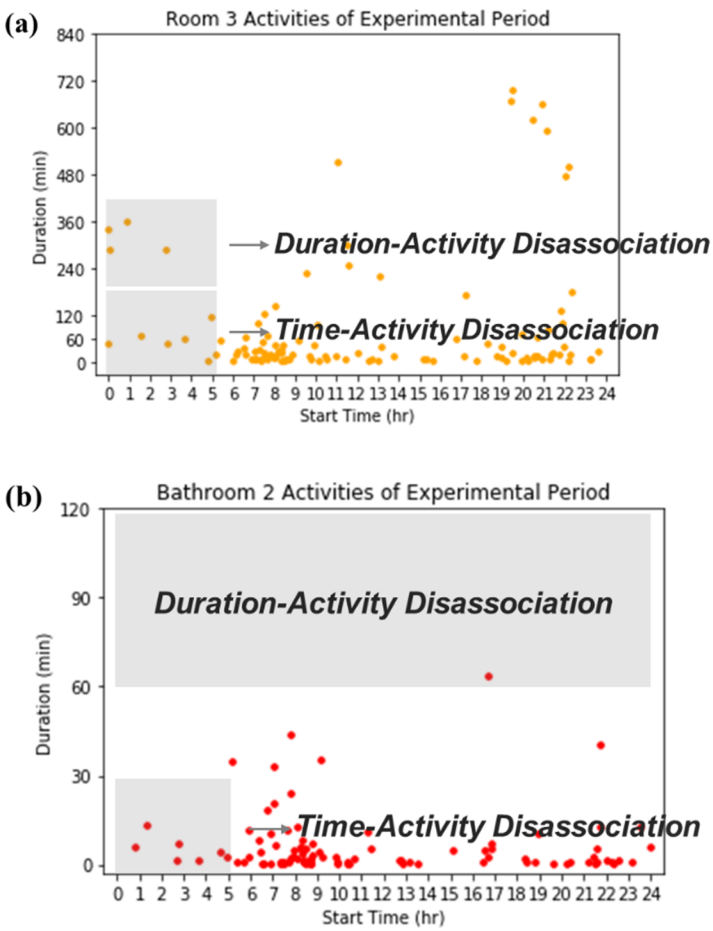


Figure 5.7 Examples of Annormality Conditions ((a): Bedroom (b) Bathroom)

1) Considering the proportion of the frequency of abnormal activities to the total home-activity

Tracking trends of the frequency of abnormal activities can be a measure to detect the time when abnormal activities increases or the activity which abnormally performed. The deviations due to the unexpected events (e.g., visitor, before and after traveling, etc.) which influenced not much to health status might be a cause of abnormality increases and therefore the threshold of each activity's abnormality should be obtained as an initial condition (from a doctor, caregiver, etc.) reflecting the subject's own routine. Thus, the cause of abnormal activities whether from exceptional events or deterioration of health status should be assessed after identifying the abnormality.

The abnormality higher than the threshold can suggest as a signal to feedback to the subject make improve his/her ADL detected as abnormal by informing the cause of abnormality (i.e., in which disassociation case).

2) Considering whether a cluster of activities belong to abnormal conditions

In case of activities belong to a cluster are detected as abnormal activities, it can be known that the activities usually performed abnormally

when the data is collected. For example, a cluster presented around the plot where the start-time at 2 am with a duration longer than 3 hours (i.e., sleeping) can be identified as time-activity disassociation case indicating 'late sleep time'. When abnormal activities becoming a pattern forming a cluster, the abnormality gets increase and it should be known to the subject to improve the pattern. Since a sudden appearance of abnormal routines also influences to increase of the irregularity, the subject should be noticed which activities are abnormally performed. In addition, monitoring the abnormality trends on a regular basis can contribute to improving quality of life and health status of the subject.

The ADL variability defined as an irregularity and an abnormality should be validated whether it can reflect the effect of actual variability of ADL as a certain value.

5.2.4 Validating Assessed ADL Variability

It is difficult to directly validate the approach proposed to assess the ADL variability since it is also difficult to find what is the actual ADL routines of the subject. In this research, an approach to quantify the ADL and the variabilities of ADL routine is proposed and it should be validated whether it can reflect the degree of change of the ADL as a value.

To validate the approach, the measured ADL variability of the subjects from the two experimental cases are compared because the two subjects have a clearly different degree of variability of ADL. The subject from the experiment conducted in chapter 3 is an office worker who has a regular pattern of commuting in weekdays and the subject from the experiment conducted in chapter 4 is an elder who does not have a fixed schedule (higher freedom of the activities). Through the previous interview with each subject and extracted results, it can be expected that the elder subject has higher ADL variability than the office worker. If the proposed approach to measure the ADL variability quantitatively well reflects the actual variability of routine, the variability of the elder subject would be devised higher than the office worker. The irregularity trends of two subjects during a month is shown in Figure 5.8.

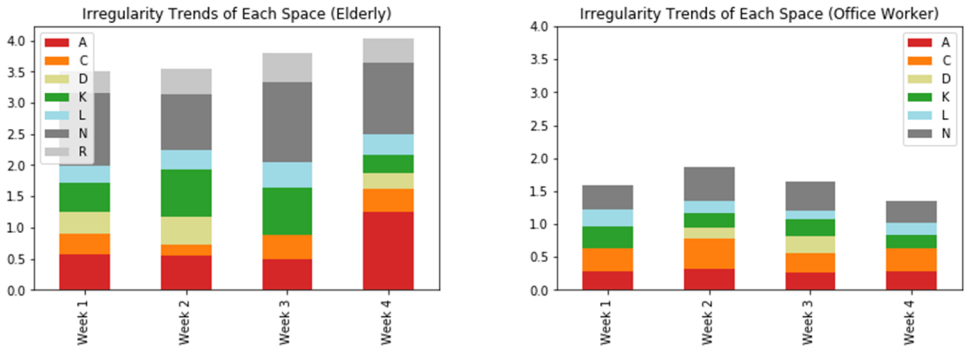


Figure 5.8 Comparing Irregularity Trends of Two Types of Subjects during a Month

As expected, the irregularity of the office worker's ADL routine shows a much higher value than the elder subject. From analyzing the value of results, it is found that the lower variability value of irregularity of the office worker is caused by the more regularly performed activities which take a large portion of the total ADL (i.e., outing and kitchen activities). In detail, the routines of the office worker has a uniform value of the irregularity of all ADL and the most irregularly performed in week 2. From the collected data of week 2, it is found that the subject had returned home very late aside as usual and it influenced all other ADL including sleeping in the bedroom. In case of a bathroom, the irregularity was kept as a similar value during the entire month and this result is from that the subject had a regular routine of using the bathroom at 8 am to 9 am and at 11 pm to 12 am with a similar

duration.

As well as the difference of actual irregularity of ADL routine, the difference in the number of activities performed in a day is also an important factor influencing the value of irregularity. The office worker spent time at his/her home for a significantly less than the elder subject and this also affected the lower value of ADL irregularity.

Though the proposed approach measuring the irregularity of ADL routine can reflect the difference of the actual ADL variability as described above, the results of the irregularity value do not have a meaning by themselves. In other words, the total irregularity of ADL in week 4 of the elder subject, 4.0239 has not identified any situation itself. Since the value from the sum of distances between an activity and the center of a cluster the activity belonged is based on the data itself, an irregularity value of other subject cannot compare directly. When the irregularity of person A has a value of 2 and person B has 4, it is not guaranteed that the irregularity of B is as twice as much than the irregularity of A so that the irregularity value should be compared as relative sizes. Instead, the size of a value can be compared within a single subject in time order to assess the trends and the approach proposed in this chapter can reflect the trends of the variability of performed ADL.

Based on the existing research and the validated approach, there is a possibility to be detected the higher variability from the elderly patient who has mental disorders than the healthy elderly though it is beyond the scope of this research.

5.3 Summary

In this chapter, the ADL of the elderly subject detected using motion sensors was quantified and assessed their variability defined as an irregularity and an abnormality. The quantified activity data presented as a vector of [space, start-time, duration] was plotted and formed as clusters presenting routines.

Since the activities performed at similar start time during a similar duration are plotted around the centroid of cluster, it was found that the distance between an activity and its center of the cluster can reflect how much the activity differently performed compared to the routine (i.e., irregularity). In addition, it was described that the abnormality can be quantified as a frequency of the activities performed as abnormal which is determined from the conditions of disassociation (i.e., time-activity disassociation, duration-activity disassociation, frequency-activity disassociation). These conditions

can be applied by the medical profession as recommendations for healthcare.

The two concepts of ADL variability was validated to confirm that the approach and the value of results can reflect the actual variability of ADL routine by comparing the two subjects who have a different variability of routine each other. The derived variability was analyzed to find which activities affect the magnitude of the value and it was described that how the approach can be applied to measure the routine variability.

Chapter 6. Discussion

This chapter introduces the expected contributions of the suggested approach which was used in extracting and assessing the ADL routines by using non-intrusive sensing techniques. The approach of this research can be used not only in monitoring the health status of the elderly living alone but also in designing a smart-home environment where this approach can be effectively applied especially for the person who is living alone in aspects of construction. For designing the residential space which is for an occupant living alone, the floorplan of each space and locations of necessary sensors can be considered in a design phase and it would contribute to building a smart-home environment. Similarly, the method used to assess the variability of ADL routine can be applied to design a personalized space and environment.

In addition, the results from the extracted and assessed ADL routine information which shows the ADL variability can be provided as a personal report related to health status, such as weekly ADL routine report to improve the quality of life in aspects of healthcare. It is possible to provide a feedback to the occupant of how he/she run their own daily living and implications of performing the ADL by noticing the trends of variability and possible causes.

6.1 Expected Applications

6.1.1 Design of Residential Space for Living Alone Occupant

The application of smart-home environment detecting an occupant by installing various sensors in residential space is increasing for not only the purpose of healthcare but also supporting an occupant's daily living. Therefore, it is necessary to consider the mechanical planning in the early stage of the design according to the locations of each home sensors, the hub for managing the data from the individual sensors, or the wireless network in aspects of the facility management. The approach introduced in this research requires a network to collect spatio-temporal data in a certain interval and store the data for assessing as the ADL routine. These conditions of hardware should have interoperability with other sensing techniques when collecting or assessing the collected data for analysis. Since the non-intrusive sensing approach can be improved the detecting accuracy in case of adapting various sensors (i.e., smart plug for energy use information, Wi-Fi channel state information for detecting short-term activities and emergency situations) which collect the environmental data, the approach can be extended to apply as a multi-layered system for further analysis.

From the results of this research, the accuracy of detected ADL information also can be improved when each space represents an single ADL since the process of detecting each activity is based on the spatial data for contextualization. In other words, when a bedroom represents sleeping activity and a dining table at the kitchen clearly represents having meals activity, assessing the ADL routine with this approach can also represent the daily living of the occupant. Thus, a floorplan of the residential space for the elderly living alone can be considered these findings and spaces would be designed for performing ADL functions. These design process can be reflected in the standard design for the residential space of living alone elderly in terms of construction coping with the aging society. In case of building a complex for the living alone elderly as a public service, the size and floorplan of the residential space can be designed considering the continuous ADL monitoring within the complex. It is also possible to compare the ADL variability of the elderly based on identical spatial information. If the elderly's health status can be known for medical professions, the level of ADL variability compared with the elderly of similar health status can be informed to the elderly and help them to make more healthy routine.

The techniques extracting the living pattern information through sensors of smart-home (e.g., controlling the temperature and illuminance of each

space or security) are already widely applied for the convenience of the occupant. The gathered information of ADL routine can also be applied with the pattern information from other sensors and used for predicting the future activities occurring at similar start-time of the day. The obtained ADL routine can be used not only for monitoring health status but also in aspects of a space-use pattern for personalizing space utilization. If the methods in this research are adapted to space where has multiple rooms, it is possible to know how the rooms are occupied in temporal aspects as a daily pattern and find the effective space utilization plan. When the methods supplemented so that each person can be distinguished by using wearable sensors, applicable spaces can be extended to the range used by multiple people at the same time, such as an office building. It can also be applied for marketing at a commercial space by understanding the activity patterns of visitors specialized for temporal aspect, if the methods are complemented to detect the detailed activities using other non-intrusive sensors.

6.1.2 Providing ADL Routine Information

From the extracted ADL routines as the results of this research, it can be founded the trends of ADL routine of the single occupant in spatio-temporal aspects during a certain period as an example shown in Figure 6.1. The

quality of daily life in a home can be improved simply by recognizing the routines of oneself. For example, an occupant would be likely to try to sleep early in the night if he/she can recognize that the start-time of sleeping becomes late from the ADL routine information. The daily frequency of the activity, such as toileting which is difficult to perceive by oneself can be used for improving related habits and health status. It is also found the routines of activities which have indirect effects on health status, such as 'how many times do I usually spend watching TV, using PC or with visitors.

1) Start time and finish time
   - Wake-up at 8:29 and going to work 8:49
   - Returning home at 10:33 and bedtime at 00:09
   - Including mealtime or taking shower
2) Duration
   - Before going to work: staying 20min
   - After returning home: staying 1hr 36min
   - Sleeping hours: 8hr 20min
3) Frequency
   - Toileting: once in morning, 5 times in night
   - Using sink: 2 times in night
   - Using dressing room: once in morning
4) Sequence
   - Eating : S-R-T-P(-T)

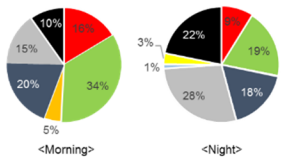


Figure 6.1 Examples of Providing ADL Routine Information

As like other applications which provide a user's health information (e.g., the quantity of time spent for exercising, sleep pattern, heart rate pattern, etc.) during a certain period, the collected and information of each ADL can be

provided as a weekly report assessed in terms of variability. As shown in Figure 6.2, an occupant's irregularity trends of total ADL routine during a certain period can be informed to the occupant for noticing from when the ADL routines are deteriorated or improved. In case of rapid deterioration, it is possible to alert recommending to see a doctor since the high variability can be suspected as symptoms of insomnia or depression.

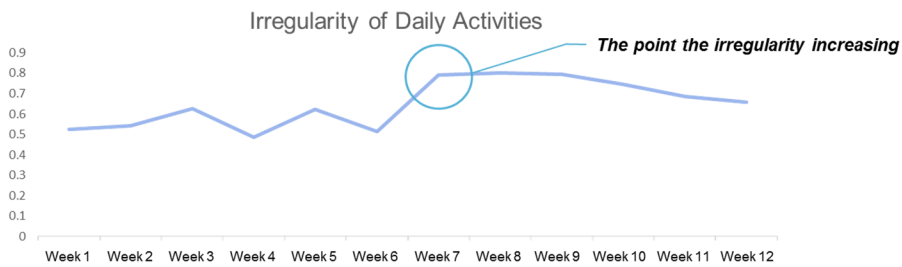


Figure 6.2 Examples of Total ADL Irregularity Trends

It can be suggested the information of suspicious activities which performed abnormally when the abnormality is higher than the recommendations by using the characteristics of possible abnormal activities shown in Figure 6.3. It can be used to provide warnings for healthcare by assessing how much the performance of abnormal activities increases over a certain period.

Time-Activity disassociation	*Duration-Activity disassociation*
• Overnight toileting • Wandering (or other activities) at midnight • Having meals at other than mealtime • No action until afternoon	• Exceptional longer stay in the bathroom • Irregular sleep hours • Short stays in several rooms (wandering) • Exceptional longer duration than average
Frequency-Activity disassociation	*Activity-Activity disassociation*
• The number of toileting in a day • The number of having meals in a day • The number of going out in a day • Exceptional change of the frequency	• Eating after cooking • Patterns of activity sequences • Multiple activities performed simultaneously (cooking and bathing)

Figure 6.3 Situations Expected as Abnormal Activity

6.2 Summary

In this chapter, the two types of expected applications for occupants of a space were described in aspects of construction and health management. It was found that the methods proposed in this research can be applied to the design of occupant-friendly space in terms of extracting human routines and assessing them in a spatial context. From the suggested examples of applications, it was also found that the results of this research can contribute to smart-home relevant techniques, especially for adapting non-intrusive sensing techniques.

Chapter 7. Conclusions

This chapter describes research results from the proposed approach to extract and assess the ADL of living alone elderly by adapting non-intrusive sensing, particularly focusing on the findings and implications. Also, the research contributions from achieving the objectives of this research are described for the technical and methodological aspects. The limitations of this research which should be addressed in future research is introduced with feasible goals for applying the results widely for the elderly living alone.

7.1 Research Results

This research developed an approach to collect and extract the ADL routines of an occupant who is living alone (i.e., especially for the elderly) by using the non-intrusive sensing techniques which can address the problems raised from the existing intrusive sensing techniques. In addition, the methods to quantify and assess the extracted ADL routine in terms of presenting spatio-temporal context was developed and introduced a concept of variability which can be used for assessing the daily routine, based on the known theory that high variability of ADL routine can present the deterioration of health status for the elderly.

From suggesting the conceptual framework for daily activity contextualization, the process was used for detecting each ADL and its start-end time, duration and frequency from the spatio-temproal log. The experiment to confirm the feasibility of detecting the ADL using non-intrusive sensors were conducted for a subject who is living alone office worker and found that most of ADL can be detected as actually performed activities. From the process to recognize the consecutive occupancy in a room as a single activity with the duration of occupying, a string sequence of a daily activity log representing each space as a character was extracted.

Based on the feasibility of applying the non-intrusive sensing for detecting the ADL of a single occupant, another experiment for a subject who is a living alone elder was conducted to extract the ADL routine of the subject during an experimental period. To extract the ADL routine from the collected spatio-temporal data log, the MSA method usually used in bioinformatics was applied as introducing two complementary alignment method, global and local alignment. Though it is almost impossible to find the actual routines, it was found that the results extracted as the ADL routine of the subject can reflect more specific ranges of possible ADL routines than existing methods of the pattern mining.

For using the extracted ADL routine information as a signal showing the

health status, the concept of routine variability including the irregularity and abnormality was defined as a quantified value. The developed metric which is based on presenting similar activities as a cluster and presenting irregularity as a distance in a plane of [start-time, duration] was applied to measure the degree of irregularity of the subject's ADL routine.

The developed metric was validated by comparing the results of two different subjects (i.e., who has a relatively regular routine as an office worker and who has a more irregular routine) and found the validity as showing the differences of irregularity as a difference of quantified value. To derive the abnormality as a quantified value, the methods to find a frequency of abnormal activities was introduced using examples of activity disassociation cases which show contradictory in aspects of spatio-temporal dimensions and activities.

In the process of developing the approaches in this research and analyzing the results, it was proven that the non-intrusive sensing can detect the ADL enough to extract and assess an occupant's ADL routine. From the finding of this research, expected applications in aspects of the construction industry were described, especially for the design considering continuous ADL monitoring and user-personalized space. In detail, the approaches used in this research can contribute to various fields which are relevant to human

activity in the spatial context. In addition, providing the ADL routine information as feedback for the occupant who provides their own spatio-temporal log was introduced as another application of this research. This can contribute to building a personalized platform monitoring the health status from the performed activities so that it is possible to meet the needs of the increasing population of living alone.

7.2 Research Contributions

The developed approach using non-intrusive sensing techniques to assess the ADL of the living alone elderly showed a feasibility as an alternative monitor the occupant's health-relevant ADL with little infringement of personal privacy. Furthermore, this research showed that it is possible to monitor the occupant's health status by assessing the ADL routine variability for the elderly living alone, contributing to a part of the welfare of the elderly. By providing a signal for a warning for high variability, an early diagnosis of mental disorders can be increased for the living alone elderly who has difficulties of monitoring and maintaining their health status.

In technical aspects, the metrics developed in this research can be extended to apply multiple existing non-intrusive sensors by matching the

spatio-temporal dimensions. It is possible to contribute as an infrastructure technology when building a smart-home environment for the healthcare.

In methodological aspects, this research introduced how the spatio-temporal log can be processed to represent activities with spatio-temporal information. Compared to the existing methods for assessing the human behavior patterns, this research has contributed to analyzing trends in the temporal dimension of activities on a daily basis. In addition, the developed method for extracting the ADL routines by adapting the MSA can be applied to similar research for considering the spatio-temporal dimensions simultaneously. The visualized results of extracted ADL routines helps intuitive understanding the routine information and can be used for a feedback. Quantifying and presenting a routine as a cluster also helps to understand the concept of the routine variability and finding a point when it was suspected to deteriorating health status.

The possible applications of this research results can contribute to designing a floorplan for the living alone people increasing rapidly in recent considering the spatio-temporal pattern as routines utilized as self-monitoring for healthcare. This research can also improve the occupant's quality of daily living by offering a feedback about their own routine information, especially for the elderly living alone.

7.3 Limitations and Future Research

Despite the efforts for contributions of this research, it is required to improve the applicability of the methods to include the various situations of human activities. For highly accurate results of assessing the ADL, the spatial information should contain ADL-relevant functions clearly, which is not usual conditions of real world. Extracted routines or assessed variability do not guarantee the detailed activity information due to the absence of posture information (e.g., walking, sitting, lying, moving upper body parts while sitting, etc.).

To address these limitations while using the non-intrusive sensing approach which is a differentiate of this research, the other sensors not hindering the daily activities of the occupant can be added as a multi-layered application. For example, a smart-plug measuring the temporal pattern or quantity of energy use can be applied to detect the ADL which uses electronic instruments (e.g., washing machine for self-care activity, using a micro oven for having meals, etc.). As an alternative sensing approach, it is also possible to use Wi-Fi CSI (i.e., Channel State Information) data which can detect the short-term movement or posture change of the occupant with the process proposed in this research.

In order to take advantages of the existing intrusive approach, future research can complementarily integrate the sensing techniques (e.g., heart-rate or posture from contact-based sensors) for improving the accuracy.

In future research, the approach developed in this research would be adapted for different demographic elderly (e.g., the healthy and the patient, where the space of a specific design considering the ADL functions and where the space randomly used) for validating and applying in general.

References

Abbott, A. (1995). "Sequence Analysis: New Methods for Old Ideas." *Annual Review of Sociology,* 21(1), 93–113.

Abbott, A, and Tsay, A. (2000). "Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect." *Sociological Methods & Research,* 29(1), 3–33.

Abouelhoda, M., and Ghanem, M. (2009). "String Mining in Bioinformatics." In *Scientific Data Mining and Knowledge Discovery*, 207–247. Springer.

Alirezaie, M., Renoux, J., Köckemann, U., Kristoffersson, A., Karlsson, L., Blomqvist, E., Tsiftes, N., Voigt, T., and Loutfi, A. (2017). "An Ontology-Based Context-Aware System for Smart Homes: E-Care@ Home." *Sensors,* 17 (7), 1586.

Andersen, C. K., Wittrup-Jensen, K. U., Lolk, A., Andersen, K., and Kragh-Sørensen, P. (2004). "Ability to Perform Activities of Daily Living Is the Main Factor Affecting Quality of Life in Patients with Dementia." *Health and Quality of Life Outcomes,* 2(1), 52.

Andrienko, N., Andrienko, G., and Gatalsky, P. (2003). "Exploratory Spatio-Temporal Visualization: An Analytical Review." *Journal of Visual Languages & Computing,* 14(6), 503–541.

Aramendi, A. A., Weakley, A., Schmitter-Edgecombe, M., Cook, D. J., Goenaga, A. A., Basarab, A., and Carrasco, M. B. (2018). "Smart

Home-Based Prediction of Multi-Domain Symptoms Related to Alzheimer's Disease." *IEEE Journal of Biomedical and Health Informatics*.

Bach, B., Dragicevic, P., Archambault, D., Hurter, C., and Carpendale, S. (2014). "A Review of Temporal Data Visualizations Based on Space-Time Cube Operations." In *Eurographics Conference on Visualization*.

Banerjee, A., Maas, D., Bocca, M., Patwari, N., and Kasera, S. (2014). "Violating Privacy through Walls by Passive Monitoring of Radio Windows." In *Proceedings of the 2014 ACM Conference on Security and Privacy in Wireless & Mobile Networks*, 69–80. ACM.

Banovic, N., Buzali, T., Chevalier, F., Mankoff, J., and Dey, A. K. (2016). "Modeling and Understanding Human Routine Behavior." In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 248–260. ACM.

Bargeman, B., Joh, C. H., and Timmermans, H. (2002). "Vacation Behavior Using a Sequence Alignment Method." *Annals of Tourism Research*, 29(2), 320–337.

Blankevoort, C. G., Van Heuvelen, M. J., Boersma, F., Luning, H., De Jong, J., and Scherder, E. J. (2010). "Review of Effects of Physical Activity on Strength, Balance, Mobility and ADL Performance in Elderly Subjects with Dementia." *Dementia and Geriatric Cognitive Disorders,* 30(5), 392–402.

Brdiczka, O., Su, N. M., and Begole, J. B. (2010). "Temporal Task Footprinting: Identifying Routine Tasks by Their Temporal Patterns." In

Proceedings of the 15th International Conference on Intelligent User Interfaces, 281–284. ACM.

Chen, D., Barker, S., Subbaswamy, A., Irwin, D., and Shenoy, P. (2013). "Non-Intrusive Occupancy Monitoring Using Smart Meters." In *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*, 1–8. ACM.

Corpet, F. (1988). "Multiple Sequence Alignment with Hierarchical Clustering." *Nucleic Acids Research,* 16(22), 10881–10890.

Covinsky, K. E., Palmer, R. M., Fortinsky, R. H., Counsell, S. R., Stewart, A. L., Kresevic, D., and Landefeld, C. S. (2003). "Loss of Independence in Activities of Daily Living in Older Adults Hospitalized with Medical Illnesses: Increased Vulnerability with Age." *Journal of the American Geriatrics Society,* 51(4), 451–458.

Davidoff, S., Zimmerman, J., and Dey, A. K. (2010). "How Routine Learners Can Support Family Coordination." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2461–2470. ACM.

Ditzler, K. (1991). "Efficacy and Tolerability of Memantine in Patients with Dementia Syndrome. A Double-Blind, Placebo Controlled Trial." *Arzneimittel-Forschung,* 41(8), 773–780.

Driver, H. E., and Kroeber, A. L. (1932). *Quantitative expression of cultural relationships,* 31(4). University of California Press.

Fillenbaum, G. G., Dellinger, D., Maddox, G., and Pfieffer, E. (1978).

"Assessment of Individual Functional Status in a Program Evaluation and Resource Allocation Model." *Multidimensional Functional Assessment: The OARS Methodology*.

Galinina, O., Mikhaylov, R., Huang, K., Andreev, S., and Koucheryavy, Y. (2018). "Wirelessly Powered Urban Crowd Sensing over Wearables: Trading Energy for Data." *IEEE Wireless Communications,* 25(2), 140–149.

Gu, T., Wang, L., Wu, Z., Tao, X., and Lu, J. (2011). "A Pattern Mining Approach to Sensor-based Human Activity Recognition." *Transactions on Knowledge and Data Engineering, IEEE,* 23(9), 1359-1372.

Guo, D., Chen, J., MacEachren, A. M., and Liao, K. (2006). "A Visualization System for Space-Time and Multivariate Patterns (Vis-Stamp)." *IEEE Transactions on Visualization and Computer Graphics,* 12(6), 1461–1474.

Hägerstraand, T. (1970). "What about People in Regional Science?" *Papers in Regional Science,* 24(1), 7–24.

Henikoff, S., and Henikoff, J. G. (1992). "Amino Acid Substitution Matrices from Protein Blocks." *Proceedings of the National Academy of Sciences,* 89(22), 10915–10919.

Hodgson, G. M. (1997). "The Ubiquity of Habits and Rules." *Cambridge Journal of Economics,* 21(6), 663–684.

Katz, S. (1963). "Studies of Illness in the Aged: The Index of ADL: A Standardized Measure of Biological and Psychosocial Function."

JAMA, 185(12), 914.

Kim, J. Y., Liu, N., Tan, H. X., and Chu, C. H. (2017). “Unobtrusive Monitoring to Detect Depression for Elderly With Chronic Illnesses.” *IEEE Sensors Journal,* 17(17), 5694–5704.

Kim, K, Kim, H., Ahn, H., Kim, Y., Hwang, J., Kim, B., Nam, H., Nah, R., and Byun, E. (2016). “Korea Dementia Observatory 2016.” NIDR-1603-0015.

Lawton, M. P., and Brody, E. M. (1969). “Assessment of Older People: Self-Maintaining and Instrumental Activities of Daily Living.” *The Gerontologist,* 9 (3_Part_1, 179–186.

Le, X. H. B., Di Mascolo, M., Gouin, A., and Noury, N. (2008). "Health Smart Home for Elders-A Tool for Automatic Recognition of Activities of Daily Living." *In Engineering in Medicine and Biology Society, IEEE,* 3316-3319.

Lee, S., Lim, J., Park, J., and Kim, K. (2016). “Next Place Prediction Based on Spatiotemporal Pattern Mining of Mobile Device Logs.” *Sensors,* 16(2), 145.

Lee, Y. J., Lee, J., and Nah, J. Y. (2015). “Older AdultsExperience of Smart-Home Healthcare System.” *The Journal of the Korea Contents Association,* 15(5), 414–425.

Lipman, D. J., and Pearson, W. R. (1985). “Rapid and Sensitive Protein Similarity Searches.” *Science* 227, (4693), 1435–1441.

Lotfi, A., Langensiepen, C., Mahmoud, S. M., and Akhlaghinia, M. J. (2012). “Smart Homes for the Elderly Dementia Sufferers: Identification and Prediction of Abnormal Behaviour.” *Journal of Ambient Intelligence and Humanized Computing,* 3(3), 205–218.

Needleman, S. B., and Wunsch, C. D. (1970). “A General Method Applicable to the Search for Similarities in the Amino Acid Sequence of Two Proteins.” *Journal of Molecular Biology,* 48(3), 443–453.

Nouri, F. M., and Lincoln, N. B. (1987). “An Extended Activities of Daily Living Scale for Stroke Patients.” *Clinical Rehabilitation,* 1(4), 301–305.

Orimo, H., Ito, H., Suzuki, T., Araki, A., Hosoi, T., and Sawabe, M. (2006). "Reviewing the Definition of Elderly." *Geriatrics & gerontology international*, 6(3), 149-158.

Paula, J. J. D., Bertola, L., Ávila, R. T. D., Assis, L. D. O., Albuquerque, M., Bicalho, M. A., Moraes, E. N., Nicolato, R., and Malloy-Diniz, L. F. (2014). “Development, Validity, and Reliability of the General Activities of Daily Living Scale: A Multidimensional Measure of Activities of Daily Living for Older People.” *Revista Brasileira de Psiquiatria,* 36(2), 143–152.

Qi, F., and Du, F. (2013). “Tracking and Visualization of Space-Time Activities for a Micro-Scale Flu Transmission Study.” *International Journal of Health Geographics,* 12 (1), 6.

Ratcliff, J. W., and Metzener, D. E. (1988). “Pattern Matching the Gestalt Approach.” *Dr Dobbs Journal,* 13(7), 46.

Roehrig, B., Hoeffken, K., Pientka, L., and Wedding, U. (2007). “How Many and Which Items of Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) Are Necessary for Screening.” *Critical Reviews in Oncology/Hematology,* 62(2), 164–171.

Rousseeuw, P. J. (1987). "Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis." *Journal of computational and applied mathematics*, 20, 53-65.

Roy, A., Bhaumik, S. K. D., Bhattacharya, A., Basu, K., Cook, D. J., and Das, S. K. (2003). “Location Aware Resource Management in Smart Homes.”, 481. IEEE.

Roy, A., Das, S. K., and Basu, K. (2007). “A Predictive Framework for Location-Aware Resource Management in Smart Homes.” *IEEE Transactions on Mobile Computing,* 6(11).

Schlich, R., and Axhausen, K. W. (2005). "Analysing Interpersonal Variability for Homogeneous Groups of Travelers." *Arbeitsberichte Verkehrs-und Raumplanung*, 296.

Schwartz, M. F., Reed, E. S., Montgomery, M., Palmer, C., and Mayer, N. H. (1991). "The Quantitative Description of Action Disorganisation after Brain Damage: A case Study." *Cognitive Neuropsychology*, 8(5), 381-414.

Shoval, N., and Isaacson, M. (2007). “Sequence Alignment as a Method for Human Activity Analysis in Space and Time.” *Annals of the Association of American Geographers,* 97(2), 282–297.

Smith, T. F., and Waterman M. S. (1981). “Identification of Common Molecular Subsequences.” *Journal of Molecular Biology,* 147(1), 195–97.

Tapia, E. M., Intille, S. S., and Larson, K. (2004). "Activity Recognition in the Home Using Simple and Ubiquitous Sensors." *In International conference on pervasive computing*, 158-175.

Taylor, R. (1950). “Purposeful and Non-Purposeful Behavior: A Rejoinder.” *Philosophy of Science,* 17(4), 327–332.

Thompson, J. D., Gibson, T., and Higgins, D. G. (2002). “Multiple Sequence Alignment Using ClustalW and ClustalX.” *Current Protocols in Bioinformatics*, 2–3.

Trochim, W. M. (2006). "Qualitative Measures." *Research measures knowledge base*, 361, 2-16.

Urwyler, P., Stucki, R., Rampa, L., Müri, R., Mosimann, U. M., and Nef, T. (2017). “Cognitive Impairment Categorized in Community-Dwelling Older Adults with and without Dementia Using in-Home Sensors That Recognise Activities of Daily Living.” *Scientific Reports,* 7, 42084.

Wilson, C. (2001). “Activity Patterns of Canadian Women: Application of ClustalG Sequence Alignment Software.” *Transportation Research Record: Journal of the Transportation Research Board*, 1777, 55–67.

Wilson, J., and Patwari, N. (2011). "See-through walls: Motion Tracking Using Variance-based Radio Tomography Networks." *IEEE Transactions on*

Mobile Computing, 10(5), 612-621.

Wilson, W. C. (1998). "Activity Pattern Analysis by Means of Sequence-Alignment Methods." *Environment and Planning A,* 30(6), 1017–1038.

Xia, X. (2007). *Bioinformatics and the Cell: Modern Computational Approaches in Genomics, Proteomics and Transcriptomics*. Springer Science & Business Media.

Zhang, J., Wei, B., Hu, W., and Kanhere, S. S. (2016). "Wifi-Id: Human Identification Using Wifi Signal." In *Distributed Computing in Sensor Systems (DCOSS), 2016 International Conference On*, 75–82. IEEE.

Ziebart, B. D., Maas, A. L., Dey, A. K., and Bagnell, J. A. (2008). "Navigate like a Cabbie: Probabilistic Reasoning from Observed Context-Aware Behavior." In *Proceedings of the 10th International Conference on Ubiquitous Computing*, 322–331. ACM.

Zoha, A., Gluhak, A., Imran, M. A., and Rajasegarar, S. (2012). "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey." *Sensors,* 12(12), 16838–16866.

Appendices

Appendix A: Terminology

Term	Acronym	Explanation
Activities of Daily Living	ADL	The basic activities to care for oneself that mainly include activities related to bathing, personal hygiene, dressing, toileting, eating, and dining etc. (Katz et al. 1963; Nouri and Lincoln 1987; Covinsky et al. 2003; Roehrig et al. 2007).
Abnormality		A degree of irregularity or being abnormal for performing the activities of daily living in spatio-temporal aspects
Cluster		A set of data objects in the same group (Driver and Kroeber 1932)
Cluster Cohesion		The clusters' quality from measuring how the data in a cluster is densely located.
Cluster Separation		The clusters' quality from measuring how the clusters are separately located.
Consensus Sequence		An optimal result of multiple sequence alignment among given set of sequences (Abouelhoda and Ghanem 2009).
Contextualization		A process of collecting specific definitions for understanding broad concept
Elderly		People whose chronological age are 65 years old or older (Orimo et al. 2006).
Fast-All	FASTA	A DNA and protein sequence alignment software package and used format (Lipman and Pearson 1985).
Geriatric		A study focusing on elderly healthcare to

		promote their quality of daily living and prevent diseases or disabilities
Global Alignment		A sequence alignment procedure used when two sequences are pre-known to be similar (Abouelhoda and Ghanem 2009).
Irregularity		A state of changing the routines inconsistently compared to its own pattern
Local Alignment		A sequence alignment procedure used when two sequences are locally similar (Abouelhoda and Ghanem 2009).
Multiple Sequence Alignment		A sequence alignment of three or more biological protein (DNA, RNA) sequences (Abouelhoda and Ghanem 2009).
Non-intrusive Sensing		A method of sensing the state of the environment surrounding an occupant rather than the data of the occupant oneself.
Poincare Plot	PP	A kind of recurrence plot used to quantify self-similarity in signal (or processes) (Urwyler 2017).
Reliability		A measure of the accuracy of the results from a model which quantifies the possibility of reproducing similar results under similar conditions of the model (William 2006).
(ADL) Routine		A group of the activities of daily living which are performed the usual or similar spatio-temporal aspects repeatedly.
Silhouette Coefficient		The technique providing a graphical representation of how well each object is included in the cluster (Rousseeuw 1987).

Similarity	A quantified measure how much the logs of being performed daily activities coincide.
Smart-home	An emerging technological solution based on the use of embedded sensors to enhance homes' intelligence, enabling the unobtrusive monitoring of occupant's behavior (Aramendi et al. 2018).
Spatio-temporal Log	A record of where (coordinates) and when (timestamp) an occupant stays at the time of state.
Tomographic Motion Sensor	A method for tracking the location of a person or object behind walls, without the need for an electronic device to be attached to the target (Wilson and Patwari 2011).
Variability	An opposite concept of the similarity presenting the quantified differences among the logs of daily ADL (Schlich and Axhausen 2005).

Appendix B: IRB Approval Letter

IRB No. 1812/002-002 **유효기간: 2019년 11월 26일**

연구참여자용 설명문

연구 과제명 : 혼자 사는 고령자의 일상생활 활동의 장기적 비일관성·이상 정도 정량화 모델 개발
연구 책임자명 : 이보경 (서울대학교 건축학과, 박사과정)

이 연구는 혼자 사는 고령자의 일상생활 활동에 관한 데이터를 비침습적인 방법으로 추출하고 장기적인 관점에서의 이상 정도를 정량화하는 모델을 개발하는 연구입니다. 귀하는 혼자 사는 65세 이상의 고령자이기 때문에 이 연구에 참여하도록 권유 받았습니다. 이 연구를 수행하는 서울대학교 소속의 이보경 연구원 (02-880-8311, 010-7271-7066)이 귀하에게 이 연구에 대해 설명해 줄 것입니다. 이 연구는 자발적으로 참여 의사를 밝히신 분에 한하여 수행 될 것이며, 귀하께서는 참여 의사를 결정하기 전에 본 연구가 왜 수행되는지 그리고 연구의 내용이 무엇과 관련 있는지 이해하는 것이 중요합니다. 다음 내용을 신중히 읽어보신 후 참여 의사를 밝혀 주시길 바라며, 필요하다면 가족이나 친구들과 의논해 보십시오. 만일 어떠한 질문이 있다면 담당 연구원이 자세하게 설명해 줄 것입니다.

1. 이 연구는 왜 실시합니까?

이 연구의 목적은 급속히 진행되고 있는 고령화 문제에 대응하기 위하여 고령자의 일상생활 활동을 지속적으로 모니터링하고, 이를 통해 고령자의 신체적, 정신적 기능저하를 선제적으로 식별함으로써 그들의 건강한 삶을 지원하는 건강관리 시스템을 개발하는 것입니다.

2. 얼마나 많은 사람이 참여합니까?

혼자 사는 건강한 65세 이상의 고령자 4명의 사람이 참여 할 것입니다.

3. 만일 연구에 참여하면 어떤 과정이 진행됩니까?

만일 귀하가 참여의사를 밝혀 주시면 다음과 같은 과정이 진행될 것입니다.

1) 귀하의 집 각 방마다 한 개 이상의 콘센트에 귀하의 움직임 여부를 확인할 수 있는 센서 (최대 10개)를 설치하도록 요청받을 것입니다. 또한 텔레비전, 전기 인덕션, 냉장고, 컴퓨터, 전자레인지, 세탁기 중 귀하의 집에 존재하는 가전제품에 해당 가전제품을 언제 사용하셨는지 확인할 수 있는 플러그를 설치하도록 요청받을 것입

니다.
2) 귀하는 이틀 간격으로 귀하의 일일생활 패턴의 내용과 그 변화에 관한 설문 조사를 하게 될 것이며 설문조사에는 최대 10분 정도 소요될 것입니다.
3) 귀하는 실험 참여 기간 동안 평상시 생활하시던 대로 일상생활을 영위하면 됩니다.

4. 연구 참여 기간은 얼마나 됩니까?

최대 (60)일 동안 일상생활 활동 데이터가 수집될 것입니다.

5. 참여 도중 그만두어도 됩니까?

예, 귀하는 언제든지 어떠한 불이익 없이 참여 도중에 그만 둘 수 있습니다. 만일 귀하가 연구에 참여하는 것을 그만두고 싶다면 담당 연구원이나 연구 책임자에게 즉시 말씀해 주십시오. 그만두는 경우 모아진 자료는 즉시 폐기됩니다.

6. 부작용이나 위험요소는 없습니까?

본 연구는 귀하의 집에서의 행동 패턴 및 가전제품 사용 패턴 데이터를 수집하는 연구이며 어떠한 부작용이나 위험요소도 없습니다.

7. 이 연구에 참여시 참여자에게 이득이 있습니까?

귀하가 이 연구에 참여하는데 있어서 직접적인 이득은 없습니다. 그러나 귀하가 제공하는 정보는 혼자 사는 고령자의 신체적, 정신적 질병의 선제적인 진단)에 대한 가능성을 확인하는데 도움이 될 것입니다.

8. 만일 이 연구에 참여하지 않는다면 불이익이 있습니까?

귀하는 본 연구에 참여하지 않을 자유가 있습니다. 또한, 귀하가 본 연구에 참여하지 않아도 귀하에게는 어떠한 불이익도 없습니다.

9. 연구에서 얻은 모든 개인 정보의 비밀은 보장됩니까?

개인정보관리책임자는 서울대학교의 이보경 (02-880-8311) 입니다. 본 연구에서 수집되는 개인정보는 (연령, 연락처, 집에서의 일상생활 활동 패턴과 가전제품 사용 패턴)입니다. 이러한 개인정보는 연구책임자에게만 접근이 허락되며, 익명화하여 보관이 될 것입니다. 동의서는 관련 법령에 따라 3년을 보관한 후 폐기할 예정이며, 연구자료의 경우는 서울대학교 연구윤리 지침에 따라 가능한 영구 보관할 예정입니다. 저희는 이 연구를 통해 얻은 모든 개인 정보의 비밀 보장을 위해 최선을 다할 것입니다. 이 연구에서 얻어진 개인 정보가 학회지나 학회에 공개 될 때 귀하의 이름 및 기타 개인 정보는 사용되지 않을 것입니다. 그러나 만일 법이 요구하면 귀하의 개인정보는 제공될 수도 있습니다. 또한 모니터 요원, 점검 요원, 생명윤리위원회는 연구참여자의 개인 정보에 대한 비밀 보장을 침해하지 않고 관련규정이 정하는 범위 안에서 본 연구의 실시 절차와 자료의 신뢰성을 검증하기 위해 연구 결과를 직접 열람할 수 있습니다. 귀하가 본 동의서에 서명하는 것은, 이러한 사항에 대하여 사전에 알고 있었으며 이를 허용한다는 동의로 간주될 것입니다.

10. 이 연구에 참가하면 사례가 지급됩니까?

귀하의 연구 참여시 감사의 뜻으로 귀하에게 30만원/월이 지급될 것입니다.

11. 연구에 대한 문의는 어떻게 해야 됩니까?

본 연구에 대해 질문이 있거나 연구 중간에 문제가 생길 시 다음 연구 담당자에게 연락하십시오.

이름: 이 보 경 전화번호: 02-880-8311 (010-7271-7066)

만일 어느 때라도 연구참여자로서 귀하의 권리에 대한 질문이 있다면 다음의 서울대학교 생명윤리위원회에 연락하십시오.
서울대학교 생명윤리위원회 (SNUIRB) 전화번호: 02-880-5153

IRB No. 1812/002-002 **유효기간: 2019년 11월 26일**

동 의 서 (연구참여자 보관용)

연구 과제명 : 혼자 사는 고령자의 일상생활 활동의 장기적 비일관성·이상 정도 정량화 모델 개발

연구 책임자명 : 이보경 (서울대학교 건축학과, 박사과정)

1. 나는 이 설명서를 읽었으며 담당 연구원과 이에 대하여 의논하였습니다.
2. 나는 위험과 이득에 관하여 들었으며 나의 질문에 만족할 만한 답변을 얻었습니다.
3. 나는 이 연구에 참여하는 것에 대하여 자발적으로 동의합니다.
4. 나는 이 연구에서 얻어진 나에 대한 정보를 현행 법률과 생명윤리위원회 규정이 허용하는 범위 내에서 연구자가 수집하고 처리하는 데 동의합니다.
5. 나는 담당 연구자나 위임 받은 대리인이 연구를 진행하거나 결과 관리를 하는 경우와 법률이 규정한 국가 기관 및 서울대학교 생명윤리위원회가 실태 조사를 하는 경우에는 비밀로 유지되는 나의 개인 신상 정보를 확인하는 것에 동의합니다.
6. 나는 언제라도 이 연구의 참여를 철회할 수 있고 이러한 결정이 나에게 어떠한 해도 되지 않을 것이라는 것을 압니다.
7. 나의 서명은 이 동의서의 사본을 받았다는 것을 뜻하며 나와 동의받는 연구원의 서명이 포함된 사본을 연구 참여가 끝날 때까지 보관하겠습니다.
8. 나는 나의 집에서의 일상생활 활동 패턴과 가전제품 사용 패턴이 수집되는 것을 알고 있으며, 연구에 사용되는 것을 허락합니다.

동의함 ( ) 동의하지 않음 ( )

연구참여자 성명	서 명	날짜 (년/월/일)
동의받는 연구원 성명	서 명	날짜 (년/월/일)

IRB No. 1812/002-002 **유효기간: 2019년 11월 26일**

동 의 서(연구자보관용)

연구 과제명 : 혼자 사는 고령자의 일상생활 활동의 장기적 비일관성·이상 정도 정량화 모델 개발

연구 책임자명 : 이보경 (서울대학교 건축학과, 박사과정)

1. 나는 이 설명서를 읽었으며 담당 연구원과 이에 대하여 의논하였습니다.
2. 나는 위험과 이득에 관하여 들었으며 나의 질문에 만족할 만한 답변을 얻었습니다.
3. 나는 이 연구에 참여하는 것에 대하여 자발적으로 동의합니다.
4. 나는 이 연구에서 얻어진 나에 대한 정보를 현행 법률과 생명윤리위원회 규정이 허용하는 범위 내에서 연구자가 수집하고 처리하는 데 동의합니다.
5. 나는 담당 연구자나 위임 받은 대리인이 연구를 진행하거나 결과 관리를 하는 경우와 법률이 규정한 국가 기관 및 서울대학교 생명윤리위원회가 실태 조사를 하는 경우에는 비밀로 유지되는 나의 개인 신상 정보를 확인하는 것에 동의합니다.
6. 나는 언제라도 이 연구의 참여를 철회할 수 있고 이러한 결정이 나에게 어떠한 해도 되지 않을 것이라는 것을 압니다.
7. 나의 서명은 이 동의서의 사본을 받았다는 것을 뜻하며 나와 동의 받는 연구원의 서명이 포함된 사본을 연구 참여가 끝날 때까지 보관하겠습니다.
8. 나는 나의 집에서의 일상생활 활동 패턴과 가전제품 사용 패턴이 수집되는 것을 알고 있으며, 연구에 사용되는 것을 허락합니다.

동의함 (　　) 동의하지 않음 (　　)

연구참여자 성명	서 명	날짜 (년/월/일)
동의받는 연구원 성명	서 명	날짜 (년/월/일)
연구책임자 성명	서 명	날짜 (년/월/일)

IRB No. 1812/002-002 유효기간: 2019년 11월 26일

연구참여자 모집 문건

다음과 같은 연구에 참여하실 분을 모집합니다.

연구 과제명

혼자 사는 고령자의 일상생활 활동의

장기적 비일관성·이상 정도 정량화 모델 개발

연구 책임자명

이 보 경 (서울대학교 건축학과)

연구 목적 : 이 연구의 목적은 급속히 진행되고 있는 고령화 문제에 대응하기 위하여 고령자의 일상생활 활동을 지속적으로 모니터링하고, 이를 통해 고령자의 신체적, 정신적 기능저하를 선제적으로 식별함으로써 그들의 건강한 삶을 지원하는 건강관리 시스템을 개발하는 것입니다.

참여자 선정조건 : 1) 혼자 사는 건강한 65세 이상의 고령자

2) 100m^2 이하의 주거공간 거주자

참여 내용 : 1) 각 방마다 한 개 이상의 콘센트에 움직임 여부를 확인할 수 있는 센서 (최대 10개)를 설치

2) 또한 텔레비전, 전기 인덕션, 냉장고, 컴퓨터, 전자레인지, 세탁기 중 일부 가전제품에 해당 가전제품을 언제 사용했는지 확인할 수 있는 플러그 설치

3) 일일생활 패턴의 내용과 그 변화에 관한 설문 조사 응답 (최대 10분 소요)

참여기간 및 장소

1) 기간 : 2018년 월 ~ 월 (조정 가능)

2) 장소 : 참여자 본인 집

참여 시 사례 : 1만원/일

모집 인원 : (최대) 4명

참여 방법 : 하기 연구 담당자에 연락 후 면담

본 연구의 내용에 관한 문의는 다음 연구 담당자에게 하십시오.

이름: 이 보 경 전화번호: 02-880-8311

<주간 리포트>

* 본인이 느끼기에 오늘은 평소 본인의 일상생활 패턴과 얼마나 차이가 있었는지 표시해주세

1주차		월	화	수	목	금	토	일
크다	5							
	4							
보통	3							
	2							
없다	1							

* 평소 본인의 일상생활 패턴과 어떤 차이가 있었는지 적어주세요.

#	월	화	수	목	금	토	일
0							
1							
2							
3							
4							
5							
6							
7							
8							
9							

國 文 抄 錄

間接感知方式 活用 獨居 高齡者의 健康管理를 위한 日常生活 活動 評價

동거인 없이 혼자 사는 독거 가구, 특히 고령자 독거 가구의 수가 전 세계적으로 급증하고 있으며 최근 우리나라에서도 고령자 독거 가구의 건강 관리 소홀로 인한 개인·사회적 문제 발생이 증가하고 있다. 스스로의 건강 상태 또는 일상 생활의 규칙적인 수행 여부를 인지하는 것 만으로도 개인의 건강을 증진시킬 수 있으므로 지속적이고 장기적인 건강 모니터링 시스템은 독거 고령자 가구의 건강 관리 관련 문제들을 해결하는 데 도움을 줄 수 있다. 치매와 같은 노인성 정신기능 질환의 경우 고령자의 일상생활 활동을 분석함으로써 관련 질환의 조기진단 근거로 활용할 수 있다. 일상생활 활동 (ADL)이 적절하게 수행되고 있는지의 여부를 평가하는 것은 개인의 건강 상태를 측정하는 수단으로서 기능할 수 있으며 이를 위해 카메라 촬영 또는 신체 부착형 센서 (wearable sensor)를 활용하는 방식으로 개인의 일상생활 활동 수행 여부를 확인하거나 그 패턴을 추출하는 연구가 시도되어 왔다.

그러나 기존의 연구들에서 도입된 방법들은 수행된 일상 활동의 시·공간적인 차원을 동시에 고려할 수 없고 일상생활 활동의 적절성 여부를 판단하기 위해 필요한 정보 이상을 수집하게 됨으로써 사생활 침해의 우려가 발생한다. 이를 보완하기 위해 본 연구는 고령자 건강 상태와 유관한 최소한의 정보인 개인 일상생활 활동의 패턴을 양적으로 측정하고 그 변동 추이를 추적하여 일상생활 활동의 적절성을 판단하는 접근 방식을 제안하고 그 가능성을

확인한다. 기존 센싱의 직접적 (Intrusive) 방식 대신 간접적 방식 (Non-intrusive) 방식인 단층촬영 움직임 감지 센서 (Tomographic motion detection system)를 활용하여 재실자의 시·공간 로그를 수집하고 이로부터 수행된 일상생활 활동을 감지하는 모델을 제안한다. 또한 일별로 수행된 일상생활 활동의 공통 패턴을 추출하고 장기적인 관점에서의 패턴 변화를 양적으로 측정하는 방법을 제시한다.
혼자 사는 고령자의 60 일 간의 시·공간 로그를 본 연구의 사례로서 수집하고 제안한 방법을 적용하여 일상생활 활동의 감지 및 패턴 추출, 불규칙 정도와 이상 정도를 나타내는 패턴의 양적 변화량을 도출하며 결과 분석을 통해 제안한 방법의 적용 가능성을 보여준다.

간접적 센싱을 통해 재실자의 일상생활 활동 데이터를 수집하고 패턴의 추출 및 변동성 평가가 자동적으로 가능하도록 함으로써 스마트 홈 기반 재실자 건강 관리 기술의 개발·활용에 기여할 수 있다. 또한 동일한 목적을 위한 기존의 방법과 달리 재실자의 시·공간 로그와 같은 행동 중심이 아닌 데이터만으로도 행동 패턴 정보를 도출하는 것이 가능함을 보여준다. 그 과정에서 스마트 홈 기반 건강 관리 기술의 도입을 위한 1 인 재실자 맞춤 주거공간 및 설비 계획에의 활용 방안을 제시하였다. 본 연구의 결과는 혼자 사는 고령자의 일상 생활의 질을 향상시키고 노인성 기능 질환의 조기 진단을 위한 피드백 제공을 통해 고령화 사회의 노인 복지로 확장될 수 있을 것으로 기대된다.

주요어: 일상생활 활동 (Activities of Daily Living); 다중서열정렬 (Multiple Sequence Alignment); 루틴 변동성; 간접적 센싱; 고령자; 스마트 홈

학 번: 2014-30186