Estimation of Lower Limb Joint Torque Using Handrail Force and Floor Reaction Force During Sit-to-Stand Motion in the Elderly

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***Abstract*— Many elderly individuals experience a decline in motor function. To provide appropriate rehabilitation programs, a sufficient and convenient evaluation method is necessary. In this study, we focused on the sit-to-stand (STS) motion, a crucial activity in daily life, and used handrail to obtain force data safely and easily. Previous studies have proposed methods for estimating scores such as the Timed Up and Go test from forces applied to the hand, hip, and foot, classifying elderly individuals into several motor function categories. However, these indicators are insufficient for evaluating the function of specific muscles or joints in the lower extremities individually. The primary objective of this study was joint torque, which more directly represents the function of specific muscles and joints. We measured the time-series data of forces acting on the body during STS motions and developed a model using Long Short-Term Memory to estimate lower limb joint torques. As a result, knee and hip joint torques were accurately estimated from force applied to hand, hip and foot. Furthermore, this method demonstrated the potential for early detection of joint disorders. This approach allows for a detailed assessment of the state of the knee and hip joints simply by standing up while holding a handrail.**

I. INTRODUCTION

The decline in motor function occurs in many elderly individuals [1], leading to a reduction in activities of daily living and, consequently, a decrease in quality of life. To prevent this problem, an increasing number of elderly individuals undergo rehabilitation to maintain or restore their motor function. To provide optimal rehabilitation, it is essential to assess the motor function of each individual. To identify the target areas for rehabilitation approaches, various measurements are conducted in rehabilitation settings.

While the assessment tools used in clinical settings are valuable, they present several limitations. In these settings, two measurements are commonly used in various conditions: the Timed Up and Go (TUG) test and standing time on one leg with eyes open. The TUG test measures the time required for an individual to stand up from a chair, walk three meters, turn around, and return to the chair. It has been shown to correlate with lower limb muscle strength and walking speed [2]. The standing time of one leg with eyes open reflects the balance function [3]. In hospitals, these measurement results are used to determine whether the subject requires rehabilitation. However, a major issue with these widely conducted tests, particularly the TUG test [2], [4], gait tests [5], [6] and standing time on one leg with eyes open, is the risk of falls during measurement. Additionally, the currently performed STS tests [7], [8] assume that individuals can complete the motion independently, making it difficult to apply them to elderly individuals who cannot perform the STS motion without upper limb support. Furthermore, elderly individuals with reduced balance ability are at risk of falling during the standing motion. As a result, healthcare professionals must always be present, making the process time-consuming and increasing the workload of physicians, physical therapists, and other rehabilitation specialists. Therefore, to reduce the burden on healthcare professionals while providing more effective rehabilitation, a system is needed that can safely, easily, and instantly estimate the current motor function of elderly individuals.

Several attempts have been made to develop remote monitoring and evaluation systems to facilitate better assessment and rehabilitation of motor function. For example, accelerometers and inertial measurement unit sensors are often used to monitor motor behavior continuously during rehabilitation [9], [10]. Previous studies utilized accelerometers to estimate locomotion parameters such as stride length and cadence. Recently, the Wii Balance Board (Nintendo) was also used to evaluate the balance function [11], [12]. The authors reported that the Wii Balance Board could reliably monitor the center of pressure length and velocity, and thereby evaluate weight shift while sitting and standing. Regarding sensor technology, RGB-depth sensors and motion sensors, are also often used for evaluation [13]. The development of sensors to evaluate the motor ability on behalf of therapists appears to be a promising direction for rehabilitation assessment.

To further promote the direction of this research, researchs have been conducted on systems focusing on handrails used in rehabilitation settings to ensure safe

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STS motions. It has been found that the weaker a patient's lower limb motor function, the greater the force applied to the handrail [14]. Based on this, studies have been conducted to evaluate whole-body motor function using force data obtained from handrails equipped with force sensors. An et al. estimated the severity of hemiplegic patients based on the force applied to the handrail [14]. Additionally, Kihara et al. developed a system that analyzes forces applied to the handrail, buttocks, and foot using machine learning to estimate TUG test performance and one-leg standing time with eyes open, enabling classification of motor function in elderly individuals [15]. However, relying solely on these evaluation metrics makes it difficult to estimate the deterioration of specific joints or muscles, making them insufficient for assessing the detailed condition of elderly individuals.

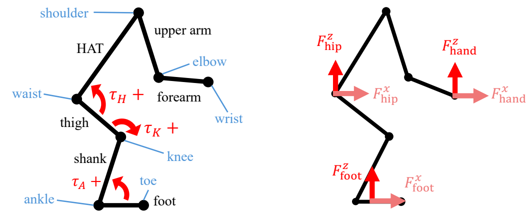
In this study, we focus on muscle strength and joint torque as key indicators for evaluating motor function. The TUG test assesses walking ability, balance, and muscle strength comprehensively. However, TUG does not evaluate these elements individually. Meanwhile, muscle weakness is one of the primary causes of motor function decline [16], and muscle strength is a key factor in generating joint torque. Therefore, joint torque has a strong correlation with motor function, and it can be considered useful for accurately estimating a patient's current condition in detail. Elderly individuals, on average, utilize 97 % of their maximum voluntary torque to perform a STS motion [17]. By estimating torque during this motion, it is possible to infer an individual's maximum voluntary torque. The minimum torque required to perform a STS motion independently has been investigated [17]. Assessing how close an individual is to this threshold, as well as tracking changes during rehabilitation and in daily life, would be highly valuable. Although calculating joint torque typically requires body trajectory data, obtaining such data during rehabilitation or daily activities is challenging. Therefore, this study aims to estimate lower limb joint torque without using body trajectory data, relying solely on information obtained from force sensors embedded in assistive devices.

II. METHODS

The proposed method evaluated lower limb function in elderly individuals based on the forces exerted on the body during the STS motion. Specifically, forces acting on the hand, hip, and foot are measured during the STS motion, and the obtained force data were used as inputs for the lower limb joint torque estimation model.

A. Calculating Joint Torque

Although body trajectory was not used as input for the estimation model, joint torque must be calculated as training data. The STS motion occurs in the sagittal plane, a two-dimensional body model was used, as



(a) Body Model (b) External Forces

Fig. 1: Body Model and External Force Directions

defined in Figure 1a. In this model, red indicates joint torques and their positive directions, blue represents key point names, and black denotes segment names. We define the joint angles and segments used in this study based on key points.

As shown in Figure 1b, external forces acting on the body were considered in both the horizontal (x direction) and vertical (z direction) axes, applied to the foot (F_{foot}), hip (F_{hip}), and hand (F_{hand}). For joint torque calculations, inverse dynamics using Newton's method was applied.

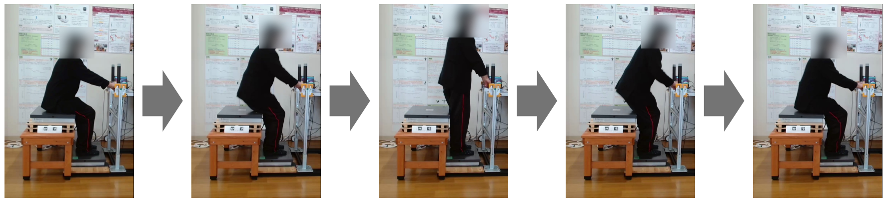
B. Estimation Model

A Long Short-Term Memory (LSTM) [18] model was employed to estimate the maximum lower limb joint torque of elderly individuals. When body trajectory data was available, joint torque could be calculated using inverse dynamics. However, in the absence of body trajectory data, torque cannot be computed directly. As stated above, this study aims to estimate the lower limb joint torque without using body trajectory data. Therefore, joint torques are computed for training data, and we employ a LSTM network, using forces acting on the body as input and joint torque as output. Instead of selecting specific features from the time-series data, it was considered that handling the data in its raw time-series form preserves more information and improves estimation accuracy. The model takes the forces exerted on the body during STS motion as input and outputs the estimated joint torques.

C. Experimental Setup

A validation experiment was conducted with elderly individuals using the day-care rehabilitation service at Asanohi Orthopedic Clinic. This experiment was approved by the Ethics Committee of the Graduate School of Information Science and Electrical Engineering, Kyushu University (Approval Number: 2021-06-1). Written informed consent was obtained from all participants.

Five males and ten females participated in the study. Table I shows the information of the participants. All participants had some form of orthopedic disorder. Eleven participants (three men, eight women) required assistance with tasks such as household chores but were generally able to live independently, while four participants (two men, two women) exhibited significant functional decline, necessitating daily assistance.



Start of Standing　Buttocks Lift-off　Completion of Standing　Start of Sitting　Completion of Sitting

Fig. 2: A Series of motions Performed by the Experimental Participants

TABLE I: Information of Participants

	Age	Weight [kg]
Mean	81.9	46.7
Standard Deviation	10.1	7.9
Maximum	97	59
Minimum	63	35

In this experiment, only the horizontal handrail among the vertical and horizontal handrails implemented in the measurement system was used. As shown in Figure 2, the participants performed a series of STS and stand-to-sit motions three times. In this experiment, we measured the forces acting on the body during the STS motion using the measurement system developed in a previous study [15]. As shown in Figure 3, the system consists of an aluminum frame base, equipped with force plates (Tech Gihan Co., TF-4060) placed under the buttocks and foot, and a load cell (Leptrino Co., FFS080YS102A6) attached to the front handrail. From the force plates, we measure anterior-posterior (x direction) and vertical (z direction) force acting on the hip and foot ($F_{\text{hip}}, F_{\text{foot}}$), likewise from the load cell, we measure two-dimensional force information in the x and z directions acting on the hand (F_{hand}). This system utilizes a Raspberry Pi to simultaneously record data from all sensors, and individual participants are managed using IC cards.

The coordinate system was defined with the forward direction toward the seat as the x-axis and the vertical direction as the z-axis. The seat height was set at 420 mm from the foot, and the horizontal handrail height was set at 700 mm from the foot. A webcam (Logicool Co., C920n) was used to record the STS motion utilizing the handrail from the right side. The webcam's frame rate was set to 30 fps, while the sampling rate of the force plates and load cell was 250 Hz. Therefore, the force data were downsampled to 30 Hz to match the webcam's frame rate. Additionally, to calculate real-world distances from the image data, two AR markers were placed to the right of the seat with a center-to-center distance of 135 mm.

Since posture data is necessary to calculate joint torques to train LSTM model, the posture estimation of the participants was performed using YOLOv8x-pose [20] from videos capturing the participants executing a STS motion using a handrail. In this experiment, only the right side keypoints of the participant's body was used.

During the estimation, the detected keypoint positions sometimes exhibited sudden changes due to misalign-

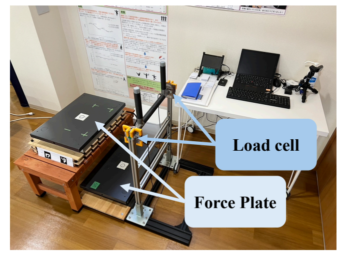


Fig. 3: Overview of the System

ment between consecutive frames. To mitigate this issue, a moving average over five frames was applied. Since YOLO does not provide the coordinates of the toe keypoint, the toe position was estimated based on the ankle keypoint. Specifically, the toe keypoint was determined by shifting the ankle keypoint 251 mm in the positive x-axis direction, which corresponds to the average foot length [21], [22]. Based on statistical data from previous research [23], the segment mass as a proportion of body weight, the center of mass position from the proximal end, and the rotational center position from the proximal end for each segment were determined, as shown in Table II. Since posture estimation was performed frame by frame, joint velocity was calculated from the change in joint angles per frame, and joint acceleration was obtained from the change in joint velocity.

Similarly, the translational acceleration of each segment's center of mass was calculated. The estimated posture information derived from keypoint coordinates, along with force data obtained from the handrail and from the force plates installed under the buttocks and foot, were used for joint torque calculation. Before calculation, the measured force data were normalized by dividing by each participant's body weight, and the segment masses were also normalized by body weight. The segment lengths were obtained from the keypoint distances in the images and converted into real-world units (mm) by multiplying them with a scale factor determined from the center-to-center distance of two AR markers visible in the same video frame.

Regarding the calculation of joint torques, we did not include the Center of Pressure (CoP) in this study. This decision was made because the force plate data, though recorded with devices from a previous study's methodology, lacked clearly identified column names for the moment data necessary for accurate CoP calculation. For the point of application of force, specifically for the reaction force from the foot, the difference between the

TABLE II: Data of Segments

Segment	Segment Weight /Body Weight	Center of Mass /Segment Length	Radius of Gyration /Segment Length
Foot	0.015	0.500	0.475
Leg	0.047	0.433	0.302
Thigh	0.100	0.433	0.323
HAT	0.678	1.142	0.903
Upper arm	0.028	0.436	0.322
Forearm	0.022	0.430	0.468

body center of mass's x-coordinate and the foot segment center of mass's x-coordinate was used, while ensuring that it remained within the foot segment range. For the buttocks, the force application point was fixed at the proximal end of the segment (waist). To remove noise and smooth all calculated torques, a moving average with a window size of 10 (0.33 seconds) was applied.

Following the previous study [15], the moment of seat-off was defined as the time when the vertical force acting on the hip (F^z_{hip}) became less than or equal to 25 N. The following data was recorded for a duration of three seconds, from one second before seat-off to two seconds after seat-off:

- Ground reaction forces at the foot in the x, z directions: $F^x_{\text{foot}}, F^z_{\text{foot}}$
- Ground reaction forces at the hip in the x, z directions: $F^x_{\text{hip}}, F^z_{\text{hip}}$
- Handrail reaction forces in the x, z directions: $F^x_{\text{hand}}, F^z_{\text{hand}}$
- Joint torques calculated using the Newton's method: torque of ankle (τ_{A}), knee (τ_{K}), and hip (τ_{H})

These data were recorded for each STS motion to train the estimation model.

The learning process was conducted independently for each joint. The input force conditions were divided into two cases:

- All forces acting on the body ($F^x_{\text{hip}}, F^z_{\text{hip}}, F^x_{\text{foot}}, F^z_{\text{foot}}, F^x_{\text{hand}}, F^z_{\text{hand}}$)
- Only forces acting on the hands ($F^x_{\text{hand}}, F^z_{\text{hand}}$)

For each case, we investigated whether it is possible to estimate lower limb joint torque using all forces acting on the body and whether it was feasible to estimate joint torque using only hand forces, which is more convenient than using all forces.

Validation and test data were randomly selected from multiple experimental participants in equal proportions. This ensured that the training, validation, and test sets contain data from mutually exclusive participants.

Figure 4 shows the proposed torque estimation model. For each training session, the data was split according to predefined conditions, and learning was performed. From the predicted torque data, the maximum estimated torque ($\hat{\tau}^{\max}_l$) was compared with the maximum torque in the test data ($\tau^{\max}_l$). Using eq. (1), the Mean Absolute

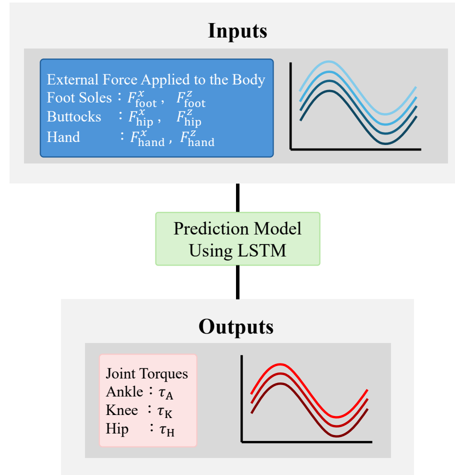


Fig. 4: Torque Estimation Model

Error (MAE) was calculated for each joint.

$$\text{MAE} = \frac{1}{m}\sum_{d=1}^{m} \left|\tau^{\max}_{ld} - \hat{\tau}^{\max}_{ld}\right| . \quad (1)$$

Here, l represents the joints: ankle (A), knee (K), and hip (H). Additionally, m denotes the total number of STS motions included in the dataset.

In this experiment, data were collected from 15 participants, with a total of 45 STS motions recorded. Therefore, data from three participants (nine instances in total) were used as test data, and another three participants were used as validation data. The process of data splitting, learning, and MAE calculation was repeated 100 times. Evaluation was performed using the mean MAE ($\overline{\text{MAE}_l}$) over 100 iterations for each joint.

This study utilized the following hyperparameters for the LSTM model: a window size of 30, in all force condition, seven LSTM layers for ankle torque prediction, and eight layers for knee and hip torque prediction. In hand force condition, only one LSTM layer for each torque. Training was conducted for 200 epochs, with early stopping applied if the validation loss did not improve for 10 consecutive epochs. The learning rate was set to 0.0005, the batch size to 32, and the hidden size to 256. The Adam optimizer was used for training.

The LSTM model was chosen as a standard unidirectional baseline model to evaluate its fundamental performance in time series prediction. Specifically, for the hand force condition, a single LSTM layer was employed to mitigate the risk of overfitting, given the specific characteristics of the data, while still aiming to capture essential time-dependent relationships.

III. RESULTS

Table III shows the mean MAE ($\overline{\text{MAE}_l}$) obtained as a result of 100 training iterations for each joint torque under different input conditions. Due to the experimental setup, all force condition and hand force condition involved testing with data from participants not included

TABLE III: Results of Lower Limb Joint Torque Estimation [Nm/kg]

	Peak torque	condition	
		all force	hand force
$\overline{\mathrm{MAE}}_{\mathrm{A}}$	1.08	0.08 ± 0.00	0.13 ± 0.01
$\overline{\mathrm{MAE}}_{\mathrm{K}}$	4.39	0.18 ± 0.01	0.58 ± 0.03
$\overline{\mathrm{MAE}}_{\mathrm{H}}$	7.05	0.38 ± 0.02	1.03 ± 0.05

Values are presented as mean absolute error $\pm$ 95% confidence interval.

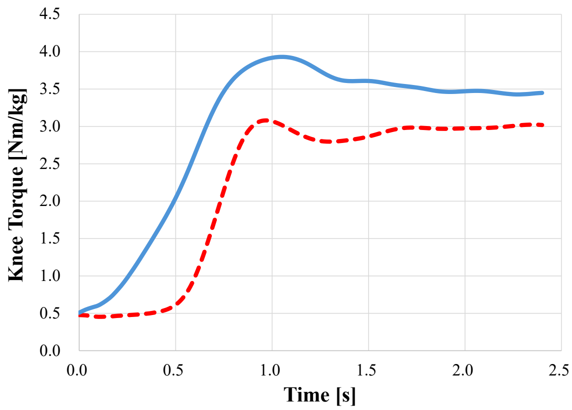


Fig. 5: Illustration of Knee Joint Torque Estimation

in the training. For the ankle joint torque (τ_{A}), percentage of $\overline{\mathrm{MAE}}_{\mathrm{A}}$ relative to peak joint torque was 8 % in all force condition, and 12 % in hand force condition. Regarding the knee joint torque (τ_{K}), all force condition showed 4 % error rate, and hand force condition showed 13 %. The hip joint torque (τ_{H}) was 5 % error rate in all force condition, and 15 % in hand force condition.

To verify the effectiveness of the proposed method in inter-individual comparisons, the estimation was performed under all force condition, which uses all forces acting on the body as input. Both participants had similar ages, weights, and levels of care required, but one participant had a knee joint disorder, which is expected to result in a lower knee joint torque. Figure 5 illustrates the estimation results. The estimated torque of the participant who had knee disorder (red dot line) was smaller than that of the participant who did not have any knee disorder (blue line).

IV. DISCUSSION

This study enabled the estimation of specific lower limb joint torque values for each individual. Particularly for knee and hip joint torque, the proposed method demonstrated high accuracy in estimating maximum torque value. Especially, the estimation of knee joint torque has the potential to contribute to the detection of knee joint disorder and the quantitative evaluation of motor function. In previous studies by An [14] and Kihara [15], participants' motor functions were only classified into a few categories. Compared to classification, estimating actual values is more useful for continuous monitoring, as it allows us to determine whether the torques tend to decrease over time.

Additionally, this method allows for easy and detailed monitoring of rehabilitation progress and changes in daily life. According to previous study [25], the prevalence of symptomatic knee osteoarthritis (OA) had been increasing in the US, with approximately 5 million patients over 65 years old. Severe OA could impair standing and walking due to joint deformities, pain during motion, and restricted range of motion. By estimating knee joint torque, early detection and intervention for these conditions may become possible.

In all force condition, the estimate error of knee joint torque was 4 % relative to the maximum torque. From previous research [17], it was found that the maximum knee joint torque (τ_{K}) in elderly individuals was approximately 100 Nm, and the minimum torque required for them to stand up from the chair independently was around 80.7 Nm. Furthermore, the knee joint torque decreases by approximately 0.1 Nm/kg every 10 years with aging, which was calculated from statistical data in the previous study [19]. This represented about 10 % of the maximum knee joint torque in elderly individuals. Because the estimate error of knee joint torque resulted in this study was lower than the change related to aging, we were able to estimate maximum knee joint torque by all force condition. Similarly, ankle joint torque and hip joint torque were also lower than 10 % error rate. Therefore, using the proposed method, it is able to estimate the maximum lower limb joint torques, especially knee and hip joint torque, of the participants by using the forces applied to the hand, hip and foot as inputs.

In hand force condition, significant errors occurred in the ankle torque estimation, which suggests that ankle joint torque is difficult to estimate using only force applied to handrail. In the same way, under the hand force condition, both knee and hip joint torque estimations failed to achieve high accuracy. Since the inverse dynamics calculations for torque estimation started from the foot segment, errors accumulated as the calculations progress from the distal to the proximal segments, leading to larger errors in the proximal segments. In other words, the errors increased on the order τ_{A}, τ_{K}, and τ_{H}. Due to the lower input dimensionality, the model was unable to learn parameters sufficient to follow the increased complexity and errors in τ_{K} and τ_{H} compared to τ_{A}.

In both conditions, ankle joint torque estimation accuracy was not high. A previous study [24] investigated that dorsiflexion of the ankle joint was necessary to facilitate STS motion. Pulling the feet backward and dorsiflexing the ankle joint shifts the center of gravity forward. However, in this study, participants used a handrail. By pulling the handrail toward themselves, they inclined their upper body forward, which allowed them to shift their center of gravity forward more easily. Therefore, a possible reason for the decreased accuracy in ankle joint torque estimation is that the maximum ankle torque values did not vary significantly among participants, resulting in no distinct relationship between the forces acting on the body and the ankle joint torque.

V. CONCLUDION

In this study, the maximum torque of the knee and hip joints during the STS motion of the elderly was accurately estimated from the forces applied to the buttocks, foot, and hands. This study enables a detailed assessment of the current lower limb function of elderly individuals simply by performing the STS motion.

As a future direction, we are considering the estimate of joint torques based solely on the force applied to the handrail. Measuring only the forces applied to the handrail is much easier than measuring forces applied to handrail, buttocks, and foot simultaneously. To facilitate clinical implementation and daily life applications, our goal is to estimate motor function by measuring only the force applied to the handrail.

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References

[1] M. R. Roos, C. L. Rice, and A. A. Vandervoort, "Age-related changes in motor unit function," *Muscle & Nerve*, vol. 20, no. 6, pp. 679–690, 1997.

[2] P. Diane and R. Sandra, "The timed "up & go": a test of basic functional mobility for frail elderly persons," *Journal of the American Geriatrics Society*, vol. 39, no. 2, pp. 142-148, Feb. 1991.

[3] M. E. Daubney and E. G. Culham, "Lower-extremity muscle force and balance performance in adults aged 65 years and older," *Physical Therapy*, vol. 79, no. 12, pp. 1177-1185, Dec. 1999.

[4] M. B. Van Iersel, M. Munneke, R. A. Esselink, C. E. Benraad and M. G. Olde Rikkert, "Gait velocity and the timed-up-and-go test were sensitive to changes in mobility in frail elderly patients," *Journal of Clinical Epidemiology*, vol. 61, no. 2, pp. 186-191, Feb. 2008.

[5] P. J. Friedman, D. E. Richmond and J. J. Baskett, "A prospective trial of serial gait speed as a measure of rehabilitation in the elderly," *Age and Ageing*, vol. 17, no. 4, pp. 227-235, Jan. 1988.

[6] Q. Lien, A. M. Galica, R. N. Jones, P.-G. Elizabeth, M. Brad, M. T. Hannan and L. A. Lipsitz, "The nonlinear relationship between gait speed and falls: the maintenance of balance, independent living, intellect, and zest in the elderly of boston study," *Journal of the American Geriatrics Society*, vol. 59, no. 6, pp. 1069-1073, Jun. 2011.

[7] I. Baltasar-Fernandez, J. Alcazar, C. Rodriguez-Lopez, J. Losa-Reyna, M. Alonso-Seco, I. Ara and L. M. Alegre, "Sit-to-stand muscle power test: comparison between estimated and force plate-derived mechanical power and their association with physical function in older adults," *Experimental Gerontology*, vol. 145, pp. 111213-111220, Mar. 2021.

[8] Y.-Y. Cheng, S.-H. Wei, P.-Y. Chen, M.-W. Tsai, I. C. Cheng, D.-H. Liu and C.-L. Kao, "Can sit-to-stand lower limb muscle power predict fall status?," *Gait & Posture*, vol. 40, no. 3, pp. 403-407, Jul. 2014.

[9] N. Gebruers, C. Vanroy, S. Truijen, S. Engelborghs, and P. P. De Deyn, "Monitoring of physical activity after stroke: a systematic review of accelerometry-based measures," *Archives of Physical Medicine and Rehabilitation*, vol. 91, no. 2, pp. 288–297, Feb. 2010.

[10] Y. Hutabarat, D. Owaki, and M. Hayashibe, "Quantitative gait assessment with feature-rich diversity using two imu sensors," *IEEE Transactions on Medical Robotics and Bionics*, vol. 2, no. 4, pp. 639–648, Jan. 2020.

[11] R. A. Clark, R. McGough, and K. Paterson, "Reliability of an inexpensive and portable dynamic weight bearing asymmetry assessment system incorporating dual Nintendo Wii Balance Boards," *Gait & Posture*, vol. 34, no. 2, pp. 288–291, Jun. 2011.

[12] D.-S. Park and G. Lee, "Validity and reliability of balance assessment software using the nintendo wii balance board: usability and validation," *Journal of Neuroengineering and Rehabilitation*, vol. 11, no. 1, p. 99, Jun. 2014.

[13] J. Bai and A. Song,"Development of a novel home based multi-scene upper limb rehabilitation training and evaluation system for post-stroke patients," *IEEE Access*, vol. 7, pp. 9667–9677, 2019.

[14] Q. An, N. Yang, H. Yamakawa, H. Kogami, K. Yoshida, R. Wang, A. Yamashita, H. Asama, S. Ishiguro, S. Shimoda, H. Yamasaki, M. Yokoyama, F. Alnajjar, N. Hattori, K. Takahashi, T. Fujii, H. Otomune, I. Miyai and R. Kurazume, "Classification of motor impairments of post-stroke patients based on force applied to a handrail," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 2399-2406, 2021.

[15] R. Kihara, Q. An, K. Takita, S. Ishiguro, K. Nakashima and R. Kurazume, "Analysis of force applied to horizontal and vertical handrails with impaired motor function," *In Proceedings of the 2023 IEEE/SICE International Symposium on System Integration (SII)*, pp. 1-6, Jan. 2023.

[16] R. Frischknecht, "Effect of training on muscle strength and motor function in the elderly," *Reproduction, Nutrition, Development*, vol. 38, no. 2, pp. 167-174, 1998.

[17] M. A. Hughes, B. S. Myers and M. L. Schenkman, "The role of strength in rising from a chair in the functionally impaired elderly," *Journal of Biomechanics*, vol. 29, no. 12, pp. 1509-1513, Dec. 1996.

[18] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735-1780, Jan. 1997.

[19] F. Lauretani, C. R. Russo, S. Bandinelli, B. Bartali, C. Cavazzini, A. Di Iorio, A. M. Corsi, T. Rantanen, J. M. Guralnik and L. Ferrucci, "Age-associated changes in skeletal muscles and their effect on mobility: an operational diagnosis of sarcopenia," *Journal of Applied Physiology*, vol. 95, no. 5, pp. 1851-1860, Nov. 2003.

[20] G. Jocher, A. Chaurasia and J. Qiu, "Ultralytics YOLOv8." Available: https://github.com/ultralytics/ultralytics, 2023, Version 8.0.0, License: AGPL-3.0, ORCID: 0000-0001-5950-6979, 0000-0002-7603-6750, 0000-0003-3783-7069.

[21] Anthropology Staff and Webb Associates, "Anthropometric source book: volume 1: anthropometry for designers." NASA, NASA RP-1024, Jul. 1978.

[22] E. Churchill, J. T. McConville and Webb Associates, "Sampling and data gathering strategies for future USAF anthropometry." Aerospace Medical Research Laboratory, Wright-Patterson Air Force Base, OH, 1976. Available: https://apps.dtic.mil/sti/tr/pdf/ADA025240.pdf

[23] D. A. Winter, Biomechanics and motor control of human movement (4th ed.), Hoboken, NJ: John Wiley & Sons Inc., 2009.

[24] S. R. Lord, S. M. Murray, K. Chapman, B. Munro, and A. Tiedemann, "Sit-to-stand performance depends on sensation, speed, balance, and psychological status in addition to strength in older people," *The Journals of Gerontology: Series A*, vol. 57, no. 8, pp. M539-M543, Aug. 2002.

[25] B. R. Deshpande, J. N. Katz, D. H. Solomon, E. H. Yelin, D. J. Hunter, S. P. Messier, L. G. Suter and E. Losina, "Number of persons with symptomatic knee osteoarthritis in the US: impact of race and ethnicity, age, sex, and obesity," *Arthritis Care & Research*, vol. 68, no. 12, pp. 1743-1750, 2016.