System Design for Affordable and Accountable Physically Assistive Robots with User State Estimation Function

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TOHOKU UNIVERSITY

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(使用者の状態推定機能を有する身体支援ロボットの
アフォーダブルかつアカウンタブルなシステム設計)

A dissertation submitted for the degree of
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by

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Mizuki Takeda

Abstract

In this dissertation, we introduce affordable and accountable system design for care robots, especially focusing on physically assistive robots which are controlled based on user state estimation.

Population aging phenomenon have increasing the demands for care robots. However, care robots have not been common yet in general households and welfare institutions. There are several challenges for care robots in real environment. Care robots are expected to provide better support by their mechanical strength and sensing technology. User state estimation is useful to provide appropriate support based on the user situation. However, it requires a lot of sensors, then cost and privacy challenges cause.

It is difficult for humans to understand the actions, plans, and behavior of autonomous robots and the reasons behind them, particularly when the robots include learning algorithms. Care robots which work closely with humans, however, should be trusted. Thus usability and ease of mind is important for care robots to use in real environment.

It is important that not to simply reduce sensors but to design considering how selecting and placing sensors influence robot functions. The design for accountable robots is also important hence there are various people who relate to the robots in each situation. However, most researches focused on specific systems, thus there is no general design. Therefore we propose a general design for affordable and accountable care robots. In this dissertation, we focus on physically assistive robots with user state estimation. Physical human-robot interaction and robot's autonomous action increase the importance of accountability. However, accurate system often requires a lot of sensors. Hence physically assistive robots which is controlled based on user state estimation is one of most important for considering affordability and accountability of care robots in real environment.

First, we propose the concept of affordable and accountable system design. User state estimation should be accurate to reduce safety risks, however, it often requires a lot of sensors. It is important to reduce cost focusing on influence for robot function. Hence we focus on user state estimation using a small number of sensors. The CoG position is useful to estimate human state, however, accurate CoG position calculation requires a lot of sensors. Then we consider that candidates of CoG can be obtained using less sensors than required to calculate CoG position. The range of CoG candidates changes by considering the selecting and placing sensors. Robots should be designed considering such relationship between cost and accuracy of robot's function. Less sensors results less accurate system, and then the accountability become more important. Physical human-robot interaction comes with safety risks, and therefore humans become anxious when they do not understand them. Then we propose a design architecture which is composed of 2 step; describing whole system and transcribing the system information for each stakeholder. There are various stakeholders and their use cases are different depending on the situations. Hence knowledge representation method should be designed according to the relationships among required information, stakeholders' expertise, and appropriate interfaces.

Subsequently, we propose concrete method to estimate user state using a small number of sensors. The new idea is presented that the user state can be estimated if candidates of CoG can be calculated and the ranges of them are narrow enough, even if the CoG position cannot be determined uniquely. Human link model in sagittal plane is used to calculate CoG candidates. By considering the unknown parameters' ranges of value, the CoG candidates can be calculated. The selecting and placing sensors are classified as measurements sets using the number of unknown parameters. The proposed CoG candidates calculation methods are experimentally validated and the CoG candidates ranges of the measurements sets are compared.

The state estimation method using the CoG candidates is also proposed. We set 7 features of CoG candidates for Support Vector Machine (SVM) to estimate user state. Experiments using developed robot validated the state estimation method.

Accountable system design is detailed explained by using the robot. System Modeling Language (SysML) is adopted to describe whole system. Describing whole system also contribute to transparency of embodied AI systems. Most researches focused on transparency of learning algorithms, however, robot systems contain not only learning algorithms. Hence there are several parts which should be transparent other than learning algorithm including relationship between estimation result and robot action. The relationships among required information, stakeholders' expertise, and appropriate interfaces are also discussed in detail. We should consider well about use cases as stakeholder-information relationship. The interface should be designed depending on the stakeholders' expertise since there are various stakeholders and the appropriate way to represent information is different. Specialized interfaces are useful and efficient, however, it is generally difficult for ordinary people to use such specialized tools. The relationship between information and interface is also important since the appropriate medium is different among information. Spatial information is easy to understand by using visual interface including a display, by contrast, temporal information is good to be transmitted by using auditory medium including a speaker.

We confirmed the importance of achieving accountability by the verbal guidance experiments. Verbal communication is important on nursing-care. And the temporal information including the timing of robot action is important, hence we analyze the importance of verbal guidance for physically assistive care robot. From the experiment results we confirm that the system without knowledge representation is not useful and users feel anxious and be scared. Appropriate verbal guidance is also determined and the effectiveness of the verbal guidance for the robot system which is controlled based on the imperfect but almost accurate estimation of user state.

User interface and investigation interface are developed based on the proposed accountable system design. Several experiments validated the interfaces and system accountability. First experiment is conducted to validate the accountability of user interface. Second experiment simulates the situation that caregiver want to check failure by using user interface. Experiment for investigation interface is also conducted.

In general, this dissertation proposes two major contributions to the field of robotics. First contribution is the design for affordable robots. We propose the state estimation method using a small number of sensors. The analysis of appropriate selecting and placing sensors contribute to the robot design. Second one is accountable robot design. We confirm the importance of accountability and clarify that there are necessary 2 steps for develop accountable robots; describing whole system and transcribing the described system for each stakeholder. Describing whole system also contribute to AI transparency. We propose a method to deal with various stakeholder and use cases by determining and designing interfaces and represented information based on the relationships among information, stakeholder, and interface.

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Chapter 1

Introduction

Recent aging population increases the demand for support systems, and various robotic systems have been developed to meet this demand. Care robots are required to provide better support using their machine power and sensing technology, for example, supporting in appropriate way depending on the user situations. User state estimation is also useful to detect anomaly for preventing accidents. However, accurate state estimation requires a lot of expensive sensors and it is difficult to use the system in real environment. Autonomous robots in elderly care raise additional problems. Autonomous systems are opaque for humans and humans become anxious and scared if such systems work closely with them. It is also difficult to investigate and fix system failures in such systems.

In this dissertation, we propose the system design for care robots. To realize the care robots in real environment, there are several challenges including cost and ease of mind. These challenges should be solved in designing step. Not only hardware and software but also people who relate to the robot and use cases should be considered.

1.1 Background

In recent years, the populations are aging all over the world, especially in developed nations. There are same tendencies in developing nations and the world's population aging will continue. Japan is the world's fastest aging country. According to 2018 annual report [1] on the aging society of Cabinet Office, Government of Japan, whole population of Japan is 126.44 million people at the date of 1th of October, 2018 as shown in Figure 1.1. The number of aged 65 and older are 35.58 million and the rate is 28.1%. Decreasing of age-adjusted mortality rate and total fertility rate is the main reason of the rapid aging of population. Male and female age-adjusted mortality rate of Japan were 23.6 and 18.3 in 1947, whereas they become 4.7 and 2.5 in 2017. Japanese total fertility rate is 1.43 in 2019, which is much smaller than the replacement-level fertility (2.07 in 2017). Living environment and diet habit improvement and advance in medical and healthcare technology are considered the reason of aging population.

The number of households with persons aged 65 and over is 23.787 million in 2017 in Japan, and it is 47.2% of all households. The rate of households consisting only of elderly (one-person households and married-couple households) is more than half of them. It causes a problem that elderly have to look after another elderly. It is hard to care elderly person for one young person, even more so for elderly one since they often have not enough power. It goes without saying that it is much harder for elderly person who have physical weakening to live alone. Aging population means that there are not enough young people to care elderly, thus it causes staff shortage in the elderly care sector. Therefore, the demands for machines and robots for caring

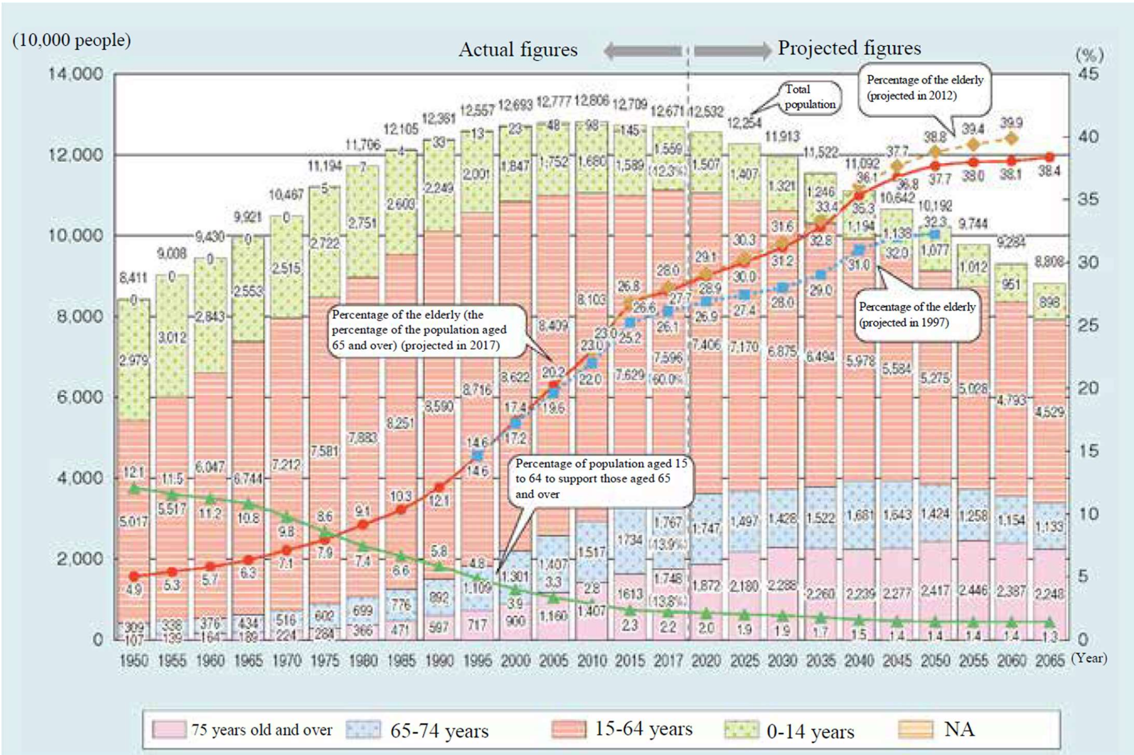


Figure 1.1: Changes of Aging and Population Projection [1].

has been increasing.

However, care robots have not become common in general households and welfare facilities. Cabinet Office, Government of Japan reported the special poll about care robots in 2013 [2]. The respondents answered several questionnaires including important point for adopting a care robot. According to the report, 74.4% of respondents answered "simplicity of use" as an important point for adopting a care robot as shown in Figure 1.2. And second most important point is "low price", which is considered important by 68.6% of respondents. The report suggest that usability, price, safety, size, and reputation are import point of care robots for caregivers and care recipients. Therefore, care robots should be affordable while they are high functional at the same time to be used in real environment. And many caregivers and care recipients are

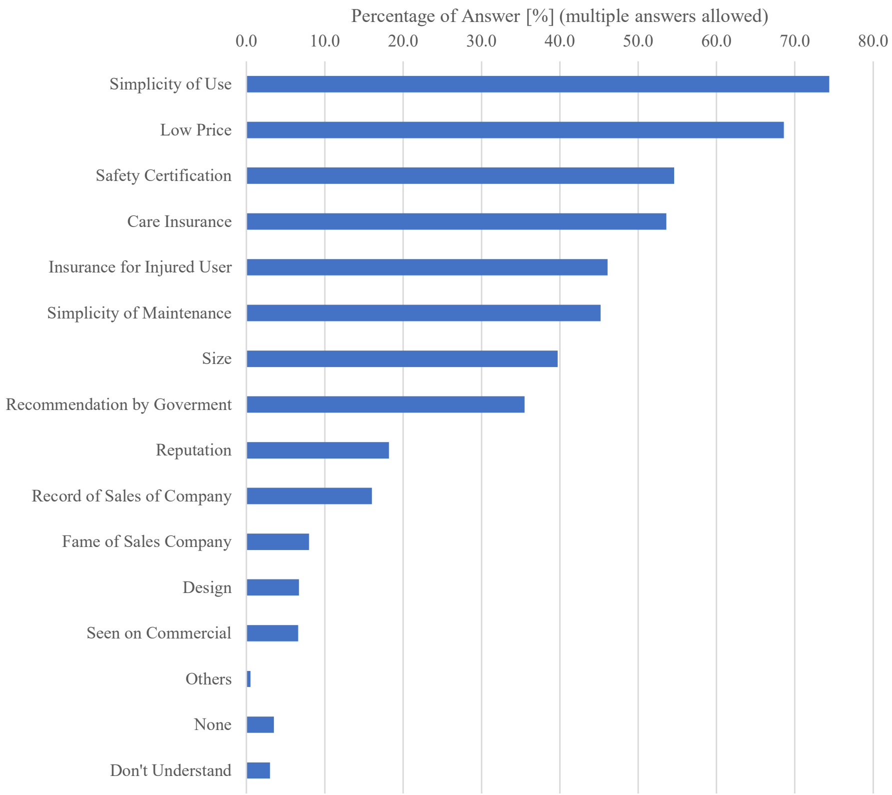


Figure 1.2: Important Point for Adopting a Care Robot. (The graph is made base on the data of the special poll about care robots [2].)

worried whether they can use robots. Hence the robot should be useful and comfort for users and caregivers.

1.2 Related Researches

1.2.1 Care Robot

With aging population, the accident of elderly also increases. According to Tokyo Fire Department [3], the number of elderly patients urgently transported by ambulance is $81,952$ people in 2018, increased by $15,930$ from 2014 as shown in Figure 1.3. Over 80% accident is tumbling as shown in Figure 1.4, and over 50% of the falling

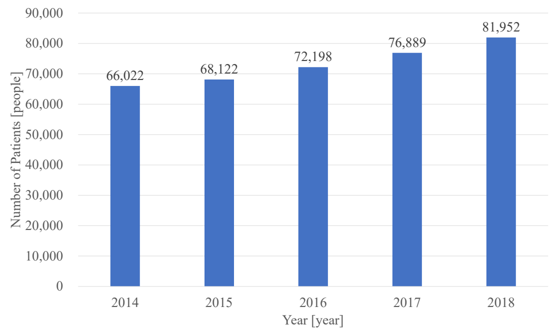


Figure 1.3: The Number of Elderly Patients Urgently Transported by Ambulance. (The graph is made base on the data provided by Tokyo Fire Department [3].)

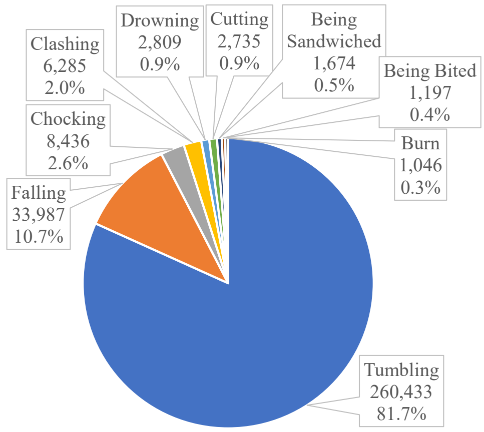


Figure 1.4: Accident Type. (The graph is made base on the data provided by Tokyo Fire Department [3].)

accident are happened indoor. For those reasons, the demands for physically assistive machines have increased.

Various types of physically assistive tools and machines have developed for elderly. Handrails are the most popular equipment for standing and walking, thus not only welfare facilities but also general house adopt them in recent years as shown in Figure 1.5. Portable type handrails are also developed for traditional house holds as shown in Figure 1.6. One of the most famous walking care tool is cane as shown in Figure 1.7, and multi-legged type is developed for stability as shown in Figure 1.8. As more stable walking assist tools, several types of walkers are developed including frame type walker and push type walker as shown in Figure 1.9 and Figure 1.10, respectively. Wheelchair (Figure 1.11) is also popular for elderly and people who have disabilities in lower limbs. Those machines consist of simple frames, casters, and wheels, thus there are some risks including unintended acceleration and tumbling of the machines. To pretend accidents and provide better support, care robots have

Figure 1.5: Handrail [4].

Figure 1.6: Stand Up Support Portable Handrail [5].

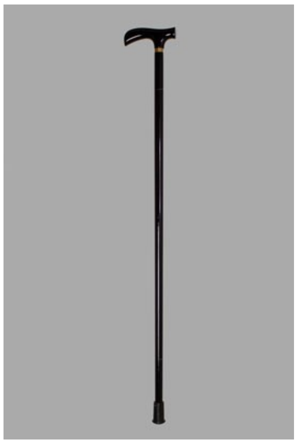


Figure 1.7: Cane [6].

Figure 1.8: Multi-legged Cane [7].

Figure 1.9: Frame Type Walker [8].

Figure 1.10: Pushcart Type Walker [9].

been developed.

Standing up is one of the most difficult motion for elderly. Elderly have disability not only in their lower limbs but also upper body. Then it is difficult for them to stand up using assistive tools including handrails. Assisting lifting power by using a kind of actuators is effective for standing support. Uplift seat (Figure 1.12) is a simple standing support tool which utilize springs and dumpers. Electric actuation

Figure 1.11: Wheelchair [10].

Figure 1.12: Uplift Seat [11].

Figure 1.13: Electric Actuation Type Uplift Chair [12].

type uplift chairs are also developed as shown in Figure 1.13. SECOM co., ltd. developed “Secom Lift” (Figure 1.14) based on robot technology [13]. It have sensors on lifting part to keep user posture and detect anomaly. Standing support system which can use by elderly oneself without caregiver has been studied. Nagai et al. developed wire-driven standing assisting device [14] as shown in Figure 1.15. It has not only power assist function and also motion guidance for self-reliant motion and keeping posture. RIKEN developed the nursing care robot “ROBEAR” [15] which can lift patient with two arms as shown in Figure 1.16. Robots have advantages in massive power and sensing systems. Analyzing sit-to-stand motion is also important for standing support and robot technology contribute the analysis. Hatsukari et al. developed relatively compact system [16, 17] to analyze the motion and proposed method to select standing way considering physical loads.

Walking assist is another main concern of physical assistive robots. Electrical wheelchair (Figure 1.19) is one solution of elderly mobility problems. Although it is effective as a mobility, the users lower limbs decay since don’t move them. Thus cycling wheelchairs (Figure 1.20) are studied [19, 49, 50]. It is particularly effective

Figure 1.14: Secom Lift [13].

Figure 1.15: Power-assisting Device for Independent Transfer [14].

Figure 1.16: ROBEAR [15].

Figure 1.17: Self-help Standing-up Device [16].

Figure 1.18: Self-help Standing-up Device [17].

for hemiplegia patients. And there are many researches which focus on robotic walkers. Hirata et al. developed human adaptive walking support system called “Walking Helper” [20, 51] which is shown in Figure 1.21. It has omni-directional moving mechanism and force sensors. “RT Walker (Robot Technology Walker)” is passive type walking assist robot which is shown in Figure 1.22, and it is developed by Hirata et al [21, 46, 52]. It adopted servo brakes and there are no motor thus basically it moves only by human force. Dubowsky et al. developed walker type and cane type walking support systems named "PAMM (Personal Aid for Mobility and Monitoring)" [22, 53, 54] as shown in Figure 1.23, Figure 1.24. The systems are developed for using indoor space in general household and welfare facilities. They measure user's force data and environmental information by using 6-axis torque sensor and CCD camera, respectively. Hitachi, ltd. also developed walking support system as shown in Figure 1.25 which have two independent wheels [23, 55]. The wheels move based on force sensor data. "Care-O-bot" (Figure 1.26) is intelligent walking support system developed by Feaunhofer IPA [24, 56, 57]. It can not only support walking but also elementary cleaning, table setting, and bring objects which is requested by humans. Huang et al. developed "Walking-aid Robot" [25] and "Intelligent Cane" [26] for walking assist which are shown in Figure 1.27 and Figure 1.28, respectively. Intelligent Cane has Laser Range Finder (LRF) to measure user's lower limbs. It also has force senor, and by using wearable sensors on shoes, it can detect user falling and estimate user intend. Assistive robot walker "RT.1" [27] and "RT.2" [28] which are shown in Figure 1.29 and Figure 1.30, respectively, are developed by RT.WORKS co., ltd. They can control speed and automatically stop on slope when user unhand the system. The robots have network system for healthcare and watching by family, doctors, and caregivers.

Body weight support using harness and wires is another focused way to support standing and walking. Body weight-Support Treadmill Training (BWSTT) is famous as an effective rehabilitation method[58, 59]. SAKAI Medical Co., Ltd. has developed Unweighg System NxStep [29]. It can automatically adjust the amount of body-weight support. Lokomat®is a body weight-support gait training system

Figure 1.19: Electrical Wheelchair [18].

Figure 1.20: Cycling Wheelchair [19].

Figure 1.21: Walking Helper [20].

Figure 1.22: RT Walker [21].

developed by Hocoma [30, 60]. Hocoma also developed body weight support walker named Andago®[31]. Ochi et al. developed NILTWAMOR, a body weight support walker which can keep wire tension [32]. Osaki et al. adopted Support Vector Machine (SVM) for user state estimation of body weight support walker named FLORA TENDER [33].

Figure 1.23: SmartWalker [22].

Figure 1.24: SmartCane [22].

Figure 1.25: Walking Support System [23].

Figure 1.26: Care-O-bot [24].

Wearable robots are also studied extensively for walking support. HAL®(Hybrid Assistive Limb®) is one of the most famous robot suit which is developed by CYBERDYNE, INC. [34, 61, 62]. It is controlled based on the muscle potential of the user. Suzuki et al. also studied wearable walking assist robot [63]. They also use cane-type walking support robot and proposed cooperation method of them [35, 64]

Figure 1.27: Walking-aid Robot [25].

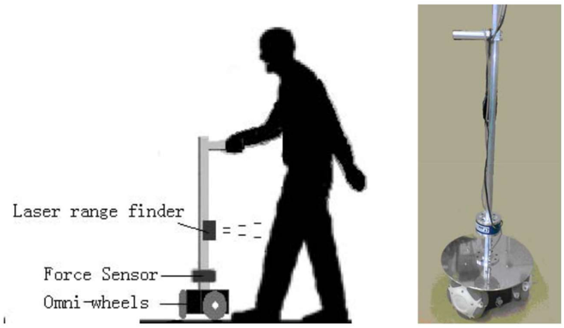


Figure 1.28: Intelligent Cane [26].

Figure 1.29: RT.1 [27].

Figure 1.30: RT.2 [28].

as shown in . Piriyakulkit et al. developed Lumbar Assistive Orthosis as a standing and walking support wearable robot [36].

Many support systems focus on either sit-to-stand motion or walking. However, systems which can support both standing and walking are effective especially for indoor use. Hence multi-legged canes which are equipped with handle on low have

Figure 1.31: Unweighg System NxStep [29].

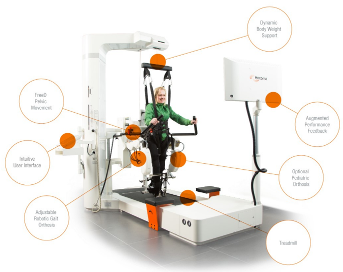


Figure 1.32: Lokomat®[30].

Figure 1.33: Andago®[31].

Figure 1.34: NILTWAMOR [32].

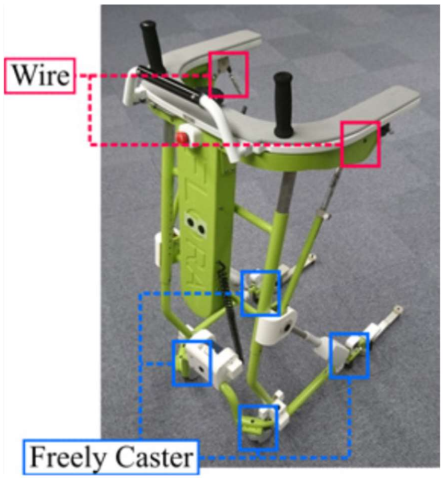


Figure 1.35: FLORA TENDER [33].

developed. Figure 1.39 shows self-reliance support robot developed by Panasonic Corporation, and it is one of those which can support both standing and walking [37, 65]. Chugo et al. also study standing and walking support system for rehabilitation [38] as shown in Figure 1.40.

Physical disability is not only issue for elderly care. There are various tasks for care including physical assist of walking, standing, and bathing, excretion assistance, meal assistance, cooking, serving, changing linens, and holding recreations. Thus

Figure 1.36: HAL [34].

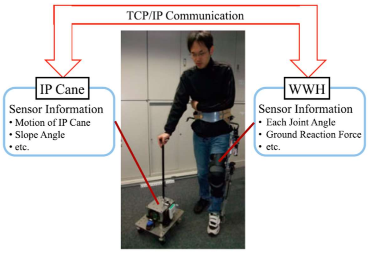


Figure 1.37: Wearable Walking Helper (WWH) and Intelligent Passive Cane (IP Cane) [35].

Figure 1.38: Lumbar Assistive Orthosis [36].

Figure 1.39: Self-reliance Support Robot [37].

Figure 1.40: Rehabilitation Robotic Walker [38].

communication, office works, and watching are important as well as physical elderly assistance. Socially assistive robotics (SAR) is an important area of elderly care.

Communication is one of main topics of SAR. “NAO” is one of the most famous communication robots which is developed by Aldebaran Robotics SAS [39]. It is small humanoid robot which can dance and talking. It is also used for teaching radio exercise to kids and elderly. SoftBank Robotics Corp. (formerly Aldebaran Robotics) developed semi-humanoid robot “Pepper” [40]. It has a display on its

Figure 1.41: NAO [39].

Figure 1.42: Pepper [40].

breast and people can select applications. It behave as it has a kind of emotion, thus it can relatively naturally communicate with humans. Sharp Corporation developed humanoid robot RoBoHoN, which also can talk and dance [41, 66]. The robot can look after the house instead of humans. The therapeutic medical robot, "PARO", is a seal type animal robot which is developed by National Institute of Advanced Industrial Science and Technology (AIST) [42, 67]. It is developed based on the idea of animal-assisted therapy. It has several types of sensors including tactile, light, and audio sensors. Effectiveness for autism and dementia of PARO have gotten a lot of attention.

Healthcare and watching is important for elderly care since caregivers cannot always stay together. There are some watching system using indoor mounted sensors [68, 69]. Yoshino et al. developed watching system using a conversational robot [70]. Takahashi et al. also developed elderly watching robot as shown in Figure 1.45 and validate the appropriate functions for the robot [43]. The robot can detect anomaly from daily conversations. The network system of RT.1 and RT.2 let not only users but also family and caregivers to check user walking [27,28] using the walking support

Figure 1.43: RoBoHoN [41].

Figure 1.44: PARO [42].

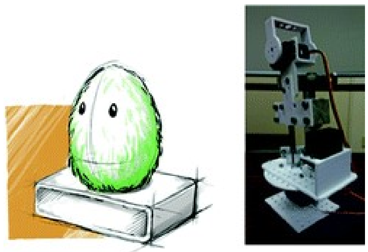


Figure 1.45: Communication Robot for the Watching System [43].

robot. It also can alert user anomaly to family and caregivers.

1.2.2 State Estimation

It is important for both physically assistive robots and communication robots to obtain information of user. If robots can recognize user situation, action, state, emotion, and so on, the robots can select appropriate action for them. It is important for physically assistive robots to provide appropriate support depending on the situation. Real-time user state estimation is also effective to detect user anomaly including falling for preventing accidents.

There are various way to measure or estimate human information. Motion capture systems are famous human motion measurement systems which often use optical information. Ground reaction force is useful information of humans especially for walking analysis. Generally, ground reaction force is measured by using force plates. Center of Pressure (CoP) can be also calculated by using force information [71–73]. Force plate is huge and expensive, thus there is a limitation for installation location. Then more small and inexpensive sensors are including shoe-type reaction force sensors have been developed. Liu et al. made shoe sole type reaction force

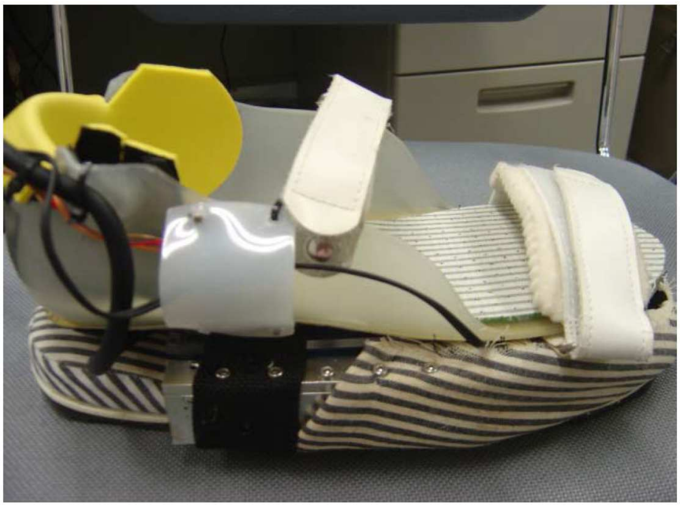


Figure 1.46: Wearable Ground Reaction Force Sensor [44].

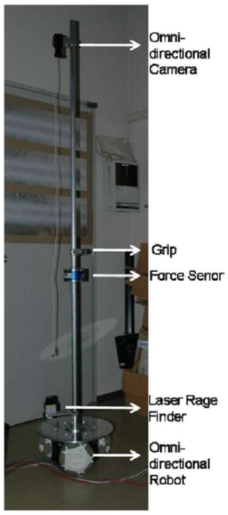


Figure 1.47: Intelligent Cane Using Camera [45].

sensor [44] as shown in Figure 1.46, and Woodburn developed wearable sensors which is set in shoes [74]. For gait analysis, acceleration is also important, thus Morita et al. install accelerometer on wearable ground reaction sensing system [75]. Muscle potential is useful for human motion analysis including gait [76], and some researchers also use visual information by using cameras [45] as shown in Figure 1.47. Center of Gravity (CoG) and Center of Mass (CoM) are also useful to estimate human state. Moe-Nilssen et al. analyzed human gait by using Inertial Measurement Unit (IMU) [77]. They set IMUs on the third lumber vertebra (L3) and second sacral vertebra (S2) where are strongly sensitive to CoG.

These measurement and estimation methods are adopted to care robots. Many communication robots use light and auditory information to estimate user words and intention. Force information is also useful to estimate user posture, state, and intention. Some walking support robots use force information as user intention and determine the direction to walk. It is also used to detect anomaly. Human CoG

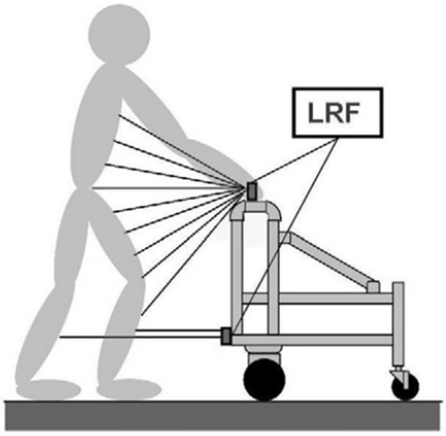


Figure 1.48: RT Walker and Human Link Model [46].

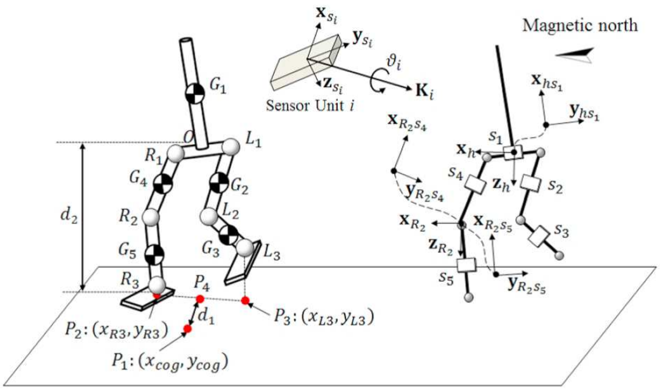


Figure 1.49: Posture Estimation of Walking-aid Robot Using Wearable Sensors [25].

position is useful to estimate human state, for example, user is going to fall if the projected point of CoG is out of base of support. There are several ways to estimate human CoG position. By using human link model, complicated human body can be considered as simplified model. The human CoG position can be calculated by measuring all link positions. Link positions can be measured by using motion capture system, a kind of distance sensors including Laser Range Finder (LRF) and Position Sensitive Detector (PSD), and IMUs [46,78,79]. RT Walker use two LRFs to calculate human link model [46] and Walking-aid Robot use five IMUs as wearable sensors in addition to the robot [25] as shown in Figure 1.48 and Figure 1.49, respectively.

There has been interest in machine learning and deep learning algorithms for state estimation. On-body sensors such as accelerometers are frequently used for human activity estimation [80, 81]. Vision-based estimation has received a lot of attention. Convolutional Neural Network is one of the most famous methods for human pose estimation [82, 83]. The user state is generally evaluated for anomaly detection or robot function changes [84,85]. User state, action, and intent can be used for motion control [86–88]. Anomaly detection can be used for accident prevention. Thus state estimation is also useful for improving safety. Accumulation of estimated data can be used for care monitoring and deep learning.

1.2.3 Transparency

Not only high functionality and safety but also usability and ease of mind are important issues of machines and robots, especially care robots. It is difficult for humans to understand the actions, plans, and behavior of autonomous robots and the reasons behind them, particularly when the robots include learning algorithms. Learning-based autonomous systems which are called Autonomous Intelligence (AI) are treated as an inherently untrustworthy "black box", because machine learning or deep learning algorithms are difficult for humans to understand. Robot systems such as assistive robots, which work closely with humans, however, should be trusted. Physical human-robot interaction comes with safety risks, and therefore humans become anxious when they do not understand them. It is difficult for humans to cooperate with or rely on such robots to support human actions. When a person is carrying out a task that involves cooperation with other people, the task cannot be completed well if they cannot communicate with each other. Communicating is much more difficult in human-robot interactions than in human-human interaction. Humans become anxious if they cannot understand the actions of robots. People feel uncomfortable consigning health care tasks to robots that are perceived as unpredictable. Learning-based robots that interact with humans need to clearly present their safety-critical actions, states, plans, and reasons for acting.

Some researchers focus on transparency of learning algorithms [89–92]. Studies on making AI transparent by representing the reasons for decisions [47, 93] can provide some understanding of learning algorithms, however, these methods cannot make all algorithms transparent for ordinary people. Hosseini et al. made original modeling language to achieve transparency for information systems [94]. Transparency of system is often studied in the computer vision and AI fields, and autonomous robot also should deal with this ethical issue.

If robots detect an anomaly, they usually stop their operations and alert users. Such alerts are useful to draw attention to the anomaly, and are effective for letting users know why robots have stopped operating. Representation of a robot's actions or plans is effective under both normal and abnormal operating conditions. If a robot has many functions, humans are unable to understand the robot's action and plan without representation, even if the system does not include learning algorithms. Song et al. set LED to represent robot state to the surrounded humans [48]. Novikova et al. study representation of artificial emotions in human-robot interaction [95]. Teaching robots also enables users to learn which actions are required of them [96]. If robot systems include learning algorithms, the system is more opaque for humans. Representation of recognition or estimation results, as well as asking humans for confirmation, facilitate the robot's tasks [97]. Confirmation of tasks which are ordered by humans can reduce the number of mistakes [98, 99].

Adopting robots that use learning algorithms raises additional problems. It is difficult to investigate and fix system failures in systems with "black boxes". It is also difficult to decide who is responsible in such cases. Complicated autonomous systems should also clarify the boundaries of responsibility. Learning-based robot systems should therefore be designed based on ethical principles. Ethical design has been

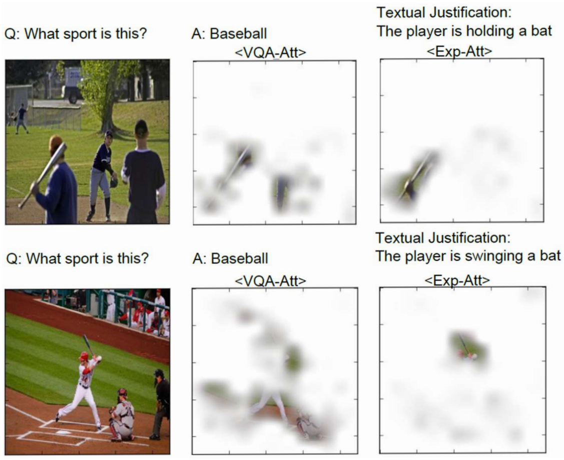


Figure 1.50: Evidence for Answers [47].

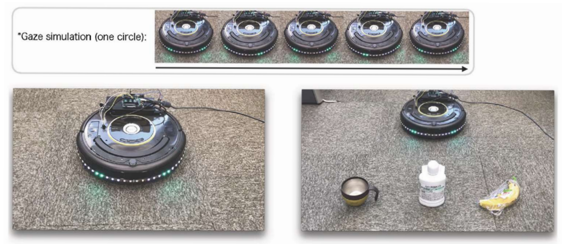


Figure 1.51: LED Light Gaze of Robot [48].

discussed in various fields such as telehealth [100] and the Internet of Things (IoT) [101]. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems has published Ethically Aligned Design, First Edition [102], which discusses general principles for autonomous and intelligent systems, including human rights, data agency, transparency, and accountability. Ethically aligned design for autonomous and intelligent systems has been discussed elsewhere [103], and its importance for assistive robots is also suggested [104].

1.3 Objectives

Systems in real environment is required to reduce costs, however, robot systems are also required to be high functional. User state estimation is important for care robots, however, accurate estimation requires a lot of expensive sensors. To obtain information from less sensor than required makes robots affordable. Autonomous robots should be transparent for humans from the perspective of usability and ease of mind. Autonomous robots raise another problem that it is difficult to investigate and fix system failures in systems with black boxes. Hence care robots should achieve accountability for various types of people who relate to the robot.

There are some researches focusing on state estimation using a small number of sensors or transparency of robots. However, the researches focused on specific situations for specific robots, aiming to improve system efficiency. It is important to consider system affordability and accountability at design step. It is not effective simply reducing sensors to cut cost. It should be designed by considering how selecting and placing sensors influence robot functions. Various types of people including the user and engineers relate to a robot by each reason. Those people who relate to system are called stakeholders and how to achieve accountability differs for each stakeholder. We should design as the whole system including how to relate as well as hardware and software. In the fields of medical technology, the importance of needs finding considering use cases and stakeholders is pointed [105]. The design procedure including repetition of inventing and screening is discussed. However, it is not concrete method, and detailed methods of sensor choosing and consideration of use cases and stakeholders are not well discussed. Therefore we propose a new general design method for affordable and accountable robots.

The general objective goal of this research is to propose a system design method considering affordability and accountability for care robots which provide physical support based on user state estimation. Specific objectives are as follows:

- Construct a user state estimation method by using a small number of sensors.
- Evaluate measurements set and determine the appropriate selecting and placing sensors.
- Develop a physically assistive robot with user state estimation function.

- Propose a method to achieve transparency for embodied AI.
- Propose a new concept that accurate human state estimations are not necessary for robots and that appropriate guidance make robots useful even if the estimation is not strictly accurate.
- Evaluate the system which is developed according to the proposed design.

1.4 Outline

This dissertation is organized in 8 chapters as follows:

In chapter 2, we propose the concept of system design for affordable and accountable care robots focusing on physically assistive robot with user state estimation.

In chapter 3, we propose CoG candidate calculation method by using a small number of sensors. We classify patterns of selecting and placing sensors and evaluate the range of CoG candidates. Through experiment we confirmed that the CoG candidates range can be narrow enough. The appropriate measurements set is also determined.

In chapter 4, we propose a user state estimation method using the CoG candidates. In this chapter the new calculation method of CoG candidates is proposed and evaluated. The proposed state estimation method which uses SVM is proposed and evaluated by experiments.

In chapter 5, detailed design architecture for accountable robot is explained. Contribution to transparency of embodied AI is also explained in this chapter.

In chapter 6, we introduce verbal guidance to sit-to-stand support system to validate the effectiveness of robot's accountability. We confirm that appropriate guidance make robots useful even if the estimation is not strictly accurate.

In chapter 7, the physically assistive robot developed according to the proposed design is validated by experiment focusing on its accountability of interface. Several experiments are conducted for simulating a situation for each stakeholder. The experiments validate the system usability and accountability.

Chapter 8 concludes this dissertation with a general discussion about the proposed design, state estimation method, and developed system. Future works are also presented based on the conclusions. The dissertation outline is shown in Figure 1.52.

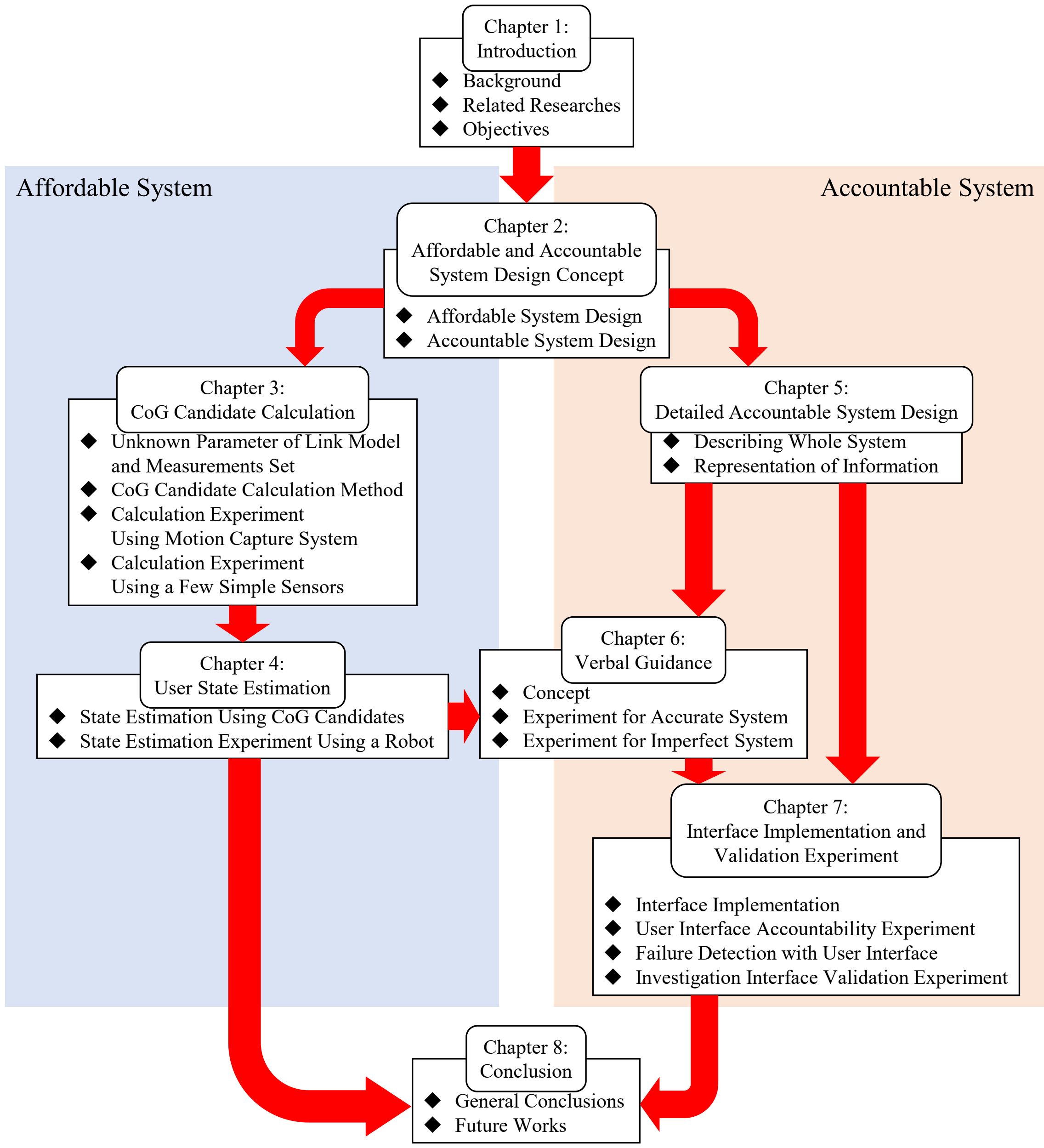


Figure 1.52: Outline of the Dissertation.

Chapter 2

Affordable and Accountable System Design Architecture

2.1 Introduction

Affordability and accountability are required to use robot in real environment, especially in the case of care robots which interact physically with humans. Systems utilizing a lot of expensive and sophisticated sensors are difficult to use in general households or institutions. And there are also privacy problems for using a lot of sensors. Therefore, systems should decrease sensors while keeping high functionality at the same time. To realize it, the method is required to obtain information from small number of sensors.

Robot systems which work closely with humans should achieve accountability. It is difficult for humans to understand the actions, plans, and behavior of autonomous robots and the reasons behind them, particularly when the robots include learning algorithms. Physical human-robot interaction comes with safety risks, and therefore humans become anxious when they do not understand them.

In this dissertation, we propose a new design architecture care robot systems which include physical human-robot interaction. Following sections explain the design architecture focusing on affordability and accountability, respectively.

2.2 Affordable System Design

Care robots are required to provide better support with their mechanical strength and sensing technology. Compensating for lack of power of elderly is effective, however, there is a safety risk if the robot do not figure out user situation. Therefore user state estimation is important for care robots. User state estimation should be accurate to reduce safety risks, however, it is difficult to realize strictly accurate estimation. More accurate estimation required more expensive and more huge number of sensors. However, systems utilizing a lot of expensive and sophisticated sensors are difficult to use in general households or facilities. And there are also privacy problems for using a lot of sensors. Therefore, systems should decrease sensors while keeping high functionality at the same time.

Affordable robots have been studied for several use including education [106], treatment intervention [107], robot hand [108]. Underactuated robot hand is a famous way to achieve affordability [108, 109]. Elderly care is one of the most familiar use of robots for general people, therefore various affordable care robots are studied [110]. Passive robotics has advantages on affordability as well as safety and simplicity of control [21,46,52]. Robot suit HAL is focused for assisting bathing care [111]. Bathing care by using fixed equipments requires rebuilding, hence robot suit has advantage. Care-O-bot has few human-like features including an arm, since unnecessary human-like robot become expensive [112]. Mayer et al. developed a care robot named HOBBIT considering affordability [113, 114]. For map building and self-localization, it uses a depth camera instead of 2D laser range finder since laser range finders are expensive.

It is important to reduce cost focusing on influence for robot function. Robot parts for unnecessary function are cause of expensiveness, moreover, we cannot reduce them if the robot cannot perform required function without them. Hence state estimation by using small number of sensors is important.

CoG is useful to estimate human state, hence there are several method to measure or estimate CoG position. Motion capture system is famous system to measure human state, and CoG position can also be measured by using it. However, motion capture system is very expensive and usable place is limited. Therefore several method to measure CoG position is studied. Human link model is a way to consider a human body as a simplified model, and human CoG position can be calculated using the link model as shown in Figure 2.1. Hirata et al. adopted LRFs on RT Walker to calculate human link model [46], and Huang et al. use wearable 5 IMUs [25] as shown in Figure 1.48 and Figure 1.49, respectively. Although a LRF is expensive, it can be replaced with several inexpensive distance sensors. These methods are effective, however, accurate CoG position calculation still requires a lot of sensors. And these methods do not consider sensor selection and placement design, hence it is difficult to be applied to other systems.

Accurate CoG position calculation requires a lot of sensors, however, if there are less sensors than required to calculate the link model, we cannot determine the position of CoG uniquely. Then we focused on the range of value of link model's

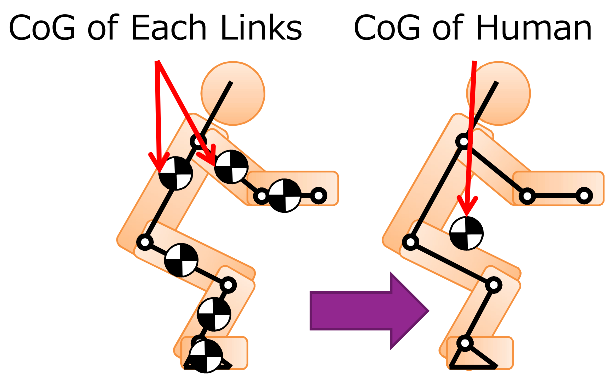


Figure 2.1: CoG Calculation Using Human Link Model

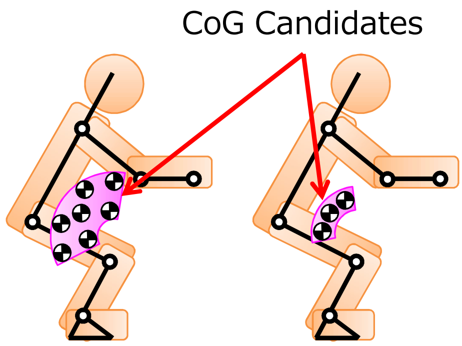


Figure 2.2: CoG Candidates

unknown parameters. And we propose the CoG candidate calculation method using the range of value of unknown parameters. If the ranges of CoG candidates become narrow enough as shown in Figure 2.2, we can estimate user state. By selecting and placing sensors, the CoG candidates ranges can be reduced. If we can find the appropriate combination of sensors to reduce the ranges of CoG candidates, this knowledge can be used not only for real-time estimation of user state but also for determining where and which sensors to set when designing robots. The detail method is explained in chapter 3.

2.3 Accountable System Design

An aging population increases the demand for support systems, and various robotic systems have been developed to meet this demand. Robotic support systems are expected to not only become alternatives to human caregivers, but also to provide better support, owing to features including mechanical strength, estimation algorithms, and AI technology.

It is possible to comfortably use home electronics or machines without knowing the internal processes of the systems. These machines have limited operations and are controlled by humans. The machines function by following simple conditional decision-making logic, which humans can easily understand. Learning-based systems that include character recognition and recommendation systems also do not require transparency in the sight of trustworthy since there is no safety risk. There are some machines which are not transparent for humans and have safety risks, including vehicles and airplanes. They are generally developed following a kind of system design methods. Such methods mainly focus on performance and safety. The operation interfaces are well designed to decrease mistakes. However, such design methods do not focus on ease of mind. Drivers can control those systems, thus they do not become anxious. Those systems are not transparent for the passengers. They trust the systems since the systems have a good record in safety. And most important point is that such systems do not interact with humans.

AI systems, including autonomous robots that use learning algorithms, however, are difficult for humans to use because they are difficult to understand. Physical human-robot interaction comes with safety risks, and therefore humans become anxious when they do not understand them. It is difficult for humans to cooperate with or rely on such robots to support human actions. When a person is carrying out a task that involves cooperation with other people, the task cannot be completed well if they cannot communicate with each other. Communicating is much more difficult in human-robot interactions than in human-human interaction. Humans become anxious if they cannot understand the actions of robots. People feel uncomfortable consigning health care tasks to robots that are perceived as unpredictable. Learning-based robots that interact with humans need to clearly present their safety-critical actions, states, plans, and reasons for acting.

Adopting robots that use learning algorithms raises additional problems. It is difficult to investigate and fix system failures in systems with "black boxes." It is also difficult to decide who is responsible in such cases.

Manual brake is a frequently used method to achieve reliability and accountability. Humans can control and stop autonomous machines by using manual brakes when there are safety risks. It can make user feel at ease, and distribution of responsibility become clearer in the case of general machines. In the case of autonomous robots, however, if humans do not understand system, they cannot determine anomaly and cannot feel at ease even if the system works normally. Anxiety and user-unfriendliness of autonomous robot come from lack of knowledge of the robot. Hence transparency is important for accountability of robots.

Knowledge representation is adopted to make systems transparent. If robots detect an anomaly, they usually stop their operations and alert users. Such alerts are useful to draw attention to the anomaly, and are effective for letting users know why robots have stopped operating. Representation of a robot's actions or plans is effective under both normal and abnormal operating conditions. If a robot has many functions, humans are unable to understand the robot's action and plan without representation, even if the system does not include learning algorithms. Displaying the robot's plan helps humans understand the robot's future actions [115]. Sound is one effective means of knowledge representation [116] and simple LED lights can also represent the robot's state [48]. These methods are considered useful for learning-based robot systems.

The ability of robots to correctly recognize visual and auditory inputs is not always reliable. Some studies in the computer vision field have addressed the reasoning behind learning-based classifications [47,93]. For robots, both the input-classification relationship as well as the relationship between the classification result and the robot's action are important. Representation of recognition or estimation results, as well as asking humans for confirmation, facilitate the robot's tasks [97]. Confirmation of tasks which are ordered by humans can reduce the number of mistakes [98,99].

When robots interact with humans, both the robot and the user actions are important. If human and robot are cooperating on a task, the robot will work more effectively if there is an understanding of what the human should do. Teaching robots also enables users to learn which actions are required of them [96]. Some researchers also study representation of artificial emotions in human-robot interaction [95].

These studies show that real-time knowledge representation is effective for using robot-based systems, as humans can understand and predict robots' actions via knowledge representations. Describing the systems in this way has advantages for designing and investigating the systems. Some researchers create original modeling languages to describe their specific systems [94,117].

Some studies evaluated the construction of accountable robot systems by making their systems transparent; however, almost all studies have focused on the stakeholders for their specific systems. Systems design should follow some sort of guideline.

Transparency of learning-based robot system is less frequently discussed, although AI transparency has been discussed in the computer vision and machine learning fields. For physical systems such as robots with AI, the surrounding AI transparency poses other issues as well as those related to the learning algorithm. However, the

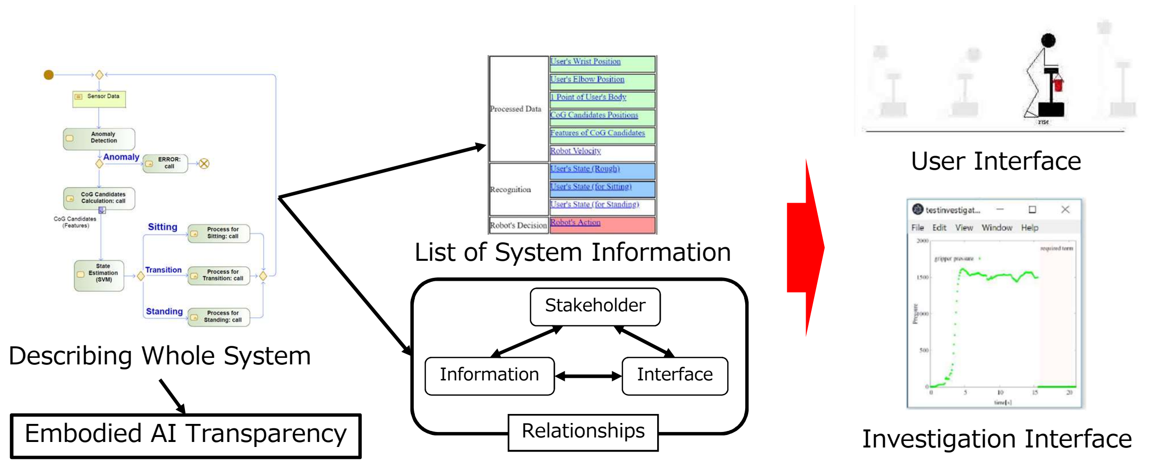


Figure 2.3: Accountable System Design Concept

general design architecture for assistive AI robot systems has not been widely discussed.

This paper proposes a design architecture to achieve accountability for learning-based support robot systems. First, the entire system should be described, then the described system should be transcribed for each stakeholder based on several principles to effectively achieve accountability as shown in Figure 2.3. Because each stakeholder requires different information, the entire system should be described to clarify the internal information of robot systems. In this study, we adopt the Systems Modeling Language (SysML) to describe the entire system; the language was created to describe systems and is popular in the systems engineering field.

Describing the system as a whole also contributes to AI transparency. It is difficult to achieve transparency in machine learning or deep learning algorithms and models. However, general systems consist of more than learning algorithms used for recognition or estimation in robot systems. Thus, the input-estimation relationship is opaque for humans. By contrast, the relationship between the decided action of the robot and the output of the actuators can be transparent because learning is not used for this function. The relationship between the estimated information and the action of the robot, which is the main interest of robot system stakeholders, can also be described. AI robot systems can be made transparent by describing the systems, even if the learning algorithms are opaque.

Relationships between stakeholders, information, and interfaces are important for providing required information to each stakeholder in the most appropriate form. Systems should represent all information, but because humans are unable to understand so much information at once, information should be represented in an appropriate way depending on the stakeholder, case, time, and other relevant factors. We considered system use cases as examples of stakeholder-information relationships. The professional ability of stakeholders should be considered as stakeholder-interface relationships, while information-interface relationships should be considered by examining the features of the information. This paper summarizes these relationships. The detailed accountable system design is explained in chapter 5.

2.4 Conclusions

This chapter proposed concept of affordable and accountable design architecture. Robot systems should achieve affordability and accountability especially in the case that the systems include learning algorithms and interact with humans physically. For use in real environment, affordability and accountability should be considered in the design step. Following chapters explain the detail and examples of the proposed design and validate them.

Chapter 3

CoG Candidate Calculation

3.1 Introduction

Various assistive machines have been developed to prevent falling accidents of the elderly. In order to achieve advanced support using robot technology, it is important to acquire data or real-time state estimation of user's various motions. However, a lot of expensive and sophisticated sensors utilized to estimate user's state accurately are difficult to use in general households or institutions. In this article, we propose a method to estimate the user's state utilizing a few inexpensive and simple sensors. We focused on CoG (Center of Gravity) to estimate user's state, but when utilizing less sensors than required to calculate the human link model parameters, the position of CoG is underspecified. Then we considered the range of value of unknown parameters to calculate candidates of CoG. The range of CoG candidates can become narrow enough to estimate human state in real-time by properly selecting and placing the sensors. Therefore, the evaluation of CoG candidates allows us to determine where and which sensors to set when designing assistive robots. We firstly selected some sensors which can be generally found on assistive machines, and we created sets of measurements using the number of unknown parameters. From the result of the experiment using a motion capture system, we confirmed that the range of the candidates was considerably narrow when using some of the created measurement sets. We validated the proposed method to estimate user's CoG candidates by actually placing the sensors according to the designed measurement sets and confirmed that the CoG candidates corresponded to those obtained using the motion capture system.

3.2 Method to Estimate CoG Candidates Using Link Model

In this section, we explain the method to estimate the state of people who use assistive robots by using reduced quantities of sensors. Firstly, we consider the human link model in section 3.2.1. By setting sensors on the system, position of user's CoG can be calculated. However, if there are less sensors than required to calculate the human link model, we can't determine the position of CoG uniquely. Then we consider actual support robots and sensors which can be used, and estimate CoG candidates using human link model by considering the range of unknown parameters.

3.2.1 Planar Link Model and CoG Calculation

When humans perform motions which are common in daily life such as sitting, standing, or walking, they move largely in the sagittal plane. Therefore, we focused on the sagittal plane link model of the human. The human body can be modeled using a planar 6-link model as shown in Figure 3.1. We assume that the length of links are

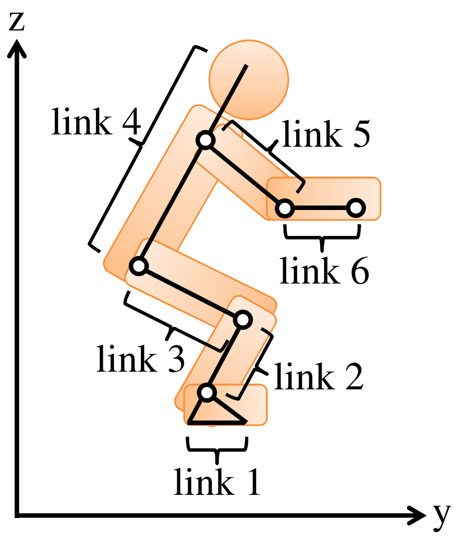


Figure 3.1: Human Link Model

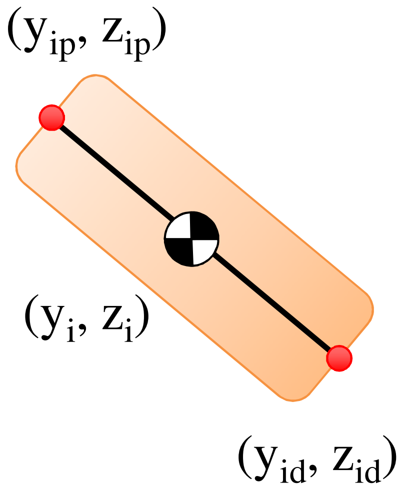


Figure 3.2: CoG of a Link

known because their body height or limbs length can be measured before using the assistive robot at general household, institutions or when doing experiments for data acquisition. Then, the number of degrees of freedom of the link model becomes 6. If the positions of all links can be determined, the CoG of all links can be calculated by using equation 3.1 as shown in Figure 3.2.

$$(y_i, z_i) = (y_{id} + (y_{ip} - y_{id})r_i, z_{id} + (z_{ip} - z_{id})r_i) \tag{3.1}$$

Then we can calculate CoG position by mass ratio [118], [119] of links as shown in Figure 3.3. The position of human CoG is given as follows;

$$(y_{CoG}, z_{CoG}) = (\Sigma m_i y_i, \Sigma m_i z_i) \tag{3.2}$$

where (y_i, z_i) and m_i is CoG position and mass ratio of link i, respectively.

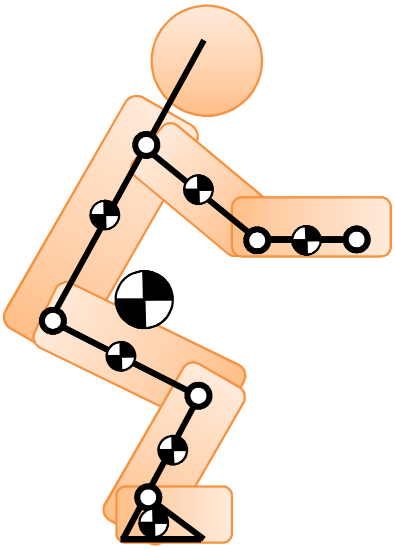


Figure 3.3: CoG of Human Body

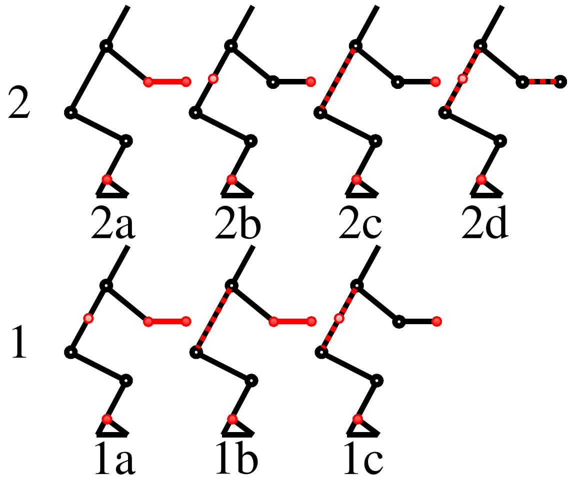


Figure 3.4: Measurement Sets

3.2.2 Unknown Parameters of Link Model

When we use less sensors than required to calculate the link model, some parameters remain unknown and CoG position can't be determined uniquely. Therefore, we consider the degrees of freedom and the unknown parameters of the link model. The quantity of unknown parameters can be expressed by mobility of linkage which is known as Kutzbach and Grübler's criterion [120] as shown in Figure 3.5;

$$M = 3(N - 1 - j) + \Sigma_{i=1}^{j} f_i \tag{3.3}$$

where M is mobility, N is the summation of fixed links and moving links, $N = n + 1$ where n is quantity of moving links, j is the joint number, f_j is the number of degrees of freedom of joint number j, $j = n$ when loop is open, and $j = n + 1$ when loop is closed. Assuming that the position of some joints can be measured, then the link model can be regarded as a combination of closed loops and open loops. The

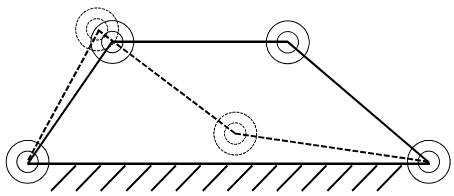


Figure 3.5: $3 + 1$ Link Closed Chain.

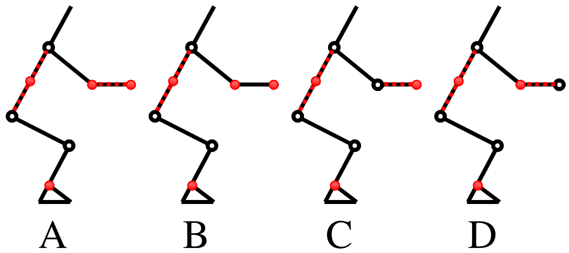


Figure 3.6: Measurement Sets (CoG Can Be Calculated.)

loops contain fixed links, and the ends of fixed links are measured joints. Then the quantity of link model's unknown parameters will be equal to the mobility. Assuming that human information other than position of joint can be measured, then unknown parameters of the link model will decrease from the mobility. Defining D as such decreasing value, the unknown parameters of the link model are given as follows;

$$X = M - D \tag{3.4}$$

where X is the number of unknown parameters of the link model. If there is less sensor information than required to calculate link model, X becomes greater than zero, and the CoG's position can't be determined uniquely. Then we classify measurement sets using the number of X as shown in Figure 3.4. We will explain the details in the following section.

3.2.3 Support Systems and Usable Sensors

The types and placing positions of the sensors depend on the support system. In this section, we assume sensors which can be set on actual assistive machines, and classify sets of measurements using unknown parameters.

Table 3.1: List of Sensor and User Information

Sensor	Place	User Information
Touch Sensor	Gripper	Position of Wrist Joint
	Armrest	Position of Elbow Joint
Distance Sensor	User Side of Robot's Under Portion	Position of Ankle Joint
	User Side of Robot's Upper Portion	Position of One Point of Body Link
Attitude Sensor	User's body	Inclination of Body Link
	User's Forearm	Inclination of Forearm Link

There are two types of typical assistive machine which support sitting, standing, or walking. One is pushcart type, and the other is armrest type. In the following part of this section, we select sensors which can be set on these two types of assistive machines to measure user's information. Sensors are selected considering price and its effectiveness for human link model. Positions of joints are more valuable than ones of points of links. However, not all joint positions are easy to measure by using inexpensive sensors which can be introduced to a care robot.

By using touch sensors, such as capacitance pressure sensors set on the gripper or armrest, we can detect whether the user touches it or not, so the position of the wrist joint can be estimated on pushcart type systems, while wrist and elbow joint can be estimated on the armrest type systems. By setting distance sensors such as PSD sensor or ultrasonic sensors, the position of ankle joints and one point of body link can be measured. Assuming that an attitude sensor such as wearable sensor or that of smartphone or smartwatch can be used, the inclination of the body or forearm link can be measured. TABLE 3.1 is the list of user's information that can be measured according to the assumptions above.

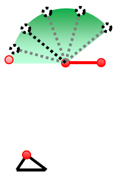
We classify the measurements sets using the number of unknown parameters X.

For example, setting touch sensors on gripper and armrest of armrest type systems, and distance sensors on top and bottom of its user's side, we can measure position of wrist, elbow, ankle joint and one point of body link, then the number of unknown parameters is given as $X = 1$ from (equation 3.4) shown in Figure 3.4 as **1a**. If we can get additional information of the other joint, such as position or rotation angle, we can calculate the link model. The measurements sets which have two or one unknown parameters are shown in Figure 3.4. The measurements sets which have no unknown parameters are shown in Figure 3.6. Red points of Figure 3.4 are positions of the point which are measured. Red lines and red dash lines mean the position and the angle of the link is measured, respectively.

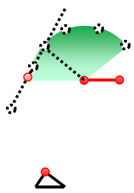
If there are too many unknown parameters, CoG candidates become too widespread. Based on this, we chose the seven measuring sets shown in Figure 3.4.

As we described in section 3.2.2, if there are unknown parameters, we can't calculate CoG uniquely. However, by considering the range of value of unknown parameters, we can calculate CoG candidates.

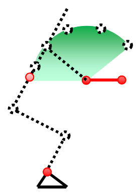
For example, on pattern **1a** of Figure 3.4, which is a measurement set in which positions of wrist, elbow, ankle joint and one point of body link are measured. In this pattern, position of forearm and foot link are identified, but the others are not. By considering the rotation range of the elbow joint, we can calculate positions of shoulder joint candidates as shown in Figure 3.7(a) because the length of upper arm is known. Since the length of the body link is known, we can calculate the position of each hip joint candidate which correspond to shoulder joint candidates from the position of one point of body link. We focus on one candidate of shoulder joint and calculate corresponding hip joint candidate as shown in Figure 3.7(b). Then the



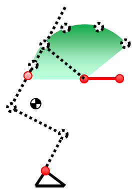
(a) All Candidates of Shoulder Joint



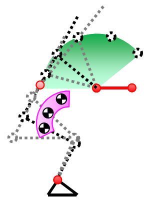
(b) Corresponding Hip Joint Candidate



(c) Corresponding Knee Joint Candidate



(d) Corresponding CoG Candidate



(e) All CoG Candidates of Whole Human Body

Figure 3.7: Calculation of CoG Candidates (1a)

Table 3.2: Range of Joints

Joint	Range of Joint (°)	
	Sitting and Standing	Walking
Shoulder	80∼190	90∼180
Elbow	-145∼0	-145∼0
Wrist	-90∼20	-90∼0
Hip	0∼135	0∼60
Knee	-110∼0	-90∼0
Ankle	80∼120	30∼150

position of corresponding knee joint candidate is calculated as shown in Figure 3.7(c). Since the rotation range of hip, knee, and ankle joint, and length of thigh and shank link are known, the position of the knee joint candidate which correspond to the hip joint candidate can be determine uniquely. From these position of joints and joint candidates, we can calculate positions of candidates of all links. Then, CoG candidates of all links can be calculated, and corresponding CoG candidate position of whole human body can be calculated from (equation 3.2) as shown in Figure 3.7(d). We can calculate all CoG candidates positions by repeating the procedure above shown in Figure 3.7(e).

3.2.4 Measurement Sets and Candidates of CoG

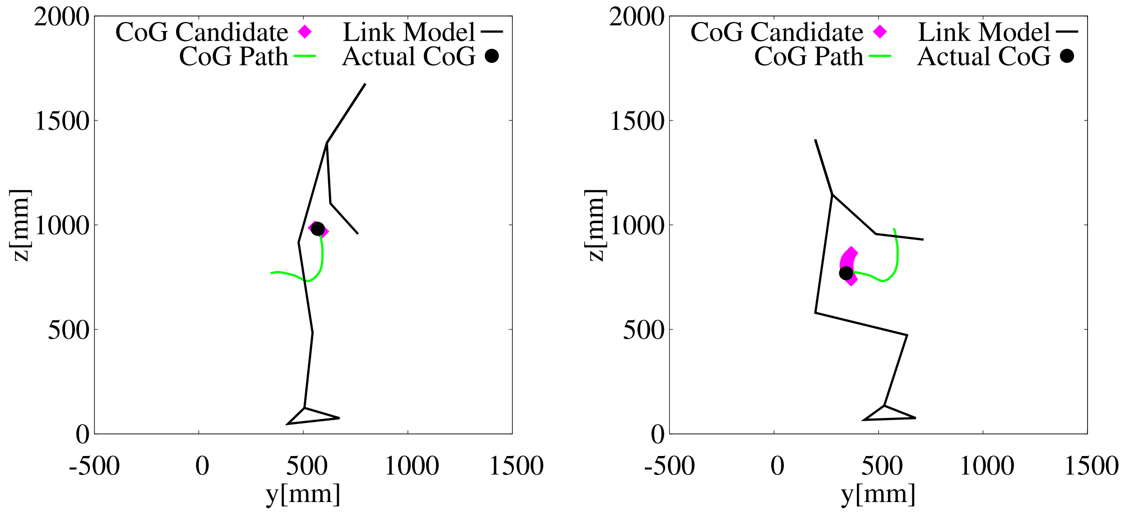
The ranges of all joints' rotation angles which are assumed to rotate in normal motion such as sitting, standing, and walking are shown in TABLE 3.2. We determine them from combination of literature-based data [121] and experimental data measured using the motion capture system. To measure them, we used 8 Raptor-E Digital Camera, made by Motion Analysis Corporation and dedicated software, Cortex.

3.3 CoG Candidates Estimation Using Motion Capture System

In this section, we estimate CoG candidates by using motion capture system assuming the data are measured by simple sensors as described in section 3.2.3. We used the same motion capture system as described in section 3.2.4.

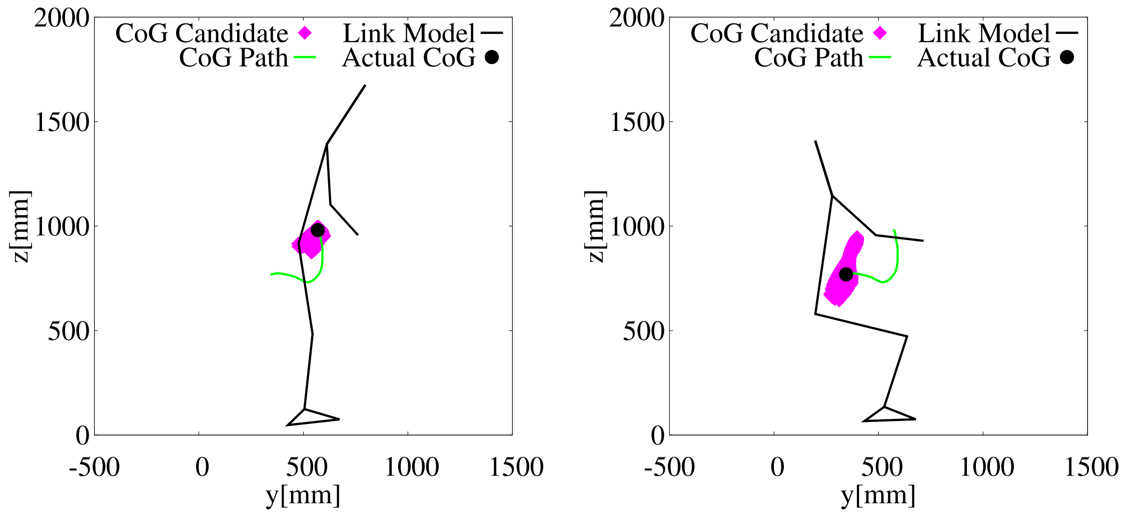
We measured subject's three type of motions; sitting, standing, and walking. The subject conducted the three motions assuming the use of a kind of support system such as walker. Then we calculated CoG candidates from selected data assuming the measurement sets previously described. Estimated CoG candidates of stand-to-sit motion are shown in Figure 3.8, Figure 3.9 as pink points. We calculated the accurate CoG from all of the motion capture data, which is represented as a black point in Figure 3.8, Figure 3.9. The green line is the trajectory of the accurate CoG.

We calculated the maximum error of CoG candidates against the accurate CoG. Maximum values of the error among each motions are shown in Figure 3.10. Purple, blue, green, orange, red, brown, and black lines are maximum error of CoG candidates of the measurement sets named **1a**, **1b**, **1c**, **2a**, **2b**, **2c**, and **2d**, respectively.



(a) 0 s (b) 4.5 s

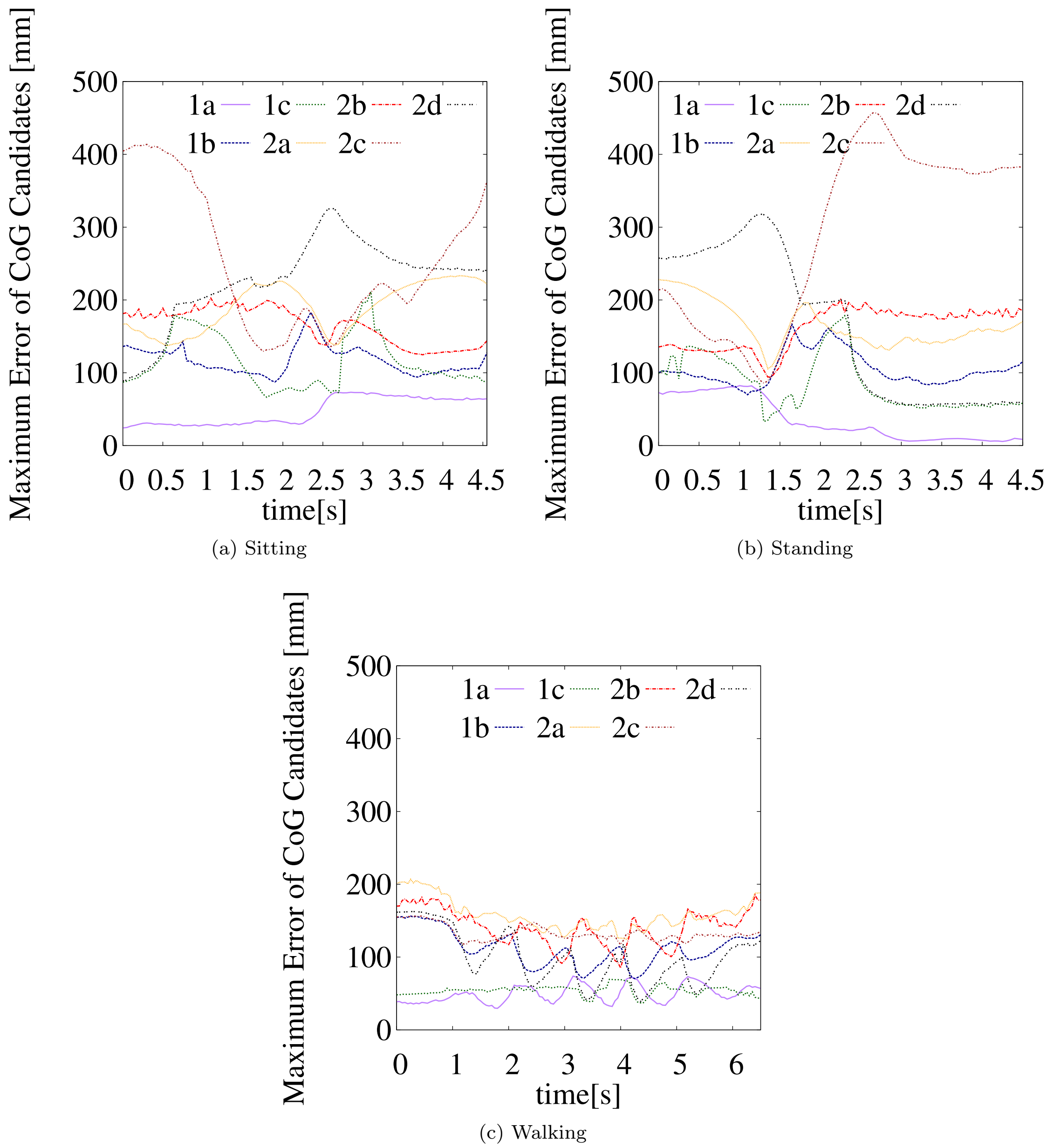
Figure 3.8: CoG Candidates (Sitting, 1a)



(a) 0 s (b) 4.5 s

Figure 3.9: CoG Candidates (Sitting, 2b)

By evaluating them, we determined that the measurement set named **1a** provides the minimum average error. In cases where sensory data result in two unknown parameters, the error of pattern **2b** is in average the smallest.



(a) Sitting

(b) Standing

(c) Walking

Figure 3.10: Maximum Error of Candidates

3.4 CoG Candidates Estimation Using a Few Simple Sensors

We developed a test model of the support system and we placed sensors presented in section 3.2.3 on it. We implemented an armrest type support system so that we can use it as both pushcart type and armrest type. The height of armrest is set to be 1100 mm. We set a distance sensor and a Laser Range Finder on the support system to measure the position of one point of body link and ankle joint, respectively. We used a GP2Y0E03 distance sensor (Figure 3.11) made by SHARP CORPORATION, which can measure from 4 to 50 cm, together with a UBG-04LX-F01 Laser Range Finder (Figure 3.12) made by HOKUYO AUTOMATIC CO.,LTD, that can measure up to 4,095 mm. In this experiment, we used a Laser Range Finder even though it's expensive. However, we consider that we can replace it with more inexpensive sensors such as distance sensors. An Adafruit LSM9DS0 IMU (Figure 3.13) is set on the epigastric fossa of the subject. We used the IMU to measure the inclination of user's body link. The IMU is around a few thousand yen, and it can be replaced by wearable devices which are frequently used by general people including smartphone. The specifications of these sensors are shown in TABLE 3.3–TABLE 3.5. Figure 3.14 shows the positions of sensors. We assumed that wrist joint is always on the gripper, and elbow joint is on the armrest, on experiments where the assistive machine is used as armrest type. By using these sensors, we can calculate CoG candidates of measurement sets: **1a**, **1b**, **1c**, **2a**, **2b**, and **2c**. We measured the same sitting and standing motion as the experiment on section 3.3 using the aforementioned sensors. Motion capture system was also used for comparison. We used 6 Kestrel Digital Cameras and dedicated software, Cortex, as motion capture system. Accurate CoG was calculated by Visual 3D software using the motion capture data.

The result of the experiment is shown in Figure 3.15 - Figure 3.18. Red points of Figure 3.15 - Figure 3.18 are positions of the point which are measured by the sensors. Blue and pink points are CoG candidates estimated by using motion capture system

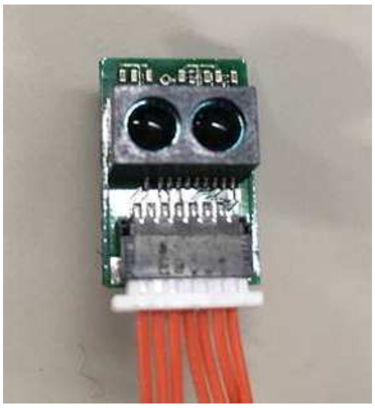


Figure 3.11: PSD (GP2Y0E03)

Figure 3.12: LRF (UBG-04LX-F01)

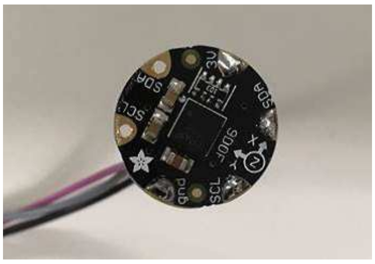


Figure 3.13: IMU (LSM9DS0)

Table 3.3: Specifications of Distance Sensor

Parameter	Symbol	Value	Unit
Measuring Distance Range	L	4–50	cm
Response Time	Ts	40	ms
Price	-	<10	US$

Table 3.4: Specifications of Laser Range Finder

Parameter	Value	Unit
Detection Distance	60–4,095	mm
Resolution	1	mm
Scan Angle	240	deg
Angular Resolution	0.36	deg
Scan Time	28	ms/scan

Table 3.5: Specifications of IMU

Parameter	Value	Unit
Linear Acceleration Sensitivity	0.061–0.732	mg/LSB
Magnetic Sensitivity	0.08–0.48	mgauss/LSB
Angular Rate Sensitivity	8.75–70	mdps/digit

and a few simple sensors, respectively. From these experimental results, we confirm that we can estimate CoG candidates by using a few simple sensors, and the results are similar as when using the motion capture with the proposed measurement sets.

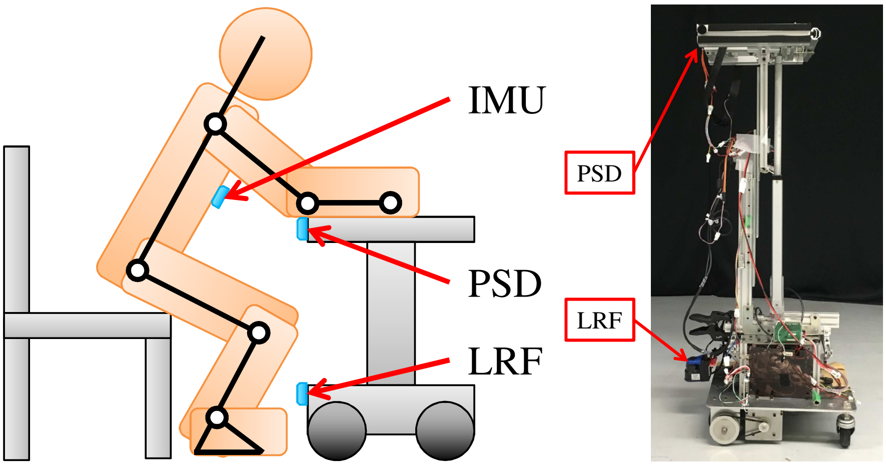
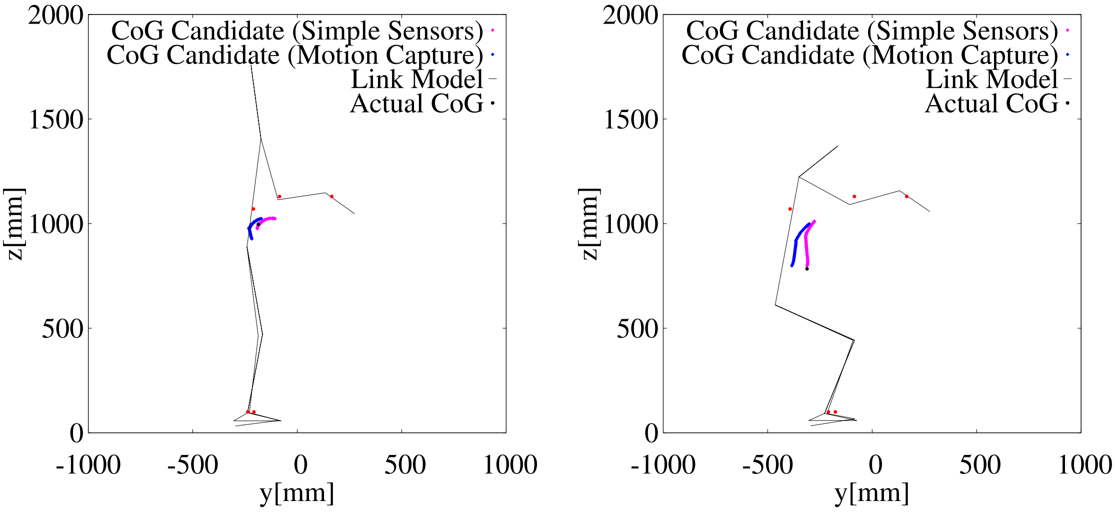


Figure 3.14: Position of Sensors

As shown in Figure 3.15 - Figure 3.18, the red points are not aligned to the black line representing the link. We consider that these misalignments increase the difference in CoG candidates estimated using the motion capture and the actual sensors. From the results, we can observe that there are different distribution trends of CoG candidates, depending on the state of the person (sitting, standing, and sit-to-stand transition). Therefore, we consider that we can discriminate the human state and determine falling from CoG candidates. We discuss the experimental results in section 3.5, and quantitative evaluation will be done in the future.

3.5 Discussion

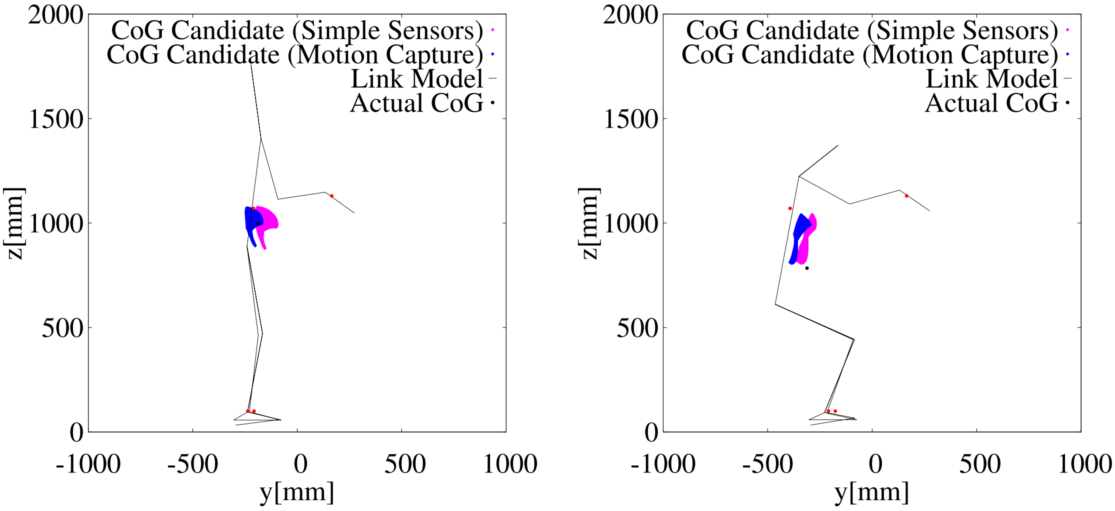
In this section, we discuss the results of the experiment presented in section 3.4. Time variation of Maximum error of CoG candidates are shown in Figure 3.19. Purple, blue, green, orange, red, and brown lines are maximum error of CoG candidates of the measurement sets named **1a**, **1b**, **1c**, **2a**, **2b**, and **2c**, respectively. Blue, pink, and green areas are the phases when user is standing, sitting, and the transition phase,



(a) 0 s

(b) 3.04 s

Figure 3.15: CoG Candidates of Sitting (1a)



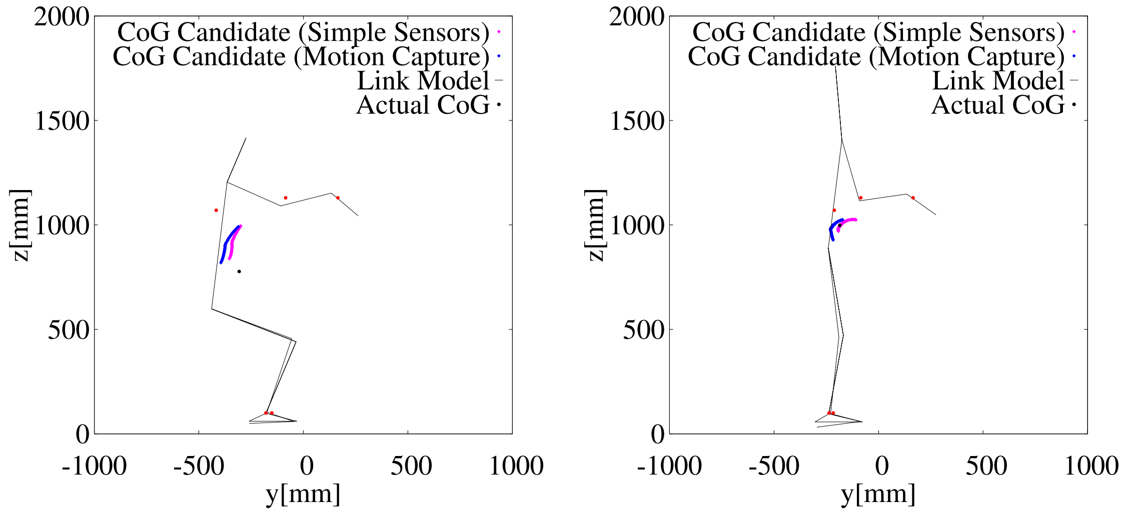
(a) 0 s

(b) 3.04 s

Figure 3.16: CoG Candidates of Sitting (2b)

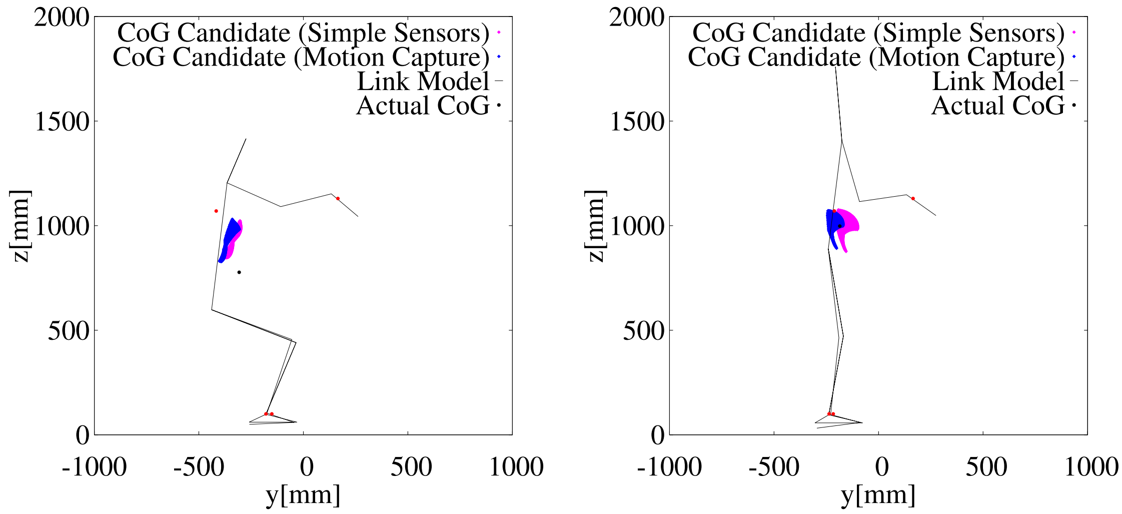
respectively.

When the user was fully sitting, the range of CoG candidates became large as shown in Figure 3.15 - Figure 3.18, and the maximum error was also increased as shown in Figure 3.19. In the sitting state, maximum errors were about 200 to 400



(a) 0 s (b) 3.84 s

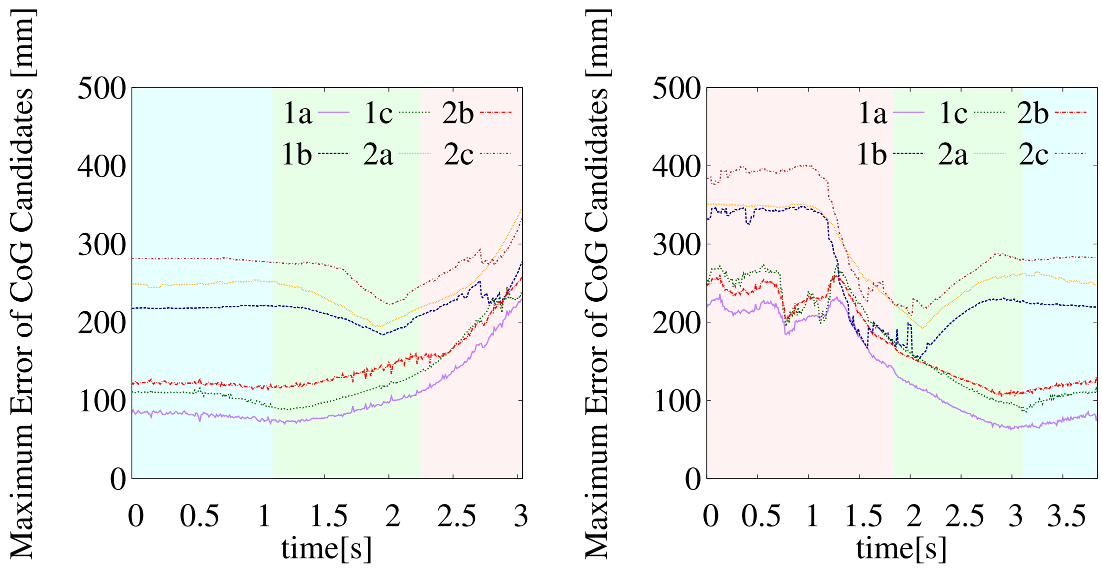
Figure 3.17: CoG Candidates of Standing (1a)



(a) 0 s (b) 3.84 s

Figure 3.18: CoG Candidates of Standing (2b)

mm, which seems large. However, the user can be considered to be comparatively safe when sitting, therefore we consider more important that the maximum errors when standing are small. In the transition phase, the ranges of CoG candidates were considerably narrow. Finally, in the standing position and close to standing



(a) Sitting

(b) Standing

Figure 3.19: Time Variation of Maximum Error of CoG Candidates

positions (ending of sit-to-stand, or start of stand-to-sit), we can appreciate that CoG candidates errors are small. Especially, in the cases of **1a**, **1c**, and **2b**, maximum errors of CoG candidates are about 100 mm and it's considered enough to estimate human state.

Time variation of Maximum error of CoG candidates of y and z direction are shown in Figure 3.20 and Figure 3.21. Maximum errors of y direction of **1a**, **1c**, and **2b** were smaller than 100 mm during most of the measurement time. This means that we may be able to detect user's falling forward or backward. As shown in Figure 3.20(b) and Figure 3.21(b), maximum errors of z direction of **1a**, **1c**, and **2b** were large when the user was in the sitting position, but they were small when the user was almost standing or standing. As we previously discussed the maximum error, these results can be considered to be good enough to estimate human state or detect abnormal states such as falling.

We also calculate area ratio and Hausdorff distance[122] to compare the CoG

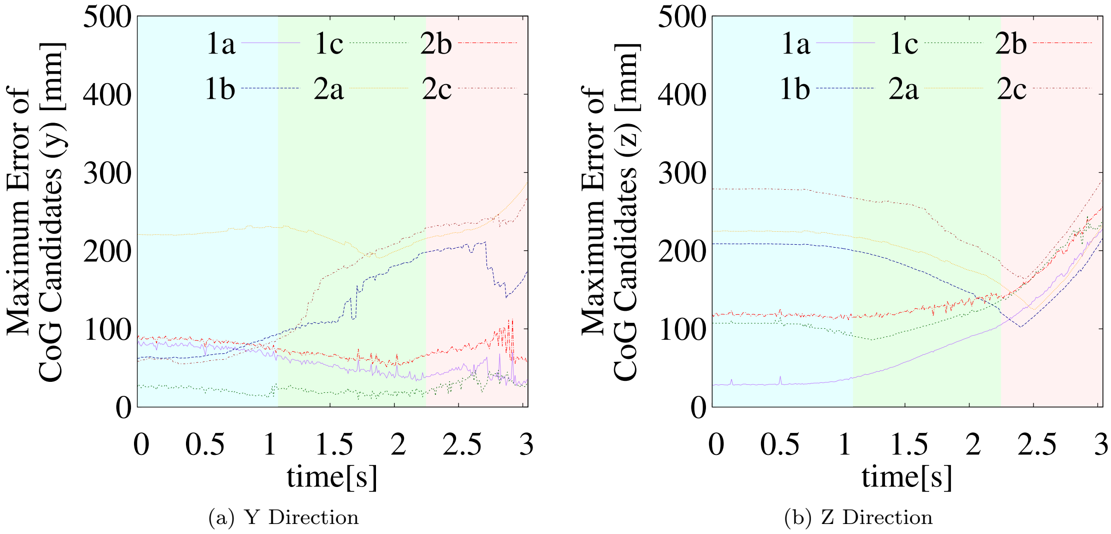


Figure 3.20: Time Variation of Maximum Error of CoG Candidates of Y and Z Direction (Sitting)

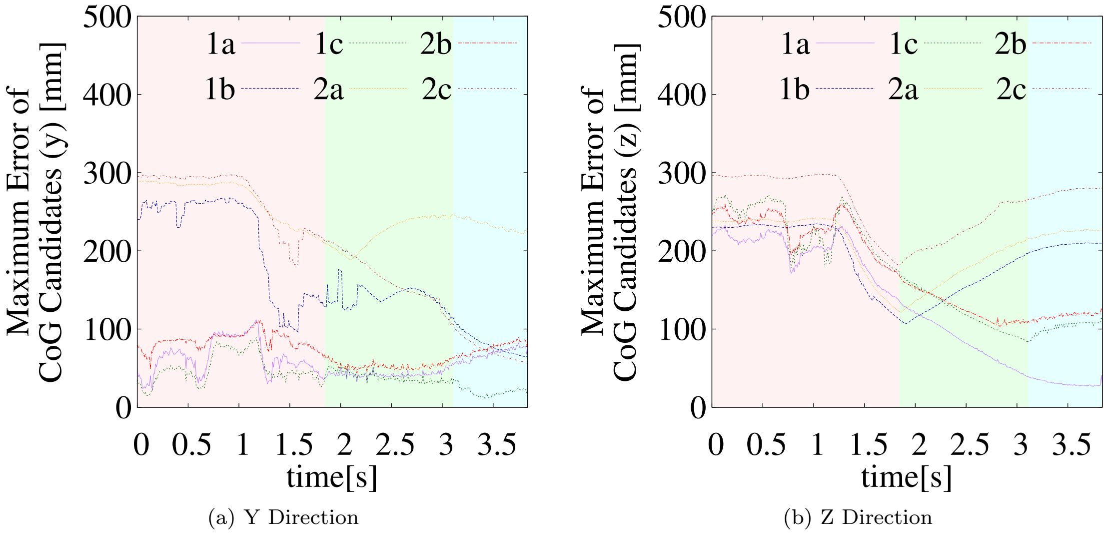


Figure 3.21: Time Variation of Maximum Error of CoG Candidates of Y and Z Direction (Standing)

candidate of motion capture system and actual system. CoG candidates are calculated as point cloud, then we consider 5[mm] $\times$ 5[mm] to calculate area of CoG candidates. The more accurate CoG candidates are on actual system, the more close to 1 the

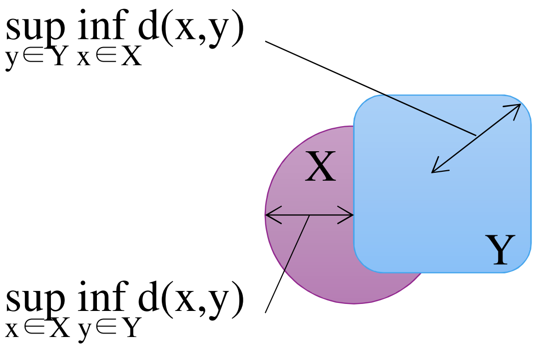


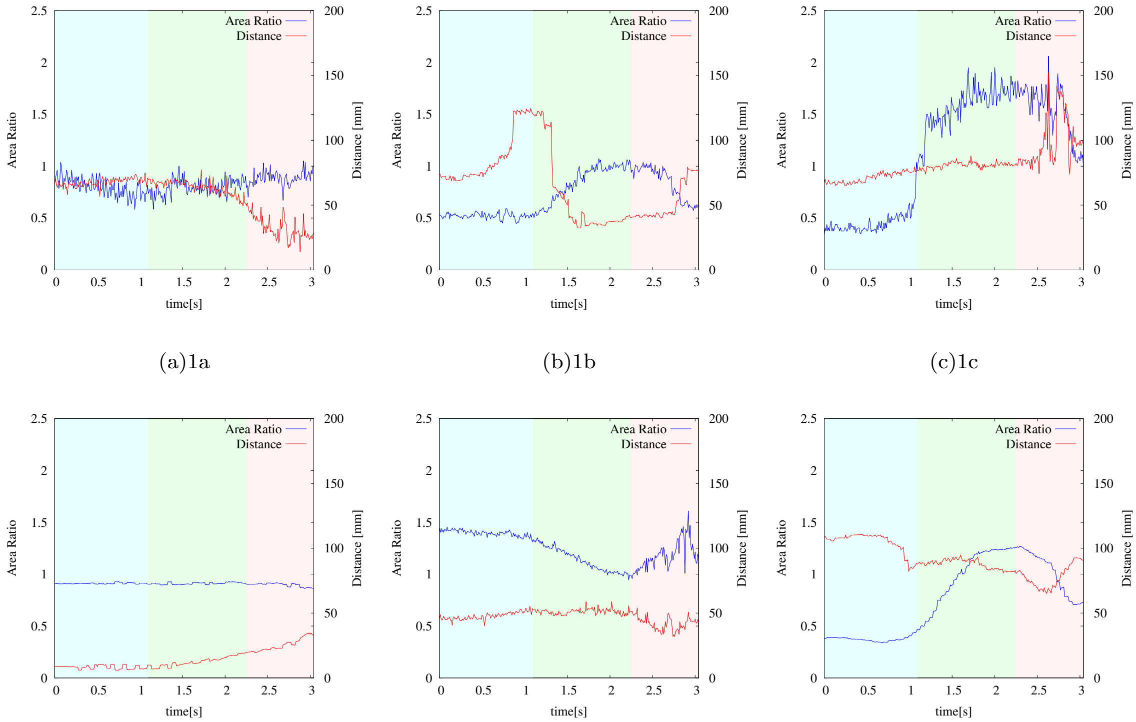
Figure 3.22: Hausdorff Distance

area ration become. By considering the CoG candidates as a set of points, Hausdorff distance can be calculated. Hausdorff distance is the maximum value of the shortest distance between each members of 2 sets as shown in Figure 3.22. Thus Hausdorff distance can be calculated by using following equation:

$$d_H(X,Y) = \max\left\{\sup_{x\in X}\inf_{y\in Y} d(x,y), \sup_{y\in Y}\inf_{x\in X} d(x,y)\right\} \tag{3.5}$$

The more accurate CoG candidates are on actual system, the more close to 0 the Hausdorff distance become. Figure 3.23 and Figure 3.24 show the calculated area ratios and Hausdorff distances. From the results, we know that if the CoG candidates is accurate on motion capture, the result cannot always be reproduced by using actual system. Information of upper body link is not reliable comparing to other information.

By comparing the results of **1b** and **2b**, less unknown parameters don't always result in smaller error of CoG candidates. Therefore, we can confirm that sensor selection is very important, and we can determine where and which sensors to place in assistive robots from these considerations.



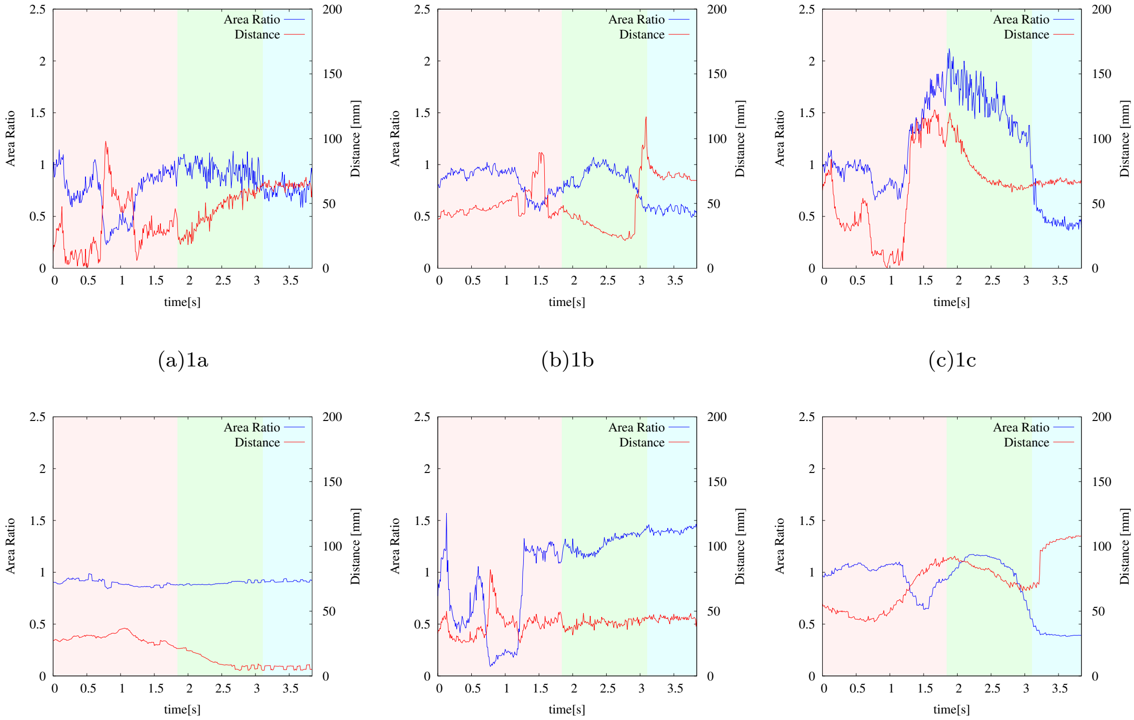
(a)1a (b)1b (c)1c

(d)2a (e)2b (f)2c

Figure 3.23: Area Ratio and Hausdorff Distance (Sitting)

3.6 Conclusions

In this chapter, we proposed a method to estimate the assistive machine user's CoG candidates using a reduced amount of sensors. In order to calculate the CoG, we used the human link model to represent the human body. Since we can't calculate the link model with unknown parameters, CoG can't be determined uniquely. Then we considered the unknown parameters' ranges of value and calculate CoG candidates. By using the mobility concept, we determined the number of unknown parameters. We discussed and selected the sensors which are frequently used in support systems, and created measurement sets labeled using the number of unknown parameters. We conducted experiments using a motion capture system to examine the effectiveness of



(a)1a (b)1b (c)1c

(d)2a (e)2b (f)2c

Figure 3.24: Area Ratio and Hausdorff Distance (Standing)

each group of measurements by comparing the CoG candidates' range. The results of experiments using a few simple sensors showed the validity of the proposed method. We used a Laser Range Finder to measure the positions of ankle joints even though the sensor is expensive, and it's difficult to measure ankle joints accurately when the user is walking. Therefore, we are currently searching for inexpensive sensors which can measure ankle joints well even when the user is walking. The effects of sensors accuracy on the CoG candidates should be analyzed as a future work.

Chapter 4

State Estimation

4.1 Introduction

Various support systems have been developed to support elderly people, and the demand for indoor support system has increased. It is important to support not only walking but also to support sit-to-stand and stand-to-sit motions. We develop a support system for indoor use that depends on the user's state such as sitting or standing. Although it is useful for assistive devices to be able to select how to support users based on sensor data, it is difficult to utilize many expensive and sophisticated sensors for accurate estimation of the user's state. In this study, we propose an estimation method of the user's state utilizing a few inexpensive and simple sensors. Firstly, we propose the method to calculate the CoG candidates using a human link model. The CoG candidates are then used to develop a state estimation method for sit-to-stand motion; this motion consists of three contiguous states: sitting, rising, and standing. A Support Vector Machine (SVM) is used to estimate the user state and the methods were experimentally validated using the developed assistive robot.

The experimental results show that the estimations are correct except in the vicinities of state transitions. The average state transition time errors are 0.175 s and 0.145 s for sit-to-rise and rise-to-stand, respectively. Since sit-to-stand motion is contiguous, the user's state is ambiguous and can be both states at the boundaries. Therefore, the accuracy of the state estimation is reasonable.

4.2 Development of the Support System

We developed an assistive robot in [123]. The robot is shown in Figure 4.1. The robot was designed based on the general activities of daily living such as sit-to-stand motion. The specifications of the robot are shown in TABLE 4.1. The robot is designed to be able to pass a typical toilet door of general households in Japan. Supporting sit-to-stand and stand-to-sit motion is important especially for indoor support. In the context of safety, supporting not only hands but also elbows is effective during walking, and especially sit-to-stand motion. Therefore, the developed robot is armrest type, and the armrest can move up-and-down by a linear actuator. It can support the user's sit-to-stand motion by moving the armrest when the user leans on the armrest. This armrest can lift a weight of 40 kg, and it's enough to assist elderly people to stand. From the simulation results of joints' load, it is designed to be able to lift 75% of the user's upper body weight. The armrest can move lowest to highest about 4 s. It is suitable for elderly people to standing, and the speed of the linear actuator is adjustable for each person. The way of support is designed on the basis of the analyses of physical therapists' sit-to-stand assist motions.

The measurements sets named **1a**, **1b**, and **2a** can be used for the developed assistive robot since the robot is armrest type. From the results of [124], the measurements

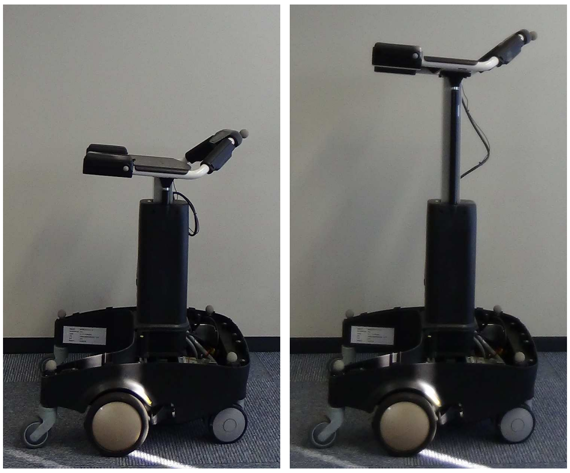


Figure 4.1: Developed Assistive Robot (Left: Lowest Armrest, Right: Highest Armrest)

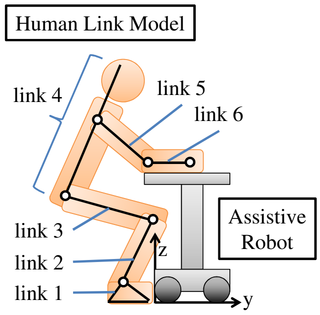


Figure 4.2: Human Link Model and Assistive Robot with Coordinate Frame

set **1a** is adopted because the CoG candidates range is narrow. It is expected that the narrow CoG candidates are better for state estimation.

It is known whether the user's wrists and elbows are on the grippers and armrests, respectively, because the robot has touch sensors on these parts. The height of armrest can determine from the displacement of the linear actuator. The wrist and elbow positions are defined as the center of each joint. The positions are determined by using the height of armrest and the thickness of the forearm link.

We set a GP2Y0E03 distance sensor made by SHARP CORPORATION on the back of the armrest. The specifications of the sensor are shown in TABLE 3.3. The armrest moves during sit-to-stand motion, and the sensor can measure the distance between the body link and armrest. The position is determined by using the thickness of the body link as same as the wrist and elbow joints. Thus, using only a few simple sensors, all required data of measurements set **1a**, except for the ankle joints positions, was obtained. The ankle positions can be measured if we use expensive sensors such

Table 4.1: Specifications of Developed Assistive Robot

	Value	Unit
Height	77 - 103	cm
Armrest Height	71 - 97	cm
Length	50	cm
Width of Armrest	46	cm
Width of Robot Body	54	cm
Armrest Moving Time	4	s
Armrest Weight Capacity	40	kg

as LRFs. However, it is too expensive and difficult to use in general households. We now propose a new calculation method of the CoG candidates that does not need ankles positions.

4.3 The CoG Candidates Calculation and State Estimation

The new method to calculate the CoG candidates without using ankles positions is presented here, along with the state estimation method using the CoG candidates.

Firstly, we propose the new CoG candidates calculation method using a small number of sensors in section 4.3.1. The range of the ankle position is used to calculate the groups of CoG candidates. We validate the method by the experiment in section 4.3.2.

In section 4.3.3, we propose a method to estimate the user's state using the CoG candidates. We consider that the sit-to-stand motion consists of three contiguous states; sitting, rising, and standing. If sitting and rising states can be discerned, the height of the armrest can be controlled. The robot should not move during sitting and rising for safety. However, when the user intends to walk, it should be able to move. We can control these if we can estimate the states of the sit-to-stand motion.

4.3.1 CoG Candidates Calculation Method Using the Ranges of Ankles Positions

When people undergo sit-to-stand motion, the ankle positions don't change since their feet sustain their whole body weight. When using the developed robot, the users' arms sustain some weight because of the armrest. However, most of whole body weight is also sustained by their feet.

We set the ranges of ankle positions as $0 \sim -350$ mm from the assistive robot. The range is set by considering the relative position of a user and the assistive robot, size of the assistive robot, and parameters of the human link model. Feet don't move from the ground during sit-to-stand motion, so the z-coordinate of ankle joint doesn't change during the motion. We set the origin on the ground just below the edge of the assistive robot as shown in Figure 4.2, and the ankle range is represented as $y = 0 \sim -350$ mm. We consider eight groups of ankle candidates as $y = 0, -50, -100, -150, -200, -250, -300$, and -350 mm. Then we can calculate users' data which is represented in Figure 4.3 by using the assumption and the sensors noted above. Black points are the measured points' positions. Black lines mean that the positions of the links are determined uniquely. Grey dash lines and circles are the candidate positions of links and joints, respectively. Only three representative foot links are shown in Figure 4.3 due to the visibility.

We can calculate eight groups of CoG candidates per frame from the data represented in Figure 4.3 by using measurements set **1a**. Firstly, we focus on one ankle joint candidate and then consider the range of elbow joint. The candidates of the

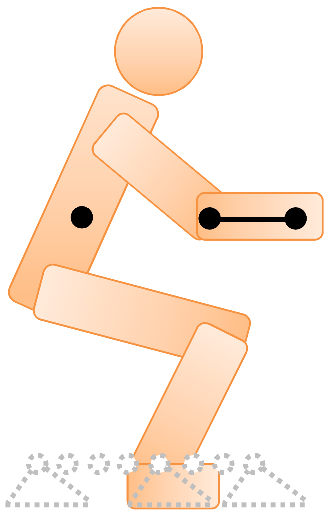
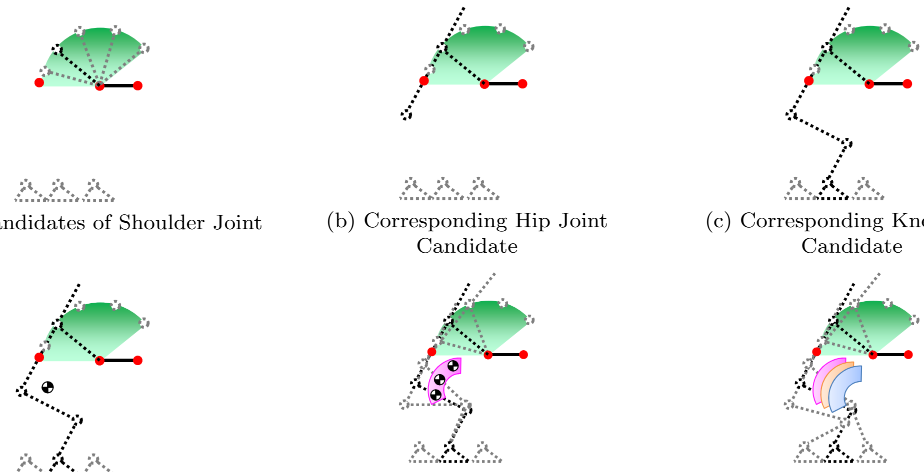


Figure 4.3: Users' Data Which Can Be Calculated by Using the Developed Assistive Robot (Black Points: Position Measured Points, Black Lines: Position Determined Links, and Grey Dash Circles: Candidate Positions of Joints, Grey Dash Lines: Representative Candidate Links)

shoulder joint can be calculated as shown in Figure 4.4(a) since the length of the upper arm link is known. Black dash lines and joints are the focused ones of the candidate links and joints, respectively. Since the body link's length is also known, the position of each hip joint candidate which corresponds to shoulder joint candidate. We focus on one candidate set of shoulder and hip joint as shown Figure 4.4(b). The corresponding knee joint candidate is calculated as shown in Figure 4.4(c). Candidate positions of all links can be calculated from the positions of joints, links, and their candidates. Thus we can calculate the corresponding CoG candidate position as shown in Figure 4.4(d). By repeating this procedure, all the candidates of CoG position corresponding to the ankle candidate can be calculated as shown in Figure 4.4(e). Therefore, we can calculate eight groups of CoG candidates by repeating the procedure above for all ankle candidates, as shown in Figure 4.4(f).



(a) All Candidates of Shoulder Joint

(b) Corresponding Hip Joint Candidate

(c) Corresponding Knee Joint Candidate

(d) CoG Candidates Corresponding to the Focused Candidates Set

(e) All CoG Candidates Corresponding to the Focused Ankle Candidate

(f) All Groups of CoG Candidates Corresponding to the Ankle Candidates

Figure 4.4: Calculation Procedure of CoG Candidates

4.3.2 Validation Experiments of the Proposed CoG Candidates Calculation Method

We conducted an experiment to validate the proposed CoG candidates calculation method. Firstly, the participant is sitting on a chair with his forearms on the armrest of the robot. When the participant finishes leaning his body, the armrest moves up from lowest to highest. The participant raises his body according to the rise of the armrest. Finally the participant stands. The robot doesn't move except for the armrest during the sit-to-stand motion for safety. We measured the user's sit-to-stand motion by using a motion capture system. The actual CoG position can be calculated by adding the value of the unknown parameters of the measurement set from the motion capture data. The CoG candidate can be compared with the actual CoG. We used six Kestrel Digital Cameras and two Osprey Digital Cameras, made by Motional Analysis Corporation. We used dedicated software, Cortex, for data processing.

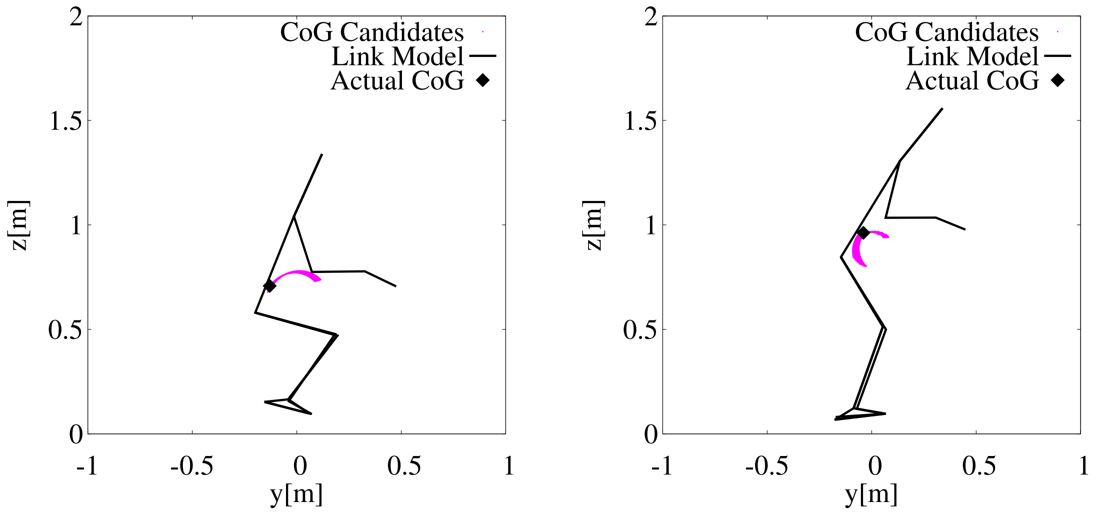
The calculation results of CoG candidates are shown in Figure 4.5 - Figure 4.7. In Figure 4.5, the calculated eight groups of CoG candidates are represented as pink points. And the black lines represent the human link model measured by using the motion capture system. The black rhombus point is the actual CoG. Figure 4.6 shows enlarged views of the CoG candidates. Each group of CoG candidates are drawn with different color in Figure 4.6. Pink, cyan, green, red, brown, grey, blue, and orange points represent the CoG candidates which are calculated by assuming that the position of the ankle joints are 0, -50, -100, -150, -200, -250, -300, -350 mm, respectively. Enlarged views of the parts of the CoG candidates are shown in Figure 4.7. Large circles, triangles, and squares are the representative candidates in the cases of 0, -200, and -350 mm, respectively. They are calculated by using larger intervals of discrete values of the elbow joint's rotation angle.

As shown in Figure 4.5–Figure 4.7, the CoG candidates are calculated; their accuracies are also similar to the previous work. We confirmed that the method is effective for the calculation of CoG candidates when the positions of the ankles are unknown; this is largely unchanged from the case using the ankle positions.

4.3.3 State Estimation Method

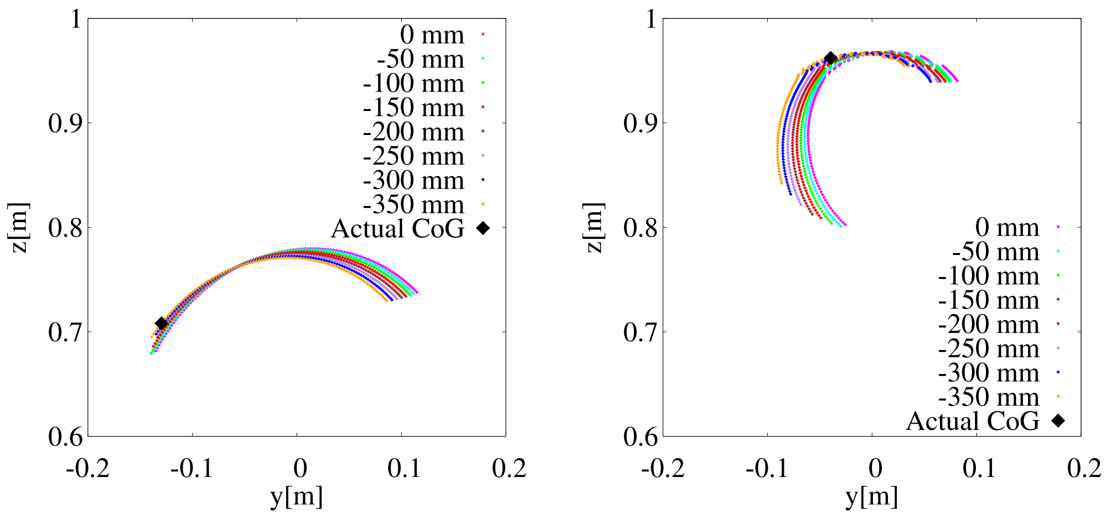
It is important to use the CoG candidates for state estimation since they have physical significance. For example, we can estimate whether the user is likely to fall by the location of the projected point of the CoG against the base of support; this is likely to be implemented in various systems.

We focus on sit-to-stand motion, and consider that the motion consists of three



(a) Sitting (b) Standing

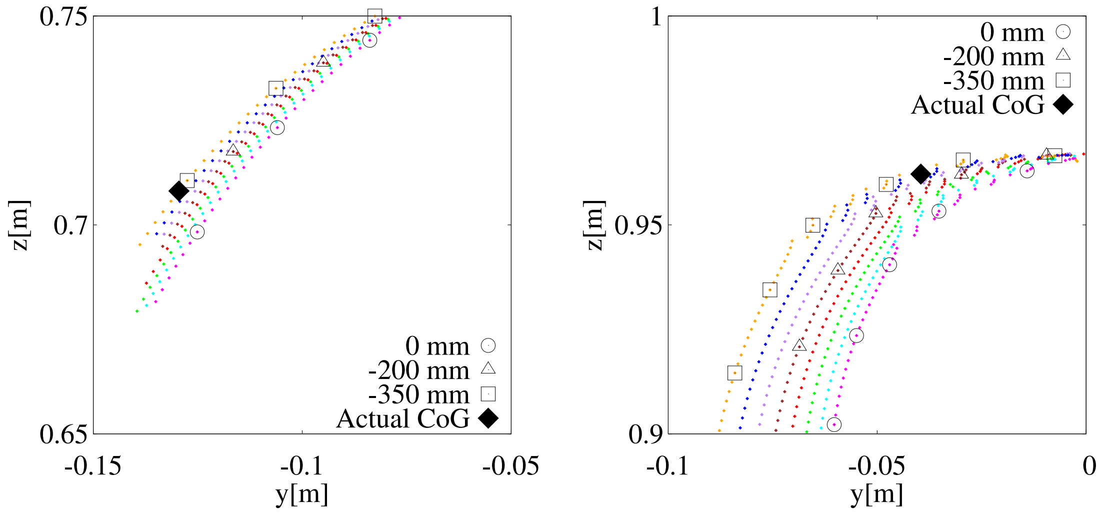
Figure 4.5: 8 Groups of CoG Candidates with Human Link Model



(a) Sitting (b) Standing

Figure 4.6: Enlarged Views of 8 Groups of CoG Candidates (Y-Coordinate of Ankle Joint Is Assumed 0$\sim$−350 mm)

contiguous states; **sitting**, **rising**, and **standing**. The users of the assistive robot basically conduct the sit-to-stand motion in the same way as described in section 4.3.2. When the user is only sitting or leaning on the robot and the armrest is lowest, the



(a) Sitting

(b) Standing

Figure 4.7: Parts of the CoG Candidates (Representative Candidates Are Emphasized by Symbols)

user is sitting. When the armrest of the assistive robot is moving upward, the user is rising. When the armrest is highest and user is leaning or straight, the user is standing.

SVM is adopted to estimate the user's state since it allows us to set features manually. It can be trained for each user since the training time is not so long. We set geometric features of the CoG candidates as the features of SVM, which are,

- Average value of y-coordinate of the CoG candidates
- Average value of z-coordinate of the CoG candidates
- Value of integral of the group of the CoG candidates
- Maximum value of y-coordinate of the CoG candidates
- Maximum value of z-coordinate of the CoG candidates
- Minimum value of y-coordinate of the CoG candidates

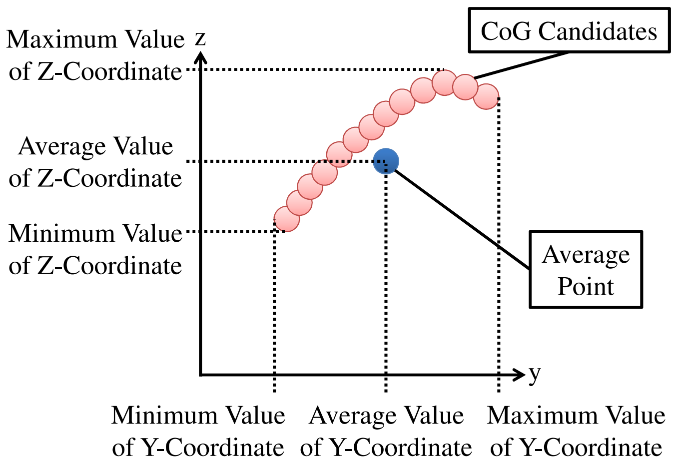


Figure 4.8: Utilized Features on the State Estimation

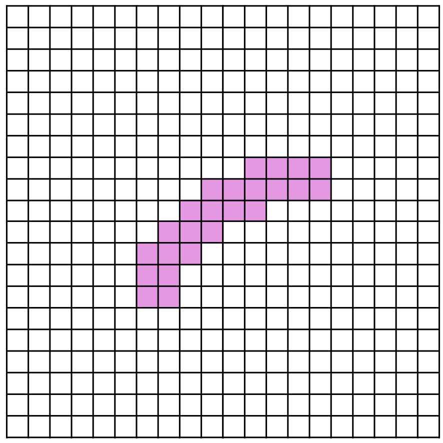


Figure 4.9: Pixels for Calculation of Integral Value of the CoG Candidates

- Minimum value of z-coordinate of the CoG candidates

as shown in Figure 4.8. The values of integral are calculated by considering pixels as shown in Figure 4.9. The size of one pixel is 5×5 mm^2. The absolute value of the integral means little since the group of CoG candidates draw a curve line with no thickness. However, the relative value of the integral which is calculated using same definition is effective for comparing the size of each group of the CoG candidates. Therefore, the integral value of the CoG candidates group can be used for state estimation as one of the features of SVM. The position and the form of the group of the CoG candidates can be figured out from the features described above. Normalized values of features are inputted to SVM. The RBF kernel is used for SVM. We confirmed that the all features are significant on the classification.

As we described in section 4.3.1, eight groups of CoG candidates can be calculated per frame. Thus, eight estimated states were obtained per frame. If the all estimates are the same in a frame, the estimate of the frame is the same. However, if estimates

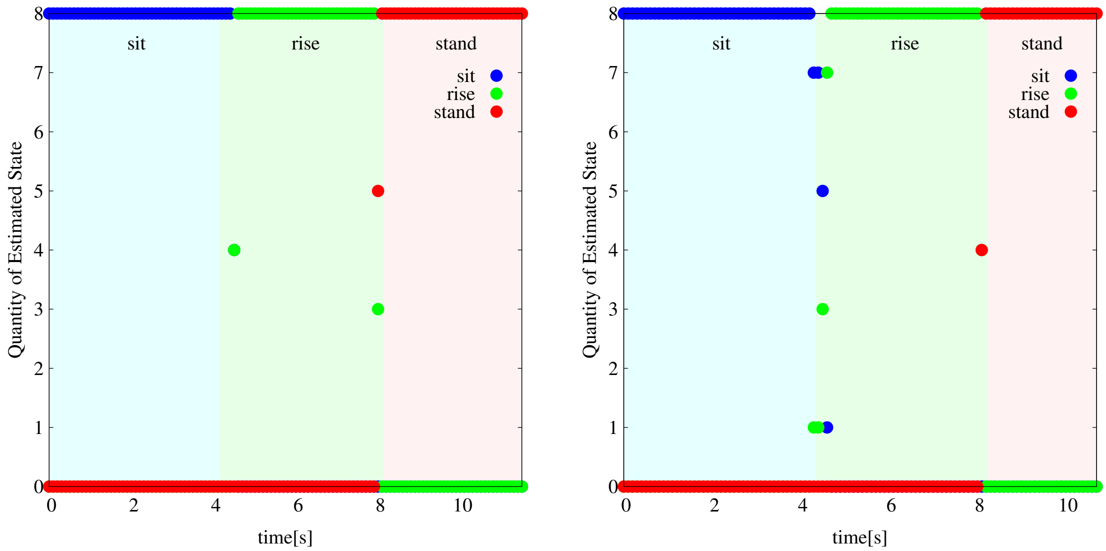
(a) Sitting (b) Rising (c) Standing

Figure 4.10: Sit-to-Stand Motion (Participant B)

are different in a frame, the majority is adopted. If more than one state is dominant, we adopt one which is same as the previous frame.

4.4 State Estimation Experiments Using Simple Sensors Which Are Set on the Assistive Machine

We conducted the experiments to validate the method which we described in section 4.3. Twenty participants conducted sit-to-stand motions using the developed assistive robot 11 times such as shown in Figure 4.10. They conducted the same sit-to-stand motion as described in section 4.3.2. Firstly, the participants sat on a chair and put their hands and elbows on the grippers and armrests of the assistive robot. Then they conducted the sit-to-stand motion using the robot. The participants are both genders, 21–31 years old, 164–189 cm tall, and weighing 52–97 kg. None had



(a) Participant A

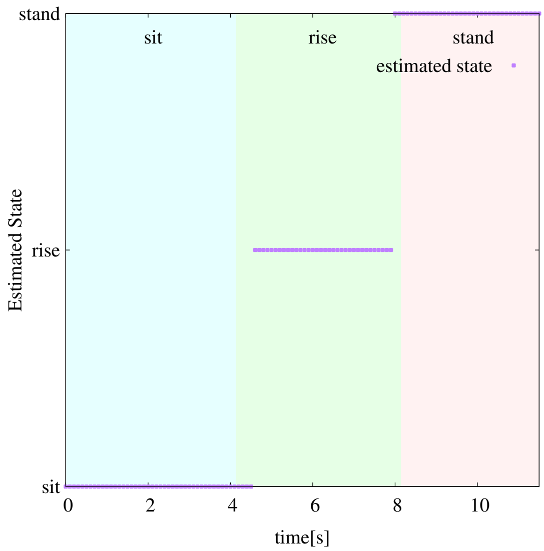
(b) Participant B

Figure 4.11: Time Variation of the Quantities of Groups Which Show Each State as the Estimation Result

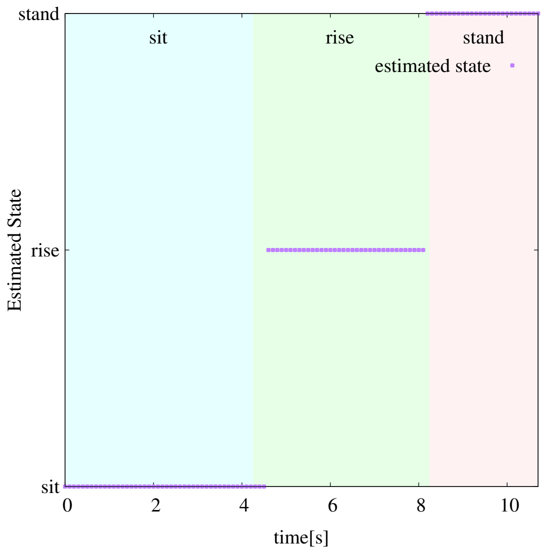
any physical disability. Informed consent was obtained from all participants before the experiments.

We calculated the candidates of CoG based on the method described in section 4.3.1. The length of each participant's links were measured and used. The thickness of bodies varied with different clothes. Since body thickness is not measured before each use, it is difficult to account for this value accurately. Therefore, the thicknesses of body and forearm links of participant A are used for all participants. Training data comprised 10 data of the measured sit-to-stand motion for each participant. The participants' states of the other data were estimated based on the method described in section 4.3.3. As SVM software, LIBSVM [125] is used. We shot the videos of the experiments, and determined the actual participants' states visually, and compared the results of estimation.

Participants A and B's time variations of the quantities of the groups which show each state as the estimation result are shown in Figure 4.11. Blue, green, and red



(a) Participant A



(b) Participant B

Figure 4.12: Time Variation of Estimated State (Participants A and B)

points are the quantities of the CoG candidates groups which show sitting, rising, and standing as the estimation result, respectively. Blue, green, and pink areas are the phases when user is sitting, rising, and standing, respectively. For example, from 0 s to 4.4 s of participant A, the quantity of groups which show **sitting** as the state estimation result is 8, with **rising** and **standing** are 0. It means that all CoG candidates groups show the same state as the estimation result in the term. At vicinities of state transition, some groups show the different state estimation results such as at 8 s of participant A. By adopting majority, the estimated state become more accurate than using only one CoG candidates group.

The participants' time variations of the estimated state are shown in Figure 4.12, and accuracies of the state estimations are shown in TABLE 4.2 and TABLE 4.3, respectively. Purple points in Figure 4.12 are the estimated state. Purple point located at the bottom, center, and top indicates that the estimated state is sitting, rising, standing, respectively. The results indicate that the estimation is almost correct. The

Table 4.2: State Estimation Accuracy (Participant A)

Quantities of Frames		Estimated State: Sit	Rise	Stand
Actual State	Sit	42	0	0
	Rise	4	34	2
	Stand	0	0	34

Table 4.3: State Estimation Accuracy (Participant B)

Quantities of Frames		Estimated State: Sit	Rise	Stand
Actual State	Sit	44	0	0
	Rise	2	36	1
	Stand	0	0	25

estimation errors occur only near the boundaries between states. In other words, the errors indicate that the estimates of the transitions start either a little early or a little late. TABLE 4.2 shows the quantities of the frames of the estimated states compared to actual states of participant A. For example, the participant A's rise was estimated as sitting in 4 frames. Since each frame is 0.1 s, the error is 0.4 s. This error occurs only at a state transition; thus, the result means that the state transition estimation at sit-to-rise was delayed by 0.4 s.

Estimation errors of state transition time is shown in TABLE 4.4. The positive numbers mean late errors of the transition time and negative ones mean early errors.

Since sit-to-stand motion is contiguous, the user's state can appear to be simultaneously in two states near the boundary; the boundaries were visually determined. We can assist users even if there is a little error of state transition time by adjusting the timing. Thus it causes no problem if we estimate the transitions a little early or late. From TABLE 4.4, we know that the state transition time errors are considerably short. We confirmed that the proposed state estimation method is effective

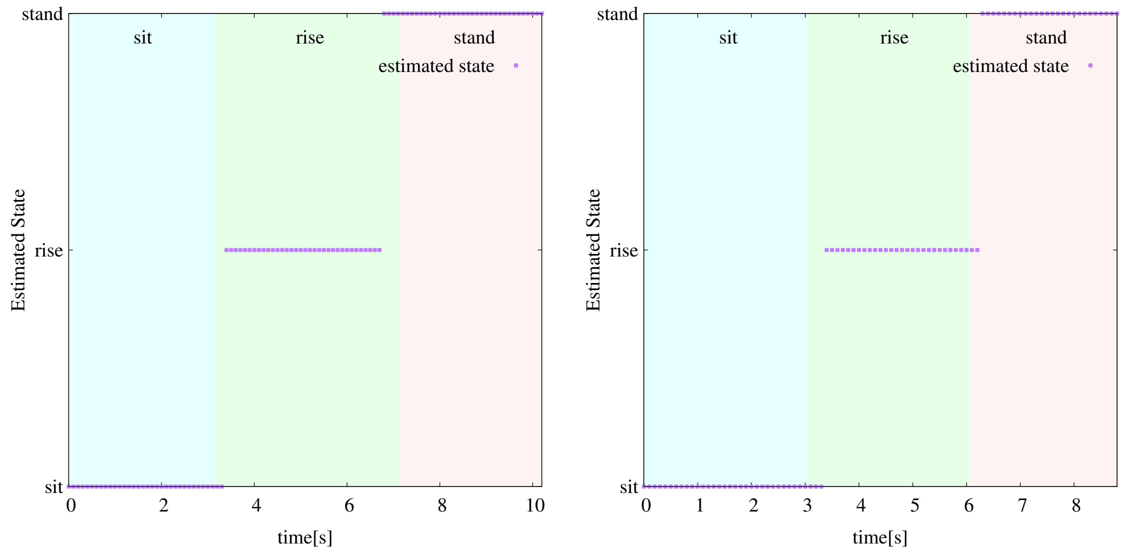
Table 4.4: State Transition Time Error

Participant Number	State Transition Time Error (s)	
	Sit-to-Rise	Rise-to-Stand
A	+0.4	−0.2
B	+0.2	−0.1
C	±0	−0.2
D	+0.1	−0.2
E	+0.2	−0.4
F	+0.2	−0.2
G	+0.2	−0.2
H	+0.2	−0.1
I	+0.3	+0.2
J	+0.1	−0.2
K	+0.1	−0.1
L	+0.2	−0.1
M	+0.1	−0.2
N	+0.2	−0.1
O	±0	−0.2
P	+0.2	−0.2
Q	+0.3	−0.1
R	+0.2	−0.1
S	+0.1	−0.1
T	+0.2	−0.1
Average	+0.175	−0.145

when using the sensors, which are actually set on the assistive robot.

As shown in TABLE 4.4, almost all participants' results have same trend. The beginning of the rising, the armrest height, and user's posture are little different from sitting. By the end of rising, they are almost identical to standing. In the case of the participant I, the state transition time error of rise-to-stand is late. It may be caused by the difference of posture. The users often lean forward when rising and stand straight after standing. So the timing of upper body movement may affect the result.

Time variation of the estimated state of participants E and I are shown in Fig-



(a) Participant E

(b) Participant I

Figure 4.13: Time Variation of Estimated State (Participants E and I)

ure 4.13. It shows that the state estimates are correct except in the vicinity of the boundaries between states. All participants' results have same trend, which means that there are no failures except in the vicinity of the state transitions. In the case of the participant E, time error of rise-to-stand state transition is a little large in contrast to the result of participant A. As described above, participant I's state transition time error of rise-to-stand is late, unlike the others'. It is likely that the posture of this participant affected the result. The user's state is ambiguous at the boundaries, and the time error is short enough to allow compensation by adjusting the support function of the robot.

From these results, it is clear that we can estimate the assistive robot users' state by using only a few simple sensors. The users' states are estimated using only 10 training data, and no SVM hyperparameters such as regularization constant C are optimized. It suggests that preparation is little enough for using the robot. This method can be applied for anomaly detection and acquisition of useful data since the

CoG position candidates can be obtained. This information can be used to select the timing of support functions such as moving the armrest. The CoG is physically meaningful and the relationship between the user's CoG and the robot position is used for the proposed state estimation method. Therefore, the method can be implemented in other systems with few changes. In this study, the experiments were conducted with young participants. Similar results are expected with elderly people who actually need such assistive robots because there are no fundamental physical differences. We plan to conduct these experiments with the cooperation of elderly people to validate our method.

4.5 Conclusions

In this study, we present a developed assistive robot which can support a user's movements for indoor support, and we proposed an estimation method of the user's state from the CoG candidates by using a reduced number of sensors.

In order to assist a user with sit-to-stand motion, the assistive robot needed to be able to sustain the user's weight over a large area during sit-to-stand motion. The development of an armrest type assistive robot followed, which can sustain some of the user's weight by the armrest; it can support sit-to-stand motion by moving the armrest higher. The user's state estimation is important to enable variation of the support methods of the system. The armrest can move at the beginning of the motion since the state estimation determines whether the user intends to stand; this decision can be used to keep the robot's wheels immobilized during sit-to-stand motion. We equipped the robot with fewer sensors than required to calculate the CoG position. Subsequently, we proposed the CoG candidates calculation method by considering the ranges of the unknown parameters of the human model. This was followed by the proposed state estimation method by using the CoG candidates. Finally, we experimentally validated the proposed method using a few simple sensors on the robot.

Though the estimation results were analyzed offline, this estimation method can be implemented in real-time without large changes. Although the learning time of the SVM is a little long, it can be finished before using the assistive robot and thus it causes no problem. The CoG candidates calculation is O(8N), and the estimation time of SVM is less than 0.005 s. In this study, training data comprised 10 data of the measured motion. We intend to explore necessary amount of data to reduce the preparation before using and the user's strain. Training data can be collected while using the assitive robot. Therefore, by renewing the SVM training data while using, the state estimation will be able to get better day by day.

Future work could involve implementation of the proposed method for other motions, such as stand-to-sit and walking. The method can also be applied to anomaly detection. The CoG candidates can also be used to decide the timing of the changing support function by detection of the user's intent. By considering the relationship between the CoG candidates and the actual CoG, it is expected that the CoG candidates can become narrower, furthermore, the actual CoG position can be estimated. Finally, we intend to conduct similar experiments with elderly people, who actually need assistive robots.

Chapter 5

Accountable System Design

5.1 Introduction

Although the development of robot-based support systems for elderly people has become more popular, it is difficult for humans to understand the actions, plans, and behavior of autonomous robots and the reasons behind them, particularly when the robots include learning algorithms. Learning-based autonomous systems which are called AI are treated as an inherently untrustworthy "black box," because machine learning or deep learning algorithms are difficult for humans to understand. Robot systems such as assistive robots, which work closely with humans, however, should be trusted.

Adopting robots that use learning algorithms raises additional problems. It is difficult to investigate and fix system failures in systems with "black boxes." It is also difficult to decide who is responsible in such cases. Knowledge representation is adopted to make systems transparent. Visualization and auditory display of knowledge representation improves system interpretability. Appropriate interfaces make systems transparent and interpretable to achieve accountability. And accountable systems can be trusted by humans, thus the user do not feel anxious and the system is usable. However, almost all research is carried out for specific stakeholders of specific systems and there are generally several stakeholders for each system as shown in Figure 5.1. In the case of a walking assistive system with sit-to-stand functionality, a user uses the system, while caregivers or family members support the user in using the system correctly and safely. Engineers should maintain the system, and if problems arise, they need to investigate and repair it. If an accident occurs, accident investigators are responsible for the investigation. Although there are different stakeholders according to the specific system properties, these people generally represent the stakeholders of support robot systems. Systems should therefore achieve accountability for all stakeholders. However, most research in this field has focused on particular systems and situations, and no general design architecture exists. Some researchers have discussed ethical design of robot systems; however, almost all research indicates general design principles or provides several examples. We therefore propose a new design architecture for accountable learning-based support robot systems. Considering accountability in the design process will be important for realization of accountable systems.

In this study, we propose a new design method, focused on accountability and transparency, for learning-based robot systems. Describing the entire system is a necessary first step, and transcribing the described system for each stakeholder based on several principles is effective for achieving accountability. The method improves transparency for systems, including learning algorithms. A standing assistive robot is used as an example of the entire system to clarify which system parts require

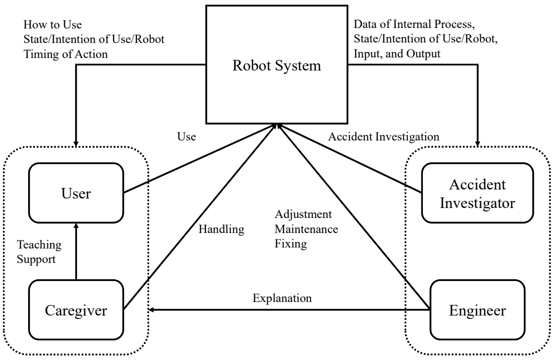


Figure 5.1: Example of System and Stakeholders.

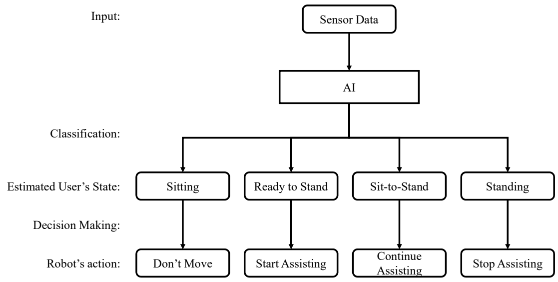


Figure 5.2: AI Robot System.

greater transparency. This study adopted the Systems Modeling Language (SysML) to describe the system and the described system is used for the information representation. Information should be represented considering the relationships between stakeholders, information, and the system interface. Because of their complexity, it is difficult for humans to understand the complete set of information available in robot systems. Systems should therefore present only the information required, depending on the situation. The stakeholder-interface relationship is also important because it is more beneficial for professionals to view information relevant to their specialized field, which would be difficult for others to understand. By contrast, the interface should be intuitive for general users. Visualization and sound are very useful means of transmitting information, with advantages and disadvantages for different circumstances. These relationships are important for achieving accountability.

5.2 System Design Concept

This section explains the main concept of design architecture of support robot systems to achieve accountability. We used a walking assistive robot with sit-to-stand function as an example. The robot has an armrest with a linear actuator for sit-to-stand assist, and its wheels have attached motors for walking assistance. The robot can estimate the user's state by means of several sensors based on Support Vector Machine (SVM), a machine learning algorithm. The design architecture can be used for other autonomous robot systems that interact with humans, such as robot sports instructors and communication AI robots.

Robot systems which include learning algorithms and interactions with humans should achieve accountability. The actions and intentions of such systems tend to be opaque for humans, making it difficult for humans to cooperate with such robots. When the systems carry out an action, they should make stakeholders understand what they are doing and why. Humans relate to such systems not only during use, but also for maintenance, repair, investigation, and other functions. Therefore, describing an entire system and transcribing it for all stakeholders is important for achieving accountability.

System description is required to determine necessary information depending on the stakeholder and situation. Machine learning algorithms are difficult for humans to understand, thus robot systems with learning algorithms are also opaque. Our method for describing the entire system can contribute to the transparency of learning-based robot systems. The method is explained in detail in section 5.2.1.

System stakeholders include different types of people, such as users, caregivers, and engineers. The information required varies according to the situations. Interfaces should also be determined according to the stakeholder. It is important to appropriately transmit the required information. The concept of information ontology is explained in section 5.2.2.

5.2.1 AI Transparency

Systems that adopt types of learning algorithms, such as Random Forest, Support Vector Machine (SVM), Logistic Regression, and Neural Network, are increasing. Learning algorithms include "black box" components that are difficult for humans to understand, and the opacity of learning algorithms makes the systems seem untrustworthy [126]. Some researchers focus on transparency of learning algorithms [89–92]. Studies on making AI transparent by representing the reasons for decisions [47,93] can provide some understanding of learning algorithms, however, these methods cannot make all algorithms transparent for ordinary people. Even though the AI included in the system is opaque, systems should be transparent.

Systems usually use learning algorithms for some types of estimation, the results of which are used for system decision making. For example, user state estimation of a standing assistive robot can be realized with data from learning sensors. Effective operation of the robot requires that assistance motion begins when the user is ready to stand up. For state estimation, teaching data is collected and models are learned before the robot is used. During use, the robot measures and collects user data such as foot position and upper body angle using sensor input, as shown in Figure 5.2. Sometimes the data is processed, and the learned model uses the raw or processed data as input and classifies it as state estimation. The action determined by the system depends on the estimation result, then the actuators provide an output to the external environment. This system can be fully described separately from the learned model itself.

Transparency of classification reasons is studied in the computer vision and AI fields [47,93]. For the systems addressed in this research, input data and classification results are transparent and classification reasoning is unclear. For example, clinical image recognition systems detect diagnostic signs based on deep learning, and report to a doctor. Thus, humans can understand classification results and decision making, while conducting the action remains the humans role. This type of research focuses on algorithmic transparency, however there are various parts of learning-based robots that are unclear, as shown in Figure 5.2. Learning-based systems are unclear for estimation results, decision making, and robot action, which are the usual stakeholders' usual interests. Users generally need to know the robot's current actions, action plans, and decision making for efficient operations; the user's required actions are also important information. Engineers who investigate or maintain robot systems should understand the internal processes of the systems for maintenance, investigation, or repair. Sensor data and actuator output torques are also required. By contrast, the relationship between input data and classification results, which is the role of a learning algorithm, is not relevant for these tasks. By using the representation of classification reasons, the system will become more transparent, however, we consider that representing the relationships between data, decisions, and actions is more important. Representation can effectively improve systems interpretability; therefore, we propose a method for describing robot systems that adopts machine or deep learning.

5.2.2 Information Ontology

Describing the entire system is essential not only for AI transparency but also for information ontology. Defining the internal processes of the system allows us to know which parts of the system are not transparent, which enables us to determine what information should be represented. For example, if a problem occurs where an actuator moves without the user's intent, engineers and accident investigators will want to investigate it. If there are no representations of internal process information, investigators can only estimate based on the system outputs. Investigators would then have to extract the required information from a large quantity of stored data, much of which is unnecessary. Meanwhile, if the whole system is described, internal processes and data relationships can be understood. The system can represent related information such as decided actions, estimation results, and inputs.

To determine the best representation of information, we should consider relationships between stakeholders, information, and interfaces. If the relationships between stakeholders and information, known as use cases, are known, the system can represent information easily according to the situation.

Stakeholder-interface relationships are also important because specialized interfaces are useful and efficient. However, it is generally difficult for ordinary people to use such specialized tools. It is therefore important to change interfaces according to the stakeholder as shown in Figure 5.3. An intuitive interface should be provided for general users, while specialized interfaces should be created according to professional standards.

Systems should provide a variety of different types of information. For example, the user state is spatial information, and does not change rapidly. By contrast, the timing of the robot's support is temporal information, and is not continuous but event-driven. There are several media by which to transmit information such as vision and sound. The medium should be selected according to the features of transmitted information.

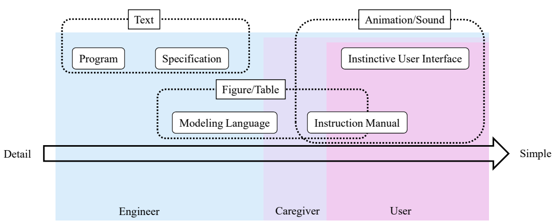


Figure 5.3: Stakeholder-Interface Relationship.

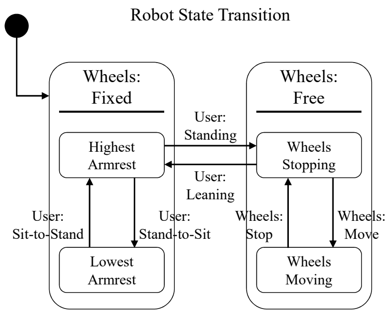


Figure 5.4: Example of State Machine Diagram.

All information can be extracted by describing the entire system. Interfaces representing the required information for specialists are created based on professional standards. By transcribing the interfaces into intuitive formats, an interface for general users can be constructed.

5.3 Describing Whole System

This section explains a method for describing the entire system. AI transparency can be achieved by describing the entire system; we can then determine which information from the described system should be represented.

There are various ways to describe algorithms, processes, and systems. Flowcharts are one of the most famous diagrams used for representing algorithms. They can represent not only processes but also conditional decisions. For describing state transitions, a Finite State Machine is used and applied to several modeling languages. Each of these have different advantages, and several modeling languages are composed by applying these models.

For this study, we adopted the modeling language SysML [127] to describe system states, internal processes, and external interactions. SysML has several types of diagrams for describing systems. Some diagrams are suitable for real-time representation, while others are useful for investigation. They can be selected depending on the intended use.

SysML itself and the features of its diagrams are explained in section 5.3.1. The uses and advantages of SysML diagrams are also explained, using an assistive robot as an example. We then explain how to describe systems that include learning algorithms by using SysML in section 5.3.2.

5.3.1 SysML

SysML is a modeling language, developed for systems engineering based on Unified Modeling Language (UML). UML is useful in software engineering; however, systems with hardware cannot be sufficiently described with UML. SysML was developed to enable experts from different fields, such as programmers, designers, and electrical engineers, to collaborate on system development. SysML consists of nine types of diagrams: Requirement Diagrams, Activity Diagrams, Sequence Diagrams, State Machine Diagrams, Use Case Diagrams, Block Definition Diagrams, Internal Block Diagrams, Parametric Diagrams, and Package Diagrams. It is unnecessary to adopt all the diagram types, and it is possible to make more than one diagram for each diagram type.

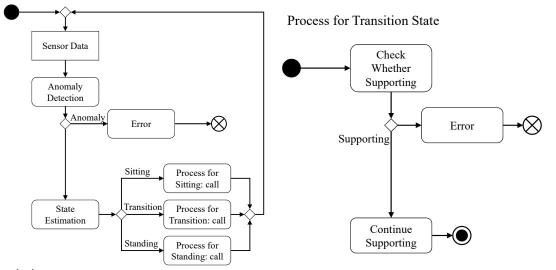
State Machine Diagrams are for describing a system's state based on a Finite State Machine (FSM). By using the diagrams, the system's state or behavior can be described as shown in Figure 5.4. The example diagram is for a support robot which can assist with standing, sitting, and walking. The robot has two basic states, in which wheels are fixed or free, and assists the user's standing and sitting by moving the armrests vertically. It is assumed unsafe if the wheels are fixed or the armrest moves when the wheels are moving; thus, a state transition between the wheels fixed state and the wheels free state can occur only when the wheels are stopped, as shown in Figure 5.4. If the system estimates user states, surrounding people, or the environment, they can also be described with State Machine Diagrams.

Activity, Sequence, and Internal Block Diagrams are useful for describing a system's internal processes, input-output relationships, and actions. Internal Block Diagrams can clearly describe input-output relationships and are especially useful in cases where the system contains many parts. Activity Diagrams are good for describing internal processes included in some kinds of algorithms, such as learning and estimation. They have advantages if there is some conditional branching. Internal processes of an example robot system are shown in Figure 5.5. The system has anomaly detection and state estimation as shown in Figure 5.5(a). First, the robot checks for anomalies using the sensor data. If no anomaly is detected, the robot classifies the user's state, whether sitting, standing, or transitioning between them. The next processes for each state are described in other diagrams; an example is shown in Figure 5.5(b). This diagram shows the process when the user is in a transition state. The robot is meant to be conducting a support action when the user's state is transitioning between sitting and standing. If no support is conducted when the user is in a transition state, the system determines that an error has occurred, as shown in Figure 5.5(b). If support is provided and the user is still in a transition state, then the support is not yet complete and the robot continues to provide support. Sequence Diagrams are most useful for describing a time sequence for internal or external systems interaction, as shown in Figure 5.6. If the user is sitting and leaning forward, the sensor data is sent to the computer embedded in the robot and the computer estimates the user's leaning from sensor data in the same way as the state estimation described above. The robot's computer then sends a command to the linear actuator of the armrest and the robot's wheels, and the armrest applies lifting force to the user to assist with the sit-to-stand motion.

Defining stakeholders and their use cases is valuable for achieving accountability. Use Case Diagrams make it possible to define the systems stakeholders and explain the purpose of their relationship with the system as shown in Figure 5.7. The example shows that the robot supports three activities for a user: sit-to-stand, stand-to-sit, and walking. Engineers interact with the robot for maintenance and repair. By using the Use Case Diagrams, the relationship between stakeholders and information, which is necessary for representation of information, can be obtained, as explained in section 5.4 in detail.

5.3.2 Describing Systems That Include Learning Algorithms

The process for a system that includes a learning algorithm is described in SysML as shown in Figure 5.5. Sensor data is first used as input for anomaly detection, as shown in Figure 5.5(a). Next, the raw sensor data are processed for state estimation based on a machine learning algorithm. The next process is determined based on the result of the state estimation. The process that occurs during user transition is shown in Figure 5.5(b). It can be determined that the output action maintains support from Figure 5.5(b). Although the relationship between the input data and estimated state cannot be fully understood, we can know the decision making reason.



(a) State Estimation and Conditional Branching

(b) Activity for User in Transition State

Figure 5.5: Examples of Activity Diagram.

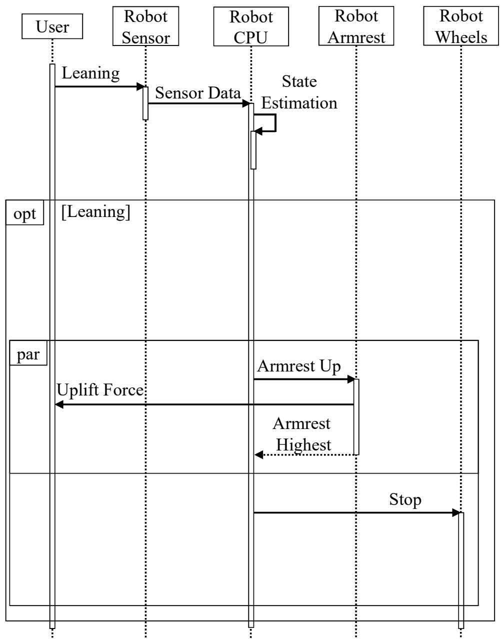


Figure 5.6: Example of Sequence Diagram.

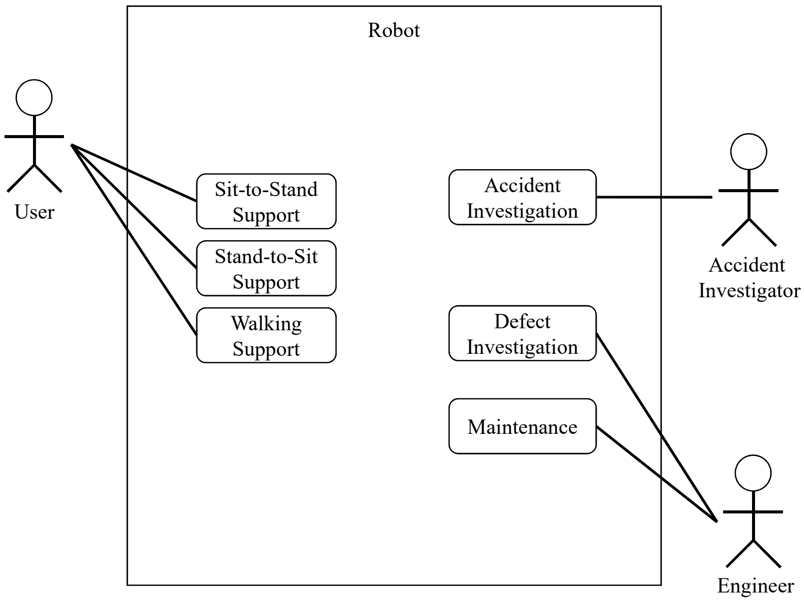


Figure 5.7: Example of Use Case Diagram.

By describing information required in various situations based on these figures, stakeholders can more fully understand the robot's actions and plans than they would without representation. Stakeholders need to understand the robot's actions and reasons to use, maintain, and repair it. For example, users can understand the robot's actions from Figure 5.5(b). It is also clear that the robot decides the appropriate action based on the estimated user state from Figure 5.5(a). A system that includes a learning algorithm can therefore be described transparently enough for internal processes to be understood in this way. Stakeholders can also investigate accumulated data based on these figures, however, the figures themselves are difficult to understand for non-engineer stakeholders, as other stakeholders rarely have SysML knowledge. Appropriate interfaces are required for each stakeholder, as explained in section 5.4.

5.4 Representation of Information

This section explains the importance of a system's accountability of the relationships between stakeholders, information, and interfaces.

To achieve accountability, systems should provide the required information to stakeholders. It is necessary to determine which stakeholders need which information. This stakeholder-information relationship can be treated as a use case of the system, which is explained in detail in section 5.4.1.

It is less than transparent if the provided information is difficult to understand. Any existing standards for presentation of the information should be followed. People who have professional knowledge can easily understand information written in specialized language, however, people who have no specialized knowledge cannot. This stakeholder-interface relationship is discussed in section 5.4.2.

It is also important to select a transfer method based on the features of the information. For example, spatial information is easily expressed visually, while temporal information can be expressed through sound. This information-interface relationship is explained in section 5.4.3.

5.4.1 Use Case: Stakeholder-Information Relationship

Use cases mainly depend on the types and functions of the system. Developers of systems invariably consider use cases of the systems, and SysML Use Case Diagrams can inform their consideration and discussions. Developers tend to focus only on use cases of users; however, there are other stakeholders for the systems. Almost all systems have users, engineers, and accident investigators as stakeholders. For assistive robots, stakeholders may include people such as caregivers, family, and certification authorities.

Who interacts with the system and how they interact is integral to the question of who needs which information; thus, use cases are important for information representation. For example, users often want to know about a system's behavior, state, or action and people become anxious if there is an autonomous robot doing something incomprehensible. Users require understanding of current behaviors and actions, as well as future plans, and they may want to know the reason for the system's actions. If there is a difference between the intended action of the user and that of the system, people want to know the reason and a solution. Therefore, "what should I do" is one of the most important pieces of information for systems that include interaction with humans.

Engineers relate to systems for development as well as for maintenance and repair. They can conduct their work more efficiently if they understand the system. To check whether a system is behaving normally, information about a system's internal and external behaviors are required. This knowledge is also useful for accident investigators.

5.4.2 Professional Standard: Stakeholder-Interface Relationship

As described in section 5.3, SysML has been popular among engineers who are involved in development. Engineers can easily understand systems by using SysML, however, it is not easy for others; therefore electing the interface according to stakeholders is therefore important.

If there are standards for required information, these should be followed. Accident investigation is governed by laws and there are standards for home electronics. Laws for robots and AI systems are now being discussed, therefore we consider other professional standards, such as engineering standards, in this paper. If standards for accident investigation for robots is determined, we intend to adapt our interface to the standard.

Generally, it should be assumed that users have no professional knowledge, and a user interface should be intuitive and usable.

5.4.3 Media: Information-Interface Relationship

Humans receive information mainly through eyes and ears. Vision and sound are therefore good options for information transfer media.

Each of these media has advantages and disadvantages. For example, visualization is useful for representing multiple or spatial information, however it is impossible to transmit information by sight if the user's focus is not where the information is being presented. In this case, sound is a more effective means of information transfer.

These features have been discussed in the interface design and feedback in motor learning fields [128–130]. Following these studies and considering the information that needs to be represented, we summarize the features of vision and sound as follows:

- Vision
  - Spatial Information
  - Multi-Information
  - Steady Information
- Sound
  - Temporal Information
  - Event-Driven Information
  - Information Which Should Be Transmitted Even If Human Is Unnoticed

Selecting media based on the features of transmitted information is especially effective for general users because it makes the interface more instinctive.

5.5 Conclusions

In this study, we proposed general design architecture for accountable learning-based support robot systems. Robot systems, especially support robots that include AI and p-HRI, should be able to account for their actions. Describing systems and representing the required information for all stakeholders can make the system transparent.

It is difficult to make a learning algorithm transparent, although a system that includes a learning algorithm can be explained. Robot systems usually adopt learning algorithms for recognition or estimation of some parameter. Input sensor data, estimation results, decided action, and actuator output can all be explained, and thus humans can understand the systems. SysML is adopted in this paper for describing the robot system.

Information should be transmitted to each stakeholder in an appropriate way, hence relationships between stakeholders, information, and interfaces are important. Use cases show the required information, which varies according to stakeholders and situations. SysML use case diagrams have particular advantages for this application. Specific factors influence the stakeholder-interface relationship. An intuitive user interface should be adopted for ordinary users, and appropriate interfaces will vary based on the different features and uses of each type of information. The effectiveness of the proposed design is validated by the experiments in chapter 6 and chapter 7.

Chapter 6

Verbal Guidance

6.1 Introduction

In this chapter, we analyze and confirm the importance of accountability by experiments. And we propose and validate the verbal guidance for physically assistive robots. The verbal guidance focuses on interpretability to achieve accountability. This chapter proposes a new concept that accurate human state estimations are not necessary for robots and that appropriate guidance make robots useful even if the estimation is not strictly accurate. If robots can convey the their actions and action timings to users, the users can adjust their actions according to the robots. We assume that the capability for users to adjust motion can realize the proposed concept.

In the nursing-care field, verbal communication is important, which is well known as one of issues of "Humanitude" [131–133]. Hence, we also adopt a verbal knowledge representation. Verbal guidance to encourage a user to stand up and countdown timer representations are adopted. Initially, an experiment is conducted to validate the usability of the system that acts according to considerably accurate estimations.

The experimental results show that system without verbal guidance is not useful and causes anxiety to humans, even if the human state is detected accurately. Furthermore, we determine the appropriate content and timing of verbal guidance based on the results. Subsequently, we conduct an experiment to confirm that the proposed method is applicable under imperfect estimations.

6.2 Verbal Guidance Concept

This section explains the main concept of knowledge representation. Even if robots estimate the appropriate timing and perform actions, if the robots move without any information, the system user may be caught unawares, and the system may be deemed unfriendly. The users may feel useless if they do not know the actions of the robot or if they cannot adjust the timing. Hence, we realize a system to ensure that the user can understand the robot, user action, and its timing.

We focus on sit-to-stand support function of the robot system. We determine the required information that is to be represented to user and the method of representing this information.

6.2.1 Knowledge Representation

It is necessary to determine the content, timing, and medium of the information to be represented. The system is simple as it has one function. The required information are robot estimation, robot action, user action, and timing of these actions. We assume that the users have been familiarized with the system simply by explanation, prior to using it. The robot recognition result, content of robot action, and required user action can be represented as a single sentence such as “let’s stand up.” The timing should be represented by sounds, such as a countdown of "3, 2, 1."

Generally, in nursing-care, the caregivers speak to the care recipients. Communication is necessary before the caregiver touches or applies a force to the care recipients. In addition, auditory information can be obtained even if we do not concentrate on guiding, and sound is effective in representing timing. Hence, we select sound as the medium of knowledge representation.

We should consider the timing of knowledge representation. The timing of information representation can be determined according to the timing of the action. The first experiment was performed to validate the effectiveness of verbal guidance under accurate estimation. Furthermore, it can also determine the appropriate timing of representation of verbal guidance, which is explained in the next section.

6.3 Validation Experiment of Verbal Guidance for the System with Accurate Estimation

First, we validate the effectiveness of knowledge representation under an accurate estimation. Subsequently, we compare groups of guidance methods to determine the appropriate method of guiding.

The system estimates the user's leaning and raises the armrest. Therefore, the verbal guidance should be represented around the user's leaning. We set the timing of verbal guidance as follows:

- Sitting (Before Leaning)
- Beginning of Leaning

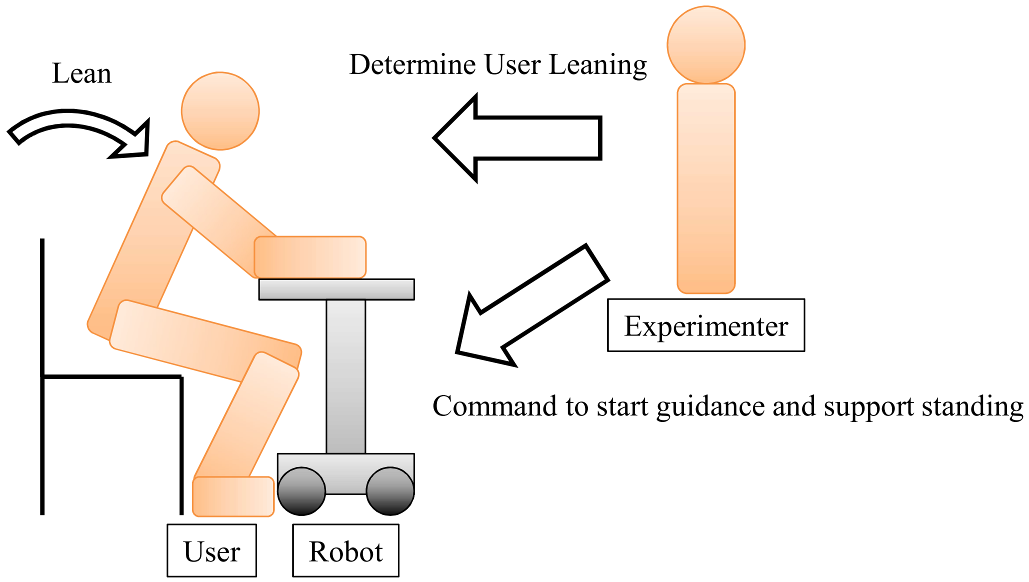


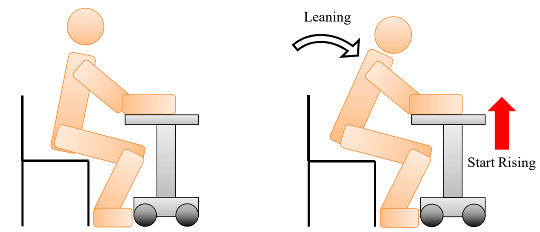
Figure 6.1: Overview of the first experiment. The experimenter determines the user's leaning motion and sends a command to start the stand support function of the robot.

- End of Leaning

In this experiment, for realizing an almost accurate estimation, the leaning estimation is conducted by a human. One of the authors determined the user's state and sent a command to the robot, as shown in Figure 6.1.

As explained in the previous section, the contents of verbal guidance are "let's stand up" and "3, 2, 1," which are a representation of the action and timing, respectively. By combining them, the contents patterns are as follows:

- Silence (Without Guidance)
- Only "let's stand up"
- Only "3, 2, 1"
- Both "let's stand up" and "3, 2, 1" Continuously



(a) Sitting (b) Beginning of Leaning

Figure 6.2: Guidance and support procedure (pattern 2.) (a) User is sitting; (b) armrest start uprising at beginning of leaning.

- Both “let’s stand up” and “3, 2, 1” Separately

As described above, there is more than one timing. Thus, the guidance can be represented in two ways, i.e., continuously at the same timing and separately at different timings.

To determine the appropriate guidance patterns, we consider all the guidance patterns and compare them. The armrest starts to rise following the ending of the last verbal guidance. Thus, there are three patterns for without guidance. Therefore, a total of 15 guidance and support patterns can be obtained by all combinations of the above mentioned timings and contents, as shown in TABLE 6.1.

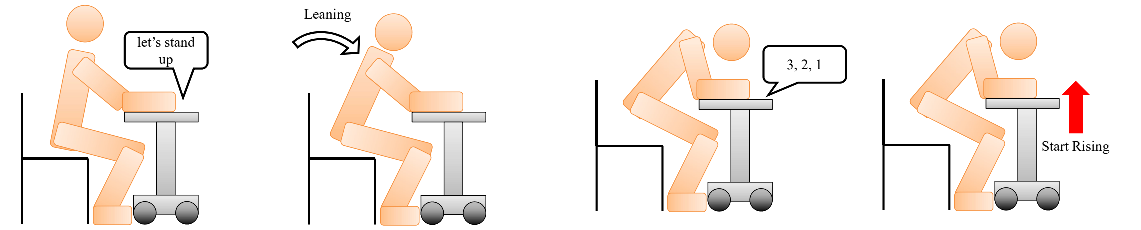
Figure 6.2 and Figure 6.3 present the guidance and support procedure examples. For pattern 2, the user is initially sitting, and there are no guidance and support patterns, as shown in Figure 6.2 (a). When the user starts to lean, the robot starts moving the armrest without guidance, as shown in Figure 6.2 (b). For pattern 14, the verbal guidance “let’s stand up” starts when the user is sitting, as shown in Figure 6.3 (a). The verbal guidance countdown “3, 2, 1” starts at the end of leaning; subsequently, the armrest moves, as shown in Figure 6.3 (c) and (d).

Ten participants performed sit-to-stand motions by using the assistive robot. The

Table 6.1: Guidance and support patterns.

	Guidance and Support Timing		
	Sitting	Beginning of Leaning	End of Leaning
1	Armrest Rise (Without Guidance)		
2		Armrest Rise (Without Guidance)	
3			Armrest Rise (Without Guidance)
4	“let’s stand up” → Armrest Rise		
5		“let’s stand up” → Armrest Rise	
6			“let’s stand up” → Armrest Rise
7	“3, 2, 1” → Armrest Rise		
8		“3, 2, 1” → Armrest Rise	
9			“3, 2, 1” → Armrest Rise
10	“let’s stand up” → “3, 2, 1” → Armrest Rise		
11		“let’s stand up” → “3, 2, 1” → Armrest Rise	
12			“let’s stand up” → “3, 2, 1” → Armrest Rise
13	“let’s stand up”	“3, 2, 1” → Armrest Rise	
14	“let’s stand up”		“3, 2, 1” → Armrest Rise
15		“let’s stand up”	“3, 2, 1” → Armrest Rise

participants were of both genders, 22–24 years old, 164–175 cm tall, and weighed 50–63 kg. None of the participants had physical disabilities. Informed consent was obtained from all participants prior to the experiments. The basic information of the



(a) Sitting (b) Beginning of Leaning (c) End of Leaning (Verbal Guidance) (d) End of Leaning (Armrest Rising)

Figure 6.3: Guidance and support procedure (pattern 14.) (a) Verbal guidance "let's stand up" when user is sitting; (b) beginning of leaning; (c) verbal guidance "3, 2, 1" at end of leaning; (d) armrest start uprising after verbal guidance.

participants is listed in TABLE 6.2. "let's stand up" and "3, 2, 1" are read out in Japanese as the participants are all Japanese. The representation order is randomly determined for each participant.

Table 6.2: Basic information of the participants.

Participant	Gender	Age	Height [cm]	Weight [kg]
A	M	23	175	63
B	M	22	165	52
C	M	22	168	60
D	M	24	167	57
E	M	23	167	53
F	M	23	167	56
G	F	23	164	52
H	M	24	174	50
I	M	23	165	53
J	M	24	174	60

The SUS [134] was used for evaluation, and participants wrote a brief comment for each pattern. The result is presented in Figure 6.4. The blue bars represent the SUS scores for each guidance pattern, and the error bars indicate the standard deviations. As shown in Figure 6.4, patterns without verbal guidance are not useful. Users require timing representation, and patterns with both guidance are the most

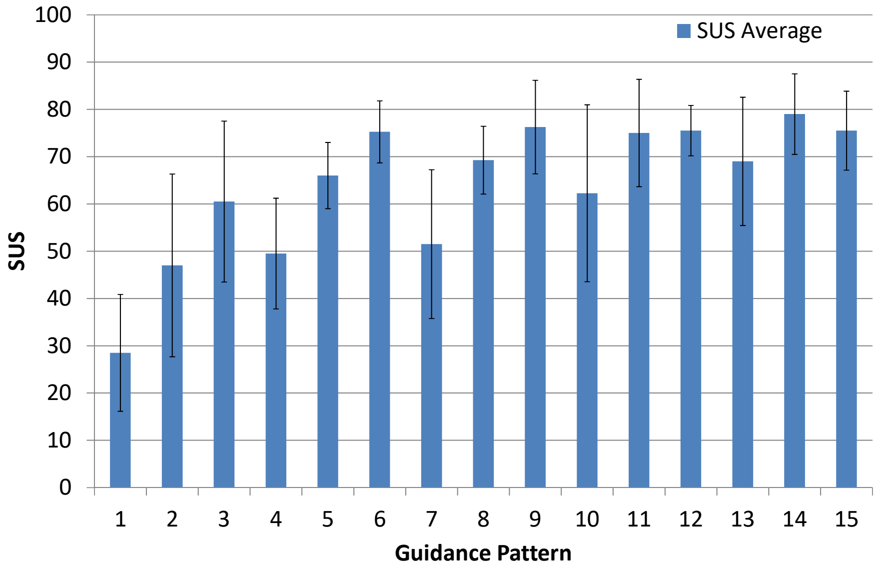


Figure 6.4: SUS score for each guidance pattern. The blue lines are the average of SUS scores for each guidance patterns. The black bars indicate the standard deviations.

useful.

From the brief comments, we confirm the same tendency as for the SUS results. For the no guidance pattern, several participants felt that the system can be used if a user prepares to stand up, whereas almost all participants felt anxious or thought that users cannot prepare to stand up. The guidance "let's stand up" is useful for preparing the user to standing up; however, it is disadvantageous for understanding the meaning. In the case of using only "let's stand up", users cannot understand the timing appropriately. By contrast, "3, 2, 1" is useful for understanding the timing; however, it is too short if it is the only guidance. If both guidance systems are used, users can prepare for standing up as well as understand the timing. Even though the guidance in this case is slightly longer, the advantage for easy understanding is considered to be significant for elderly care.

Based on the comments, we know that the users feel that the beginning and the end of leaning is similar for verbal guidance. This tendency can be confirmed on the SUS results, especially for the patterns that adopt both guidance systems (patterns 10–15). It is believed that this is because the leaning motion does not require a significant amount of time. This indicates that the system can function even if the guidance timing is not strictly accurate.

6.4 Experiment for Imperfect Estimation System

In this section, the experiments validated the proposed method with the actual system that could estimate a user's state almost accurately. We adopted an estimation method that we previously proposed in [135]. A more accurate system can be developed using another estimation method for robot control, for example, admittance control or impedance control. However, accurately detecting user state transition is difficult even if such estimation method is adopted. Then, we validated that the verbal guidance is effective for robot systems that is based on imperfect estimation.

From the SUS scores and participants comments obtained from the previous section's experiments, patterns 11, 12, 14, and 15 were adopted for the next experiments. the previous experimental results showed that that people at the beginning and end of the leaning motion feel the same for guidance timing. Thus, we unified them as "leaning" and set two patterns as follows;

A. leaning: "let's stand up" and "3, 2, 1"

B. sitting: "let's stand up", leaning: "3, 2, 1"

An estimation method was implemented to the developed robot. Using a distance sensor and pressure sensors on armrest, the participants' CoM candidates can be calculated as explained in [135], [124]. The robot system estimates the user state from the two states; only sitting or sitting with the upper body leaning, using a method which is proposed in [135]. The user state can be estimated using a support vector machine (SVM).

An experiment is conducted to validate the estimations. Ten participants conducted leaning and sit-to-stand motions using the assistive robot. The participants were the same as used for the previous experiment. Informed consent was obtained from all the participants before the experiments.

The learning start and end time and estimated state transition time are listed in TABLE 6.3. As an example,participant J's time variation of estimated state is shown in Figure 6.5.

Table 6.3: State transition time.

Participant	Actual Leaning Start Time [s]	SVM Estimated Leaning End Time [s]	Actual Leaning End Time [s]
A	4.8	5.6	6.3
B	4.6	5.5	6.5
C	4.0	4.5	5.6
D	2.5	3.2	3.4
E	5.8	6.8	7.6
F	7.8	8.2	8.8
G	5.6	5.8	7.1
H	7.4	7.7	8.9
I	5.6	5.9	6.9
J	3.9	4.5	5.2

As shown in TABLE 6.3 and Figure 6.5, the system can estimate a user's leaning motion while they are leaning. The leaning motion is continuous and there is no noticeable boundary between the two states; only sitting and sitting while leaning.

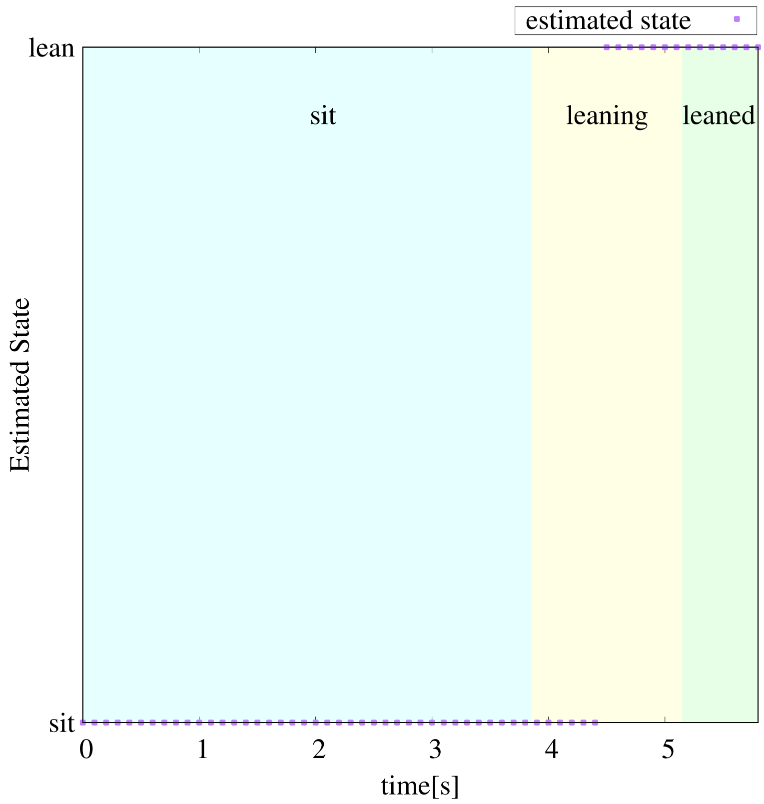


Figure 6.5: Time variation of estimated state (participant J.) Background colors represent the actual state. Blue: sitting; yellow: leaning; green: leaned. The purple points indicate the estimated state.

Therefore, accurate detection of state transition timing is difficult. The system performance should be validated to determine whether the estimation is enough for the target function, i. e., user standing support. We considered that the performance can be sufficient for supporting if there is knowledge representation. The user can adjust the timing using the represented knowledge if the representation is appropriate.

For simulating the actual use, various types of chairs and a bed are adopted and put on the experimental area as shown in Figure 6.6. The height of chairs and the bed are as follows;

- Chair 1: 600 mm

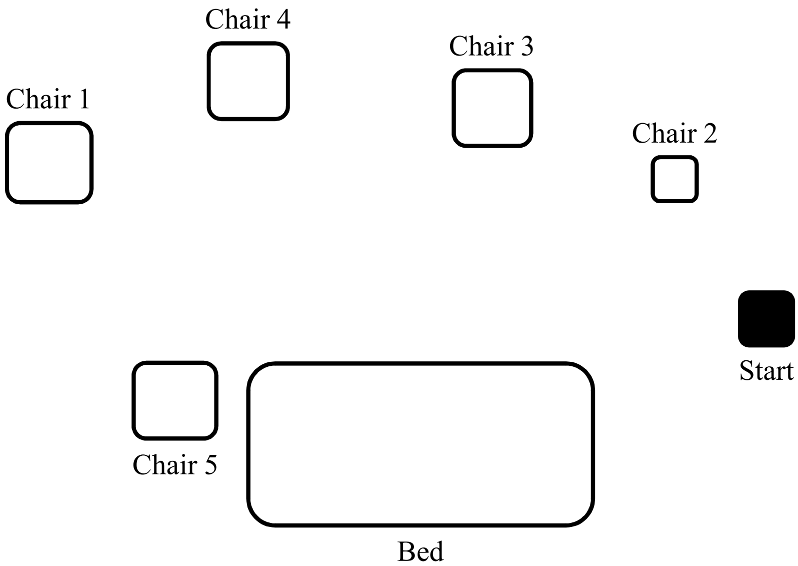


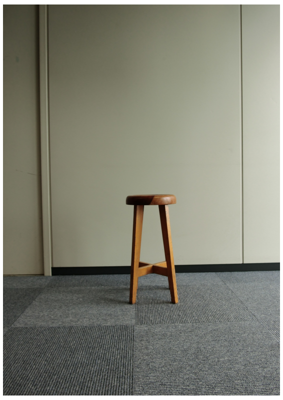
Figure 6.6: Overview of the last experiment. Chairs and a bed are put on the experimental area.

- Chair 2: 500 mm
- Chair 3: 460 mm
- Chair 4: 430 mm
- Chair 5: 400 mm
- Bed: 390 mm

The pictures of the chairs are shown in Figure 6.7. Chair 3 is the same chair as used in the previous experiments.

The participants first stood up from a chair using the robot. Then, they walk toward another chair, and sit with the help of the robot. They conducted the above procedure for all chairs and the bed. The robot provided verbal guidance and support when the user stood up. The user can sit with the armrest moving down. The armrest moves down when the user turn on the switch. When the user is walking,


(a) Chair 1


(b) Chair 2


(c) Chair 3


(d) Chair 4


(e) Chair 5


(f) Bed

Figure 6.7: Pictures of chairs and a bed. (a) Chair 1; (b) chair 2; (c) chair 3; (d) chair 4; (e) chair 5; (f) bed.

the robot does not provide any assistance and it act as a non-robotic walker. The order of guidance pattern and chairs were determined randomly for each participant. The same participants that were used in the previous experiments were employed in this experiment. Informed consent was obtained from all the participants before the experiments. The experimental setup is shown in Figure 6.8.

The results are shown in Figure 6.9. From the results, we confirm that the proposed method works even for the case in which the estimations are not strictly accurate. The SUS scores of chairs which have similar seat height as chair 3 were high. Moreover, the SUS scores were low for low sheet chairs and bed. The main reason

Figure 6.8: Experimental setup. Participants sit and stand from all chairs and bed using the robot.

is that the hardware is not suitable for a chair with too low sheet. These results suggest that the verbal guidance makes system more useful even if the estimation is not accurate.

6.5 Discussion

In this section, we discuss the results of the experiments presented above. From the experimental results obtained from Validation Experiment of Verbal Guidance for the System with Accurate Estimation section, it is confirmed that verbal guidance was needed for usability even if the estimation was considerably accurate. Both the content and timing of action are effective. From the participants comments, we

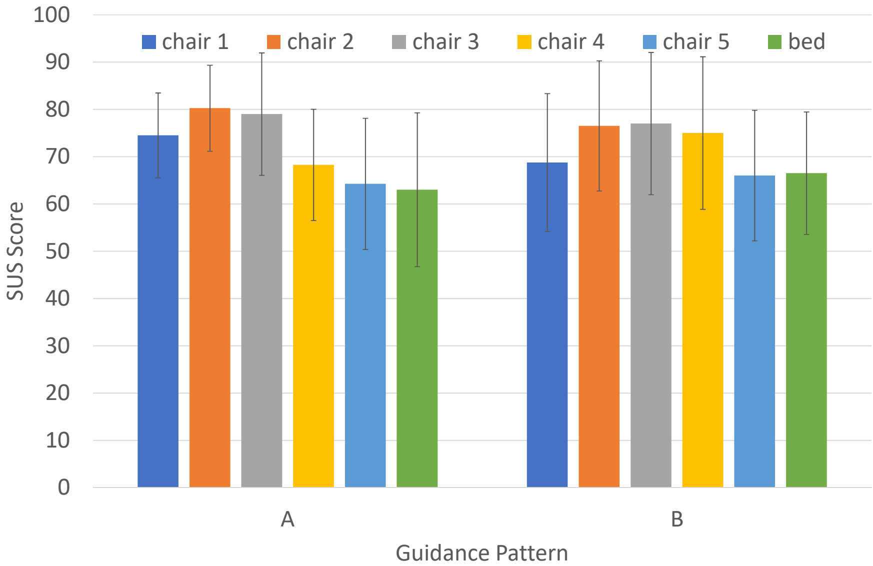


Figure 6.9: SUS scores. Blue, orange, grey, yellow, aqua, and green lines are average SUS scores for chair 1, 2, 3, 4, 5, and bed, respectively. The black bars show the standard deviations.

concluded that there was no significant difference experienced between the verbal guidance given to the participants at the beginning and end of leaning. The appropriate verbal guidance patterns are determined from the SUS scores and participants comments. The two guidance patterns were adopted for the imperfect estimation system experiment in the previous section. Several types of chairs and a bed are used for simulating actual use in the experiment. The effectiveness of verbal guidance for imperfect estimation system is confirmed from the experimental results using SUS.

The SUS scores for cases without guidance were low even if the estimations were accurate as shown in Figure 6.4. Participants commented that they became scared if the robot moved without any guidance even if the timing was appropriate and they knew when the robot would move. The results suggested that accurate estimation does not directly result in good performance and usability. It is important for p-HRI that users know about the robot action and can adjust their actions according to the robots.

The SUS scores of the imperfect estimation system were similar to those of the accurate estimation experiments. Even if the estimation was not accurate, the use of verbal guidance resulted in a high usability of the robot. Users could stand up well with the help of guidance system and could deal with any failure as they know the robot actions through verbal guidance. Thus, it is expected that verbal guidance can improve the performance and safety.

In this paper, we focused on the developed sit-to-stand support robot, however, the proposed method can also be applied to other robot systems. For example, it can be used for motion support systems and it can be applied easily. In the case of walking support system that can predict user's fall, the robot can stop the wheels, robot represent the estimated user state and tell user that robot will stop.

Robots that are capable of decision making based on estimation should communicate that to humans. If there are p-HRI or cooperation between robots and humans, the cooperation tasks can be carried out by representing contents and timing of the actions. For example, if robots that are designed to carry something with humans provide verbal guidance, humans can also cooperate with robots in the similar way as with humans.

The more appropriate the timing of robot motion is, the more high the SUS score become. It indicates that the system can be used without guidance if the system can be move depending on the user intention correctly. To realize it, the system should be more trustworthy. If the system can move more naturally by using force control, users will feel more comfort. Such subtle and unnoticed support can be realized in the future, however, it requires a kind of perfect trust, hence it is a difficult and important issue.

6.6 Conclusions

In this study, we proposed a verbal knowledge representation method. The robot that act based on the estimations should achieve accountability and can make the system useful even if the estimations are not strictly accurate.

We developed a robot system that support a user's standing motion by raising its armrest up when the user is leaning on it. The guidance for encouraging the user to stand up and timing representation of robot action are adopted. Verbal interaction is important for nursing-care, thus the knowledge are represented by sound.

Experiments are conducted for validating the proposed method. From the results, we confirmed that system without the guidance is not useful and causes anxiety in humans even if the estimation is accurate. We also know the appropriate guidance pattern from the experimental results and confirmed that systems based on imperfect estimation can be useful with verbal knowledge representation. Moreover, the proposed method can be applied to other robot systems.

Tests with elderly people should be conducted as future work. Adding visual knowledge representation is believed to bring good result. Particularly, in the case the support or user motion is not carried out well, the verbal or visual knowledge representation will be very effective. Representation of failure reason and solution can bring comfort and relief to the user and such systems are user-friendly.

Chapter 7

Interface Implementation and Validation Experiments

7.1 Introduction

This section explains experiments to validate the proposed design and developed system. Interface implementation is explained in section 7.2, and experiments are conducted to validate the proposed method using the interface and the developed system. First we conducted the experiment to validate the accountability of the system for users by using user interface. Then the failure detection experiments are conducted. We simulated the situation that a caregiver want to detect failure by using the user interface. And the experiment simulated the situation that an engineer detect failure by using investigation interface is conducted.

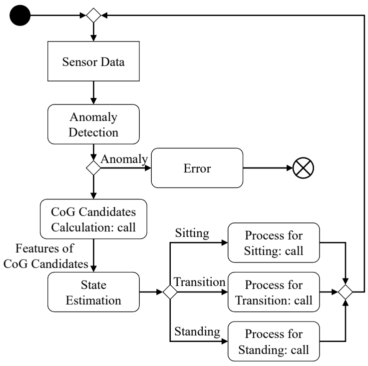
7.2 Interface Implementation

In this section, the assistive robot system developed based on the proposed design method is explained. The robot has been developed to assist the user's walking, sit-to-stand, and stand-to-sit motions. It estimates the user's state by using a machine learning algorithm and decides on its action based on the result of the estimation.

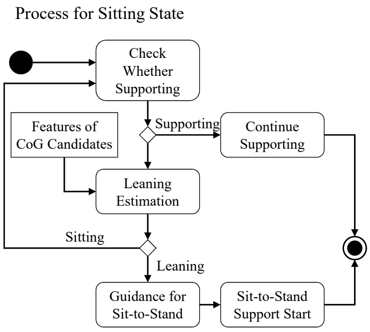
Two types of interfaces are explained in section 7.2.2 and section 7.2.3. The investigation interface should be effective for accident investigation, especially for an autonomous robot, as it makes it easier to determine responsibility for accidents as well as to detect and fix failures. The user interface makes the system transparent for users and helps them use the system. The system uses the user's estimated state to decide the robot's action. Misunderstanding the user's state is a safety critical issue, so the user interface representing the estimation result is important.

7.2.1 Describing in SysML

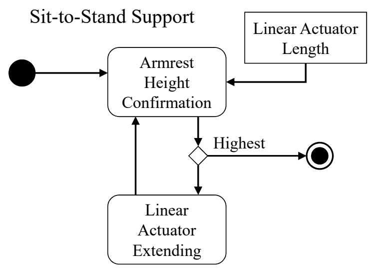
Data from the robot's sensors is used for anomaly detection as shown in Figure 7.1(a). If the user's hands and elbows are not touching the gripper and armrest, the robot does not move for security reasons. CoG candidates are calculated by using sensor data if no anomaly is detected. The CoG candidates calculation method is explained in detail in [124, 135]. The features of CoG candidates are used for SVM and the system estimates the user's state from three possibilities: sitting, standing, or the transition between them. The state estimation method is explained in [135]. The system then carries out functions depending on the estimated user's state. Functions for each state are described in other diagrams, and an example is shown in Figure 7.1(b).



(a) Rough State Estimation



(b) Activity During Sitting



(c) Activity for Sit-to-Stand Motion

Figure 7.1: Activity Diagrams.

The process for the case where the user is sitting is shown in Figure 7.1(b). If the user is estimated to be sitting, the system checks whether the robot is carrying out the sit-to-stand support action. If no support action is being conducted, the system estimates whether the user is only sitting or sitting with a leaning upper body using the same method as the state estimation described above. The system begins supporting the user's sit-to-stand motion if the user is leaning on the armrest of the robot. The output of the system for sit-to-stand support is extending the linear actuator and moving the armrest upwards as shown in Figure 7.1(c). Extension of the linear actuator continues at constant speed until the armrest reaches its maximum height. These processes can be described in SysML as shown in Figure 7.1. Sequence diagrams can also describe the processes as shown in Figure 7.2.

Use cases are shown in Figure 7.3. Users and caregivers of the system primarily interact with the system before and during its use. The most important pre- and during-use information are the instructions on how to use the system.

The system is autonomous and includes learning algorithms, hence users need to know what the system does and why. Engineers usually interact with the system before and after its use. Before use, engineers adjust the system for the user in

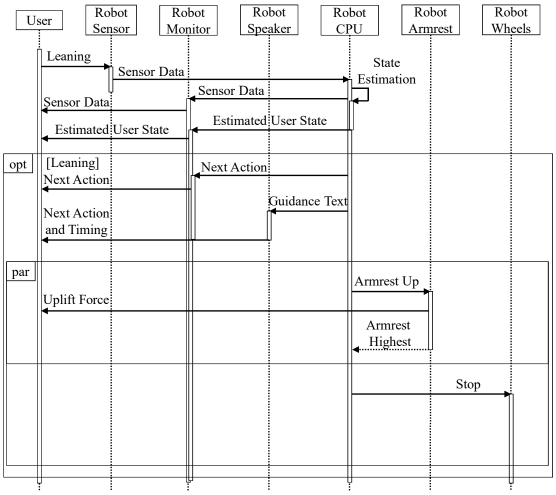


Figure 7.2: Sequence Diagram.

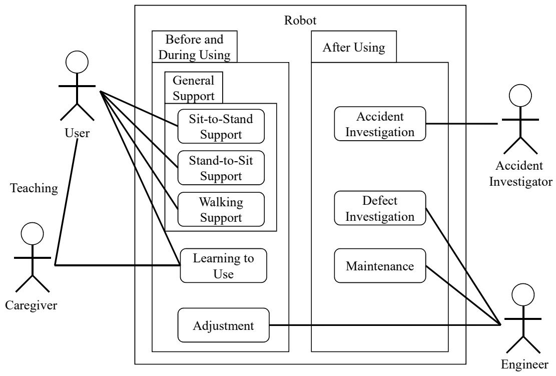


Figure 7.3: Use Case Diagram.

cases where the user's personal parameters are required for adjustment. After using, engineers interact with the system for maintenance and trouble or accident handling, and accident investigators relate to it for investigating accidents.

It is confirmed by Figure 7.1, Figure 7.2, and Figure 7.3 that the internal processes of the robot system can be described by SysML. Effectiveness of modeling languages for describing systems is also presented in [94, 117]. SysML was created to describe systems and is becoming popular in the system engineering field; thus, it is thought to be effective. We can detect the required information from the system as described. Examples of transcription of the information to the appropriate interface for each stakeholder are explained in section 7.2.2 and section 7.2.3.

7.2.2 Interface for Investigation

When a failure or accident happens, engineers and accident investigators need to investigate or repair it. They want to know the system architecture, reasons for the accident, solutions to faults, and other information. In this section, an example of representation for investigation is explained.

As explained in section 7.2.1, when a user leans forward while sitting, the armrest moves up. If the linear actuator does not move, the user believes that it is defective and wants an engineer to solve the problem. During investigation, the engineer enters their professional title, required time, and known information, and the system extracts and presents related information. Internal processes are also presented based on described system architecture.

An example of the interface is shown in Figure 7.4. In this case, the engineer knows only the robot's action (failure to move the armrest) and the time. The engineer first wants to compare the robot's actual action with its decided action. Related information is required for investigation, namely: raw input data (PSD, pressure), processed input data (CoG candidates and their features), estimation (user's basic state: sitting, standing, or transition; user's state for sitting: normal sitting or leaning forward), decided action (none or moving the armrest up), and actuator output (linear actuator torque). The system shows the internal process for that time as SysML diagrams, as shown in the right part of Figure 7.4. The related information is marked using different colors according to the type of information.

A list of all information is represented in the left part of the interface. Related pieces of information are marked with the same color as the SysML diagrams. By selecting the information, a graph of the data is displayed as shown in Figure 7.4. From the graph on the right, the system estimation appears to be correct, and from the graph on the left, we can see that the defect was caused by abnormal gripper sensor data. In this way, the interface make it possible to investigate defects and detect the causes of them.

7.2.3 Interface for Users in Use

An intuitive interface is required for system users. Required information and features are shown in TABLE 7.1. The user's state of contact with the gripper and armrest is used for anomaly detection, while the user's estimated state is used for deciding on the robot's action. The user can check whether there is a difference between the user's actual state and that recognized by the robot. The user's intended action, such as the sit-to-stand motion, is also useful. The user's required action such as leaning forward, the robot's intended action such as moving the armrest up, and the support timing are required information, as they are useful for assisting the user's action.

Contact information is for both the gripper and the armrest; thus, it contains two data streams. The contact situation, user's state, and robot's armrest height change infrequently and are all comprised of spatial information. The actions of the user and the robot are also spatial information, and are event-driven, while the timing of support is temporal information. When the robot carries out an action, it should make the user aware of the action.

From TABLE 7.1, the best means of communication, whether vision or sound, can be determined. Vision is selected for the user's state, armrest height, and user's required action, while sound is adopted for transmitting support timing. The robot's intended action is transmitted using both vision and sound.

An example of the displayed user interface is shown in Figure 7.5. The user's body is represented with black lines and a black circle. On the upper part of the interface, the user's state and robot's armrest height are displayed. Current status is shown in black, while other statuses are in grey as shown in Figure 7.6. The armrest movement is described by a red arrow, drawn according to the armrest height as

Table 7.1: Selecting Media for Each Information

	Vision			Sound		
	Spatial	Multi	Steady	Temporal	Event-Driven	Make Aware
Contact Situation	○	○	○			
User's State	○		○			
Armrest Height	○		○			
User's Intended Action	○				○	
User's Required Action	○				○	
Robot's Intended Action	○				○	○
Support Timing				○	○	

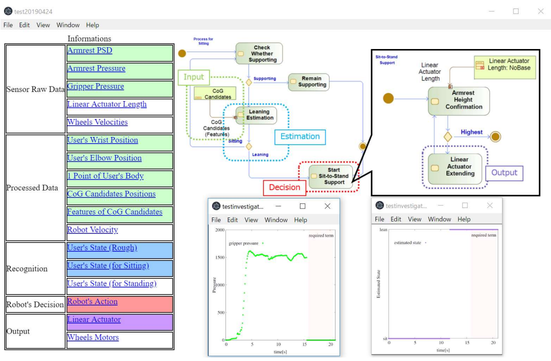


Figure 7.4: Investigation Interface.

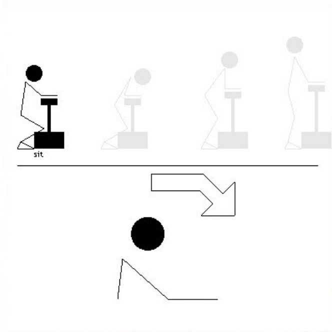
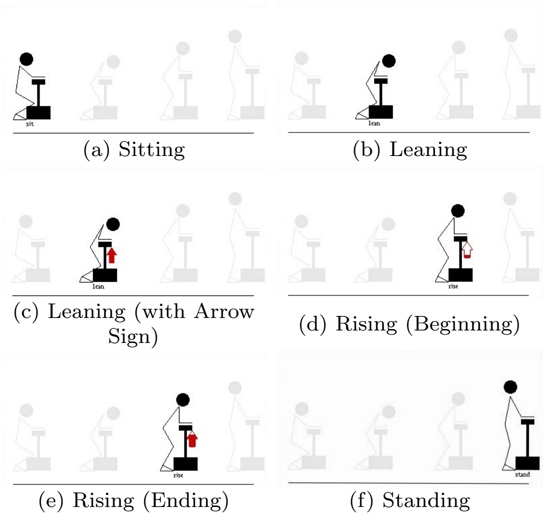


Figure 7.5: Overall View of User Interface.

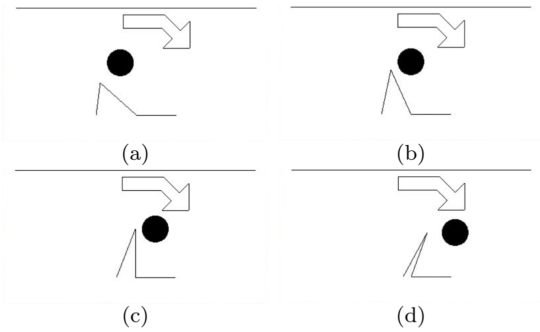
shown in Figure 7.6(d) and (e). The robot's intended action, in this case moving the armrest up, is displayed with a flashing red arrow as shown in Figure 7.6(b) and (c), and is also denoted by sound from a speaker. Timing of the support is represented by sound as a countdown.

The lower half of the display represents the user's required action. Black lines and circles represent the user's body in the same manner as on the upper part of the display. This represents the user's leaning action by animation as shown in Figure 7.7. The four figures are displayed in sequence to represent a leaning motion.



(a) Sitting (b) Leaning (c) Leaning (with Arrow Sign) (d) Rising (Beginning) (e) Rising (Ending) (f) Standing

Figure 7.6: Upper Part of User Interface.



(a) (b) (c) (d)

Figure 7.7: Lower Part of User Interface. The animation consist of four figures which appear in order of (a) to (d).

7.3 User Interface Accountability Validation Experiment

This section explains the experiment to validate the accountability of the user interface. The user interface is developed according to the proposed design architecture as explained in section 7.2.3. We implemented the user interface to the developed robot.

In the experiment, 8 participants conducted sit-to-stand motion by using the robot system. The participants are both genders, 22–24 years old. None had any physical disability. Informed consent was obtained from all participants before the experiments.

We set 4 patterns of knowledge representation by the user interface as shown in TABLE 7.2. Each participant conducted all patterns once and the order is determined randomly.

Table 7.2: User Interface Patterns of Validation Experiment

Patterns	Vision			Sound	
	User State	Robot Action	User Action	User Action	Robot Timing
①	○	○	○	○	○
②	-	○	○	○	○
③	○	○	-	-	○
④	-	-	-	-	-

The participants answered the questionnaire after the experiment for each pattern. The questionnaire items are;

A. I can know that the robot recognized user state.

B. I can know that the armrest would rise.

C. I can know the timing of the armrest rising.

D. I can know what should I do.

E. I can trust the robot.

F. I can use the robot without anxiety feeling.

G. The robot is useful for me.

The participants answered all questionnaire items from 1–5, where 5 means strong agreement and 1 is strong disagreement. We also obtained brief comments from the participants for each experiment. After the all patterns, participants prioritized them and made a brief comment about the experiment. All questionnaires are written in Japanese since all participants are Japanese.

The frequency distributions of the questionnaires of each UI pattern are shown in TABLE 7.3–TABLE 7.6. It is confirmed from the results that information can be transmitted to user by the user interface. And it contribute to usability and peace of mind.

Table 7.3: Frequency Distribution of the Questionnaires (UI Pattern ①)

UI ①		Questionnaire						
		A	B	C	D	E	F	G
Evaluation	5	7	6	7	6	5	4	6
	4	1	2	1	2	2	3	1
	3	0	0	0	0	1	1	1
	2	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0

Table 7.4: Frequency Distribution of the Questionnaires (UI Pattern ②)

UI ②		Questionnaire						
		A	B	C	D	E	F	G
Evaluation	5	1	6	7	5	2	2	2
	4	4	2	1	3	5	4	5
	3	3	0	0	0	1	2	1
	2	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0

Table 7.5: Frequency Distribution of the Questionnaires (UI Pattern ③)

UI ③		Questionnaire						
		A	B	C	D	E	F	G
Evaluation	5	0	1	4	0	0	0	0
	4	0	5	3	1	2	2	2
	3	5	2	1	1	4	3	5
	2	2	0	0	4	2	3	1
	1	1	0	0	2	0	0	0

The frequency distribution of ranking of the UI knowledge representation pattern is shown in TABLE 7.7. From the results of questionnaires and brief comments, we know that the UI patterns ① and ② are useful. The results suggested that the user action is important knowledge for users. Estimated user state is also effective,

Table 7.6: Frequency Distribution of the Questionnaires (UI Pattern ④)

UI ④		A	B	C	D	E	F	G
Evaluation	5	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0
	2	4	1	0	6	3	4	6
	1	4	7	8	2	5	4	2

however, user action is more. Most participants comment that user state information is not essential but it is better to be represented. On the other hand, several participants feel that there are too many information, hence they prefer UI pattern ②.

Table 7.7: Frequency Distribution of the UI Patterns Ranking

		①	②	③	④
Rank	1	6	2	0	0
	2	2	6	0	0
	3	0	0	8	0
	4	0	0	0	8

We confirmed that the developed user interface is effective for user in use. The knowledge successfully transmitted to user by the interface. And the knowledge representation enhances system usability and relief.

7.4 Failure Investigation with User Interface

There are various types of stakeholders of care robots. Even if the care robots are effective and reliable, demands for caregivers will never disappear. If the care robot user is in need, then a caregiver will help the user. We assume a situation that a caregiver relate to the robot and validate the system accountability on the situation by the experiment.

When user think the robot do not act naturally, the user will ask to a caregiver. Then the caregiver will check and use the robot as a trial, and determine whether the problem is caused by user's operating way or the robot's failure. Caregivers do not have detailed knowledge about the robot, however, they are assumed to be familiar to the robot. Hence the caregiver will check what is failure simply and determine whether it should be fixed by expert. Therefore, it is better that the failure can be detected by using simple interface. The user interface represent some information, hence we considered that caregivers can detect some types of failure by using the user interface. Therefore we conducted failure investigation experiments using user interface.

The participants are same as the previous experiment. They are not actual caregiver, however, we assumed that the situation can be simulated. Informed consent was obtained from all participants before the experiments. First, participants standing up by using the robot several time since the participants are assumed to be familiar to the robot. Then we purposely cause some errors on the robot simulating the robot's failure. The participants can use the robot and try to stand up several time. According to the information from the user interface, the participants determine the failure.

Contents of the failures are as follow:

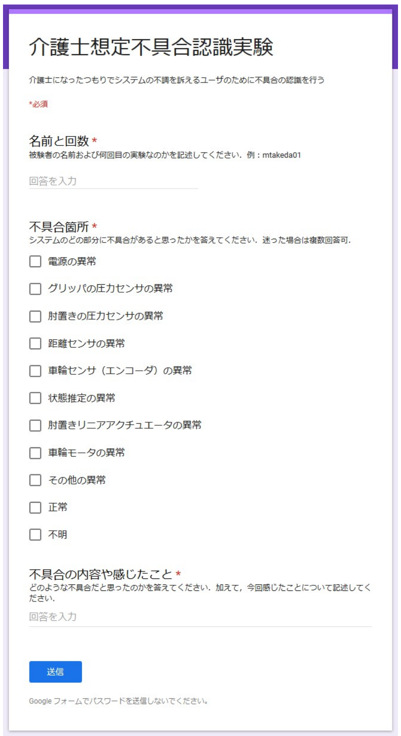
- Gripper or armrest sensor does not respond.
- Gripper sensor always behaves as if user touches to the gripper.
- PSD sensor data is always too large.

- Robot estimates user is only sitting even if the user is leaning.
- Linear actuator does not move.

The experimental conditions are that one of above failure is occurred or no failure is occurred. The order of the condition was randomly determined.

Participants answered the questionnaire after they determined the failure for each condition. On the questionnaire, participants first select which part of the robot the failure is. If participants cannot determine the failure, the candidates can be selected multiply. Subsequently, they answer what is happened. And brief comments for the experiment are also answered. The choice of answer are as follow:

- Failure of the electric power source.
- Failure of the pressure sensor of the gripper.
- Failure of the pressure sensor of the armrest.
- Failure of the PSD sensor.
- Failure of the Encoder sensor of the wheel.
- Failure of the user state estimation.
- Failure of the linear actuator of the armrest.
- Failure of the wheel motor.
- Other failures.
- No failure is occurred.
- Unidentified.



介護士想定不具合認識実験

介護士になったつもりでシステムの不調を訴えるユーザのために不具合の認識を行う

*必須

名前と回数 *

被験者の名前および何回目の実験なのかを記述してください．例：mtakeda01

回答を入力

不具合箇所 *

システムのどの部分に不具合があると思ったかを答えてください．迷った場合は複数回答可．

- 電源の異常
- グリッパの圧力センサの異常
- 肘置きの圧力センサの異常
- 距離センサの異常
- 車輪センサ（エンコーダ）の異常
- 状態推定の異常
- 肘置きリニアアクチュエータの異常
- 車輪モータの異常
- その他の異常
- 正常
- 不明

不具合の内容や感じたこと *

どのような不具合だと思ったのかを答えてください．加えて，今回感じたことについて記述してください．

回答を入力

送信

Google フォームでパスワードを送信しないでください。

Figure 7.8: Questionnaire of Failure Detection Experiment Using the User Interface.

Figure 7.9: Overview of Failure Detection Experiment Using the User Interface.

The displayed questionnaire screen is shown in Figure 7.8. The all questionnaires are written in Japanese. The overview of the experiment is shown in Figure 7.9.

The experimental result is shown in TABLE 7.8. Almost failures were detected correctly, except that some participants confused PSD failure with state estimation failure. The reason of the confusion is supposed that the state estimation result is profoundly affected by the data of PSD sensor. Some participants thought that there is a failure even though there is no error since they want to detect a failure. The correct rates of each failure including multi answers which include correct answer are all 75% or higher. From the results, we confirmed that failures can be detected at some level by using the user interface.

Table 7.8: Failure Detection Result (UI).

		Answer		
		Correct	Correct+ Incorrect	Incorrect
Failure	A	8	0	0
	B	8	0	0
	C	5	2	1
	D	1	5	2
	E	7	1	0
	F	6	1	1

7.5 Investigation Interface Validation Experiment

This section explains the validation experiment of investigation interface. The investigation interface is developed mainly for engineers. It assumed that engineers can detect failure from the data which are provided by the interface.

The contents of failures and the questionnaire is same as the previous experiment. The participants first use the robot and try to stand up. Subsequently, they detect failure by using the investigation interface. The overview of the interface is shown in Figure 7.10. The represented graphs do not use the real-time data. We obtained the data in the previous experiments and made the graphs. The participants answer the same questionnaire as previous experiment.

The participants are 6 of same as the previous experiments. They are not actual expert of engineering, however, they major in engineering and they are familiar to the system through the previous experiments, hence we assumed that the situation can be simulated. Informed consent was obtained from all participants before the experiments.

The experimental result is shown in TABLE 7.9. Almost failures were detected

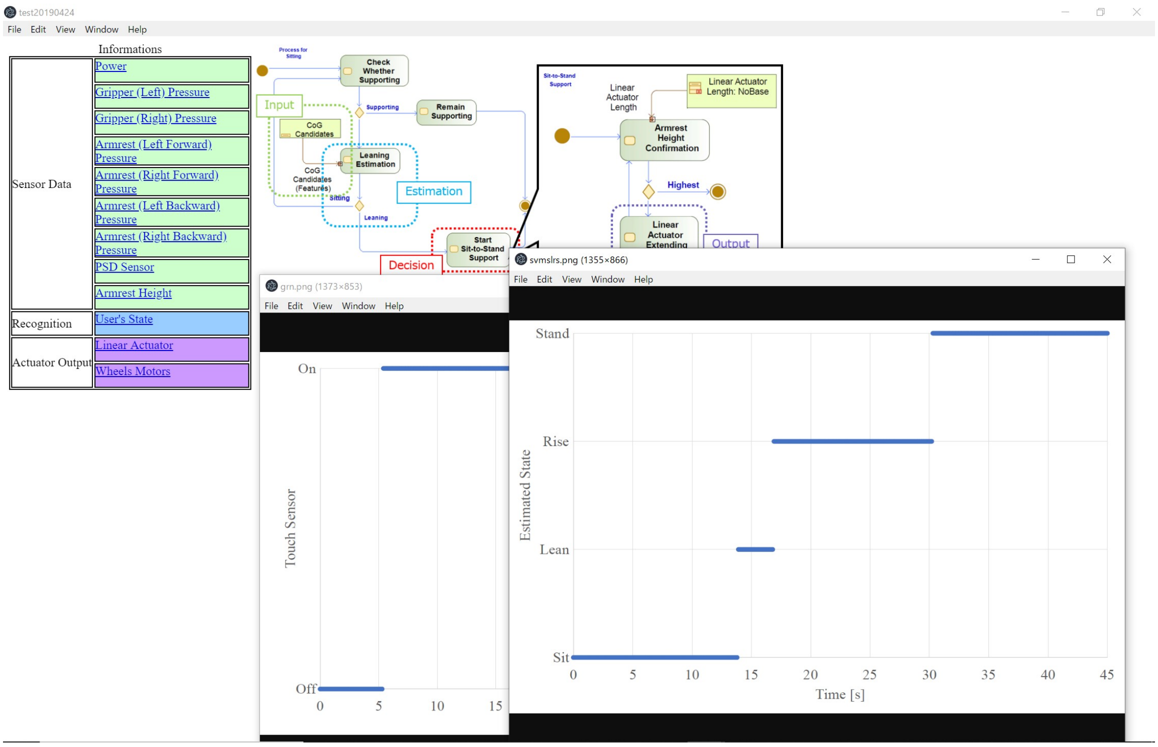


Figure 7.10: Overview of the Investigation Interface for the Validation Experiment.

correctly, except that some participants confused PSD failure with state estimation failure. The reason of the confusion is same as previous experiment, that the state estimation result is profoundly affected by the data of PSD sensor. We use SVM which is one of machine learning algorithms, for state estimation. Hence the relationship between PSD sensor data and estimated state is not transparent for humans. The confusion can be solved by using the ways to make machine learning model transparent including the researches which we explained in chapter 1 [47, 93].

Table 7.9: Failure Detection Result (Investigation Interface).

		Answer		
		Correct	Correct+ Incorrect	Incorrect
Failure	A	6	0	0
	B	6	0	0
	C	1	3	2
	D	6	0	0
	E	6	0	0
	F	6	0	0

7.6 Conclusions

In this section, the robot system which is designed and developed according to the proposed method is explained. First, the system is described by using SysML. Subsequently, implemented two types of interfaces are explained. The interfaces and the system are validated by several experiments. Three types of stakeholders, user, caregiver, and engineer are simulated and validation experiments are conducted for each stakeholder. From the experimental results, we confirmed that the interfaces and their information representation are effective to achieve accountability for various stakeholders and make system useful.

Chapter 8

Conclusions

8.1 General Conclusions

In this dissertation, we proposed system design for affordable and accountable physically assistive robots with user state estimation. There should be engineering and ethical approaches for robot systems which are used in real environment. User state estimation is important for care robots, however, accurate estimation requires a lot of expensive sensors. To obtain information from less sensor than required makes robots affordable. Robots should be designed by considering how selecting and placing sensors influence robot functions. And autonomous robots should be transparent for humans from the perspective of usability and ease of mind. We should design as the whole system including how to relate as well as hardware and software. Therefore we propose a new general design method for affordable and accountable robots.

In chapter 2, we proposed system design concept considering affordability and accountability. User state estimation is important for care robots, however, accurate estimation requires a lot of expensive sensors. It is not effective simply reducing sensors to cut cost. It is important to reduce cost focusing on influence for robot function. Hence we proposed CoG candidate calculation and selecting sensors as an affordable system design concept. Robot system should also be accountable for usability and user's ease of mind. Various types of stakeholders including the user and engineers relate to a robot by each reason. Therefore, robots should be designed as the whole system including how to relate as well as hardware and software. We proposed design concept consisting of 2 steps; describing whole system and transcribing system information for each stakeholder.

On the third chapter of this dissertation, we proposed CoG candidate calculation method. The CoG position is useful to estimate user state, however, accurate CoG position calculation requires a lot of sensors. Using the range of value of unknown parameters, we can calculate the candidates of the CoG. We discussed and selected the sensors which are frequently used in support systems, and created measurements sets labeled using the number of unknown parameters. By comparing the CoG candidates, we select an appropriate measurements set for state estimation.

State estimation method using the CoG candidates was proposed and evaluated in chapter 4. We set 7 geometric features of the CoG candidates as the features of SVM. The proposed method was experimentally validated.

The fifth chapter introduced new accountable design architecture of robot systems. Most research has focused on particular systems and situations or simply indicates general design principles. There are various stakeholders, hence care robots should be designed to be accountable for different stakeholders. Therefore we proposed a new design method, focused on accountability and transparency. Describing the entire system is a necessary first step, and transcribing the described system for each stakeholder based on several principles is effective for achieving accountability. Describing the system as a whole also contributes to AI transparency. Most research focused on transparency of algorithms of machine learning or deep learning. However, general systems consist of more than learning algorithms used for recognition or estimation in robot systems. Describing whole system make embodied AI system transparent even if the learning algorithm is opaque.

In chapter 6, we proposed new attitude that perfect human state estimation is not necessary for robots and appropriate guidance make robots useful even if the estimation is imperfect. We analyzed and confirmed the importance of accountability for care robot, and proposed verbal guidance. Strictly accurate estimation is difficult to realize. And even if robots estimate the appropriate timing and perform actions, if the robots move without any information, the system user may be caught unawares, and the system may be deemed unfriendly. If robots can convey the their actions and action timings to users, the users can adjust their actions according to the robots. Hence we adopted verbal guidance. The robot recognition result, content of robot action, and required user action can be represented as a single sentence such as "let's stand up." The timing should be represented by sounds, such as a countdown of "3, 2, 1." 15 guidance and support patterns can be obtained by all combinations of them. We confirmed that system is not usable if there are no guidance even if the estimation is accurate from experimental results. And we determine the appropriate verbal guidance and validate the effectiveness of it for imperfect but almost accurate estimation system.

Finally, the proposed designs are validated by the experiments using the robot system which is developed according to the proposed design in chapter 7. According to the design method proposed in chapter 5, we made user interface and investigation interface. Several experiments validated the accountability of the developed robot with the interfaces. The experimental results indicated the effectiveness of the proposed affordable and accountable system design.

8.2 Future Works

The CoG candidates are calculated without consideration of motion and force effect. By considering dynamics of humans, the range of CoG candidates can be more narrow, then the sensors can be reduced more. Time consideration will also improve the state estimation.

The proposed CoG candidate calculation focused only on 2D space, since the user mainly moves in sagittal plane and anomaly can be detected by using each sensor. However, information of staggering in coronal plane is useful for anomaly detection. The CoG candidate calculation method can be applied to 3D space by using 3D link model.

This dissertation focused on design, hence robot functions are a little mentioned. Although we consider that anomaly can be detected by using each sensor data, the CoG candidates can also be used for anomaly detection. The knowledge of CoG position is frequently used for various control methods of robots. Thus the CoG candidates can also be used for such methods, for example, falling detection by comparing the position of CoG and support area. In this dissertation, the proposed user state estimation method focused on the sit-to-stand motion, however, it can be applied to other motions including stand-to-sit motion and walking.

Developed interfaces are not well designed beautiful to look at since they are made by the author who are not expert of interface design. The interfaces can become more useful by designing according to the interface design methods. By implementing the interface design theory, the interfaces can be automatically developed.

The interfaces are not well reviewed by actual stakeholders including various experts. The law of autonomous robots is now being discussed, thus the proposed design architecture should be refined based on the discussion. Investigation interface uses storage data now, hence it should be improved to be able to represent data in real-time as a future work.

In this dissertation, we focused on the sit-to-stand assistive robot, however, the proposed design can also be applied to not only physically assistive robots with user state estimation function, but also other systems which require affordability and accountability. For example, pet robots also automatically conduct some motions based on estimation and interact physically with humans. Autonomous vehicles are controlled by using learning algorithms and have several safety risks, hence they should also be accountable. These systems interact with humans based on learning algorithms, hence the proposed design can be adopted. Although the sit-to-stand assistive robot which is explained in this dissertation is a simple system, the proposed design method is more important for more complicated systems. The proposed design should be applied to such various systems.

Bibliography

[1] Cabinet Office, Government of Japan, "2018 annual report on the aging society," https://www8.cao.go.jp/kourei/whitepaper/w-2019/zenbun/01pdf_index.html (In Japanese, Accessed 21th Nov., 2019).

[2] Cabinet Office, Government of Japan, "2013 Special Poll about Care Robots," https://survey.gov-online.go.jp/tokubetu/tindex-h25.html (In Japanese, Accessed 25th Nov., 2019).

[3] Tokyo Fire Department, "Elderly patients urgently transported by ambulance," http://www.tfd.metro.tokyo.jp/lfe/topics/201509/kkhansoudeta.html (In Japanese, Accessed 21th Nov., 2019).

[4] LIXIL Group Corporation, "Accessory bar," https://www.lixil.co.jp/lineup/toiletroom/ (In Japanese, Accessed 27th Nov., 2019).

[5] Family Life, Super Delivery, "Standing up handrail," https://www.superdelivery.com/p/r/pd_p/6530889/ (In Japanese, Accessed 28th Nov., 2019).

[6] Tsueya Kyoto, "Ta537bl," https://www.tsueya.co.jp/ta537bl-%e6%9c%a8%e8%a3%bd1%e6%9c%ac%e6%a5%93-%e9%bb%92-g%e6%9c%a8%e8%a3%bd/ (In Japanese, Accessed 27th Nov., 2019).

[7] Tsueya Kyoto, "Th-4point-bk," https://www.tsueya.co.jp/%ef%bc%94%e7%82%b9%e6%9d%96-%e8%bb%bd%e9%87%8f%e3%82%a2%e3%83%ab%e3%83%9f%e8%a3%bd-%e9%95%b7%e3%81%95%e8%aa%bf%e7%af%80%e6%a9%9f%e8%83%bd%e4%bb%98%e3%81%8d-th-4point-bk/ (In Japanese, Accessed 27th Nov., 2019).

[8] L. UBER INDUSTRY CO., "Slide fit," http://www.uber.co.jp/ncp/slide_fit01_detail.html#htype (In Japanese, Accessed 27th Nov., 2019).

[9] UBER INDUSTRY CO.,LTD., "Silver car," http://www.uber.co.jp/ncp/sliver_car01.html (In Japanese, Accessed 27th Nov., 2019).

[10] MATSUNAGA MANUFACTORY Co., Ltd., "Wheelchair," http://www.matsunaga-w.co.jp/search/ (In Japanese, Accessed 28th Nov., 2019).

[11] SCRiO, "Uplift chair," https://www.scrio.co.jp/fs/kaigo/c/support-chair (In Japanese, Accessed 27th Nov., 2019).

[12] PARAMOUNT BED CO., LTD., "Electric uplift chair kd-823," https://www.paramount.co.jp/product/detail/index/30/P0003139 (In Japanese, Accessed 27th Nov., 2019).

[13] SECOM co., ltd., "Secom Lift," https://www.itmedia.co.jp/lifestyle/articles/0410/05/news081.html (In Japanese, Accessed 20th Nov., 2019).

[14] K. Nagai, I. Nakanishi, and H. Hanafusa, "Assistance of self-transfer of patients using a power-assisting device," in *2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422)*, vol. 3, Sep. 2003, pp. 4008–4015 vol.3.

[15] RIKEN, "The strong robot with the gentle touch," https://www.riken.jp/en/news_pubs/research_news/2015/20150223_2/index.html (Accessed 21th Nov., 2019).

[16] T. Hatsukari, S. Kuroko, N. Miyake, J. Higuchi, R. Kawazoe, Y. Hirata, and K. Kosuge, "Self-help standing-up method based on quasi-static motion," in *2008 IEEE International Conference on Robotics and Biomimetics*, Feb 2009, pp. 342–347.

[17] T. Hatsukari, N. Miyake, Y. Hirata, and K. Kosuge, "Method for selecting standing-up assist devices based on standing-up classification with human model," *Transaction of JSME (In Japanese)*, vol. 77, no. 774, pp. 429–438, 2011.

[18] WHILL, Inc., "Model A," https://whill.jp/features (In Japanese, Accessed 28th Nov., 2019).

[19] A. Kaisumi, Y. Hirata, and K. Kosuge, "Pedaling assistive control method of cycling wheelchair for hemiplegia patients," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, May 2015, pp. 6191–6196.

[20] Smart Robots Design Lab, "Omni-directional walking helper," http://srd.mech.tohoku.ac.jp/omni-directional-walking-helper/ (Accessed 21th Nov., 2019).

[21] Y. Hirata, A. Muraki, and K. Kosuge, "Standing up and sitting down support using intelligent walker based on estimation of user states," in *2006 International Conference on Mechatronics and Automation*, June 2006, pp. 13–18.

[22] FIELD AND SPACE ROBOTICS LABORATORY, "A personal aid for mobility and health monitoring: Pamm," http://robots.mit.edu/projects/old_projects/pamm/index.html (Accessed 21th Nov., 2019).

[23] I. Takeuchi and S. Egawa, "The development of walking support machine," *Journal of the Robotics Society of Japan (In Japanese)*, vol. 21, no. 4, pp. 385–389, 2003. [Online]. Available: https://www.jstage.jst.go.jp/article/jrsj1983/21/4/21_4_385/_article/-char/ja/

[24] Feaunhofer IPA, "Care-O-bot II," https://www.care-o-bot.de/en/care-o-bot-3/history/care-o-bot-ii.html (Accessed 27th Nov., 2019).

[25] J. Huang, W. Xu, S. Mohammed, and Z. Shu, "Posture estimation and human support using wearable sensors and walking-aid robot," *Robotics and Autonomous Systems*, vol. 73, pp. 24 – 43, 2015, wearable Robotics. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921889014002863

[26] J. Huang, P. Di, T. Fukuda, and T. Matsuno, "Motion control of omni-directional type cane robot based on human intention," in *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sep. 2008, pp. 273–278.

[27] RT.WORKS co., ltd., "RT.1," https://www.rtworks.co.jp/product/rt1.html (In Japanese, Accessed 23th Nov., 2019).

[28] RT.WORKS co., ltd., "RT.2," https://www.rtworks.co.jp/product/rt2.html (In Japanese, Accessed 23th Nov., 2019).

[29] L. SAKAI Medical Co., "Unweighg system nxstep," https://www.sakaimed.co.jp/rehabilitation/exercise-therapy/standing_walking_training/unweighgsystemnxstep/ (In Japanese, Accessed 25th Nov., 2019).

[30] Hocoma, "Lokomat®," https://www.hocoma.com/solutions/lokomat/ (Accessed 25th Nov., 2019).

[31] Hocoma, "Andago®," https://www.hocoma.com/solutions/andago/ (Accessed 25th Nov., 2019).

[32] Y. Ochi, K. Matsuo, K. Kubo, T. Yamamoto, T. Sakakibara, K. Kakihara, T. Iwade, and K. Terashima, "Control of NILTWAMOR aiming at walking assist," *54th Control Engineering Associated Conference (In Japanese)*, vol. 54, pp. 87–87, 2011.

[33] K. Osaki, T. Shiomitsu, and Y. Hirta, "Development of body weight support walking assistive system with steered casters," in *2019 JSME Confernce on Robotics and Mechatronics (In Japanese)*, 2019, pp. 2A2–A07.

[34] IEEE Spectrum, "Cyberdyne's Medical Exoskeleton Strides to FDA Approval," https://spectrum.ieee.org/the-human-os/biomedical/devices/cyberdynes-medical-exoskeleton-strides-to-fda-approval (Accessed 25th Nov., 2019).

[35] S. Suzuki, Y. Hirata, K. Kosuge, and H. Onodera, “Motion support during the swing phase using cooperative walking support system,” *Advanced Robotics*, vol. 27, no. 17, pp. 1337–1349, 2013. [Online]. Available: https://doi.org/10.1080/01691864.2013.826412

[36] S. Piriyakulkit, Y. Hirata, and H. Ozawa, “Lumbar assistive orthosis with torsion spring-based joint for lumbar degenerative kyphosis patient,” in *2018 IEEE International Conference on Cyborg and Bionic Systems (CBS)*, 10 2018, pp. 161–166.

[37] Panasonic Corporation, “Self-reliance Support Robot,” https://news.panasonic.com/jp/topics/2014/38643.html (In Japanese, Accessed 23th Nov., 2019).

[38] D. Chugo, Tai Asawa, T. Kitamura, Songmin Jia, and K. Takase, “A rehabilitation walker with standing and walking assistance,” in *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sep. 2008, pp. 260–265.

[39] Aldebaran Robotics, “NAO Documentation,” http://doc.aldebaran.com/2-1/home_nao.html (Accessed 23th Nov., 2019).

[40] Softbank, “Pepper for Home,” https://www.softbank.jp/robot/pepper/home/ (In Japanese, Accessed 23th Nov., 2019).

[41] robot start inc., “RoBoHoN,” https://robotstart.info/2019/02/18/new-robohon.html (In Japanese, Accessed 23th Nov., 2019).

[42] The Star, “Robot gets seal of approval,” https://www.thestar.com/life/breakingthrough/2014/06/09/robot_gets_seal_of_approval.html (Accessed 23th Nov., 2019).

[43] Y. Takahashi, M. Takagi, and K. Inoue, “Development of robot system for elderly who live alone,” in *Computers Helping People with Special Needs*, K. Miesenberger and G. Kouroupetroglou, Eds. Cham: Springer International Publishing, 2018, pp. 383–386.

[44] Tao Liu, Yoshio Inoue, and Kyoko Shibata, “New method for assessment of gait variability based on wearable ground reaction force sensor,” in *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug 2008, pp. 2341–2344.

[45] J. Huang, P. Di, K. Wakita, T. Fukuda, and K. Sekiyama, “Study of fall detection using intelligent cane based on sensor fusion,” in *2008 International Symposium on Micro-NanoMechatronics and Human Science*, Nov 2008, pp. 495–500.

[46] Y. Hirata, S. Komatsuda, and K. Kosuge, “Fall prevention control of passive intelligent walker based on human model,” in *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sep. 2008, pp. 1222–1228.

[47] D. H. Park, L. A. Hendricks, Z. Akata, B. Schiele, T. Darrell, and M. Rohrbach, “Attentive explanations: Justifying decisions and pointing to the evidence,” *CoRR*, vol. abs/1612.04757, 2016.

[48] S. Song and S. Yamada, “Designing led lights for a robot to communicate gaze,” *Advanced Robotics*, vol. 33, no. 7-8, pp. 360–368, 2019. [Online]. Available: https://doi.org/10.1080/01691864.2019.1600426

[49] T. Takahashi, Y. Nishiyyama, Y. Ozawa, E. Nakano, and Y. Handa, “Cycling chair: A novel vehicle for the lower limbs disabled,” in *SPIE - The International Society for Optical Engineering*, vol. 6040, 12 2005, pp. 60 401X–60 401X.

[50] Y. Hirata, S. Ando, and K. Kosuge, “Cadence control of cycling wheelchair with continuously variable transmission and servo brake,” in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, May 2016, pp. 3062–3068.

[51] Y. Hirata, T. Baba, and K. Kosuge, “Walking support system with omni-directional mobile base -walking helper-,” in *JSME Conference on Robotics and Mechatronics*, 2003, pp. 2P1–2F–C7. [Online]. Available: https://jglobal.jst.go.jp/detail?JGLOBAL_ID=200902273855024622&rel=0

[52] Y. Hirata, A. Hara, and K. Kosuge, “Passive-type intelligent walking support system ”rt walker”,” in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*, vol. 4, Sep. 2004, pp. 3871–3876 vol.4.

[53] S. Dubowsky, F. Genot, S. Godding, H. Kozono, A. Skwersky, Haoyong Yu, and Long Shen Yu, “Pamm - a robotic aid to the elderly for mobility assistance and monitoring: a ”helping-hand” for the elderly,” in *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065)*, vol. 1, April 2000, pp. 570–576 vol.1.

[54] M. Spenko, H. Yu, and S. Dubowsky, “Robotic personal aids for mobility and monitoring for the elderly,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, pp. 344–351, 2006.

[55] M. Fujie, “Walk supporting robot,” *Journal of the Robotics Society of Japan (In Japanese)*, vol. 14, no. 5, pp. 628–631, 1996. [Online]. Available: https://www.jstage.jst.go.jp/article/jrsj1983/14/5/14_5_628/_article/-char/ja

[56] J. M. H. Wandosell and B. Graf, "Non-holonomic navigation system of a walking-aid robot," in *Proceedings. 11th IEEE International Workshop on Robot and Human Interactive Communication*, Sep. 2002, pp. 518–523.

[57] B. Graf, "Reactive navigation of an intelligent robotic walking aid," in *Proceedings 10th IEEE International Workshop on Robot and Human Interactive Communication. ROMAN 2001 (Cat. No.01TH8591)*, Sep. 2001, pp. 353–358.

[58] L. Finch, H. Barbeau, and B. Arsenault, "Influence of body weight support on normal human gait: Development of a gait retraining strategy," *Physical therapy*, vol. 71, pp. 842–55; discussion 855, 12 1991.

[59] R. Mustafaoğlu, B. Erhan, İ. Yeldan, B. E. Hüseyinsinoğlu, B. Gündüz, and A. R. Özdinçler, "The effects of body weight-supported treadmill training on static and dynamic balance in stroke patients: A pilot, single-blind, randomized trial," *Turkish Journal of Physical Medicine and Rehabilitation*, vol. 64, pp. 344–352, 11 2018.

[60] S. Hesse, H. Schmidt, C. Werner, and A. Bardeleben, "Upper and lower extremity robotic devices for rehabilitation and for studying motor control," *Current opinion in neurology*, vol. 16, pp. 705–10, 01 2004.

[61] H. Kawamoto, S. Kanbe, and Y. Sankai, "Power assist method for hal-3 estimating operator's intention based on motion information," in *The 12th IEEE International Workshop on Robot and Human Interactive Communication, 2003. Proceedings. ROMAN 2003.*, Nov 2003, pp. 67–72.

[62] CYBERDYNE, INC., "HAL®," https://www.cyberdyne.jp/english/products/HAL/index.html (Accessed 25th Nov., 2019).

[63] S. Suzuki, Y. Hirata, and K. Kosuge, "Walking support by wearable system based on the spring-mass model," in *2014 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, July 2014, pp. 285–290.

[64] S. Suzuki, Y. Hirata, K. Kosuge, and H. Onodera, "Walking support based on cooperation between wearable-type and cane-type walking support systems," in *2011 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, July 2011, pp. 122–127.

[65] Y. Okazaki, "Self-reliance support robot," *The Japan Society of Mechanical Engineers*, vol. 119, no. 1166, p. 46, 2016. [Online]. Available: https://ci.nii.ac.jp/naid/110010032702/

[66] Sharp Corporation, "RoBoHoN," https://robohon.com/ (In Japanese, Accessed 23th Nov., 2019).

[67] PARO, "PARO Therapeutic Robot," http://www.parorobots.com/ (Accessed 23th Nov., 2019).

[68] L. SECOM CO., "Secom home security," https://www.secom.co.jp/homesecurity/plan/seniorparents/ (In Japanese, Accessed 26th Nov., 2019).

[69] I. Hitachi Global Life Solutions, "Watching service, doshiteru," https://kadenfan.hitachi.co.jp/doshiteru/ (In Japanese, Accessed 26th Nov., 2019).

[70] K. Yoshino, Y. Murase, N. Lubis, K. Sugiyama, H. Tanaka, S. Sakti, S. Takamichi, and S. Nakamura, "Spoken dialogue robot for watching daily life of elderly people," in *International Workshop on Spoken Dialogue Systems Technology (IWSDS2019)*, Apr. 2019. [Online]. Available: https://ahcweb01.naist.jp/papers/conference/2019/201904_IWSDS_koichiro/201904_IWSDS_koichiro.paper.pdf

[71] K. Masani, A. H. Vette, M. O. Abe, and K. Nakazawa, "Center of pressure velocity reflects body acceleration rather than body velocity during quiet standing," *Gait & Posture*, vol. 39, no. 3, pp. 946 – 952, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0966636213007030

[72] V. M. Zatsiorsky and D. L. King, "An algorithm for determining gravity line location from posturographic recordings," *Journal of Biomechanics*, vol. 31, no. 2, pp. 161 – 164, 1997. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0021929097001164

[73] K. Zabjek, C. Coillard, C. Rivard, and F. Prince, "Estimation of the centre of mass for the study of postural control in idiopathic scoliosis patients: A comparison of two techniques," *European spine journal : official publication of the European Spine Society, the European Spinal Deformity Society, and the European Section of the Cervical Spine Research Society*, vol. 17, pp. 355–60, 04 2008.

[74] J. Woodburn and P. Helliwell, "Observations on the F-Scan in-shoe pressure measuring system," *Clinical Biomechanics*, vol. 11, no. 5, pp. 301 – 304, 1996. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0268003395000712

[75] Y. Morita, J. Okamoto, K. Kawamura, M. Seki, S. Sessa, M. Zecca, Z. Lin, H. Ishii, S. Takasugi, A. Takanishi, and M. G. Fujie, "Gait analysis system of presumption of method to estimate right and left separated ground reaction force using acceleration sensor," in *WWLS (Welfare, Wellbeing, Life Support) 2010*, 2010.

[76] J. Skidmore and P. Artemiadis, "Unilateral floor stiffness perturbations systematically evoke contralateral leg muscle responses: A new approach to robot-assisted gait therapy," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 4, pp. 467–474, April 2016.

[77] R. Moe-Nilssen, "A new method for evaluating motor control in gait under real-life environmental conditions. part 2: Gait analysis," *Clinical Biomechanics*, vol. 13, no. 4, pp. 328 – 335, 1998. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0268003398000904

[78] P. Di, J. Huang, S. Nakagawa, K. Sekiyama, and T. Fukuda, "Fall detection and prevention in the elderly based on the zmp stability control," in *2013 IEEE Workshop on Advanced Robotics and its Social Impacts*, Nov 2013, pp. 82–87.

[79] M. Miezal, B. Taetz, and G. Bleser, "Real-time inertial lower body kinematics and ground contact estimation at anatomical foot points for agile human locomotion," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, May 2017, pp. 3256–3263.

[80] A. Mannini and A. M. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors*, vol. 10, no. 2, pp. 1154–1175, 2010. [Online]. Available: http://www.mdpi.com/1424-8220/10/2/1154

[81] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine," in *Ambient Assisted Living and Home Care*, J. Bravo, R. Hervás, and M. Rodríguez, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 216–223.

[82] D. Tome, C. Russell, and L. Agapito, "Lifting from the deep: Convolutional 3d pose estimation from a single image," *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jul 2017. [Online]. Available: http://dx.doi.org/10.1109/CVPR.2017.603

[83] J. J. Tompson, A. Jain, Y. LeCun, and C. Bregler, "Joint training of a convolutional network and a graphical model for human pose estimation," in *Advances in Neural Information Processing Systems 27*, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 1799–1807. [Online]. Available: http://papers.nips.cc/paper/5573-joint-training-of-a-convolutional-network-and-a-graphical-model-for-human-pose-estimation. pdf

[84] K. Kiguchi and Y. Hayashi, "An EMG-based control for an upper-limb power-assist exoskeleton robot," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 4, pp. 1064–1071, Aug 2012.

[85] Y. Hirata, H. Yamaya, K. Kosuge, A. Koujina, T. Shirakawa, and T. Katayama, "Anomaly state assessing of human using walker-type support system based on statistical analysis," in *2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, Aug 2015, pp. 146–152.

[86] T. Takeda, K. Kosuge, and Y. Hirata, "Hmm-based dance step estimation for dance partner robot -ms dancer-," in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Aug 2005, pp. 3245–3250.

[87] Y. Hirata, A. Muraki, and K. Kosuge, "Motion control of intelligent walker based on renew of estimation parameters for user state," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2006, pp. 1050–1055.

[88] O. Chuy, Y. Hirata, Zhidong Wang, and K. Kosuge, "Motion control algorithms for a new intelligent robotic walker in emulating ambulatory device function," in *IEEE International Conference Mechatronics and Automation, 2005*, vol. 3, July 2005, pp. 1509–1514 Vol. 3.

[89] G. Bologna and Y. Hayashi, "Characterization of symbolic rules embedded in deep dimlp networks: A challenge to transparency of deep learning," *Journal of Artificial Intelligence and Soft Computing Research*, vol. 7, p. 265, 07 2017.

[90] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," *Artif. Intell.*, vol. 267, pp. 1–38, 2019.

[91] A. Weller, "Challenges for transparency," *CoRR*, vol. abs/1708.01870, 2017.

[92] B. Boscoe, "Creating transparency in algorithmic processes," *Delphi - Interdisciplinary Review of Emerging Technologies*, vol. 2, no. 1, 2019. [Online]. Available: https://doi.org/10.21552/delphi/2019/1/5

[93] J. De Fauw, J. R. Ledsam, B. Romera-Paredes, S. Nikolov, N. Tomasev, S. Blackwell, H. Askham, X. Glorot, B. O'Donoghue, D. Visentin, G. van den Driessche, B. Lakshminarayanan, C. Meyer, F. Mackinder, S. Bouton, K. Ayoub, R. Chopra, D. King, A. Karthikesalingam, and O. Ronneberger, "Clinically applicable deep learning for diagnosis and referral in retinal disease," *Nature Medicine*, vol. 24, 08 2018.

[94] M. Hosseini, A. Shahri, K. Phalp, and R. Ali, "A modelling language for transparency requirements in business information systems," in *Advanced Information Systems Engineering*, S. Nurcan, P. Soffer, M. Bajec, and J. Eder, Eds. Cham: Springer International Publishing, 2016, pp. 239–254.

[95] J. Novikova and L. Watts, "Towards artificial emotions to assist social coordination in hri," *International Journal of Social Robotics*, vol. 7, no. 1, pp. 77–88, Feb 2015. [Online]. Available: https://doi.org/10.1007/s12369-014-0254-y

[96] D. F. Paez Granados, B. A. Yamamoto, H. Kamide, J. Kinugawa, and K. Kosuge, "Dance teaching by a robot: Combining cognitive and physical human-robot interaction for supporting the skill learning process," *IEEE Robotics and Automation Letters*, vol. 2, no. 3, pp. 1452–1459, July 2017.

[97] R. Kurnia, M. A. Hossain, A. Nakamura, and Y. Kuno, "Generation of efficient and user-friendly queries for helper robots to detect target objects," *Advanced Robotics*, vol. 20, no. 5, pp. 499–517, 2006. [Online]. Available: https://doi.org/10.1163/156855306776985559

[98] A. Green and K. S. Eklundh, "Designing for learnability in human-robot communication," *IEEE Transactions on Industrial Electronics*, vol. 50, no. 4, pp. 644–650, Aug 2003.

[99] Kazuhiko Shinozawa, Takahiro Miyashita, Masayuki Kakio, and N. Hagita, "User specification method and humanoid confirmation behavior," in *2007 7th IEEE-RAS International Conference on Humanoid Robots*, Nov 2007, pp. 366–370.

[100] S. Pakrasi, O. Burmeister, J. Coppola, T. McCallum, and G. Loeb, "Ethical telehealth design for users with dementia," *Gerontechnology*, vol. 13, no. 4, pp. 383–387, 2015, imported on 12 Apr 2017 - DigiTool details were: Journal title (773t) = Gerontechnology. ISSNs: 1569-1101;.

[101] G. Baldini, M. Botterman, R. Neisse, and M. Tallacchini, "Ethical design in the internet of things," *Science and Engineering Ethics*, vol. 24, no. 3, pp. 905–925, Jun 2018. [Online]. Available: https://doi.org/10.1007/s11948-016-9754-5

[102] T. I. G. I. on Ethics of Autonomous and I. Systems, "Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems, first edition," https://standards.ieee.org/content/ieee-standards/en/industry-connections/ec/autonomous-systems.html, 2019. [Online]. Available: https://ethicsinaction.ieee.org/

[103] J. Bryson and A. Winfield, "Standardizing ethical design for artificial intelligence and autonomous systems," *Computer*, vol. 50, no. 5, pp. 116–119, May 2017.

[104] Y. Weng and Y. Hirata, "Ethically aligned design for assistive robotics," in *2018 IEEE International Conference on Intelligence and Safety for Robotics (ISR)*, Aug 2018, pp. 286–290.

[105] P. G. Yock, S. Zenios, J. Makower, T. J. Brinton, U. N. Kumar, F. J. Watkins, L. Denend, T. M. Krummel, and C. Q. Kurihara, *Biodesign: the process of innovating medical technologies*. Cambridge University Press, 2015. [Online]. Available: https://books.google.co.jp/books?hl=ja&lr=lang_ja|lang_en&id=S0ghAwAAQBAJ&oi=fnd&pg=PR8&ots=xt28jMFRJT&sig=LvHFIEGr-fWkmBQ62yfWFHp_INM#v=onepage&q&f=false

[106] T. C. Major, B. B. Rhoades, and J. M. Conrad, "A novel and affordable robot kit for completion of the requirements for the boy scouts of america robotics merit badge," in *SoutheastCon 2015*, April 2015, pp. 1–4.

[107] L. Dickstein-Fischer, E. Alexander, X. Yan, H. Su, K. Harrington, and G. S. Fischer, "An affordable compact humanoid robot for autism spectrum disorder interventions in children," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug 2011, pp. 5319–5322.

[108] A. G. Zisimatos, M. V. Liarokapis, C. I. Mavrogiannis, and K. J. Kyriakopoulos, "Open-source, affordable, modular, light-weight, underactuated robot hands," in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sep. 2014, pp. 3207–3212.

[109] K. Yamaguchi, Y. Hirata, and K. Kosuge, "Underactuated robot hand for dual-arm manipulation," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2015, pp. 2937–2942.

[110] R. Katz, "Tele-care robot for assisting independent senior citizens who live at home." in *AAATE Conf.*, 2015, pp. 288–294.

[111] H. Satoh, T. Kawabata, and Y. Sankai, "Bathing care assistance with robot suit hal," in *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Dec 2009, pp. 498–503.

[112] C. Parlitz, M. Hägele, P. Klein, J. Seifert, and K. Dautenhahn, "Care-o-bot 3 — rationale for human-robot interaction design," in *39th International Symposium on Robotics*, 10 2008. [Online]. Available: https://www.researchgate.net/publication/200036383_Care-O-bot_3_-_Rationale_for_human-robot_interaction_design

[113] P. Mayer and P. Panek, "Towards a multi-modal user interface for an affordable assistive robot," in *Universal Access in Human-Computer Interaction. Aging and Assistive Environments*, C. Stephanidis and M. Antona, Eds. Cham: Springer International Publishing, 2014, pp. 680–691.

[114] D. Fischinger, P. Einramhof, K. Papoutsakis, W. Wohlkinger, P. Mayer, P. Panek, S. Hofmann, T. Koertner, A. Weiss, A. Argyros, and M. Vincze, "Hobbit, a care robot supporting independent living at home: First prototype and lessons learned," *Robotics and Autonomous Systems*, vol. 75, pp. 60 – 78, 2016, assistance and Service Robotics in a Human Environment. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921889014002140

[115] R. H. Wortham, A. Theodorou, and J. J. Bryson, "Improving robot transparency: Real-time visualisation of robot ai substantially improves understanding in naive observers," in *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, Aug 2017, pp. 1424–1431.

[116] R. H. Wortham, A. Theodorou, and J. J. Bryson, "Robot transparency: Improving understanding of intelligent behaviour for designers and users," in *Towards*

Autonomous Robotic Systems, Y. Gao, S. Fallah, Y. Jin, and C. Lekakou, Eds. Cham: Springer International Publishing, 2017, pp. 274–289.

[117] R. H. Wortham, S. E. Gaudl, and J. J. Bryson, "Instinct: A biologically inspired reactive planner for embedded environments," in *Proceedings of ICAPS 2016 PlanRob Workshop, London, UK*, 2016.

[118] M. Ae, H.-P. Tang, and T. Yokoi, "Estimation of inertia properties of the body segments in japanese athletes," *Biomechanisms (In Japanese)*, vol. 11, pp. 23–33, 1992.

[119] H. Okada, M. Ae, N. Fujii, and Y. Morioka, "Estimation of inertia properties of the body segments in japanese elderly," *Biomechanisms (In Japanese)*, vol. 13, pp. 125–139, 1996.

[120] K. H. Hunt, *Kinematic geometry of mechanisms.* Oxford University Press, 1978.

[121] J. Ohara, K. Uchida, Y. Ueno, and K. Hatta, *Measuring Human Body - Design Document of Measurement Value (In Japanese)*, J. P. Service, Ed. Japan Publication Service, 1986.

[122] F. Hausdorff and J. R. Aumann, *Set Theory*, C. P. Co., Ed. Chelsea Pub. Co., 1957.

[123] S. Kawazoe, D. Chugo, S. Yokota, H. Hashimoto, T. Katayama, Y. Mizuta, and A. Koujina, "Development of standing assistive walker for domestic use," in *2017 IEEE International Conference on Industrial Technology (ICIT)*, March 2017, pp. 1455–1460.

[124] M. Takeda, Y. Hirata, K. Kosuge, T. Katayama, Y. Mizuta, and A. Koujina, "Human cog estimation for assistive robots using a small number of sensors," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, May 2017, pp. 6052–6057. [Online]. Available: http://doi.org/10.1109/ICRA.2017.7989717

[125] C.-C. Chang and C.-J. Lin, "Libsvm: A library for support vector machines," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 27:1–27:27, May 2011. [Online]. Available: http://doi.acm.org/10.1145/1961189.1961199

[126] B. Waltl and R. Vogl, "Explainable artificial intelligence - the new frontier in legal informatics," *Jusletter IT*, vol. 4, pp. 1–10, 2018. [Online]. Available: https://jusletter-it.weblaw.ch/services/login.html?targetPage=http://jusletter-it.weblaw.ch/issues/2018/IRIS/explainable-artifici_fbce1ac1d0.html__ONCE&handle=http://jusletter-it.weblaw.ch/issues/2018/IRIS/explainable-artifici_fbce1ac1d0.html__ONCE

[127] OMG, "OMG Systems Modeling Language (OMG SysML), Version 1.3," http://www.omg.org/spec/SysML/1.3/ (Accessed 20th Nov., 2019), Object Management Group, 2012. [Online]. Available: http://www.omg.org/spec/SysML/1.3/

[128] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, "Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review," *Psychonomic Bulletin & Review*, vol. 20, no. 1, pp. 21–53, Feb 2013. [Online]. Available: https://doi.org/10.3758/s13423-012-0333-8

[129] J. Burke, M. Prewett, A. A. Gray, L. Yang, F. Stilson, M. Coovert, L. Elliott, and E. S. Redden, "Comparing the effects of visual-auditory and visual-tactile feedback on user performance: A meta-analysis," in *ICMI'06: 8th International Conference on Multimodal Interfaces, Conference Proceeding*, 01 2006, pp. 108–117.

[130] M. Funk, J. Heusler, E. Akcay, K. Weiland, and A. Schmidt, "Haptic, auditory, or visual?: Towards optimal error feedback at manual assembly workplaces," in *Proceedings of the 9th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, ser. PETRA '16. New York, NY, USA: ACM, 2016, pp. 43:1–43:6. [Online]. Available: http://doi.acm.org/10.1145/2910674.2910683

[131] G. Y and P. J, *Humanitude : comprendre la vieillesse, prendre soin des hommes vieux*. Armand Colin, 2007.

[132] R. C. A. n. C. P. d. Melo, P. J. Costa, L. V. L. A. c. Henriques, L. H. Tanaka, P. J. P. QueirÃ³ s, and J. A. o. P. A. t. AraÃº jo, "Humanitude in the humanization of elderly care: experience reports in a health service," *Revista Brasileira de Enfermagem*, vol. 72, pp. 825 – 829, 06 2019. [Online]. Available: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0034-71672019000300825&nrm=iso

[133] S. Biquand and B. Zittel, "Care giving and nursing, work conditions and humanitude®," *Work*, vol. 41, no. 1, pp. 1828–1831, 2012.

[134] J. Brooke *et al.*, "SUS-a quick and dirty usability scale," *Usability evaluation in industry*, pp. 189–194, 1996. [Online]. Available: https://books.google.co.uk/books?hl=en&lr=&id=IfUsRmzAqvEC&oi=fnd&pg=PA189&ots=Gaowybqp6p&sig=RrTLeFbRa5u-KumW_O38UX_T2bA#v=onepage&q&f=false

[135] M. Takeda, Y. Hirata, T. Katayama, Y. Mizuta, and A. Koujina, "State estimation using the cog candidates for sit-to-stand support system user," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3011–3018, Oct 2018. [Online]. Available: http://doi.org/10.1109/LRA.2018.2849551

[136] M. Takeda, Y. Hirata, Y.-H. Weng, T. Katayama, Y. Mizuta, and A. Koujina, "Accountable system design architecture for embodied AI: a focus on physical human support robots," *Advanced Robotics*, vol. 33, no. 23, pp. 1248–1263, 2019. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/01691864.2019.1689168

[137] ——, "Verbal guidance for sit-to-stand support system," *ROBOMECH Journal*, 2020.

Appendix A

CoG Candidates Calculation Procedures and Results for Each Measurements Set

A.1 CoG Calculation Procedure

In this section, the CoG calculation procedures on the measurements sets which can calculate CoG position uniquely are explained.

On the measurements set A, we can obtain information as follow;

- position of wrist
- position of elbow
- position of ankle
- position of one point of body link
- inclination of body link

- inclination of forearm link

As explained in chapter 3, foot link is assumed that its bottom keeps facing ground, hence the foot link position is determined by using the ankle joint position. Forearm link is also determined since the positions of both end are known.

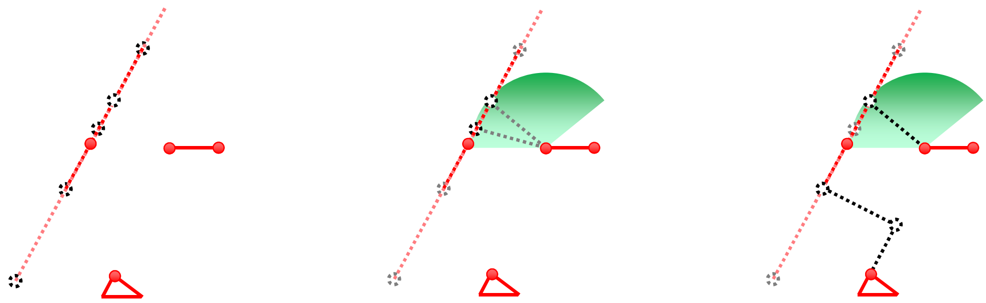
Since upper body link's inclination and position of one point are measured, the body link is on the line which is represented as equation A.1;

$$y = (\tan\alpha)z - (\tan\alpha)Z + Y \tag{A.1}$$

where α[rad] is the inclination and (Y, Z) is the position of one point of body link. As shown in Figure A.1(a), the body link is limited in the range that the measured point is on the body link.

Subsequently, we consider the upper arm. By considering the circle with a radius of upper arm link length and centered at elbow joint, the intersection of the circle and the line which is represented as equation A.1 is the shoulder joint position. 2 points can be calculated as the intersection, however, it is confirmed by using motion capture data that the point can be determined by considering the shoulder joint range for normal sit-to-stand, stand-to-sit, and walking motion. Thus the upper arm link and upper body link positions are determine, and the hip position is also identified. Then the ankle joint position can be calculated geometrically by using the positions of hip and ankle, link lengths of thigh and shank, and the ranges of motion of ankle, knee, and hip joints as shown in Figure A.1(c). Finally the CoG position is calculated since the all link position is determined.

On the measurements set B, positions of wrist, elbow, and ankle joint, one point of body link, and inclination of body link are measured. As similar to measurements



(a) (b) (c)

Figure A.1: Calculation of CoG (A)

set A, foot and forearm link positions are determined. Positions of the other links are also calculated in a similar way. Therefore, CoG position can also be calculated.

On the measurements set C, positions of wrist, ankle, and one point of body link and inclinations of body and forearm links are measured. One end and inclination of forearm link are measured, thus the other end can be calculated by using the length of forearm. Therefore, positions of forearm link can be determined. Then the other link positions are also be calculated as similar to measurements sets A and B, thus the CoG position can be identified.

On the measurements set D, positions of elbow, ankle, and one point of body link and inclinations of body and forearm links are measured. The position of forearm link can be calculated in a similar way to the measurements set C. The other links are also determined, and the COG position is identified.

A.2 CoG Candidate Calculation Procedure for Each Measurements Set

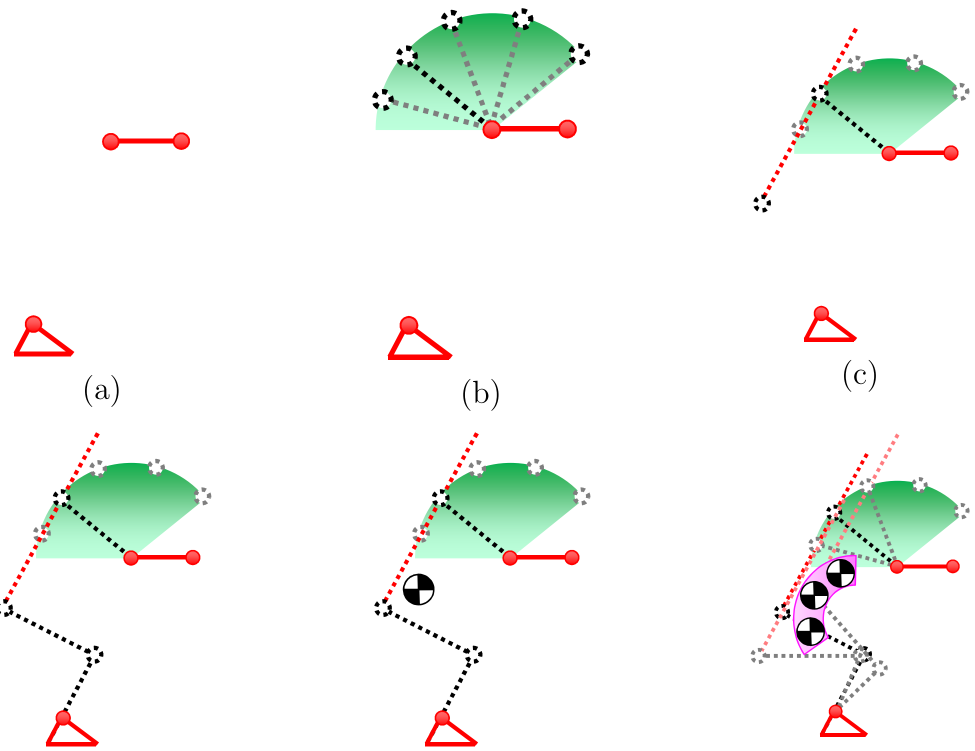
This section shows the CoG candidates calculation procedure of measurements sets which are represented in chapter 3 except 1a which was already explained.

A.2.1 Measurements Set 1b

Measurements set 1b consists of positions of wrist, elbow, and ankle, and inclination of body link. Foot and forearm link positions are identified as similar to measurements set 1a as shown in Figure A.2(a). Candidates of shoulder joint can be calculated by considering the range of motion of elbow joint as shown in Figure A.2(b). Subsequently, we focus on a shoulder candidate. By using the length and inclination of body link, the hip candidate which is corresponding to the focused shoulder candidate can be calculated as shown in Figure A.2(c). Then the corresponding knee candidate is identified in a similar way to the measurements set 1a as shown in Figure A.2(d). Since all corresponding candidates of link positions are calculated, the CoG candidate corresponding to the focused shoulder candidate can be calculated as shown in Figure A.2(e), by using equation 3.2 which was explained in section 3.2.1. All CoG candidates can be calculated by repeating the procedure above as similar to the measurements set 1a, as shown in Figure A.2(f).

A.2.2 Measurements Set 1c

On the measurements set 1c, positions of wrist, ankle, and one point of body link and inclination of body link are measured. Foot link position is identified as shown in Figure A.3(a). Since upper body link's inclination and position of one point are measured, the body link is on the line which is represented as equation A.1. As similar to measurements set A which is explained in section A.1, the body link is limited in the range that the measured point is on the body link as shown in Figure A.3(b). Both end of body link are shoulder and hip, thus we focus on one candidate of body link, then the corresponding shoulder and hip candidates are determined. Then corresponding



(a) (b) (c) (d) (e) (f)

Figure A.2: Calculation of CoG Candidates (1b)

elbow candidate can be calculated by using the positions of shoulder candidate and wrist, lengths of upper arm and forearm, and ranges of motion of shoulder, elbow. and wrist joints, as shown in Figure A.3(c). The corresponding knee joint candidate can be calculated as similar to measurements sets 1a and 1b as shown in Figure A.3(d). Then corresponding CoG candidate is calculated as shown in Figure A.3(e) since the all corresponding link positions are determined. All CoG candidates can be calculated by repeating the procedure above as shown in Figure A.3(f).

A.2.3 Measurement Set 2a

On measurements set 2a, wrist, elbow, and ankle positions are measured. Foot and Forearm links are determined as shown in Figure A.4(a). First, we focus on upper arm

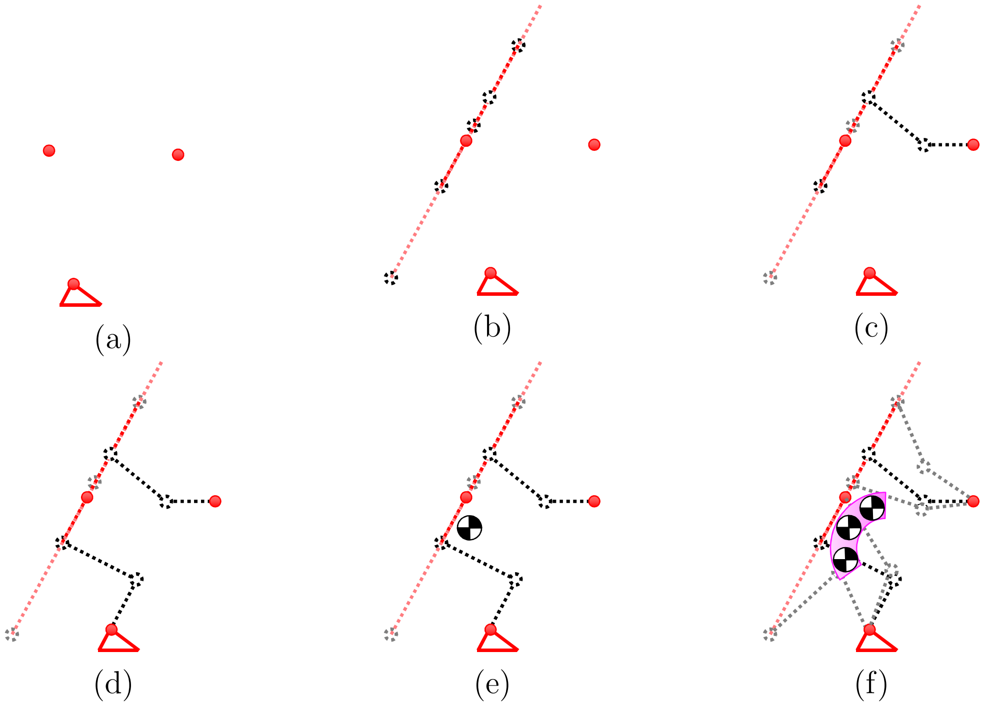


Figure A.3: Calculation of CoG Candidates (1c)

and calculate shoulder candidates by considering the range of motion of elbow joint as shown in Figure A.4(b). Subsequently, we focus on one candidate and consider the body link. Since the length of body link is known, corresponding hip candidates can be calculated by using the range of motion of shoulder joint as shown in Figure A.4(c). By considering one hip candidate, the corresponding knee candidate can be calculated as shown in Figure A.4(d), and the corresponding CoG candidate is also calculated as shown in Figure A.4(e). All CoG candidates can be calculated by repeating the procedure above for all combinations of shoulder candidate and corresponding hip candidate as shown in Figure A.4(f).

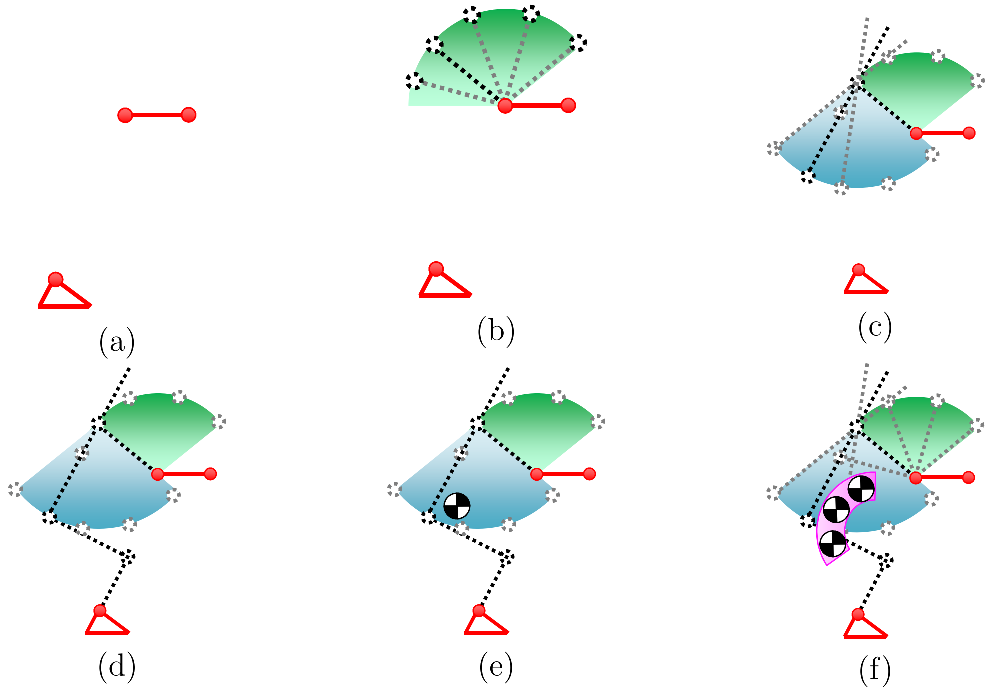


Figure A.4: Calculation of CoG Candidates (2a)

A.2.4 Measurements Set 2b

On measurements set 2b, positions of wrist, ankle, and one point of body link are measured. As shown in Figure A.5(a), foot link position is identified as similar to the other measurements sets. The candidates of elbow joint can be calculated by using range of motion of wrist joint as shown in Figure A.5(b). Then we focus on one elbow candidate and calculate shoulder candidates which are corresponding to the focused elbow candidate. By focusing on one shoulder candidate, the corresponding hip candidate can be calculated by considering the line segment of which length is body link length and the line segment pass thorough the measured one point of body link as shown in Figure A.5(c). The corresponding knee candidate can be calculated as similar to the other measurements sets as shown in Figure A.5(d). Then all link positions are determined, thus the corresponding CoG candidate is calculated as

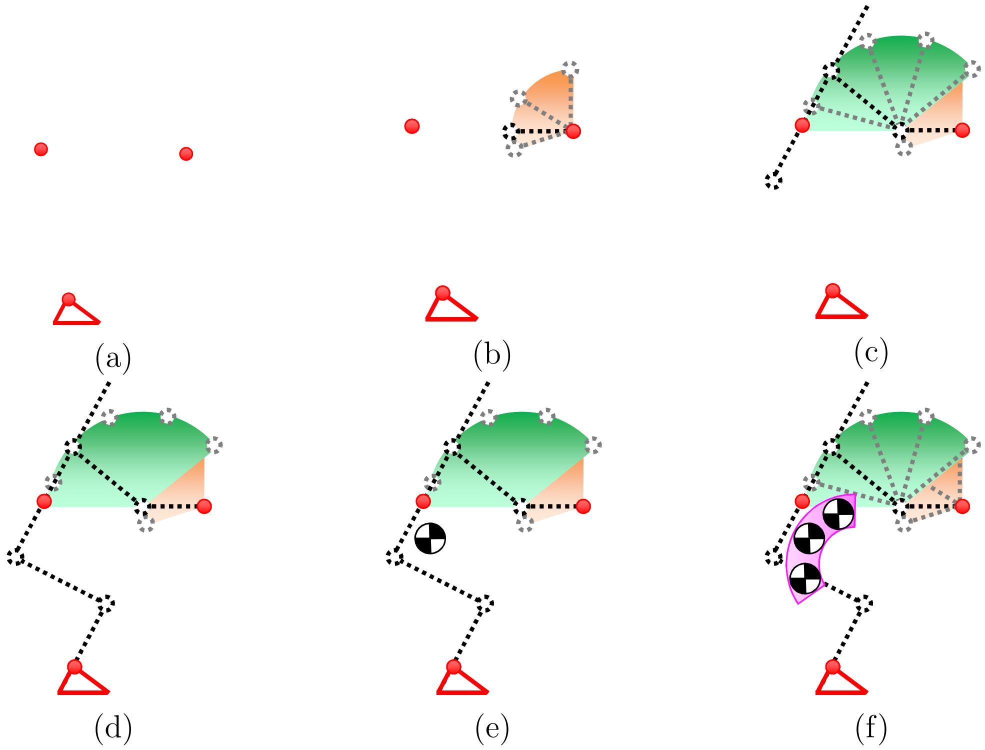


Figure A.5: Calculation of CoG Candidates (2b)

shown in Figure A.5(e). By repeating the procedure above for all combinations of elbow candidate and the corresponding shoulder candidate, all CoG candidates can be calculated as shown in Figure A.5(f).

A.2.5 Measurements Set 2c

On measurements set 2c, wrist and ankle positions and inclination of body link are measured. As similar to the other measurements sets, foot link position is identified as shown in Figure A.6(a).

First, we focus on the forearm as similar to the measurements set 2b, and calculate elbow candidates and the shoulder candidates which are corresponding to the focused elbow candidate as shown in Figure A.6(b). Subsequently, we focus on one shoulder candidate, then the corresponding hip candidate can be calculated by using the length

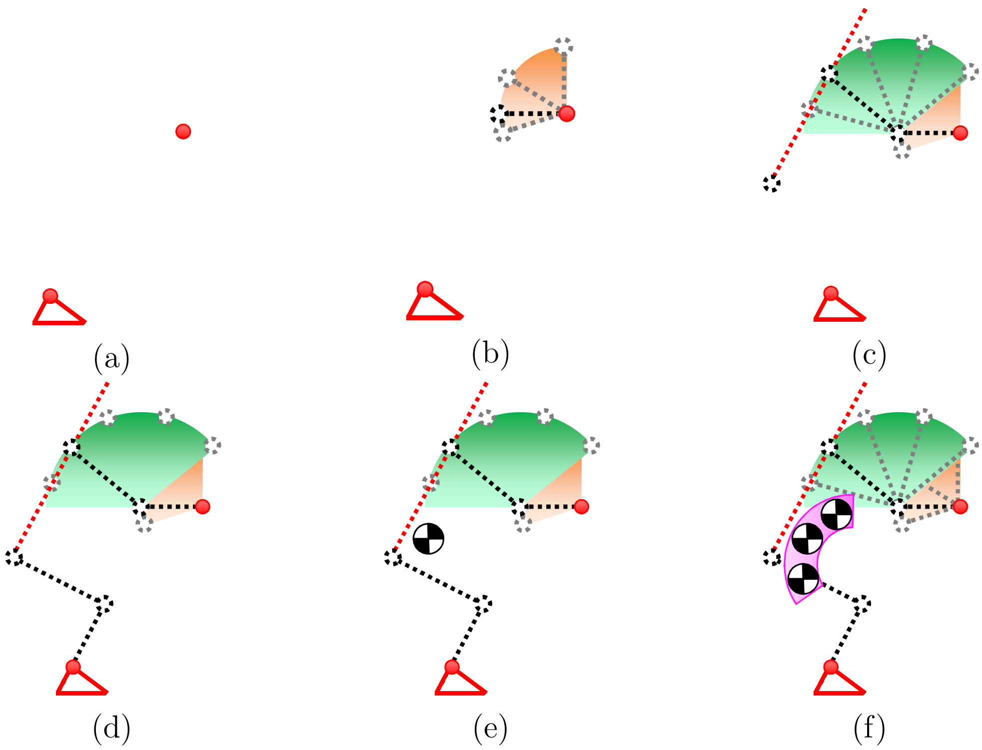


Figure A.6: Calculation of CoG Candidates (2c)

and inclination of the body link as shown in Figure A.6(c). As similar to the other measurements sets, corresponding knee candidate, all link positions, and the CoG candidate can be calculated as shown in Figure A.6(d) and (e). All CoG candidates can be calculated by repeating the procedure above for all combinations of elbow candidate and corresponding shoulder candidate as shown in Figure A.6(f).

A.2.6 Measurements Set 2d

On measurements set 2d, positions of ankle and one point of body link and inclinations of body and forearm links are measured. The foot link is identified as shown in Figure A.7(a), and body link candidates can be calculated as link segments on the line which is represented as equation A.1 as shown in Figure A.7(b). We focus on one candidate of shoulder joint and calculate the corresponding elbow candidates as shown

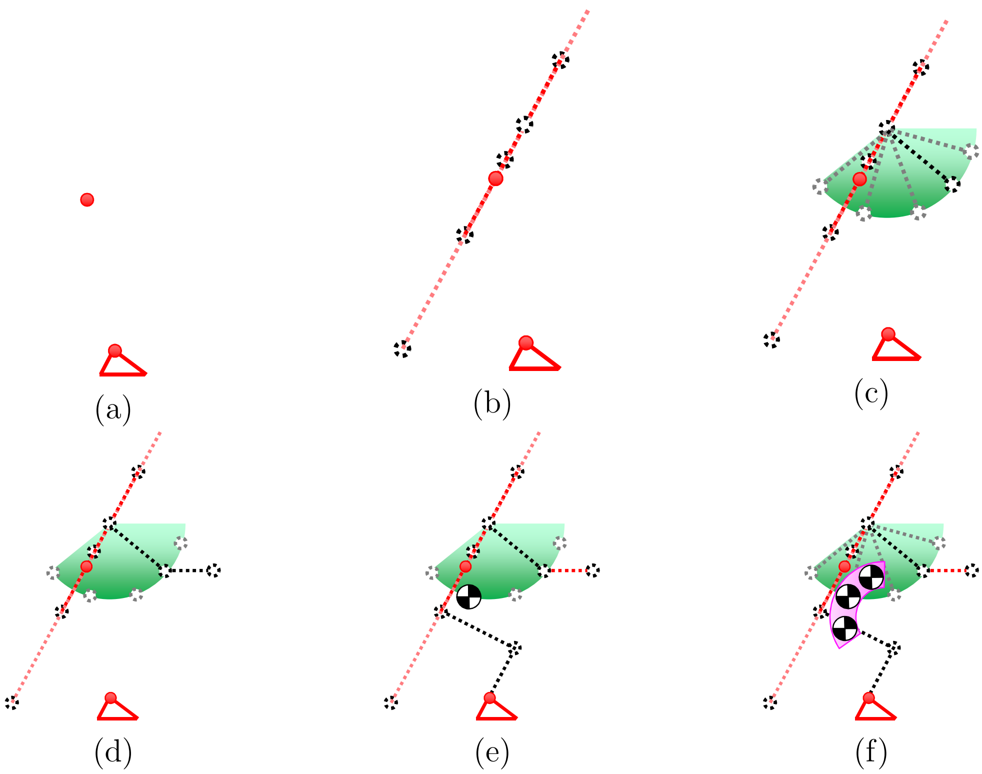
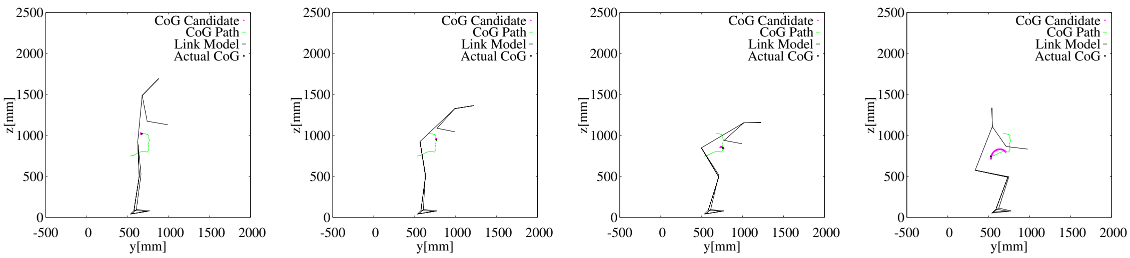


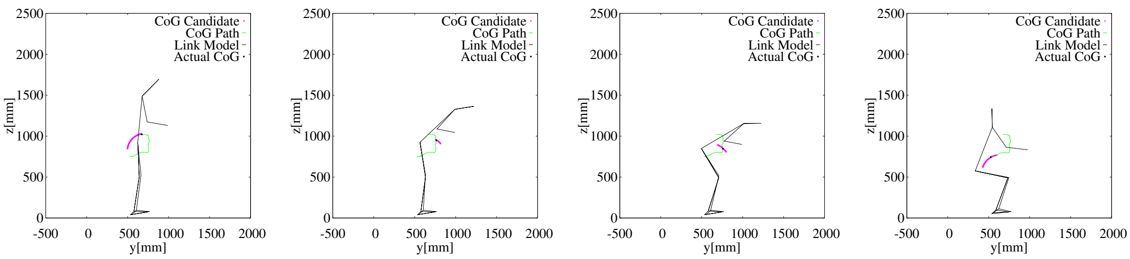
Figure A.7: Calculation of CoG Candidates (2d)

in Figure A.7(c) by considering the range of motion of shoulder joint. Subsequently, we focus on one elbow candidate and calculate the corresponding wrist joint by using the inclination of forearm link as shown in Figure A.7(d). As similar to the other measurements sets, corresponding knee candidate, all link positions, and the CoG candidate can be calculated as shown in Figure A.7(e). All CoG candidates can be calculated by repeating the procedure above for all combinations of body link candidate and corresponding elbow candidate as shown in Figure A.7(f).



(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.8: CoG Candidates (Sitting, Pattern 1a)



(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

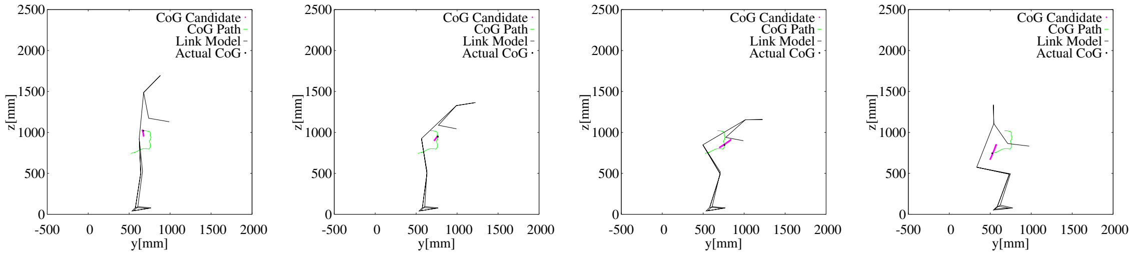
Figure A.9: CoG Candidates (Sitting, Pattern 1b)

A.3 CoG Candidate Calculation Results for Each Measurements Set

A.3.1 Calculated CoG Candidates of the Motion Capture Experiment

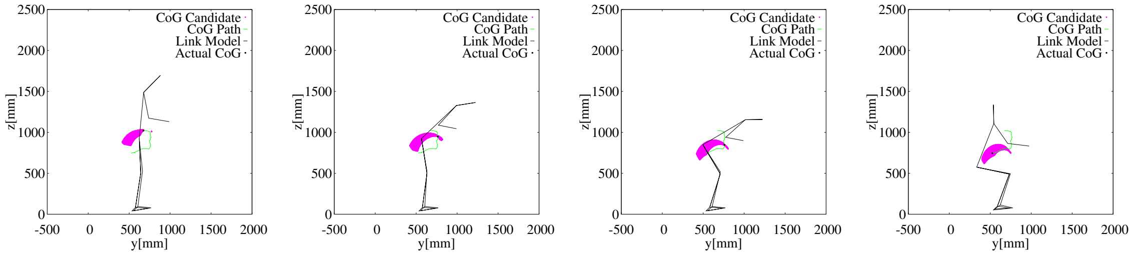
The experimental results of stand-to-sit, sit-to-stand, and walking motion are shown in Figure A.8–Figure A.14, Figure A.15–Figure A.21, and Figure A.22–Figure A.28, respectively.

The maximum errors are shown in Figure A.29.



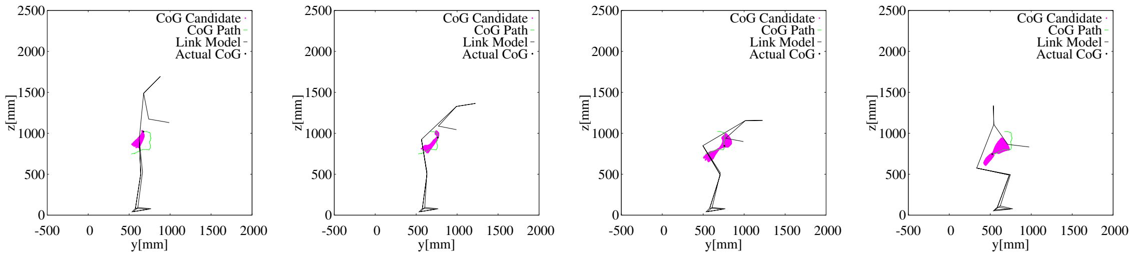
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.10: CoG Candidates (Sitting, Pattern 1c)



(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.11: CoG Candidates (Sitting, Pattern 2a)

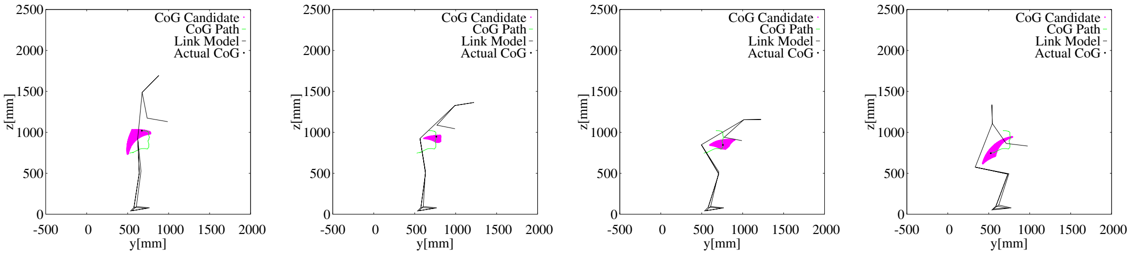


(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.12: CoG Candidates (Sitting, Pattern 2b)

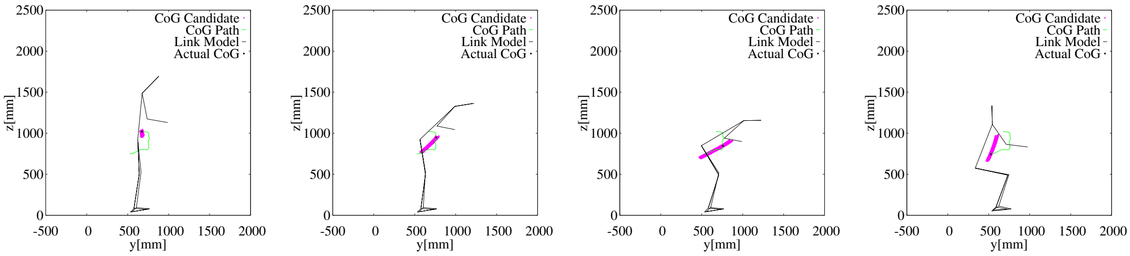
A.3.2 Calculated CoG Candidates of the Experiment Using Simple Sensors

The experimental results of stand-to-sit and sit-to-stand motion are shown in Figure A.8–Figure A.13, Figure A.36–Figure A.41, respectively.



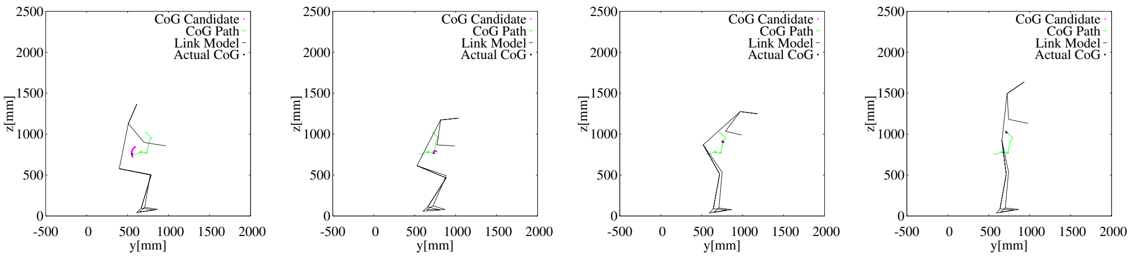
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.13: CoG Candidates (Sitting, Pattern 2c)



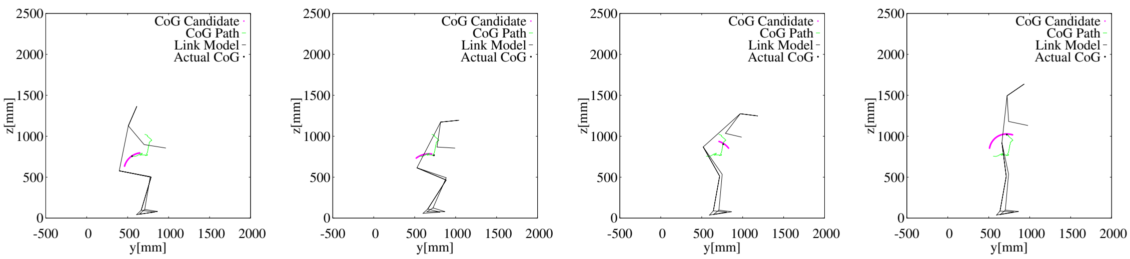
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.14: CoG Candidates (Sitting, Pattern 2d)



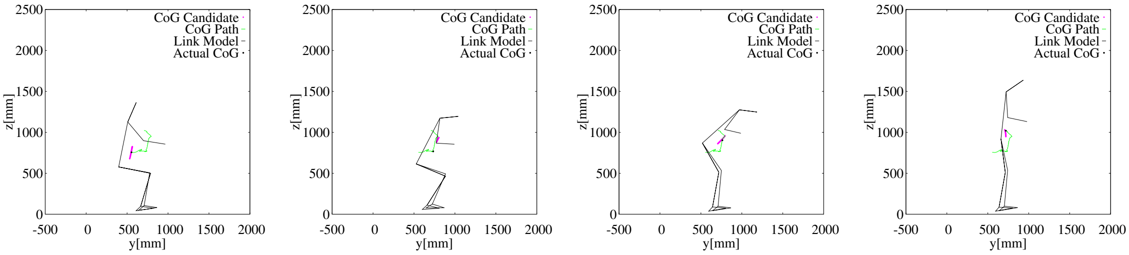
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.15: CoG Candidates (Standing, Pattern 1a)



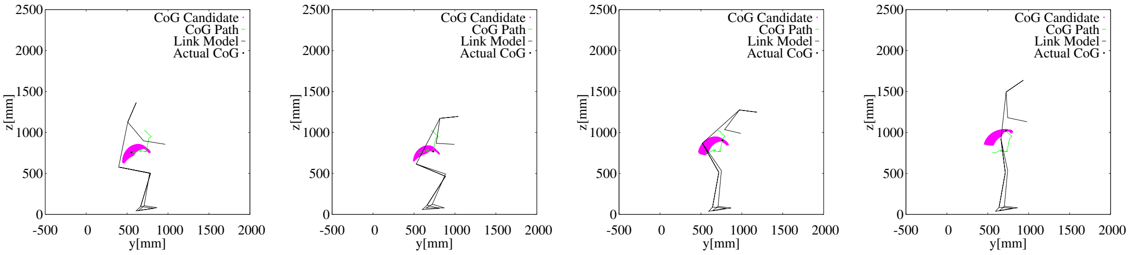
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.16: CoG Candidates (Standing, Pattern 1b)



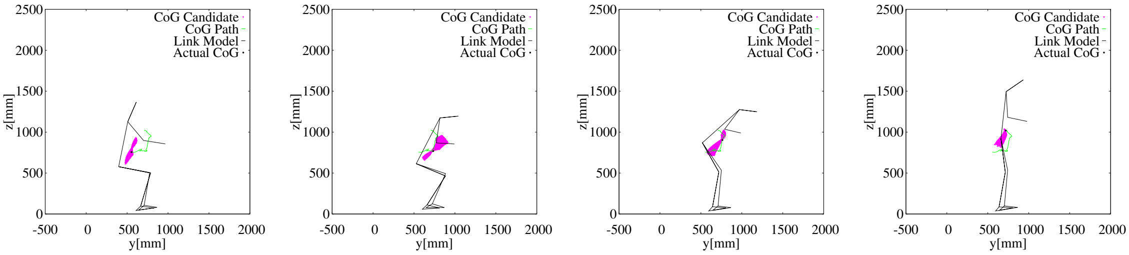
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.17: CoG Candidates (Standing, Pattern 1c)



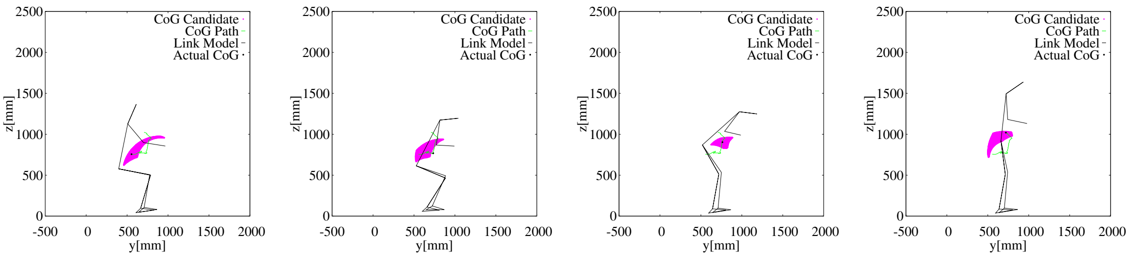
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.18: CoG Candidates (Standing, Pattern 2a)



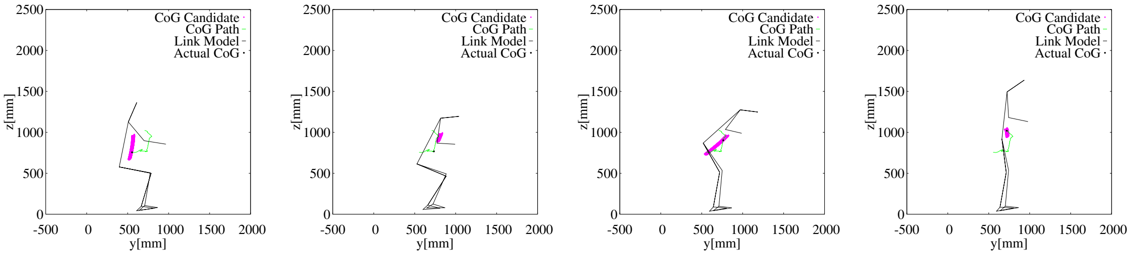
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.19: CoG Candidates (Standing, Pattern 2b)



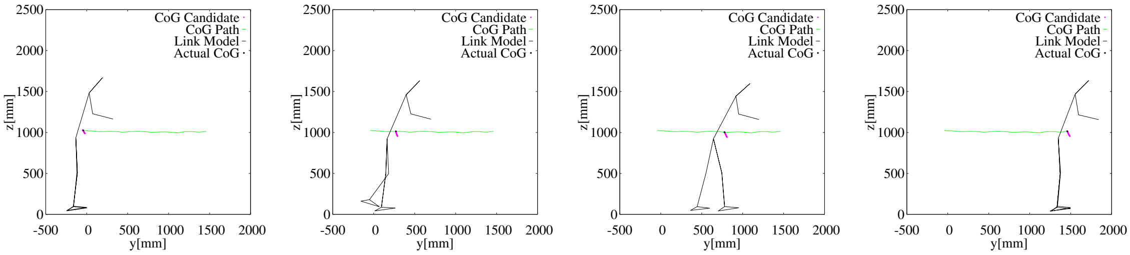
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.20: CoG Candidates (Standing, Pattern 2c)



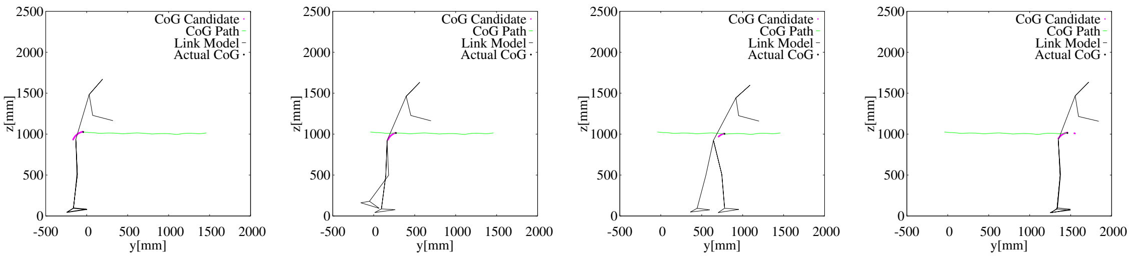
(a) 0[s] (b) 9[s] (c) 18[s] (d) 27[s]

Figure A.21: CoG Candidates (Standing, Pattern 2d)



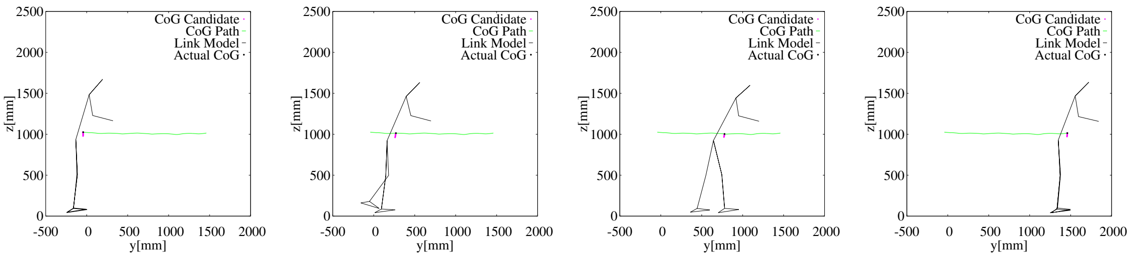
(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.22: CoG Candidates (Walking, Pattern 1a)



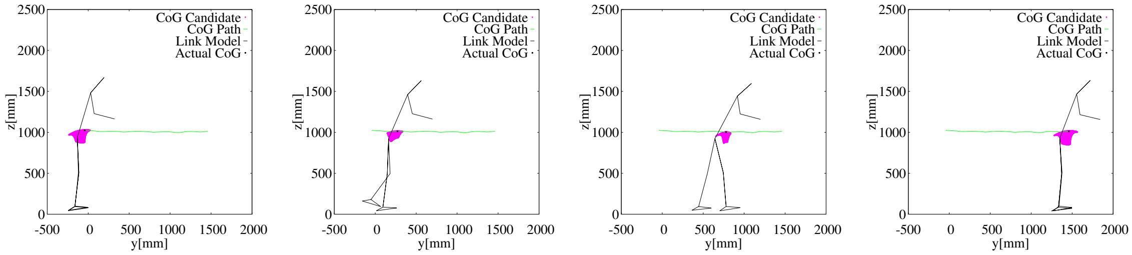
(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.23: CoG Candidates (Walking, Pattern 1b)



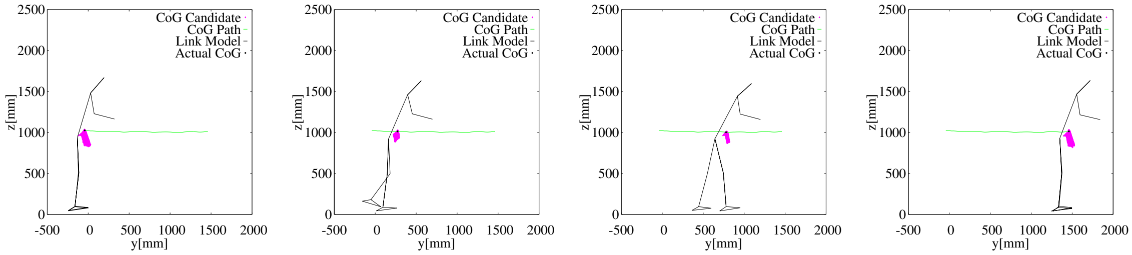
(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.24: CoG Candidates (Walking, Pattern 1c)



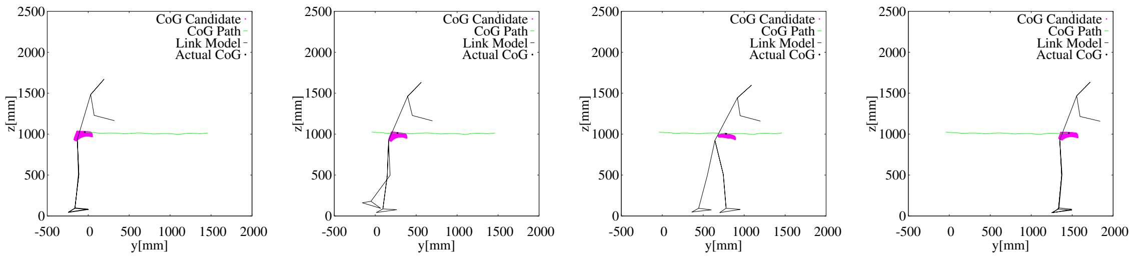
(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.25: CoG Candidates (Walking, Pattern 2a)



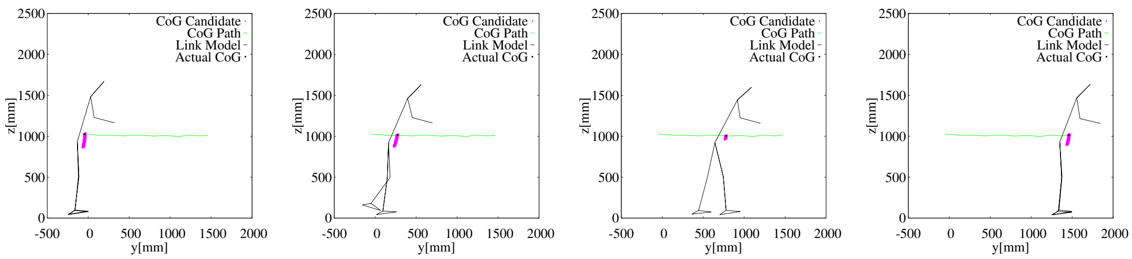
(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.26: CoG Candidates (Walking, Pattern 2b)



(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.27: CoG Candidates (Walking, Pattern 2c)



(a) 0[s] (b) 2[s] (c) 3.5[s] (d) 6.5[s]

Figure A.28: CoG Candidates (Walking, Pattern 2d)

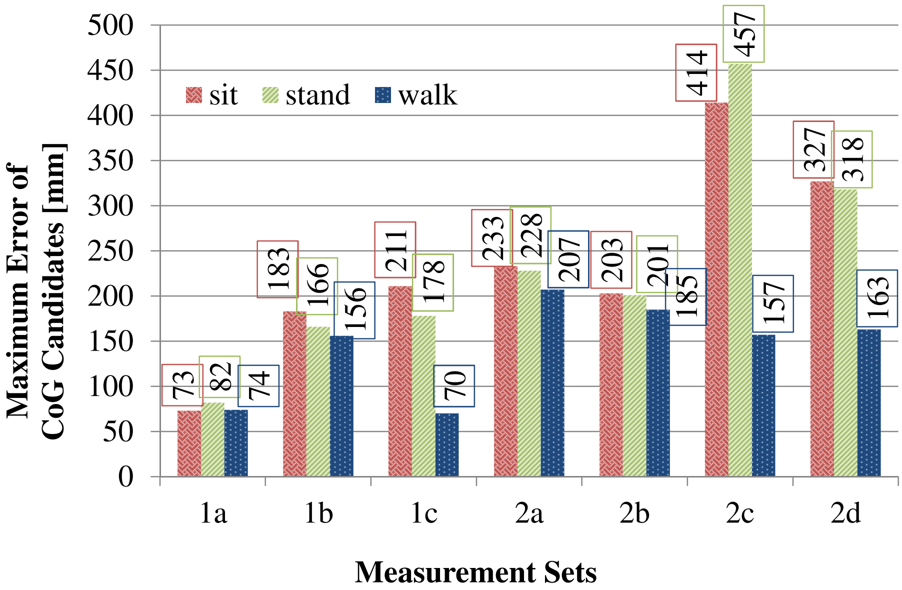
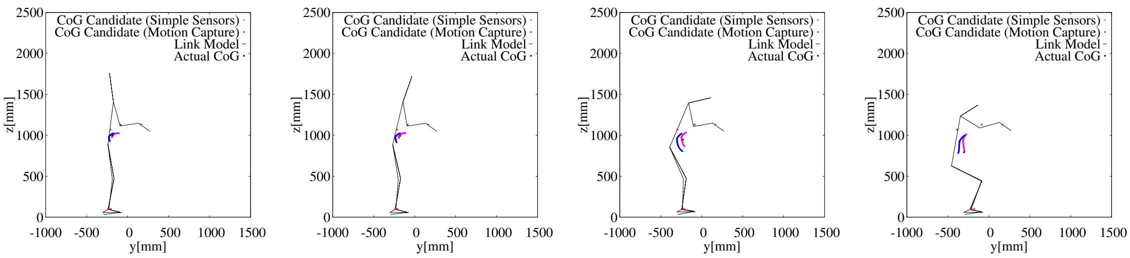
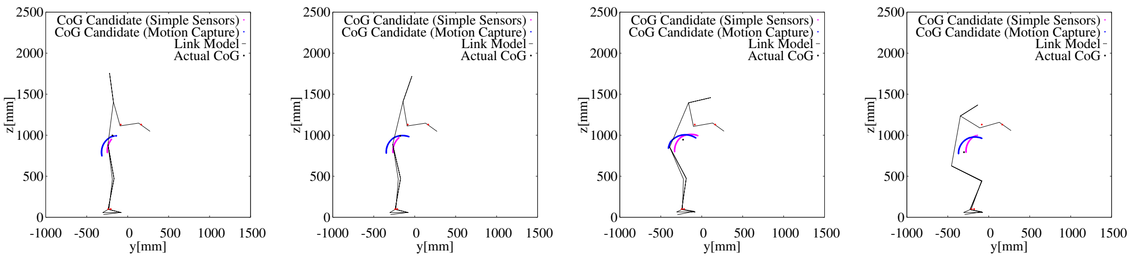


Figure A.29: Maximum Error of CoG Candidates.



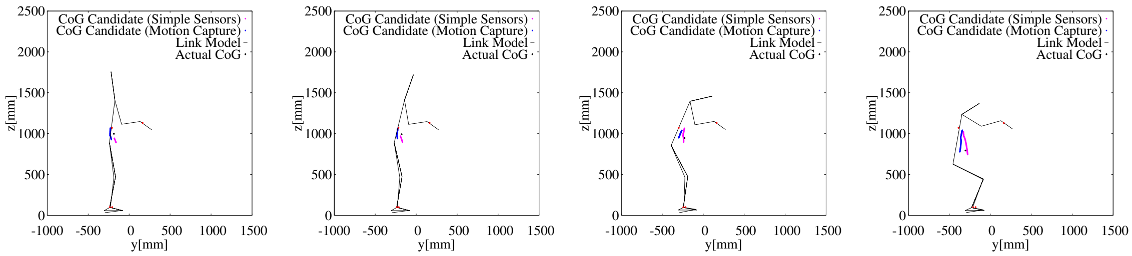
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.30: CoG Candidates of Sitting (1a)



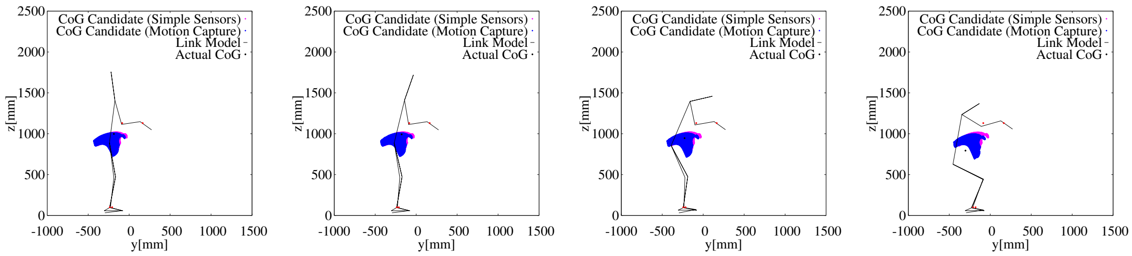
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.31: CoG Candidates of Sitting (1b)



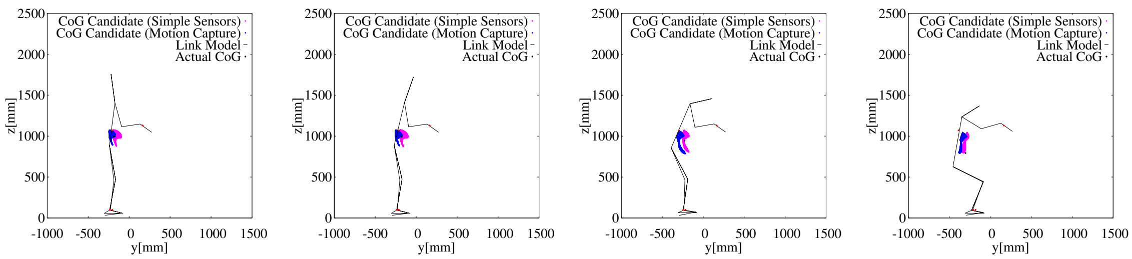
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.32: CoG Candidates of Sitting (1c)



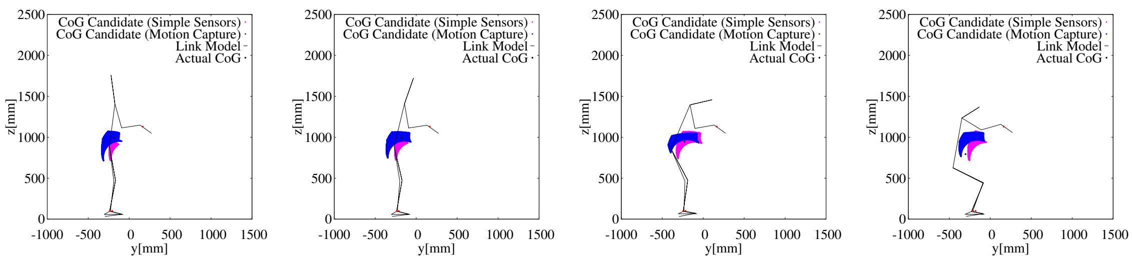
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.33: CoG Candidates of Sitting (2a)



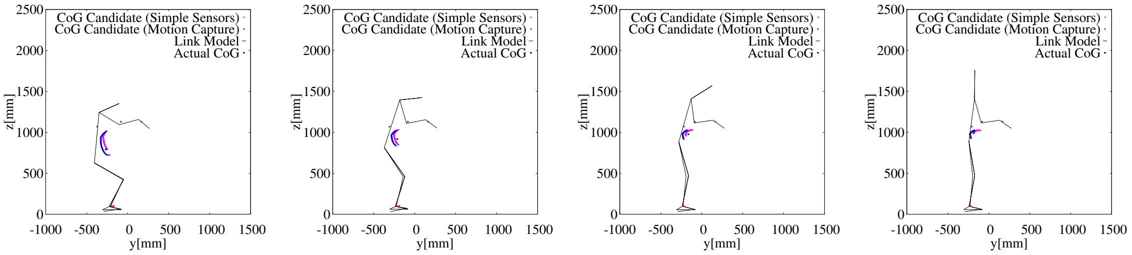
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.34: CoG Candidates of Sitting (2b)



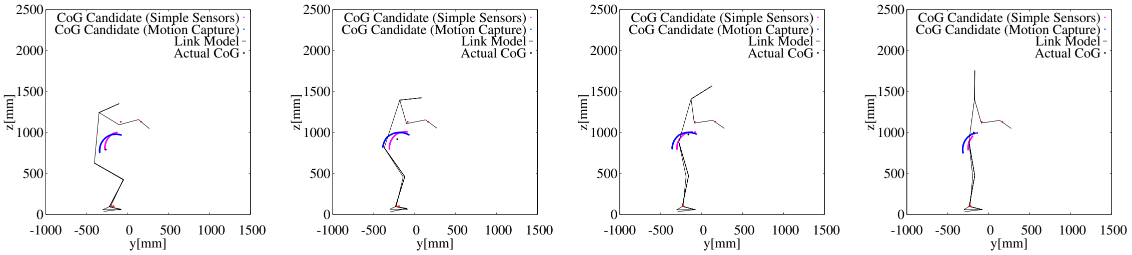
(a) 0[s] (b) 1[s] (c) 2[s] (d) 3[s]

Figure A.35: CoG Candidates of Sitting (2c)



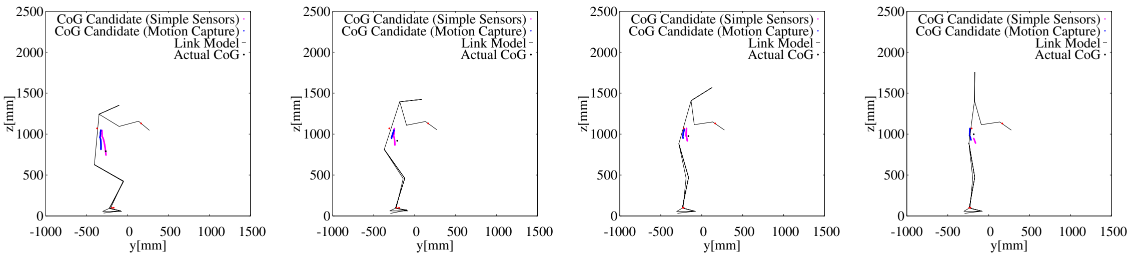
(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.36: CoG Candidates of Standing (1a)



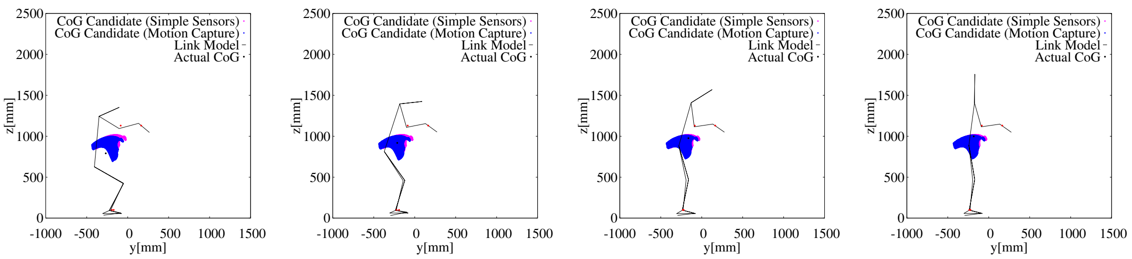
(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.37: CoG Candidates of Standing (1b)



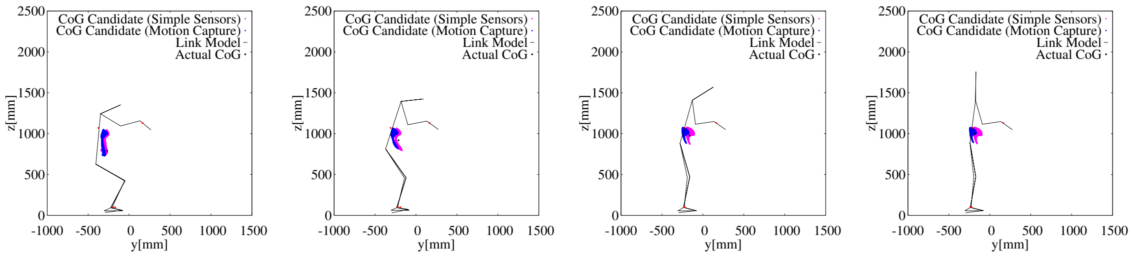
(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.38: CoG Candidates of Standing (1c)



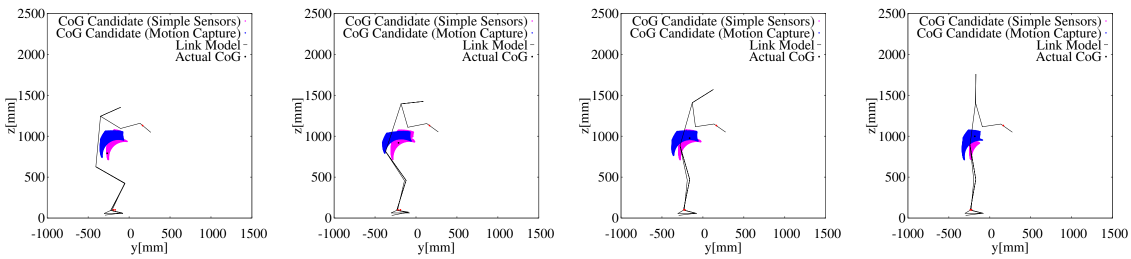
(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.39: CoG Candidates of Standing (2a)



(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.40: CoG Candidates of Standing (2b)



(a) 0[s] (b) 0.8[s] (c) 1.6[s] (d) 2.4[s]

Figure A.41: CoG Candidates of Standing (2c)

Appendix B

List of Published Papers

Journal Papers

1. M. Takeda, Y. Hirata, T. Katayama, Y. Mizuta, and A. Koujina, "State estimation using the cog candidates for sit-to-stand support system user," in IEEE Robotics and Automation Letters, vol. 3, no. 4, pp. 3011–3018, 2018. doi: 10.1109/LRA.2018.2849551.

2. M. Takeda, Y. Hirata, Y.-H. Weng, T. Katayama, Y. Mizuta, and A. Koujina, "Accountable system design architecture for embodied AI: A focus on physical human support robots," in Advanced Robotics, Taylor & Francis, vol. 33, no. 23, pp. 1248-1263, 2019. doi: 10.1080/01691864.2019.1689168.

3. M. Takeda, Y. Hirata, Y.-H. Weng, T. Katayama, Y. Mizuta, and A. Koujina, "Verbal Guidance for Sit-to-Stand Support System," in ROBOMECH Journal (in press).

Proceedings of Peer Reviewed International Conference

1. M. Takeda, Y. Hirata, K. Kosuge, T. Katayama, Y. Mizuta, and A. Koujina, "Human cog estimation for assistive robots using a small number of sensors," 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 2017, pp. 6052-6057. doi: 10.1109/ICRA.2017.7989717.

Oral Presentations in International Conferences

1. M. Takeda, Y. Hirata, K. Kosuge, T. Katayama, Y. Mizuta, and A. Koujina, "Human cog estimation for assistive robots using a small number of sensors," 2017 IEEE International Conference on Robotics and Automation (ICRA), May 29 - June 3, 2017, Singapore.

2. M. Takeda, Y. Hirata, T. Katayama, Y. Mizuta, and A. Koujina, "State estimation using the cog candidates for sit-to-stand support system user," in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), October 1-5, 2018, Madrid, Spain.

Publications in Domestic Conferences

1. M. Takeda, Y. Hirata, and K. Kosuge, "Estimation of CoG for Standing/Walking Support Robot Users Based on Reduced Sensor Measurements," LIFE 2016 in Sendai, September 4-6, 2016, Tohoku University, Aobayama Campus, Sendai.

2. M. Takeda, Y. Hirata, K. Kosuge, T. Katayama, Y. Mizuta, and A. Koujina, "CoG Candidates Estimation for Standing/Sitting Support System Users," The Robotics and Mechatronics Conference 2017 in Fukushima, May 10-13, 2017, Big Pallet, Fukushima.

3. M. Takeda, Y. Hirata, K. Kosuge, T. Katayama, Y. Mizuta, and A. Koujina, "State Estimation Using CoG Candidates for Standing Support System User," The Robotics and Mechatronics Conference 2018 in Kitakyushu, June 2-5, 2018, Kitakyushu Convention and Visitors Association, Kitakyushu.

4. M. Takeda, Y. Hirata, Y.-H. Weng, T. Katayama, Y. Mizuta, and A. Koujina, "Care Robot Design Considering Accountability," The 37th Annual Conference of the Robotics Society of Japan, September 3-7, 2019, Waseda University, Waseda Campus, Tokyo.

Appendix C

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   doi: 10.1109/ICRA.2017.7989717

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"Verbal Guidance for Sit-to-Stand Support System," in ROBOMECH Journal, SpringerOpen (in press).