# 博士論文

# Fundamental Studies toward Fall Risk Assessment of the Elderly in the Light of Relationship between Stumble and Depth Perception

# (躓きと奥行知覚の関係に着目した高齢者の転倒リスク評価法に関する基礎的研究)

A dissertation presented by


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## Abstract

The locomotive ability is an essential specificity for human beings to keep their physical/mental health and social connectivities. Falls and consequencing fractures can be a trigger of depriving this ability of the elderly and lead to be in the lower quality of life (QoL). In this dissertation, we aim at clarifying the factors of the falls and constructing the system that evaluates the elderly's frailty level to prevent falls. We focus on stumbles, which is one of fall pattern and is said to be seen popularly among relatively active and healthy community-dwelling elderly. To achieve the purpose of this study, we set three research questions as follows:

(1) Can we clarify the dependency of the motion to the depth perception?

(2) Can we estimate the fall risk from the questionnaire response patterns?

(3) Can we place our measurement dataset that is in small-scale but has detailed data into the large-scale mother-set data and analyze them?

For the 1st research question, we approach in chapter 2 and 3. In chapter 2, we focused on the difference of the foot control for avoiding the stumbles to objects. The target motion for the analysis was an approaching and contact motion to the object that is placed in the going direction. We showed that the difference of the foot control for doing the target motion might be caused not only by aging but also by the difference of the localizing an object, in other words, the difference of the ability of the depth perception. In chapter 3, we proposed the depth perception estimation model using the difference of the strength of the manifestation of the visual illusion. In our proposed model, we set a hypothesis that the reason that a human perceives the virtual depth information during seeing the image that causes the visual illusion can be explained by the estimation of the position of the camera placed at a fixed point. We introduced the visual illusion $k$ that indicates the scaler ratio of two objects illustrated in the image to express the level of manifestation of the visual illusion. In this chapter, it was observed that the bigger the visual illusion ratio $k$ value was identified for a participant, the closer he/she perceive an object. The relationship between the difference of the level of the manifestation of the visual illusion and the difference of the toe-off position just before contacting an object in the target motion in chapter 2 was also analyzed. The bigger $k$ group, who showed the bigger visual illusion showed the larger distance between the object to contact and toe-off position compared with other elderly groups. Thus, the people who are considered to perceive objects closer than their ideal position in the virtual depth direction in the 2D image also perceive objects closer in the 3D space.

For the 2nd research question, we approach in chapter 4. We conducted interview research to 36 hospitalized patients who had experienced a fall-related hip fracture. The patients were also asked to answer the 25-question Geriatric Locomotive Function Scale (GLFS-25; The questionnaire for asking about their physical function). In this chapter, we proposed to use the log-likelihood for the questionnaire response pattern analysis and data imputation. The three categories of falls (Category (a): falls by unexpected external forces; Category (b): falls by losing balance or supporting forces; Category (c): others) are defined to categorize the patients' falls based on the interview. After the confirmation of the validity of our categorizing of falls using the clustering method and analysis of the frequency of the co-occurrence words, we trained the fall category classifier and the stumble risk estimator. The fall category classifier is modeled by the naive Bayes model, which utilizes the frequency of the words from the interview data in each fall category. Also, the log-likelihood of the GLFS-25 response patterns of the hospitalized patients and the participants in chapter 2 and 3 are used to train the fall category classifier and the stumble risk estimator. For the GLFS-25 response pattern classifier, we achieved 76.1% average classification rate (16 out of 21 cases) for category (a) and (b). Also, it is clarified that people who showed the abnormal (bigger/smaller) visual illusion ratio $k$ in chapter 3 are at higher risk of falls compared with other elderly.

For the 3rd research question, we approach in chapter 5. We proposed the feature extraction method for the consecutive data such as motion capture data, EEG data, and for the discrete response pattern data of the questionnaires. The coordinate con-

version method using matrix decomposition is also proposed. We used the large-scale data as the mother set and approximated it as the normal/exponential distribution so that we can calculate the probability of generation of the data. Using this large-scale mother-set, we generalize the results of the small-scale dataset. The data is transformed into the coordinate system in which the physical characteristics and the cognitive characteristics are separately extracted.

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# Contents

[1]The researches described in this subsection, the author of this dissertation is included as the first author or one of the co-authors. However, the author doesn't include these works as contributions to this dissertations.

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# Chapter1

# Introduction

## 1.1 Background

### 1.1.1 Motions are created as a result of interaction between surroundings and body

Motions of creatures are generated from the interaction with the mechanisms of their body and the structures of the environments. Decomposing tasks parallelly and using simple reflection models, Brooks[5] created a robot that moves like creatures.

Thinking about the interaction with the environments, the perception of the visual inputs is coming up. It is known that kittens cannot develop their visual systems enough if we keep closed its eye before the 3 months after birth[6]. For the human beings, infants can make eye contact with their mother just 6 weeks after birth and look at the face of the speaker at the 4 months after birth[7], and around the 5 months after birth, the McGurk effect emerges[8]. McGurk effect is the phenomenon we feel strange if we are shown inconsistent audio stimuli and visual stimuli simultaneously. The fact means that infants can integrate the visual and audio stimuli at the 5 months after birth. Comparing that the acquisition of the linguistic ability (emergence of utterance) is the 10-18 months after birth, the development of the visual/audio perception is very early. That's why the preferential looking method[9] is often used in the developmental psychology study. The preferential looking method requires infants to see the stimuli and researchers measure the duration of looking at different stimuli and it can be used from the few days after birth[10]. The preferential looking method requires infants to see the stimuli and researchers measure the duration of looking at different stimuli. The larger duration infants look at the stimuli means that the more infants are getting interested in the stimuli. These facts mean that creatures don't have their perception system intuitively and develop their own perception system through interaction with their surroundings.

Bell - Magendie law is widely known as the law in anatomical fields. The law explains that efferent neurons that control motion outputs come from the ventral spinal nerve roots and the afferent nerve that controls sensory inputs come from the dorsal spinal nerve roots. Generally, important organs are allocated on the ventral side. It means that the motion output is more important than the sensory inputs for survival. In other words, we need to focus on not only the visual perceptional inputs but also motion outputs that enable us to interact with environments.

Exploring and mobility abilities are highly important interaction with environments. *Ardipithecusramidus*, which is a hominid fossil excavated in Ethiopia in 1994 is a species that shows the shows the transit to bipedality[11]. Lovejoy et al.[12] reconstructed the model of this fragile fossil using computer tomography techniques and analyzed the pelvis structure that enable them to realize bipedality anatomically. Realizing bipedality enabled humans(, or hominid) to expand their habitats, secure a lot of foods, and increase the population. Then, we become to utilize hands freely. Homunculus[13] is the mapping that shows which regions are correspondent with which body parts on the primary motor cortex and the somatosensory motor cortex, and the wider areas compared to our body size are allocated for hands and mouth.

Through exploring, human develops their perception systems. Infants act as if they know the physical laws intuitively[14][15], however, the fear of higher place is amplified after experiences of the actual falling down[16]. Also, Yamamoto[17] suggests that infants explore the relationship between their orientation to their surroundings and their movements dynamically during the process of acquiring rolling over movements.

Not only exploring by their own feet, humans developed the tools for mobility. It is well known that the invention of the steam engine had contributed to the development of the mechanical engineering field such as safety ratio. Human beings have invented cars, trains, ships, airplanes, to expand their habitats or exploring regions. These days, various human-aid techniques become to be studied such as automobile system, controlling theory of the wheelchair[18], walking assistive robot[19], for more people to maintain mobility abilities for a longer time.

### 1.1.2 Falls as events that prevent people to go outside

We think that expanding mobility abilities both by bipedality and by machines is one of the most important characteristics of humans. However, there is an event that impairs this ability significantly. Falls. In this dissertation, we adopted the World Health Organization (WHO) fall definitions: "Inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture" (cited from [20]). In Japan, the number of mortality due to falls are more than mortality due to traffic accidents[21]. It's not only a problem of the number of mortalities. In the case of the elderly people who have experienced falls and fall-related fractures, their quality of life (QoL) is significantly impaired. Falls look like only problems of physical functions such as the locomotive functions, balance functions, etc. In fact, there are various biomechanical or epidemiological analysis were conducted [22][23][24][25]. However, as WHO guideline[26] says, excluding hazards from the physical environments of elderly people is important for fall preventions. Also, from a point of view of perception of environments and execution of motions, declining cognitive abilities has a deep relationship with falls. Especially, for dementia patients, there are some reports that they show changes on their gait patterns[27] or their visual perception might be changed[28][29]. In the medical fields, the concept of the sarcopenia[30] and the locomotive syndrome[31] are proposed as the examples of the declining of physical abilities. Recently, the Japan geriatrics society proposed a concept of the frailty that treats declining physical, mental, social abilities comprehensively. Now, a concept of the cognitive frailty as the mixture of the declining of physical and cognitive abilities is widely accepted.[32][33].

## 1.2 Objective of this Dissertation

In this dissertation, we aimed at clarifying the dependency of the depth perception to the stumbles and evaluating elderly people frailty level to prevent falls. If there is a clear relationship between the depth perception and the motions, we can utilize it to estimate the risk of stumbles that is the most likely to happen on the community-dwelling elderly people[34]. To construct a more realistic estimation of stumble risks, knowing how falls and consequencing hip fractures happen is also an important purpose of this research. Another purpose of this dissertation is constructing a system that estimates and evaluates elderly people frailty level using multi-modal information such as motion data or brain activity data. Throughout these kinds of data, we can acquire the participants' physical/cognitive status more clearly and precisely. However, acquiring these detailed data of many participants costs a lot. Thus, we aimed to construct a method of combining the small, precise data of the sampled dataset with the large-scale, statistic mother dataset.

There are various causes of falls: Declining cognitive abilities such as dementia, declining locomotive functions such as locomotive syndromes, declining visual acuity or lacking field of vision due to cataracts or glaucoma. In this dissertations, we don't consider the falls due to their lack of field of vision or visual acuity by eye diseases. We focus on the locomotive functional weakness as physical frailty and declining depth perception abilities and cognitive function as cognitive frailty.

In this research, 3 datasets were used. One is small-scale, but detail dataset. It is composed of the motion capture, the electroencephalogram (EEG), and the questionnaire data of the elderly. The measurement for this dataset is divided into 2 studies. The first study is held during the period from November 2016 to February 2017. In the first study, we did motion capture and the 25-question Geriatric Locomotive Function Scale (GLFS-25; The questionnaire for asking about their physical function)[31]. Sixteen elderly and 7 young participants participated. The second study is held from September 2017 to March 2018. In the second study, we did EEG measurement during cognitive tasks and the revised Hasegawa's dementia scale (HDS-R; The questionnaire for evaluating participants' cognitive function. Only to the elderly participants we asked to answer)[35][36]. Fourteen elderly and 5 young participants participated in both the first and the second study.

Another one is a large-scale dataset that is a part of the cohort study for sarcopenia and frailty of the community-dwelling elderly; Kashiwa study[30]. This dataset is composed of the result of the physical tests (e.g. the walk speed, the limb skeletal muscle mass, etc.) and the score of the GLFS-25 and Mini-Mental State Examination (MMSE; The questionnaire for evaluating participants' cognitive function)[37], the experience of falls. The data is processed statistically and used as a mother set of the elderly i.e. the reference of the distribution of the community-dwelling elderly. We used data of the study held during the period from September 2016 to November 2016 (the 4th study). The participants except 1 elderly and all the young participants of the measurement in the first dataset are recruited from the participants of Kashiwa study cohort. Among the 16 participants of the first dataset, 11 participants participated in all the 2 studies for the 1st dataset and the 4th study of Kashiwa study.

The other one is the qualitative research dataset of hospitalized patients due to falls and consequencing hip fractures whose age are over 60. This dataset is composed of the text data of interview research, the summary text data by researchers after the interview, and the score of GLFS-25. This dataset is used for grabbing the real situation of falls of the elderly, i.e., this dataset is used as a reference of the fallers. The interview research was held during the period from September 2016 to April 2018 at the University of Tokyo Hospital. The relationships among each dataset and their participants' characteristics are shown in Fig.1.1.

## 1.3 Outline of this Dissertation

This dissertation is consist of 6 chapters. In chapter 2 and chapter 3, the depth perception as a factor of causing stumbles is analyzed. In chapter 2, we focus on the foot control for avoiding an obstacle. Instead of studying on an avoiding motion, the ball approaching motion was measured and analyzed from the view of the simplicity, safety, and the easiness for measurements. In chapter 3, we propose the estimation model of the depth perception. In the model, we show the 2D images that cause the size illusions and modeled the depth perception abilities from the level of manifestation of the size illusion. The difference of the 3D motion in chapter 2 is also analyzed based on the difference of the level of manifestation of the visual illusion.

In chapter 4 chapter 5, we describe the frailty estimation/evaluation method that links to falls. In chapter 4, interview research to patients who had been in the University of Tokyo Hospital are reported. The quantitative analysis method of the interview data is proposed. Also, the quantitative evaluation method using log-likelihood is applied to the data of the questionnaires. We constructed 2 fall category classifiers, using the interview data and the questionnaire data, for each. Also, we construct the stumble risk classifier. The works in chapter 4 are composed of a collaborate work in the Graduate program in gerontology (Global Leadership Initiative for an Age-Friendly Society; GLAFS) at Institute of Gerontology (IOG) in the University of Tokyo, as cross-sectional research with various researchers and ph.D. students. The main contribution of the author of this chapter is that quantitative analysis of the interview data of hospital patients and the converting method of the questionnaires. Other work will not be included as contributions to this dissertation.

In chapter 5, we proposed feature extraction method for the frailty evaluation using multi-modal consecutive data such as physical motion data and brain activity data. A method that converts the categorical data to the quantitative data using probabilistic distributions proposed in chapter 4 is also proposed to do comprehensive frailty evaluations. The large-scale cohort study dataset is used as the mother-set, and the mother-set distribution is used for more precise analysis. Also, the coordinate transformation method using matrix decomposition is proposed to convert and generalize the results of the small-scale dataset into the results of the large-scale dataset.

Fig. 1.2 shows the outline and relationships among the dataset groups. From chapter 2 to 5, we mainly use the Dataset (1); the group of our measurement. In chapter 4, we also use the Dataset (3); the hospitalized patient group. In chapter 5, we use both Dataset (1) and (2); the group of our measurement and Kashiwa study to establish the coordinate converting method. Also, Dataset (2) is used for making a more precise analysis of Dataset (3).

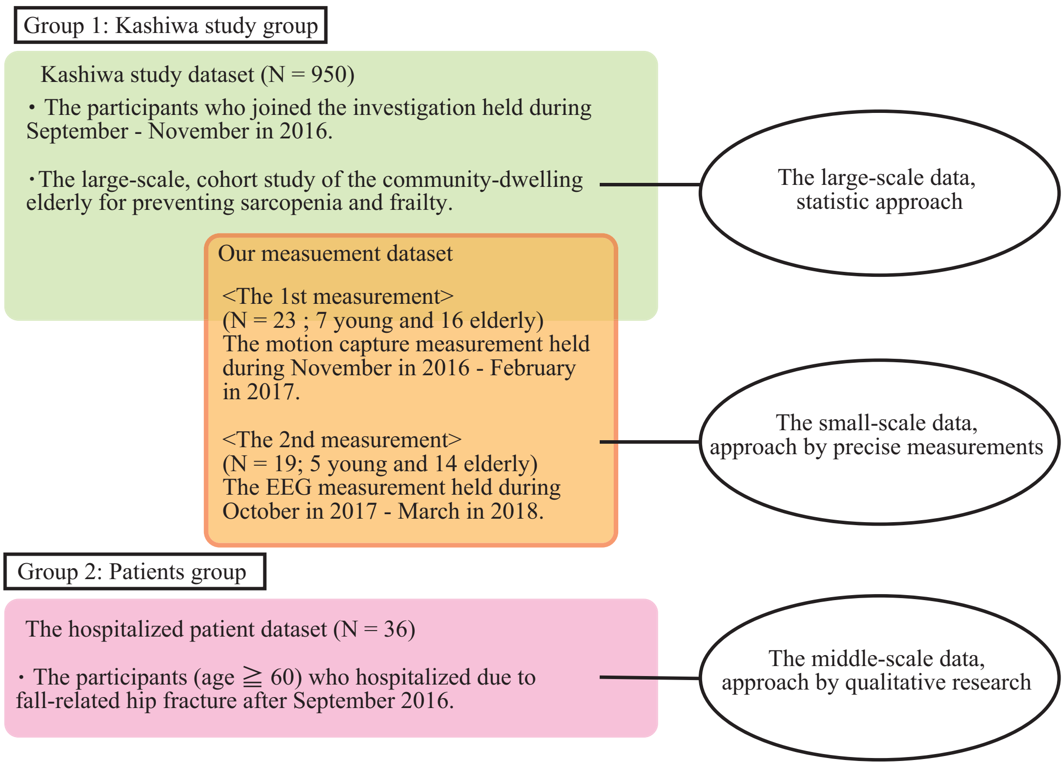



Figure 1.1: The relationships among group and dataset. Three datasets are used to analyze. Dataset (1): The small-scale, detailed dataset. The measurement is divided into 2 studies; physical measurement and cognitive measurement. The cumulative number of participants in the 2 studies was 30 elderly and 12 young participants. Dataset (2): The 4th study of Kashiwa study dataset. The participants are in the large-scale cohort study named Kashiwa study. We used the data of 950 participants who participated in the 4th study of this longitudinal study. In this dataset, the data of 11 elderly participants who participated in both the 1st and the 2nd study in the Dataset (1) are included. Dataset (3): The qualitative research dataset of the hospitalized patients who had experienced falls and consequently fractures.

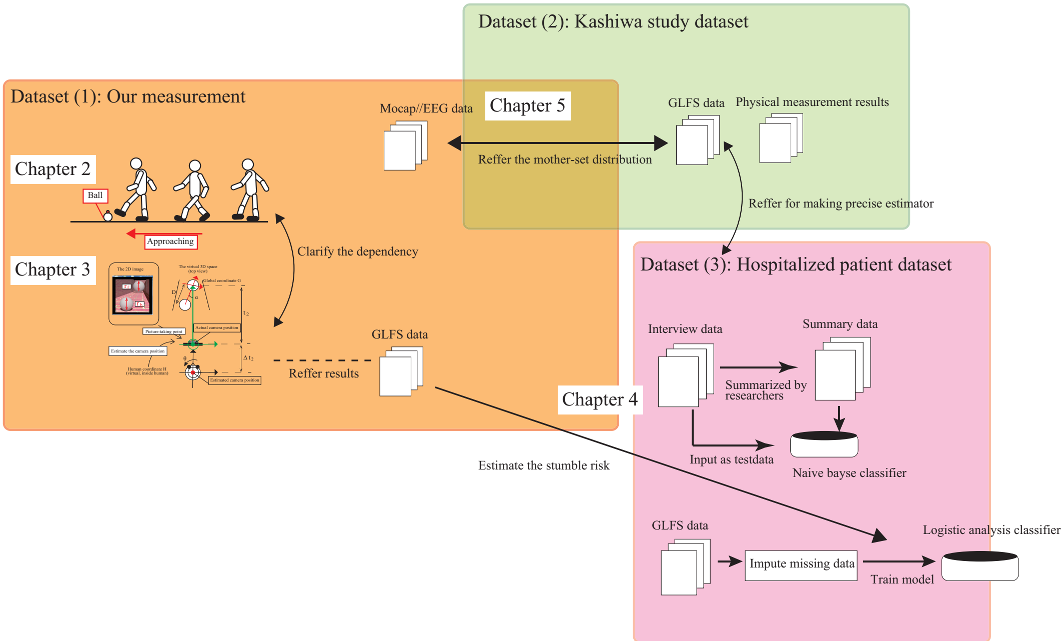



Figure 1.2: The outline and relationships among the dataset groups of this dissertation.

# Chapter2

# Foot Control Analysis for Risk Evaluation of Stumbles of the Elderly

## 2.1 Introduction

### 2.1.1 Background

Falls and following hip fractures are one of the big problems in hyper-aged society. Trip/stumble is one of the common patterns of falls. Morita et al.[38] report the results of the 3-year prospective research of the community-dwelling elderly fallers. They examined the ratio of the visiting to hospitals and fracture, and found that the elderly people who fell by external factors and noticed the factors before their falling showed the bigger fracture ratio (the ratio of visiting hospital was 22% and the ratio

This capter is under review as [1]

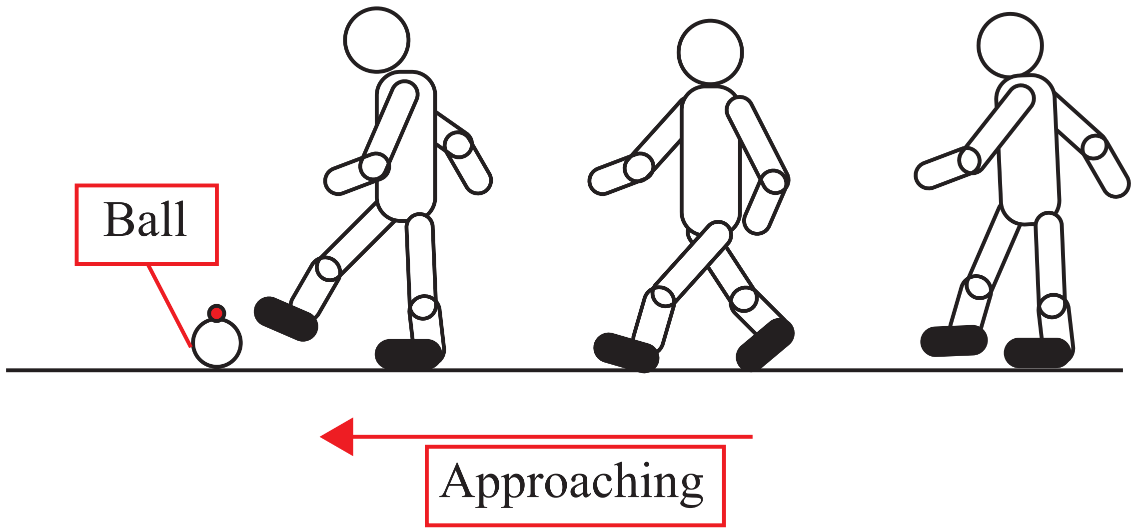



Figure 2.1: The outline of the measurement. The experimenter asked participants to approach the ball from about 3-step distance and to touch the marker attached on the top surface of the ball by their foot.

of fracture was 7.9%), compared to the other group; the other 3 groups were group in which the elderly people who fell by external factors but did not notice the factors (the ratio of visiting hospital was 19.1% and the ratio of fracture was 4.4%), group in which the elderly people who fell without external factors (the ratio of visiting hospital was 12.4% and the ratio of fracture was 1.9%), group in which the elderly people whether external factors relate to their cause of falls are unknown (the ratio of visiting hospital was 25.2% and the ratio of fracture was 1.0%). Relationships among cognitive abilities, visual perception, and motions, especially relationships between dementia and motions are attracting interests these days from the perspective of early detection of dementia. Non-Alzheimer's type dementia, especially vascular dementia often shows particular abnormal gait patterns[27]. There are several screening tools for detecting declining cognitive abilities; Mini-Mental State Examination

(MMSE)[37] and The revised version of Hasegawa's dementia scale (HDS-R)[35][36] are widely used for detecting dementia, and Moca-J[39] is used for a detecting Mild Cognitive Impairment (MCI). In these screening tools they sometimes have the coordination tasks that require both motions and visual perceptions[40][39][41], there are also researches to investigate the prediction effects of dementia of these visual perception tasks [28][29]. Gait analysis has a long history as motion tests[42][23][43][44]. Some researchers are studying visual attention during walking[45], and it is pointed out that bad depth perception leads to a higher risk of falls[46][22][47]. Elderly people's brain alterations were drawn in [48]. Not only dementia but normal aging alters brain construction, the quantity and quality of the neural transmitters, and functional networks. These aging alterations make elderly people take different strategy for using different brain regions that have never been used before to compensate such as alterations. In this strategy, elderly people more rely on cognitive function to control motions and as a result, they become to have difficulty with doing cognitive task and motion simultaneously. From these findings, there are strong connections between cognitive abilities and motions, especially for elderly people. The concept of frailty, which indicates the declining physical/mental/social abilities is proposed these days. It is said that the declining of cognitive abilities and the physical frailty should be treated as one comprehensive phenomenon (the cognitive frailty)[33][32].

### 2.1.2 Research purpose

In this chapter, our aim is to analyze the motion of approaching an obstacle and to clarify the difference of the motion among people. People stumble when they perceive an obstacle and cannot avoid it. We set for this situation as a hypothesis that people who are more likely to stumble will show a specific motion when approaching an obstacle on their pathway, which may be a cause of a stumble. We set two assumptions. The first one is that stumbles are results of the alteration of the depth perception. This is about the alteration of perceptions. The second one is the alteration of motion planning abilities. If the motion planning ability declines, however people plan their motions based on their perceived information, the output motion becomes different from what people intend to. From the first assumption, some people would show earlier/later toe-off before the obstacle due to failure in object localizations. From the second assumption, some of the people who don't show the difference of the position of swing legs would put their support leg on the further position from the obstacle. Fig.2.1 shows the main target motion that we focus on; This is the motion of approaching a small object on their pathway.

## 2.2 Research hypothesis and proposed method of the experiments

### 2.2.1 Research hypothesis

The hypotheses are set for the explanation of the trips to obstacles. Let us assume the case that elderly people notice an obstacle during their walking and they judge it avoidable by stepping it over, then, generally they step over it without paying any special attention to its position precisely. However, as [48] says, the elderly people depend on much more cognitive controls when they do motions compared to the young people. We divide the cognitive control into two phases and set the following hypotheses. Elderly people (1) firstly perceive the position of themselves and obstacles on their pathway (the localization phase), and (2) secondly, they plan motions so as to execute the stepping over motion at the appropriate position (the planning phase). If either or both the ability for the visuo-spatial perception or/and the motion planning is impaired, then the risk for falling will rise up. Also, to make measurements easier and safer, we change the condition to approaching an obstacle from the avoidance of an obstacle.

### 2.2.2 Target motion

While there has been a lot of work on an analysis of stepping over of obstacles[24][49], there is less work on the analysis of fail on stepping over or real falls[50][51]. According to the hypothesis we set in the previous section, the stumble happens when people perceive an obstacle and cannot avoid it by stepping over. This event occurs when people have incorrect information for planning motions or people cannot execute their motions as they planned before. If so, there must happen the nearly same things when we intend to approach an object deliberately on their pathway. In this research, we set a target motion as the approaching task in which people approach an 8-cm small ball. We measured and analyzed their motions by the motion capture system.

### 2.2.3 Other measurement items

We used the revised Hasegawa's dementia scale (HDS-R)[35][36] results as a reference because it is widely used for grabbing participants' cognitive abilities.

## 2.3 Experimental settings

### 2.3.1 Participants

Fourteen elderly participants (6 male, 8 female, age 79.5 ± 6.91) and 5 young participants (all are male, age 24.6 ± 0.89) were measured. The elderly participants were recruited from the participants in the Kashiwa cohort[30], the young participants were recruited from the student in the graduate school of information science and technology, the University of Tokyo.

### 2.3.2 Cognitive task settings

We used the HDS-R scoreHDS-R is a screening test for dementia that is widely used in Japan. It has a full score of 30, the lower score indicates more decreasing of cognitive abilities. The examiner (in this research, nurses execute the test) asked several questions such as how old are you, or where are you, repeat words, etc., and scored along with their response. Score 20 is the cutoff for the doubt of dementia. We referred [39] and set score 26 as the cutoff for the doubt of start declining cognitive ability.

### 2.3.3 Ball approach task settings

Thirty-five optical reflective markers were attached to the whole body of the participants. Twelve cameras were used and captured their motions. We put a ball 2-3 strides advance manually, then asked participants to contact the marker that is attached to the top of the ball and the measured marker positions were analyzed.

Though the starting position was the same for all the participants, the positions of the ball were changed in each trial by experimenter's hand. In the statistical analysis, we set the significant level as $p = 0.05$.

## 2.4 Experimental results

### 2.4.1 Results of the cognitive tasks

One people (B03) showed score 20 in the HDS-R that indicates he is doubted as dementia. Three people (B02, B05, B18) showed the HDS-R score less than 26, which indicates starting declining of the cognitive ability[39].

### 2.4.2 Analysis of the ball approaching motion

The distance of the left/right thumb from the ball position at the toe off time of the swing leg (right leg) are shown on Tab. 2.1. The distance is normalized by each participant's height (the height of the marker that is attached on their front side of the head). From the results on Tab. 2.1, young participants put their left feet at the position less than 0.1, and put their right feet at the position less than 0.5, so we set both values as thresholds so that we can judge the results are close with young participants or not. Fig. 2.2 illustrates the distance (normalized to the height) from the swing/support legs to the ball position at the time of the toe off time of the swing leg just before the ball. The red dotted line indicates the thresholds. The horizontal line is the distance between support leg (left leg) thumb and the ball normalized by participants' height, and the vertical line is the distance between

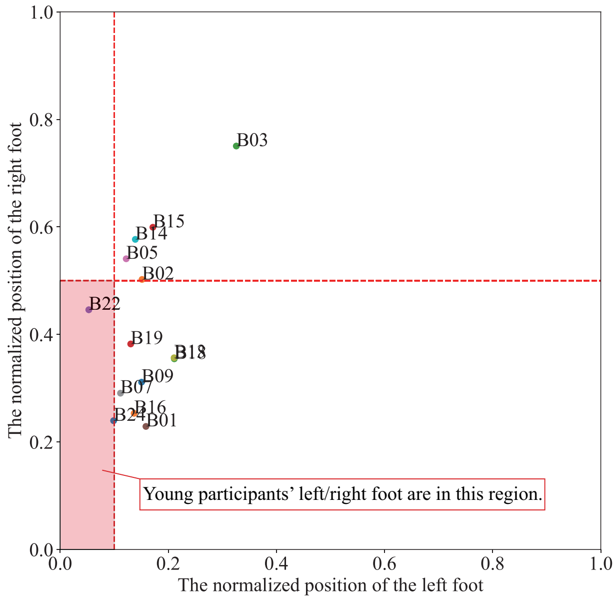



Figure 2.2: The position of the support/swing leg. The horizontal axis indicates the distance from the ball in the progressing direction (x-axis) of the support leg when the toe of the swing leg is off. The vertical axis indicates the distance from the ball in the progressing direction (x-axis) of the swing leg when the toe of the swing leg is off. The distance is normalized by the participant's height.

swing leg (right leg) thumb and the ball normalized by participants' height. From Fig. 2.2, 12 participants exceed the threshold for left feet position, and 5 participants also exceed the threshold for right feet position. The participants who approach a ball in 5 steps are plotted at the bottom side in the figure, and almost all (except a participant B07) the participants who approach a ball in 3 steps are plotted at the upper side in the figure. We grouped the participants as 'young (approach a ball in 3 steps)', 'elderly (approach a ball in 3 steps)', 'elderly (approach a ball in 5steps)'. The one way ANOVA (analysis of variance) showed a significant main effect of group ($F(2,15)=3.68$, $p=0.022$ for the left feet and $F(2,15)=3.68$, $p=0.006$ for the right feet). The post hoc comparison was showed no significant difference between the position

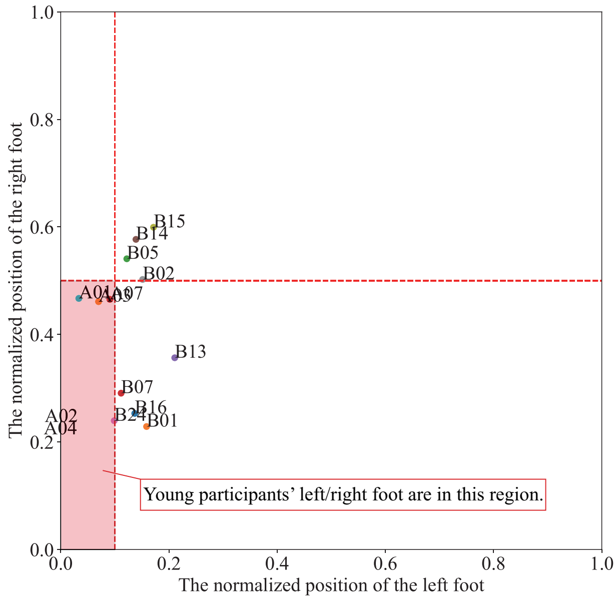



Figure 2.3: The position of the support/swing leg of the elderly who are in their 70's. The horizontal axis indicates the distance from the ball in the progressing direction (x-axis) of the support leg when the toe of the swing leg is off. The vertical axis indicates the distance from the ball in the progressing direction (x-axis) of the swing leg when the toe of the swing leg is off. The distance is normalized by the participant's height.

of the left foot of 'elderly (approach a ball in 3 steps)' and 'elderly (approach a ball in 5 steps)' and the position of the right foot of 'young' and both 'elderly (approach a ball in 3 steps)' and 'elderly (approach a ball in 5 steps)' (p=0.93, 0.21, 0.16, for each). However, both 'elderly (approach a ball in 3 steps)' and 'elderly (approach a ball in 5 steps)' group put their left foot further position from the ball compared with the 'young' group (p=0.01 for the '3 steps' elderly group and p=0.02 for the '5 steps' elderly group). Also, the '3 steps' elderly group approach a ball from further position compared with the '5 steps' elderly group ($p < 0.01$). Next, we grouped the participants as 'young (approach a ball in 3 steps)', 'elderly (their right foot position $\geq 0.5$)', and 'elderly (their right foot position $< 0.5$)'. The one way ANOVA (analysis of variance) showed a significant main effect of group ($F(2,16)=3.63$, $p=0.002$ for the left feet and $F(2,8)=4.45$, $p=0.04$ for the right feet). The post hoc comparison was showed no significant difference between 2 'elderly' groups for both left and right foot position ($p=0.34$, $0.14$, for each). Both 'elderly' group put their left feet in further distance from the ball compared with the 'young' group ($p= 0.004$ for the $< 0.5$ group and $p=0.01$ for the $\geq 0.5$ group). For the right foot position, on the other hand, 'elderly (their right foot position $\geq 0.5$)' put their foot in further distance compared with the 'young' group ($p=0.04$) whereas the 'elderly (their right foot position $< 0.5$)' group showed no significant difference with the 'young' group ($p=0.76$). Almost all elderly people put their left feet in further position from the ball compared with young participants. Analyzing only the elderly who are in their 70s, we could see this trend clearly. Fig.2.3 shows their and young participants' foot positions. It is known that human plans their motion at least before 2 steps[45], so when participants step just before approaching the ball, they have already planned their motions. Thus, these differences would come from either the declining ability of localization of an obstacle or the declining motion planning ability. We focused on the participants who approach a ball in 3steps and whose toe off position was bigger than 0.5. The statistical analysis revealed that their toe off position was further than young participants and other elderly participants whereas the other elderly participants showed no significant difference with young participants' toe off positions. On the other hand, their left foot positions showed no significant difference between the elderly participants whose toe off position was bigger than 0.5 and other elderly participants. There is a possibility of that the participants whose toe off position was bigger than 0.5 had no problem on

Table 2.1: $x$ [mm], which is the toe off distance from the ball that is normalized $x$ by heights.

| ID | Normalized distance [mm] (Left foot) | Normalized distance [mm] (Right foot) |
|---|---|---|
| Elderly people who approach a ball in 5 steps | | |
| B01 | 0.15 | 0.22 |
| B24 | 0.09 | 0.23 |
| B16 | 0.13 | 0.25 |
| B09 | 0.15 | 0.31 |
| B13 | 0.21 | 0.35 |
| B18 | 0.21 | 0.35 |
| B19 | 0.13 | 0.38 |
| | Average ± S.D | |
| | 0.15 ± 0.04 | 0.29 ± 0.06 |
| Elderly people who approach a ball in 4 steps | | |
| B07 | 0.11 | 0.29 |
| Elderly people who approach a ball in 3 steps | | |
| B07 | 0.11 | 0.29 |
| B22 | 0.05 | 0.44 |
| B02 | 0.15 | 0.50 |
| B05 | 0.12 | 0.54 |
| B14 | 0.13 | 0.57 |
| B15 | 0.17 | 0.59 |
| B03 | 0.32 | 0.75 |
| | Average ± S.D. | |
| | 0.15 ± 0.08 | 0.52 ± 0.14 |
| Young people who approach a ball in 5 steps | | |
| A02 | -0.02 | 0.23 |
| Young people who approach a ball in 3 steps | | |
| A04 | -0.03 | 0.21 |
| A07 | 0.09 | 0.46 |
| A03 | 0.06 | 0.46 |
| A01 | 0.03 | 0.46 |
| | Average ± S.D. | |
| | 0.03 ± 0.05 | 0.39 ± 0.12 |

their motion planning ability but localized a ball position closer than it actually is. The approaching motion from the toe off position of the participants whose toe off position was bigger than 0.5 are illustrated in Fig. 2.4. At first, their ankle joint show plantar flexion but as approaching a ball their foot become to be flat, and after that, their foot show dorsal flexion as they are approaching a ball, so at the marker position, 3 out of 5 participants' toes were upward whereas other 2 participants' toes were still flat. This implies that at least 3 participants who showed their toes upward localize the ball position closer. They intended to put their feet at their localized ball position so their foot postures became flat, but they missed to place their feet because the ball was placed further than they think. Then they pulled their feet again, resulted in showing the toes' upward postures. Perhaps, for the other 2 participants, it was enough just to extend their feet slightly. We clarified the difference of approaching motion and clarify that for some elderly participants the object localization (, or the depth perception ability) is deeply related to the approaching motion. Interestingly, the participant B03 who showed the lowest HDS-R score placed his right/left foot the furthest position from the ball, and 3 out of 5 participants (B02, B03, B05) whose right foot was placed further from the ball position showed HDS-R score less than 26. Cognitive ability may also relate to the localization of the obstacles. However, from these experimental settings, we cannot clarify how the participants' depth perception varied. Further measurements are required.

## 2.5 Conclusion

Conclusions are as followings:

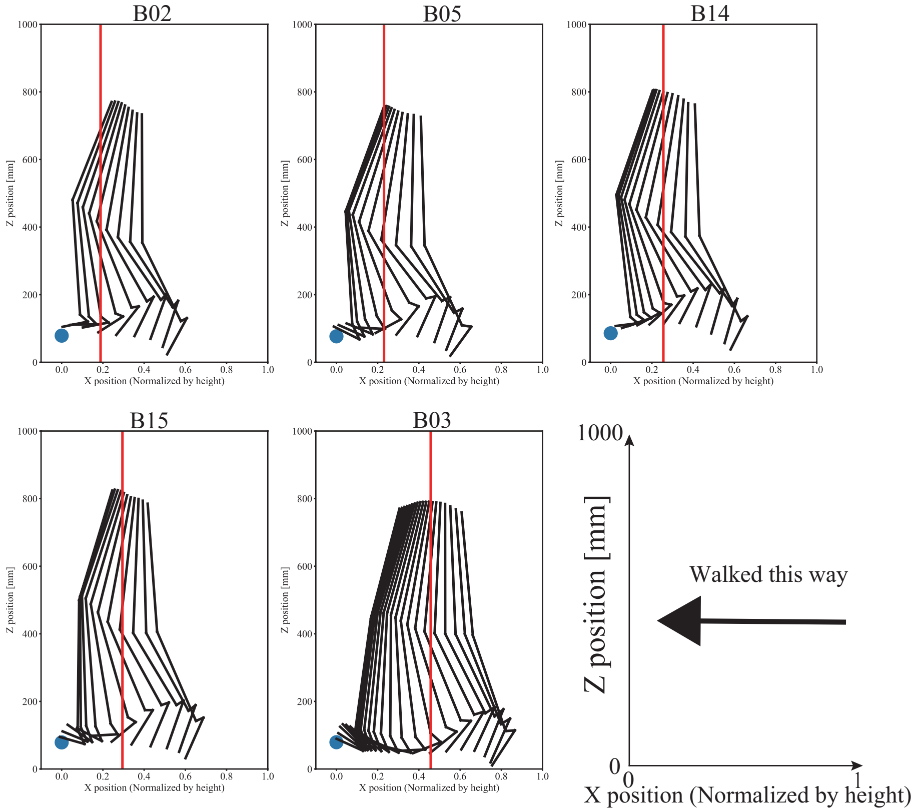



Figure 2.4: The approaching motion from the toe off position. The blue circle indicates the position of the marker attached on the top of the ball. The right leg (from the hip joint marker to the thumb joint marker) are illustrated in each 10 frame (the sampling rate was 256 frame per second).

1. We set a hypothesis that elderly people who have a higher risk for stumbling cannot approach an obstacle placed on their pathway well. The motions of approaching a ball of 14 elderly and 5 young participants were measured and analyzed.

2. We found that 12 out of 14 elderly people place their support leg significantly further from the ball than young participants. Moreover, 5 out of 12 participants' swing legs were leaving from further distance compared with young

participants.

3. We analyzed the distance between the toe off position and the ball, and foot posture during approaching a ball, and showed a possibility of their declining of obstacle localization abilities. In other words, the difference of the depth perception abilities affects ball approaching motions of elderly people.

# Chapter3

# Analysis of Depth-Perception Dependency of Foot Control by Pseudo Visuo-Spatial Test

## 3.1 Motivation

### 3.1.1 Background

In 2016, of the causes of death, 21% of unexpected accidents is due to fallings. This number is larger than the cases of car accidents(13% of unexpected accidents). In the falling cases, most cases are by slippings, trips, or staggers, on the same flat plane and it accounts for 15% of all the falling cases[1]. When limited the causes of the death to the unexpected accidents at home, fallings is the third large causes of death following the drowning in bathtubs and food aspirations[21][2].

Concerning trips, elderly people show smaller toe clearance in the height direction

[1] Data can be acquired from https://www.e-stat.go.jp/dbview?sid=0003214739. (in Japanese)

[2] Data can be acquired from https://www.e-stat.go.jp/dbview?sid=0003214742. (in Japanese)

when climbing up larger steps. Especially when they wear the multifocal glasses, the variance of the toe clearance becomes larger and much more trips tend to occur[52]. Kobayashi et al.[25] used principal component analysis and found that the kinematic key points of the elderly who experienced fallings are the larger hip/knee/ankle angle variance. They also found that these risk indices have a correlation with the size of a variance of the minimum toe clearance and duration of the swing/stance phase during walkings.

Frailty status results from a declining of both physical function and cognitive function[33][32]. As aging, the brain structure gets shrink, starts declining of the neurotransmitter, and functionally changes networks in the brain. These age-related alternations of the brain make elderly people use not only the regions they have ever used for motions but also other regions of the brain. This is thought as because they take a strategy to control integrations of the visuo-spatial perception and the sensory input during motion tasks[48]. The depth perception is a risk factor of fall and fractures[46]. The multiple fallers had poor depth perception[46]. The stereopsis is significantly associated with hip fractures[22][47].

Piaget's 3 mountain task is a very traditional and famous cognitive task in the developmental psychology. In this task, experimenter shows pictures taken from various measurement points around a model of 3 mountains and asks where the picture was taken from. This is the test to estimate the ability to perceive the relationships between their environments and the participants themselves. McDonald et al.[53] confirmed that the difference in the results of the 3 mountain task among elderly and students. The measurement points were allocated each 36° around the mountains model, and they found that the largest mistakes made by the seventies were selecting just next in series to the correct point. This result implies that our skill to perceive relationships between the environment and ourselves may be age-related changing.

We hypothesized that when this kind of visuo-spatial perception changing occurs, elderly people misestimate the position of an obstacle on their pathway, or their error generated during motion planning becomes larger, leads stumbles. The standard depth perception test is a Howard-Dolman depth perception test that requires participants to move the position of one of two rods in the depth direction[54]. This test examines the distance between 2 rods and calculates the participant's depth perception.

In chapter 3, we reported that the elderly's abnormality of the foot position control during approaching to a ball compared with young participants. To state out the cause of this phenomenon, we hypothesized that the perception of the situation comes from the difference of the localization of the objects. If there is an abnormality of the perception, the size of objects would be seen differently for the participants compared with the participants who have the normal perception ability. Usually, if we see the objects aligning in the going direction, we can perceive their size in accordance with the distance from the position of the objects. If the perception ability is changed, this size perception will change, too. Thus, we think that the level of manifestation of the visual size illusion would be changed in accordance with their perception abilities, and this difference would be an explanation of the difference of the object localization at the beginning of the motion. In this research, we focus on the visual illusion as the estimator of the depth perception and propose a method to estimate depth perception

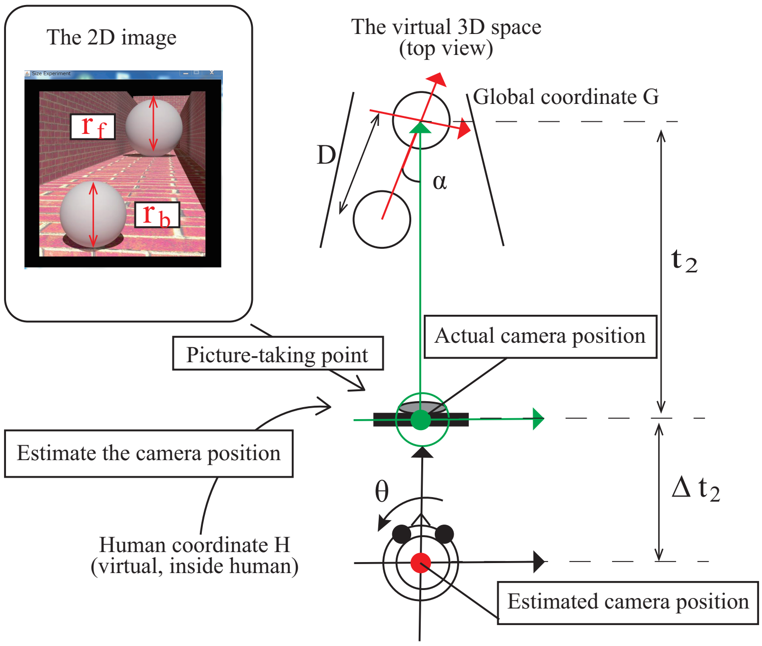



Figure 3.1: The outline of the proposed model. In this model, people estimate the camera position.

easily without any moving of objects to state out the difference of the ball approaching motions.

### 3.1.2 Research purpose

In this chapter, our aim is constructing a mathematical model to clarify the effects of the changing of the visuo-spatial perceptions on motions. In our proposed model, we focus on the visual illusion task in the depth direction on a 2D image. We'd like to estimate the level of each human depth perception from the level of manifestation of the visual illusion task, and express their visuo-spatial perception abilities quantitatively. Fig. 3.1 shows the outline of the proposed model. Also, we're going to discuss how such kind of differences in the depth perception affect motions. We analyze the 3D motions and examine how much the depth perception estimated from 2D images

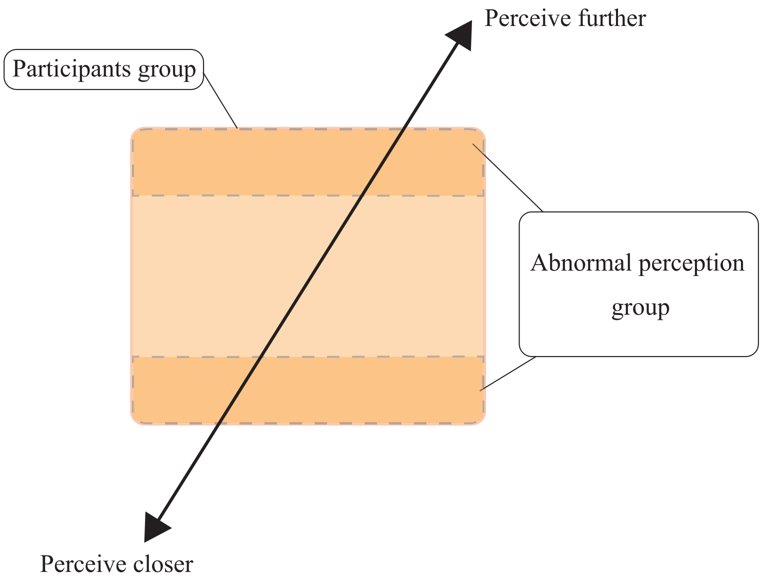



Figure 3.2: The relationship between the expected results of this chapter and the supposed risk for stumbles.

have a relationship with the motion, especially relationship with the motion planning abilities that integrate the perceived information to plan motions. The analyzed motion is the ball approaching motion proposed in the previous chapter[1].

Fig.3.2 shows the relationship between the participants' group and the expected results. The biomechanical study[55] clarified that humans take two types of strategies to prevent falls; An elevating strategy and a lowering strategy. The former strategy appears when people trip in the early swing phase, and the latter strategy appears when people trip in the later swing phase. If people perceive an obstacle further/closer than its real position, then people will be likely to stumble in the earlier/later swing phase. Thus, the abnormal perception group, colored red in Fig.3.2 has a higher risk of stumbles.

## 3.2 The perceived depth acquired from the coordinate transition

### 3.2.1 The visual illusion and the proposed model

In our research, we show a perspective image to the participants (the visual illusion task). We set 2 hypotheses: First, there are 2 types of coordinate systems - the global system $G$, and the human internal coordinate system $H$ to understand their environment as shown in Fig. 3.1. Second, human estimates The origin of the camera position and set their own origin to the estimated origin point. So, the problem we need to solve here is to estimate the transform from the global coordinate system to the camera coordinate system using the result of the visual illusion task under the third hypothesis that the estimated camera coordinate system (the human coordinate system) and the actual camera coordinate system should be in accordance. We'd like to express the model by parameters as calculating the homogeneous transition matrix ${}^{H}T_{G}$, where $T$ is the homogeneous transition matrix from the global coordinate system $G$ to the estimated camera coordinate system (the human internal coordinate system) $H$. The $X$-axis corresponds to the horizontal direction and $Y$-axis corresponds to the depth direction, whereas $Z$-axis indicates the vertical direction in this paper.

Fig.3.3 shows an example of the visual illusion. This figure information is illustrated by the perspective projection method. The size of the 2 spheres on the 2D plane with background information looks the same, whereas the lower (we feel it is placed in the front side) one is larger than the upper (we feel it is placed in the back side). This is a kind of Ponzo Illusion and it can be explained by the size constancy[56]. Let $r$ be the diameter of the sphere and $Y$ be depth, $\hat{a}$ be the perceived sphere size. Then the perceived size can be expressed as

$$r \approx \frac{\hat{a}}{Y}. \tag{3.1}$$

From this equation, when we perceive the depth information from the image and perceive as if it was placed at the front side, we feel the object size smaller than actual it is. This equation is completely the same with the equation of the perspective projection method. Let the diameter of the sphere placed in the front position be $r_f$, the diameter of the sphere placed in the back position be $r_b$. Also let the perceived size of the sphere placed in the front position be $a_f$, the perceived size of the sphere placed in the back position be $a_b$, the coordinate value in depth direction of the sphere placed in the front position be $\hat{Y}_f$, and the coordinate value in depth direction of the sphere placed in the front position be $\hat{Y}_b$, then,

$$\frac{r_f}{r_b} = \frac{\hat{a}_f}{\hat{a}_b}\frac{\hat{Y}_b}{\hat{Y}_f}. \tag{3.2}$$

If the retinal image, or projected diameter onto a 2D image is the same ($r_f/r_b = 1$) and when $\hat{Y}_b/\hat{Y}_f > 1$, $\hat{a}_f/\hat{a}_b < 1$ and the sphere placed in the front position looks smaller. Measuring brain activity under such visual illusion revealed that brain activity changes according to the perceived visual angle size.[57].

Under visual illusion occurs, we ask a participant to fit the size of the sphere placed in the front side so as 'to be the same size' with the sphere placed in the backside in the image. Optically there are 2 disks on a flat 2D plane and they are projected onto the retina of participants, so the size of the retina for 2 disks are the same ($\frac{r_b}{r_f} = 1$, see Fig.3.4(a)). However, participants perceive the depth $\hat{Y}_f$ and $\hat{Y}_b$ for each sphere from the image, so they modify the perceived size for the front sphere $r_f$ to $\hat{a}_f$ and the perceived size for the back sphere $r_b$ to $\hat{a}_b$. At that time participants change the diameter of the front sphere $r_f$ so as to fit the perceived size $\hat{a}_f$ correspond with the retina size $r_i$ and the perceived depth $\hat{Y}_f(< \hat{Y}_b)$. We hypothesized that the visual illusion could be explained by confusing the diameter $r$ and the perceived size $\hat{a}$. In other words, when we ask participants to adjust $r_f/r_b$ to 1, participants will adjust the size of these spheres so as to

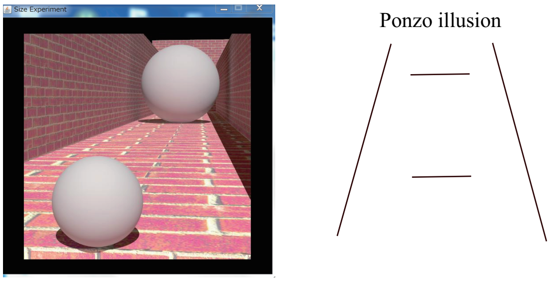
$$\frac{\hat{a}_f}{\hat{a}_b} = 1. \tag{3.3}$$

Though they think they are adjusting the diameter (the retinal image size) of the spheres in the image, the $r_f/r_b$ becomes bigger than 1 as a result. We examine the level of the manifestation of the visual illusion. We introduce the visual illusion ratio $k$ that indicates the ratio of the diameter of the sphere placed in the front side to the diameter of the sphere placed in the backside, calculating following equation:

$$k = \frac{r_f}{r_b}(= \frac{\hat{Y}_b}{\hat{Y}_f}), \tag{3.4}$$

and use this $k$ for the analysis to estimate the depth ratio that the participants perceive.

The images shown to the participants in our research were from the website published by Boyaci[58]. Among these images the background information is constant and only sphere sizes were changed, so we can consider it as the picture taken from the camera at the fixed position. So the problem is rewritten as follows: How participants estimate the fixed camera point and perceive the front sphere position relative to the back sphere. In this problem, the participants estimate the camera coordinate system of which origin is fixed and position themselves between the environments (camera and spheres).




(Left figure) Apparently 2 spheres are the same size on the 2D image.
(Right figure) This illusion is called Ponzo illusion. These 2 lines have the same length, but the lower line looks shorter than the upper one.

Figure 3.3: Two balls were illustrated in the virtual corridor illustrated by the perspective projection. Due to the virtual depth perception, people feel the upper side ball illustrated as if it were put in the far position from the lower ball illustrated. This illusion can be explained as a kind of Ponzo illusion.

Let the origin of the global coordinate system places at the center of the sphere placed at the backside. The Y-axis is set along the 2 spheres and directs from the front side to the back side. The Z-axis is set in the height direction, the X-axis is set as to orthogonal to each Y- and Z-axis (right-hand system). As transitioning the origin on the X-Y plane, we can acquire the camera coordinate system. $t_1$, $t_2$, $t_3$ are the transition components of the origin in direction of each axis. In our research problem, since the camera is fixed, $t_1$, $t_2$, $t_3$ is all the constants. The estimated camera coordinate system (human internal coordinate system) can be regarded as the coordinate system that transit and $\theta$ rotate from the camera coordinate system. So the homogeneous transformation matrix${}^{H}T_G$ will be

$$
\begin{aligned}
&{}^{H}T_G \\
&= \begin{bmatrix} \cos(\theta+\alpha) & -\sin(\theta+\alpha) & 0 & \cos\theta t_1 - \sin\theta t_2 + \Delta t_1 \\ \sin(\theta+\alpha) & \cos(\theta+\alpha) & 0 & \sin\theta t_1 + \cos\theta t_2 + \Delta t_2 \\ 0 & 0 & 1 & t_3 + \Delta t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix},
\end{aligned} \tag{3.5}
$$

where the estimated camera coordinate system (the human coordinate system) is $H$, the global coordinate system is $G$. $\Delta t_1$, $\Delta t_2$, $\Delta t_3$ mean the transition components after coordinate transform. In other words, these values indicate the error between the estimated camera position and actual camera position.

When there are 2 spheres, let the actual distance between these 2 spheres be $D$, then the global coordinate of these 2 spheres be as follows: $X_{(b,G)} = X_{(f,G)} = 0, Y_{(b,G)} = 0, Y_{(f,G)} = -D, Z_{b,G)} = Z_{(f,G)} = 0$, where the $b$ means the coordinates of the sphere of the backside and the $f$ means the coordinates of the front side sphere. So

$$Y_{b,H} = \hat{Y}_b = \sin\theta t_1 + \cos\theta t_2 + \Delta t_2, \tag{3.6}$$

$$Y_{f,H} = \hat{Y}_f = \sin\theta t_1 + \cos\theta t_2 + \Delta t_2 - D\cos(\theta+\alpha). \tag{3.7}$$

Using Eq. (3.4),

$$k = \frac{\hat{Y}_b}{\hat{Y}_f}, \tag{3.8}$$

$$= \frac{\sin\theta t_1 + \cos\theta t_2 + \Delta t_2}{\sin\theta t_1 + \cos\theta t_2 + \Delta t_2 - D\cos(\theta+\alpha)}. \tag{3.9}$$

Since $D$ is the constant number,

$$D = \frac{k-1}{k}\frac{\sin\theta t_1 + \cos\theta t_2 + \Delta t_2}{\cos(\theta+\alpha)}, \tag{3.10}$$

is also the constant number. Let set the visual illusion ratio k be K if the estimated camera coordinate system completely according to the actual one. At that case $\theta = 0, \Delta t_2 = 0$, so Eq. (3.10) will be transformed into

$$D = \frac{k-1}{k}\frac{t_2 + \Delta t_2}{cos\alpha}. \tag{3.11}$$

We cannot know the actual value of $K$, calculate it from the average of the results of the young participants.

Let us consider the position of the origin of the camera coordinate system explained in Sec3.2.1 as the model parameter. Since the depth distance $D$ between the sphere in front side and the sphere in the backside is constant, if the rotation of the coordinate system can be neglected,

$$K = \frac{r_f}{r_b} \approx \frac{Y_b}{Y_f} = \frac{t_2}{t_2 - D\cos\alpha}. \tag{3.12}$$

Then,

$$t_2 = \frac{K}{K-1} D\cos\alpha. \tag{3.13}$$

However, even young people their visual illusion ratio $k$ is shifted from $K$ by a personal difference. This can be explained by the transition in direction of the depth. From above discussion, we can calculate $\Delta t_2$ as following:

$$\Delta t_2 = \frac{k}{k-1}\cos(\theta+\alpha)D - \sin\theta t_1 - \cos\theta t_2. \tag{3.14}$$

Now we're thinking about the case of $\theta = 0$, this equation will be

$$\Delta t_2 = \frac{k}{k-1} D\cos\alpha - t_2 = (\frac{k}{k-1} - \frac{K}{K-1})D\cos\alpha \tag{3.15}$$

Since we cannot acquire the real value of $D$, we analyzed the coefficients of $D$ (i.e. $k\cos\alpha/(k-1) - 1/(K-1))$ in the following discussion. We set $\alpha = 35°$. This is calculated as an angle between the vertical line from the backside sphere to the lower side of the image and the line that connects the centers of the 2 spheres. In the statistical analysis, we set a significance level as $p = 0.05$ and adjusted p-value by Bonferroni method will be 0.008.

## 3.3 The experimental settings for the visual illusion task

### 3.3.1 Participants

Nineteen participants (Fourteen were elderly, 5 were young) have joined the measurement. For the elderly, they were 6 male and 8 female (age: 79.5 $\pm$ 6.91). For young, all were male and they were the student of the graduate school of information science and technology at the University of Tokyo.(Age: 24.6 $\pm$0.89). No participants report the difficulty of seeing the contents on the monitor before/after the measurement.

### 3.3.2 The visual illusion task on a 2D plane

At the measurement, we ask the participants to do the task that can experience the visual illusion easily using the keyboard and the monitor and published by Boyaci[58]. No participants report the difficulty of seeing the contents on the monitor before/after the measurement.

In the task, 2 spheres that have randomly different size were shown on the monitor with the background drawn by the perspective projection method. The participants can change the size of the sphere in front side using the up/down key of the keyboard. The results are shown on the monitor so we can acquire $r_f$ and $r_b$ (the diameter of each sphere) for each trial.

The participants did this task for 20 trials. For one trial, it takes 5-10 sec. The time for each trial was changed by the experimenter. First, participants did 5 trials and each trial they had 6 sec. Second, they were asked to do the task and not mind the time. This was for 10 trials. After that, they were asked to do 5 trials and each trial they had 10 sec. Since the results can be checked on the monitor when the participants push a key after the task after each trial was done, they were asked to close their eyes and the experimenter checked the results so as to the participants cannot check their own results. Even when the task starts, they asked to keep closing their eyes, and if they hear the beeping sound then open eye and start doing the task.

While the young participants major the information technology field and they get used to operating PCs, some of the elderly participants don't have enough experience of using PCs. So we analyzed the average of the results of the first 5 trials for each young participant, and for each elderly participant, we analyzed the average of the results of the final 5 trials.

We also conducted the revised version of Hasegawa's dementia scale (HDS-R; the screening tool for dementia) as a rough indication of their cognitive abilities. The cutoff value of the HDS-R is 20. In our research, we treated the participant who has under 26 points as the doubt for mild cognitive impairment (MCI) and the participant who has under 20 points as the doubt for dementia.

The dataset using in this research is a part of the series of brain activity measurements (total time: 90 min). All the participants had experienced 3 tasks; the cognitive task (P300 task) that measures the concentration skills of them before the visual illusion task, the visual illusion task, and the imitate hands task though we won't use the data of the P300 task and the imitate hands task in this research.

### 3.3.3 The ball approaching motion[1]

In this chapter, we analyze the 3D motions and examine how much the depth perception estimated from 2D images have a relationship with the motion in the 3D space, especially relationship with the motion planning abilities that integrate the perceived information to plan motions. The target motion is the ball approaching motion[1] proposed in chapter 2. We put an 8-cm small ball in front of the participant and asked to scratch their foot on the reflective marker attached on the top of the ball. Thirty five reflective markers are attached on the participant and the motion is measured by 12 cameras. The ball is put about 2-3 strides advance manually by the experimenters. The measured reflective marker positions were analyzed. In the statistical analysis, we set the significant level as $p = 0.05$.

## 3.4 The experimental result and calculated perceived depth information

### 3.4.1 Measurement results

The visual illusion ratio $k$ calculated from Eq. (3.4) is shown on Fig.3.5. Fourteen from the left side shows the average and standard deviation of the visual illusion ratio of the elderly, five from the right side shows the average and standard deviation of the visual illusion ratio of the young.

From the average of the young participants, $K$ (the actual value of the visual illusion ratio $k$, and that estimates the camera coordinate system completely when it doesn't rotate) is calculated as 1.18. Murray[57] conducted the behavioral experiments on the manifestation strength of the visual illusion and its result was 1.17 (on average, the backside sphere is reported 17% smaller in their experiments) that almost correspond with our results. Moreover, we confirmed the pixel-based corridor width in the background of the image. The width at the point where the front side sphere is put illustrated 18% wider than that of the point where the back side sphere is put. From the above confirmations, we regard $K = 1.18$ as the valid value for the average of young participants. We calculate the correlation coefficients $r$. Between the age and the visual illusion ratio ($r = -0.36, p = 0.19$), between the HDS-R and the visual illusion ratio ($p > 0.3$) had no significant difference, but the age and the HDS-R had a negative correlation ($r = -0.68, p < 0.01$). From Fig.3.5, there is a group of participants whose deviation is very big.

There are also participants whose visual illusion ratio was much bigger compared with young participants. There is a positive correlation between the size of the visual illusion ratio and the deviation ($r = 0.79, p < 0.01$). The maximum of the deviation of the visual illusion ratio of the young participants was 0.11. So we divided 14 elderly participants into 2 group; A group is the big deviation group (7 people) and another group is the other participants (7 people). We calculated the correlation coefficients $r$. The big deviation group doesn't show the significant correlation between the age and the visual illusion ratio ($p > 0.3$), whereas the other group showed the tendency of the negative correlation with the age ($r = -0.56, p = 0.18$). Both groups showed no significant correlations with the score of HDS-R ($p > 0.3$).

### 3.4.2 Analysis on the depth perception information and transition components of the estimated coordinate system

There was one young participant who showed $k = 1.05$, he reported that he cannot elicit the visual illusion because he sees the image so as not to feel the depth information. So for this participant, we think that visual illusion was not elicited enough. Without this participant, young participants showed $k$ in range of $1.12 < k < 1.3$. From this result and the result in the former section, we categorized elderly people into 3 group so as to the number of participants be close. The groups were called as Group (A) $Small(k \leq 1.13; n = 4)$, Group (B) $Normal(1.13 < k \leq 1.4; n = 6)$, and Group (C) $Big(1.4 < k; n = 4)$, Group (D) $Young(n = 5)$.

The transition error from the ideal state of the origin (The coefficient of $D$ of $\Delta t_2$) was calculated by Eq. (3.15). The average of them for each group is shown on Tab. 3.1. The one way ANOVA (analysis of variance) showed a significant main effect of group (F(3,15) = 4.73, $p = 0.016$). The post-hoc comparison showed that the participants in Group (C) *Big* estimates the camera position significantly closer to the ball compared with Group (A) *Small* ($p = 0.01$), Group (B) *Normal* ($p = 0.01$), and they showed a tendency of significance of estimating the camera position closer to the ball than Group (D) $Young$ ($p = 0.08$). Also, Group (A) *Small* estimates camera position further to the ball than Group (B) $Normal$ ($p = 0.04$), whereas there are no significant difference of the estimated camera position between Group (D) $Young$ and both Group (A) *Small* ($p = 0.36$) and (B) $Normal$ ($p = 0.29$).

Since the experimenter changed the distance between the ball and the participants, we examined the average and standard deviation of the distance to the ball from the

Table 3.1: Result of the difference between estimated origin and the ideal origin ($\Delta t_2$; coefficient $\frac{1}{k} - \frac{1}{K}$ of the depth $D$).

| | Group (D) *Young* | Group (A) *Small* | Group (B) *Normal* | Group (C) *Big* |
|---|---|---|---|---|
| Average difference $\Delta t_2$ | 2.02 | 4.91 | -0.78 | -3.09 |

start line. Participants had various heights so we normalized the distance between ball (the distance between the marker on top of the ball) and the participants (the marker on right foot thumb of the participant) by their height (the marker on the center of their forehead). Average of the normalized distance between ball and participant was $1.03 \pm 0.16$. Participants approach a ball in 3 steps to 5 steps. Six participants approached a ball in 3 steps, 7 participants approached a ball in 5 steps, and 1 participant approached a ball in 4 steps. For the participants who approached a ball in 3 steps and 5 steps, we conducted t-test and compared the distance to a ball. There are no significant difference between these participants groups ($p = 0.18$).

Our hypotheses is that the participants in the bigger $k$ group take their toes off earlier than the other groups because they perceive the ball position closer as it really is, and for the small $k$ group, vice versa, participants take their toes off closer to the ball. We analyzed the distance $x[mm]$ between the ball and the toe off position right before the ball.

The one way ANOVA (analysis of variance) showed a significant main effect of group (F(3,15) = 4.97, $p = 0.01$). The post-hoc comparison showed no significant difference between each group. However, Group (C) *Big* showed significantly larger distance $x$

compared with Group (A) *Small* ($p = 0.01$) and Group (B) *Normal* ($p < 0.01$), and showed tendency of significant larger distance $x$ compared with Group (D) *Young* ($p = 0.06$), whereas there were no significant difference among Group (A), (B), and (D) ($p > 0.29$).

Though the difference is shown, there is a possibility of declining physical abilities. [43] points out that elderly people who have high risk of falling show shorter stride length during normal walking. To confirm the difference of the toe off point is not due to the declining physical ability, we also analyzed the normalized $x$ by heights and the normalized stride length by heights of the same leg (right leg). Note that we used the former step before the contact to the ball (i.e. the 1st step for the participants who approach a ball in 3 steps, the 2nd step for the participants who approach a ball in 4 steps, the 3rd step for the participants who approach a ball in 5 steps) as the stride. The average and S.D (standard deviation) of each datum is shown on Tab. 3.2. ANOVA showed a significant main effect of group (F(3,15) = 5.62, $p < 0.01$) to the normalized $x$, and not a significant main effect of group (F(3,15) = 0.63, $p = 0.60$) to the normalized stride length. The post-hoc comparison was showed no significant difference among each group for both the normalized $x$ and the normalized stride length ($p > 0.17$ for all the combination). However, for the normalized $x$, Group (C) *Big* showed significantly larger normalized $x$ than other 3 groups ($p = 0.04$ for Group (A) *Small*, $p = 0.03$ for Group (B) *Normal*, and $p = 0.05$ for Group (D) *Young*) whereas there were no significant difference among the other groups (for all combination of groups $p > 0.5$).

Table 3.2: The average and SD of (1) $x$, which is distance between the position of toe off right before the ball and the ball [mm], (2) normalized $x$ by height, and (3) the normalized stride length by height.

| (1) $x$ | | |
|---|---|---|
| Group | Average [mm] | S.D[mm] |
| Young | 598 | 222 |
| The big $k$ | 866 | 150 |
| The normal $k$ | 465 | 145 |
| The small $k$ | 497 | 145 |
| (2) the normalized $x$ | | |
| Group | Average [mm] | S.D[mm] |
| Young | 0.36 | 0.13 |
| The big $k$ | 0.60 | 0.10 |
| The normal $k$ | 0.32 | 0.11 |
| The small $k$ | 0.35 | 0.07 |
| (3) the normalized stride length | | |
| Group | Average [mm] | S.D[mm] |
| Young | 0.51 | 0.22 |
| The big $k$ | 0.38 | 0.11 |
| The normal $k$ | 0.38 | 0.16 |
| The small $k$ | 0.27 | 0.070 |

### 3.4.3 Consideration of the case $\theta \neq 0$

In this paper, we don't consider the rotation around Z-axis ($\theta = 0$) of the human coordinate system. Since there is previous research that suggests the possibility of the human coordinate system rotation [53], let us consider the case of $\theta \neq 0$ as one of the possible cases to explain the variability of the visual illusion ratio $k$ of the elderly people.

If the human coordinate system $\theta°$rotates in the positive direction around Z-axis, the distance between the objects and the origin will be $1/\cos\theta$ times further (see the right side of Fig.3.6), whereas the distance between the objects and the origin will be $\cos\theta$ times shorter when the human coordinate system $\theta°$ rotates in the negative direction around Z-axis (see the right side of Fig.3.7). The estimation error coefficients of $D$ of $\Delta t_2$ taken into account positive rotation around the z-axis (the left side of Fig. 3.6) and negative rotation around the z-axis (the left side of Fig.3.7) are calculated. We set angle $\theta$ as $\pm 20°, \pm 30°, \pm 35°$, and calculate the errors for each. In both figures, the vertical red line indicates the average visual illusion ratio of the young participants $k = K = 1.18$. The horizontal red line indicates the deviation of the coefficients of the $D$ of the $\Delta t_2$ of the young participants.

Taking into account the negative rotation around the z-axis, the error of the participants who have bigger visual illusion ratio becomes within the range as same as the young participants as shown in Fig 3.7. When the rotation angle $\theta = 35°$, the error of the elderly participant who showed the largest visual illusion ratio becomes 0.15, the smallest value.

On the other hand, the small group ($k \leq 1.13$), taking into account the positive rotation around the z-axis, the error of the participants who have the smaller visual illusion ratio becomes within the range of the young participants. The smallest visual illusion ratio that showed by elderly people was almost the same with the ratio showed by the young participant who responded that he cannot elicit visual illusion. Moreover, this participants showed the smallest error 0.005 when the rotation angle $\theta$ is set $35°$.

This image illustrates the back side sphere on the right side whereas the front side sphere is illustrated on the left side. So if the rotation around the z-axis is positive (see Fig. 3.6) and let project the 2 spheres onto the estimated camera axis, the distance between 2 spheres becomes very close. This inhibits for elderly people to perceive the depth information. The same things may happen when the participant neglects the background information. As far as this proposed method, we cannot tell apart the status that elderly participants rotate coordinates unintendedly and the status that voluntary rotate the coordinates to neglect depth information. Meanwhile, negative rotation makes two spheres difference look far as shown in Fig.3.7, the right side. Taking into account the nature of the visual illusion task, which elicits the confusing the 2D input to the retinal image coming from the depth perception and the 3D size estimated from the size constancy, making the spheres distance intendedly far as rotating the estimated coordinate system is unnatural. That's why we think this negative rotation is generated unintendedly. And perhaps, this unnatural and unintended rotation may be a cause for making the big deviation of the visual illusion ratio. Since the rotation is unnatural referred to the task's nature, then, the visuo-spatial input process may become confusing.

There is previous research suggests that elderly people become to do motion task as integrating visuo-spatial perception inputs and sensory inputs[48]. It is also found that the variability of the joint angle during walking becomes bigger for the elderly people who experienced fallings[25], and the visuo-spatial perception variability could be affected by these motion variability.

There are some limitations to this research. As we mentioned above, in our model the unintended/intended changing of the estimated coordinates cannot be told apart. Also, the angle of the camera to the objects (the types of images showing to the participants) should be varied more. Otherwise we cannot discuss the rotation angle $\theta$ on the plane, and also the rotation angle to the ground further. We modeled the possibility of altering the visuo-spatial perception inputs but still needs further investigations on the age-related changing/deficits of motions.

### 3.4.4 Analysis on the ball approaching motion

It is known that human plans their motion at least before 2 steps[45], so when participants step just before approaching the ball, they have already planned their motions. The relationship between $k$ and both left/right foot positions at the toe off time for contacting a ball are shown on Fig. 3.8. The horizontal axis indicates the visual illusion ratio $k$, and the vertical axis indicates the distance between the swing (right)/support (left) leg positions from the ball at the toe off time of the swing leg. The distances are normalized by each participant's height. The participants who showed the visual illusion ratio $k$s larger than the vertical red dotted line are categorized as Group (C) *Big* in the previous statistical analysis. The horizontal dotted line indicates a threshold set in the previous chapter 2 for the right foot position compared with young participants. From the Fig. 3.8, the swing leg (right leg) position showed larger variance than the support leg (left leg) position. Also, as shown in Fig. 3.8, the participants who showed larger $k$ than 1.4 also put their swing foot on the further position from the ball compared with other participants. There is a significant correlation between the visual illusion ratio $k$ and the distance from the ball to the swing leg toe off position at the toe off time just before contacting a ball (the correlation coefficient $r$ was 0.53, $p = 0.04$). Participants B01, B07, B24 put their swing legs close to the participants B09, B16. We regard this phenomenon as due to internal rotation of the participants' coordinate system discussed in section 3.4.3. So, we calculate the correlation coefficient between visual illusion $k$ and the position of the right foot except for B01, B07, B24. The regression analysis revealed that there is a significant correlation between the visual illusion $k$ and the distance between the swing leg and the ball at the toe-off time (correlation coefficient $r = 0.74$, $p = 0.008$).

Figure 3.9 shows the relative trajectory of the right foot thumb to the ball from the toe off to the contact to the ground/ball. The toe off point is set as 0 for each stride. The red line indicates the trajectory from the time of toe off at the right before ball to the time of contact to the ball. The blue line indicates the trajectory from the time of toe off at the 2 steps before of contact to the ground (i.e. the blue line indicates the trajectory during the 1st/2nd/3rd of the right foot for the participants who approach a ball in 3/4/5 steps). The horizontal axis indicates the x-axis, the progressing (depth) direction. The vertical axis indicates the z-axis, the height direction.

From Fig. 3.9 we can see the wider waveform of the big $k$ group that means they stretched their foot after their toe was off. At the point of 0.2-0.4 distance to the height from the toe off point, the flat phase appears in the waveforms. If the flat phase indicates the position of the target of the participants, then this is the evidence that participants feel the position of the ball closer than it really is.

## 3.5 Conclusion

The conclusion of this research is as follows:

1. We hypothesized that depth perception changes as aging and the altering can be shown on the level of the manifestation of the visual illusion. We proposed 2D image-based depth perception estimation using the visual illusion.

2. To estimate the perceived depth quantitatively, we proposed the mathematical model that is based on the idea of the coordinate transforms and calculate the perceived depth of people.

3. Using this mathematical model and estimate perceived depth information, it is found that if we don't take into account rotation, the participants who showed bigger visual illusion ratio set the origin of the estimated further depth distance than it really is.

4. We also analyzed the ball approach task that requires the participants to approach the marker attached top of the small ball. The participants in the big $k$

group raise their foot from the point former of the ball when approaching the ball on average.

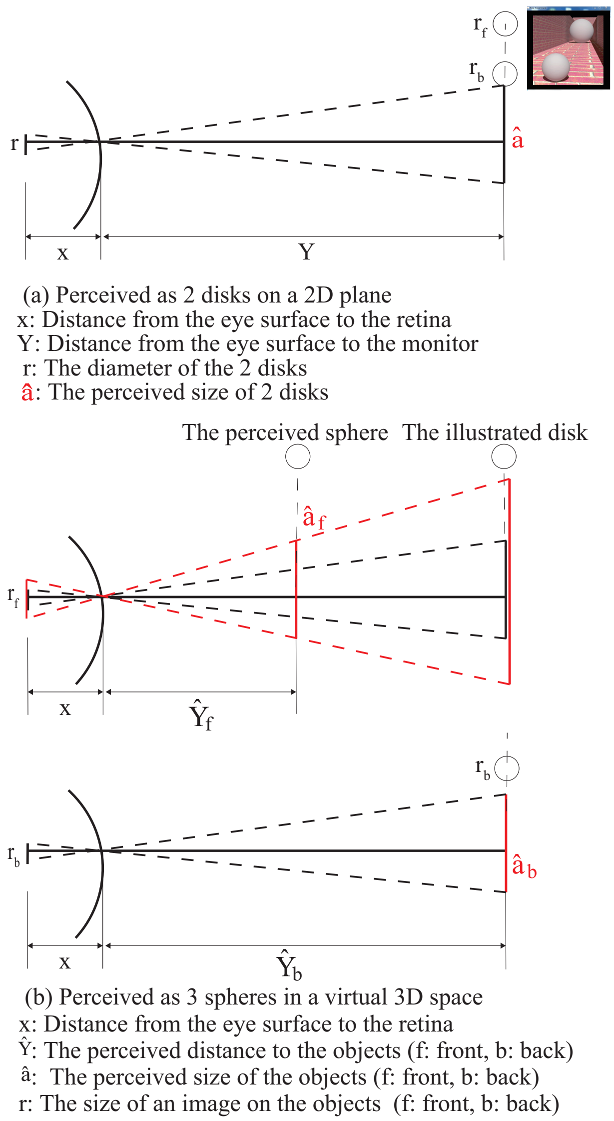



Figure 3.4: (a)If we see the 2 spheres as illustrated disks on a 2D plane, the retina size corresponds with the actual diameter of the disks. (b) If we perceive the depth and see the 2 spheres as it was placed in a 3D space, the retina size for the front sphere is corrected so as to the perceived size of the back / the front sphere will be the same.

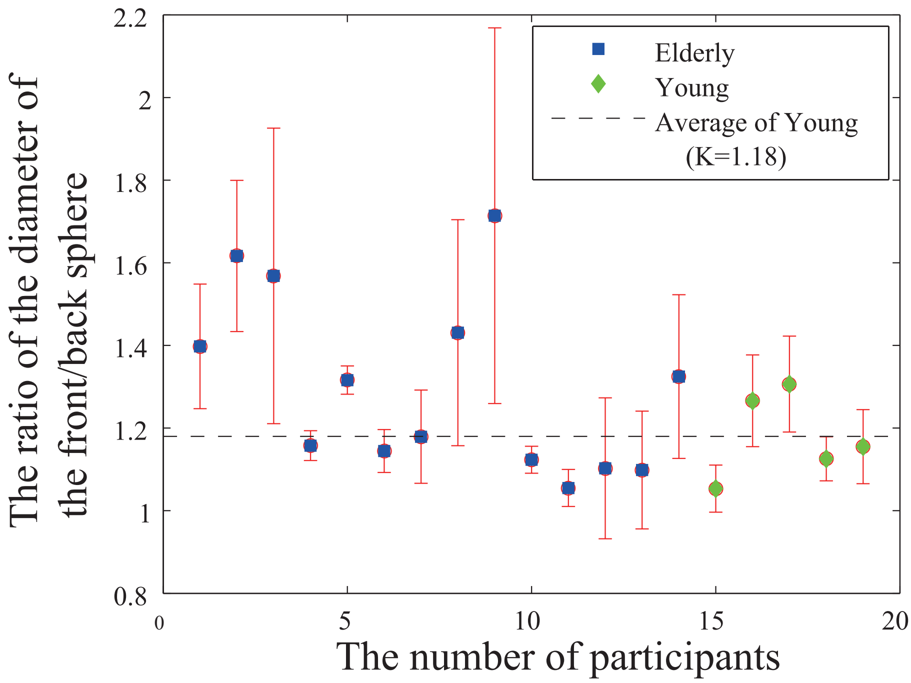



Figure 3.5: The result of the visual illusion task. The horizontal axis indicates the number of participants, whereas the vertical axis indicates the ratio of the visual illusion ratio (i.e. the ratio of the diameter of the front/back sphere on the 2D image.)

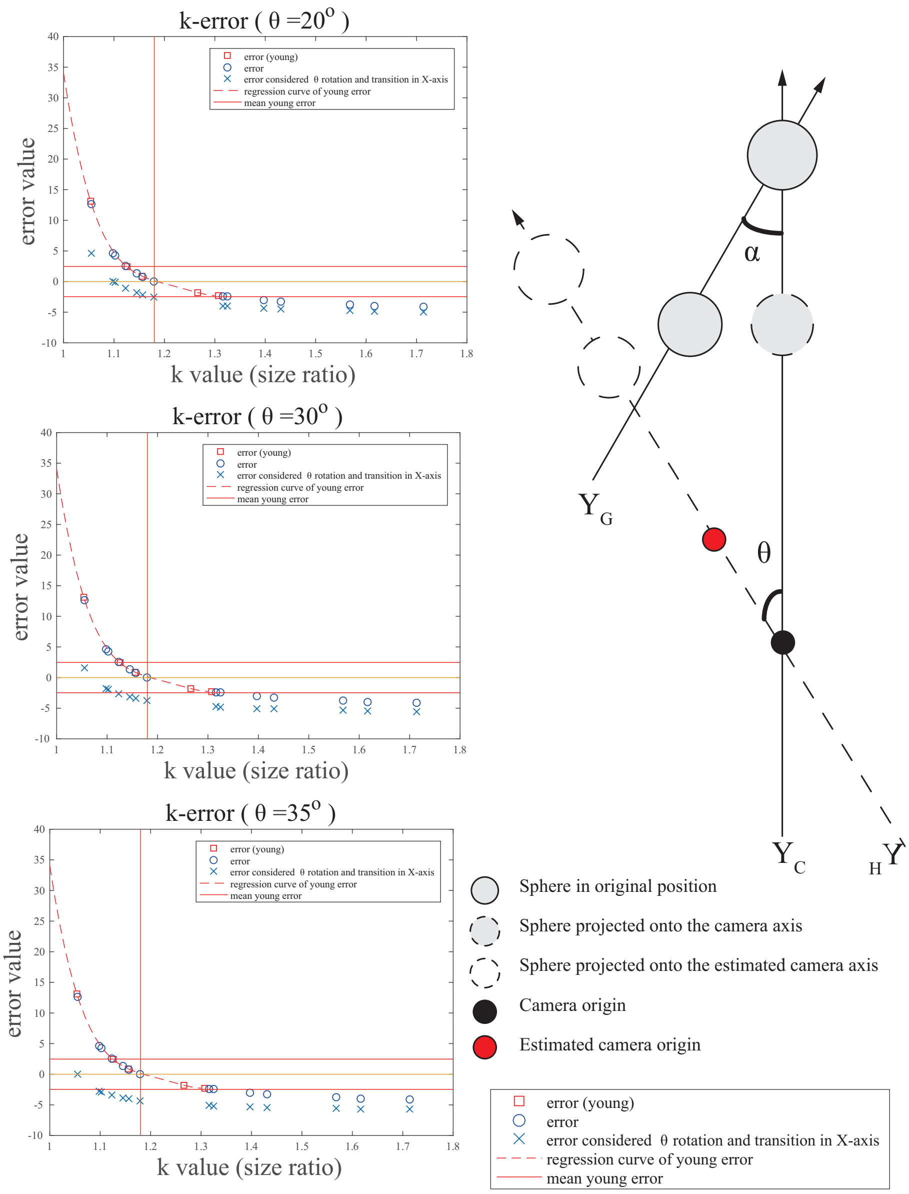



Figure 3.6: Transition error ($\Delta t_2$) of the origin of the estimated camera coordinate system calculated from the illusion ratio $k$. If $k = K$, $\Delta t_2$ will be 0. The rotate angle $\theta$ is set as $20°, 30°$, and $35°$ for each calculation.

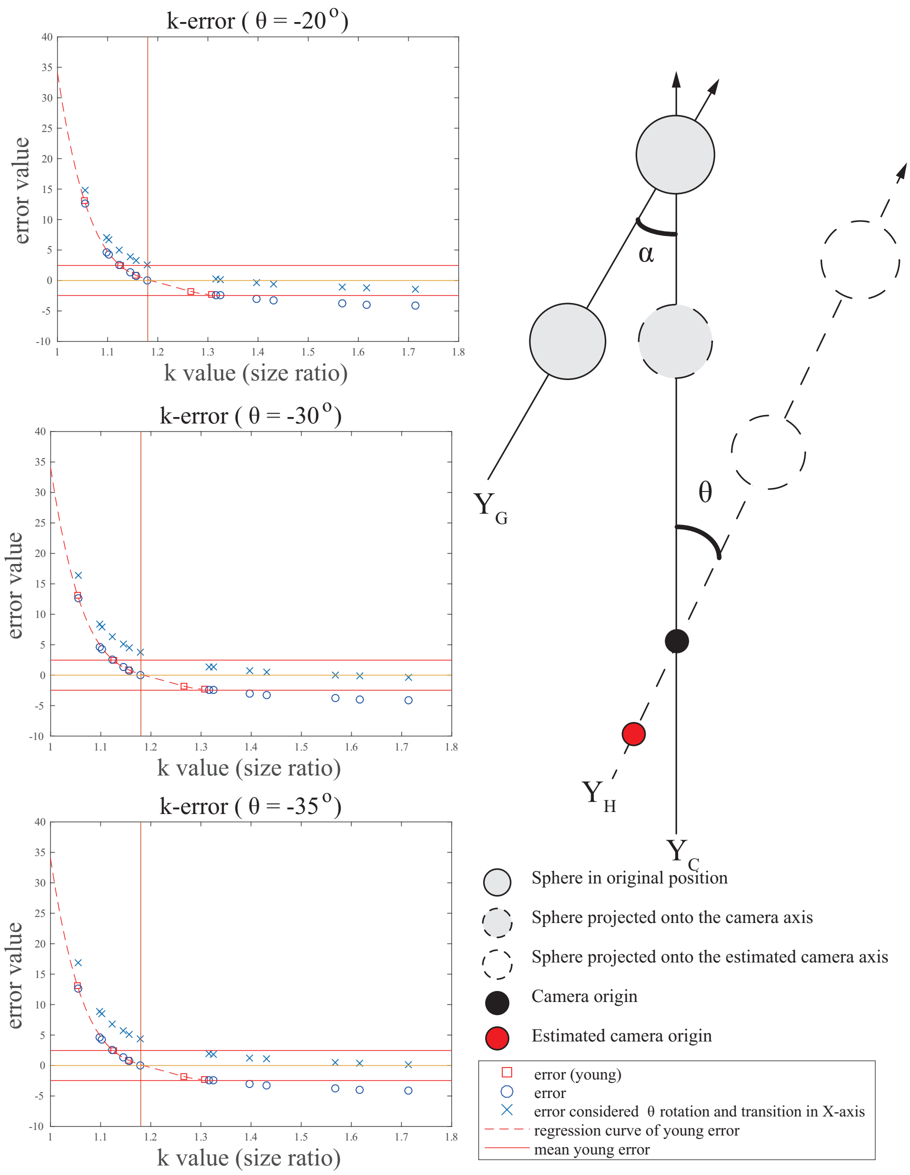



Figure 3.7: Transition error ($\Delta t_2$) of the origin of the estimated camera coordinate system calculated from the illusion ratio $k$. If $k = K$, $\Delta t_2$ will be 0. The rotate angle $\theta$ is set as $-20°$, $-30°$, and $-35°$ for each calculation.

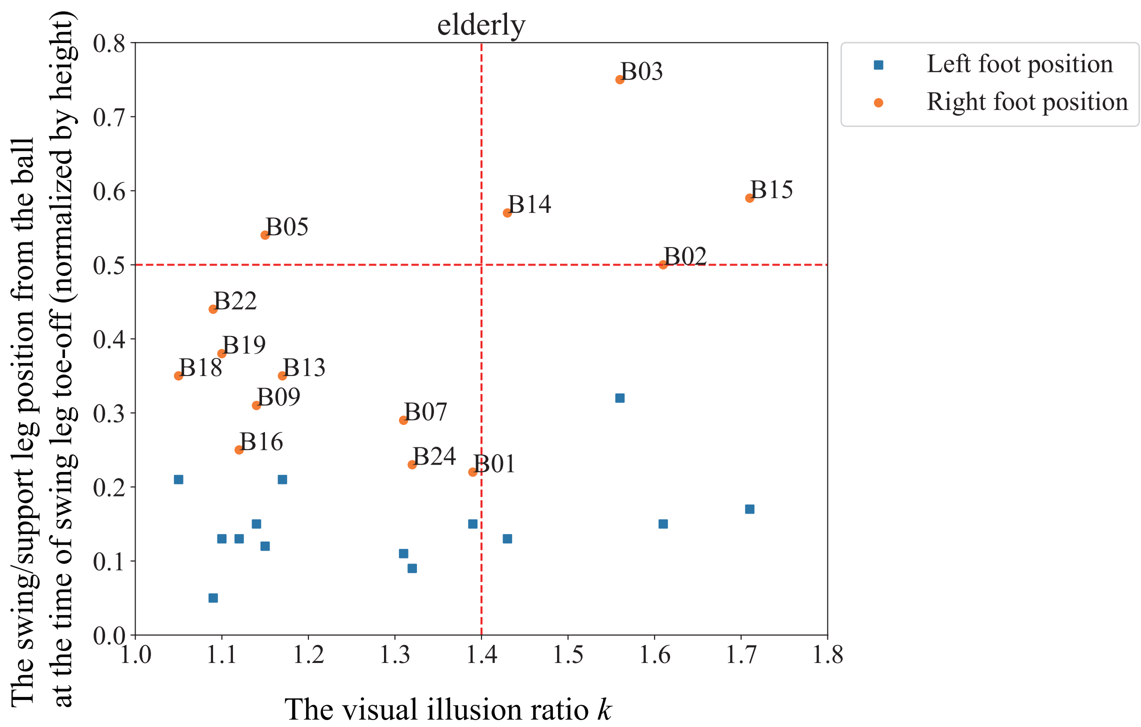



Figure 3.8: The relationship between $k$ and both left/right foot positions. The horizontal axis indicates the visual illusion ratio $k$, and the vertical axis indicates the distance between the swing (right)/support (left) leg positions from the ball at the toe off time of the swing leg. The distances are normalized by each participant's height. The participants who showed the visual illusion ratio $k$s larger than the vertical red dotted line are categorized as Group (C) *Big* in the previous statistical analysis. The horizontal dotted line indicates a threshold set in the previous chapter 2 for the right foot position compared with young participants.

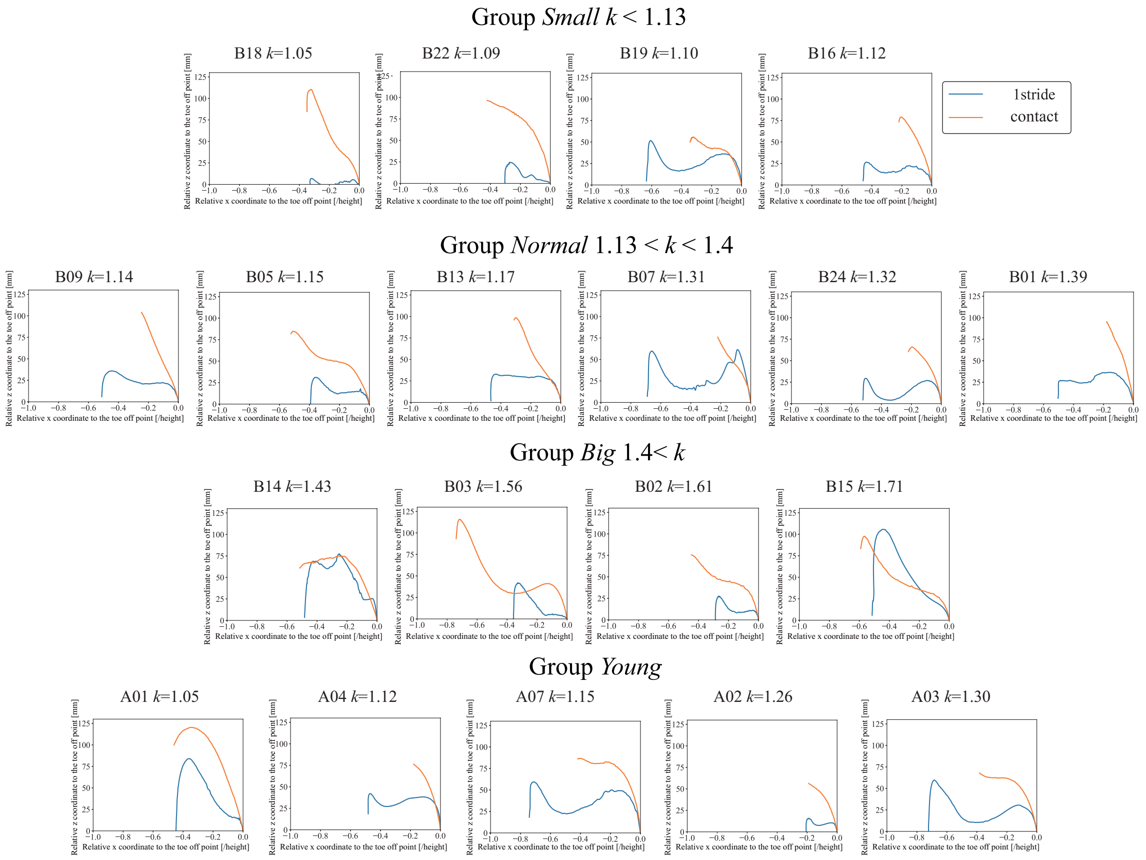



Figure 3.9: Compare waveforms of the right foot thumb trajectory normalized by participants' heights. The starting point is set to the toe off point. From the 1st raw, (a) the trajectory of the participant whose $k < 1.13$, (b) the trajectory of the participant whose $k > 1.13$ and $k < 1.4$, (c) the trajectory of the participant whose $k > 1.4$, and (d) the trajectory of the young participants.

# Chapter4

# Classifying Hospitalized Patients of Falls and Fractures by Mining from Functional Inquiries and Semi-Structured Interview

## 4.1 Introduction

Falls, and especially its consequent hip fractures cause declining QoL (Quality of Life) and a start of using the nursing care service. As a factor of falls, experience falls or wrist fractures have a big effects[22]. Also, it is known that once the elderly falls then the risk of another fall within 1 year is increasing. It is getting clarified that the shorter the duration from the falling and fracture to undertake an operation leads the smaller long-term mortality[59]. Detecting falls[60] as soon as it happens and/or preventing falls themselves in a home is one of the big problems.

We distributed self-administered questionnaires and analyzed 1561 people aged over 40 years old (mean $\pm$ SD were $68.1 \pm 13$ years old), and it is clarified that 28% people had experienced falls at home, and people who live in a home with a barrier are more likely to experience fall-related fractures[61]. The adjustments of living environments including their home are necessary for elderly people to prevent falls, however, there are various falling patterns and it is not easy to clarify and take enough measures of them.

In chapter3, we proposed the 2D-image based estimation model to evaluate the elderly depth perception abilities quantitatively. In the model, the visual illusion ratio $k$ is defined as the ratio between the 2 sphere diameters on the monitor. If a participant has a normal depth perception, $k$ would be around 1.18 (average of the results of the young participants). If a participant perceive an object closer, $k$ would be bigger than 1.4 and a participant perceive an object further, $k$ would be smaller than 1.13. Then, the following question might be aroused: Can we predict the risk of stumbles using the 2D image?

The outline of the proposed system is shown in Fig. 4.1. In this chapter, we use the data collected from the participants who have experienced falls and hip fractures and try to construct the risk estimator for stumbles from the physical functional inquiries. Fig.4.2 illustrate the relationship between the group in this chapter (hospitalized patients' group) and the group in the previous chapter (participants of the measurements). If the participant showed an abnormal visual illusion ratio $k$ and also showed the decline of physical functional abilities, then the fall risk might arise.

## 4.2 Interview research[1]

### 4.2.1 Preliminary interview research to elderly people in 3 metropolitan cities[2][3][4]

As a preliminary survey, we conducted 3 interview research for 27 participants in total. The first was in 2014, we interviewed 10 people who live in A ward in Tokyo, aged 53-98, and who have experienced falls and fractures (including fractures) within 3 years, or their families. The second was in 2015, we interviewed 10 people who live in B city in Kanagawa, aged 67-98, and who have experienced falls and fractures (including cracks). The third was in 2016, we interviewed 7 people who live in C city in Chiba, aged 75-87, and who have experienced falls and fractures (including cracks). We visit their homes and did semi-structured interviews, asking about their falls (date, time, place, what they did, what they have, what they wear), their homes and living environments (what types of house, person who they live with, opportunities to go outside), and the changing after falls (changing daily lifestyle, supports from family, whether to start the nursing care service).

Tab. 4.1 - 4.3 shows the demographic attributes, place of falls, and the outline of their falls. People who had experienced hip fractures show in red in the 4th column. The * sign in the 5th column indicates that the participant had experienced multiple falls. Seven out of 10 participants in A ward interview showed both inside and outside falls (including near-miss cases). 5 out of 10 changed their lifestyle after falls. The

[1]The researches described in this subsection, the author of this dissertation is included as the first author or one of the co-authors. However, the author doesn't include these works as contributions to this dissertations.

main influence on changes in lifestyle was the living environments changes including the changing arrangements of the furniture. One participant said that she noticed the step but she couldn't stride over it. Trips are likely to occur outside, and more aged people tend to lose their balance. These findings are coincident with discussions in [34] that community-dwelling elderly people are more likely to trip and elderly people in facilities are more likely to show incorrect transfer & shifting of body weight. For B city people, 4 out of 9 missed a step of stairs. In 3 out of 9 cases, they had something heavy with their both hands. There is a report that elderly people get to have difficulty with doing cognitive tasks and motion tasks simultaneously[48], and these findings are coincident with it. In C city, there were few people who had experienced multiple falls. Three out of seven was tripping outside, this is also coincident with [34] discussion as well as A ward. Summarizing the findings of these 3 interviews, the most number of falls were following 2 types: (1) Losing balances, or incorrect shifting of their weights and (2) falls by external forces (tripping, slipping). For each type, 9 cases were reported. The other falling cases were accidents (n=2) and missing a step (n=4). Among various falling patterns, all of the participants who had experienced a hip fracture lost their balances, and the most of participants who had experienced the wrist fracture that increases the risk of hip fractures in the future[22] tripped (3/4 cases, the one left was an accident). There is a possibility that the floor materials and the culture that most people stays their home with bared feet are related to the way of falls. The research limitation was that a long time has passed since they had experienced falls, and the memory of the participants tend to be ambiguous.

### 4.2.2 Definitions of the falling types in this research

For the architectural considerations, Imaeda[4] categorized the falls into 6 types that are focused on the interaction between environments and the direction of the force to the fallers. Also, the 18 falling modes are defined under the 6 falling types. The falling modes are determined by the force to the center of gravity when people fall down, the relationship between objects surroundings people, and the existence of actions just before the falls (See Fig. 4.3), whereas Robinobitch[34] categorized falls that occurred in their video survey as following 7 groups: (1) incorrect transfer & shifting of body weight, (2) trip/stumble, (3) hit/bump, (4) loss of support with external object, (5) collapse or loss of consciousness, (6) slip, (7) could not tell.

From Fig. 4.3, fall type A, C, fall mode D(1), D(2) in [4] and fall group (2), (3), (6) in [34] can be regarded as "falls by unexpected external forces (not mind the direction of force, acceleration, or deceleration)". Also, Fall mode B, E, F, and Fall mode D(3), D(4) in [4] and fall group (1), (4), (5) in [34] can be regarded as "falls by losing balance or supporting force from the outside". Focusing on the forces to the fallers, we divided the latter case into 2 cases: Falls by losing balance or supporting forces due to their perturbation (without any external forces), and falling downs by losing balance or supporting forces by gravity (free fall, from the higher plane). Thus, based on the forces to the fallers, we propose the following 3 categories: (a) falls by unexpected external forces, (b) falls by losing balance or supporting forces due to their perturbation, and (c) falling downs by losing balance or supporting forces by gravity. The corresponding with our proposed categories and the other 2 fall categories are shown on Tab. 4.4.

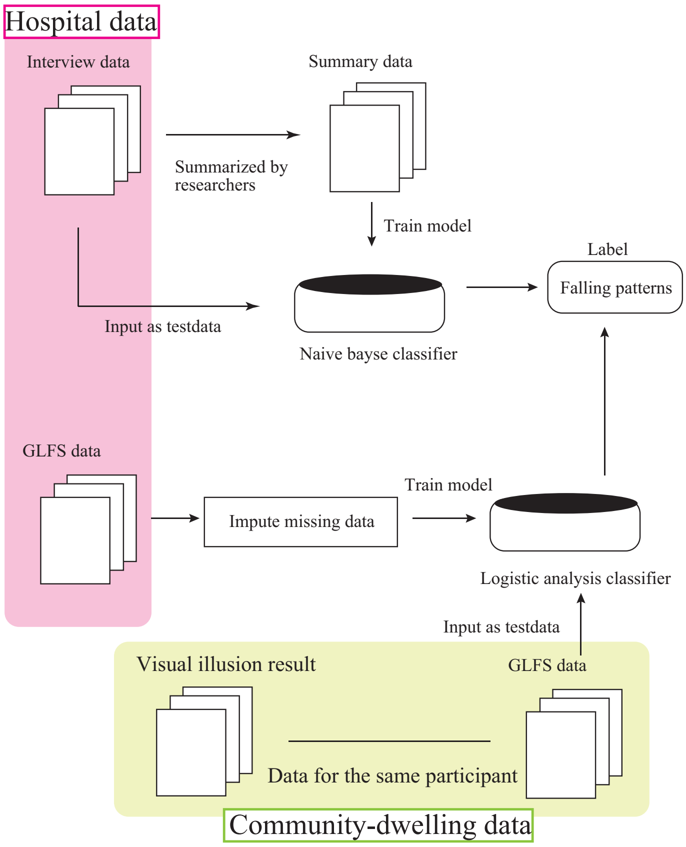



Figure 4.1: The outline of the proposed system. We'd like to construct two types of classifiers. The first one is a text data classifier that is trained by the summary text data by researchers and estimates the falling patterns from interview text data. The other one is a questionnaire classifier that is trained by response patterns of the questionnaire, GLFS-25 and estimates the falling patterns from the response patterns of questionnaires

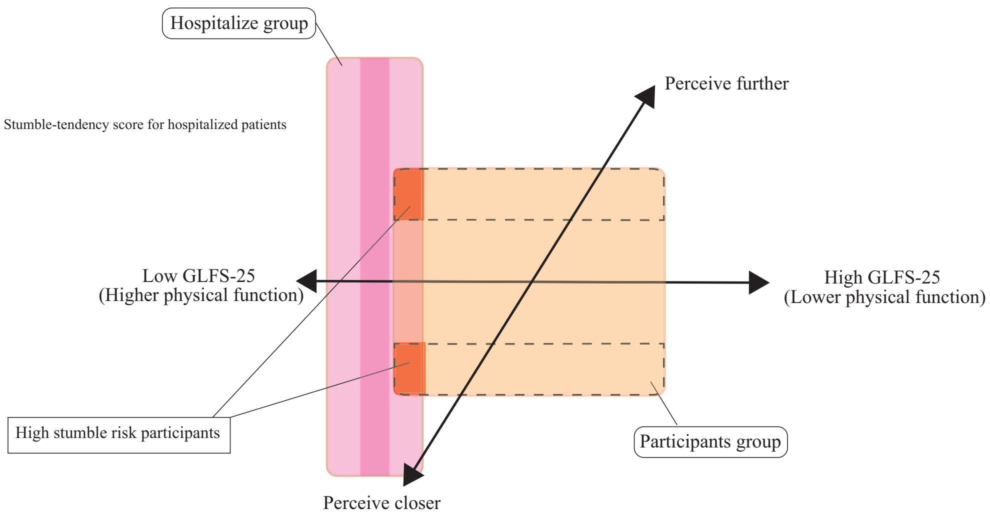



Figure 4.2: The relationship between two groups; The hospitalized patients' group approaching in this chapter and the participants' group in the previous chapters. We will analyze the hospitalized group and estimate a stumble risk of the participants.

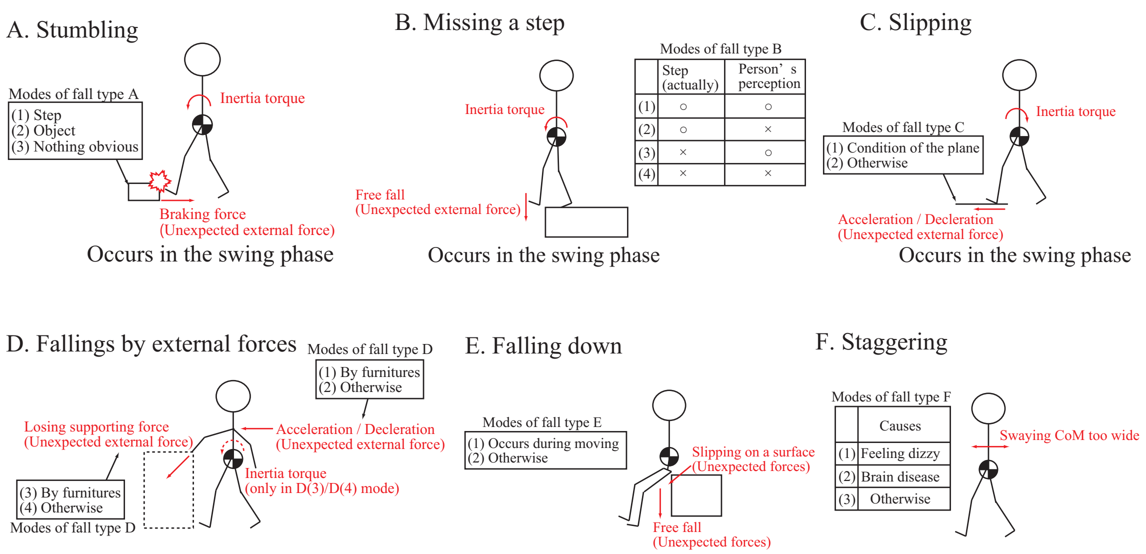



Figure 4.3: Dynamics of each fall type (A: Stumbling, B: Missing a step, C: Slipping, D: Falls by external forces, E: Falling down, and F: Staggering). The external forces, inertia torque, and CoM (center of mass) sway were drawn. The fall modes are defined by the environmental objects that triggers falls (in fall type A-D), the timing falling occurs (in fall type E), and the causes of falls (in fall type F).

Table 4.1: Results of interview research in (1) A ward, Tokyo. We conducted home-visiting interviews with 10 people who had experienced falls and fractures (or their family). This table shows the falling place and the reason for the falls of the 24 participants who had experienced falls and fractures. The first 2 rows are about falling place of causing fractures. The 1st row indicates the category of place (in home / outside of home / facility / pavement), the 2nd row indicates the more concrete information of place. The 3rd-6th column shows the basic information of the participants (ID, age, gender, the part of fracture). The reason of falls were shown on the last column.

| (1) A ward, Tokyo | | | | | |
|---|---|---|---|---|---|
| Place of falls | | Age | Gender | Part of fracture | Reason of falling |
| In home | Dining room | 93 | F | Thigh bone | feeling dizzy, nothing was there.* |
| Outside of home | Rooftop | 78 | F | Pinky | Tripping (wearing sandals)* |
| Facility | Hospital | 90 | F | Thigh bone | Losing her balance when standing to give her seat* |
| | Hospital | 82 | F | Thigh bone | Losing her balance when she was standing up* |
| | Stairs in office bld. | 72 | F | Wrist | Missing her step on the stairs when climbing down |
| Pavement | | 53 | F | Ankle | Twisted ankle* |
| | | 59 | F | Foot | Too tired to care of her spouse's parent and too fast to walk, then twisted her ankle* |
| | | 80 | F | Thigh bone | She had spinal canal stenosis and was feeling numbness on legs. |

Table 4.2: Results of interview research in (2) B city, Yokohama. We conducted home-visiting interviews with 10 people who had experienced falls and fractures (or their family). This table shows the falling place and the reason for the falls of the 24 participants who had experienced falls and fractures. The first 2 rows are about falling place of causing fractures. The 1st row indicates the category of place (in home/outside of home/facility/pavement), the 2nd row indicates the more concrete information of place. The 3rd-6th column shows the basic information of the participants (ID, age, gender, the part of fracture). The reason for the falls was shown in the last column.

| (2) B city, Kanagawa | | | | | |
|---|---|---|---|---|---|
| Place of falls | | Age | Gender | Part of fracture | Reason of falling |
| In home | Stairs | 86 | F | The 5th lumbar vertebrae | Missing the last step when stepping down and bringing a flower pot for watering |
| | Living room | 72 | F | Wrist | Tripping to something (maybe Japanese cushion) when holding her grandchildren in her arms* |
| | Stairs | 68 | M | - | Missing a step when climbing down in hurry with luggage in her both hands* |
| Outside of home | The back door | 98 | F | Thigh bone | Falling on her backside when dragging used papers (they were heavy to carry) |
| | Stairs in front of home | 86 | F | - | Slipping at the last step when climbing up stairs |
| Facility | Stairs in a station | 86 | F | Lower limb | Missing the last step* |
| | Stairs in front of a station | 80 | F | - | She was going down on the slope but the slope is adjacent to the stairs and she entered the stairs area unconsciously, and maybe missed a step.* |
| Pavement | | 74 | F | - | Tripping to a small step. |
| Others (Accident) | Ski resort | 67 | F | - | Skiing and falling. The plane was ice burn. |

Table 4.3: Results of interview research in (3)C city, Chiba. We conducted home-visiting interviews with 10 people who had experienced falls and fractures (or their family). This table shows the falling place and the reason for the falls of the 24 participants who had experienced falls and fractures. The first 2 rows are about falling place of causing fractures. The 1st row indicates the category of place (in home/outside of home/facility/pavement), the 2nd row indicates the more concrete information of place. The 3rd-6th column shows the basic information of the participants (ID, age, gender, the part of fracture). The reason for the falls was shown in the last column.

| C city, Chiba | | | | | |
|---|---|---|---|---|---|
| Place of falls | | Age | Gender | Part of fracture | Reason of falling |
| In home | Bedroom | 75 | F | Heel | Leaning down on heels too much when standing up* |
| | Living room | 85 | F | - | Feeling dizzy and staggering, stumbling to Kotatsu* |
| Outside of home | A step in a garden | 85 | M | Shoulder | Tripping to a step when trying to pick an orange from tree |
| Facility | Judo hall | 76 | F | Foot fingers | Slipping on tatami when dancing |
| | Platform of a station | 77 | F | Wrist | Trying to jumping onto the train and her bag and umbrella were caught by the train door, the train starts leaving and she was dragged* |
| Pavement | | 78 | F | Wrist | She was drunk and walking a bike, the front wheel was stacked at a step between a crosswalk and a sidewalk |
| | | 77 | F | Ankle | Tripping to a step between the boundary of road and sidewalk |

Table 4.4: Correspondence table between each falling type

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Imaeda et al.[4] | A | C | D | | B | E | F | Do not tell |
| | | | (1)(2) | (3)(4) | | | | |
| Robinovitch et al.[34] | Trip/stumble | Slip | Hit/bump | Loss of support with external object | | | Collapse or loss of consciousness | Do not tell |
| Proposed taxonomy | Unexpected external forces | | | Losing balance or supporting forces | Others | | Losing balance or supporting forces | Others(including accidents) |

### 4.2.3 Bedside interview research to elderly people who have experienced hip fractures

The limitation of the preliminary interview research are as followings:

- There were few males
- Participants had ambiguous memory because a long time has passed from their falls
- We cannot tell apart falling and fracture effects from other effects because a long time has passed from their falls
- We cannot know the participants' lifestyle before their falls

So, we planned the bedside interview at the University of Tokyo Hospital. Here is the flow of the research: The participants are the patients who experienced falls, following hip fractures and hospitalized at the University of Tokyo Hospital. After getting the informed consent, within about 1-2 weeks after their surgery we conducted the bedside interview research. We surveyed the basic information (age, gender, medical history, the nursing care level, medication, key person, the presence of the housemate) from the clinical records beforehand. In the semi-structured interview, we ask participants about the falls (date, place, what they did at that time, what they have), the home and living environments (type of their house, the presence of their housemate, the opportunities to go outside), and the physical functions (falling experience, near-miss falling experience, the presence of the feet pain/numbness/sensory information, their visual performance). After that, we ask questions based on the questionnaire

GLFS-25[31]. The GLFS-25 consists of 25 items and it scored from 0 to 4 points for each item (the full score is 100). This questionnaire is used for the criteria of the locomotive syndrome. If participants get 7 points or more, it indicates they are starting declining of their locomotive functions. If participants get 16 points or more, their locomotive functions declined. Note that we asked participants to answer the questionnaire based on their status before they had experienced falls.

## 4.3 Construct the risk estimator

### 4.3.1 Confirmation of the validity of labels based on clustering analysis

We confirmed the validity of the researchers' evaluation of the falling patterns by clustering analysis of text data. The interview text data were tokenized by MeCab[2] and analyzed morphology. A vocabulary list is created from all the interview data and only noun, adjective, adverb, and verb that are shown 5-20 times during one interview data were extracted to create Bag of Words. We analyzed the cluster of the Bag of Words $\mathbf{x}$ for each participant. The clustering method was k-means. We set the initial cluster $c$ of participant $i$'s Bag of Words $\mathbf{x_i}$ as the researcher's label $l$. The researcher's label means the falling patterns that are attached to each participant's text data. We remove the data if the researcher could not attach one label to the interview text data. Though to each falling situation, other researcher labeled falling type[4], the author relabeled along with the proposed 3 falling categories from the

[2]http://taku910.github.io/mecab/

summary data. As a result, each participant has 2 types of labels. If the two labels don't in the relationships of the correspondence shown on Tab. 4.4, we treat the falling case as the 'could not tell' case.

Let the number of participants in cluster $c$ be $N_c$ and the cluster mean $\mu_{\mathbf{c}}$ of Bag of Words be

$$\mu_{\mathbf{c}} = \frac{\sum_{\mathbf{i}}^{\mathbf{N_c}} \mathbf{x_i}}{\mathbf{N_c}} \tag{4.1}$$

Then, we can calculate the Euclidean distance between each cluster mean $\mu_{\mathbf{c}}$ and participant $i$'s Bag of Words $\mathbf{x}_i$, and update the cluster $c(i)$ that participant $i$ belongs. The cluster is updated so that the cluster which has the closest cluster mean is the cluster participant $i$ belongs to. We set the number of the cluster as (1) 3 (the number of the proposed falling groupings) and (2) 6 (the number of falling patterns [4].

### 4.3.2 Validating researchers' evaluation and estimate falling pattern from co-occurrence words

In qualitative research, contents that participants talk to the researcher are evaluated by the researchers subjectively. We propose to set the criteria for validating the participants/researchers subjective in order to analyze the interview research quantitatively. In this research, researchers summarize the outline of participants' falls after the interview. We call it summary data and analyzed together with the interview data. In the proposed method, we compared the most 10 frequent noun and their co-occurrence words in the interview text and the most 10 frequent nouns in the researcher's summary text data. In our hypothesis, the most taken topic is the main theme of the interview and if correctly share the understandings of the main topic (falling situations), the researchers and the participants would share the frequent words or co-occurrence words. Through this analysis, we can acquire the criteria of the common understandings to the topic of the participants and the researchers.

We also did a classification experiment. We re-categorized from [4] falling type to our proposed 3 falling categories, and trained summary data, and construct a naive Bayes model. The interview data were input and test the classification of the falling cases. The naive Bayes model calculates the likelihood $P(w|t)$ that word $w$ in the input document emerges in the $i$-th document $D_{t,i}$ of the topic $t$, and estimates the topic of the input document as the topic that shows the biggest $P(w|t)$. In this research, we set the topic $t$ as the proposed 3 falling categories: (a) Falls by unexpected external forces, (b) falls by losing balance, and (c) Other falls (Free fall, accidents, could not tell).

The naive Bayes model is trained as follows: First, we create the vocabulary list of all the words in the documents in all the topic. Second, the emergence frequency of the words in the list for each topic is calculated, and the probability $P(w,t)$ that the word $w$ emerges from the documents in the topic $t$. Also, $P(t)$ that the topic $t$ emerges is also calculated from the ratio of the documents allocated to each topic. From that, if a word is listed on the vocabulary list, log-likelihood can be calculated as

$$\log p(w|t) = \log \frac{p(w,t)}{p(t)}. \tag{4.2}$$

Under the assumption that each word emerges independently, we can calculate the log-likelihood that input data emerges from the topic $t$. If a word in the input data is not listed, we hypothesized $p(w_i|t) = 0.00001$ for calculating the log-likelihood. In the classification experiment, we used the most 10 frequent noun and their 11 most co-occurrence words. If there are no duplications, total input data for one participant is to be 120. We classified the input data as following 3 falling cases; (a) Falls by unexpected external forces, (b) falls by losing balance, and (c) other cases of falls. The classification rate was calculated. In the training phase and classification phase, we excluded cases that are labeled as 'could not tell' in (c) other cases of falls.

### 4.3.3 Converting the categorical variables to the probabilistic-based variables

Only the total score of the answers to a questionnaire is often used in the analysis of the questionnaires. However, the questionnaire response pattern itself has rich information and the total score are the results from the reducing of the dimensions of the patterns from the number of the questionnaire response patterns to 1. In this research, we'd like to utilize the whole response patterns to estimate the frailty level. The problem is that each response of the questionnaire is the categorical variable, so we cannot directly compare with the consecutive variables as it is. Thus we propose the method to convert the categorical variables to the consecutive ones.

In this research, we focus on the specificity of the questionnaires that are developed epidemiologically. Commonly, this kind of questionnaires are developed based on the statistical analysis that collects response patterns from a large amount of population group, and the response patterns or some kind of probabilistic distributions are usually open for public. We utilize these distributions to convert the categorical variables to the consecutive ones, then we can compare how our participants far out of the distribution (i.e., where the participants placed) in the observation group in the previous research.

We confirmed the tendency of the data distributions of the GLFS-25 response patterns in our research by principal component analysis (PCA). Fig. 4.4 shows the results of the 1st to the 3rd components of the PCA. Seeing the response patterns (data not shown) and Fig. 4.4, we concluded that the 1st component indicates the total scores of the GLFS-25, the 2nd component indicates the number of items whose score was not zero, and the 3rd component indicates how far the not zero response pattern from the original distribution in the previous research. Also, we calculated the accumulated contribution ratio and 73.5 % of the information were explained by the 1st - the 3rd components of PCA.

From above, for GLFS-25, we design the feature vectors as to contain the information of the total score, the response to each item, and the rarity of the emergence from distributions under the same total score. The dimension of the feature vector is 27. The first dimension is the total score. The second dimension is the log-likelihood for the response pattern $\mathbf{x}$ that emerges when the total score is $n$;

$$C^i = \log(P(\mathbf{x}|n)) = \log P(\mathbf{x}) - \log P(n), \tag{4.3}$$

and the 25 left dimensions are calculated as followings:

From the distributions in [62], we can access the distributions that show which item tend to be responded as non-zero values under the score ranges $D_n$. Using these distributions, we can calculated both $P(x_i \in D_n = 0|x_i = 0)$ and $P(\mathbf{x_i} \in \mathbf{D_n} \neq \mathbf{0}|\mathbf{x_i} \neq \mathbf{0})$, where $P(x_i \in D_n = 0|x_i = 0)$ indicates the log-likelihood of emergence the response pattern $x_i$ (response to the item $i$) $= 0$ and score $n$ is in the score range $D_n$

under the $x_i = 0$ is given, and $P(x_i \in D_n \neq 0 | x_i \neq 0)$ indicates the log-likelihood of emergence the response pattern $x_i$ (response to the item $i$) $\neq 0$ and score $n$ is in the score range $D_n$ under the $x_i \neq 0$ is given. There are 7 types of $D_n$: (1) The score ranged from 0 to 6, (2) the score ranged from 7 to 15, (3) the score ranged from 16 to 23, (4) the score ranged from 24 to 32, (5) the score ranged from 33 to 40, (6) the score ranged from 41 to 49, and (7) the score is over 50. Then, we can calculate

$$\begin{cases} \frac{P(x_i=0,\mathbf{x}\in D_j)}{P(x_i=0)} (x_i = 0) \\ \\ \frac{P(x_i\neq 0,\mathbf{x}\in D_j)}{P(x_i\neq 0)} (x_i \neq 0), \end{cases} \tag{4.4}$$

for each response pattern $x_i$ to item $i$ using the distributions under a score range $D_n$ for the total score $n$. Since GLFS-25 consists of 25 questions, we can acquire 25 log-likelihoods, and it will be the 3rd to the 27th dimension of the feature vectors. Thus, from the total score and Eq. (5.22) and Eq. (4.4), we can extract 27-dim feature vector. The visualized extracted feature vector in 3-dim is shown in Fig. 4.5.

GLFS-25's full score is 100. The smaller score means the better locomotive function they have. If the score $\geq$ 7, the participant starts declining of their locomotive function and if the score $\geq$ 16, the participant's locomotive function declined. The response ratio to each item and the zero-scored response ratio of each item in some score groups (0-6 points, 7-15 points, 16-23 points, 24-32 points, 33-40 points, 41-49 points, 50- points) are available for GLFS-25. Using these distributions, we can reflect kinds of information such as which function is more damaged and convert to the consecutive variables.

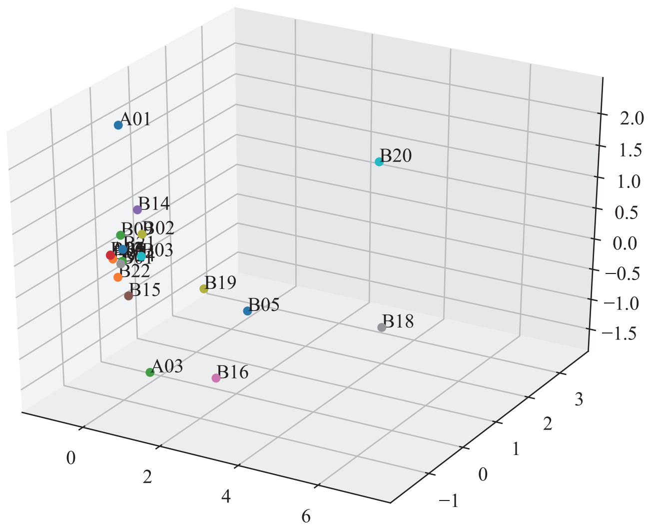



Figure 4.4: The 1st, the 2nd, and the 3rd principle component of the GLFS-25 response patterns.

### 4.3.4 The log-likelifood maximization method for imputation of missing GLFS-25 response items

Some participants showed a declining of their physical/cognitive abilities, and there were some cases that participants could not answer all the items of the GLFS-25. There were 7 cases (out of 39 cases) that showed at least 1 missing item. Excluding the 2 cases in which all the responses to the item are missing, we try to impute the missing items. There are two types of conventional imputation method. One is using the statistic model (the most frequent value, the average value, the log-likelihood, and the regression coefficients etc.) and calculating from these values. The other one is using the value in other data under some hypotheses. For example, in the hot deck method, we use the value of a person who has the close attribution to the person who has missing data. Another example is the cold deck method. In this method, we use a value outside of the measured data. The participants' age was

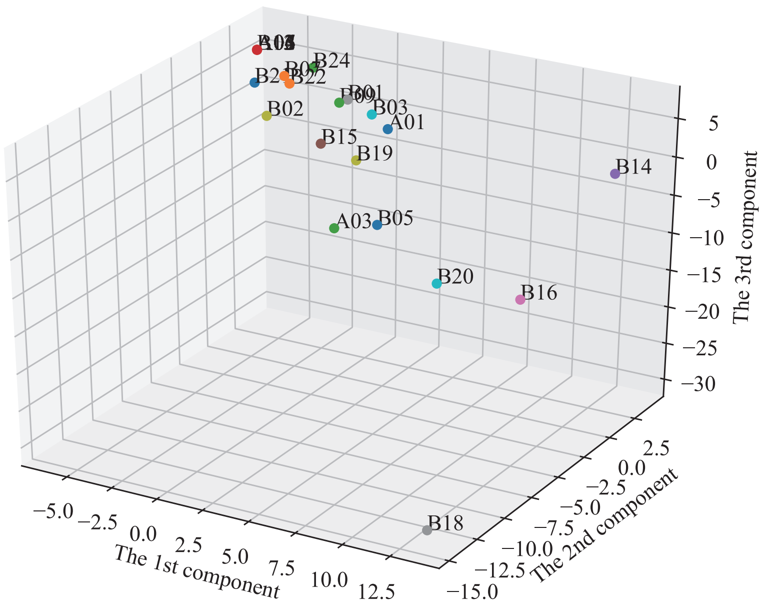



Figure 4.5: The 1st, the 2nd, and the 3rd components of the features visualized by multi dimension scaling.

varied widely, so imputation with the most frequent value is not appropriate. GLFS-25 items are categorical variance, so the average of values doesn't have meanings, too. Our approach is the mixture of the hot deck method and using the log-likelihood maximization model. Since GLFS-25 is an assessment tool, the validity of the tool has been tested epidemiologically. That means there is a large population group who takes the same test, and the response rate to each item is usually open for public in the development process. So, we use these probabilistic distributions to calculate the log-likelihood and use it for missing data imputations. Since this method uses the data of the population group in the previous epidemiological research that is larger than our own research participants' group, we would achieve the better precision of estimating missing data.

Let the response to all the items be $\mathbf{X} = \{x_1, x_2, \cdots, x_{25}\}$. If a participant missed a response to $i$, then let that response to the items be $\hat{\mathbf{X}}_{(i)} = \{x_1, x_2, \cdots, x_{i-1}, x_{i+1}, \cdots, x_{25}\}$.

In this case, the imputation candidate $y_{(i,j)}$ for the response pattern $x_i$ means that response $j$ to the item $i$. Since GLFS-25 scores from 0 points to 4 points in integer for each item, $j$ is to be $1 \leq j \leq 5$. The imputed response pattern $\tilde{\mathbf{X}}_{(\mathbf{i},\mathbf{j})}$ that has imputed by $y_{(i,j)}$ is expressed as

$$\tilde{\mathbf{X}}_{(i,j)} = \hat{\mathbf{X}}_{(i)} \oplus y_{(i,j)}. \tag{4.5}$$

We set the most optimized imputation candidate set as $Y$, and set the missing item $i$ set as $S$, then the evaluation function of log-likelihood $J(Y)$ be

$$J(Y) = \underset{y_{j(i)}}{\arg\max} \sum_{i \in S} \log P(y_{j(i)}), \tag{4.6}$$

under hypothesis that the response to all the items are independent, where $P(x)$ is the likelihood for response pattern $x$, $y_{j(i)}$ is the response $j$ to the item $i$ in the missing item set $S$. $Y$ is to be the $y_{j(i)}$ such that maximize the log-likelihood in Eq. (4.6) . For example, if $S = 2, 3, 4$ and Eq. (4.6) is maximized when $y_{j(2)} = 1, y_{j(3)} = 0, y_{j(4)} = 2$ are imputed, then $Y = \{1, 0, 2\}$. We impute each missing data by $Y$.

GLFS-25 response distributions is the left-skewed distribution(Mean: 22, Median: 19.5, Most frequently score: 12, Standard Deviation: 15.76, Maximum score: 73)[62]. If we apply Eq. (4.6) directly, almost all missing items would be imputed as 0. [62] reports there is a tendency that the items in GLFS-25 become non-zero in a certain rule. So, first of all, we calculate Eq. (4.4), and if $P(x \neq 0)$ is bigger than $P(x = 0)$ then we didn't consider the case of $y_{(i,j)} = 0$ in calculating Eq. (4.6).

### 4.3.5 Constructing falling pattern prediction system from GLFS-25

We also analyzed GLFS-25 response patterns. If there are missing data and if we can impute them, we used the imputed response patterns. The GLFS-25 response patterns (25dim) are converted to the feature vector (27dim) using a method proposed in the next chapter. The 1st dimension was the total score, the 2nd dimension was the log-likelihood $P(x|n)$. The 3rd to the 27th dimensions were the log-likelihood of $P(x)$ is calculated as following:

$$\begin{cases} \frac{P(x_i=0,\mathbf{x}\in\mathbf{T_n})}{P(x_i=0)}(x_i = 0) \\ \frac{P(x_i\neq0,\mathbf{x}\in\mathbf{T_n})}{P(x_i\neq0)}(x_i \neq 0) \end{cases} \tag{4.7}$$

We did a classification experiment using the logistic regression analysis. The logistic regression analysis is a analysis method for the binary outputs using sigmoid function. The output $y_n$ of the input data $\mathbf{x_n}$ is calculated as

$$y_n = \frac{1}{1+\exp\{-(\mathbf{w}^T\mathbf{x_n})\}}, \tag{4.8}$$

where $\mathbf{w}$ is a weight coefficient vector. If $\mathbf{w}^T\mathbf{x} > 0$, $y_n = 1$ and if $\mathbf{w}^T\mathbf{x} < 0$, $y_n = 0$. The objective function for training $\mathbf{w}$ is

$$\arg\min_{\mathbf{w}} - \sum_{(\mathbf{x}_n, t_n \in X)} t_n \log y_n + (1-t_n)\log(1-y_n). \tag{4.9}$$

$\mathbf{w}$ is updated by

$$\mathbf{w}^{(i+1)} = \mathbf{w}^{(i)} - \eta(y_n - t_n)\phi(\mathbf{x}_n), \tag{4.10}$$

where $t_n$ is a label of the training data $x_n$, $X$ is the set of the training data set $(\mathbf{x}_n, t_n)$, $\phi(\mathbf{x}_n)$ is a operation that add component 1 to the vector $\mathbf{x}_n$ and set the dimension of

$\mathbf{x}_n$ from $dim(\mathbf{x}_n)$ to $dim(\mathbf{x}_n) + 1$. In this research, we set the learning coefficient $\eta$ as 0.0001. In the training phase and classification phase, we excluded cases that are labeled as 'could not tell' in (c) other cases of falls.

### 4.3.6 Calculate the fall and stumble risk

For the fall risk $r_{fall}$, we calculate the risk using Eq. (4.8), where $w$ is the trained weight vector and $r_{fall} = 100y_n$ is the estimated fall risk. The fall risk has trained to output 0 if the input data is close to the young participants and output 1 if the input data is close to the participants who had experienced falls and hip fractures due to stumbles. For the fall type tendency, we used the trained logistic analysis estimator of which boundary line is depicted in Fig. 4.8. In this estimator, using Eq. (4.8), the estimator outputs 0 if the input data is close to the participants who had experienced falls and hip fractures due to unexpected falls (category (a)), and the estimator outputs 1 if the input data is close to the participants who had experienced falls and hip fractures due to losing balance (category (b)). So we defined following equation to calculate the tendency $r_{tendency}$ [%]:

$$r_{tendency} = (0.5 - y_n)/0.5 \times 100. \tag{4.11}$$

So, if the participant's input data is close to the data of participants who had experienced falls and hip fractures due to unexpected forces, $r_{tendency}$ would be the negative value between 0 and 100, and if the participant's input data is close to the data of participants who had experienced falls and hip fractures due to losing balance, $r_{tendency}$ would be the positive value between 0 and -100. Then, stumble risk $r_{stumble}$ is calculated as the product of the $r_{fall}$ and $r_{tendency}$ ($r_{stumble} = r_{fall} r_{tendency}$).

## 4.4 Results

### 4.4.1 Bedside interview research

The number of the participants were 36 (9 males and 27 females, $82.1 \pm 8.13$ years old). The falling situation of each participant are shown on Tab. 4.6-4.14. Tab. 4.6 - Tab. 4.9 show the cases of participants who had experienced fall and fracture at homes (or inpatient ward of hospitals). Tab. 4.10 and Tab. 4.11 show the cases of participants who had experienced fall and fracture at hospitals or other public facilities (ex. commercial facilities). Tab. 4.12 - Tab. 4.14 show the cases of participants who had experienced fall and fracture on pavements. Seventeen out of 36 cases occurred at homes or inpatient ward of hospitals. Eight including 1 in hospital public space cases were falls at facilities, and 11 cases occurred on pavements. Inside home or facilities, falls related with toilet showed the most number of falls (12 cases; Ten were at homes and 1 was at a facility). There is a possibility that changing blood pressure or turning actions inside or moving from/to a toilet caused dizzy. It is also found that over half of the falls (7 cases) in home occurred from midnight to the early morning.

Along the proposed 3 falling cases, 11 cases were categorized as category (a) (falls by unexpected forces), 13 cases were categorized as category (b) (falls by losing balance), and 12 cases were categorized as category (c) (other falling cases). Category (c) includes 7 cases with 'could not tell' labels. The most number of falls were caused by losing balance.

Table 4.5: The relationships between the GLFS score, log likelihood, and the response patterns. The 1st, 2nd, 3rd columns show the ID, Age, log likelihood of the participants. The 4th column indicates the total scores and the 5th-8th columns show the number of items that participants ' response scored 1, 2, 3, and 4 for each. The 9th column indicates that the number of items that participants response scored non-zero value though responses usually become getting score non-zero in 2 or higher level than the participant is allocated of the score group.

| ID | Age | The 2nd dim of the feature | The 1st dim of the feature (Total score of GLFS) | # of items scored 1 | # of items scored 2 | # of items scored 3 | # of items scored 4 | # of repsonse that is far from their score level |
|---|---|---|---|---|---|---|---|---|
| B18 | 99 | -30.5 | 32 | 9 | 4 | 5 | 0 | 0 |
| B16 | 75 | -21.7 | 13 | 9 | 2 | 0 | 0 | 4 |
| B20 | 79 | -18.5 | 14 | 6 | 1 | 2 | 0 | 1 |
| B14 | 78 | -15.7 | 6 | 6 | 0 | 0 | 0 | 3 |
| B19 | 80 | -9.35 | 6 | 6 | 0 | 0 | 0 | 0 |
| B15 | 75 | -8.35 | 3 | 3 | 0 | 0 | 0 | 1 |
| B03 | 81 | -7.28 | 3 | 3 | 0 | 0 | 0 | 1 |
| B01 | 72 | -6.01 | 2 | 2 | 0 | 0 | 0 | 1 |
| B09 | 84 | -5.81 | 2 | 2 | 0 | 0 | 0 | 0 |
| B02 | 77 | -5.35 | 2 | 2 | 0 | 0 | 0 | 0 |
| B22 | 80 | -3.42 | 1 | 1 | 0 | 0 | 0 | 0 |
| B07 | 77 | -2.70 | 1 | 1 | 0 | 0 | 0 | 0 |
| B24 | 69 | -2.63 | 1 | 1 | 0 | 0 | 0 | 0 |
| B21 | 71 | -2.57 | 1 | 1 | 0 | 0 | 0 | 0 |
| B05 | 78 | -1.30 | 11 | 11 | 0 | 0 | 0 | 0 |
| B13 | 74 | 0.00 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 4.6: Results of the bedside interview (1)-1: Participants information and how they fall in a case of falling down in their home. The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate that the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Living room | Living room | Toilet | 1 | 69 | F | 23:30 | She got tangled up when started moving and about to wear slippers | F(3) | 'could not tell' |
| | - | - | 30 | 87 | M | 8:15 | When he was about to change his trousers he lost his balance | F(3) | (b)Balance |
| | Toilet | Living room | 35 | 69 | F | 12:30 | Stumbled to a heavy toy placed by her grandchildren while going back from the toilet. | A(2) | (a)Unexpected force |
| Corridoor in front of a toilet | Toilet | Living room | 9 | 76 | F | 17:00 | The toilet door is opened too wide and she staggered | D(4) | (b)Balance |

Table 4.7: Results of the bedside interview (1)-2: Participants information and how they fall in a case of falling down in their home. The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate that the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Corridor | Toilet | Living room? | 11 (same person with 8) | 92 | F | AM | She fell down during the way from a toilet (Since her cognitive ability was decreased the cause is estimated by an interviewer) | F(3) | 'could not tell' |
| | Toilet | Living room | 14 | 93 | M | 23:30 | He staggered after going to a toilet. He experienced falls several times at the same place of the corridor and he felt staggering when he stands up after going to a toilet (He also had hydrocephalus) | F(3) | (b)Balance |
| | Washroom | Living room? | 21 | 90 | F | around 17:00 | Se was heading to the living room from the washroom by putting her hand along the wall, she stumbled to a bag of rice made by paper (Soon after falling she told staff that she slept on her clothes) | A(2)/C(2) | (a)Unexpected force |

Table 4.8: Results of the bedside interview (1)-3: Participants information and how they fall in a case of falling down in their home. The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate that the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Bedroom | Bedroom | Toilet | 6 | 83 | F | 9:00 | Since she had incontinence during sleep, woke up to go to toilet and stride over futon, then stumbled to it | A(2) | (a)Unexpected force |
| | Bedroom | Toilet | 25 | 82 | M | 5:00 | He woke up to go to toilet, started walking then fell down (Maybe stumbled to futon or missing a step between the bedroom and the living room) | A(2)/B(4) | 'could not tell' |
| | Toilet | Bedroom | 2 | 86 | F | 6:00 | When she realized, she had fell down. It was happened during going back from the toilet to the bedroom in the morning (maybe it was due to staggering or she wore slippers and stumbled to something) | F(3)/A(3) | 'could not tell' |
| | Toilet | Bedroom | 28 | 86 | F | 6:00-6:30 | She got tangled up with her feet during going back from a toilet. She tried to support her body by chest of drawers but failed and fell on her backside | D(4) | (b)Balance |
| | Toilet | Bedroom | 5 | 92 | F | 5:30 | She fell down in front of the bed, going back from the toilet (maybe slept on tatami or newspaper on a floor. Her sense of sole of left foot is not so sensitive) | C(1) | (a)Unexpected force |

Table 4.9: Results of the bedside interview (1)-4: Participants information and how they fall in a case of falling down in their home. The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate that the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Kitchen | - | - | 29 | 83 | F | AM | Fell on her backside at the kitchen (Though she doesn't think it as falling, maybe it was staggering) | F(3) | (b)Balance |
| | Living room | Kitchen | 15 | 86 | F | 11:00 | During going to pick up food in a microwave (maybe her sox was slept on a floor or a carpet was moved) | C(1) | (a)Unexpected force |
| Toilet | - | - | 33 | 86 | F | 2:00 | When she realized, she had fallen down at the door (Maybe due to staggering by decreasing by the blood pressure) | F(3) | (b)Balance |
| Hospital room | - | - | 16 | 86 | F | around 14:00 | She practiced rehabilitation of walking with walker alone in the hospital room. She wore new shoes and the sole of the shoes was thick and made by rubber | F(3) | 'could not tell' |
| Hospital corridor | Room? | Toilet | 3 | 94 | F | AM | She was walking with a cane to go to the toilet along with a wall (Maybe it was happened due to slipping a cane or slippers, or staggering?) | C(2)/F(3) | 'could not tell' |

Table 4.10: Results of the bedside interview (2)-1: Participants information and how they fall in a case of falling down in inside of the facilities (hospital, commercial facilities, public space, etc.). The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Hospital corridoor | Entrance | Reception | 13 | 86 | F | 9:30 | She fell down while going to the outpatient reception. It was rain on that day, she wore shoes that she does not be used to it, she felt that her shoe was caught on the floor | A(3) | (a)Unexpected force |
| The entrance of a hotel | - | - | 31 | 77 | F | 16:30 | She was about to take a photo with her husband, missed a step and fell down backward (Maybe missed a step but possibly she stumbled and there were no steps) | B(2)/A(1) | (c)Others (free fall) |
| Bank | Entrance | Reception? | 12 | 79 | F | AM | When she put her walker and started walking, the bank staff stopped her for taking a numbered ticket and she looked back or stepped backwards | A(3)/F(3) | 'could not tell' |

Table 4.11: Results of the bedside interview (2)-2: Participants information and how they fall in a case of falling down in inside of the facilities (hospital, commercial facilities, public space, etc.). The 1st column indicates where they had experienced falls, the 2nd and 3rd column indicate the origin and terminate place of the motion, the 4th-6th column is the basic information of participants, the 7th column indicates when they fall, the 8th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | From | To | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|---|---|
| Civic center | Room | The toilet | 18 | 81 | F | 20:10 | She was heading to toilet, walking sidle along between desks and chairs, and stumbled to a desk leg or chair leg | A(2) | (a)Unexpected force |
| Restaurant | Toilet | Room | 4 | 85 | F | 18:00 | When she was back from the toilet, she did not noticed and missed a step | B(2) | (c)Others (free fall) |
| Washing place at the public bath | Bathtub | washing place | 10 | 85 | F | 16:00 | When she was about to sit on a chair in a washing place after taking a bath for about 3 min, she tried to support her body by both hands on a mirror table but failed (She has experienced her arm fracture and she does not recover enough from that) | D(4) | (b)Balance |

Table 4.12: Results of the bedside interview (3)-1: Participants information and how they fall in a case of falling down outside of the facilities (hospital, commercial facilities, public space, etc.) or on pavements. The 1st column indicates where they had experienced falls, the 2nd-4th column is the basic information of participants, the 5th column indicates when they fall, the 6th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|
| Concourse of a station | 34 | 61 | M | around noon | A big carry bag was hit on him | D(2) | (c)Others (accident) |
| The platform of a station | 19 | 92 | M | 15:00 | He was waiting for a train for a while and was about to get into the train, he lost his balance (He feels his right leg had weaker supporting force) | F(3) | (b)Balance |

Table 4.13: Results of the bedside interview (3)-2: Participants information and how they fall in a case of falling down outside of the facilities (hospital, commercial facilities, public space, etc.) or on pavements. The 1st column indicates where they had experienced falls, the 2nd-4th column is the basic information of participants, the 5th column indicates when they fall, the 6th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|
| Roadway | 23 | 65 | F | 10:05 | It was a rainy day and she did not notice that the bicycle was coming from right side until just before approaching her at an intersection with poor visibility, she turned the steering wheel and hit the brakes immediately then lost her balance | F(3) | (c)Others (accident) |
| | 36 | 73 | F | 16:30 | When she was getting off from a car her feet were tangled up and fell down (The height of the car was so high. She said her feet were tangled up but her left knee and ankle are artificial joints so interviewer estimated that having artificial joints affect to her balancing ability in some points) | F(3) | (b)Balance |
| | 7 | 76 | F | around noon | After visiting her relatives, she climbed down stairs in front of an entrance with her son. While his son was going to pick up his car she was waiting at an entrance and falling (staggering or slipping cane) | F(3) | (b)Balance |
| | 8 (same person as 11) | 92 | F | 10:00 | When she was taking a dog for a walk, the lead of the dog was connected a walker and the dog pulled it | D(4) | (b)Balance |
| | 17 | 84 | M | 18:00 | He stumbled to a speed bump on a road | A(2) | (a)Unexpected force |
| | 24 | 89 | M | 9:10 | He was going to a hospital and soon after leaving his home, he looked to a neighborhood and greeting each other, turned right, and then he fell down | F(3) | (b)Balance |

Table 4.14: Results of the bedside interview (3)-3: Participants information and how they fall in a case of falling down outside of the facilities (hospital, commercial facilities, public space, etc.) or on pavements. The 1st column indicates where they had experienced falls, the 2nd-4th column is the basic information of participants, the 5th column indicates when they fall, the 6th column shows how they fall precisely, the 9th column indicates fall mode labeled by the same 1 interviewer, and the 10th column indicates fall category labeled by the same 1 interviewer different with the researcher who labeled the fall mode label.

| Place | ID | Age | Gender | Time | How they fall | Fall mode | Fall category |
|---|---|---|---|---|---|---|---|
| | 20 | 80 | F | around noon | Soon after getting off from a bus then her body was tilted then fell on her backside | F(3) | (b)Balance |
| | 22 | 80 | F | 15:00 | On the way to going shopping, when she crossed a road a bicycle was coming from the left side and it crashed to her | D(2) | (c)Others (accident) |
| Sidewalk | 26 | 74 | M | 15:00 | He toward from roadway to a sidewalk, and tried to stride over chains of which the height was about 30 cm, then fell down | A(2) | (a)Unexpected force |
| | 27 | 74 | F | 18:30 | Soon after crossing road, her carry bag was stumbled to a step between roadway and sidewalk | D(2) | (a)Unexpected force |
| | 32 | 83 | F | 11:00 | When she was getting off from a bus she slept on fallen leaves | C(1) | (a)Unexpected force |

### 4.4.2 The validity of the researchers' evaluation

#### Cluster analysis

We analyzed 34 out of 36 cases of which the text data could be acquired. The clustering analysis was done for (1) 3 falling categories and (2) 6 falling types and checked whether any changings occurred. For the analysis, we exclude the 11 'could not data' in falling categories condition and 6 cases that more than 2 labels were attached in falling types condition. For (1) condition, a cluster for 1 file (ID 36, category (b)) updated to the cluster for category (c), but after that, any other changes didn't occur. For (2) condition, no changes occurred. From these results, our categorization for both 3 falling categories and 6 falling types were valid to some extent.

#### Co-occurrence words analysis

In the most 10 frequent emergence noun in the summary data by researchers, 27 out of 34 cases include the most 10 frequent emergence noun in the interview data. Fig. 4.6, Fig. 4.7 shows examples of the most 10 frequent words in the interview data (left) and the summary data (right). Fig. 4.6 is a case that the participant's walker is pulled by a dog (ID8). Fig. 4.7 is a case that the participant failed to put his hand when he sits down on a chair at the washing place in a public bath. In Fig. 4.6, we can see "犬 (dog)", "歩行 (walking)", "器 (item)". Maybe since the word "歩行器 (walker)" was not included in the dictionary of MeCab, the word "歩行器 (walker)" was tokenized into 2 words, "歩行 (walking)" and "器 (item)". On the contrary, in Fig. 4.7, only "風呂 (bath)" and "銭湯 (public bath)" are counted as the most 10 frequent words, whereas "椅子 (chair)" and "洗い場 (washing place)" emerged in the summary data and regarded as related words to the falling. Perhaps these words are co-occurred with some of the most 10 frequent words in the sentence, so we decided to analyze the co-occurrence words.

For each of the 10 most frequent noun, we picked up the 11 most co-occurrence words. In total, 10 nouns $+11\times 10$ co-occurrence words $= 120$ (including duplications) words were selected from the interview data and compared with the 10 most frequent emergence nouns whether it contains at least one of the 110 co-occurrence words or the 10 most frequent words. It is confirmed that 31 out of 34 cases there is at least one accorded word. The results are shown on Tab. 4.15 and Tab. 4.18. 24 out of 31 cases include either the falling place or the objects related to the falls. Thus, checking the frequent words and their co-occurrence words can be used as the indices of the objectiveness of the estimated falling causes. Other 3 cases were followings: One participant is mentioned about declining of cognitive abilities in the clinical record. Another one participant has been pointed out the increasing of forgetfulness in his clinical records. Also, the falling situation is very complex. Few days before he experiences fall and fractures, he also experiences falling and the 2nd fall had happened when he went to a hospital for his injury of the 1st falling. Though there are no comments on his cognitive abilities in the clinical records for the last participant, during interview research, researchers had questioned of his cognitive ability from his response (for example he said the floor plan of his house as "15LDK"). From these facts, co-occurrence word analysis would be able to use as an estimation of the level of the cognitive ability of participants, too.

Table 4.15: The 10 most frequent words and their co-occurrence words in the text data, and the words coincident with either the 10 most frequent words in the summary data (1).

| ID | Fall mode | Place | Objects | The most 10 frequency word | Co-occurrence word shown on the summary |
|---|---|---|---|---|---|
| 1 | F(3) | Living room (to toilet) | Slippers | 'スリッパ', 'カーペット', '感じ', '主人', 'ほう', 'よう', '後ろ', 'ベランダ', '何', 'もの' | 'カーペット', '転倒', 'スリッパ', 'リビング', '時', '手' |
| 2 | F(3)/A(3) | Bedroom (from toilet) | Slippers? | 'トイレ', 'ベッド', '何', '普段', 'スリッパ', '私', '感じ', '部屋', '今', '普通' | '寝室', '転倒', 'トイレ', 'フローリング' |
| 3 | C(2)/F(3) | Hospital corridor (to toilet) | Slippers/Cane | '何', '普段', '前', 'トイレ', '廊下', 'みたい', '回', '入院', '1', 'スリッパ' | 'トイレ', '午前', '廊下', '転倒', '中', '壁' |
| 4 | B(2) | Restaurant (from toilet) | Step | '前', '1', '年', '何', '段', '段差', '感じ', '3', '2', '自信' | '段差' |
| 5 | C(1) | Bedroom (from toilet) | Bed/Tatami/Newspaper/Floor | '何', '所', 'ベッド', '自分', '車', '畳', 'トイレ', 'よう', '感じ', '大丈夫' | 'ベッド', '畳' |
| 6 | A(2) | Bedroom (to toilet) | Futon | 'お父さん', '布団', '何', '所', 'テレビ', 'こっち', '階', '普段', 'トイレ', '2' | '布団', '時', 'テレビ', '台', '畳' |
| 7 | F(3) | Roadway | Cane? | '息子', '1', '何', '車', '前', '普段', 'うち', 'さん', '階段', '工場' | '玄関', '転倒' |
| 8 | D(4) | Roadway | Dog/Walker | '器', '歩行', '私', '犬', '道', '前', 'うち', '1', '自転車', '感じ' | '犬', '歩行', '器', '道' |
| 9 | D(4) | Corridor (from toilet) | Door | '何', '全部', '月', '2', '階', '10', '今', 'がん', 'うち', '1' | '転倒', '星', '手すり' |

Table 4.16: The 10 most frequent words and their co-occurrence words in the text data, and the words coincident with either the 10 most frequent words in the summary data (2).

| ID | Fall mode | Place | Objects | The most 10 frequency word | Co-occurrence word shown on the summary |
|---|---|---|---|---|---|
| 10 | D(4) | Washing place at the public bath | Chair/Mirror table | '何', '風呂', '銭湯', 'こっち', 'そこ', '分', '手', '3', '普通', '足' | '銭湯', '3', '分', '台', '両手' |
| 11 | F(3) | Corridor (from toilet) | - | '階段', '何', '月', '下', '足', '感じ', '3', '前回', 'うち', 'よう' | '転倒' |
| 12 | A(3)/F(3) | Bank | Walker | '何', '主人', '器', '歩行', '膝', '所', 'さん', '手術', 'そこ', '普段' | '銀行', '札', '番号' |
| 13 | A(3) | Hospital corridor (to toilet) | Wall/Cane/Slippers? | '前', '1', '何', '日', '感じ', 'こっち', '靴', '2', '右', '左' | '受付', '前', '雨' |
| 14 | F(3) | Corridor (from toilet) | - | '時', '何', '感じ', '所', '廊下', '普段', 'さん', 'トイレ', '娘', '部屋' | 'トイレ', '廊下', '娘', '時', '所' |
| 15 | C(1) | Kitchen | Sox/Floor/Carpet | '階', 'さん', '2', '1', '何', '自分', '車', '台所', '日', '娘' | '階', '3' |
| 16 | F(3) | Hospital room | Walker/Shoes | '私', '前', '感じ', '何', 'リハビリ', '息子', 'さん', '今', '人', 'ほう' | 'リハビリ', '靴', '歩行', '器' |
| 17 | A(2) | Roadway | Speed bump | '前', '所', '2', '時', 'うち', 'よう', 'ダンス', '人', '階', '生活' | '道', '車' |
| 18 | A(2) | Civic center (to toilet) | Desk/Chair | '感じ', '椅子', '人', 'よう', '前', '年', '1', '手', '方', '足' | '左', '椅子', '移動' |

Table 4.17: The 10 most frequent words and their co-occurrence words in the text data, and the words coincident with either the 10 most frequent words in the summary data (3).

| ID | Fall mode | Place | Objects | The most 10 frequency word | Co-occurrence word shown on the summary |
|---|---|---|---|---|---|
| 19 | F(3) | Platform of a station | - | '感じ', '前', '1', '電車', '人', '年', '普段', '新宿', '何', 'わけ' | 'ホーム', '上', '駅', '年', '電車', '前' |
| 20 | F(3) | Sidewalk (from bus) | - | '前', '1', 'バス', '時', '何', '日', '私', '6', '普通', '年' | 'バス' |
| 21 | A(2)/C(2) | Living room | Bag of rice/Clothes | '何', '米', '袋', '部屋', 'わけ', 'トイレ', '廊下', 'こっち', 'ベッド', '自分' | × |
| 22 | D(2) | Sidewalk | Bicycle | '私', 'こっち', '自転車', '所', 'ほう', '眼鏡', 'あれ', '人', '歩道', '感じ' | '自転車' |
| 23 | F(3) | Roadway | Bicycle | '時', '自転車', '車', '仕事', '感じ', '私', '前', '何', '自分', 'そこ' | '自転車', '仕事' |
| 24 | F(3) | Roadway | - | '日', '前', 'ほう', '何', '道', '感じ', '9', '1', '歩', '所' | × |
| 25 | A(2)/B(4) | Bedroom (to toilet) | Futon?Step? | 'ほう', '1', '時', 'こっち', '感じ', '何', '前', '朝', '所', '今' | × |
| 26 | A(2) | Sidewalk | Chains | '僕', 'わけ', '人', '前', 'よう', '所', '車', 'あれ', '病気', '何' | '車', '方', '中', '病院' |
| 27 | D(2) | Sidewalk | Carry bag | - | - |

Table 4.18: The 10 most frequent words and their co-occurrence words in the text data, and the words coincident with either the 10 most frequent words in the summary data (4).

| ID | Fall mode | Place | Objects | The most 10 frequency word | Co-occurrence word shown on the summary |
|---|---|---|---|---|---|
| 28 | D(4) | Bedroom (from toilet) | Chest of drawers | 'トイレ', '畳', '感じ', 'ところ', '1', '前', '2', '目まい', '今', '何' | '上', 'トイレ' |
| 29 | F(3) | Kitchen | - | '人', '1', '今', '台所', 'さん', 'よう', '前', '中', '何', '食事' | '台所', '記憶', '中' |
| 30 | F(3) | Living room | -(Trousers?) | '感じ', 'よう', '前', '普段', '何', '1', '2', '3', '椅子', 'ところ' | '中', '3' |
| 31 | B(2)/A(1) | Entrance of a hotel | Step (photo?) | '前', '階', '2', '何', '日', '今', '転倒', '時', '感じ', '道路' | '前', '主人', 'ホテル' |
| 32 | C(1) | Sidewalk (from bus) | Fallen leaves | '年', '前', 'バス', '今', '私', 'ほう', '感じ', '1', 'もん', '手' | '手', 'バス', '歩道', '前' |
| 33 | F(3) | Toilet | -(Door?) | 'トイレ', '普段', '時', '奥さま', '2', '何', '中', '布団', '電気', '回' | '自宅', 'トイレ', '月', '肩', '状況' |
| 34 | D(2) | Concourse of a station | Carry bag | - | - |
| 35 | A(2) | Living room (from toilet) | Toy | '1', '私', '先生', '感じ', '何', '妹', '手術', '車', 'BM', '救急' | '孫' |
| 36 | F(3) | Roadway (from car) | - | '私', '何', '車', '前', '今', '娘', '感じ', '方', '年', 'みたい' | '車', '前', '娘', '足' |

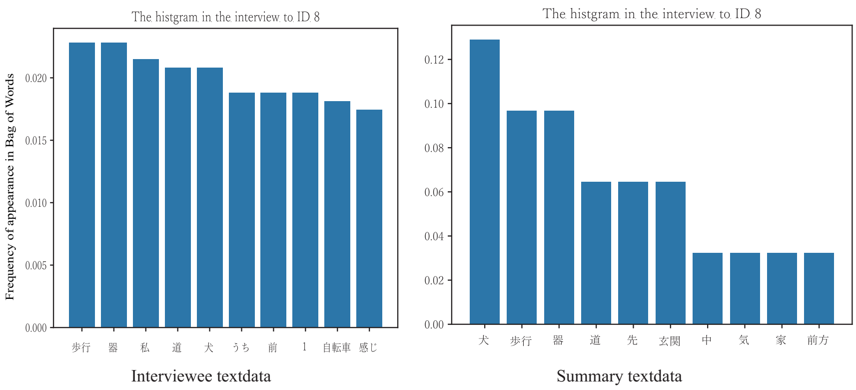



Figure 4.6: The 10 most frequent noun shown in the interview text data (left side) and in the summary data (right side) in interview to ID8.

### 4.4.3 Confirming the causes of falls from the frequent words and their co-occurrence words

We did a falling category classification experiment by the naive Bayes classifier. The text data and the summary data are available for 34 cases, and we excluded 7 cases labeled as 'could not tell'. In total 27 cases were tested for the classification. The summary data were used as training data and 90.0% (9/10 cases) for the category (a) (falls by unexpected external forces), 53.8% (7/13 cases) for the category (b) (falls by losing balance), and 25.0% (1/4 cases) for the category (c) (other falls, excluded 'could not tell') were classified correctly. The average classification rate was 62.9%. Since the summary data summarizes the interview, we also did the leave-one-out cross-validation test. We exclude the summary data of the participant whose text data was used as test data, and trained the classifier. We acquired the same results.

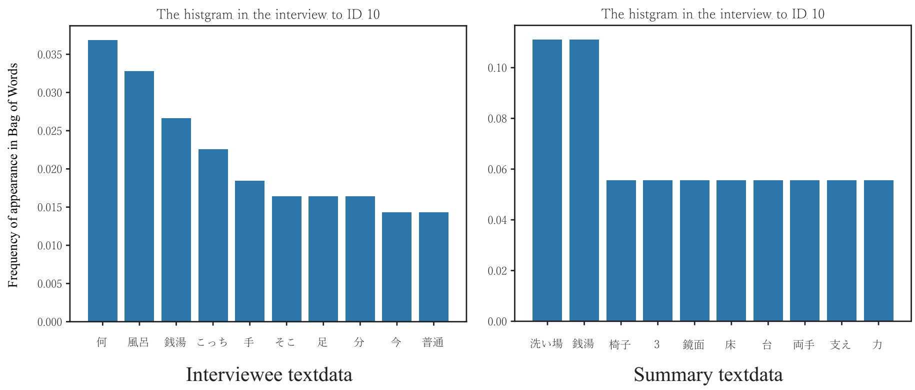



Figure 4.7: The 10 most frequent noun shown in the interview text data (left side) and in the summary data (right side) in interview to ID10.

### 4.4.4 Falling pattern estimation from GLFS-25 data of hospitalized participants

For 21 participants whose text data are available and of whom the GLFS-25 data are not completely missing were used to analyze. Ten participants were in category (a) (fallings by unexpected forces) and the other ten participants were in category (b) (fallings by losing balance). The classifier was constructed by using logistic regression analysis method. As a result of training, 100 % of both category data classified correctly. Then, we did a leave-one-out cross-validation test. 80% (8/10 cases) for category (a) and 54.5% (6/11 cases) were classified correctly. The classification result for category (b) was relatively worse. We hypothesized this badness of the results comes from the number of feature vector dimensions, we used the first 2-dim of the feature vector and did the leave-one-out cross-validation test. 80% (8/10 cases) for category (a) and 72.7% (8/11 cases) were classified correctly.

The classification rate for the category (b) was enhanced. Also, we reduced the feature vector dimension to 1 using linear discrimination analysis, then, the classi-

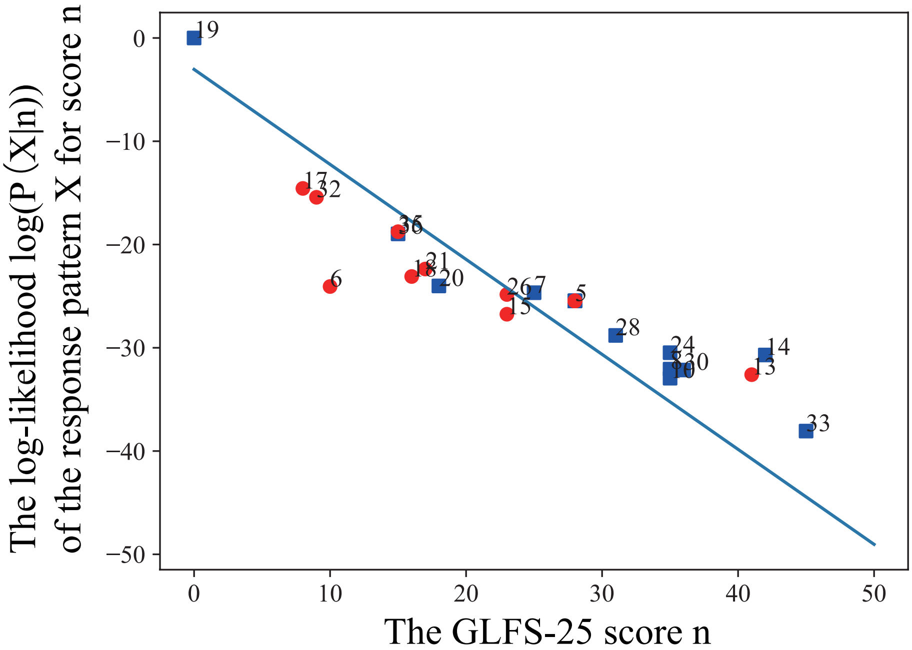



Figure 4.8: The trained boundary line is illustrated as a blue line. The horizontal axis indicates the GLFS-25 score n, and the vertical axis indicates the calculated $P(X|n)$ for the response pattern $X$ of each participant who scored $n$. The participants who fell by unexpected forces are plotted in red circles, the participants who fell by losing balance are plotted in blue rectangles.

fication results were 50% (5/10 cases) for category (a) and 54.5% (6/11 cases) for category (b). From these results, if we add more training data, we can construct a falling category classifier for the 27-dim feature vectors, too. The trained boundary line is illustrated on Fig. 4.8

### 4.4.5 Stumble risk estimator from GLFS-25 data of community-dwelling participants

The trained boundary line is illustrated on Fig. 4.9. The participants had a higher score for GLFS tend to fall by losing balance, and the participants who show the further scoring pattern from the common distribution tend to fall by unexpected falls even if they showed the smaller score. The GLFS features of the community-dwelling participants who participated in the measurement in Chap 3 are plotted in green. The green rectangles indicate the features of the community-dwelling participants who showed the smaller visual illusion $k$, and the green triangles indicate the features of the community-dwelling participants who showed the bigger visual illusion $k$. From the calculation, 9 participants are judged as to have a higher risk for falls due to unexpected forces including stumbles compared with the risk for staggering. Among the participants who showed the bigger visual illusion $k$, all participants (B02, B03, B14, B15) were judged as to have a higher risk for falls due to unexpected forces. Among the participants who showed the smaller visual illusion $k$, 2 (B16, B19) out of 4 participants (B16, B18, B19, B22) were judged as to have the higher risk for falls by unexpected forces.

Next, we trained the boundary line by the participants who had experienced falls and fractures by stumbles (fall probability = 100 %) and the young participants (fall probability = 0 %). The data, the trained boundary line, and the boundary line in Fig. 4.9 are illustrated in Fig.4.10.

For the participants who are close to the pink region in Fig. 4.10, we estimated the risk for falls and stumbles. The calculated risks are listed on Tab. 4.19. For the participant B18, the risk for falls by losing balance is higher than the risk of falls by unexpected forces. Her feature of the score was close to the hospitalized participants who had experienced falls by losing balance and fractures. B05, B18 reported their experiences of falls in recent 1 year, and B14, B19 reported their experiences of falls in 1 year after the measurement, so the risk estimator would have enough sensitivity.

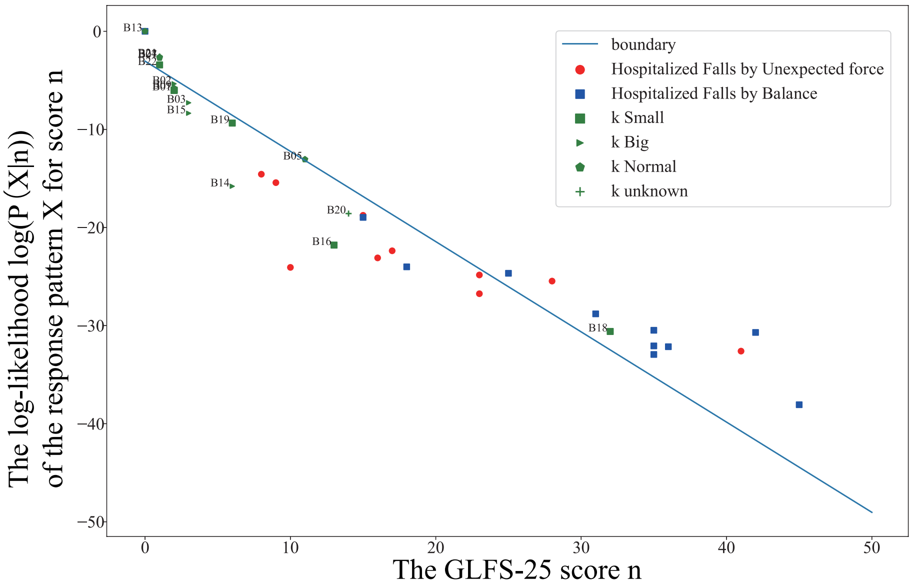



Figure 4.9: The trained boundary line is illustrated as blue line. The horizontal axis indicates the GLFS-25 score n, and the vertical axis indicates the calculated $P(X|n)$ for the response pattern $X$ of each participant who scored $n$. The participants who fell by unexpected forces are plotted in red circles, the participants who fell by losing balance are plotted in blue rectangles. The green plots are the participants of the measurement in chapter 3

## 4.5 Conclusion

The conclusion of this research is as follows:

1. A bedside interview research was conducted to patients aged over 60 years old and who had experienced falls and consequently hip fractures. The number of participants was 36 (9 males, 27 females, age was 82.1 ± 8.13). The most number of falls occurred at home (15/36 cases) and 12 out of 15 cases were falls related to going from/to the toilet.

2. We categorized the falling types as following 3 category: (a) Falls by unexpected forces, (b) falls by losing balance or supporting forces, and (c) other falls (including free fall, accidents, and 'could not tell'). Of 36 cases, 11 cases were

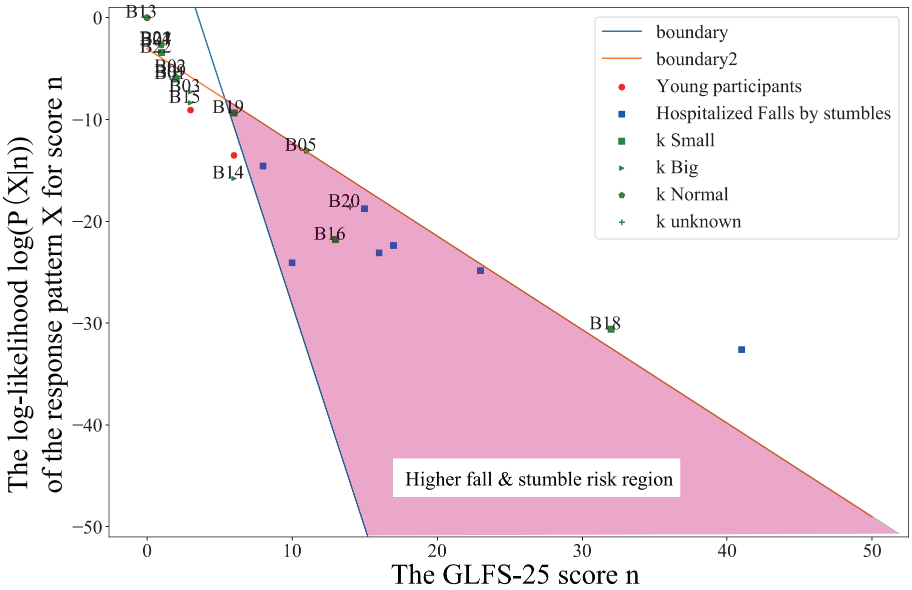



Figure 4.10: The boundary line trained by participants who fell by stumbled and the young participants are illustrated as a blue line. The boundary line trained by participants who fell by unexpected falls and participants who fell by losing balance is illustrated as an orange line. The line is the same as in Fig. 4.9. The horizontal axis indicates the GLFS-25 score n, and the vertical axis indicates the calculated $P(X|n)$ for the response pattern $X$ of each participant who scored $n$. The young participants are plotted in red circles, the participants who fell by stumbles are plotted in blue rectangles. The green plots are the participants of the measurement in chapter 3.

categorized into category (a) and 13 cases were categorized into category (b). 12 cases including 7 'could not tell' were categorized into category (c). The most number of falls were categorized into category (b).

3. We set labels that researchers attached to the text data as the initial cluster of the clustering analysis and did the clustering analysis. Almost all the cluster was not updated. Also, we analyzed the 10 most frequent noun and their 11 most co-occurrence words, 31 out of 34 cases showed at least one coincidence word. 23 out of 31 cases showed some of the coincidence words indicates the falling place or objects related to the falls. From above, the falling category

Table 4.19: The estimated risk.

| ID | Fall risk $r_{fall}$[%] | Fall tendency $r_{tendency}$[%] | Stumble risk $r_{stumble}$[%] |
|---|---|---|---|
| B05 | 99.9 % | -1.34 % | -1.34 % |
| B14 | 2.36 % | 74.1 % | 1.75 % |
| B16 | 99.9 % | 71.3 % | 71.4 % |
| B18 | 100.0 % | -24.2 % | -24.2 % |
| B19 | 74.0 % | 10.4 % | 7.60 % |
| B20 | 99.9 % | 33.6 % | 33.6 % |

label attached by the researcher and the summary data by the researchers were appropriate to some extent.

4. Several classification experiments were conducted. The falling category was classified from the text data using the naive Bayes classifier trained by summary data by the researchers. The classification rate for category (a) was 90.9%, and the classification rate for category (b) was 80.0%. Also, the falling category was classified from the GLFS-25 data. The classification rate was 80.0% (8/10 cases) for category (a) and 54.5% (6/11 cases) were classified correctly. We achieved 76.1% for averaging category (a) and category (b) when we use the first 2 dimensions of the feature vector of GLFS-25.

5. Using the estimator trained by hospitalized participants' GLFS-25 data, we constructed the stumble risk estimator for the community-dwelling participants.

Nine participants were judged to have a high risk of stumbles. Especially, almost all the participants who showed the abnormal (bigger/smaller) visual illusion $k$ were judged to have a high risk of stumbles. The estimator has high sensitivity for risk estimation.

# Chapter5

# Frailty Mother-Set Analysis by Generalizing Enriched Sample-Set Analysis

## 5.1 Motivation

### 5.1.1 Background

Falls is one of the risk factors that change elderly people lives drastically and cause starting to use the nursing care service. In the gerontological field, there is a concept of "frailty" that indicates becoming physical, mental, social weakness or functional decline comprehensively. When humans get older, their physical/cognitive function gets worse, then these declinings of functions easily cause falls. The confinement at home after falling leads to a decline of the social function of them and that reduces physical/mental function lower and lower, and it causes another new falling. From this point of view, preventing frailty is closely related to preventing falls. Recently, the concept "cognitive frailty" was proposed [32]. This concept regards frailty as a mixture of physical frailty and mild cognitive impairment (MCI).

For the physical frailty, the concept of the locomotive syndrome that especially focuses on the disorders of the locomotive functions is proposed by the Japanese orthopedic association. Mild cognitive impairment is regarded as the pre-stage of Alzheimer's disease. There are some screening tools for dementia and the results of those tools are regarded as an indication of their cognitive abilities. However, there are limitations to evaluate their cognitive abilities only from the point of view of dementia. We need to consider the declining of physical and cognitive abilities comprehensively.

### 5.1.2 Research purpose

In this research, the purpose is to develop quantitatively and comprehensively evaluation system for the frailty. We aimed at utilizing this system for preventing falls. This system estimates and visualizes the level of subjects' physical abilities and brain activities (see Fig. 5.1), and subjects can know characteristics of their physical/cognitive abilities based on the results from motions or cognitive tasks.

In this paper, we propose the feature extraction method for scoring their frailty. We call the mean of the extracted 1-dim feature as 'frailty score'. The frailty score will be calculated for each task for each person. Defining the frailty score, we can consider the level of elderly people's physical/cognitive abilities quantitatively in a multi-dimensional space. Also, we propose the method to convert the categorical questionnaire response patterns to the consecutive log-likelihood data so that we can treat the data as consecutive data.

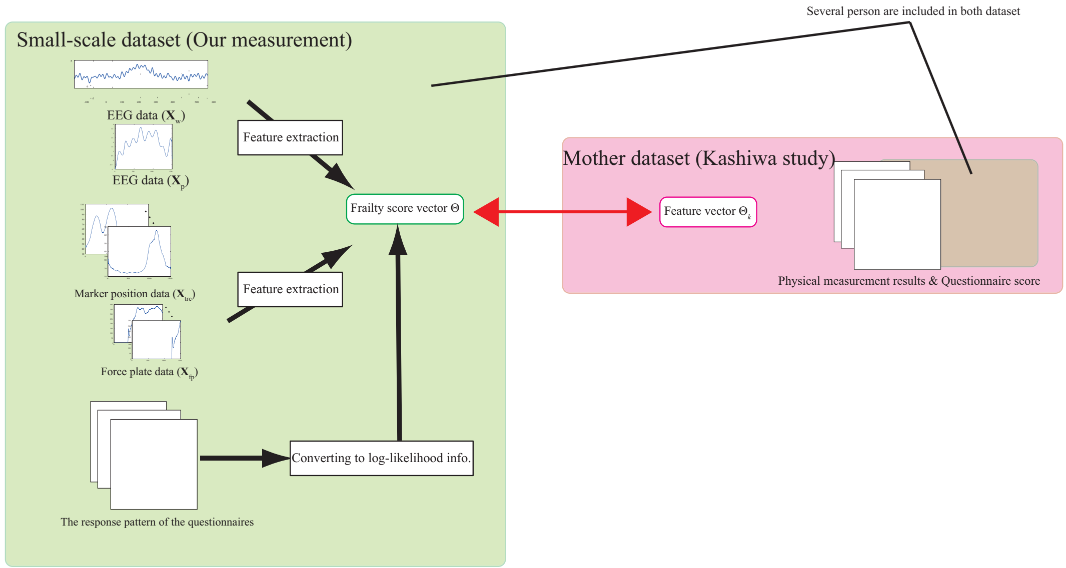



Figure 5.1: The outline of the frailty evaluation system based on the proposed method.

The relationships among each dataset and the concept of this chapter are illustrated in Fig. 5.2. The orange one is our measurement dataset, the green one is the Kashiwa study dataset. In this chapter, we regard the Kashiwa study dataset as the mother-set, our measurement dataset as the sampled-set. The pink one is the hospitalized patient dataset. In chapter 2 - 4, we analyzed the data along with the GLFS-25 score and the extent of the depth perception. In this chapter, the coordination system (kind of the axis shown in the black arrows) will be converted to the red arrows by using a matrix decomposition.

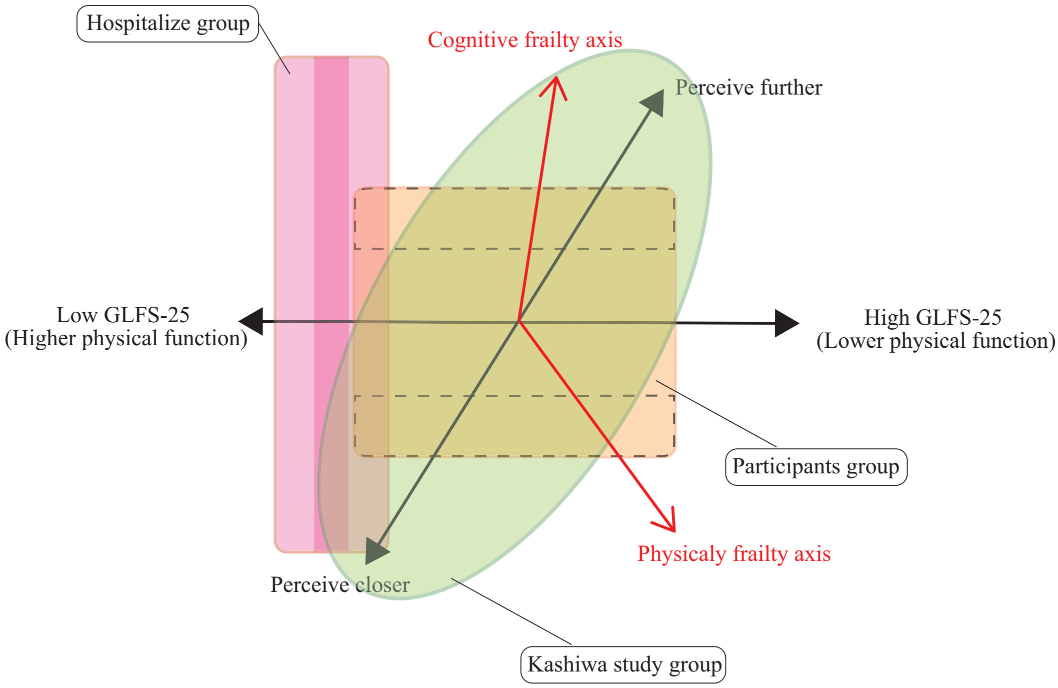



Figure 5.2: The dataset used in this chapter. The orange one is our measurement dataset, the green one is the Kashiwa study dataset. In this chapter, we regard the Kashiwa study dataset as the mother-set, our measurement dataset as the sampled-set. The pink one is the hospitalized patient dataset. In chapter 2 - 4, we analyzed the data along with the GLFS-25 score and the extent of the depth perception. In this chapter, the coordination system will be converted by using a matrix decomposition.

## 5.2 Feature extraction method for calculating the frailty score

### 5.2.1 Multiple training data from measured data for one person

In this section, we propose a feature extraction method to calculate the frailty score. This method enables us to use both whole macroscopic data and specific microscopic data for training, and we can acquire multiple training data from one data. We apply this method not only to physical motion data but also Electroencephalogram (EEG) data so that we can quantitatively compare extracted features from different types of data at the same multi-dimensional space. Aligning the macroscopic data $\mathbf{X}^i_{macro} \in \mathcal{R}^{T\times ch}$ and the microscopic data $\mathbf{X}^i_{micro} \in \mathcal{R}^{T\times ch}$, we create a matrix $\mathbf{X}^i$ for person $i$ as follows:

$$\mathbf{X}^i = \begin{bmatrix} {\mathbf{X}^i_{macro}}^T \\ {\mathbf{X}^i_{micro}}^T \end{bmatrix} \tag{5.1}$$

$$= \begin{bmatrix} \mathbf{x}^i(1) & \cdots & \mathbf{x}^i(t) & \cdots & \mathbf{x}^i(T) \end{bmatrix}, \tag{5.2}$$

where $\mathbf{x}^i(t)$ is the measured data for person $i$ at time $t$.

In the next step, we sampled column vector $\mathbf{x}^i(t)$ of the matrix $\mathbf{X}^i$ every 10 points from $t = s$. The $s$ is moved from 1 to 10, then, training data vector

$$\mathbf{z}^i_s = \begin{bmatrix} \mathbf{x}^i(s) \\ \mathbf{x}^i(s+10) \\ \vdots \\ \mathbf{x}^i(T-10+s) \end{bmatrix} \tag{5.3}$$

was created. We shifted the start point of sampling one by one and finally could acquire 10 training data from one $\mathbf{X}^i$.

We apply the same filter $\mathbf{w}$ to all the participants who did the same motion/cognitive task, and convert the centerized training data $(\mathbf{z}^i_s - \bar{\mathbf{z}}^{\mathbf{i}})$ to $\mathbf{y}^i_s$ for each person as follows:

$$[y^i_1, \cdots, y^i_{10}] = \mathbf{w}^T\hat{\mathbf{Z}}^i, \tag{5.4}$$

where

$$\hat{\mathbf{Z}}^i = \begin{bmatrix} \mathbf{z}^i_1 - \bar{\mathbf{z}}^{\mathbf{i}} & \cdots & \mathbf{z}^i_{10} - \bar{\mathbf{z}}^{\mathbf{i}} \end{bmatrix}, \tag{5.5}$$

and $\bar{\mathbf{z}}^{\mathbf{i}}$ is the average on $s$ of $\mathbf{z}_s^i$s. We call the mean of the projected value $\mathbf{w}^T(\mathbf{z}_s^i - \bar{\mathbf{z}}^{\mathbf{i}})$ for one person for one motion as 'the frailty score' of the motion of the person $i$.

In our research, we find a projection vector $\mathbf{w}$ such that minimizes within-class variance solving the following optimizing problem:

$$\arg\min_{\mathbf{w}} \sum_i \sum_s \|y_s^i - \mu^i\|^2, \tag{5.6}$$

where $\mu^i$ is the average on $s$ of $\mathbf{y}_s^i$ that indicates features extracted from dataset $\mathbf{z}_s^i$. The projection vector $\mathbf{w}$ is subject to

$$\|\mathbf{w}\|^2 = 1. \tag{5.7}$$

We set the optimization problem so that it minimizes the within-person variance of the extracted features since we'd like to design the frailty score that has robustness for changing sampling points of the training data. In other words, we designed our feature extraction method so that we can extract relatively constant features for the same person for a specific motion. Using Lagrange multipliers method, the optimization problem above can be translated into the following eigenvalue problem:

$$\mathbf{S}_w \mathbf{W} = \mathbf{W}\mathbf{\Lambda}, \tag{5.8}$$

where $\mathbf{S}_w$ is the total sum of the within-person variance-covariance matrix

$$\frac{1}{N_i} \sum_{i=1}^{N_i} \sum_{s=1}^{10} (\mathbf{z}_s^i - \bar{\mathbf{z}}^i)(\mathbf{z}_s^i - \bar{\mathbf{z}}^i)^T, \tag{5.9}$$

$N_i$ is the total number of participants, $\mathbf{W}$ is the matrix in which the eigenvectors are aligned, and $\mathbf{\Lambda}$ is the diagonal matrix of which diagonal components are eigenvalues. The projection vector $\mathbf{w}$ is the eigenvector that is corresponding to the smallest eigenvalue $\lambda$ in the matrix $\mathbf{\Lambda}$.

### 5.2.2 Integrating frailty scores for different tasks into a multi-dimensional space

From the proposed method, we can calculate the frailty scores for different tasks one by one, so we can acquire various filters to calculate features for several tasks. Let the filter for task 1 be $\omega_1$ and the filter for task 2 be $\omega_2$. Each filter is trained by each training data of each task $\mathbf{Z}_i^{task}$. In other word, we solve these 2 optimization problems separately:

$$\arg\min_{\omega_1} \sum_i \sum_s \|y^i_{s,task1} - \mu^i_{task1}\|^2, \tag{5.10}$$

subject to

$$\|\omega_1\|^2 = 1; \tag{5.11}$$

$$\arg\min_{\omega_2} \sum_i \sum_s \|y^i_{s,task2} - \mu^i_{task2}\|^2, \tag{5.12}$$

subject to

$$\|\omega_2\|^2 = 1. \tag{5.13}$$

Then we can acquire two 1-dim frailty score for one person ($y^i_{task1}$ and $y^i_{task2}$). This frailty score can be treated as the vector in 2-dim space from following transformation:

$$\left[y^i_{task1}, y^i_{task2}\right]^T = \mathbf{A}\left[(\hat{\mathbf{Z}}^i_{task1})^T, (\hat{\mathbf{Z}}^i_{task2})^T\right] \tag{5.14}$$

$$= \begin{bmatrix} \omega_1^T & \mathbf{0}^T \\ \mathbf{0}^T & \omega_2^T \end{bmatrix} \left[(\hat{\mathbf{Z}}^i_{task1})^T, (\hat{\mathbf{Z}}^i_{task2})^T\right], \tag{5.15}$$

where $\hat{\mathbf{Z}}^i_{taskn}$ is the centerized training data matrix for task $n$ of person $i$. The dimension of $\hat{\mathbf{Z}}^i_{taskn}$ can be different among tasks, and we can combine them. Aligning the filters for task n $\mathbf{w}_{taskn}$ along to the diagonal block of the matrix $\mathbf{A}$, we can extend this method to the $n$-dimensional space (for $n$ tasks). This operation means that we convert the measured data in the space of $taskn$ into the set of frailty scores in the 'frailty space'. In other words, we designed the 'frailty space' by taking the direct sum of the subspaces for various tasks.

## 5.3 Physical motion measurements and brain activity measurements

### 5.3.1 Measurement conditions and tools

The participants for motion capture were 16 elderly people (7 males and 9 females, age: $78.0 \pm 6.81$) and 3 young people (3 males, age: $25.0 \pm 0.81$). This research is approved by the ethical committee at the University of Tokyo.

Thirty-five marker-set and 8 wireless electromyography (EMGs; Delsys, "Trigno System") were attached to a participant. Markers were attached to their whole body, and EMGs were attached to their lower body. We use 12 motion capture camera (Motion Analysis, "Raptor system") to capture motions.

EEG (electroencephalogram) is one of the electrophysiological tools to capture electrical potentials. For EEG measurement, 14 participants were measured. We mark on the head of a participant, and put electrodes along with extended 10-20 method[63] and measure brain activity. a cap was put on the participant's head for fixing the electrodes. We can obtain the active potential of neurons noninvasively. gUSBamp (g.tec medical engineering GmbH, Austria) was used to measure brainwaves. Electrodes are Ag/AgCl active electrodes. We use the filters in measuring as follows: 0.5

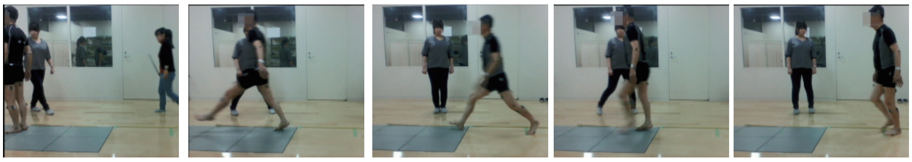


Figure 5.3: The snapshots of 2-step motion. Participants try to reach the distance as far as they can in 2 strides. The distances of 2 strides were normalized by their heights and it is called as the "2-step value".

Hz high-pass filter, 30 Hz low-pass filter, 48-52 Hz notch filter. The sampling rate was 256 Hz.

### 5.3.2 Physical motion measurement items

In this research, we record three tests for locomotive syndrome[64] (GLFS-25, 2-step test[65], and Stand-up test[66]), One-leg stand duration with vision, velocity for walking, and Time Up & Go test so that we can use these data as criteria of physical frailty in the learning phase of the system. Motion capture marker positions, EMG data, and force plate data were acquired during these motions, and walking time for 1.8 m during 5-meter walking test, one-leg stand duration with vision (up to 60 sec), 2-step value (the distance in 2 stride that is normalized by the participant's height), time for TUG test, and the number of success for stand-up test (stand up from about 40-cm-high seat by one leg) were also recorded. In this paper, we calculated the frailty score from the 2-step test motion data. Fig. 5.3 shows the snapshots of the 2-step motion. Participants were asked to reach the distance as far as they can in 2 strides.

### 5.3.3 Brain activity measurement items

In this paper, we used the data that is acquired during the P300 task. The P300 is one of the event-related potentials that is shown after 300 ms of the target that a participant pays attention. The relationship between dementia and P300 has been studied since 1980s[67][68], it is known that dementia patients show slower latency and smaller amplitude of P300[69]. In the P300 task, we used P300Speller application that is provided in BCI2000[70][1] and measured EEG data during these tasks. The electrodes were put onto $P_3$, $P_4$, $PO_7$, $PO_8$, $F_z$, $C_z$, $P_z$, and $O_z$, respectively. GND is $AF_z$ and reference electrodes are on both earlobes. The participant sees a monitor on which Japanese characters are aligned. He/she counts the number of flashes of the target character (the target stimulus) that is pointed by the experimenter before the task starts. The number of the trial was 11. The last one is used as the baseline, so the participant is asked to just watch the monitor. The target stimulus was changed in each task. We set the number of the target stimulus was 30 in one task and asked participants how many stimuli they counted so that we could estimate whether they could understand our instruction and could achieve the task.

### 5.3.4 Applying proposed method to physical motion data during 2-step motion

We applied the proposed method to the marker position data of the motion capture $\mathbf{X}_{trc}$ and the reactance force data from the force plates $\mathbf{X}_{fp}$ during the 2-step test. Different 2 types of data (the marker position data and the reactance force data) were

[1] http://www.schalklab.org/research/bci2000

used and they have different time width. Marker position data were measured in 200 fps, force plate data were measured in 1000 fps. In our research, time width for the marker position data $\mathbf{X}_{trc}$ is one walking cycle (from the time when a participant's foot first contacts to the floor to the time when the same foot contacts to the floor again). We interpolate data to 1500 frames. For the reactance force data $\mathbf{X}_{fp}$, the time width is 1.5 sec from the time a participant's foot contacts to the floor. Because of the sampling rate for the reactance force data, it is 1500 frames. We put 35 markers on a participant body and reactance force data includes position of COP (x, y, z), force (x, y, z), and moment around z-axis. From above, $\mathbf{X}_{trc} \in \mathcal{R}^{1500\times(35\times3)}$, $\mathbf{X}_{fp} \in \mathcal{R}^{1500\times7}$. $\mathbf{X}_{trc}$ and $\mathbf{X}_{fp}$ is normalized by the average and the standard deviation. We used $\mathbf{X}_{trc}$ as $\mathbf{X}_{macro}$ and $\mathbf{X}_{fp}$ as $\mathbf{X}_{micro}$.

### 5.3.5 Grouping based on the frailty scores

We divided participants into 2 groups based on the frailty scores. The criteria value $C^i$ for participant $i$ is calculated from $y^i$ as follows:

$$C^i = \frac{1}{10}\sum_{s=1}^{10} \ln \|y^i\| \tag{5.16}$$

The participant in group (a) has $C^i < -41.0$, the participant in group (b) has $C^i \geq -41.0$. For comparison, we also set participants into 3 groups based on the level of the locomotive syndrome. The first group is the Locomo-1 stage group. People in this group are regarded to be starting to decline their motor functions. We set the participants into the Locomo-1 stage group when they meet following one of these criteria[71]:

- The 2-step value $< 1.3$

- They could not succeed in the stand-up test by one leg.
- The score of GLFS-25 $\geq 7$

Another group is the Locomo-2 stage group. People in this group are regarded to be declining in their motor functions. We set the participants into the Locomo-2 stage group when they meet one of these following criteria:

- The 2-step value $< 1.1$
- They could not succeed in the stand-up from the 20-cm-high seat by both legs (Data were not captured this time).
- The score of GLFS-25 $\geq 16$

The last group is the Non-locomo stage group. If participants don't meet any criteria above, they are regarded to have no problems with their locomotive functions.

### 5.3.6 Applying proposed method to EEG data during P300 task

We also applied our method preliminarily to EEG data during the P300 task. EEG data were measured in 256 fps. At the first step, as preprocessing, we subtract average in time from EEG data to remove DC noise and applied Common Average Reference filter (CAR filter)[72] that is one of spatial filters. Applying CAR filter to the channel $c$, the EEG data of $c$ ($\mathbf{x}_c$) is calculated as following:

$$\mathbf{x}_c - \frac{1}{n}\sum_j \mathbf{x}_j, \tag{5.17}$$

where $n$ is the total number of the electrodes. Second, we segmented the EEG data 2 sec before and after the stimuli appear, resampled them to 1000 fps, and only data from 0.1 sec before to 0.6 sec after the stimuli appear were sampled. Third, we remove the data following 3 criteria:

- The maximum/minimum value of the amplitude was over/under $\pm$ 90 $\mu$V
- The gap of the maximum and minimum of the amplitude was over 140 $\mu$V
- The flat line (the amplitude is under 5 $\mu$V) lasts for over 100ms

After removal of data was done, we put EEG data into 2 categories. One is the target stimuli, the other is the non-target stimuli. Then, the grand average for each category was calculated. Though these grand average were calculated for each channel, we select the electrode that clearly shows peak 250 ms - 550 ms after the target stimuli (and shows the bigger coefficient of determination $r^2$ value) and use it for analysis. $r^2$ value is calculated as follows:

$$r^2 = \frac{cov(x,y)^2}{var(x)var(y)} \tag{5.18}$$

where $var(*)$ is the variance of data, and $cov(i,j)$ is the covariance between category $i$ and $j$. $x$ is the EEG data measured at a certain time point, and $y$ is the label data that is set as 1 when it is the target stimulus and set as -1 when it is the non-target stimulus.

We used $\mathbf{X}_w$ as $\mathbf{X}_{macro}$ and $\mathbf{X}_p$ as $\mathbf{X}_{micro}$ and conducted the same process described in section 5.3.4, and acquire training data. For $\mathbf{X}_w$, the time width is 700 ms (before 100 ms to after 600 ms the stimuli was shown). We interpolate the EEG data (700 frames) for the target/non-target stimuli to 1500 frames. For $\mathbf{X}_p$, the time width is 150 ms from the time the P300 peak starts rising. In this research we selected 1 electrode that shows clear P300 peak, so $\mathbf{X}_w \in \mathcal{R}^{1500\times 1}$, $\mathbf{X}_p \in \mathcal{R}^{1500\times 1}$. $\mathbf{X}_w$, $\mathbf{X}_p$ are normalized by the average and the standard deviation.

## 5.4 Converting the qualitative variables to the consecutive variables

### 5.4.1 Converting the categorical variables to the probabilistic-based variables

Only the total score of the answers to a questionnaire is often used in the analysis of the questionnaires. However, the questionnaire response pattern itself has rich information and the total score are the results from the reducing of the dimensions of the patterns from the number of the questionnaire response patterns to 1. In this research, we'd like to utilize the whole response patterns to estimate the frailty level. The problem is that each response of the questionnaire is the categorical variable, so we cannot directly compare with the consecutive variables as it is. Thus we propose the method to convert the categorical variables to the consecutive ones.

In this research, we focus on the specificity of the questionnaires that are developed epidemiologically. Commonly, this kind of questionnaires are developed based on the statistical analysis that collects response patterns from a large amount of population group, and the response patterns or some kind of probabilistic distributions are usually open for public. We utilize these distributions to convert the categorical variables to the consecutive ones, then we can compare how our participants far out of the distribution (i.e., where the participants placed) in the observation group in the previous research.

We used the revised Hasegawa's dementia scale (HDS-R)[35][36] and the 25-question Geriatric locomotive function scale (GLFS-25)[31] in our research. HDS-R's full score is 30. The larger score means a better cognitive function they have. If the score $\leq 20$, the participant is doubt of dementia. The response patterns from the dementia group and non-dementia group are available from [35] for HDS-R. GLFS-25's full score is 100. The smaller score means the better locomotive function they have. If the score $\geq 7$, the participant starts declining of their locomotive function and if the score $\geq 16$, the participant's locomotive function declined. The response ratio to each item and the zero-scored response ratio of each item in some score groups (0-6 points, 7-15 points, 16-23 points, 24-32 points, 33-40 points, 41-49 points, 50- points) are available for GLFS-25. Using these distributions, we can reflect kinds of information such as the existence of dementia or which function is more damaged and convert to the consecutive variables.

### 5.4.2 Calculate the log-likelihood for HDS-R

For HDS-R, the response rate distributions to each item by dementia group $D_{dem}$ and non-dementia group $D_{non}$ are available[35]. Let the total score of the HDS-R be $n$, the response pattern of the participant be $X = \{x_i\}$ ($x_i$ indicates the response to the item $i$). We calculate the log-likelihood of which the response pattern $X$ emerges from each distribution ($\log P(X|D_{dem})$ or $\log P(X|D_{non})$). If we assumed that the response to each item is independent, then, the log-likelihood is easily calculated as the product of the response ratio to $N$ items under distribution $D$:

$$\log P(n, X|D) = \log\{P(x_1|D)P(x_2|D) \cdots P(x_N|D)\} \tag{5.19}$$

$$= \sum_{i=1}^{N} \log(P(x_i|D)). \tag{5.20}$$

To keep the consistency of the log-likelihood values, we take the difference between log-likelihood from the non-dementia group and from the dementia group. Then converted consecutive variables $C^i$ to be

$$C^i = \log(P(X_0|D_{dem})) + log(P(X, n|D_{non})) \tag{5.21}$$
$$-log(P(X, n|D_{dem})),$$

where $X_0$ is the response pattern that all response to the items were 0, n is the score of the HDS-R. Eq. (5.22) shows the smaller value when the response patterns are more likely to emerge from the dementia group distribution. On the other hand, if the response patterns are more likely to emerge from the non-dementia group distribution, Eq. (5.22) outputs a large value.

We can also impute the missing data using Eq. (5.22).

### 5.4.3 Calculate the log-likelihood for GLFS-25

The features for GLFS-25 is calculated as 2-dim feature vector. The method is proposed in chap4. The first dimension of the feature vector is the score for GLFS-25. The second dimension of the feature vector is calculated as follows for the score

$n$ of GLFS-25 for the participant $i$ whose GLFS-25 response pattern was $\mathbf{x}$:

$$C^i = \log(P(\mathbf{x}|n)) = \log P(\mathbf{x}) - \log P(n), \tag{5.22}$$

In chap4, we calculated P(n) theoretically. However, the distribution of the response of GLFS-25 skewed to the left, so we referred the result of the large-scale longitudinal study (Kashiwa study[30]) conducted in 2016. We acquire the distribution of the GLFS-25 score and analyzed by curve-fitting using the exponential model. The model is written as follows using the parameter $a$ and $b$:

$$P(n) = a \exp{(bn)} \tag{5.23}$$

### 5.4.4 Clustering participants from the information of the large-scale investigations (Kashiwa study)

The participants of this dissertation except B24 are the sub-sampled group of the Kashiwa-study[30], which is the large-scale longitudinal study for sarcopenia and frailty. We referred the participants' data in the Kashiwa study held during April in 2015 to March in 2016 and confirmed each participant's level of their physical/cognitive status. We checked the results of the walk speed, the 2-step test, the stand-up test, the limb skeletal muscle mass, the score of MMSE, and the score of GLFS-25 of the participants who participated both the motion measurement mentioned in 5.3.2 and the EEG measurement mentioned in 5.3.3. One participant (B02) did not participate in the measurement of Kashiwa study in 2016, so totally 11 participants data (participants in 5.5.2 except B02 and B24) were analyzed. In the walk speed test, the average walking speed for 5 m is recorded. In the 2-step test, the

2-step value (the distance in 2 strides divided by the participant's height) is recorded. In the stand-up test, the combination of the height of the chair (10 cm, 20 cm, 30 cm, and 40cm) and the using leg (both legs, single-leg) is recorded. For the stand-up test, the results ('cannot for all heights', '40 cm by both legs', '30 cm by both legs', '20 cm by both legs', '10 cm by both legs', '40 cm by single-leg', '30 cm by single-leg', '20 cm by single-leg', '10 cm by single-leg') are coded as the number 0 (for the 'cannot for all heights') to 8 (for the '10 cm by single-leg'). For the limb skeletal muscle mass, the limb skeletal muscle mass is recorded. We analyzed the limb skeletal muscle mass separately for men and women.

To grab the characteristics of the participants, we set the feature vector for each participant using these results of the tests. We calculate the survival function $P(x \geq x_0)$ for the result value $x_0$ for each test and use it as the feature for each test. For the result of the walk speed, $x_0 = x_{walk}$. For the result of the 2-step test, $x_0 = x_{2step}$. For the result of the stand-up test $x_0 = x_{stand}$, and for the result of the limb skeletal muscle mass, $x_0 = x_{muscle}$. For each test, the survival function $\theta$ is calculated as follows:

$$\theta = P(x \geq x_0) = \int_{x_0}^{\infty} \frac{1}{\sqrt{(2\pi\sigma^2)}} \exp\{-\frac{(t-\mu)^2}{2\sigma^2}\}dt, \tag{5.24}$$

where $x_0$ is the result of each test, $\sigma^2$ is the variance of the result of each test, and $\mu$ is the mean of the result of each test. For the score of MMSE $x_{MMSE}$, $x_0 = 30 - x_{MMSE}$, i.e., $x_0$ expresses how many scores they lost from the full score whereas for the score of GLFS-25, $x_0 = x_{GLFS}$. For each questionnaire, the survival function is calculated as follows:

$$\theta = P(x \geq x_0) = \int_{x_0}^{\infty} \frac{1}{\mu} \exp(\frac{t}{\mu})dt, \tag{5.25}$$

where $x_0$ is the result of each test, $\sigma^2$ is the variance of the result of each test, and $\mu$ is the mean of the result of each test. We used a value on Tab. 5.6 as $\mu$ and $\sigma^2$ for each test. From the above definition of the feature, the declining of the survival function value means the better physical abilities (better achievement of the measurement or better condition at muscle mass), and the declining of the survival function value means the worse cognitive abilities (losing many points from the full score of MMSE) and the worse physical abilities (getting difficulties and showing the higher score of GLFS-25).

The feature vector is acquired as aligning the survival function value $\theta$ for each test, i.e., $\mathbf{\Theta} = [\theta_{\mathbf{walk}}, \theta_{\mathbf{2step}}, \theta_{\mathbf{stand}}, \theta_{\mathbf{muscle}}, \theta_{\mathbf{MMSE}}, \theta_{\mathbf{GLFS}}]^{\mathbf{T}}$. We did a principal component analysis and reduced the feature vector dimension to 2.

### 5.4.5 Analysis of the sub-sampled dataset using the frailty scores and the log-likelihood

From the results of the correlation analysis of the large-scale cohort data, we could not extract features so as to separate the evaluation of the physical/cognitive abilities. Now, for the small size of the sub-sampled dataset, we enrich the data using the features from motion capture, EEG data, and the questionnaire data that is converted to the probabilistic variables.

To the 13 participants we mentioned above, we have done the motion and EEG activity measurements (see 5.3.2 and 5.3.3 for more detail). We used these results on Tab. 5.1. As the features, we used the frailty score $C^i$s for participant $i$ described in 5.3.4, 5.3.6, 5.4.2, and 5.4.3; i.e., the response pattern log-likelihood for the questionnaires and the extracted features from the motion capture and EEG data. For the GLFS-25 feature $\theta_{\mathbf{GLFS}}$, we calculate $\log P(\mathbf{x}|\mathbf{n})$ using Eq. (5.22) and Eq. (5.41). Then we defined the feature $\theta^{\mathbf{i}}_{\mathbf{GLFS}}$ as $[n, \log P(\mathbf{X}|\mathbf{n})]^T$ for the score $n$ and the response pattern $\mathbf{x}$ of participant $i$. For the HDS-R feature $\theta^{\mathbf{i}}_{\mathbf{HDS}}$, we used the log-likelihood $\log P(\mathbf{X}|\mathbf{D})$ calculated by Eq. (5.22) for the response pattern $\mathbf{X}$ and the distribution of the response pattern $D$ of participant $i$. For the 2-step motion data and P300 EEG data, we used the features $C^i$ for participant $i$ extracted in 5.3.4 ($C^i_{2step}$)and 5.3.6 ($C^i_{P300}$). We aligned the features as $\mathbf{\Theta^i_s} = \left[\theta^{\mathbf{i}}_{\mathbf{HDS}}, \theta^{\mathbf{i}}_{\mathbf{GLFS}}, \mathbf{C^i_{2step}}, \mathbf{C^i_{P300}}\right]^{\mathbf{T}}$ and created the 6-dim feature vector of participant $i$ for the measurement.

## 5.5 Creating physical-cognitive coordinate system using matrix decomposition

### 5.5.1 Designing the physical-cognitive space using the singular value decomposition

Let $\mathbf{\Theta} \in \mathcal{R}^{n\times N} = \left[\theta^1, \cdots, \theta^N\right]$ be the set of the data, where $n$ is the dimension of the feature vector of the participant $i$ ($\theta^i$) and $N$ is the number of the participants of the dataset. The data is decomposed by the singular value decomposition:

$$\mathbf{\Theta} = \boldsymbol{U}\mathbf{\Sigma}\boldsymbol{V}^T, \tag{5.26}$$

where $\boldsymbol{U} \in \mathcal{R}^{n\times n}$, $\mathbf{\Sigma} \in \mathcal{R}^{n\times N}$, $\boldsymbol{V} \in \mathcal{R}^{N\times N}$. The diagonal components of $\mathbf{\Sigma}$ are called as the singular value of $\mathbf{\Theta}$. Now, let us consider the condition of $\sigma_1 > \sigma_2 \cdots > \sigma_m (>> \sigma_{m+1})$. Let $\boldsymbol{U}_m \in \mathcal{R}^{n\times m}$ be the first m column vectors of $\boldsymbol{U}$, $\mathbf{\Sigma}_m \in \mathcal{R}^{m\times m}$ be the diagonal matrix whose diagonal components are the singular values, and $\boldsymbol{V}_m^T \in \mathcal{R}^{m \times n}$ be the first m row vectors of $\boldsymbol{V}^T$, The data $\boldsymbol{\Theta}$ can be approximated as follows:

$$\boldsymbol{\Theta} \approx \boldsymbol{U}_m \boldsymbol{\Sigma}_m \boldsymbol{V}_m{}^T. \tag{5.27}$$

Our purpose of this approach is to design the basis of the coordinate system in which the data is divided into the physical characteristic direction and the cognitive characteristic direction. First, let us design the vector $\mathbf{r_{phys}}$ and $\mathbf{r_{cog}}$ of which components have the value 0 or 1. The components of these vectors are defined by the author as follows; If the $i$-th component of feature vector has a relation with physical (cognitive) characteristics, then, we set $r_{phys}(i) = 1(r_{cog}(i) = 1)$, otherwise $r_{phys}(i) = 0(r_{cog}(i) = 0)$. Using $\mathbf{U_m}$, $[\mathbf{r_{phys}}, \mathbf{r_{cog}}]$ can be decomposed as follows:

$$\mathbf{R} = [\mathbf{r_{phys}}, \mathbf{r_{cog}}] = \mathbf{U_m c_{mr}}, \tag{5.28}$$

where $\mathbf{c_{mr}}$ is the reduced m-dimensional vectors. From this equation, $\mathbf{c_{mr}}$ can be formulated as

$$\mathbf{c_{mr}} = \mathbf{U_m}^{\#}\mathbf{R} = (\mathbf{U_m}^{\mathbf{T}}\mathbf{U_m})^{\mathbf{-1}}\mathbf{U_m}^{\mathbf{T}}\mathbf{R} = \mathbf{U_m}^{\mathbf{T}}\mathbf{R}, \tag{5.29}$$

where $\mathbf{U_m}^T\mathbf{U_m} = \mathbf{E}$. Thus, $\mathbf{R}$ can be approximated by $\mathbf{R}_m = \mathbf{U_m U_m}^T\mathbf{R}$. We create the basis for the physical/cognitive characteristics $\mathbf{W}_{CP} = [\mathbf{w}_{phys}, \mathbf{w}_{cog}]$ by normalizing each column vectors of $\mathbf{R}_m$.

From the singular value decomposition of the features, the dimension of the projected space is expected to be $m \geq 2$, whereas the number of the basis $\mathbf{W}_{CP}$ defined above was 2. Next, we design the rest basis vectors $\mathbf{W}_{rest} \in \mathcal{R}^{n \times (m-2)}$, i.e., $\mathbf{W}_m = [\mathbf{W}_{CP}, \mathbf{W}_{rest}] \in \mathcal{R}^{n \times m}$. Let us design the $\mathbf{W}_{rest}$ so as to meet the following criteria:

1. The range space of the $\mathbf{W}_{rest}$ will be the orthogonal complement of the range space of $\mathbf{W}_{CP}$, and the range space of the $\mathbf{W}_m$ will be the same with the range space of $\mathbf{U}_m$.

2. Each column vector of the $\mathbf{W}_{rest}$ will be the orthonormal vector.

For the first criteria, $\mathbf{W}_{rest}$ needs to orthogonal to $\mathbf{W_{CP}}$ and to be included only in the range space of $\mathbf{U}_m$. To meet this criteria, $\mathbf{W_{rest}}$ needs to meet these two conditions: Firstly the equation $\mathbf{W_{CP}}^T\mathbf{W}_{rest} = \mathbf{0}$ is required. Thus,

$$\mathbf{W}_{rest} = \mathbf{W_{CP}}^{T\#}\mathbf{0} + \{\mathbf{E} - (\mathbf{W_{CP}^T}^{\#}\mathbf{W}_{CP}^T)\}\mathbf{Y} \tag{5.30}$$

$$= \{\mathbf{E} - (\mathbf{W_{CP}}\mathbf{W_{CP}}^{\#})^{\mathbf{T}}\}\mathbf{Y} \tag{5.31}$$

$$= (\mathbf{E} - \mathbf{W_{CP}}\mathbf{W_{CP}}^{\#})\mathbf{Y}, \tag{5.32}$$

where $\mathbf{Y}$ is the arbitrary vector. Secondly, the equation

$$(\mathbf{E} - \mathbf{U_m}\mathbf{U_m}^{\#})\mathbf{W_{rest}} = \mathbf{0} \tag{5.33}$$

is required. Equation (5.33) means that $\mathbf{W_{rest}}$ is the subspace of the range space of $\mathbf{U}_m$. From Eq. (5.32) and Eq. (5.33),

$$(\mathbf{E} - \mathbf{U_m}\mathbf{U_m}^{\#})(\mathbf{E} - \mathbf{W_{CP}}\mathbf{W_{CP}}^{\#})\mathbf{Y} = \mathbf{0}. \tag{5.34}$$

Putting $\mathbf{E} - \mathbf{U_m}\mathbf{U_m}^{\#} = \mathbf{z_1}$ and $\mathbf{E} - \mathbf{W_{CP}}\mathbf{W_{CP}}^{\#} = \mathbf{z_2}$, Eq. (5.34) is solved as

$$\mathbf{Y} = \mathbf{z_2}\{\mathbf{E} - (\mathbf{z_1}\mathbf{z_2})^{\#}(\mathbf{z_1}\mathbf{z_2})\}\mathbf{z}, \tag{5.35}$$

where $\mathbf{z}$ is the arbitrary vector. The matrix $\mathbf{z_2}\{\mathbf{E}-(\mathbf{z_1}\mathbf{z_2})^{\#}(\mathbf{z_1}\mathbf{z_2})\}$ has a rank $= m-2$, so from this matrix, we can acquire $\mathbf{W_{rest}}$.

When the basis of the coordinate system is defined as mentioned above, the data of the participants are plotted onto the physical-cognitive plane. Let $\mathbf{C_k}$ the coordinates on the physical-cognitive plane of the mother set and let $\mathbf{C_s} \in \mathbf{C_k}$ the coordinates on the physical-cognitive plane of the sampled data from the mother set. $\mathbf{C_k}$ is calculated as

$$C_k = [\mathbf{W}_{CP}, \mathbf{W}_{rest}]^{\#}\,\Theta. \tag{5.36}$$

For the sampled dataset, we also have another feature vectors $\Theta_s$ for each participant in the dataset. Through the same algorithm, we can acquire $\tilde{\mathbf{W}}_\mathbf{m} = \left[\tilde{\mathbf{W}}_\mathbf{CP}, \tilde{\mathbf{W}}_\mathbf{rest}\right]$ for $\Theta_s$, and using $\tilde{\mathbf{W}}_\mathbf{m}$, we can acquire the coordinates on the other physical-cognitive plane $\tilde{\mathbf{C}}_\mathbf{s}$, i.e., $\tilde{\mathbf{C}}_\mathbf{s}$ and $\mathbf{C_s}$ are the feature vectors for the same person in different dataset.

Since the basis of the physical-cognitive plane $\mathbf{W_m}$ and $\tilde{\mathbf{W}}_\mathbf{m}$ designed on the purpose of express the physical and cognitive frailty characteristics independently, we can regard them as to be transformed linearly. Thus, $\mathbf{C_s}$ is calculated as the deformation of $\tilde{\mathbf{C}}_\mathbf{s}$, so the transforming matrix $\mathbf{K}$ is calculated as follows:

$$\mathbf{K}\tilde{\mathbf{C}}_\mathbf{s} = \mathbf{C_s} \tag{5.37}$$

$$\mathbf{K} = \mathbf{C_s}\tilde{\mathbf{C}}_\mathbf{s}^{\#}. \tag{5.38}$$

Once we acquire $\mathbf{K}$, we can generalize features acquired from our measurement $\Theta_s$ into the mother dataset. We use the survival function for $\Theta$, so we will be able to estimate at what percentage to the top rank the participants who hadn't participated in the large-scale cohort study places in the mother set.

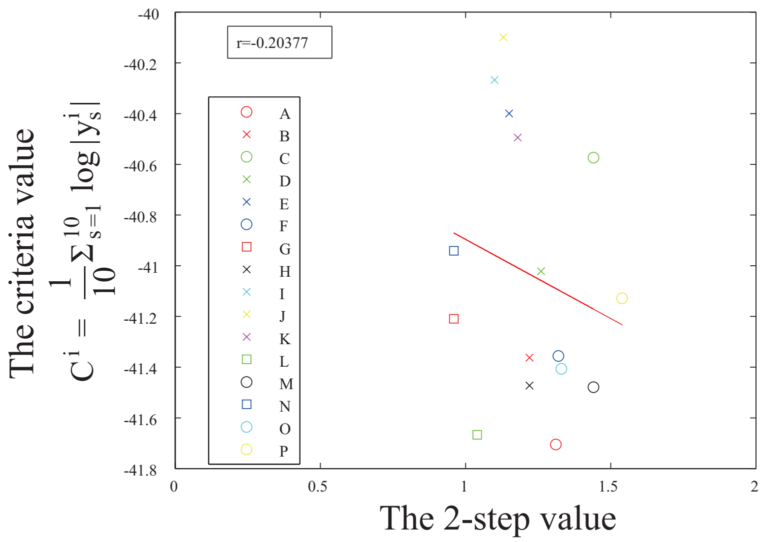



Figure 5.4: The extracted features from 2-step motion data for each participant.

## 5.5.2 Results

### Features acquired from the trained filter for 2-step motion data

Figure 5.4 shows the extracted features for each participant. The scores were extracted by the filter that is trained by motion data of 16 elderly people. Fig. 5.4 shows the relationship between 2-step value and the frailty scores (the mean of the extracted features) in semi-log scale. As shown in Fig. 5.4, the correlation coefficient between the 2-step values and the criteria value $C^i$s was -0.20, so 2-step values and the criteria value $C^i$s have a weak correlation. From this result, we can say that we could extract features that have a weak relationship with 2-step value. From Fig.5.4, the frailty scores for participants who have the closer 2-step value are varied, so the frailty score may include other sets of information for their physical abilities, and there is a possibility for clustering participants.

### The result and qualitative analysis of grouping based on the frailty score

The result of clustering based on the frailty score (, or $C^i$ in Eq. (5.16)) is shown on Tab. 5.1. In the 6th-8th column, we put underline for the values that exceed the criteria for the locomotive syndrome stage 1 and changed the color of the values that exceed the criteria for the locomotive syndrome stage 2. In the 9th-11th column, we changed the color of the values when the values meet one of these following criteria:

- For the 9th column, walking speed $< 1$ m/s[33]
- For the duration on one-leg stand duration with vision $< 15$ s
- For the time for Time UP & Go test $> 11$ s

First, as a qualitative considering, we compared the participants in each group from a point of view of results among various tests and caught the tendency of each group.

It is clarified that the elderly participants in each group have a tendency as follows:

- Group (a): Their 2-step values are relatively better. Or in case of the worse 2-step value, their results of other tests were relatively better compared with other participants who have the same scores with them (the better score in other tests were underlined on Tab. 5.1).
- Group (b): Their 2-step values are relatively worse.

Table 5.1: Results of motion measurements and the score value (extracted feature value). The participants are divided into 4 frailty groups based on the score in the 5th column.

| Frailty Group | ID | Gender | Age | Score (mean of the feature) | 2-step value | # of success in Stand-up test | GLFS-25 score | Average walking speed (m/s) | Time for TUG test (s) | Duration on Stand one-leg test (s) |
|---|---|---|---|---|---|---|---|---|---|---|
| | A(B24) | M | 69 | -41.7 | 1.31 | 3 | 1 | 1.05 | 5.36 | 60 |
| | L(B15) | M | 75 | -41.6 | 1.18 | 0 | 3 | 1.16 | 7.14 | 14 |
| | M(B13) | F | 74 | -41.4 | 1.44 | 3 | 0 | 1.06 | 5.32 | 60 |
| | H(B21) | M | 71 | -41.4 | 1.22 | 2 | 1 | 1.01 | 5.55 | 37 |
| (a) | O(B07) | M | 77 | -41.4 | 1.33 | 3 | 1 | 0.95 | 5.52 | 60 |
| | B(B02) | M | 77 | -41.3 | 1.22 | 3 | 2 | 1.05 | 6.10 | 37 |
| | F(B19) | F | 80 | -41.3 | 1.32 | 0 | 6 | 1.05 | 6.45 | 22 |
| | G(B18) | F | 99 | -41.2 | 0.96 | 1 | 32 | 0.59 | 10.41 | 8 |
| | P(B14) | F | 78 | -41.1 | 1.54 | 3 | 0 | 1.03 | 4.96 | 60 |
| | D(B01) | F | 72 | -41.0 | 1.26 | 2 | 2 | 1.03 | 7.18 | 60 |
| | N(B20) | F | 79 | -40.9 | 0.96 | 0 | 14 | 0.74 | 8.54 | 7 |
| | C(B22) | M | 80 | -40.5 | 1.44 | 3 | 1 | 1.22 | 5.14 | 25 |
| (b) | K(B03) | M | 81 | -40.4 | 1.04 | 1 | 3 | 0.76 | 7.18 | 38 |
| | E(B16) | F | 75 | -40.3 | 1.15 | 0 | 13 | 0.95 | 6.85 | 20 |
| | I(B05) | F | 78 | -40.2 | 1.13 | 3 | 11 | 1.05 | 6.89 | 60 |
| | J(B09) | F | 84 | -40.0 | 1.10 | 1 | 2 | 0.54 | 9.99 | 15 |

**The result and quantitative analysis of clustering based on the frailty score**

Second, we calculated the thigh joint angles and the trajectories of their hands during the 2-step motion. For the thigh joint angles, we calculated the thigh joint angles in the flexion/extension direction for both legs during their 1st step to the 3rd step. The joint angle data were normalized in time by one walking-cycle. We acquired the maximum amplitude and period of the waveforms by Fast Fourier Transform. Note that the 2-step motion is different from the walking motions in the point that the 3rd step will be stepping so that both toes will be aligned. Tab. 5.2 shows the relationship between the group and the mean ± SD of the maximum amplitude of the component of waveforms of the thigh joint angle data and its period. The upper side is the group based on criteria for locomotive syndrome for comparison, the lower side is the group based on the frailty scores. From the upper side of Tab. 5.2, participants in the higher stage of the locomotive syndrome group showed the relatively smaller amplitude of the joint angle. All groups showed a longer period of waveforms for the 2nd step joint angle data compared with the 1st step joint angle data. Also, for the Locomo-1 stage group participants, their period of the 2nd step is relatively small compared with other groups. This can be explained that participants in the Locomo-1 stage cannot stand firm enough during their 2nd step. The same tendency on the amplitude and the period can be shown on the lower side of the Tab. 5.2.

For the trajectory of the hand, we calculated the length of the trajectory as follows:

$$\frac{\|X_m - X_e\| + \|X_e - X_s\|}{L_{arm}}, \tag{5.39}$$

where $X_m$ is the coordinate of the marker position on the MP joint of the middle finger, $X_e$ is the coordinate of the marker position on the elbow joint, $X_s$ is the

Table 5.2: The relationship between the groups based on criteria for the locomotive syndrome / frailty scores and the mean ± SD of the maximum amplitude of the component of the waveforms and its period.

| | Frailty group | Mean±SD | | | |
|---|---|---|---|---|---|
| | | Amplitude | | Period | |
| | | 1st step | 2nd step | 1st step | 2nd step |
| Group based on criteria for locomotive syndrome | Non-Locomo stage group | 46.5±3.99 | 22.9±4.26 | 0.78±0.03 | 1.17±0.42 |
| | Locomo-1 stage group | 35.5±9.01 | 23.2±5.63 | 0.64±0.16 | 0.94±0.46 |
| | Locomo-2 stage group | 24.2±4.42 | 17.0±4.72 | 0.80±0.28 | 1.17±0.91 |
| | Frailty group | Mean±SD | | | |
| | | Amplitude | | Period | |
| | | 1st step | 2nd step | 1st step | 2nd step |
| Group based on frailty scores | Group (a) | 40.4±10.5 | 21.7±4.26 | 0.74±0.09 | 1.09±0.47 |
| | Group (b) | 33.7±9.84 | 22.2±6.69 | 0.70±0.23 | 1.04±0.62 |

coordinate of the marker position on the shoulder joint, and $L_{arm}$ is approximated length of the upper arm that is calculated from the initial values of $X_m$, $X_e$, $X_s$:

$$L_{arm} = \|X_m(0) - X_e(0)\| + \|X_e(0) - X_s(0)\|. \tag{5.40}$$

The relationships between groups based on criteria for the locomotive syndrome / frailty scores and the mean ± SD of the trajectory length of the MP marker are shown on Tab. 5.3. The upper side is the group based on criteria for locomotive syndrome for comparison, the lower side is the group based on frailty scores. From the upper side, the participants in the higher stage of the locomotive syndrome group show the longer hand trajectory for the same side with the 1st step, this can be regarded as balancing during stepping the 2nd step. On the other hand, Locomo-1 stage group shows a longer trajectory for the same side with the 2nd step, too. This can be explained that the participants in this group cannot balance during the 2nd step and they also move their hands widely during the 3rd step. For the lower side, The same tendency of the length of the trajectory was shown. The participants in group (b) showed a longer trajectory than group (a), which means that participants in group (b) moved their arms more than participants in group (a).

**Features acquired from the trained filter for P300 EEG data**

The average percentage of perceived stimuli was 88 %. The worst participant perceived 71 % of the target stimuli, however, 11 participants perceived over 85 % stimuli. One participant reported 2-3 more stimuli (i.e., one participant perceived 32-33 stimuli though we showed him 30 stimuli). For the participants who are in their 70s, the average percentage of perceived stimuli was 91 %. Features are extracted from EEG data of 13 people (1 people was excluded when calculating the features since the participant did not meet the including criteria for the EEG data written in sec. 5.3.6). The relationship between the latency (the time P300 peak starts rising up) and the absolute value of the extracted features in semi-log scale are plotted on Fig. 5.5, and the relationship between the amplitude of the P300 peak and the absolute value of the extracted features in semi-log scale are plotted on Fig. 5.6. Fig. 5.5 shows that the absolute value of extracted features gets bigger when the latency gets shorter ($r$ = -0.48, p = 0.09), and Fig. 5.6 shows that the absolute value of extracted features

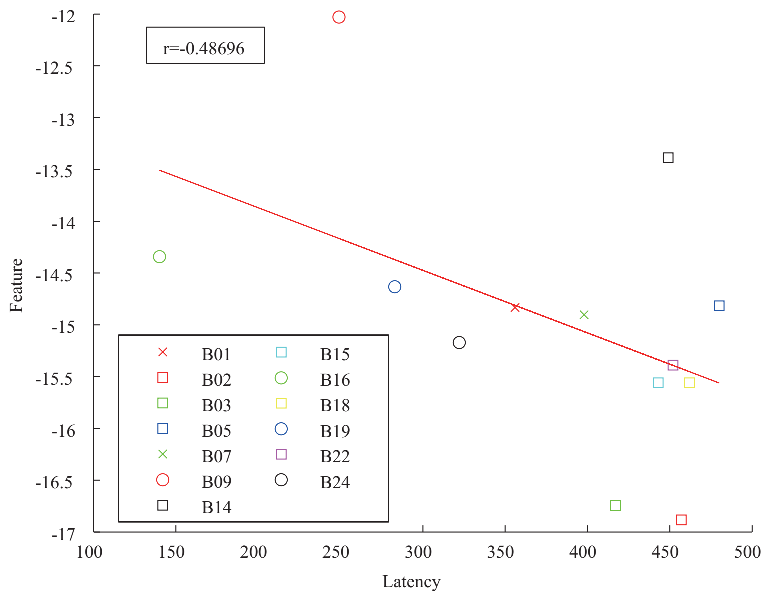



Figure 5.5: The relationship between the extracted feature in log-scale and the P300 latency.

gets bigger when the amplitude gets bigger ($r = 0.56$, p $= 0.04$).

### Plotting features onto one 2D plane

The $C^i$s extracted from the 2-step motion data and the $C^i$s from the EEG data during the P300 task of 13 participants were plotted on Fig. 5.7. The smaller features extracted from the 2-step motion and the larger features extracted from the EEG data during the P300 task indicates better physical/cognitive functions. So, plotting onto the upper left side indicates the healthier person and plotting onto the lower right side indicates declining both physical and cognitive abilities.

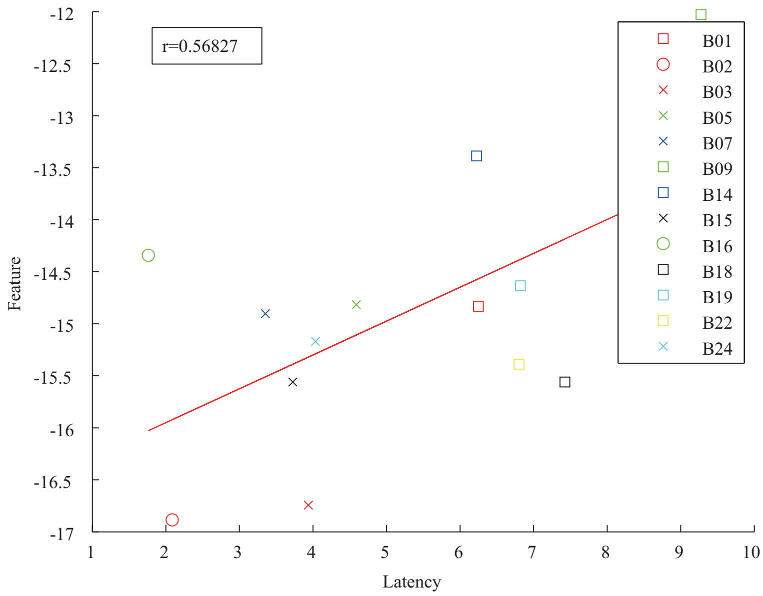



Figure 5.6: The relationship between the extracted feature in log-scale and the P300 amplitude.

### Calculated log-likelihood scores for HDS-R

The calculated $C^i$ from Eq. (5.22) for the HDS-R score are shown on Tab. 5.4.

For the imputation, the leave-one-out cross-validation tests were executed in response to each item of the 14 participants and check whether the imputed missing score was correct. The average classification rate was 88.4% and the error between the estimated score and the actual value was $-0.16$.

### Curve-fitting results for GLFS-25 score distribution

Fig. 5.8 shows P(n) calculated theoretically, and Fig. 5.9 shows P(n) calculated based on the result in the Kashiwa-study. From the curve-fitting analysis, $a$ was 0.142 and $b$ was -0.163. Thus, the regression curve was expressed as

$$P(n) = 0.142 \exp(-0.163n). \tag{5.41}$$

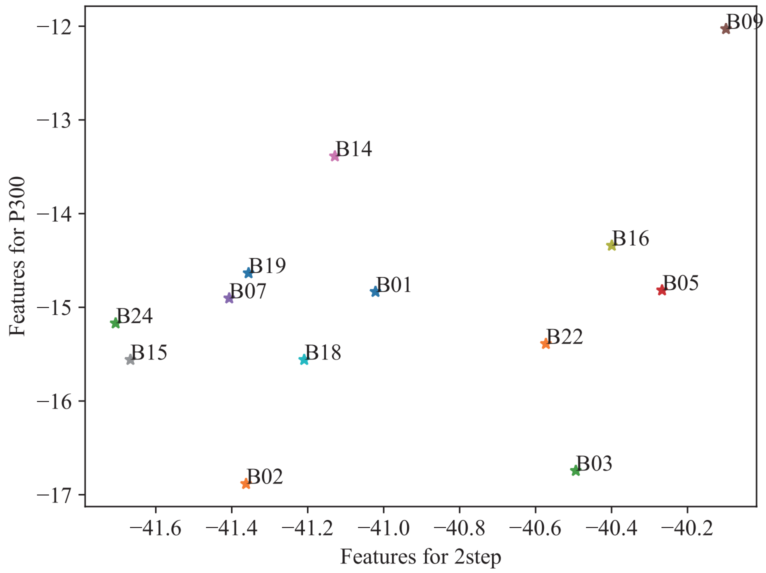



Figure 5.7: The plotted frailty scores (absolute value) of 13 elderly participants in log-scale on a physical-brain activity plane.

The calculated $\log P(\mathbf{x}|\mathbf{n})$ is illustrated on Fig 5.10.

Using Eq. (5.41), we trained the stumble risk estimator constructed in 4.4.5 again. The modified stumble risk for the participants who showed nonzero fall risk are on Tab. 5.5.

#### Statistical approximation from the Kashiwa study

The statistical information (mean and variance) of all over the Kashiwa study in 2015-2016 is on Tab. 5.6 and the results of each test of the 11 participants are on Tab. 5.7. To calculate the statistical information, we avoided the participants who have missing data (8 for walk speed; 11 for the 2-step test; 1 for the stand-up test; 15 for the limb skeletal muscle mass; 2 for MMSE; 11 for GLFS-25) from 950 participants' data. In the following part, 914 participants with no missing data for all the items were analyzed.

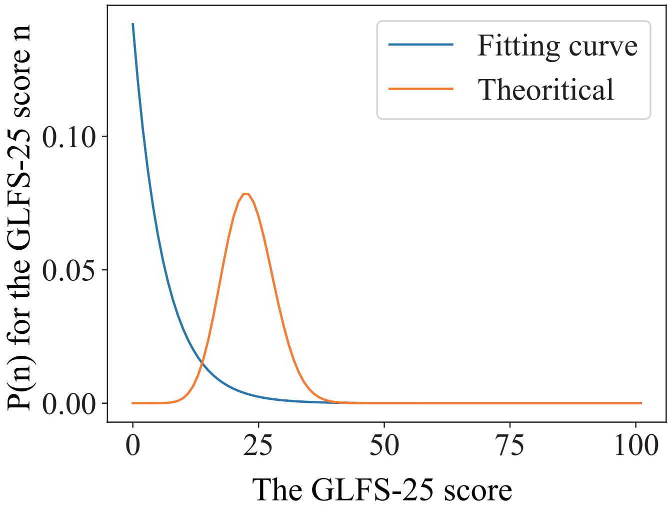



Figure 5.8: The likelihood P(n) for the GLFS-25 score n calculated theoretically (the red line) and the fitting-curve of the probability P(n) calculated from the Kashiwa study (the blue line).

The probability of the results of the walk speed, the 2-step test, the stand-up test, and the limb skeletal muscle mass are calculated by the probabilistic density function of the normal distributions. The probability of the score of MMSE and the score of GLFS-25 are calculated by the probabilistic density function of the exponential distributions.

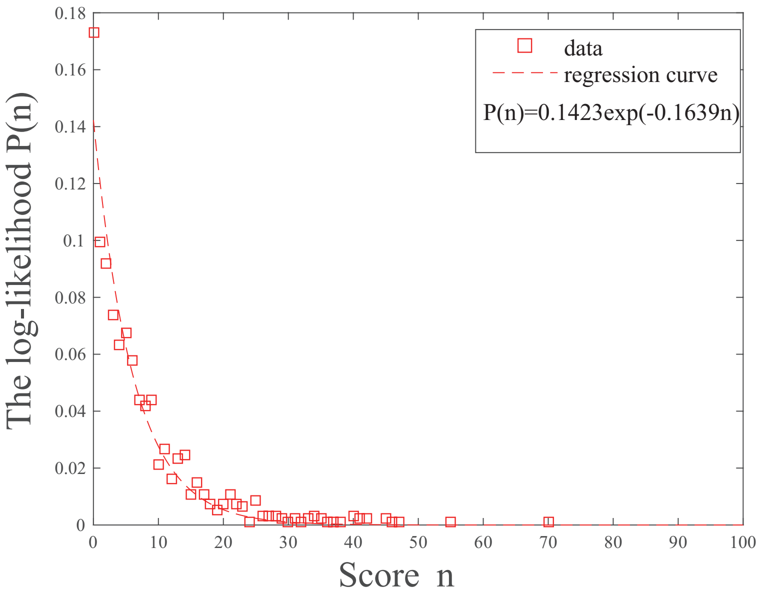



Figure 5.9: The probability P(n) for the GLFS-25 score n calculated from the result of Kashiwa study.

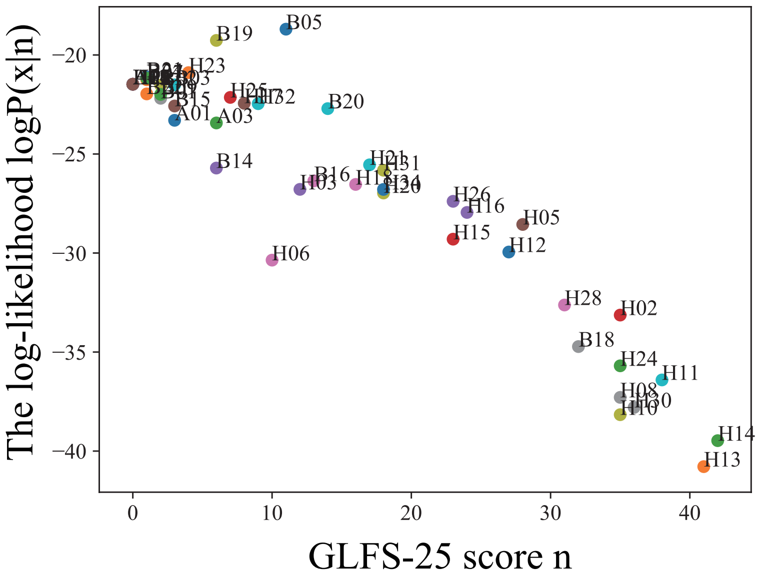



Figure 5.10: The calculated $\log P(\mathbf{x}|\mathbf{n})$ for the GLFS-25 score n using the regression curve from the result of Kashiwa study. The ID starts from ‘A’ indicates the young participant, the ID starts from ‘B’ indicates the elderly participant of the measurement, and the ID starts from ‘H’ indicates the elderly who is in the hospitalized patients’ group.

Table 5.3: The relationship between groups based on criteria for the locomotive syndrome/frailty scores and the mean ± SD of the trajectory length of the MP marker.

| | Frailty group | Mean±SD of the trajectory length | |
|---|---|---|---|
| | | 1st step side | 2nd step side |
| Group based on criteria for locomotive syndrome | Non-Locomo stage group | 0.14±0.06 | 0.09±0.06 |
| | Locomo-1 stage group | 0.24±0.21 | 0.14±0.11 |
| | Locomo-2 stage group | 0.22±0.14 | 0.08±0.05 |
| | Frailty group | Mean±SD of the trajectory length | |
| | | 1st step side | 2nd step side |
| Group based on frailty scores | Group (a) | 0.15±0.07 | 0.10±0.06 |
| | Group (b) | 0.26±0.21 | 0.13±0.11 |

Table 5.4: calculated $C^i$ for the HDS-R response patterns

| ID | Gender | Age | Score | HDS-R |
|---|---|---|---|---|
| B24 | M | 70 | 2.93 | 30 |
| B13 | F | 75 | 2.93 | 30 |
| B16 | F | 76 | 1.96 | 29 |
| B15 | M | 76 | 1.51 | 29 |
| B01 | F | 73 | 1.51 | 29 |
| B14 | F | 79 | 0.74 | 29 |
| B07 | M | 78 | 0.55 | 28 |
| B19 | F | 81 | 0.55 | 28 |
| B22 | M | 81 | 0.42 | 28 |
| B09 | F | 86 | -1.97 | 27 |
| B05 | F | 79 | -2.84 | 25 |
| B02 | M | 78 | -3.93 | 25 |
| B18 | F | 99 | -8.51 | 22 |
| B03 | M | 83 | -15.4 | 20 |

Table 5.5: Estimated risk by the modified P(n) for the score $n$ for GLFS-25.

| ID | Fall risk $r_{fall}$[%] | Fall tendency $r_{tendency}$[%] | Stumble risk $r_{stumble}$[%] |
|---|---|---|---|
| B05 | 100 % | 75.7 % | 75.7 % |
| B14 | 0.016 % | 40.3 % | 0.006 % |
| B16 | 100 % | 35.1 % | 35.1 % |
| B18 | 100 % | -32.2 % | -32.2 % |
| B19 | 81.5 % | 73.9 % | 60.3 % |
| B20 | 100 % | 57.9 % | 57.9 % |

Table 5.6: Statistic information of each test in the Kashiwa study. In the walk speed test, the average walking speed for 5 m is recorded. In the 2-step test, the 2-step value (the distance in 2 strides divided by the participant's height) is recorded. In the stand-up test, the combination of the height of the chair (10 cm, 20 cm, 30 cm, and 40cm) and the using leg (both legs, single-leg) is recorded. We converted this combination to the code 0 to 8. For the limb skeletal muscle mass, the limb skeletal muscle mass is recorded. We analyzed the limb skeletal muscle mass separately for men and women.

| Test item | Mean | Variance |
|---|---|---|
| Walk speed [m/s] | 1.38 | 0.0581 |
| The 2-step test | 1.37 | 0.0260 |
| The stand-up test | 4.42 | 1.50 |
| The limb skeletal muscle mass[kg] (Men) | 19.8 | 7.54 |
| The limb skeletal muscle mass[kg] (Women) | 13.5 | 3.96 |
| MMSE | 28.4 | 3.05 |
| GLFS-25 | 7.01 | 71.3 |

Table 5.7: The results of walk speed, the 2-step test, the stand-up test, the limb muscle mass, the score of MMSE, and the score of GLFS-25. The stand-up test results are 'cannot for all heights', '40 cm by both legs', '30 cm by both legs', '20 cm by both legs', '10 cm by both legs', '40 cm by single-leg', '30 cm by single-leg', '20 cm by single-leg', '10 cm by single-leg' and coded them as the number 0 to 8.

| ID | Gender | Walk speed [m/s] | 2-step value | The stand-up test | The limb muscle mass [kg] | MMSE score | GLFS-25 score |
|---|---|---|---|---|---|---|---|
| B01 | F | 1.32 | 1.53 | 4 | 12.6 | 29 | 6 |
| B03 | M | 1.14 | 1.35 | 3 | 17 | 27 | 8 |
| B05 | F | 1.35 | 1.42 | 5 | 8.7 | 27 | 6 |
| B07 | M | 1.39 | 1.47 | 5 | 19.9 | 27 | 0 |
| B09 | F | 1.25 | 1.35 | 5 | 7.8 | 27 | 2 |
| B14 | F | 1.43 | 1.61 | 6 | 12.2 | 30 | 4 |
| B15 | M | 1.47 | 1.43 | 4 | 19.7 | 30 | 3 |
| B16 | F | 1.47 | 1.27 | 3 | 11.3 | 29 | 14 |
| B18 | F | 0.85 | 1.30 | 5 | 8.1 | 24 | 16 |
| B19 | F | 1.22 | 1.26 | 4 | 11.2 | 29 | 13 |
| B20 | F | 1.35 | 1.32 | 2 | 13.4 | 29 | 10 |
| | | (Did not participated our 2nd measurement) | | | | | |
| B22 | M | 1.47 | 1.38 | 5 | 18 | 29 | 1 |

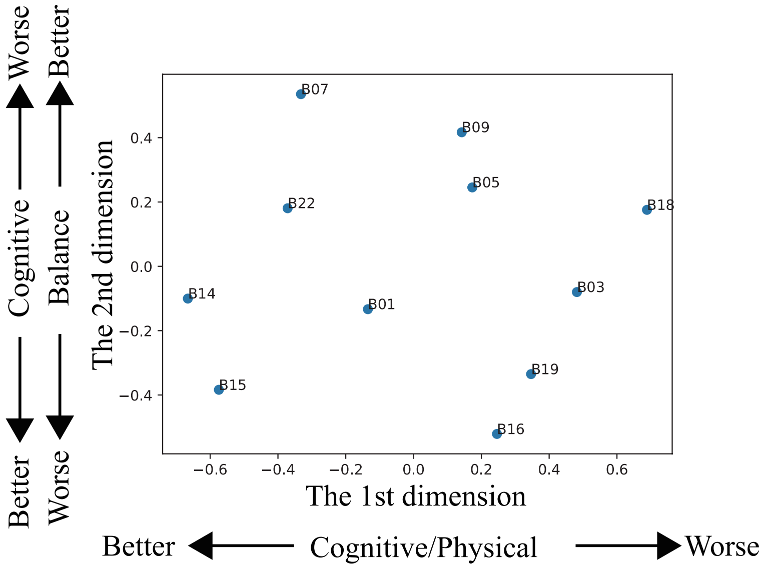



Figure 5.11: The 1st and the 2nd principle component of the result features of the Kashiwa study.

We did a principal component analysis and reduced the feature vector dimension to 2. The 1st and the 2nd principal components are plotted onto Fig. 5.11. The Pearson's correlation coefficient $r$ between the 1st/2nd principal component and the features $\Theta$. For the 1st component, the walk speed ($r = 0.80$, $p < 0.01$), the 2-step test ($r = 0.76$, $p < 0.01$), the limb muscle mass ($r = 0.75$, $p < 0.01$) had the strong and significant positive correlations and the score of MMSE ($r = -0.72$, $p = 0.01$), the score of GLFS-25 ($r = -0.71$, $p = 0.01$) had the strong negative correlations, whereas the stand-up test ($r = 0.38$, $p = 0.24$) had no significant correlation. Thus, the bigger value in the 1st principal component indicates the declining of the cognitive and physical abilities. For the 2nd principal component, the stand-up test ($r = -0.66$, $p = 0.02$) and the score of MMSE ($r = -0.64$, $p = 0.03$) had the relatively strong and significant negative correlations, whereas the walk speed ($r = 0.22$, $p = 0.50$), the 2-step test ($r = -0.22$, $p = 0.50$), the limb muscle mass ($r = 0.08$, $p = 0.79$) the score of GLFS-25 ($r = 0.59$, $p = 0.05$) showed no significant correlations.

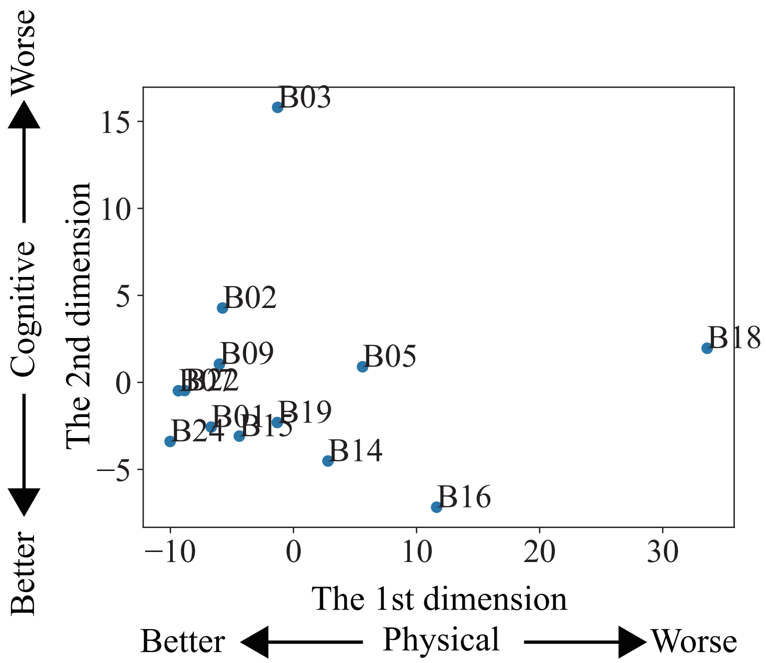



Figure 5.12: The 1st and the 2nd principle component of the result features of our measurement calculated from the 6-dim feature vectors.

**The principal component analysis on the small-scale dataset**

We did the principal component analysis (PCA) and reduced the dimension of the feature vector to 2. The 1st/2nd principle components are plotted on Fig. 5.12. The Pearson's correlation coefficient $r$ between the 1st/2nd principal component and the features $\Theta$. For the 1st dimension, both of the components of $\theta_{\mathbf{GLFS}}$ (for the score n, $r = 0.98$, p $< 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{n})$ of the pattern $x$, $r = -0.97$, p $< 0.01$). For the 2nd component, both of the components of $\theta_{\mathbf{HDS}}$ showed the large and significant correlation (for the score n, $r = -0.87$, p $< 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{D})$, $r = -0.92$, p $< 0.01$). Though there is only a tendency of significance, the frailty score for P300 EEG data $C_{P300}$ also showed a correlation ($r = -0.52$, p $=$ 0.06). Thus, we could extract features separately into the physical declining axis and the cognitive declining axis.

Next, we added the estimated depth perception ability $\theta_{depth}$ calculated from the visual illusion ratio $k$ described in chapter 3 so that we can connect the physical/cognitive ability declining and the stumble risk. The estimated depth perception ability feature $\theta_{depth}$, we calculate $\frac{k}{k-1} - \frac{K}{K-1}$ in Eq.3.15 that expresses the estimation error of the depth ($K = 1.18$, $\alpha = 35°$). We aligned the features as $\mathbf{\Theta^i} = \left[\theta^{\mathbf{i}}_{\mathbf{depth}}, \theta^{\mathbf{i}}_{\mathbf{HDS}}, \theta^{\mathbf{i}}_{\mathbf{GLFS}}, \mathbf{C^i_{2step}}, \mathbf{C^i_{P300}}\right]^{\mathbf{T}}$ and created the 7-dim feature vector of participant $i$ for the measurement.

We did the principal component analysis (PCA) and reduced the dimension of the feature vector to 2. The 1st/2nd principle components are plotted on Fig. 5.13. The Pearson's correlation coefficient $r$ between the 1st/2nd principal component and the features $\Theta$. For the 1st component, the estimated depth perception ability $\theta_{depth}$ ($r = 0.77$, $p < 0.01$) and both of the components of $\theta_{\mathbf{GLFS}}$ showed the large and significant correlation (for the score n, $r = 0.99$, $p < 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{n})$ of the pattern $x$, $r = -0.96$, $p < 0.01$). For the 2nd component, both of the components of $\theta_{\mathbf{HDS}}$ showed the large and significant correlation (for the score n, $r = -0.88$, $p < 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{D})$, $r = -0.92$, $p < 0.01$). Though there is only a tendency of significance, the frailty score for P300 EEG data $C_{P300}$ also showed a correlation ($r = -0.52$, $p = 0.06$). No other features did not show correlations ($p > 0.1$). Thus, the bigger value of the 1st component indicates the declining of the physical abilities whereas the lower value of the 2nd component indicates the declining of the cognitive abilities.

Seeing the Fig. 5.14, the participant B18 (the oldest participant) seems to affect the correlation between the 1st principal component and the estimated perception ability.

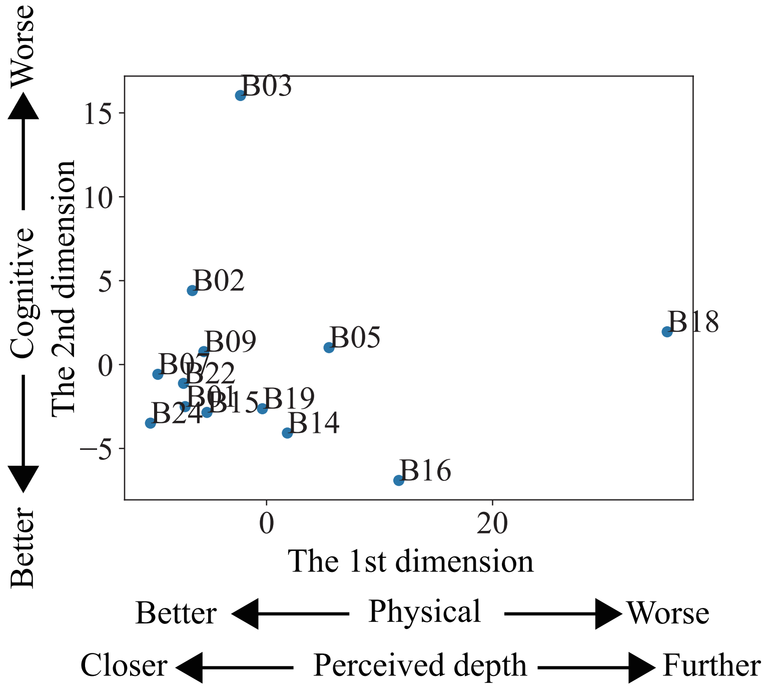



Figure 5.13: The 1st and the 2nd principle component of the result features of our measurement calculated from the 7-dim feature vectors.

We select participants who are in their 70's (7 participants), did PCA again. The data are plot on Fig 5.14. For the 1st dimension, the estimated depth perception ability $\theta_{depth}$ ($r = 0.80$, $p = 0.02$), both of the components of $\theta_{\mathbf{GLFS}}$ (for the score n, $r = 0.95$, $p < 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{n})$ of the pattern $x$, $r = -0.98$, $p < 0.01$), the frailty score for the 2-step motion capture data $C_{2step}$ ($r = 0.77$, $p = 0.04$) showed the large and significant correlation. For the 2nd dimension, both of the components of $\theta_{\mathbf{HDS}}$ showed the large and significant correlation (for the score n, $r = -0.98$, $p < 0.01$; for the log-likelihood $\log P(\mathbf{X}|\mathbf{D})$, $r = -0.92$, $p < 0.01$). Thus, we can evaluate the participant's perception ability with the physical/cognitive abilities.

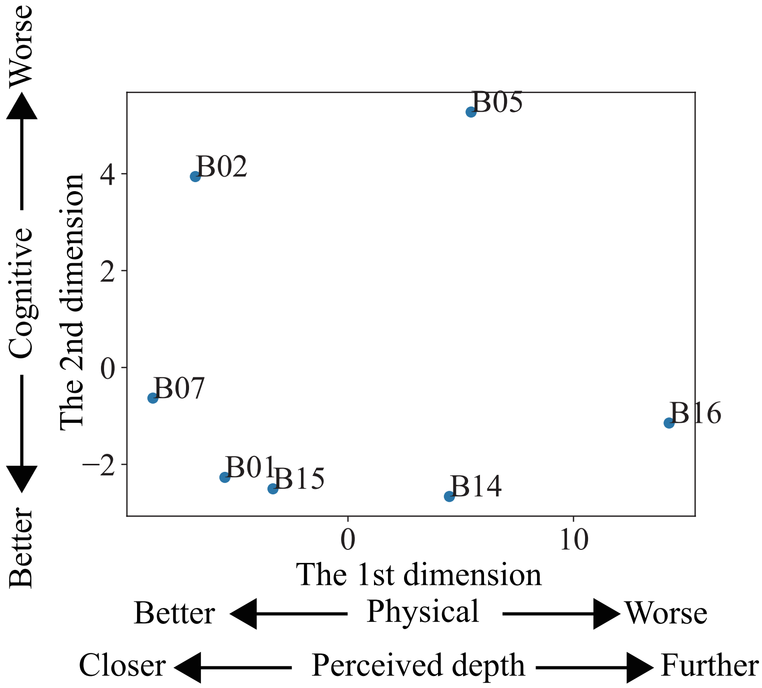



Figure 5.14: The 1st and the 2nd principle component of the result features of our measurement calculated from the 7-dim vectors. The participants are only in their 70's.

### Coordinate system transformation using matrix decomposition

The results in 5.5.2, the survival function of each participant are calculated by using the statistical information on Tab. 5.6. From the principal component analysis in 5.5.2, the walk speed, the 2-step value, the limb muscle mass, the score of GLFS-25 had a correlation with the 1st principal component. Though the score of MMSE also had a correlation with the 1st principal component, it has a correlation with the 2nd principal component, too. For the 2nd principal component, the stand-up test had a correlation, too. However, the direction of the correlation was opposite with the score of MMSE; Both showed negative correlation and it means that the bigger principal component indicates the lower cognitive ability / the better stand-up test results. From this result, we decided to treat the score of MMSE and the stand-up test separately. Then, for $\mathbf{\Theta} = [\theta_{\mathbf{walk}}, \theta_{\mathbf{2step}}, \theta_{\mathbf{standup}}, \theta_{\mathbf{muscle}}, \theta_{\mathbf{MMSE}}, \theta_{\mathbf{GLFS}}]^{\mathbf{T}}$, $\mathbf{R} = \mathbf{R_k}$ was set as

$$\mathbf{R_k} = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}^{\mathbf{T}}. \tag{5.42}$$

The singular value of the feature vector was $[38.7, 13.4, 9.91, 8.61, 6.94, 5.65]$, thus, we define $m$ as 3 for decomposing the feature vector set by Eq. (5.28).

The physical-cognitive plane is illustrated in Fig. 5.15. On Fig. 5.15, 11 participants who participated in both the 4th Kashiwa study in 2016 and the 1st and 2nd study of our experiments in 2016 and 2017.

There are layer-like distributions along with the cognitive axis of Fig. 5.15. We separated the data into 4 categories: Category (1) the value of the cognitive axis $>$ 1.0; Category (2) 0.6 $>$the value of the cognitive axis $>$ 0.5; Category (3) 0.4 $>$ the value of the cognitive axis $>$ 0.3; Category (4) 0.2 $>$ the value of the cognitive axis. The mean of each result of the Kashiwa study data $\mathbf{\Theta}$ projected in each category was calculated. The results are on Tab. 5.8. As shown in Tab. 5.8, the survival function of MMSE declines. Since we approximated the distribution of the score of MMSE as the exponential distribution, lower survival function indicates the lower score of the survival function; i.e., lower the value of the cognitive feature axes indicates the lower cognitive function of the participants.

From the results in 5.5.2, we adopt the 7-dim feature vectors;

$$\mathbf{\Theta_s} = [\theta_{\mathbf{depth}}, \theta_{\mathbf{HDS-R}}, \theta_{\mathbf{GLFS}}, \mathbf{C_{2step}}, \mathbf{C_{P300}}]^{\mathbf{T}}. \tag{5.43}$$

From the principal component analysis results, the analysis revealed that the pair

Table 5.8: The mean of each component of $\mathbf{\Theta}$ in each category. Category (1) the value of the cognitive axis $> 1.0$; Category (2) $0.6 >$the value of the cognitive axis $> 0.5$; Category (3) $0.4 >$ the value of the cognitive axis $> 0.3$; Category (4) $0.2 >$ the value of the cognitive axis.

| | Category (1) | Category(2) | Category(3) | Category(4) |
|---|---|---|---|---|
| Walk speed | 0.63 | 0.51 | 0.76 | 0.50 |
| 2-step value | 0.36 | 0.48 | 0.43 | 0.54 |
| Stand-up test | 0.34 | 0.46 | 0.40 | 0.57 |
| Limb skeletal muscle mass | 0.47 | 0.49 | 0.39 | 0.54 |
| MMSE | 1.0 | 0.53 | 0.28 | 0.10 |
| GLFS-25 | 0.58 | 0.54 | 0.64 | 0.50 |

of $\theta_{\mathbf{GLFS}}$ and $C_{2step}$, and the pair of $\theta_{\mathbf{HDS-R}}$ and $C_{P300}$ showed the correlation with the same principal component. The feature of the depth perception $\theta_{depth}$ showed a correlation together with $\theta_{\mathbf{GLFS}}$ and $C_{2step}$, however, in chapter 3, the visual illution ratio $k$ showed a correlation with the score of HDS-R. Thus, we regarded the $\theta_{depth}$ as affecting both on the physical/cognitive characteristics. Thus, the small-scale dataset, $\mathbf{R} = \mathbf{R_s}$ was set as

$$\mathbf{R_k} = \begin{bmatrix} 1 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}^{\mathbf{T}}. \tag{5.44}$$

The singular value of the feature vector was $[175.3, 40.0, 18.1, 10.7, 4.48, 2.77, 0.54]$, thus, we define $m$ as 3 for decomposing the feature vector set by Eq. (5.28).

The result of the projection onto the physical-cognitive plane is illustrated on Fig. 5.16. The $\mathbf{K}$, which is the conversion matrix from the physical-cognitive plane of the sample dataset to the physical-cognitive plane of the mother dataset was

$$\mathbf{K} = \begin{bmatrix} -0.023 & -0.020 & -0.011 \\ -0.0093 & -0.028 & -0.0055 \\ 0.0079 & -0.014 & 0.016 \end{bmatrix}. \tag{5.45}$$

From Eq. (5.45) and Eq. (5.38), we can project $\tilde{\mathbf{C}}_{\mathbf{s}}$ to $\hat{\mathbf{C}}_{\mathbf{s}}$. The projected $\hat{\mathbf{C}}_{\mathbf{s}}$ and the original $\mathbf{C}_{\mathbf{s}}$ are plotted on Fig. 5.17. From the figure, $\hat{\mathbf{C}}_{\mathbf{s}}$ tend to be projected lower side of the figure. This may be due to the bias of the measurement place or by experimenters. The mean and variance of the Kashiwa study was on Tab. 5.6 and the results of the Kashiwa study of the participants in our dataset was on Tab. 5.7, however, for all the participants, the results of our measurement lower than that of Kashiwa study (see Tab. 5.1 for more detail). Also, the difference may come from the difference between the cognitive function tests. The error in the cognitive feature axes direction is bigger than the other axis, and the lower value of the cognitive feature axes means that the lower survival function value of the MMSE scores in the Kashiwa study as we show above. As shown in [35], MMSE and HDS-R has a strong correlation, but from our calculation of the average and standard deviation of the error for each test from Tab. 5.1 and Tab. 5.6, the result of HDS-R showed lower average and bigger standard deviation ($28.0 \pm 3.20$ for MMSE; $26.7 \pm 9.61$ for HDS-R). That may make the output of the projected $\hat{\mathbf{C}}_{\mathbf{s}}$ lower.

We can calculate the survival function from Eq. (5.36), i.e., $\hat{\Theta} = [\mathbf{W}_{CP}, \mathbf{W}_{rest}]\,\hat{\mathbf{C}}_{\mathbf{k}}$.

## 5.6 Conclusion

The conclusion of this chapter is as follows:

1. To construct the system for evaluation of frailty and falling risks of elderly people, we proposed and applied a feature extraction method that can be trained by different types of data (including both macroscopic and microscopic data) to physical motion/EEG data and extracted 1-dim features.

2. Both from physical motion data and EEG data, it is suggested that the extracted features have some relationships with declining physical/brain functional abilities. We plot extracted features both from physical motion data and from brain activity data on the 2D plane and showed the frailty level can be evaluated by considering the boundary surface in the plane.

3. We also proposed the converting method from the categorical data to the consecutive data, using the distributions in the probabilistic distributions that are available from the previous research. Using this method, we converted the response patterns of the HDS-R and the GLFS-25 and extracted features using canonical correlation analysis.

4. Using the proposed method for the feature extraction, we proposed the converting method of the features from the distribution of the mother-set to the physical/cognitive declining evaluation space.

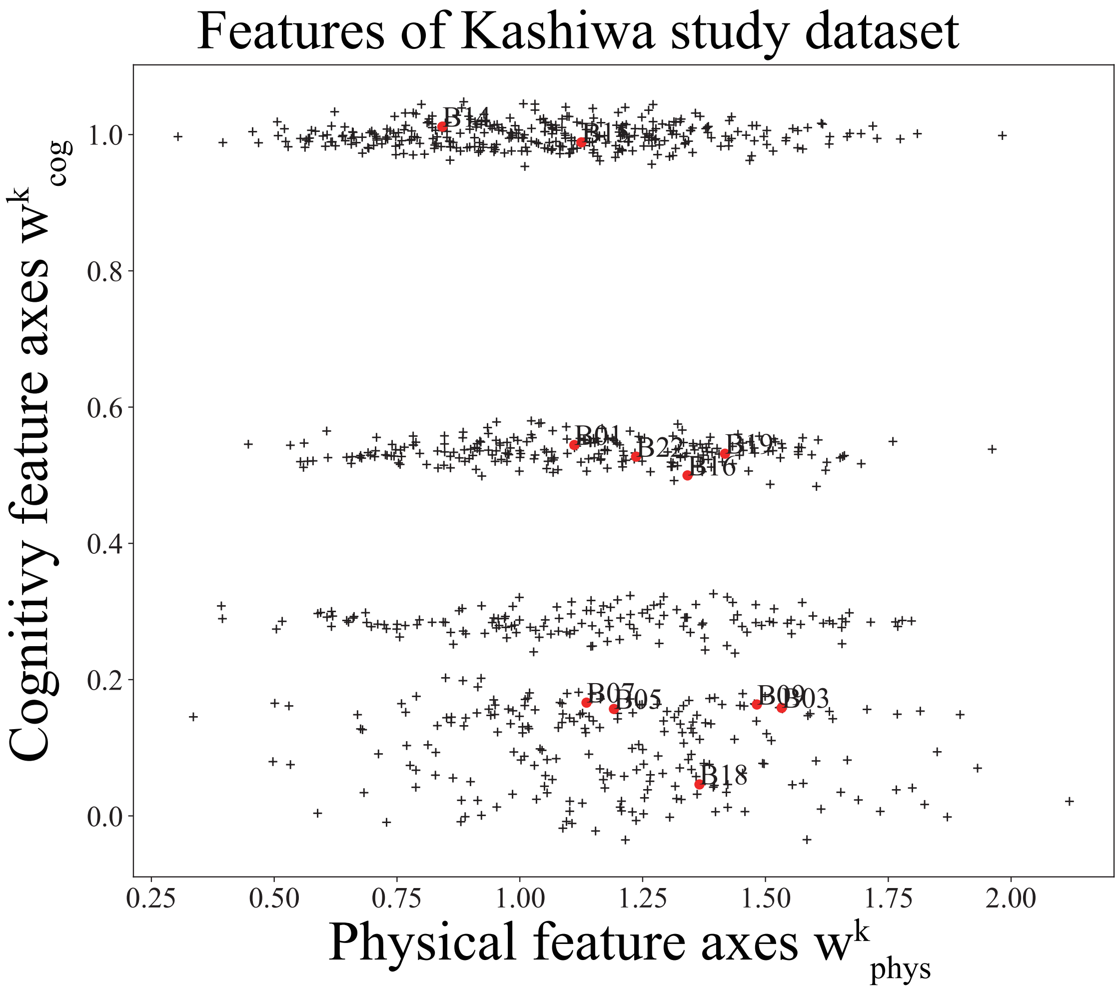



Figure 5.15: The projected coordinates of the data from Kashiwa study dataset. The black plot is of all the participants, the red circle is of the participants who participated in all of our measurement and Kashiwa study.

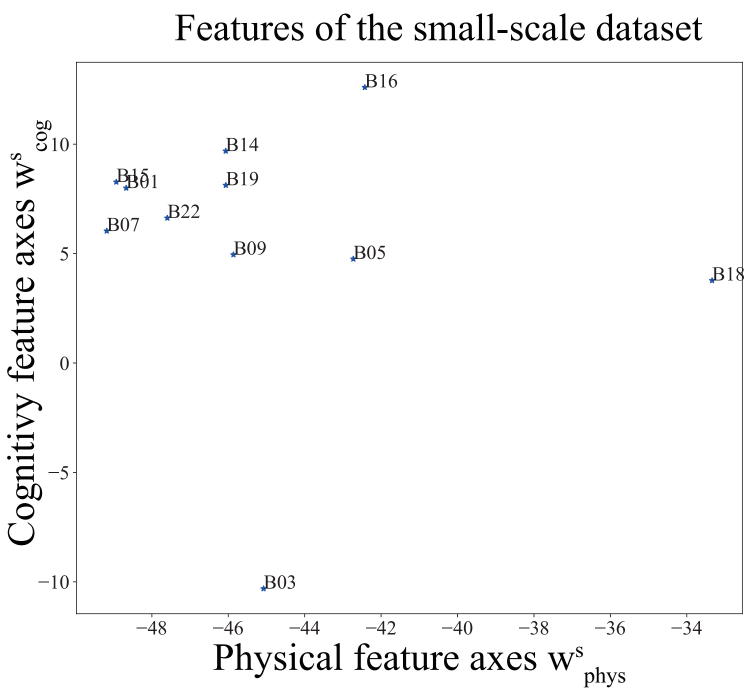



Figure 5.16: The projected coordinates of the data from the small-scale dataset.

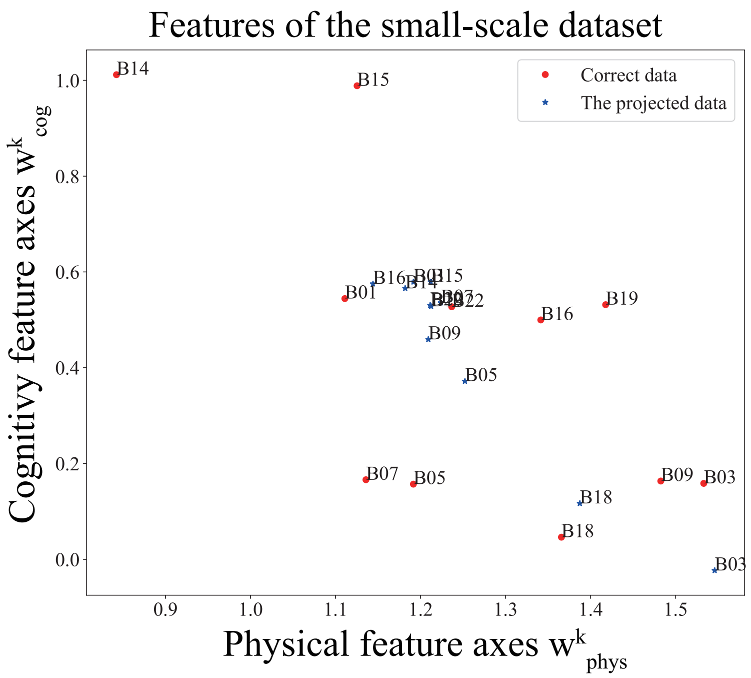



Figure 5.17: The projected $\hat{\mathbf{C}}_{\mathbf{s}}$ are plotted as the blue star, the original $\mathbf{C}_{\mathbf{s}}$ are plotted as the red circle.

# Chapter6

# Conclusion

A purpose of this dissertation was set at clarifying the dependency of the motion to the depth perception and estimating and evaluating elderly people frailty level to prevent falls. To achieve the purpose, estimating human internal depth perception is required. Another purpose of this dissertation was constructing a system that estimates and evaluates the frailty level of elderly people using multi-modal information such as motion data or brain activity data. To achieve the purpose, how to convert discrete variables such as questionnaires and how to generalize the result of the small-scale dataset were the key points. The main contributions of this dissertation would be summarized by the following three sentences: (1) By clarifying the dependency of depth perception and motions, we claimed the alternation of depth perception as a factor of stumbles. (2) A method of fall-risk estimation was established by using the log-likelihood converted from the questionnaire response patterns. (3) The frailty level of the elderly people was estimated by feature extraction from the multi-modal data consisting of motion capture data, EEG data, and the questionnaire response patterns.

In chapter 2, we asked participants to approach and touch the marker attached on the top of the ball by foot a few strides away from them. The positions of the support and swing legs just before contacting the ball was analyzed. We found that 12 out of 14 elderly participants placed their support legs significantly further from the ball than young participants. Moreover, 5 out of the 12 participants had their toes of swing legs leave at a distance further than that of the young participants. The results of the distance between the toe-off position and the ball led us to the observation that the difference of the abilities of depth perception should affect ball approaching motions of elderly people.

In chapter 3, the visual illusion by the perspective drawing of pseudo-3D scenes was used as the method to estimate the ability of depth perception. We set a hypothesis that participants estimate the position of the camera by which the image was taken as a photo. The error between the estimated camera position and the correct camera position quantitatively indicates the ability of depth perception. The visual illusion ratio $k$ was defined by the scaler ratio of 2 spheres on the 2D images. It was observed that the larger the $k$ value was identified for a participant, the closer he/she perceive an object. The visual illusion test was conducted for the same participants of chapter 2. It was statistically concluded that a participant who has a larger distance between the toe-off point and the ball position shows a larger value of $k$.

In chapter 4, we conducted the research on the interview results to the patients who were hospitalized and had experienced falls and fall-related hip fractures. We set three categories of falls: (a) falls by unexpected forces, (b) falls by losing balance, (c) other falls. The 10 most emerged nouns and their 11 most co-occurrence words were analyzed. A summary text was written by researchers after interview research. 31 out of 34 cases included at least 1 frequent or co-occurrence words in the 10 most frequent nouns in the summary text. We constructed a classifier using extracted features from the questionnaire data using log-likelihood. The leave-one-out cross-validation tests revealed that the average classification rate was 76.1% for 2-dim extracted features. We constructed the stumble risk estimator using the GLFS-25 response patterns using the proposed method to convert them into the log-likelihood. The comparison of the results of this chapter with those of chapter 3 led to the conclusion that the $k$ value of visual illusion shows the risk of fall and stumble.

In chapter 5, we described the method to evaluate the frailty level in the multi-dimensional space using the extracted features from the multi-modal data consisting of motion capture data, EEG data, and the questionnaire response patterns. We confirmed that the extracted features from motion capture data during the 2-step test and the extracted features from EEG data during the P300 task have a correlation with each result of the test/task. The extracted features were plotted onto the 2D plane. Moreover, we also converted the questionnaire response patterns into features using log-likelihood. At the final, using the large-scale data as the mother set of the elderly, we converted the extracted feature vectors into the physical-cognitive coordinate system and made a linkage with the mother set distribution in the physical-cognitive coordinate system.

The limitation of this dissertation is the fewer number of participants who had experienced falls. For further discussion, we need to see the relationships between the abnormalities of the visual illusion and fall experiences. These results showed a possibility of developing easy screening tools of the stumble risk and would help making an intervention plan to enhance the elderly's physical/cognitive status. The dissertation would provide everyone with the baseline to pursue his/her healthy life in the elderly society.

## Ethical considerations

Measurement plans in this research have been approved by the ethical committee at the University of Tokyo. When we ask elderly participants to execute motions, we check their health status through interview and blood pressure measurement by nurses beforehand and confirmed with the nurse whether they can attend the measurements or not. The participants take enough rest during each measurement tasks, the nurse and the experiment assistants were watching over their motions carefully at the side or backward of the elderly participants for not causing fallings or happening other accidents. All the participants had been explained the research purpose and the outline of the measurement before the measurement and submitted their consent forms.

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# List of Publications

## Reviewed Journals

[J-1] Tomoki Tanaka, Hiroshige Matsumoto, Bo-Kyung Son, Shujirou Imaeda, Emiko Uchiyama, Sakiko Taniguchi, Akiko Nishino, Takahiro Miura, Toshiaki Tanaka, Toshio Otsuki, Kazuhiko Nishide, Katsuya Iijima, and Junichiro Okata, "Environmental and physical factors pre-disposing middle-aged and older Japanese adults to falls and fall-related injuries in homes", Geriatrics & Gerontology International, 2018(doi:10.1111/ggi.13494).

[J-2] Emiko Uchiyama, Wataru Takano, Yoshihiko Nakamura, "Multi-class grasping classifiers using EEG data and a common spatial filter", Advanced Robotics, Vol.31, Issue. 9, pp. 468-481, 2017.(doi:10.1080/01691864.2017.1279569.)

## Reviewed Journals (in Japanese)

[J(J)-1] 今枝秀二郎, 孫輔卿, 大月敏雄, 内山瑛美子, 田中友規, 谷口紗貴子, Suthutvoravut Unyaporn，三好友良，西野亜希子，田中敏明，飯島勝矢，田中栄，松原全宏，西出和彦，「在宅高齢者における転倒状況の把握と建築的な転倒予防対策-東大病院へ入院した大腿骨近位部骨折患者の調査-」，日本建築学会 住宅系研究報告会論文集，2018(in Japanese, in printing).

[J(J)-2] 今枝秀二郎，内山瑛美子，田中友規，谷口紗貴子，金ギョンミン，長木美緒，高田遼介，三浦貴大，孫輔卿，西野亜希子，田中敏明，飯島勝矢，西出和彦，大月敏雄，"在宅高齢者の転倒実態調査に基づく転倒プロセスのモデル化 ー文京区・横浜市・柏市を対象とした調査研究 ー．" 日本建築学会 住宅系研究報告会論文集， Vol.12, pp.217-226, 2017.

## Reviewed Conference Proceedings

[C-1] Emiko Uchiyama, Toshihiro Mino, Tomoki Tanaka, Yosuke Ikegami, Wataru Takano, Yoshihiko Nakamura, Katsuya Iijima,"Exploratory research on stumble risk assessment from the motion data of the elderly", IFToMM World Congress,2018(under review).

[C-2] Shujirou Imaeda, Bo-Kyung Son, Emiko Uchiyama, Tomoki Tanaka, Sakiko Taniguchi, Suthutvoravut Unyaporn, Yusuke Miyoshi, Toshiaki Tanaka, Katsuya Iijima, Toshio Otsuki, "Combined interviews of bedside and home-visit clarify factors related with continuity of living for the elderly who experienced falls and femoral fractures", ISAIA, 2018.

[C-3] Tianwei Zhang, Emiko Uchiyama, Yoshihiko Nakamura, "Dense RGB-D SLAM for humanoid robnots in the dynamic human environments", Humanoids, 2018.

[C-4] Emiko Uchiyama, Hiroshige Matsumoto, Marina Hamada, Mio Choki, Chie Suzuki, Yufei Fu, Akiko Nishino, “Falling, fractures, and changing lifestyles for elderly Japanese: A qualitative exploratory study”, GSA’s 68th Annual Scientific Meeting proceedings, Session 185. Addressing Disability, Falls, and Mobility, Poster No.4, 2015.

[C-5] Hiroshige Matsumoto, Emiko Uchiyama, Shingo Yoshida, Kyoungmin Kim, Kouhei Miki, Bokyung Son, Akiko Nishino, “Designing built environments to prevent falls, fall-related fractures, and post-fall home confinement”, GSA’s 68th Annual Scientific Meeting proceedings, Session 1810. Disability, Falls, and Mobility 2, Poster No.47, 2015.

## Reviewed Conference Proceedings (in Japanese)

[C(J)-1] 内山瑛美子，小原大輝，味野俊裕，田中友規，中村仁彦，高野渉，飯島勝矢，「射影画像の提示による奥行知覚能力の評価」，第 24 回ロボティクスシンポジア，2018 (発表予定).

[C(J)-2] 内山瑛美子，孫輔卿，今枝秀二郎，田中友規，松本博成，森田光治良，三好友良，スタッヴォラヴット・アンヤポーン，田中敏明，飯島勝矢，松原全宏，大方潤一郎，「大腿骨近位部骨折による入院患者への聞き取り調査内容の定量的分析に基づいた転倒に関わる環境要因の推定」，転倒予防学会，2018.

[C(J)-3] 今枝秀二郎，孫輔卿，内山瑛美子，田中友規，谷口紗貴子，スタッヴォラヴット・アンヤポーン，馬場絢子，角川由香，松原全宏，大月敏雄，田中敏明，飯島勝矢，大方潤一郎，「入院時ベッドサイドインタビューと自宅訪問調査による大腿骨骨折患者の転倒状況の正確な把握」，転倒予防学会，2018.

[C(J)-4] 内山瑛美子，味野俊裕，田中友規，飯島勝矢，高野渉，中村仁彦，“フレイルのマルチモーダル情報に基づく段階評価法の研究”，講演 No. 3B1，第 23 回ロボティクスシンポジア，pp.162-167, 2018.

[C(J)-5] 味野俊裕，池上洋介，山田文香，内山瑛美子，中村仁彦，“介在ニューロンを含む脊髄神経系と有限要素筋モデルによる上腕反射系のモデリング”，講演 No. 2B3，第 23 回ロボティクスシンポジア，pp. 109-114, 2018.

[C(J)-6] 今枝秀二郎、孫輔卿、内山瑛美子、松本博成、田中友規、谷口紗貴子、金ギョンミン、高田遼介、三浦貴大、西野亜希子、西出和彦、大月敏雄、田中敏明、飯島勝矢、大方潤一郎, “地域や自宅における在宅高齢者の転倒事例に基づく建築的な転倒予防対策”, 講演 No. 4-7-4, 日本転倒予防学会学会誌 4 巻 2 号, p.97, 2017.

[C(J)-7] 内山瑛美子, 孫輔卿, 今枝秀二郎, 田中友規, 松本博成，森田光治良, スタッヴォラヴットアンヤポーン, 松原 全宏, 西野亜希子, 秋下 雅弘, 大月敏雄, 西出和彦, 田中敏明, 飯島勝矢, 大方潤一郎, “大腿骨近位部骨折により入院した

患者への聞き取り調査による転倒実態調査", ポスター No5C-9-3, 日本転倒予防学会学会誌 4 巻 2 号, p.133, 2017.

[C(J)-8] スタッヴォラヴット・アンヤポーン, 孫輔卿, 田中友規, 今枝秀二郎, 内山瑛美子, 松本博成, 森田光治良, 松原全宏, 西野亜希子, 秋下雅弘, 大月敏雄, 西出和彦, 田中敏明, 飯島勝矢, "転倒に伴う大腿骨近位部骨折により入院した高齢患者の特徴：服用薬物・合併症・ロコモティブシンドロームの観点から", ポスター No.5C-9-4, 日本転倒予防学会 4 巻 2 号, p.133, 2017.

[C(J)-9] 田中友規, 今枝秀二郎, 谷口紗貴子, 金炅敏, 松本博成, 内山瑛美子, 西野亜希子, 孫輔卿, 三浦貴大, 大月敏雄, 西出和彦, 田中敏明, 飯島勝矢, 大方潤一郎,「都市部・都市郊外部に住む中高齢者における住居内転倒状況と関連する内的要因・外的要因の検討」, 第 3 回日本転倒予防学会学術集会, 一般口演 No. 3-1-5, 日本転倒予防学会学会誌 3 巻 2 号, p.74, 2016.

[C(J)-10] 今枝 秀二郎, 田中 友規, 谷口 紗貴子, キムギョンミン, 松本 博成, 内山瑛美子, 西野 亜希子, 孫 輔卿, 三浦 貴大, 飯島勝矢, 田中 敏明, 大月敏雄, 西出和彦, 大方 潤一郎, "横浜市における高齢者の転倒事例報告と地域居住を継続可能とする環境要因の究明", 第 3 回日本転倒予防学会学術集会, ポスター No. 4-2-3, 日本転倒予防学会学会誌 3 巻 2 号, p.89, 2016.

## Oral Presentations (all in Japanese)

[O(J)-1] 内山瑛美子, 小原大輝, 田中友規, 中村仁彦, 高野渉, 飯島勝矢,「錯視課題を用いた奥行き方向の知覚能力の推定」, 第 36 回日本ロボット学会学術講演会, 論文 No.2J1-03, 2018.

[O(J)-2] Tianwei Zhang, Emiko Uchiyama, Kaixuan Guan, and Yoshihiko Nakamura, "Humanoids dense RGB-D SLAM in dynamic human environment", The 36th RSJ2018, 1I2-02, 2018.

[O(J)-3] 内山瑛美子, 味野俊裕, 田中友規, 飯島勝矢, 高野渉, 中村仁彦, "脳活動情報及び身体運動情報からの特徴量抽出による認知的フレイル評価に関する検討", 第 35 回日本ロボット学会学術講演会, 論文 No. 1B1-03, 2017.

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## Awards

[A-1] 内山瑛美子，日本ロボット学会第 33 回研究奨励賞，“脳活動情報及び身体運動情報からの特徴量抽出による認知的フレイル評価に関する検討”，第 36 回日本ロボット学会学術講演会，2018.

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