Improvement of Physical Activity Estimation Using the Inertial Measurement Unit based Cane Measurement Device

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Abstract. Daily exercise is necessary for the elderly to stay healthy. In order for the elderly to engage in appropriate amount of activity, they need a way to record daily physical activity. Previous studies on physical activity estimation identified the need for new device as well as significant errors in physical activity as challenges. Therefore, in this study, we improved the problems of the inertial measurement unit(IMU)-based cane measurement devices that estimate physical activity in previous study. Specifically, we solved the dataset and activity recognition model. We also considered the data segment size and IMU combination patterns. We further evaluated the proposed method by physical activity estimation error. The 300 sample segment size was optimal, and there was no significant difference in accuracy by IMU combination patterns. The physical activity estimation error was 7.37%. The proposed system was more accurate and easier to estimate physical activity than existing activity meters.

1. Introduction

According to the World Health Organization, between 2020 and 2050, the global population over 60 will double (2.1 billion), and by 2030, one in six people worldwide will be more than 60 [1]. Additionally, obesity among the elderly over 65 years of age is increasing worldwide [2], and the elderly need physical activity because obesity causes an age-related decline in physical function [3]. Approximately 28.9% of the current Japanese population is over 65 years old [4], and the mortality rate associated with lifestyle-related diseases, such as hypertensive heart diseases and diabetes, is 26.5% [5]. Daily exercise is considered necessary to maintain and improve health, including preventing lifestyle-related diseases [6]. An index called the physical activity METs*h indicates the amount of daily exercise a person has performed. Physical activity can be calculated by multiplying the metabolic equivalent of task (MET) determined for each activity of daily living (ADL) by the activity time (hour). It is defined that those aged 65 or older need a physical activity of 10 METs*h to stay healthy, according to the Ministry of Health, Labor and Welfare of Japan [7]. Therefore, it is necessary to monitor physical activity to prevent lifestyle-related diseases in the elderly.

Several inertial measurement unit (IMU)-based methods have been developed to estimate physical activity. For example, E. Sazonov et al. [8] proposed a system to estimate physical activities such as walking, standing upright, sitting, and cycling by attaching five pressure sensors and a single IMU to both shoes. However, the large size of the device makes it difficult to use in daily life. Nathan et al. [9] estimated energy expenditure (EE) at rest and during activity for middle-aged and older adults; acceleration sensors were attached to three locations at the center of gravity, hip joint, and ankle, and a formula for calculating the physical activity was obtained for each sensor by multiple regression analysis. Jaime et al. [10] estimated the physical activity at 10 different walking speeds with three IMUs attached to the wrist and thigh. The physical activity estimation was validated using equations that calculate EE differently for men and women. However, it has been found that estimating physical activity by equation does not use age as an input; therefore, it cannot accurately estimate the physical activity of the elderly. Zachary et al. [11] estimated walking, running, and resting physical activity with four different smartwatches with embedded IMUs and compared them to physical activity derived from indirect calorimetry. As a result, even with the highest physical activity estimation accuracy, the average absolute error of the activity measurement was reported to be 35.4%. Furthermore, Patrick et al. [12] developed a highly accurate physical activity estimation system using an IMU attached to the thigh to solve the problem of large physical activity estimation errors in smartwatches. The ability to recognize movements of the lower extremities, rather than from the wrist or trunk, indicates that it can monitor activity with greater accuracy than a smartwatch. However, most previous studies required that new devices and sensors be always worn on the body. From a usability perspective, it is psychologically burdensome for the elderly to use these devices in their daily lives. Therefore, it is necessary to develop a system that can estimate physical activity with high accuracy without requiring special equipment or being worn at all times.

With the rapid growth of the world's elderly population, the use of assistive devices has become increasingly important. In 2000, approximately 6.1 million residents used mobility aids, such as canes, walkers, and crutches, two-thirds of whom were over the age of 65 [13]. According to a survey on the use of welfare equipment by the elderly, 51.7% of men and 71.8% of women who need assistance use a cane [14]. Considering that many elderly people use canes, we developed a cane measurement device with two attached IMUs in our laboratory to recognize four ADLs (walk, stand to sit/sit to stand, go upstairs, and go downstairs) and attempted to estimate physical activity [15]. However, several issues emerged, such as "the need to measure multiple activities continuously rather than individually," "the need to measure data on staircase activities over a long time," "the need to add a new ADL to the recognition target," and the "need to make the activity recognition model more accurate."

In this study, we created a dataset of continuous activities with new ADLs using the Elderly Experience Kit (Sanwa Manufacturing Co., Ltd., Japan, Tokyo). We proposed a model that can accurately recognize activities using deep learning. Additionally, we considered the data segment size and IMU combination patterns to improve accuracy and reduce the cost of the cane measurement device. We further evaluated the proposed method by physical activity estimation error based on the results for data segment size and IMU combination patterns.

The remainder of this paper is organized as follows. In Section 2, the cane measurement device and flow of physical activity estimation in previous studies are explained. The proposed dataset and activity recognition model are also explained in this section. In Section 3, we discuss the subjects and Elderly Experience Kit, as well as the multiple activities that were continuously measured. Section 4 presents the experimental results and discussion. Finally, Section 5 presents the conclusion.

2. Proposed System

2.1 Previous study on a cane measurement device for physical activity estimation

2.1.1 Cane measurement device

Two IMUs (LP-WS1104, 9-axis wireless motion sensor; Logical Products Corporation, Japan, Fukuoka) were attached to a T-cane handle and cane tip. Figure 1 shows the positions where IMUs are attached. The 3-axis acceleration and angular velocity obtained from the IMUs at 100 Hz sampling frequency were used for activity recognition by machine learning [15]. The target activities included four ADLs (walk, stand to sit/sit to stand, go upstairs, and go downstairs). The physical activity METs*h was estimated using the METs defined for each ADL multiplied by the activity time (hour) obtained from the activity recognition model. Figure 2 shows an overview of the physical activity estimation flow with the cane measurement device.

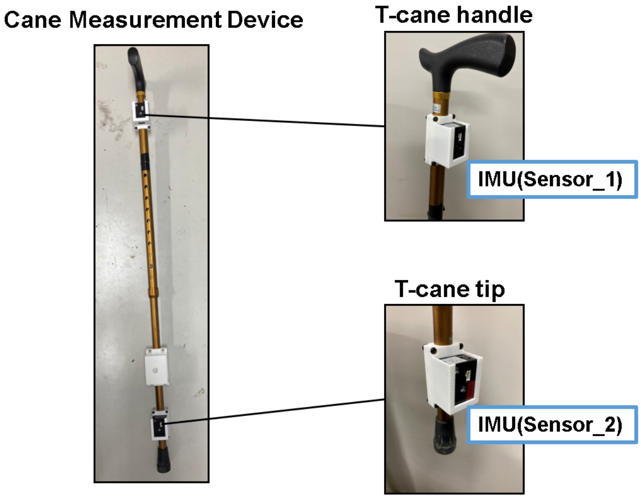


Fig. 1. The positions where IMUs are attached to a T-cane.

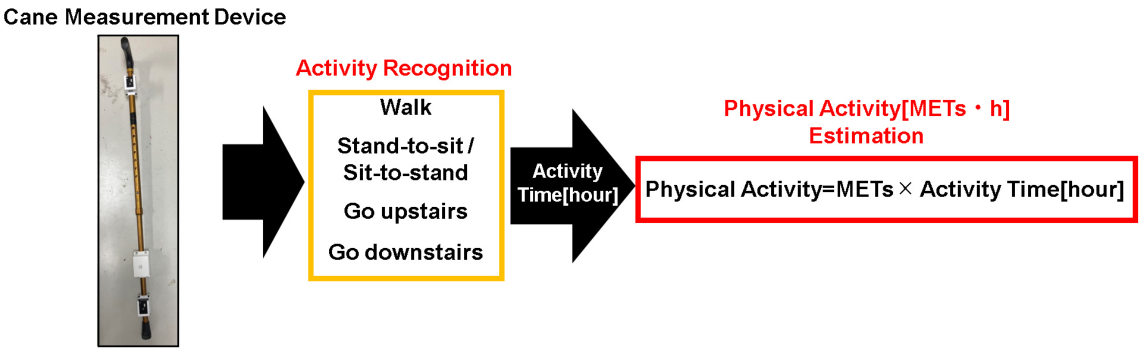


Fig. 2. Overview of the physical activity estimation flow with a cane measurement device.

2.1.2 Data segmentation

The 3-axis acceleration and angular velocity obtained from the IMU were segmented using the sliding window method. The sliding window method is a preprocessing method for time-series data to obtain features by dividing the data into certain intervals, and it is often used in the activity recognition field [16]. The size of an interval for segmentation is called the window size, and it is well-known that the window size affects the activity recognition accuracy [16]. The sliding window method also allows segments to cover a certain percentage of the window, which is called the overlap rate. In this paper, the overlap rate was set to 50%, following previous study on activity recognition [17]. Figure 3 shows an example of a data segmentation using sliding window method.

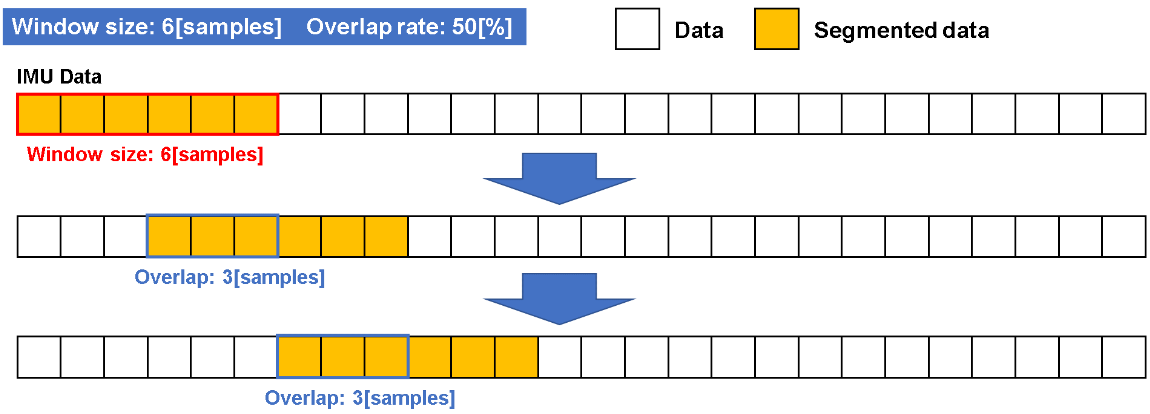


Fig. 3. Example of a data segmentation using sliding window method.

2.1.3 Activity recognition using machine learning

In a previous study [15], the k-nearest neighbor (k-NN) was used for machine learning of activity recognition. The k-NN is a supervised machine learning algorithm that determines labels for unknown data by majority voting based on k neighborhood samples. The accuracy of the model is evaluated by F-measure. F-measure is the value of the harmonic mean of Precision and Recall. F-measure is obtained in the range of 0 to 1. The closer F-measure is to 1, the higher the recognition accuracy of the model. The average of the highest F-measure for the four ADLs recognized by k-NN was 0.735, indicating low activity recognition accuracy as an issue.

2.1.4 Calculation of physical activity

Table 1 shows the METs defined for each ADL [4,18]. The physical activity (METs*h) was calculated by multiplying the METs of the activity label obtained from Subsection 2.1.3 by the activity time from the input data length. For example, when one "walk" label was recognized with a window size of 300 samples and an overlap rate of 50%, physical activity was estimated by assuming that 1.5 × 1/3600 hours of walking was performed and multiplying it by 3 METs.

Table 1. METs defined for each ADL

ADL	METs
Walk	3.0
Stand-to-sit/Sit-to-stand	4.3
Go upstairs	4.0
Go downstairs	3.5
Stand upright	1.8

2.1.5 Problems identified in the previous study

There were four problems with the cane measurement device in previous study. First, although data were obtained from the elderly, sufficient data on "go upstairs" and "go downstairs" were not gathered because of the experimental setup and physical ability of the elderly. Then, the recognition accuracy was low because of insufficient learning by machine learning. Second, it was not possible to segment the data during activity transitions because the four ADLs were measured individually. Therefore, it is necessary to verify whether activity recognition can be performed during motion transitions. Third, "walk" was output when the patient was standing upright; therefore, physical activity could not be estimated correctly. Thus, it is necessary to add "stand upright" to the measurement target to estimate physical activity more accurately in daily life. Fourth, the average of the highest F-measure for the four ADLs was not high. Thus, we propose a new method to solve these four issues.

2.2 Proposed method

2.2.1 Creating a new dataset with the Elderly Experience Kit

To solve the problem of the small amount of data on "go upstairs" and "go downstairs," a previous study proposed a method that used the Elderly Experience Kit (Sanwa Manufacturing Co., Ltd., Japan, Tokyo) to create a dataset. This kit could make the young movements resemble those of the elderly.[19,20]; as shown in Figure 4, the elbow/knee supporter made elbows/knees difficult to bend, the 1-kg weight band made the legs difficult to lift, and the weighted vest with four 1-kg weights made it difficult to move the entire body. Furthermore, the slouching posture was forced by a slouching postural experience belt.

(a) Front view of the subject (b)Side view of the subject

Fig. 4. Elderly Experience Kit worn by the subject.

To validate the activity recognition accuracy made during the activity transition, we continuously measured multiple activities to create a dataset, as explained in Section 3. Additionally, the "stand upright" position was added to activity recognition to more accurately estimate the physical activity in daily life.

2.2.2 Activity recognition model using deep learning

In this study, the proposed method used a deep learning model. Table 2 summarizes previous studies on activity recognition using deep learning models. In the activity recognition field, several models have been proposed using convolutional neural networks (CNNs) [21,22]. CNN is a deep learning model commonly used in image processing to extract features of IMU waveform shapes. Additionally, many models have been proposed using long short-term memory (LSTM) [23,24]. LSTM is a deep learning model commonly used for training time-series data, and it can extract the time variation of IMU waveforms as features. It has also been shown that combining CNN and LSTM allows for recognizing activity more accurately than each individually [25,26]. Furthermore, comparative experiments have shown that bidirectional gated recurrent unit (BiGRU), which can learn from past time-series data, as LSTM does, and new time-series data, can identify actions with higher accuracy than LSTM [27]. Therefore, the proposed method uses a deep learning model that combines CNN and BiGRU to recognize activity.

Table 2. Previous studies on activity recognition using deep learning

	Deep learning model	Sensor	Mounting position	Number of target actions	Window size	Accuracy[%]
[21]/2018	CNN	2 IMUs	Waist, Wrist	6	200	93.3
[22]/2021	CNN	1 IMU	Smartphone	6	128	96.1
[23]/2016	LSTM	2 IMUs	Waist, Wrist	6	50	92.1
[24]/2017	LSTM	1 IMU	Waist	6	128	90.5
[25]/2020	CNN+LSTM	2 IMUs	Waist, Wrist	6	200	95.9
[26]/2021	CNN+LSTM	2 IMUs	Waist, Wrist	6	200	98.5
[27]/2020	BiGRU	3 IMUs+Heart rate monitor	Hand, Chest, Ankle	12	50	99.6

CNN is a deep learning model commonly used in image processing, devised from the structure of the viewing angle of living organisms [21]. It can extract the shape features of the IMU waveform by shifting and multiplying the input data by numerical data called a kernel for each set stride size. Convolving an input vector $\mathbf{x} \in R^n$ and a filter vector $\mathbf{f} \in R^m$ takes an output vector $\mathbf{c} \in R^{n-m+1}$. Each element is $\mathbf{c}_i = \mathbf{f}^T \mathbf{x}_{[i:i+m-1]}$ and can be computed as a scalar product of the vector **f** and the corresponding part of **x**. Furthermore, the proposed method used max pooling to enhance the output after convolution. Max pooling is a method for dividing output data by pooling size and extracting only the data with the largest value among the divided data.

GRU is a deep learning model that uses a gating mechanism to solve the gradient loss problem that makes long-term learning of recurrent neural networks difficult. GRU can be weighted for temporal dependencies by the reset and update gates. A unit of the GRU is shown in Figure 5. The update gate adjusts the rate of memorizing new memories, and the weight of the update rate z_t can be obtained using equation (1) of the input data x_t. The reset gate also adjusts the forgetting rate of the memory, and the weight of the forgetting rate r_t can be obtained using equation (2). The weight r_t of the forgetting rate can then be used to obtain $\tilde{h}_t$ to update the memory using equation (3). The final process is to update the long-term memory h_t by weighting h_{t-1} and $\tilde{h}_t$ using the update ratio weight z_t, respectively, and then using equation (4). BiGRU is an extension of GRU, a deep learning model that learns from the past order of time-series data and the new order [27].

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$

$$\tilde{h}_t = tanh\{W_h x_t + U_h(R_t \odot h_{t-1}) + b_h\} \tag{3}$$

$$h_t = (1 - z_t) \circ \tilde{h}_{t-1} + z_t \circ h_t \tag{4}$$

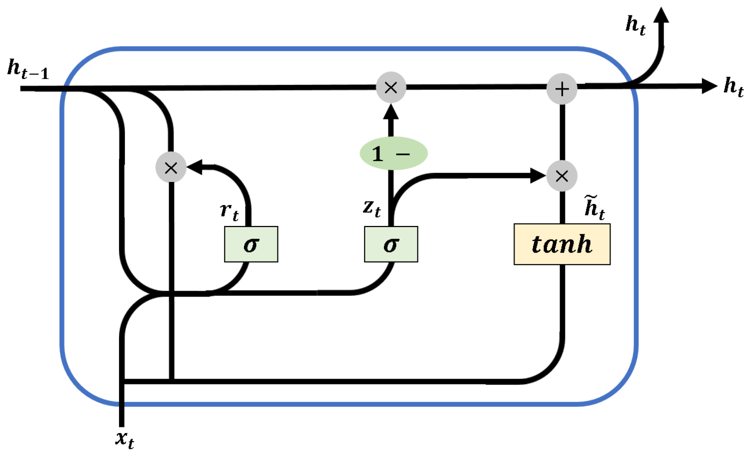


Fig. 5. Unit of the GRU.

The proposed model consists of a parallel combination of CNN layers using multiple CNNs and BiGRU layers using BiGRUs. Figure 6 shows an overall view of the combined model. Figures 7 and 8 show the models of the CNN and BiGRU layers, respectively. The proposed method also used the rectified linear unit as an activation function to suppress overlearning and performed batch normalization in the dimensional direction of features when merging data. We used the dropout layer to learn while inactivating a certain percentage of nodes. The final output was determined based on a softmax layer.

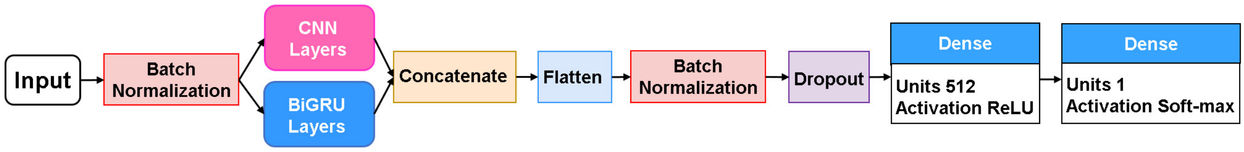


Fig. 6. Overall view of the proposed model.

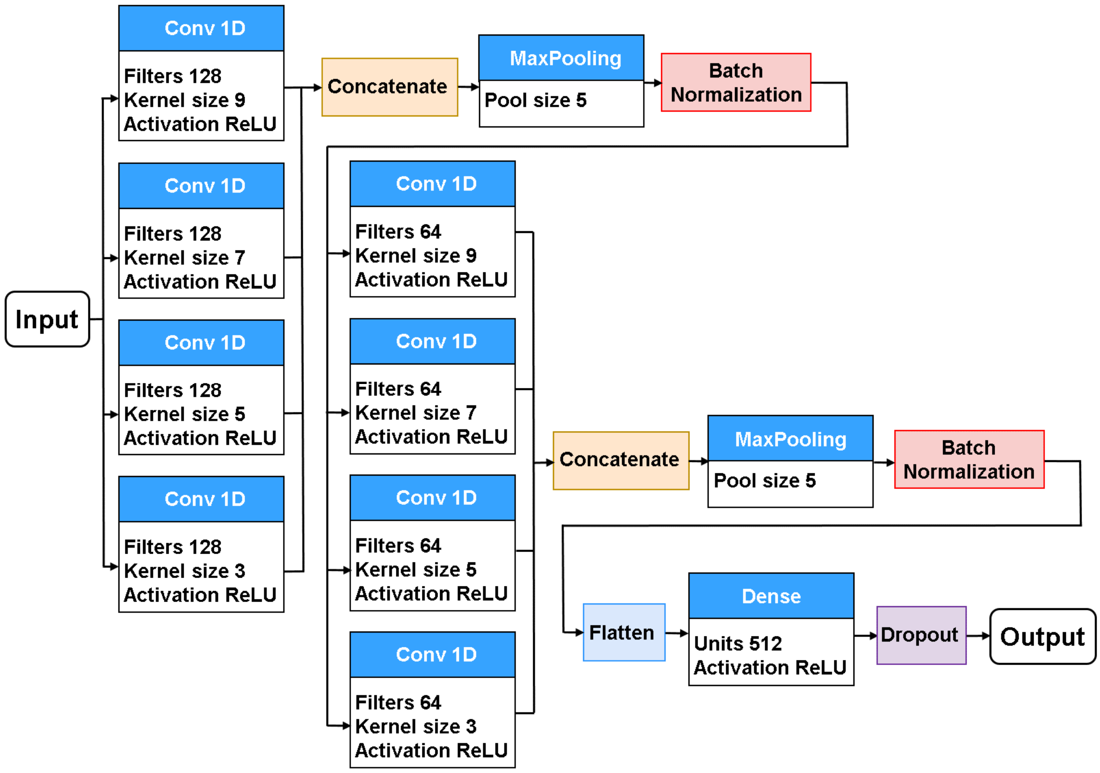


Fig. 7. Model of the CNN layers.

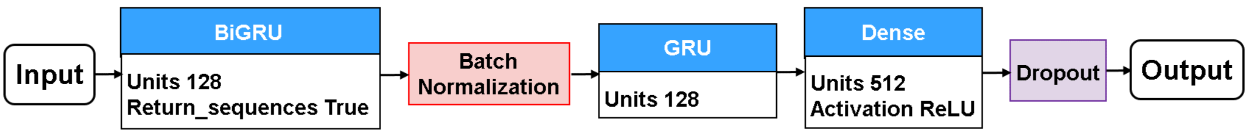
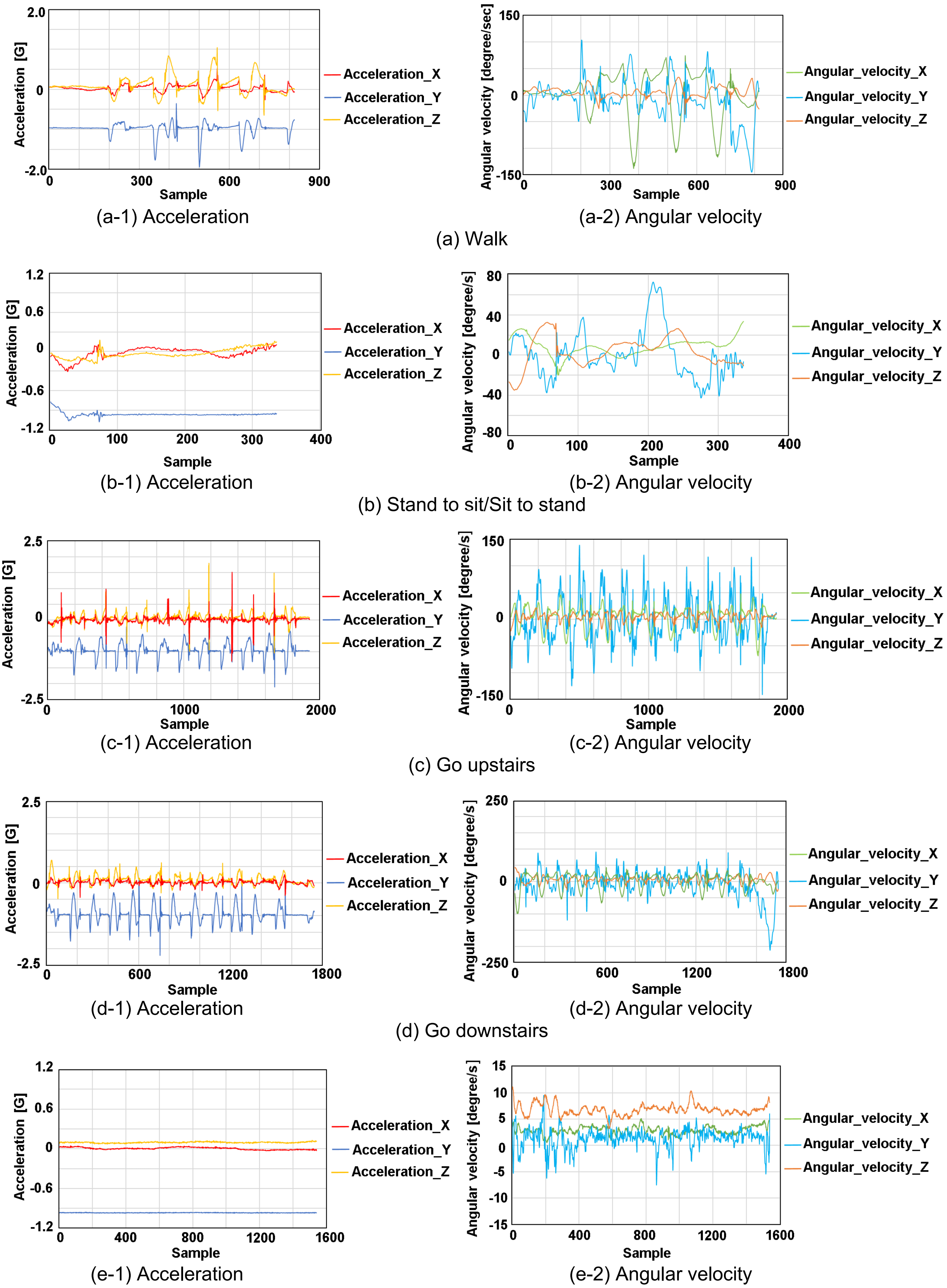


Fig. 8. Model of the BiGRU layers.

3. Experiment

In this experiment, we measured the data used to train a cane measurement device. The subjects were 10 healthy young adults (8 males and 2 females; age: 23 ± 0.63 years old; body height: 1.69 ± 0.85 $\times$ 10^{-1} m; body weight: 65.9 ± 14 kg). The length of the cane was decided by placing the cane 0.15 m forward and 0.15 m to the side from the cane user's toes, with the handle coming to the hand with the elbow bent 30°. All participants received a description of this study and signed a written informed consent form before participating. All experimental procedures were approved by the Ethics Committee for Human Research of the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology (approval number: 22-10).

Subjects were asked to wear the Elderly Experience Kit and perform five ADLs (walk, stand to sit/sit to stand, go upstairs, go downstairs, and stand upright) in succession. The flow of continuous multiple activities was as follows: (1) walk (3 m), (2) stand to sit/sit to stand, (3) walk (3 m), (4) stand to sit/sit to stand, (5) walk (5 m), (6) go downstairs (12 steps), (7) go upstairs (12 steps), and (8) stand upright.



(a-1) Acceleration (a-2) Angular velocity

(a) Walk

(b-1) Acceleration (b-2) Angular velocity

(b) Stand to sit/Sit to stand

(c-1) Acceleration (c-2) Angular velocity

(c) Go upstairs

(d-1) Acceleration (d-2) Angular velocity

(d) Go downstairs

(e-1) Acceleration (e-2) Angular velocity

(e) Stand upright

Fig. 9. Typical acceleration and angular velocity of five ADLs.

Five measurements were taken for each subject, and the model was trained for each subject using the leave-one-out method. For labeling, a button switch was attached to a data logger (wireless 8-channel logger, LP-WS1311; Logical Products Corporation, Japan, Fukuoka). The switch was pressed at the time when the activity changed, and the motion was labeled as changed at 5 V. The IMU was controlled by the LabVIEW (National Instrument Corporation, USA, State of Texas)-based software (LP-WSD009-0A; Logical Product Corporation, Japan) and started and stopped the measurements wirelessly. The IMU data were saved to a PC via a USB-wired connection. Figure 9 shows typical acceleration and angular velocity of five ADLs.

Since the proposed method used a sliding window method for IMU data segmentation, we compared the activity recognition accuracy for each activity when the window size was changed to 100, 200, and 300 samples to investigate whether the activity recognition accuracy was improved. The F-measure, i.e., the recognition accuracy of each subject's activities, was compared when the window size was changed. To reduce the system's cost, we compared the recognition accuracy among the patterns using Sensor_1 and Sensor_2, Sensor_1 only, and Sensor_2 only. Here Sensor_1 was the IMU on the cane handle, and Sensor_2 was on the cane tip, as shown in Figure 1. For comparison, we used accuracy, which is a measure of recognition accuracy per subject. Furthermore, we evaluated the physical activity estimation error based on the results of the window size and IMU combination patterns. As a statistical analysis, significant differences between the window size and IMU combination patterns were evaluated using the Mann–Whitney's *U* test (significance level, $p < 0.05$). Statistical analysis was performed using Easy R(EZR) [28].

4. Results and Discussion

Figure 10 shows a box-and-whisker diagram of the F-measure for the five activities of the model trained for each window size. The results showed significant differences by changing the window size in the two activities of "stand to sit/sit to stand" and "go downstairs." There was a significant difference between 100 and 300 samples for "stand to sit/sit to stand."

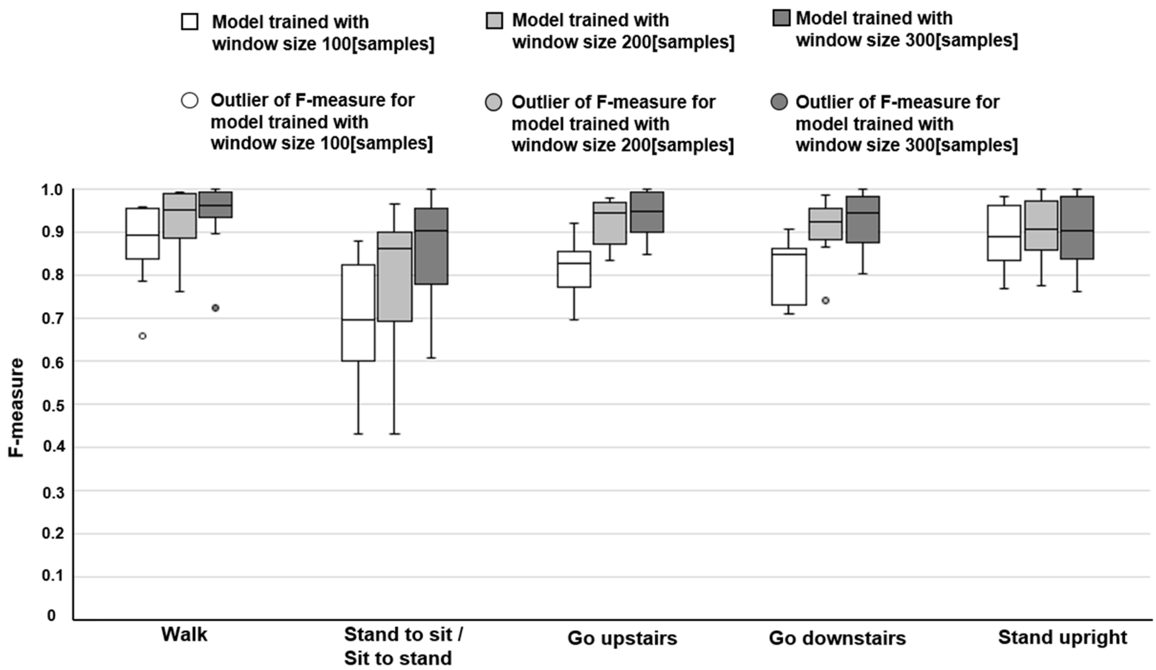


Fig. 10. F-measure for the five activities of the model trained for each window size.

Additionally, there was a significant difference between 100 and 200 samples and between 100 and 300 samples for "go downstairs." These results showed that a window size of 300 was optimal for recognizing the five ADLs. The larger window size was more accurate for "stand to sit/sit to stand" and "go downstairs" because the activity time per step was longer than 200 samples, and the activity features did not fit within the window. The average F-measure of the five ADLs with a window size of 300 samples was 0.912. This result indicates that proposed model was possible to recognize multiple activities continuously with higher accuracy than previous study [15].

Figure 11 shows the average recognition accuracy of the subject's obtained for each IMU combination pattern. The results showed that there was no significant difference in the recognition accuracy by IMU combination patterns, indicating that a single IMU was sufficient to recognize activities compared with two IMUs. There was no significant difference for IMU combination pattern because the acceleration and angular velocity of each axis of Sensor_1 and Sensor_2 were correlated, and there was no difference in the obtained feature values.

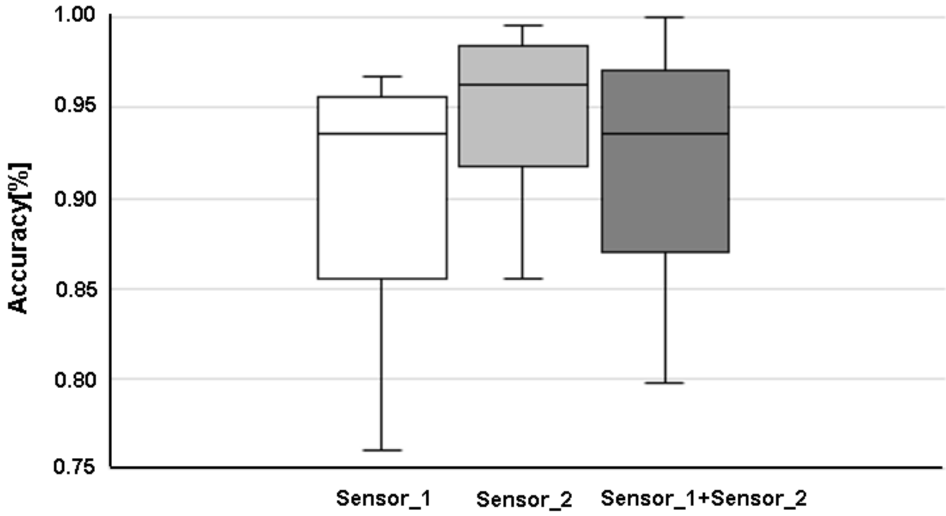


Fig. 11. Average recognition accuracy of the subject's obtained for each IMU combination pattern (*significant difference: $p < 0.05$).

Table 3. Physical activity estimation error for each of the five ADLs and the average of the five ADLs when the IMU combination pattern is Sensor_1 or Sensor_2 with a window size of 300 samples.

	Physical activity estimation error[%]	
	Sensor_1	Sensor_2
Walk	6.07	4.57
Stand to sit / Sit to stand	1.77×10	1.28×10
Go upstairs	1.94×10	5.99
Go downstairs	8.74	4.19
Stand upright	1.93×10	9.36
Avg	1.43×10	7.37

Based on the results of the window size and IMU combination patterns, Table 3 shows the physical activity estimation error for each of the five ADLs and the average of the physical activity estimation error for each sensor of the five ADLs when the window size is 300 samples. The true physical activity was calculated from the true activity label. The physical activity estimation error of eight commercially available activity meters, such as BodyMedia FIT and ActiGraph, is 9.30% [29]. In contrast, the proposed cane measurement device can estimate the physical activity with an error of 7.37%. Our cane measurement device could be used to monitor the physical activity of the elderly using a cane.

Figure 12 shows the confusion matrix of the subject with the largest physical activity estimation error. This figure shows that the activity recognition model incorrectly predicts “stand upright” as “go upstairs.” Therefore, the activity of “go upstairs” was 18.2% smaller than the true value, and that of “stand upright” was 38.2% larger than the true value. Figure 13 shows acceleration and angular velocity in the three axes obtained from the IMU of the stand upright label of the subject with the largest physical activity estimation error. As shown in Figure 13, the cause of misrecognition was the cane vibrating in the z- and x-axes directions when it changed from a “go upstairs” motion to a “stand upright” motion. For the coordinates of the IMU, leftward means positive on the x-axis, upward means positive on the y-axis, and direction of travel means positive on the z-axis. This waveform was probably obtained because the body swayed back and forth due to an unstable center of gravity during the change to “stand upright.” Therefore, a filter that can suppress the minute acceleration and angular velocities caused by body wobble could be used to solve this problem.

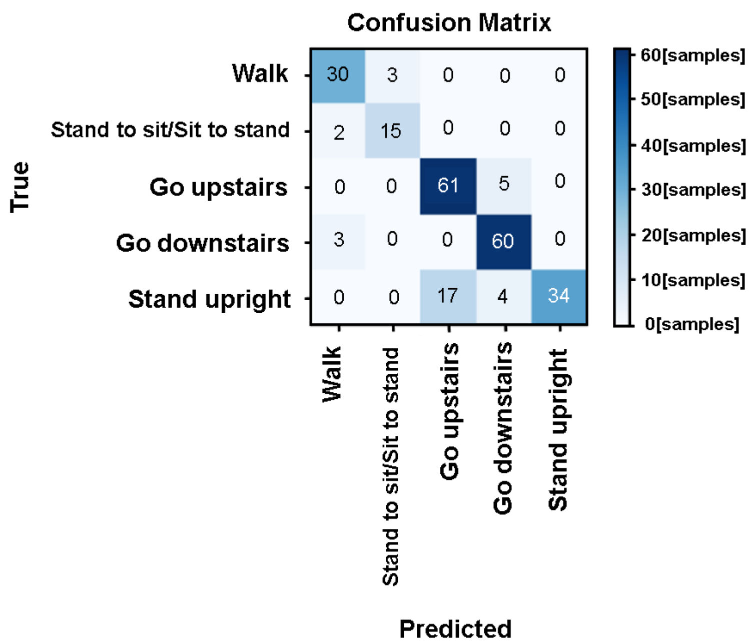


Fig. 12. Confusion matrix of subject with the largest physical activity estimation error.

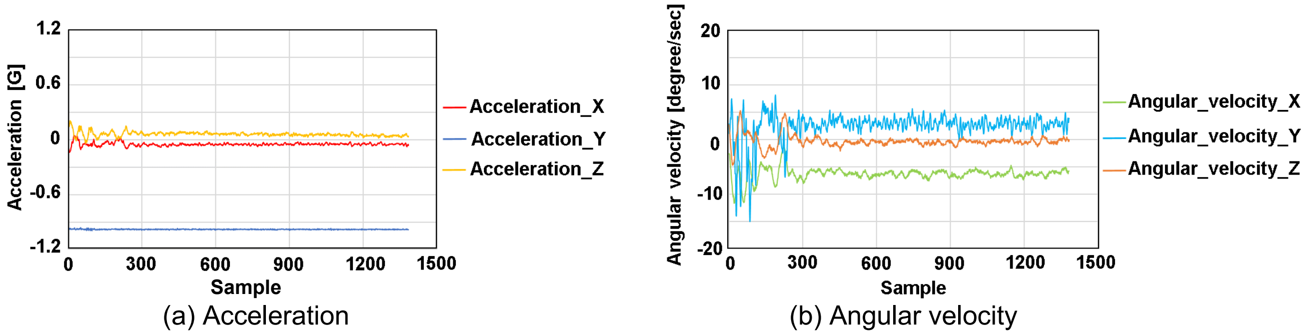


Fig. 13. Acceleration and angular velocity from the IMU of the stand upright label.

The experimental results show that the proposed system solves the problem of the cane measurement device in the previous study and can estimate the physical activity of the elderly with higher accuracy than existing activity meters. The issues of the previous research on the cane measurement device were solved by creating a dataset using the Elderly Experience Kit and activity recognition model based on deep learning. However, this study has potential limitations. In reality, the elderly might perform a movement, such as holding onto a handrail and walking upstairs and downstairs, without swinging the cane. This exceptional cane movement makes it difficult to recognize the activity. Since this system could not recognize such exceptional movements, it is necessary to obtain data that more accurately resemble the movements of the elderly. Thus, we propose developing a system that can accurately estimate physical activity, even when elderly-specific movements are included.

4. Conclusion

In this study, we proposed a method for estimating physical activity with high accuracy by solving the issues of the dataset and activity recognition model of the IMU-based cane measurement device in the previous study[15]. In the experiment, we compared the window size of the IMU data input to the deep learning model and the IMU combination patterns. We also evaluated the physical activity estimation error based on the results of the window size and IMU combination patterns. The results showed that the optimal window size of the proposed system was 300 samples, and no significant difference was observed in the IMU combination pattern. Furthermore, the physical activity estimation error of the cane measurement device was 7.37%, rendering it more accurate than existing activity meters. These results showed that physical activity could be monitored by attaching a single IMU to a cane used by the elderly daily.

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