A System for Collecting Motion Data for Use in Quantitatively Evaluating Activities of Daily Living

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***Abstract*— A system is needed for quantitatively evaluating the activity recovery level of functional disable people. Although functional recovery is administered to hemiplegic patients during rehabilitation, some patients who have recovered function in a rehabilitation facility are still unable to perform daily activities at home. Therefore, recovering activities of daily living (ADL) has become more important than functional recovery. Since existing ADL recovery level indices are based on responses to questionnaires, judgment of recovery level is easily affected by an evaluator's subject. We have developed a system for collecting and storing motion data on daily life activities for use in quantitatively evaluating ADL recovery levels. Evaluation of the system using data measured for a healthy participant with restricted movement and two actual hemiplegic patients demonstrated that slight differences in disability levels can be detected. This system is thus well suited for quantitative ADL assessment for patients with a disability.**

Keywords-rehabilitation; functionary recovery; activities in daily living; ADL; BLE beacon; Google Firebase.

I. INTRODUCTION

Most patients suffering from cerebrovascular disease have paralysis on one side of the body, and their bodies lean and twist to the paralyzed side. Also, because of unusual muscle strain, their hands and feet become stiff. In some cases, muscles of the upper body go into convulsions. Functionary recovery is administered to hemiplegic patients as rehabilitation. However, some patients are not always to live less inconveniently in their home. Some patients who recover hand and arm functionality better in a rehabilitation facility cannot eat meals better in their home. Therefore, recovering Activities of Daily Living (ADL) has recently become more significant than recovering functionaries. We proposed a system to collect motion data on patient's ADL in IARIA eTELEMED 2019 [1].

The Barthel Index, which is based on questionnaires, is popularly used to quantitatively evaluate ADL recovery levels [2][3]. With questionnaires, however, recovery level judgments easily change in accordance with the evaluator's subject. Each recovery level is digitized to a few levels. For example, answers for feeding include "unable," "needs help cutting, spreading butter, etc., or requires modified diet" and "independent." Each answer is scored 0, 5, or 10. However, the recovery level for feeding with help ranges from "a patient eating food directly from dishes without using a spoon or fork" to "a patient eating a meal with a knife and fork in almost the same way as a healthy person." Also, it takes too much time to ask and observe whether a patient can do an activity independently without needing help.

Functional Independence Measure (FIM) [4] and Katz Index [5]-[7] scores are also used to evaluate ADL. FIM scores cover not only functional disease but also mental disease. Scores are broken down into seven levels for each activity, including feeding. Katz Index scores are usually applied to cure elder patients or those suffering from chronic disease.

The question formats for these evaluation methods are basically the same, and an evaluator needs much time to ask questions and observe a patient. We think that a quantitative evaluation system with a computer is needed to evaluate patients objectively without needing to ask them any questions and/or observe them.

Judging ADL recovery levels is based on whether patients can do tasks, such as eating, getting dressed, bathing, washing, and discharging bodily waste by themselves. Therefore, a system that collects motion data of patients in daily life needs to not only measure and collect the motions of body parts but also detect which activities are performed. However, it is very difficult to estimate these merely from changes in acceleration and/or gyro sensor data obtained from devices attached to body parts. Therefore, we estimate activities by using information about places, such as a dining table, bathroom, dressing room, or bedroom. We used the BLE beacon [8] to detect places in this system.

Most surgeons also think that postoperative patient functions assessed by ADL and quality of life have become especially important ways to measure surgical treatment outcomes for the elderly [9].

In this study, we developed a system to collect and store patients' motion data to quantitatively judge **the recovery level of activities in daily living**. The system can use up to seven sensors for simultaneously measuring the motions of seven body parts. A patient's name, measured location, sensor-attached body parts and time-stamps are described as the file names for each measured data file in this system.

The system only requires that recognized medical doctors or physiotherapists can access measured data to maintain security. To ensure this, we developed a data collecting system based on Google Firebase [10]. Since the Firebase application can be independently implemented for any organization, high level security can be maintained.

To confirm whether this cloud-based system can distinguish between normal and restricted movements, we first had a healthy participant rotate both lower arms and then extend them forward to ensure that the system measured these movements correctly. We then restricted movement of the person's elbows and collected movement data during teeth brushing, face washing, and eating.

Next, we applied this system to tow actual hemiplegic patients. Drinking and walking motions were measured.

The measurement data differed slightly depending on the level of movement restriction or disability; this system is thus suitable for quantitatively assessing the ADL level of patients with a disability.

After introducing related work in Section II, we describe the system's design concept and its implementation in Sections III and IV. Confirmation of its performance for a healthy participant with restricted movement is presented in Section V, and that for actual hemiplegic patients is presented in Section VI. Section VII concludes with a summary of the key points and a mention of future work.

II. Related work

To develop a quantitative evaluation system for the recovery level of activities in daily living of hemiplegic patients, we have to know how to evaluate ADL quantitatively, existing life log systems and healthcare information cloud service.

A. *Evaluation index for function level*

Three indexes to evaluate function level in daily living are widely used: the Barthel Index, the FIM and the Katz Index. They are basically questionnaires for daily life activities, such as feeding. The Barthel Index and FIM are popularly applied to evaluate function levels for rehabilitation patients, such as those afflicted with cerebrovascular disease. There are ten question items in the Barthel Index: Feeding, Moving from wheelchair to bed and return, Personal toilet (washing face, combing hair, shaving, cleaning teeth), Getting on and off the toilet (handling clothes, wiping, flushing), Bathing self, Walking on level surfaces, Ascending and descending stairs, Dressing (includes tying shoes, fastening fasteners), Controlling bowels and Controlling bladder [2] [3]. A score of independently doing an activity is usually 10 points, doing it with help is usually 5 points, and not doing it is 0 points.

FIM evaluates not only physical functions but also social abilities, such as communication or social recognition [3]. The number of questions covers 18 issues; 13 for physical functions and five for social abilities. Questions about physical functions are more segmentized. For example, the dressing function is divided into dressing the upper body and the lower body, moving activities are divided into the moving between a wheelchair and a bed/chair, and sitting on a toilet seat and moving to a bathtub. Scores are given on a seven-point system. Independently doing an activity gets seven points, doing it with full help gets one point, and doing it with partial help gets scores ranging from two to six points.

The Katz Index is usually applied to elder patients or those suffering from chronic disease in a variety of care settings [4 - 6]. The index ranks adequacy of performance in six activities: bathing, dressing, toileting, transferring, continence, and feeding. Clients are scored yes/no for independence in each of the six functions.

Every three indexes evaluate whether a patient can do activities in daily living. Therefore, our proposed system must know what kinds of activities a patient tries to do.

In addition, one of the most widely recognized and clinically relevant measures of body function impairment after stroke is the Fugl-Meyer (FM) assessment. Of its 5 domains (motor, sensory, balance, range of motion, joint pain), the motor domain, which includes an assessment of the upper extremity (UE) and lower extremity (LE), has well-established reliability and validity as an indicator of motor impairment severity across different stroke recovery time points. Consistently, greater motor severity as indicated by lower UE and LE FM motor scores is correlated with lower functional ability, such as spontaneous arm use for feeding, dressing and grooming, or walking at functional gait speeds. [11].

B. *Life log system*

Over the years, many researchers have tried to estimate daily life human activities, such as walking and sitting up and down from acceleration and/or gyro sensor data obtained from wearable devices and/or smartphones. In this paper, we refer to the research done respectively by Zhan et al. and Wang et al. [12] [13]. Only a few motions were given in this research; distinctions among activities were not recognized. In contrast, Debraj et al. tried to recognize 19 daily living activities [14]. They collected environment information, such as that for temperature and location in addition to activity information. They used GPS and BLE beacons to identify places. However, they did not consider the Barthel Index or other indices and consequently their target activities did not correspond to activities in the index of function recovery levels.

C. *Healthcare cloud service*

Zhang et al. developed a cyber-physical system for patient-centric healthcare applications and services [15]. They called it Health-CPS. It was built on cloud and big data analytics technologies. It consisted of a data collection layer, a data management layer and an application service layer to collect and follow up on many kinds of big data. It used a security tag to maintain security.

Doukas et al. proposed a mobile system that enables electronic healthcare data storage, update and retrieval using cloud computing [16]. A mobile application was developed using Google's Android OS and Amazon's S3 to provide management of patient health records and medical images.

We developed a cloud service whose collecting function for medical data is basically the same as that for the above systems. However, our system is specialized so that it can collect activity and place information to functionally evaluate recovery levels that correspond to existing evaluation methods, such as the Barthel Index. In this paper, we show how we implemented the system with Eri BLM620 [17] as the sensor node, as well as Android smartphone, BLE beacon, and Google Firebase.

III. SYSTEM DESIGN CONCEPT

We designed the proposed system so that it could not only evaluate ADL for a patient, but also develop algorithms for detecting whether a patient can do a designated activity. The system collects and stores sensor data and video data synchronously and allows appropriate persons to access stored data. We designed the system while taking the following issues into consideration:

1) Suppressing battery consumption for wearable sensor devices,
2) Suppressing recorded data and collecting necessary data,
3) Maintaining security.

Google Firebase service provides many functions, including authentication and real-time database functions, to enable systems to be managed effectively, such as through the means of allowing access to authorized persons. Since any organization can independently implement Firebase applications, it becomes possible to maintain high level security. This is why we implemented our data collecting system on Google Firebase.

The image of a data collecting system that collects data about the motions that a patient performs daily is shown in Figure 1. The system we propose consists of sensor devices, a sensor relay unit (smartphone), BLE beacons, and Google Firebase. A smartphone is used as the sensor relay unit that controls sensor devices and temporarily stores and forwards measured data to the Firebase.

BLE beacons are placed in various locations: under a dining table, on top of a toilet, in a bathroom, in a bedroom, in a closet. When the smartphone receives a BLE beacon signal level that exceeds the threshold level, it sends a message to sensor devices to start measuring data. And when the smartphone receives a receiving signal level lower than the threshold level, it sends a message to sensor devices telling them to stop measuring data. Sensor devices and smartphones are managed by the Realtime Database on Google Firebase. Security is maintained by enabling only authorized persons using the system, including patient, readers, such as medical doctor and installation personnel, such as nurse are also managed by the Realtime Database is used to maintain security. In this system, measured data are downloaded for pre-registered persons from the web server.

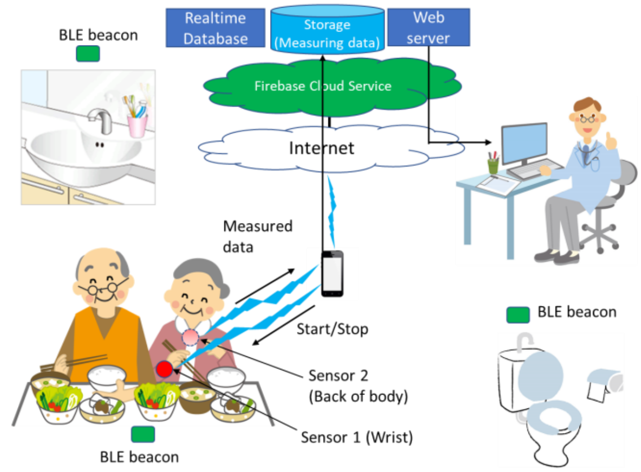


Figure 1. Image of the data collecting system for patient's daily life motions.

IV. SYSTEM IMPLEMENTATION

We developed a PatientApp program that works on the sensor relay unit and a DataCollectionServer program that works on Firebase. The PatientApp manages sensor devices, gets measured data from sensor devices and uploads the data file to the DataCollectionServer.

A. PatientApp

This time, we developed a PatientApp program based on the Android Framework. With this program, a developer must first access the Firebase and download a configuration file. An Android application package file (Apk File) is then made as a building application and is connected to Firebase. This makes it possible to securely download the Apk File for each organization.

Before starting to measure sensor data and/or video data, it is necessary to enter a patient's name, bind a sensor with a body part, bind a BLE beacon with a place of activity and select a video recording on/off function. Therefore, we designed a transition diagram of UI pages as shown in Figure 2. There were three alternatives for a user name at the login; the patient's name, the medical worker's name with measuring devices set up, and the medical professional's name with measured data analyzed. For the latter two cases, a patient's name must be entered after the login. Therefore, we decided on the first one, login with a patient's name.

After login, a "List of setting up" page is presented. An example of this page is shown in Figure 3. With it, a user can confirm a state of setting. When the "Change" button is clicked, the page will change to the "Sensor" page to bind a sensor with a body part. When the "Next" button is clicked, the page will change to the "Beacon" page to bind a BLE beacon with a place in activity. When the "Next" button is clicked, the page will change to the "Video" page to select video ON/OFF. When the "Next" button is clicked, the page will change to the "List of setting up" page. When the "Next" button is clicked in the "List of setting up" page, the page will change to the "Measuring" page. When the "Start" button on this page is clicked, the PatientApp sends a message to the sensor messages to start measuring, and the "Start" button changes to the "Stop" button. When the "Stop" button is clicked, the PatientApp sends a message to the sensor messages to stop measuring, and the "Stop" button changes to the "Start" button. When the "End" button is clicked, the PatientApp finishes.

When a sensor receives a BLE beacon signal, it starts measuring, and, when a sensor loses a BLE beacon signal, it stops measuring. After clicking the "Stop" button, measured data are changed to a measured data file. Its file name is "Patient name_place_body part_timestamp" to recognize its properties. The file is uploaded to the storage in Firebase.

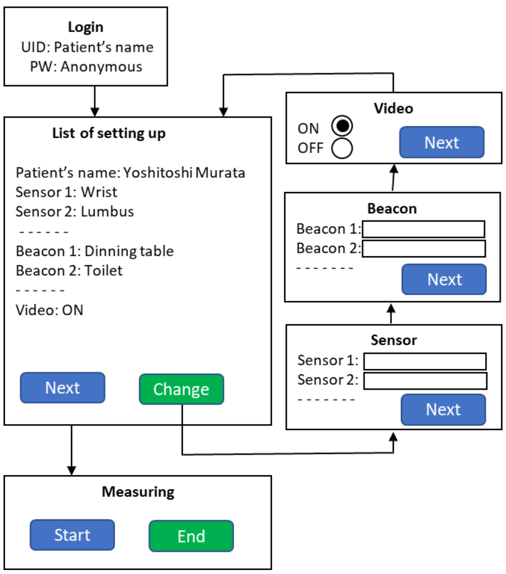


Figure 2. Transitions of UI pages in the PatientApp.

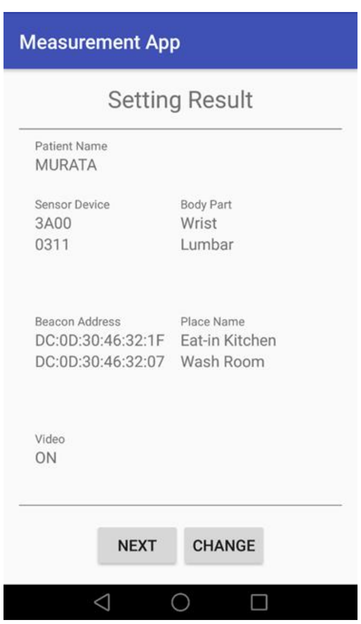


Figure 3. Example of setting up page list.

We developed the following six packages of classes to achieve the above proceedings:

- Beacon: receiving beacon signals and handing their information to other classes.
- Mobile2wear: controlling a sensor device and receiving measured data.
- Camera: managing a video camera.
- Firebase: converting measured data and transferring the data to the Firebase storage.
- View: managing transition of pages
- Viewmodel: listening events on buttons or input boxes and handing, such information to other classes.

B. *DataCollectionServer*

The DataCollectionServer has the following functions;

- Data upload function: The sensor relay unit temporarily stores measured data and forwards them to the server.
- Data download function: Authorized persons, such as medical doctors can access the DataCollectionServer and download measured data files securely.

It consists of the Storage and WebSite. The WebSite collaborates with the Storage and provides a file download function to a medical professional through the Web browser.

In this subsection, we mainly introduce how to upload and download measured data file.

1) Data upload function (Figure 4)

After a measured file has been made, the PatientApp uploads the file to the storage server in Firebase as shown in Figure 4. The storage server generates the file download URL, which is managed in the Realtime Database.

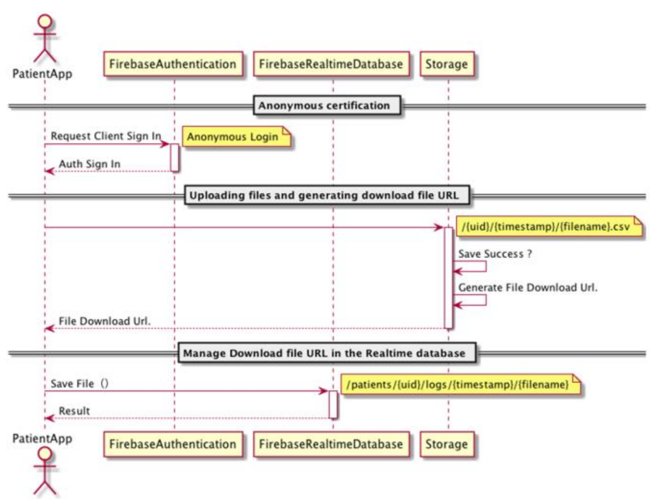


Figure 4. Sequence flow to upload measured files.

2) Measured data download function (Figure 5)

Supervisors input the access account of medical professionals from the management page in Firebase. The sequence flow with which medical professionals download their patients' files is shown in Figure 5. When medical professionals access the Website, they log in with their assigned ID and password on the page of Figure 6 (a).

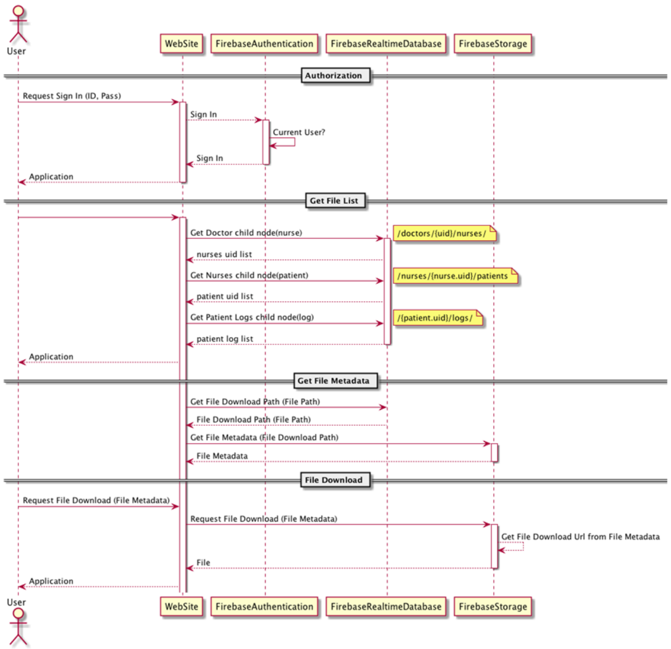
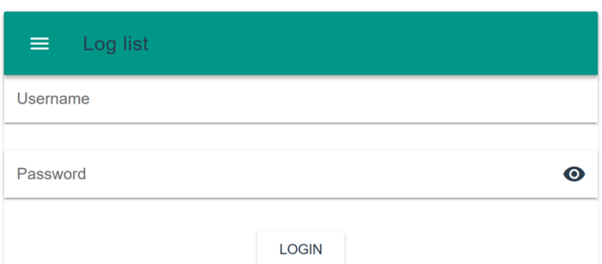


Figure 5. Sequence flow to download measured files.



(a) Login page

(2) File list page

Figure 6. WebSite user interface.

After login, the Website application accesses the Realtime Database to get information related to nurses and patients. The Website application also gets meta-data such as an access path to a stored file. When a medical professional clicks a file on the page of Figure 6 (b), the Website application accesses the indicated file on the Storage through the access path. Finally, the indicated file is downloaded.

C. *Wearable device*

We initially used a SONY Smart Watch III [18] as the wearable device, as reported at eTELEMED 2019. However, SONY no longer produces this device, so we worked with Eri, Inc. [17] to develop the BLM620 wearable sensor to ensure a stable supply.

Its appearance and configuration are shown in Figures 7 and 8. It contains a 3D digital accelerometer and a 3D digital gyroscope packaged together (LSM6DSL, STMicroelectronics [19]) and a Bluetooth and CPU module packaged together (HRM1062, Hosiden [20]). Its acceleration and gyro axes are shown in Figure 9. The maximum number of simultaneous connections is seven.

Its connection performance was measured using an Android terminal wirelessly connected to seven wearable devices, as shown in Figure 10, for two types of connection: multi-thread and sequential. The flow for each type is shown in Figure 11. The data were measured in lower and higher radio interference environments. The interference in the latter one was generated by a nearby 2.8 GHz WiFi access point. There was no such interference source in the former one. The terminal connected to each device 30 times. The connection error rate (CER) is shown in Figure 12. While there were differences in the CER between devices, the CER was generally higher in the higher radio interference environment than in the lower one. It was also higher for the multi-thread connections than for the sequential connections. Therefore, we used sequential connections in this application program.

Figure 7. Appearance of the developed wearable device

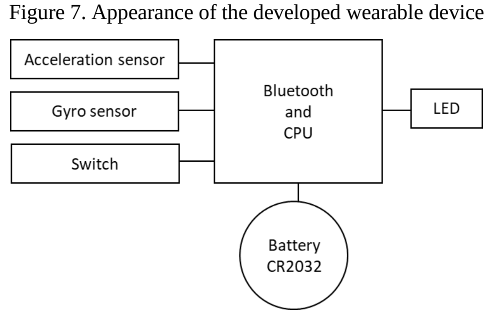


Figure 8. Configuration of the developed wearable device

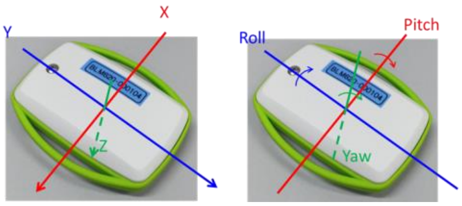
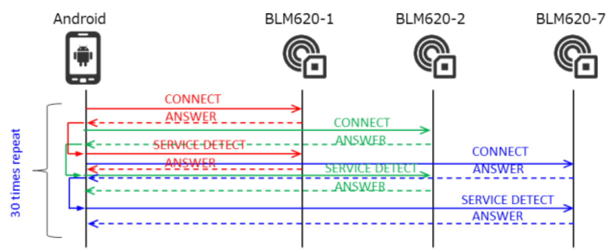
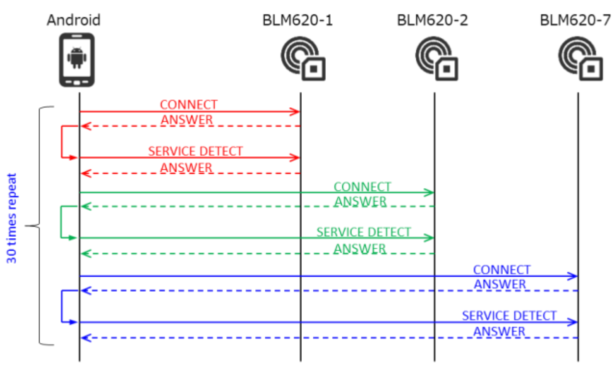


Figure 9. Acceleration and gyro axis

Figure 10. A scene of experiment



(a) Multi-thread connection



(b) Sequential connection

Figure 11. Connection flow

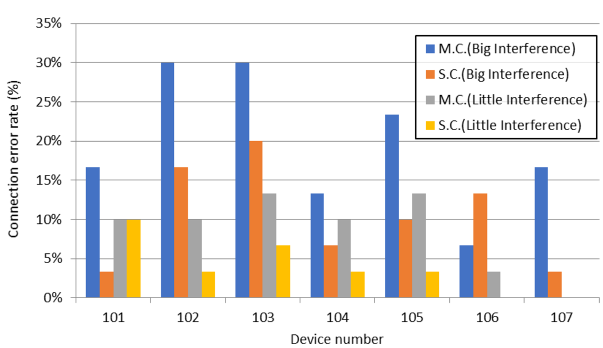


Figure 12. Connection error rate

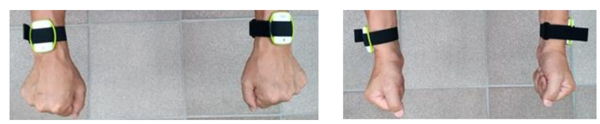
V. COMFIRMATION OF SYSTEM PERFORMANCE

Prior to collecting motion data for actual hemiplegic patients, we collected motion data for a healthy participant with and without elbow restrictions to confirm that the proposed system can detect differences between normal and restricted joint movement.

A. *Simple motions*

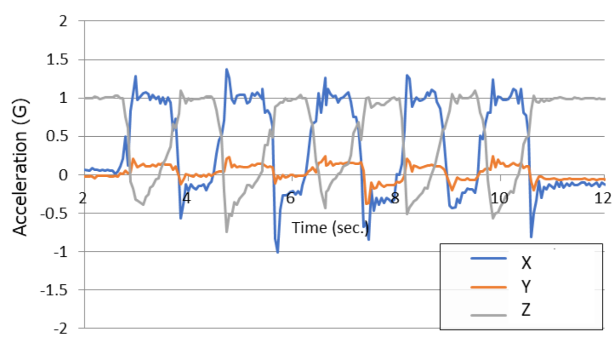
We started with simple motions for which it is easy to confirm the accuracy of measured data. We first had the participant rotate both lower arms 90°, as shown in Figure 13, five times. The measured acceleration and yaw/roll/pitch angle data are shown in Figure 14. The acceleration along the X and Z axis basically changed from 0 to 1 G alternately (Figure 14 (a)) five times. The acceleration along the X axis changed from 0 to −1 G while that along the Z axis changed from 0 to 1 G alternately (Figure 14 (c)) five times.

The roll angles for the two arms (Figures 14 (b) and (d)) were symmetrically opposite due to their symmetrical motions. The acceleration along the Z axis when both thumbs were in the “right up” position (Figures 14 (a) and (c)) was not zero. This reason is caused by over actions of the arms. The yaw/roll/pitch angles in Figures 14 (b) and (d) include the drift error.

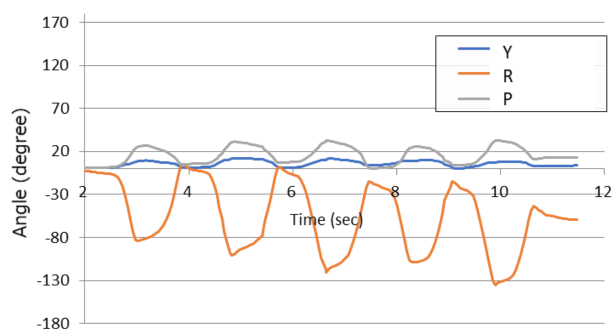


(a) Start (b) End

Figure 13. Rotating the lower arm



(a) Acceleration (left arm)



(b) Yaw/Roll/Pitch (left arm)

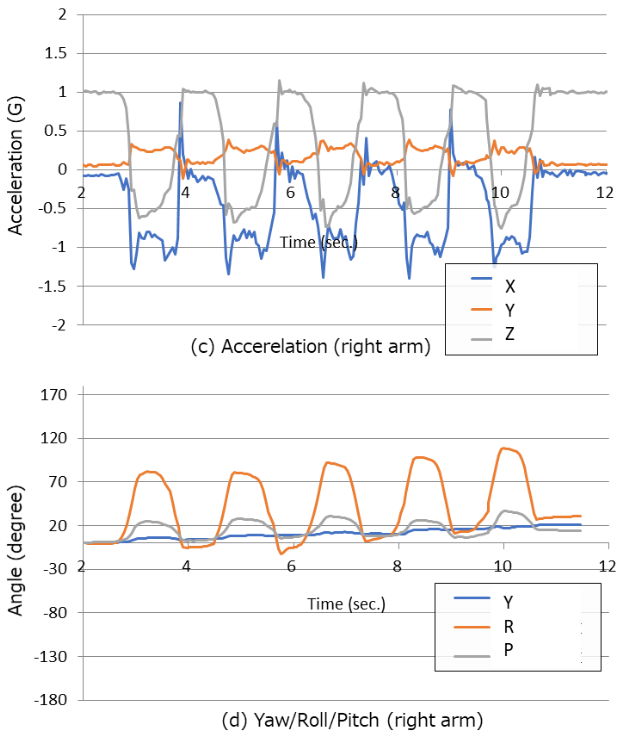
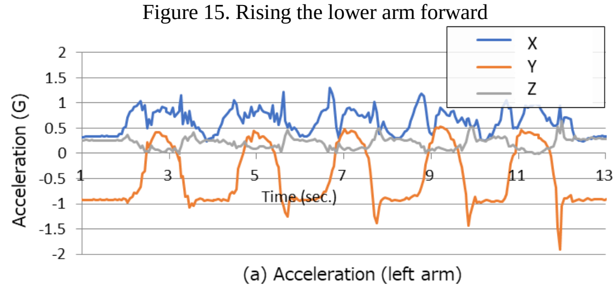


Figure 14. Measured data of rotating the lower arm

The participant raised both lower arms from the straight down position to the forward position, as shown in Figure 15, five times. The measured acceleration and yaw/roll/pitch angle data are shown in Figure 16. The acceleration along the Y axis for the straight down position was roughly −1 G (Figures 16 (a) and (c)) since the sensors simply measured gravity. The acceleration along the X axis corresponded to the centrifugal force. The symmetric differences in yaw angle between Figures 16 (b) and (d) were due to the symmetrical motion. The yaw/roll/pitch angles in Figures 16 (b) and (d) include the drift error, the same as in Figures 14 (b) and (d). The measured data in Figures 14 and 16 basically represent the changes in motion accurately.

(a) Start (b)End

Figure 15. Rising the lower arm forward



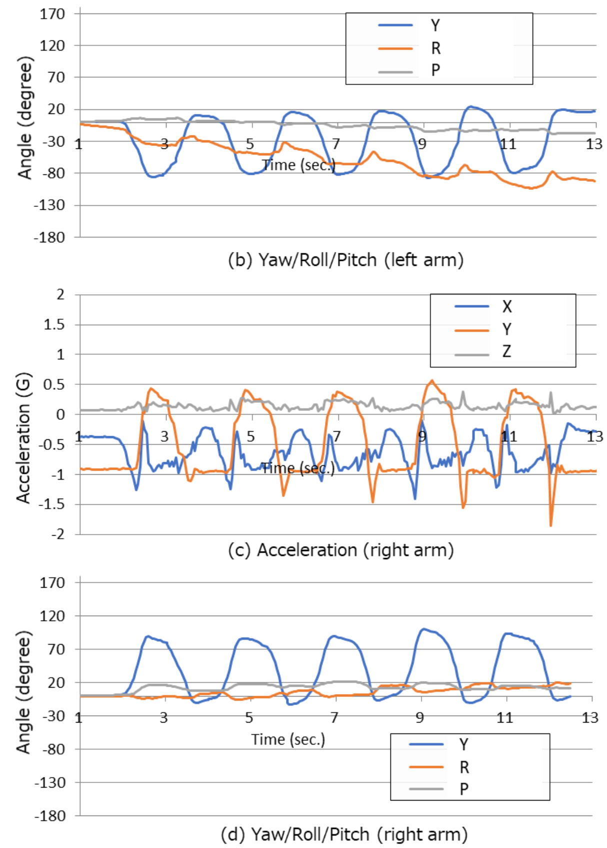


Figure 16. Motion data of rising the lower arm forward

B. *Restricted motions*

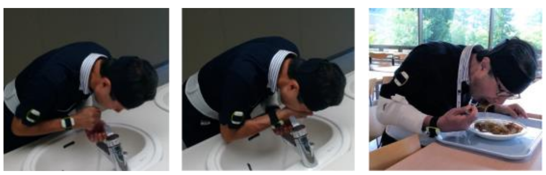
To confirm whether the proposed system can detect differences between different motion restrictions, we measured the participant's motions during eating, face washing, and teeth brushing under three conditions;

a. Bending of the right elbow was restricted by placing it in a plaster cast (Figure 17), wrapping it in a bandage, and fixing it to his upper body with a bandage,
b. Bending of the right elbow was restricted by placing it in a plaster cast and wrapping it in a bandage, without fixing it to anything.
c. No restriction.

Wearable devices were attached to the head, the mid-lumbar region, both lower arms, and both upper arms, as shown in Figure 18. Under conditions a and b, the participant brushed his teeth with his right hand, as shown in Figure 19 (a). Under condition c, he brushed his teeth with his left hand since he usually brushes with his left hand. The acceleration data for the lower arms and head are presented in Figure 20. The other data are not presented as they did not have any particular features of interest. Since there was a lot of right and left or up and down motion and little rolling motion in brushing teeth, the angle data for the tooth-brushing arm had little variation. There were big differences in the data between conditions a and b, as shown in Figures 20 (a-2) and (b-2) while there was little difference between conditions b and c, as shown in Figures 20 (b-2) and (c-1). There was little head movement under any condition, as shown in Figures 20 (a-3), (b-3), and (c-3).

Figure 17. Plaster cast

Figure 18. Participant with sensors and restrictions

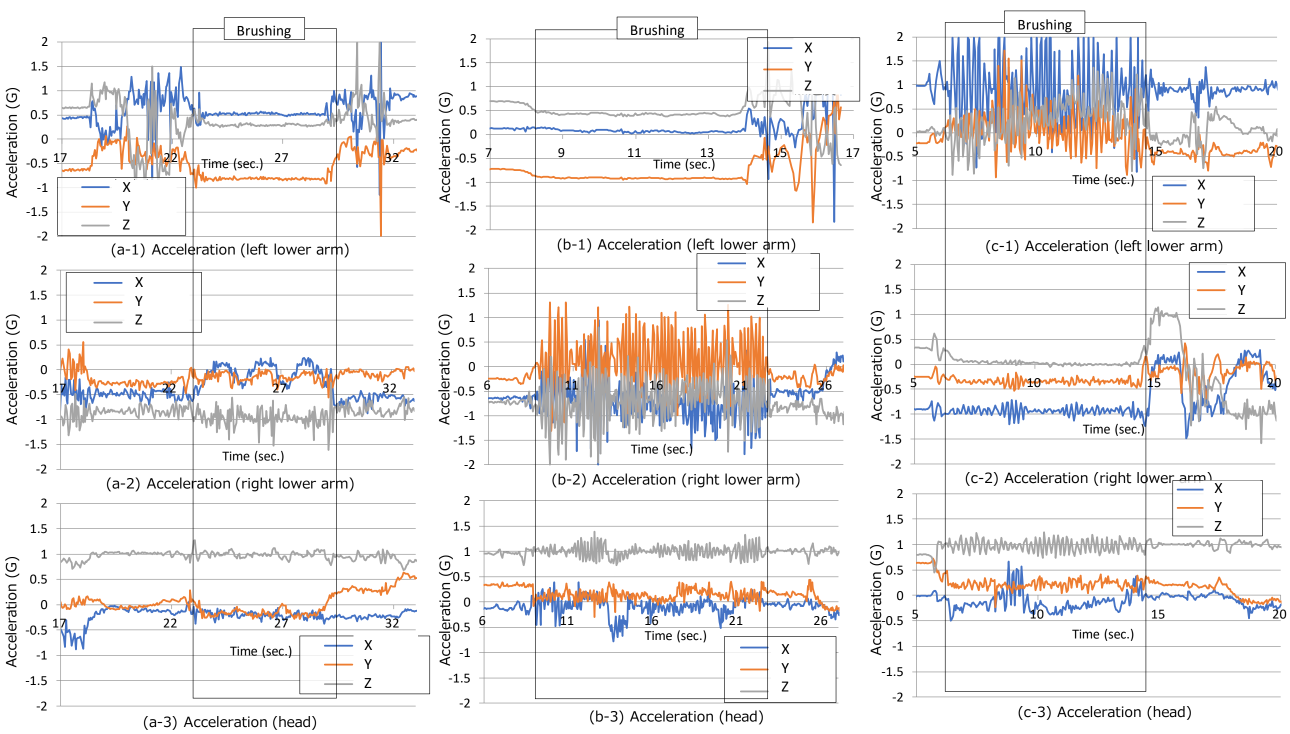


(a)Brushing teeth (b)Washing face (c)Eating food

Figure 19. Restricted motions

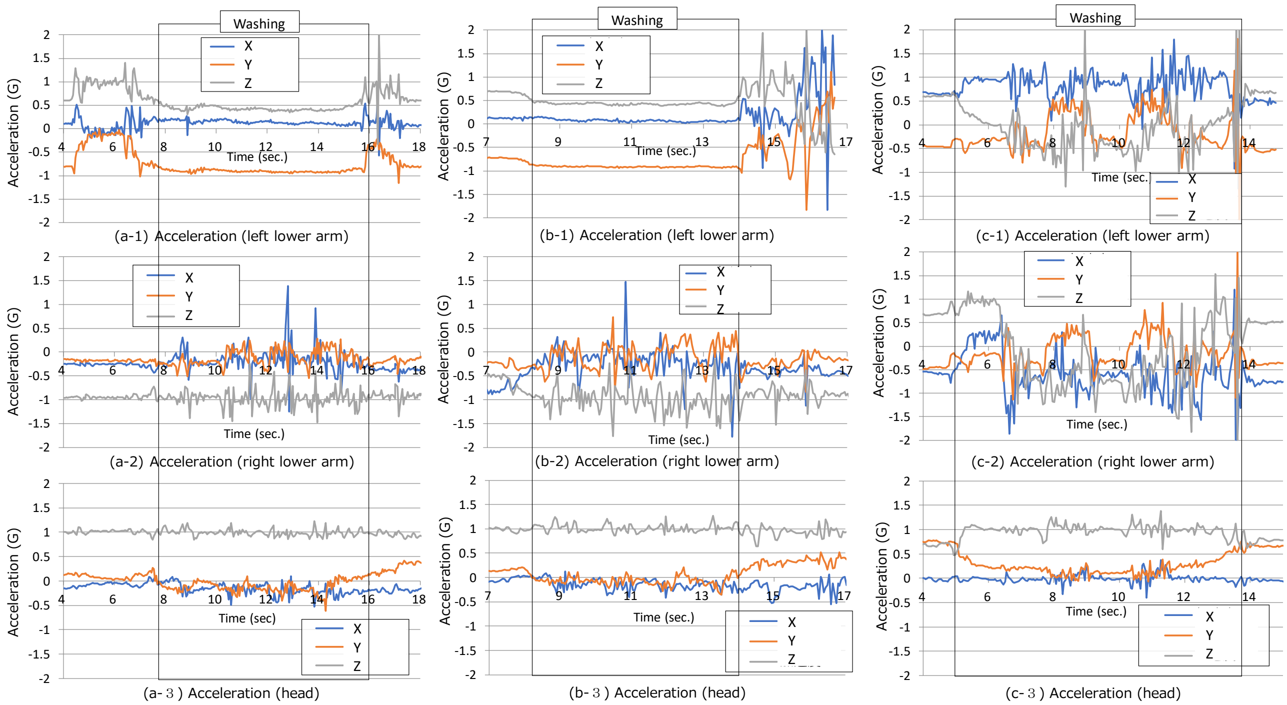
The participant washed his face with his right hand under conditions a and b, as shown in Figure 19 (b). He washed his face with both hands under condition c. The acceleration data for the lower arms and head are presented in Figure 21. The other data are not presented as they did not have any particular features of interest. Since there was a lot of up and down motion and little rolling motion in washing face, the angle data for the face washing arm had little variation. There were not any big differences in the data between conditions a and b, as shown in Figures 21 (a-2) and (b-2). There was a big difference in the data between condition c and the other two conditions: the acceleration data for the lower arms varied widely, as shown in Figures 21 (c-1) and (c-2) due to using both hands. There was little head movement under any condition, as shown in Figures 21 (a-3), (b-3), and (c-3).

The participant ate curry rice with his right hand under all three conditions, as shown in Figure 19 (c). The acceleration and angle data for the right lower arm are presented (Figure 22), since eating food with a spoon involves much rolling motion. The angle of head for the direction of gravity is also presented (Figure 22 (a-3), (b-3), and (c-3)). The range of change in the acceleration Y, Z, and pitching of his right hand are bigger, as there was less motion restriction. The angle of head for the direction of gravity during eating is bigger, as there was less motion restriction. The participant had to close his face to curry and was hard to roll his hand during eating in condition a.



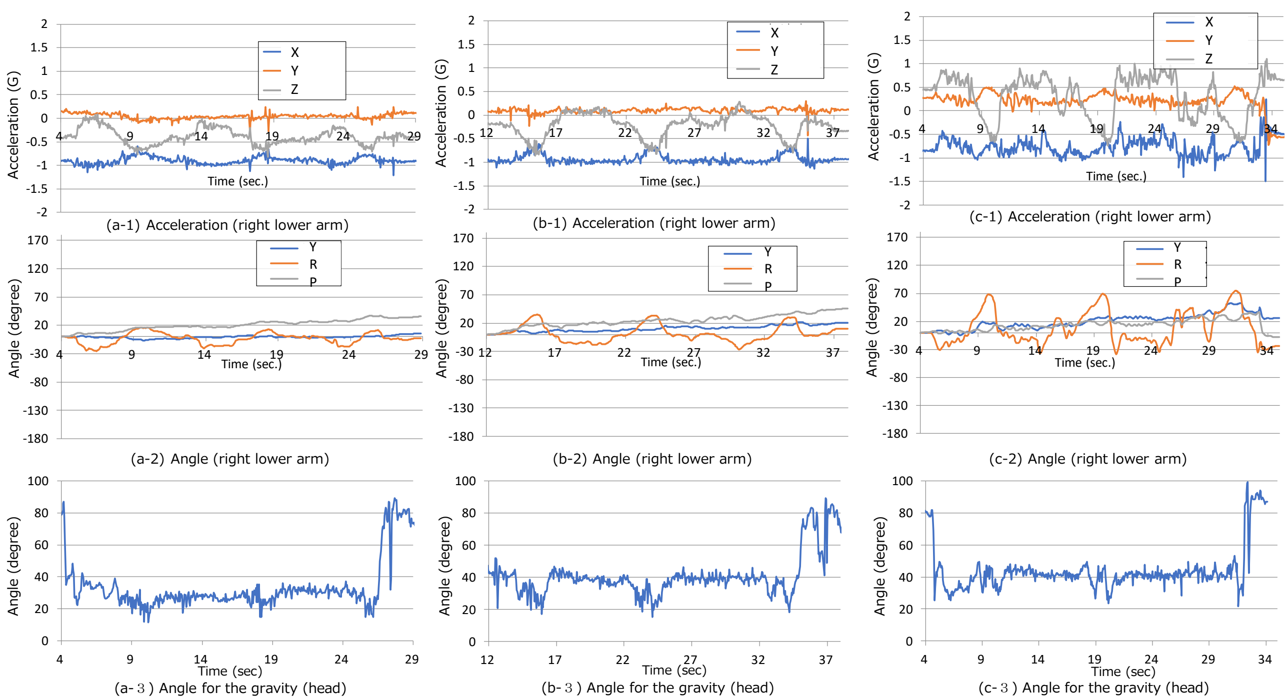
(a) Condition a (b) Condition b (c) Condition c

Figure 20. Data collected during teeth brushing.



(a) Condition a (b) Condition b (c) Condition c

Figure 21. Data collected during face washing.



(a) Condition a (b) Condition b (c) Condition c

Figure 22. Data collected during eating.

These results demonstrate that measured data for lower arm motions are effective for detecting differences in motion restriction levels. Although it impossible to detect a difference using data for a single activity, such as teeth brushing or face washing, it is possible to detect one using data for a combination of activities, such as teeth brushing, face washing, and/or eating.

VI. MEASUREMENT FOR HEMIPLEGIC PATIENTS

We collected and analyzed data for the walking and drinking motions of two hemiplegic patients and three healthy participants who wore seven wearable devices for collecting data. Their placements for each motion are shown in Figure 23. Data were collected for three stable walking cycles and for one drinking motion on the paretic side. The UE and LE functionalities of the two hemiplegic patients were assessed on the basis of FMA by physical and occupational therapists. Hemiplegic patient A had severe impairment on the paretic side (FMA UE score: 25; LE score: 14) while hemiplegic patient B had mild impairment on the paretic side (FMA UE score: 58; LE score: 26).

The data were collected safely and smoothly for both the hemiplegic patients and healthy participants. The walking and drinking motions during collection were the same as their usual motions. The periods were longer for the patients due to their severe impairment. Since the period of time during walking and drinking and the acceleration and angle data for every healthy participant were similar, data for a typical healthy participant were presented in this paper.

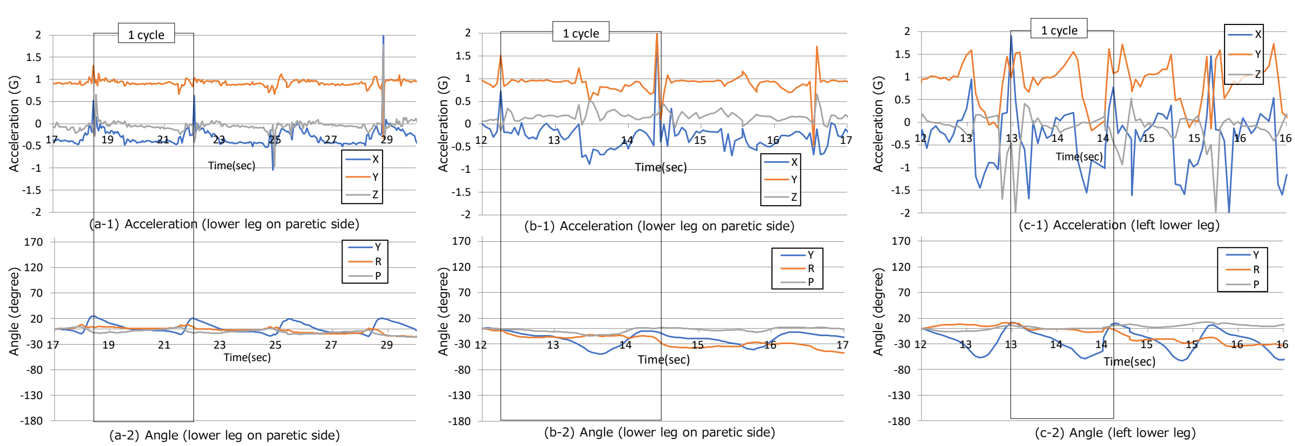
Figure 24 shows the raw acceleration and angle data for the paretic-side lower leg for hemiplegic patients A (a-1 and 2) B (b-1 and 2), and for the left lower leg for the healthy participant (c-1 and 2) for the walking motion. While it is difficult to recognize walking gait cycles from the acceleration data for hemiplegic patients B and the health participant, the walking gait cycles are clearly recognized in the yaw angle data for all participants. The yaw angle indicates forward movement in the lower leg. The range for the healthy participant is biggest in three participants. The range is smaller for the hemiplegic patients due to their severe impairment.

Figure 25 shows the raw acceleration and angle data for the paretic-side lower arm and for the head for hemiplegic patients A (a-1, 2, and 3) and B (b-1, 2, and 3), and for the left lower arm and head for the healthy participant (c-1, 2, and 3) for the drinking motion. The data indicate a larger forward movement of the head for the hemiplegic patients than for the healthy participant. And, the range of yaw angle of the lower arm of patient A is smaller than that of patient B and the healthy participant. This difference is attributed to the severe impairment and compensatory movements of the patients.

This experiment demonstrated that this device and system can safely and smoothly collect motion data for hemiplegic patients as well as healthy individuals. They are thus suitable for quantitative assessment of ADL for hemiplegic patients.

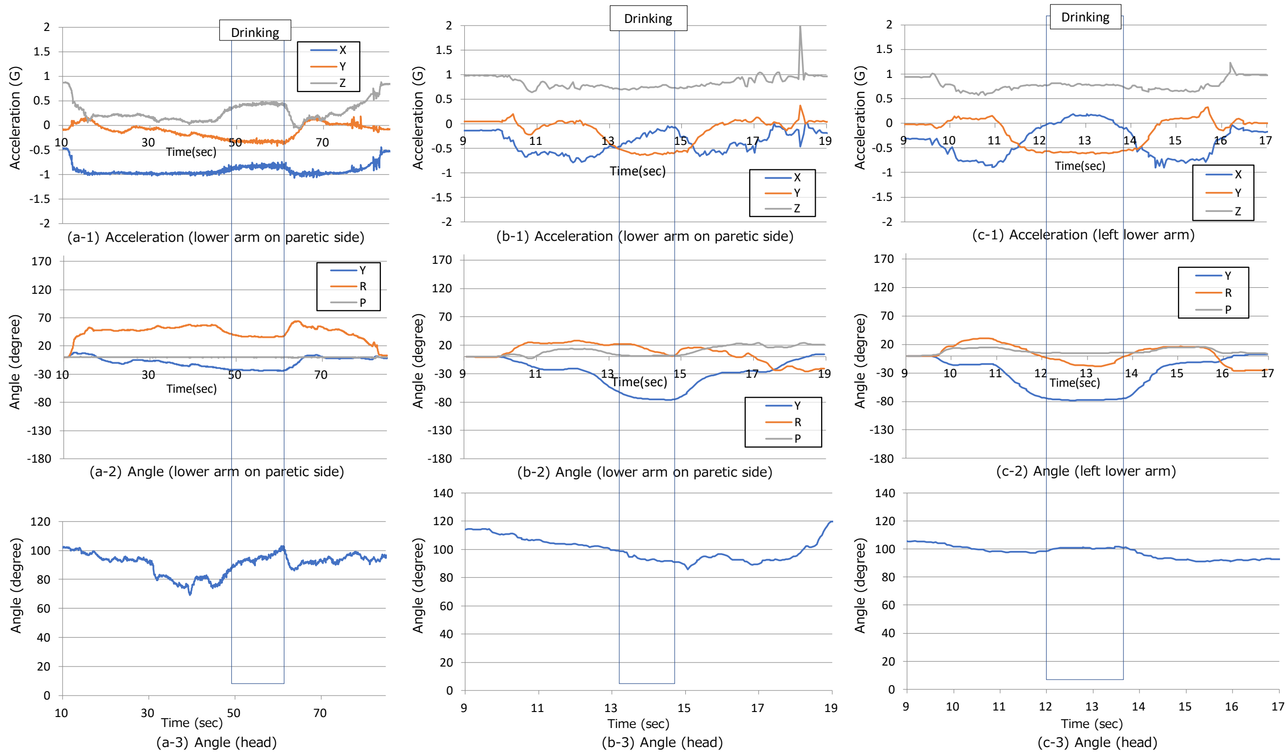
(a) Drinking a cup of water (b) Walking

Figure 23. Experimental scenes with a hemiplegic patient



(a) Hemiplegic patient A (b) Hemiplegic patient B (c) Healthy participant

Figure 24. Data collected walking



(a) Hemiplegic patient A (b) Hemiplegic patient B (c) Healthy participant

Figure 25. Data collected drinking

VII. Conclusion and Future Work

Existing evaluation indexes for activities in daily living (ADL) recovery levels such as the Barthel Index are based on responses to questionnaires. Therefore, the judging of recovery levels can be easily affected by an evaluator's subject. We have presented a system for collecting and storing motion data about daily life activities for use in quantitatively evaluating ADL recovery levels. The system was developed on the basis of Google Firebase. We used information about places such as a dining room and a bathroom to estimate the type of activity. The places are detected using Bluetooth beacons.

Measurement results obtained for a healthy volunteer with restricted movement demonstrated that it is possible to detect slight differences in the restriction level. However, it is difficult to estimate whether the motions can be performed without help.

Through the experiment measuring for hemiplegic patients, the proposed system can collect motion data safely and smoothly. Measurement results obtained from two hemiplegic patients whose severity of impairment were different shows that it is possible to detect slight differences in the severity.

Planned improvements to the proposed system include uploading video and GPS data to a cloud server. GPS data will enable measurement of motion during walking or running outdoor.

Our goal is to develop a new index for evaluating ADL recovery levels on the basis of big motion data measured for people performing various activities.

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