Estimation of Lumbar Load from Webcam Images Using Convolutional Neural Network for Standing Forward Bending Stationary Posture

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***Abstract*—To prevent lumbago, it is effective to understand one's current posture situation and how to improve one's posture. Therefore, this study proposes a method to constantly observe posture and evaluate the load on the body. The realization of this method visualizes the body loads in daily life and can be used as one of the means to maintain health. Hence, this study proposes to use a web camera for sensing and deep learning as a tool for estimating body load from web image. The body load is derived using a musculoskeletal model simulation based on the skeletal information extracted from the images, and a deep learning model is prepared in advance using this as the true value. In this paper, the first subject is a stationary standing forward bending posture. The accuracy of the created deep learning model is evaluated and the results indicate that the proposed estimation method can be useful in the case of a standing forward bending posture.**

Keywords-Deep learning; Lumbar load; Musculoskeletal model simulation.

I. Introduction

Many people of all ages and genders experience lumbago, and lumbago has become a social problem because of its potential impact on daily life. Lumbago is occurred by the load associated with postural distortions. To prevent lumbago, it is useful to have a system that can improve his/her own posture. Therefore, first, this study proposes a method to constantly observe posture and evaluate the load on the body. Based on these methods, we will be developed into a posture improvement system in the future.

In our previous reports [1] [2], postures were observed using inertial sensors or optical motion capture, and noninvasive lumbar load estimation was performed using biomechanics and statistics, these estimation results confirmed a similar trend to the measured lumbar load ratio in the static posture of Nachemson et al. [3]. However, because specialized equipment and analysis are required, they are not suitable for routine observation and estimation. Hence, in this study, body load is estimated using based on data obtained from non-contact sensing method. Until now, previous researches have used skeletal detection software and deep learning from videos and images to detect the posture and motor status of children [4] [5] and falls of the elderly [6] as a method for observing daily life. In addition, several systems that use AI to evaluate posture based on skeletal position has been commercialized (Posen: Posen Co., Ltd, Sportip: Sportip, Inc.). Therefore, in this study, a web camera is used for sensing, as everyone has one and images can be gotten on a daily basis without any burden. Also, this study proposes to use deep learning as a means of estimating body load from images taking web camera. The purpose of this study is to use this estimation method to obtain body loads that can be used as a new indicator for systems that encourage voluntary postural improvement.

Figure 1 shows an overview of the proposed body load estimation system in this study. During system operation, user inputs an image of his/her posture, along with his/her height and weight, into the system, which outputs the estimated/evaluated results of the body load. To achieve this, a deep learning model is created in advance during development. In this study, the skeletal position coordinates are detected from images using AI skeletal detection software (VisionPose: NEXT-SYSTEM Co., Ltd.). After that, body load is derived using a musculoskeletal model simulation (AnyBody: AnyBody Technology) based on the skeletal position coordinates. This is used as the true value to create a deep learning model. The advantage of using AnyBody is that the various loads on the body can be obtained from a single image data set. Therefore, if dealing with a variety of body loads, create a deep learning model for each load.

The body load used in this paper is described. Previous research [7] has shown that the intervertebral disc compression force between the 4th and 5th lumbar vertebrae

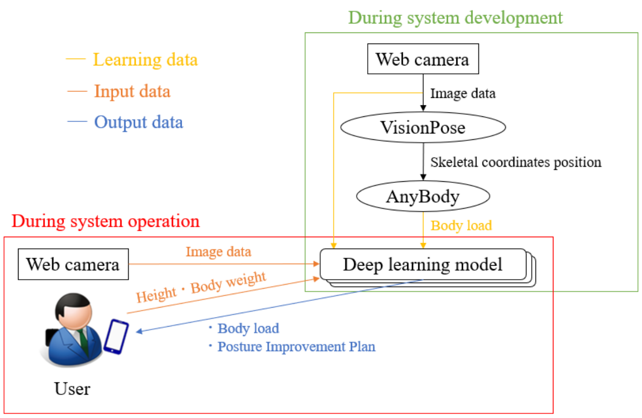

Figure 1. Overview of the proposed body load estimation system.

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derived by AnyBody is useful. In response to this result, in this report, the intervertebral disc compression force between L4L5 derived by AnyBody is used as the lumbar load, which is one of the body loads. However, the input data for AnyBody is the skeletal coordinate positions of the human body. Therefore, VisionPose is used to detect skeletal position coordinates from web images. A total of 30 skeletal positions are detected by VisionPose, including hip and shoulder joints. In our previous report [8], as a preliminary step in creating a deep learning model, we confirmed whether the intervertebral disc compression force between L4L5 derived by AnyBody using the skeletal position coordinates detected by VisionPose from web images of standing forward bending posture could be used as training data for deep learning. The results confirmed its usefulness by showing an increasing trend in disc compression force with forward bending of the upper body. Hence, in this paper, we decided to use the intervertebral disc compression force between L4L5 derived by AnyBody along with the web images as the true value of the training data. In this paper, as the first step in creating the proposed system, a deep learning model is created for a stationary standing forward bending posture, and the accuracy of the lumbar load estimation by the deep learning model is evaluated. The rest of this paper is organized as follows. Section II describes the methods and conditions for creating the lumbar load estimation system proposed in this paper. Section III describes additional evaluation of the lumbar load estimation system created in Section II. The acknowledgement and conclusions close the article.

II. LUMBAR LOAD ESTIMATION SYSTEM

In this paper, we use Convolutional Neural Network (CNN) for deep learning to estimate lumbar load. This section describes the experimental methods used to collect training and validation data, the preprocessing applied to the measured data, and the training conditions for the CNN. Furthermore, the created deep learning model is used to estimate the lumbar load and confirm its accuracy.

A. *Experiment*

One webcam (StreamCam: logicool) is used to get video. Three male subjects (age 21±1, height 1.70±0.02 [m], weight 67.0±1.70[kg]) who gave their consent to the experiment after obtaining approval from the Ethics Committee of the University and after explaining the experiment to the subjects in advance is the subjects of this study. Subjects are unified as male in this paper because of skeletal structure differences based on gender. The camera is placed at a distance of 3 [m] from the subject's body center and at a height of 0.85 [m] from the floor. Movies are shot at 1080p/30fps. To obtain image data of random anteversion angles in the standing forward bending posture, subjects are asked to perform the following actions. The body gradually bends from an upright standing posture to about 30 degrees, then the body gradually raises to an upright standing posture. This is taken as one trial and 5 trials are obtained. A total of three videos are obtained for each subject and used as training data. In addition, one trial of video is obtained from one of the same subjects on a different day and used as data for verification.

TABLE I. CNN LEARNING CONDITIONS

		Set value
Batch size		32
Classes		120
Epoch		200
Dropout		0.2
Convolution layer	Filter size 1	32
	Filter size 2	64
	Stride	1
Pooling layer	size	(2, 2)
Fully connected layer		64

B. *Estimation Methods*

This study uses frame-by-frame images for learning and estimation, rather than processing on video with a time component, to estimate the posture load at a specific point in time. Therefore, the video obtained by the experiment for a total of 15 trials for 3 subjects is converted into images for each frame rate using the Python module OpenCV (image processing library). The training data totaled 3217 images, and the validation data for one trial subject totaled 657 images. Estimation uses CNN used for image classification. Numerical estimation is based on images, we consider that the same mechanism can be used for estimation as in the classification problem. The CNN structure in the deep learning model consists of an input layer, followed by two convolutional layers, one pooling layer, two convolutional layers with dropout to prevent overlearning, one pooling layer, smoothing to prevent dropout to prevent overlearning, and output to an output layer after passing through all coupled layers one layer. The Relu function is used as the activation function in the convolution layer and the Softmax function in the all-coupling layer. Keras Documentation [9] was used to create the above structure in Python. Keras.Callbacks.EarlyStopping is used as the termination condition, with the training error used as the monitor and auto as the mode. The values of each parameter are shown in Table I.

To accommodate the estimation of new subjects that will not be used for training in the future, a deep learning model is created by dividing the derived disc compression force by height and weight, normalizing it, and labeling it as the true value for each frame of training data. After that, using the deep learning model created, lumbar load estimation is performed on the validation data, and the normalized values are converted to disc compression force [N (Newton)] by multiplying by height and weight.

C. *Estimation Results*

To evaluate the accuracy of the lumbar load estimated by the deep learning model from each of the 657 images in the validation data, the lumbar load derived from the same validation data using AnyBody is compared with the estimated value as the true value. Figure 2 plots the estimated values from the deep learning model and the true values derived by AnyBody. Poisson's correlation coefficient r^2 is 0.997, showing a high correlation and accurately capturing the changes caused by the forward bending of the upper body. Also, the Mean Absolute Error (MAE) between the deep learning estimate and the true value derived by AnyBody was

14.7 [N]. This is 2.25 [%] of body weight, which means that the margin of error is small. Furthermore, in the next section, the results of this study will be re-evaluated through additional experiments.

III. EVALUATION METHODS

The anterior tilt angle calculated from the skeletal position coordinates detected by VisonPose is the calculated value, and the anterior tilt angle measured by a digital angle meter is the measured value. Evaluate the MAE of the deep learning lumbar load estimation shown in Section II using the error between the calculated and measured values as an indicator.

A. Additional experiment

Image acquisition experiment is performed to obtain the error in the upper body anterior tilt angle detects by VisionPose, and the change in disc compression force per unit anterior tilt angle derives by AnyBody. The experimental procedure is the same camera position and the same three subjects as in the experiment in Section II to obtain images in a static posture. Three pictures are taken at each of the following conditions: upright posture (0 degrees), 10 degrees, 20 degrees, and 30 degrees of upper body forward tilt angle. The forward bend angle is determined by pressing the board against the lower back and measuring with a digital angle meter.

Based on the obtained images, one is, the skeletal position coordinates indicating the body center shoulder and hip positions detected by VisionPose are used to calculate the anterior tilt angle using a trigonometric function. After that, the error is calculated from the results of the measured and calculated values. The other is, based on the images, the skeletal position coordinates are detected from each image using VisionPose, and the skeletal position coordinates are input to AnyBody to derive the intervertebral disc compression force between L4L5.

B. Estimation Results

Table II shows the error between the calculated and measured values of each upper body forward tilt angle, and the intervertebral disc compression force between L4L5 derived by AnyBody.

From the derivation results, it can be read that the L4/L5 Intervertebral disc load increases almost linearly in 10-degree increments. From the results, the average change in compressive force per unit angle was found to be 21.1 [N]. As described in Section II-C, the MAE for lumbar load estimation by deep learning was 14.7 [N]. This is converted into the amount of change in the upper body forward tilt angle by dividing by 21.1 [N], the amount of change in compression force per unit angle. As a result, the MAE of the lumbar load estimation by deep learning corresponds to the increase in lumbar load when the upper body forward tilt angle changes by 0.70 degrees. The average change in the upper body forward tilt angle of 0.70 degrees is smaller than the angular error detected by VisionPose shown in Table II, so the MAE of the waist load estimation by deep learning shown in Section II is small. For this reason, the deep learning model created in this paper for the standing forward bending posture is useful.

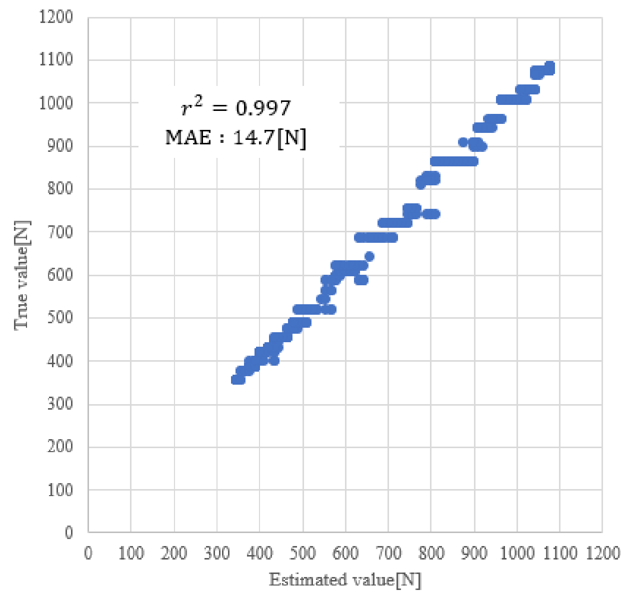

Figure 2. Comparison with disc compression force estimated by the deep learning model and the derived values by AnyBody as the true value. Presented data shows the accuracy of the deep learning model.

IV. CONCLUSIONS

The purpose of this study is to create a body load estimation system based on a deep learning model that uses web images and body load derived by AnyBody as training data. As a preliminary step, we examined the estimation of lumbar load from web images using a deep learning model that was created using the L4L5 intervertebral disc compression force derived by AnyBody as the training data for the standing forward bending posture and lumbar load, one of the body loads.

From a single image, the intervertebral disc compression forces were estimated in two different methods, one using deep learning and the other using AnyBody. In this way, the two types of forces were estimated for all validation data images, and compared with each other. The results showed high correlation and small error. Therefore, the deep learning model created in this paper for the standing forward bending posture may be useful as an estimation method for posture improvement systems.

The deep learning model developed in this paper only estimates lumbar load in the upper body forward bending posture. Therefore, the postures and their body load to be targeted by the deep learning model will be increased in the future. AnyBody can derive various body loads applied to the body from a single measured data. Hence, various body loads are obtained from a single image data, and a new deep learning model is created using this as training data. That is, it is possible to estimate selected body loads in each posture by acquiring various loads applied to each body part from images of postures that are considered to have a large load on the lumbar, such as hunching back and warped back, including the upper body forward bending posture targeted in this paper, and learning them together with the images. In addition, the accuracy of the deep learning model is improved by optimizing the program through filtering and attention mechanisms. If these can be used to estimate body loads in all postures with a high accuracy, we assume that adding body loads as a new indicator to the currently commercialized posture improvement system will lead to a further increase in awareness and lead to health maintenance.

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TABLE II. MEAN ABSOLUTE ERROR BETWEEN CALCULATED AND MEASURED VALUES AND INTERVERTEBRAL DISC COMPRESSION FORCE BETWEEN L4L5 AT EACH UPPER BODY FORWARD TILT ANGLE.

Upper body forward tilt angle [degrees]	0	10	20	30
MAE of angle [degrees]	2.17	2.58	4.58	3.46
L4/L5 Intervertebral disc load [N]	365	584	798	998

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