Journal of Systemics, Cybernetics and Informatics (2022) 20(4), 34-39
https://doi.org/10.54808/JSCI.20.04.34

Gait Analysis Method Focused on Skeleton Pose Estimation Using Wheeled Gait-Training Walker

Hidehisa NAKAYAMA, Kazutoshi OGAWA, and Tsugito MARUYAMA
Electrical and Electronic Engineering, Tohoku Institute of Technology
Sendai, Miyagi, 982-8577, Japan

ABSTRACT[1]

We studied a gait analysis method focusing on skeleton pose estimation based on videos taken during gait-training with a wheeled walker for a person with a case history. For skeleton pose estimation, OpenPose was used. Thirteen gait parameters were designed from the extracted keypoints considering the opinions of some rehabilitation staff. As a result, we found a correlation between the load balance of a left-right elbow and the stability of a left-right posture. This suggests that the stability of walking can be evaluated by training with our developed wheeled walker.

Keywords: Gait Analysis, Skeleton Pose Estimation, Gait-Training, Wheeled Walker.

1. INTRODUCTION

In Japanese Journal for fall prevention [1], it has been reported that the average annual incidence of falls among elderly people aged 65 and over at home is about 20 percent. There are the risk factors of falling in the older persons, include lower legs muscle weakness, gait deficit, and balance deficit [2]. When focusing on the balance deficit, there is no difference in the front-back direction, while the center of gravity sway is significantly larger in the left-right direction, comparing the elderly people and the young [3]. In addition, it has been reported that postural stability in the left-right direction is important in predicting the risk of future falls in the elderly [4].

Since gait-training is necessary to prevent falling down due to muscle weakness, many people go to rehabilitation salons. Currently, the effectiveness of rehabilitation is determined empirically by skilled rehabilitation staff. Understanding gait assessment, it is necessary to design appropriate evaluation indicators rather than empirical knowledge. In order to establish a quantitative evaluation method for gait functions, we have modified a commercial wheeled walker and have developed the gait-training walker for a rehabilitation that incorporate a load measurement mechanism [5-6]. This walker is capable of measuring the support load of elbows and hands. First, as our first goal, we chose to evaluate the stability in the left-right direction among the walking functions, and studied the parameter of left-right load ratio, that represents the left-right load balance of elbows and hands on the walker in [7].

Next, in this paper, we studied a method of gait analysis using the video taken during gait-training, instead of the conventional method of gait analysis using various sensors attached person. In the gait analysis, we focused on skeleton pose estimation using OpenPose [8]. With the opinions of some rehabilitation staff, thirteen gait parameters were designed based on the extracted 25 keypoints Finally, postural stability was discussed by analyzing the data acquired in actual walking. As a result, it was found that there was a correlation between the load balance of a left-right elbow and the stability of a left-right posture.

2. LOAD MEASUREMENT SYSTEM FOR GAIT-TRAINING WALKER

Fig. 1 shows the configuration of the load measurement system for wheeled gait-training walker that we have developed until now [5-7]. To measure the load applied to the elbows and hands, we modified a commercial wheeled walker and attached load cells to the elbow and hand supports for both the left and right sides. Assuming that W_L and W_R represent the left and right loads, respectively, the parameter of left-right load ratio “Blr” is defined by the following Eq. (1).

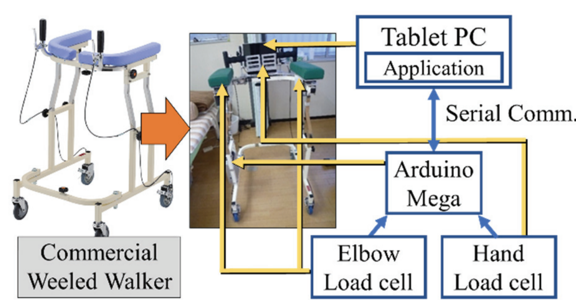


Fig. 1: Configuration of the developed wheeled walker with load measurement function

[1] The authors wish to thank our non-anonymous, peer reviewer, Prof. Toyomi Fujita.

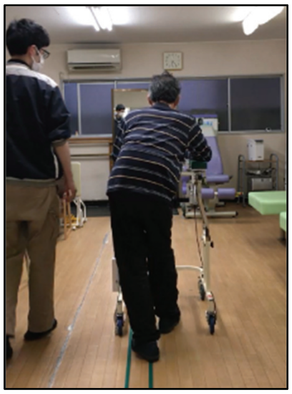


Fig. 2: Gait-training accompanied by rehabilitation

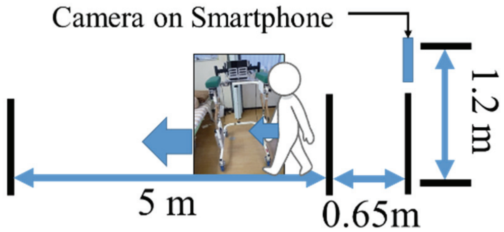


Fig. 3: Layout of gait-training course and position of camera on smartphone

$$\mathrm{Blr} = \frac{\min\{W_L, W_R\}}{\max\{W_L, W_R\}} \qquad (0 \leqq \mathrm{Blr} \leqq 1) \qquad (1)$$

As shown in Fig. 2, the person can refer to the tablet PC when performing gait-training accompanied by rehabilitation staff. The tablet PC is equipped with a special our own application, where the load evaluation values are displayed. Af ter gait-training, the graph of load changes is displayed, which can be used as a reference for reviewing rehabilitation methods and for motivating the trainee. In addition, since the measurement data is sequentially saved as a CSV file, it is possible to accumulate data and see long-term changes.

3. GAIT ANALYSIS METHOD FOCUSED ON SKELETON POSE ESTIMATION

Setting of taking videos on gait-training

We received the cooperation of Rehabilitation Salon Rakudou Nagamachi in Sendai as a place for gait-training. Three subjects who attend the salon are Mr. A (Parkinson's disease), Mr. B, and Mr. C (both with Hemiplegia). This cooperation was approved by the Ethics Committee of Tohoku Institute of Technology. During this gait-training, as shown in Fig. 2, the rehabilitation staff stayed with the subject. As shown in Fig. 3, they walked a 5-meter straight section using the gait-training walker.

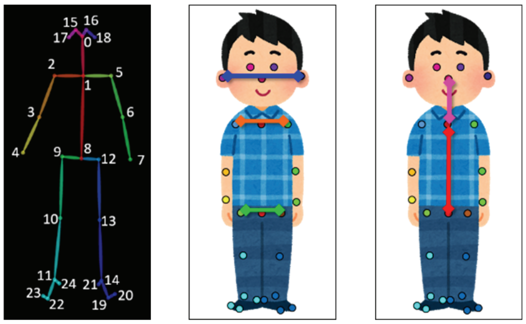
Table 1: Gait angle parameters

No.	Name	Line from two points	Body parts
1	Ear	Left-right ears	Head (horizontal)
2	Shoulder	Left-right shoulders	Shoulder
3	Hip	Left-right hips	Whole Hip
4	NeckNose	Neck and Nose	Head (vertical)
5	HipNeck	Middle Hip and Neck	Stem
6	LAnkleHip	Ankle and Hip (left)	Lower limb
7	RAnkleHip	Ankle and Hip (right)	Lower limb
8	LHeelHip	Heel and Hip (left)	Lower limb
9	RHeelHip	Heel and Hip (right)	Lower limb
10	LKneeHip	Knee and Hip (left)	Thigh
11	RKneeHip	Knee and Hip (right)	Thigh
12	LAnkleKnee	Ankle and Knee (left)	Lower leg
13	RAnkleKnee	Ankle and Knee (right)	Lower leg

Conventional gait analysis methods include research on objective evaluation indices for gait abnormality using acceleration sensors and research on the relationship between the amount of left right sway due to differences in gait and the amount of physical activity by applying motion capture gait analysis to elderly people. However, these studies require the physical stress on the subjects and the burden on a staff when preparing for the measurement, since the accelerometers and markers need to be worn on a body.

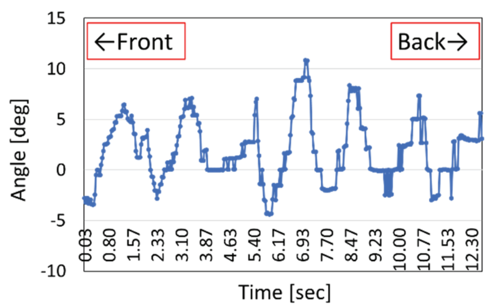
Body image recognition using a camera has the advantages of low physical stress, low preparation time, and low financial cost by using a built-in smart phone or a web camera. Therefore, we used a camera built into a smartphone as a recognition sensor, as shown in Fig. 3.

In a previous study [9], they use videos recorded from patient's walking tests in the diagnosis of gait disorders in order to extract the coordinates of the joints of the patient over time, while importing OpenPose results. In [10], OpenPose was applied to videos taken from the side while walking to determine the risk of falling. Therefore, we intend to measure the stability of a left-right posture and extract the skeleton pose estimation from videos using OpenPose. Because of the limited size of the room in the rehabilitation facility, we set the camera not from the side but in the same line with the walking direction. And more we took videos from the front or the rear, so that the subject person would be on the central axis of the screen.



(a) (b) (c)

Fig. 4: 25 keypoints by OpenPose
(a) BODY_25 model
(b) Lines of Ear, Shoulder, Hip
(c) Lines of NeckNose, HipNeck



Targeted area become smaller →

Fig. 5: Time-series variation of the gait angle parameter "Shoulder"

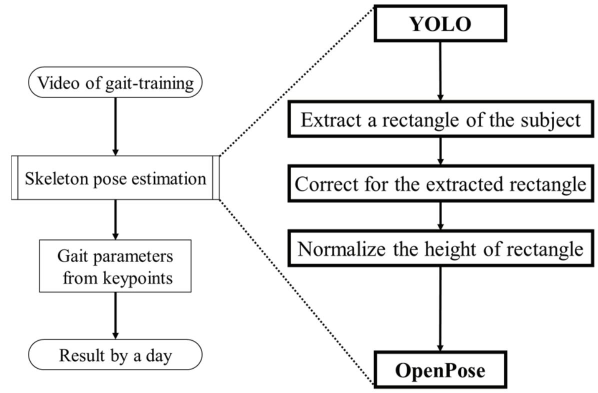
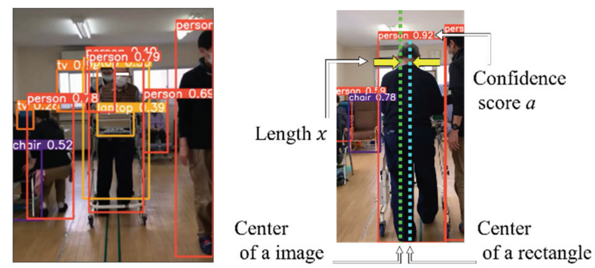


Fig. 6: Flow of skeleton pose estimation about a video of gait-training



(a) (b)

Fig. 7: (a) Objects detected by YOLO
(b) Settings for calculating EID

Gait parameters from skeleton pose estimation

By using the BODY_25 model of OpenPose, we can estimate coordinates of 25 keypoints (see Fig. 4a). Extracted keypoints are important joints of skeleton pose. With the opinions of some rehabilitation staff, thirteen gait parameters were designed, as shown in Table 1. These gait parameters represent the characteristics of the gait. Here, we observe the angular about 13 gait parameters (specifically named as the gait angle parameter). Furthermore, from the time series of a gait parameter within the measurement time, we select the five features, that are most relevant to the stability of a left-right posture, are used such as Ear, Shoulder, Hip, NeckNose, and HipNeck (see Fig. 4b and 4c). We used the Fast Fourier Transform (FFT) algorithm to obtain the first-order power density in the frequency spectrum and used it as the feature of amplitude (referred to as the gait amplitude parameter).

Proposed method

When we set the camera in a straight line with respect to the subject's walking direction, the subject's movement causes the area of the object to shrink and the resolution to decrease. Therefore, as shown in Fig. 5, an example of the time-series variation of the gait angle parameter "Shoulder", the continuity (smoothness) of this graph is lost as the subject moves toward the back. In other words, the continuity of the parameters is lost in response to the loss of smoothness of the video.

In this paper, we propose a method for skeleton pose estimation (the flow is shown in Fig. 6). When we take a video of the subject moving along a linear course, the individual image frames shrink as they get farther from the camera. Thus, the gait parameters may not be sufficiently extracted due to the resolution reduction. Therefore, using YOLO (the object detection method [11]), it is possible to construct an appropriate time series of gait parameters within the measurement time by correctly selecting subjects and normalizing the selected images.

Extracting a Rectangle of the subject: In the rehabilitation facility, many staffs and others come and go frequently. First, the object detection method YOLO extracts the candidate rectangles of the subject. This is because YOLO is one of the most famous object detection algorithms in real-time. The output of YOLO is the candidate rectangles and their confidence scores. Fig. 7a shows an actual detection example, and we can see that a person other than the subject is generated as a candidate rectangle. Therefore, as shown in Fig. 7b, the length from

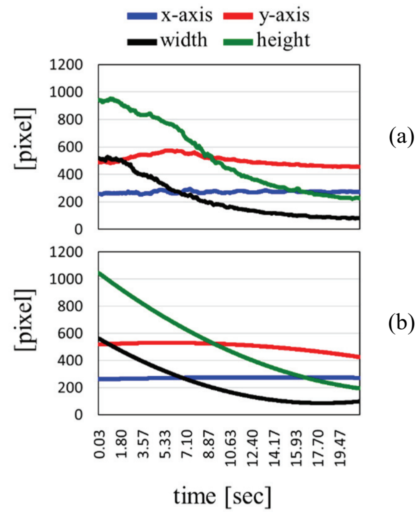


Fig. 8: Sizes and coordinates of a rectangle
(a) Discontinuous curve (b) Approximating with a quadratic function

the center axis of the image to the center axis of a detected person's rectangle is x, the confidence score of a rectangle is a ($0 \le a \le 1$), and the extraction index " EID" of the subject is defined by the following Eq. (2).

$$\mathrm{EID} = x + (1 - a) \times C \qquad (2)$$

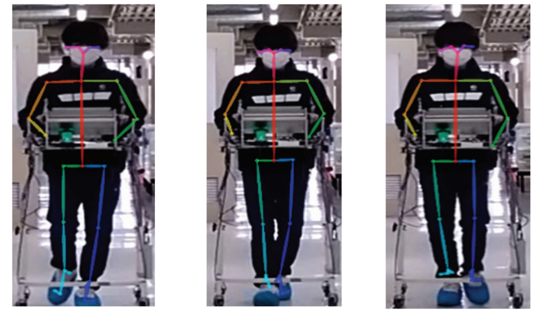
Where C is a constant that is adjusted according to the resolution of the video, candidate rectangles, are closer to the central of an image and have a higher confidence score of YOLO simultaneously, will have a smaller value of this index. Therefore, the rectangle with the smallest value of this index is set as the subject, and we proceed to the next step.

Normalizing the height of rectangle: The sizes and coordinates of rectangles obtained in the previous step are discontinuous (Fig. 8a). However, since gait-training is a continuous event, the sizes and positions should be continuous values within the measurement time. Therefore, we propose to correct this positional shift by approximating the sizes and positions of rectangles with a quadratic function (Fig. 8b). This completes the pre-processing to select the subject correctly. In preparation for the analysis by OpenPose, we normalize the height of the corrected image.

In the following process, we can estimate coordinates of 25 keypoints by the BODY_25 model of OpenPose and extract the gait parameters, shown in the first half of this paragraph.

4. RESULTS OF GAIT ANALYSIS

Example of the gait angle parameters on the training



(a) 4.1s (b) 4.4s (c) 4.7s

Fig. 9: Walking images and skeleton estimations during training

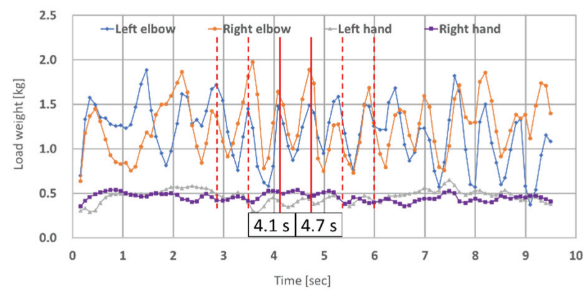


Fig. 10: Time-series changes about the elbow load and hand load in upright posture

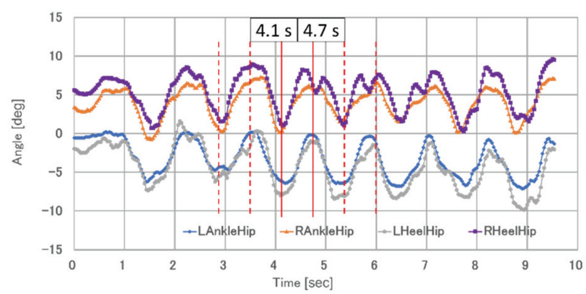


Fig. 11: Time-series changes about gait angle parameters

As an example, walking images and skeleton estimations during our staff's gait training are shown in Fig. 9. Then, a time-series graph of the elbow load and hand load in the upright posture is shown in Fig. 10, and the waveforms of the time-series changes in the gait angle parameters of the left and right AnkleHip and HeelHip, which are the inclination of the lower body, are shown in Fig. 11. In Fig. 10 and Fig. 10, six auxiliary lines have been added at about 3 to about 6 seconds for illustrative purposes.

The change in load shows that the left and right elbow loads increased and decreased simultaneously, indicating that the change in load was caused by the shift of the center of gravity. At 4.1 s, the moment when the trainee puts the right foot forward, the elbow load increases while the

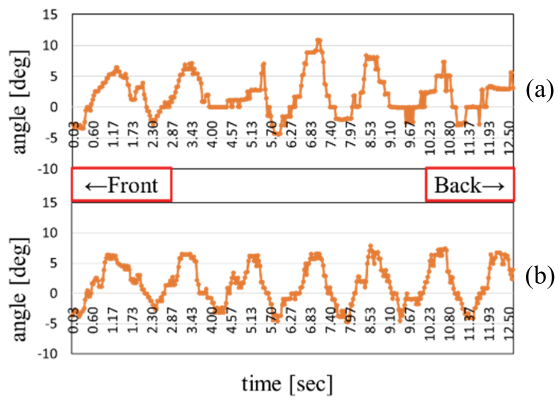


Fig. 12: Gait angle parameter of Shoulder
(a) Conventional method (b) Proposed method

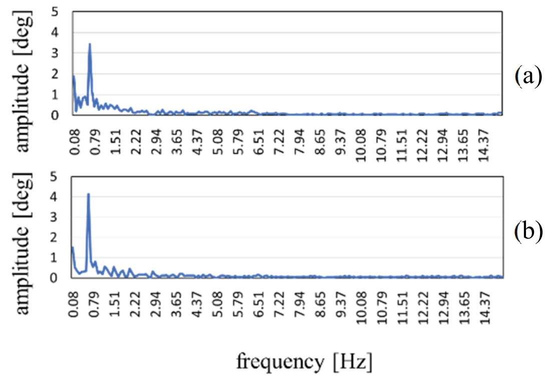


Fig. 13: Frequency spectrum of Shoulder
(a) Conventional method (b) Proposed method

angles of the AnkleHip and HeelHip decrease. At 4.7 s, the moment when the trainee brings the left foot forward, the angles of the AnkleHip and HeelHip decrease while the elbow load increases. However, the elbow load decreased once at 4.4 s between 4.1 s and 4.7 s. The increase and decrease were repeated at half the cycle of the increase and decrease of the AnkleHip and HeelHip angles. This indicates that the elbow load increases when the foot is brought forward and decreases when the foot is stepped down. In other words, the elbow load increases when the foot is brought forward to support the weight on the shaft foot, and then the elbow load decreases when the foot reaches the ground, because the weight can be supported by both feet. In conclusion, it was possible to obtain the gait angle parameters from the training videos using a walking car by analyzing the videos using skeletal estimation, and to visualize the gait state by expressing the changes in the obtained gait angle parameters as a waveform.

Example of the frequency spectrum on the training
Fig. 12 compares the conventional and proposed methods for the time series of Shoulder, a gait angle parameter, about Mr. B. It can be seen that the proposed method suppresses the collapse of the waveform and the periodic motion is clearer. Fig. 13 then shows the frequency spectrum of the waveform (Shoulder) in Fig. 12 and compares the conventional and proposed methods. The power density of the first order of the proposed method is larger than the first of the conventional method. In other words, we can also see that the power density of the other orders is less compared to the first order on the proposed method.

On the frequency spectrum of the waveform (Shoulder), each integrated value was divided into signal component (low frequency) and noise component (high frequency), and the signal-to-noise ratio was calculated with a threshold value of 5[Hz]. For example, for the waveform (Shoulder) shown in Fig. 14, the S/N ratio was 3.33[dB] for the conventional method and 4.21[dB] for the proposed method. Moreover, for the time series of five gait angle parameters, the S/N ratios of the conventional and proposed methods were calculated. For Mr. B, we averaged 8 days of gait-training data from Feb. 2021 to Apr. 2021, the calculated results are shown in Table 2. The S/N ratios of the conventional and the proposed methods were calculated for the time series of the five gait angle parameters, and the results showed that all the parameters improved by more than 0.8[dB].

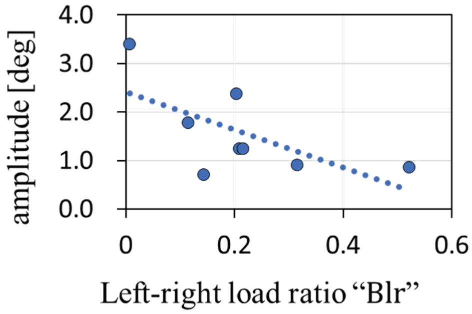
Correlation between load ratios and gait parameters
Fig. 13 shows the correlation graph between the left-right load ratios and the gait amplitude parameters. By calculating the correlation coefficient between two metrics, as a result in Fig. 14, the values of (a) -0.64, (b) -0.56, (c) -0.61 were obtained respectively, indicating that there was a somewhat correlation.

5. CONCLUSION

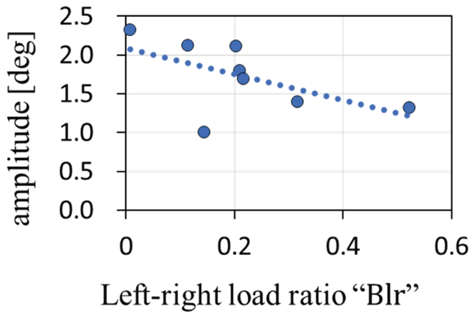
In this paper, we proposed a gait analysis method for gait-training using a wheeled walker by using the video taken during gait-training. We proposed the extraction index to extract a subject from the YOLO results, and devised the method to obtain good gait parameters with OpenPose by continuously changing sizes and coordinates of a rectangle generated by normalization. The experimental results showed that the proposed method improved the S/N ratio of the gait amplitude parameters.

Table 2: Comparison of S/N ratios of the conventional and the proposed methods

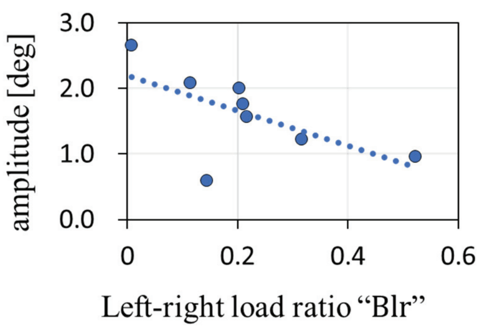
No.	Name	Conventional [dB]	Proposed [dB]
1	Ear	2.36	3.17
2	Shoulder	3.33	4.21
3	Hip	1.22	2.19
4	NeckNose	2.94	4.68
5	HipNeck	3.84	4.77



(a) “Shoulder” amp. vs. “Blr”



(b) “Hip” amp. vs. “Blr”



(c) “HipNeck” amp. vs. “Blr”

Fig. 14: Comparison results about 3 gait amp.

We believe that we have found the possibility to evaluate the left-right postural stability both by measuring the load measurement and by analyzing images with our developed wheeled walker, and we plan to increase the number of training days and the number of subjects in the future.

ACKNOWLEDGEMENTS

We would like to acknowledge Mr. Shinya Seko and his staffs from “Rehabilitation Salon Rakudou Nagamachi” for facilitating our access to the data in gait-training and taking videos. This work was supported by on-campus public offering fund of Tohoku Institute of Technology at 2021.

REFERENCES

[1] Y. Otaka, Fall Prevention in Older People: Present and Future Perspectives, **Japanese Journal for Fall Prevention**, Vol. 1, No. 3, 2015, pp. 11-20.

[2] “Guideline for the prevention of falls in older persons. American Geriatrics Society, British Geriatrics Society, and American Academy of Orthopaedic Surgeons Panel on Falls Prevention”, **Journal of the American Geriatrics Society**, Vol. 49, No. 5, 2001, pp. 664-672.

[3] T. Ikai, H. Tatsuno, and S. Miyano, Relationship between Walking Ability and Balance Function, **Japanese Journal of Rehabilitation Medicine**, Vol. 43 No. 12, 2006, pp. 828-833.

[4] B. Maki, P. Holliday, and A. Topper: A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population, **Journal of Gerontology**, Vol. 49, No.2, 1994, pp. 72-84.

[5] K. Tamiya, D. Chiba, and T. Maruyama, “A Basic Study of the Evaluation of Functional Training Using Wheeled Walker for Rehabilitation Part 1: A Study of Load Measurement Method”, **2019 Tohoku-region young researchers research conference, Japan**, YS-17-P13, 2019.

[6] D. Narisawa, T. Mori, K. Suzuki, and T. Maruyama, “A Basic Study of the Evaluation of Functional Training Using Wheeled Walker for Rehabilitation Part 3: Examination of the Whole System and the Hand Load Measurement Method”, **2020 Tohoku-region young researchers research conference, Japan**, R2-D-1, 2020.

[7] K. Ogawa, T. Maruyama, and H. Nakayama, “A Study of the Evaluation of Gait-Training Using Wheeled Walker with Load Measurement Function”, **2021 Tohoku-section joint convention of institutes of electrical and information engineers, Japan**, 4D-04, 2021.

[8] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh, “OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields”, **IEEE Trans. on PAMI**, Vol. 43, Issue 1, pp. 172-186, 2021.

[9] S. Esmaeilzadeh, O. Khebzegga, and M. Moradshahi, Clinical Parameters Prediction for Gait Disorder Recognition, arXiv preprint arXiv:1806.04627, 2018.

[10] T. Konnno, M. Chikano, F. Tomiyasu, and S. Awai, Gait Training Support System for Improving the Fall Risk Using a Contactless Sensor, **Journal of the Institute of Image Electronics Engineers of Japan**, Vol. 50, No. 1, 2021, pp. 169-176.

[11] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection”, **Proc. of the IEEE conf. on CVPR**, pp. 779-788, 2016.