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

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Development of Posture Improvement System

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The topic of research interest

Posture analysis for posture improvement system

Healthcare system based on human dynamics.

Introduction (Research Background)

To prevent lumbago, it is useful to have a system that can improve his/her own posture.

A method to constantly observe posture and evaluate the load on the body is proposed.

Introduction (Conventional methods in my research group)



Fig.1 Optical motion capture

Although the optical motion capture shown in Figure 1 can be measured accurately, it has some disadvantages such as high cost, and limited measurement range.



Fig.2 Inertial sensor

Although the inertial sensor shown in Figure 2 is inexpensive, it has contact sensing and require expertise for analysis.

Not suitable for routine observation and estimation.

Introduction (Conventional methods in other institutions)

Methods using skeletal detection software and deep learning from videos and images

Observing daily life

Detection the posture or motor status of children [4] [5]

Falls of the elderly [6]

Observing posture

Systems that use AI to evaluate posture based on skeletal position.

(Posen: Posen Co., Ltd, Sportip: Sportip, Inc.)

[4] Satoshi Suzuki, Yukie Amemiya, and Maiko Sato, "Deep Learning Assessment of Child Gross-Motor," 13th International Conference on Human System Interaction (HSI), 2020, pp. 189-194

[5] Rong Fu, Tongtong Wu, Zuying Luo, Fuqing Duan, Xuejun Qiao, and Ping Guo, "Learning Behavior Analysis in Classroom Based on Deep Learning," Tenth International Conference on Intelligent Control and Information Processing (ICICIP), 2019, pp. 206-212

[6] M. D. Solbach, and J. K. Tsotsos, "Vision-Based Fallen Person Detection for the Elderly," CoRR, abs/1707.07608.

Research Objective



To obtain body loads that can be used as a new indicator for systems that encourage voluntary postural improvement.

Proposal Method

During system development — Learning data Web camera — Input data Image data — Output data VisionPose Skeletal coordinates position AnyBody During system operation Body load Image data Deep learning model Web camera Height • Body weight Body load Posture Improvement Plan User

Fig.3 Overview of the proposed body load estimation system

Using Software (VisionPose)



Available with only one webcam AI Skeleton Recognition System

Skeletal information can be easily obtained

Detection of skeletal position coordinates from web images

Fig.4 Skeletal coordinate positions that can be detected by VisionPose

https://www.next-system.com/visionpose

Using Software (AnyBody)



Motion Analysis Software by Musculoskeletal Modeling

Derivation in vivo load from skeletal position

Lumbar load = L4/L5 disc compression force [N]

Fig.5 AnyBody's human body model

How to Create Deep Learning Model



Experimental Methods

- Webcam (StreamCam: logicool, 1080p/30fps) 1 unit (height: 0.85[m], distance: 3[m])
- Three male subjects (age 21 ± 1 , height 1.70 ± 0.02 [m], weight 67.0 ± 1.70 [kg])
- The body gradually bends from an upright standing posture to about 30 degrees, then the body gradually raises to an upright standing posture

5 trials \times 3 subjects: Training data \rightarrow 3217 images 1 trial \times 1 subject: Verification data \rightarrow 657 images



Learning Condition

Estimation uses CNN used for image classification.

Table I. CNN LEARNING CONDITIONS

		Set value	
Batch size		32	
Classes		120	
Epoch		200	
Dropout		0.2	
Convolution layer	Filter size1	32	
	Filter size2	64	
	Stride	1	
Pooling layer	size	(2, 2)	
Fully connected layer		64	

Input layer Convolutional layer Convolutional layer Pooling layer Dropout Convolutional layer Convolutional layer Pooling layer Dropout All coupled layer Output layer

Terminal when learning error stops decreasing using Keras.Callbacks.EarlyStopping

Results of Evaluation of Deep Learning Models

Comparison with the estimation results from the deep learning model with the lumbar load derived from the validation data using AnyBody as the true value.

Poisson's correlation coefficient

 $r^2 = 0.997$

Mean Absolute Error (MAE)

MAE = 14.7 [N]



Fig.6 Comparison with disc compression force estimated by the deep learning model and the derived values by AnyBody as the true value. Presented data for the accuracy of the deep learning model.

Image Acquisition Experiment Methods

- Webcam (StreamCam: logicool, 1080p/30fps) 1 unit (height: 0.85[m], distance: 3[m])
- Digital angle meter 1 unit
- Three male subjects (age 21 ± 1 , height 1.70 ± 0.02 [m], weight 67.0 ± 1.70 [kg])
- Three pictures are taken for each condition: upright posture (0 degrees), and upper body forward bending angle of 10 degrees, 20 degrees, and 30 degrees. The forward bending angle is measured with a digital angle meter by pressing the board against the waist.



Revaluation Methods



Estimation Results

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 $angle[^{\circ}]$	0	10	20	30
	MAE of $angle[^{\circ}]$	2.17	2.58	4.58	3.46
	L4/L5 Intervertebral disc load[N]	365	584	798	998
Lumbar load estimation by deep learning $$		21.1 [N/°]			

The amount of change in the upper body forward tilt angle

1

14.7/21.1 = 0.70 < MAE of angle

MAE of the lumbar load estimation by deep learning is small.

Conclusion

- In this paper, we have proposed a body load estimation system based on a deep learning model that uses web images and body load derived by AnyBody as training data.
- 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 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.

Future Work

- In the future, the postures and their body load to be targeted by the deep learning model will be increased.
- 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.

Thank you for listening