Development of Caregiving Posture Load Assessment System by Skeleton Vision

Xin Han[1], Zhongwei Jiang[1]*, Yunjin Zhang[1],
Norihiro Nishida[2], Mao Mitsuda[2], Takeshi Nishimoto[2], Takashi Sakai[2]
Graduate School of [1]Sciences and Technology for Innovation,
[2]Medicine, Yamaguchi University, Yamaguchi, Japan
jiang@yamaguchi-u.ac.jp

Abstract: As Japan's aging population intensifies, the demand for caregiving services is steadily increasing. Caregiving has placed a heavy physical burden on caregivers, and many caregivers suffer from occupational diseases. Aiming at the problem that incorrect caregiving posture is likely to cause back pain and caregiving postural load is difficult to assess, we developed an end-to-end computer vision-based automatic caregiving postural load assessment system. The system uses depth camera data as input, and the OPENPOSE algorithm is used to recognize the dynamic human body and obtain human skeletal information. The skeletal information is computed and integrated and mapped to the REBA load assessment framework to obtain a postural load score. The experiment results demonstrate that the system is capable of capturing caregiver skeletal feature information from depth camera video data. The feature information is fed into the REBA framework for body load assessment, and the assessment results are aligned with the difficulty of the posture. The greatest advantage of the system is its simplicity and speed, and in a non-contact data acquisition manner that avoids work disruptions to the caregiving process.

Key-Words: *OPENPOSE; REBA; Caregiving; body load assessment*

1. Introduction

According to the simplified life expectancy table for 2020 released by the Ministry of Health, Labour and Welfare, the average life expectancy in Japan is 81.47 years for men and 87.57 years for women, which is the highest ever [1]. According to the Cabinet Office announcement [2], as of October 1, 2018, 28% of the total population in Japan is over 65 years old and the total population of Japan is in a long-term decreasing trend. According to the survey report of the Japan Population and Social Security Research Institute [3], the total population of Japan will fall below 100 million in 2053, and the number of people over 65 years old will continue to increase. The "aging society" has become one of the most important challenges for Japan. With the development of an aging society, the number of people who need caregiving for those with mobility problems will increase as the number of elderly people increases. The number of people who need caregiving is 6.76 million. However, the number of caregivers is 2.11 million, which is much lower than the number of people in need of care. Despite the high demand for caregiving work, the resignation rate is 14.2%. According to a survey by the Japan Institute of Medical Sciences, 24% of caregiving staff are considering retirement due to occupational diseases, and low back pain is one of the reasons why there is fewer caregiving staff [4]. The health and sanitation industry has taken various

Received: 2022/12/13, Accepted: 2023/04/21
*Corresponding author: Zhongwei Jiang
E-mail address: jiang@yamaguchi-u.ac.jp

measures against low back pain. The Central Industrial Accident Prevention Association of the Ministry of Health, Labour and Welfare has developed a "back pain prevention checklist for caregivers" to learn in advance what kind of behaviors may lead to back pain diseases [5]. However, 70% of caregivers answered that they were unable to obtain the correct posture for caregiving [6]. Therefore, reducing the burden of caregivers with a proper caregiving posture is an important issue.

With the development of human posture algorithm techniques, image processing, and computer vision have gradually become the mainstream techniques for analyzing human posture and load. Li et al [7] constructed a simple load assessment system with contact posture capture sensors and computer vision techniques, but the system relied on skeletal posture data from the contact sensors. Our research is aimed at the posture assessment of caregiving staff. Contact sensors will have an impact on caregiving staff, and the operation of contact sensors is complex, so the system is not suitable for posture load assessment in caregiving analysis. At present, researchers have proposed many non-contact pose estimation algorithms, among which OPENPOSE [8] is a convolutional neural network algorithm that uses a partial affinity domain to estimate human pose, and the algorithm is highly open source. Therefore, we will adopt the OPENPOSE algorithm to build a non-contact postural load assessment system. Considering that caregiving will involve the skeletal muscles of the whole body, inspired by the Rapid Entire Body Assessment (REBA) [9] method, we quantify the body load of caregiving according to the REBA framework. The depth camera will serve as the data input and the load assessment system will incorporate the OPENPOSE algorithm to capture caregiving postures, then parse dynamic skeletal information, and finally visualize the postural load quantification results. The caregiving posture quantification and visualization provide caregivers with an intuitive posture load reference, and postures with high load scores can be adjusted in time.

2. Method

2.1 REBA

Rapid Entire Body Assessment (REBA) is an assessment method for work-related musculoskeletal disorders, which consists of two parts. Part 1 consists of the neck, trunk and legs, and the scores for each joint are combined using table A of the REBA worksheet to obtain individual values. Different angles of extension for each joint will result in different scores. For example, to obtain a score for part 1, the scores for the trunk, legs and neck need to be assessed separately. The assessed scores and joint angles are shown in Fig 1. The scores obtained for each part are then brought into Table A and matched to obtain the scores for the joint angles, and the scores associated with the postural load are added to obtain the final scores of Part 1. Part 2 consists of the upper arm, lower arm, and wrist, and the scores are summarized using Table B in the REBA worksheet. To obtain the scores for Part 2, the scores for the upper arm, lower arm, and wrist are evaluated separately. The scores obtained for each section are then brought into Table B and matched to obtain the scores for the joint angles in Section 2. The scores related to the ease of coupling are then added to obtain the final scores for Part 2.

The scores for Part 1 and Part 2 will be entered into Table C for integration. The final REBA load score is obtained by adding the additional action type-related scores. This is shown in Fig 2.

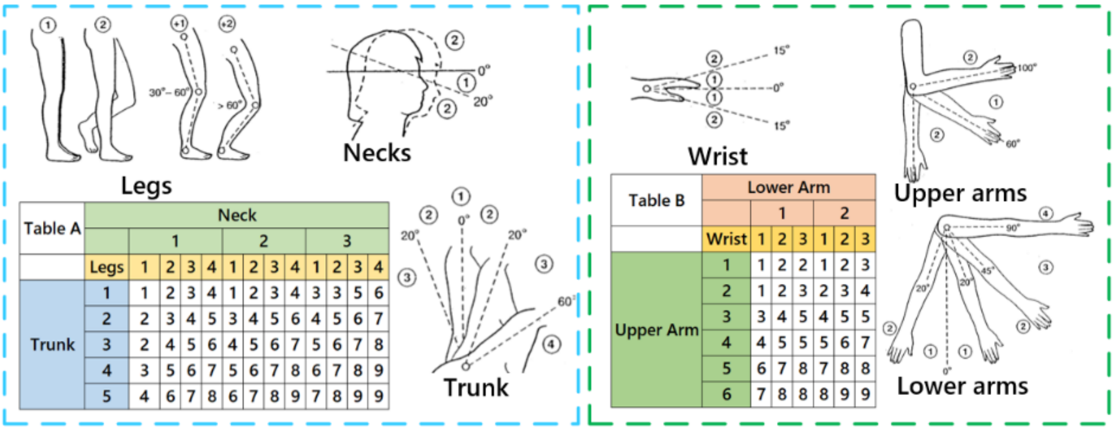

Table A	Neck	1				2				3			
	Legs	1	2	3	4	1	2	3	4	1	2	3	4
Trunk	1	1	2	3	4	1	2	3	4	3	3	5	6
	2	2	3	4	5	3	4	5	6	4	5	6	7
	3	2	4	5	6	4	5	6	7	5	6	7	8
	4	3	5	6	7	5	6	7	8	6	7	8	9
	5	4	6	7	8	6	7	8	9	7	8	9	9

Table B	Lower Arm	1			2		
	Wrist	1	2	3	1	2	3
Upper Arm	1	1	2	2	1	2	3
	2	1	2	3	2	3	4
	3	3	4	5	4	5	5
	4	4	5	5	5	6	7
	5	6	7	8	7	8	8
	6	7	8	8	8	9	9

Fig 1. Joint extension angle assessment scores

This figure is from literature [9] to illustrate the REBA scoring details.

Table C	Score B											
Score A	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	2	3	3	4	5	6	7	7	7
2	1	2	2	3	4	4	5	6	6	7	7	8
3	2	3	3	3	4	5	6	7	7	8	8	8
4	3	4	4	4	5	6	7	8	8	9	9	9
5	4	4	4	5	6	7	8	8	9	9	9	9
6	6	6	6	7	8	8	9	9	10	10	10	10
7	7	7	7	8	9	9	9	10	10	11	11	11
8	8	8	8	9	10	10	10	10	10	11	11	11
9	9	9	9	10	10	10	11	11	11	12	12	12
10	10	10	10	11	11	11	11	12	12	12	12	12
11	11	11	11	11	12	12	12	12	12	12	12	12
12	12	12	12	12	12	12	12	12	12	12	12	12

Table C + Activity Score = REBA Score

Fig 2. Table C Load Score Matching Rules

This figure is from literature [9] to illustrate the REBA scoring details.

REBA scores range from 1 to 12, with higher REBA scores representing greater physical load. These scores and the associated action levels are shown in Table 1. According to the REBA movement level table, the caregiver can be aware of the body load level of the posture, and adjust the incorrect or high load level posture in time to avoid prolonged maintenance of high-risk posture for causing musculoskeletal disorders. Detailed scoring rules can be found in the literature [2].

Table 1 REBA action levels

Action Level	REBA Score	Risk level	Correction Suggestion
0	1	Negligible	None necessary
1	2-3	Low	May be necessary
2	4-7	Medium	Necessary
3	8-10	High	Necessary soon
4	11-15	Very high	Necessary NOW

2.2 OPENPOSE skeleton angle calculation

OPENPOSE [3] is an open-source library for human skeleton recognition based on convolutional neural networks and the CAFFE framework developed at Carnegie Mellon University (CMU). The algorithm enables human skeletal motion capture, facial expression and hand motion pose estimation. OPENPOSE skeletal feature recognition is shown in Fig 3, which contains a total of 24 nodes. The output results are json files, and each json contains the pixel coordinate information of the 24 joints.

0	Nose	12	LHip
1	Neck	13	LKnee
2	RShoulder	14	LAnkel
3	RElbow	15	REye
4	RWrist	16	LEye
5	LShoulder	17	REar
6	LElbow	18	LEar
7	LWrist	19	LBigToe
8	MidHip	20	LSmallToe
9	RHip	21	LHeel
10	RKnee	22	RBigToe
11	RAnkle	23	RSmallToe
		24	RHeel

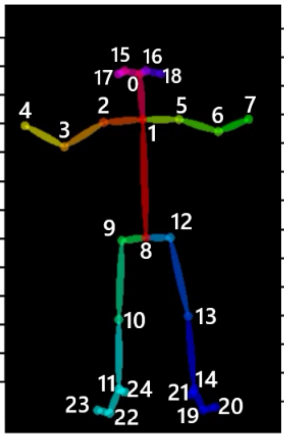

Fig 3. OPENPOSE skeletal feature recognition information

According to the REBA scoring rules, different joint angles have different load scores, so the calculation of joint angles can be implemented from the OPENPOSE level to obtain the corresponding load score. The calculation of the joint angle follows the trigonometric function theorem. Take the calculation of the leg angle as an example, as shown in Fig 4.

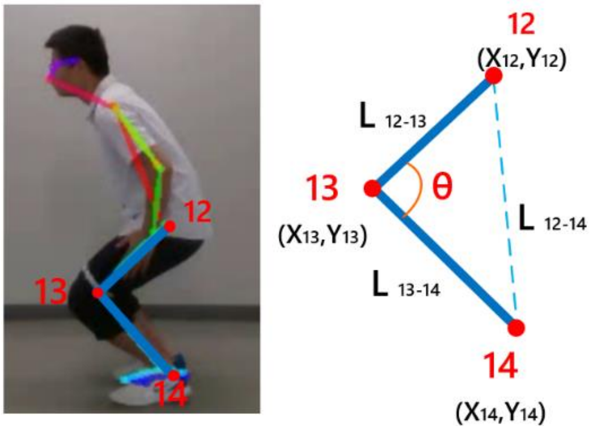

Fig 4. Calculation of joint point angle

To calculate the leg angle θ, it can be calculated from the joint points 12, 13 and 14. The pixel coordinates X and Y values of the three joint points can be obtained in the json file. The mathematical formula for the leg angle is shown below.

$$L_{12\text{-}13} = \sqrt{\left(x_{12} - x_{13}\right)^2 + \left(y_{12} - y_{13}\right)^2} \tag{1}$$

$$L_{13\text{-}14} = \sqrt{\left(x_{13} - x_{14}\right)^2 + \left(y_{13} - y_{14}\right)^2} \tag{2}$$

$$\theta = \operatorname{acos}\left(\frac{L_{12-13}}{L_{13-14}}\right) \tag{3}$$

Where $L_{12\text{-}13}$ represents the joint length between joint point 12 and joint point 13, and $L_{13\text{-}14}$ and $L_{12\text{-}14}$ are the same [4].

3. Experiments and results

3.1 Experimental settings

In the experiments, all system development tasks are executed on the TensorFlow framework, and the programming language environment version is configured as python 3.7. The experimental hardware environment uses RTX 2080 GPU, Intel i7-7700 CPU, and PyCharm Community 2021 is the mainstream development tool. In the data acquisition process, we used the depth camera Realsense as the visual data input, the camera was placed parallel to the coronal or sagittal plane of the human body, and the camera shooting distance was 3 meters.

To verify the effectiveness of the postural load assessment system. We designed a two-stage experiment based on the ease of postural loading. Experiment 1 is a common posture in our daily life. We choose two actions of using a vacuum cleaner and lifting a box and use different postures to complete the same task to verify whether the assessment is effective. Experiment 2 aimed at caregiving work as the research goal. We selected the patient transfer task in caregiving work, and also, we invited a professional caregiver to participate in the simulated patient transfer experiment. At the same time, an inexperienced person was also invited to participate in the simulated patient transfer experiment as a comparison group. Experiment 1 and Experiment 2 are shown in Fig 5.

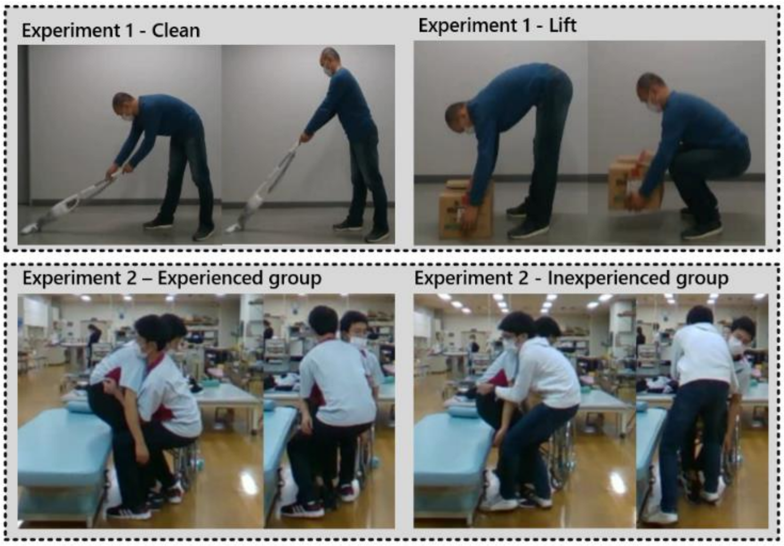

Fig 5. Postural Load Assessment Experiment 1 and Experiment 2

Fig 6. Postural load assessment results of the Clean group and Lift group in Experiment 1

3.2 Results Analysis

In the experiment 1-Clean group, the experimenter used a vacuum cleaner to clean, and in experiment 1-Lift group, the experimenter lifted the box to a certain height and then put it back. In each group, group A and group B were additionally set up as a comparative experiment, in which the posture of group A was prone to cause musculoskeletal disease, and the posture of group B was less related to musculoskeletal disease. The processing effect of the postural load assessment system on Experiment 1 is shown in Fig 6, and the postural load score is displayed in real-time in the upper left corner of the video.

From the results of Experiment 1, it can be seen that in the Clean group, if their waists maintain a large bending angle when using a vacuum cleaner for cleaning, the load on the waist will increase, and long-term standing in this posture will cause musculoskeletal diseases. Postural load scores showed that the Clean-A group had a larger postural load score than the Clean-B group, it proved that the posture of the Clean-B group had less impact on the body, which met the criteria for predicting postural load and musculoskeletal disease risk. According to the scoring results, when using a vacuum cleaner for cleaning, keeping the waist bending angle within 20 degrees can reduce the load on the waist. In the Lift group, the lifting posture of the experimenter in the Lift-A group had the greatest risk of injury to the waist, while the posture in the Lift-B group was better. Postural load score results in the Lift group were also matched to the waist injury risk class, which also demonstrated the effectiveness of the postural load assessment system.

In experiment 2, we applied the posture load assessment system to caregiving work. The experienced group and the inexperienced group were arranged for comparison. In the caregiving experiment of transferring patient, the experienced group and the inexperienced group will complete the experiment according to their way. Fig 7 shows the processing effect of experiment 2 in the postural load automatic assessment system.

From the experimental caregiving work of the experienced and inexperienced groups, it is clear that the caregiver in the experienced group used the posture with the least loss of waist to transfer the patient, and his postural load score was seen to fluctuate between 6 and 8. In contrast, the caregiver in the inexperienced group had no caregiving experience and adopted his customary posture to transfer the patient, and in addition, he experienced an unstable center of gravity while transferring the patient. The entire caregiving postural load score for the inexperienced group fluctuated between 7 and 11. The professional rehabilitation doctor considered that postural assessment scores were informative for caregiving posture assessment. The caregiving posture of the inexperienced group has a higher risk of waist injury and it is also highly susceptible to acute polar psoas strain and other diseases, and the posture is not recommended. It also proved the validity of the postural load assessment system for caregiving posture assessment.

3.3 Application

We proposed a non-contact posture loading assessment system that can be used by both caregivers and patients. For caregivers, maintaining incorrect care posture for a long time will bring irreversible damage to the body. The system can provide caregivers with real-time assessment and early warning of postural load, and remind them to change their posture when the postural load reaches a high-risk stage. At the same time, the posture load evaluation algorithm is a lightweight model, and the system can also be deployed on mobile phones, which increases the convenience of operation of the system. For patients, the system deployed on the mobile phone can be used to conveniently assess the postural load in daily life, so as to understand high-risk postures, avoid maintaining high-risk postures frequently, reduce the load on the waist, and improve the rehabilitation effect.

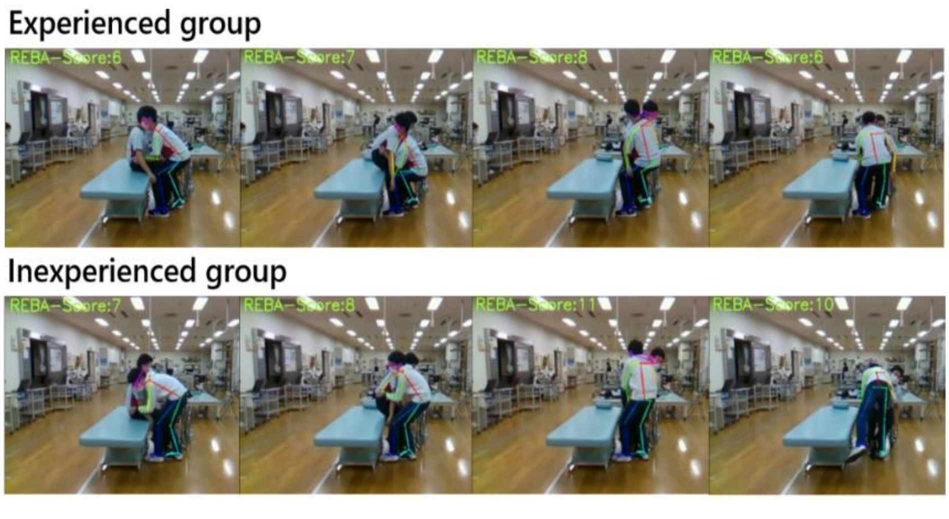

Fig 7. Results of caregiver postural load assessment in the experienced and inexperienced groups

4. Conclusion

In this study, we explored a computer vision-based method for body load assessment and integrated a novel automatic assessment system for postural load. It not only integrates human pose estimation algorithms and fast body load assessment frameworks, but also provides users with visual results of skeletal features and load scores. In the experiment, we designed a two-stage experiment to verify the efficiency of the posture load assessment system. Experiment 1 was designed for posture assessment in daily life, and experiment 2 was designed for caregiving work, in addition, comparison experiments were set up in both stages of the experiment. The experimental results showed that the system is suitable for a variety of different caregiving scenarios, and is also suitable for the evaluation of patients' daily activities, which can provide users with visual posture analysis and easy-to-understand posture load reference. At present, the depth camera data of the system has the highest efficiency in the sagittal and coronal planes of the human body. In the following research, we will focus on improving the evaluation efficiency of various visual angles.

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