Attempt for Estimation of Vertical Ground Reaction Force by Deep Learning with Time Factor from 2D Walking Images

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Presenter

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Development of AI-based ground reaction force estimation system

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The topic of research interest

Gait analysis

Healthcare system

Simple and accurate ground reaction force estimation

Introduction (The usefulness of gait analysis)



Gait analysis is the quantitative analysis of gait using measured data. Analyzed data will be used as important information in the fields of medicine, sports and rehabilitation.

Introduction (Conventional method for measuring ground reaction force)

The equipment used to measure the ground reaction force



Fig.1 Force plate W600 × D900 × H100 [mm], 45[kg]

Although the ground reaction force shown in Figure 1 can be measured accurately, it has some disadvantages such as high cost, disruptive gait, and limited measurement range.



Fig.2 Inertial sensor

There is a method of estimating from the inertial sensor shown in Figure 2 [2]. Although this method is inexpensive, it is prone to noise and can only estimate the composite ground reaction force of both feet.

[2] A. Isshiki, Y. Inoue, K. Shibata, and M. Sonobe, "Estimation of Floor Reaction Force During Walking Using Physical Inertial Force by Wireless Motion Sensor," HCI Int'l, vol. 714, pp. 249-254, May 2017, DOI: 10.1007/978-3-319-58753- 0_37, 2017, pp.22-33, ISSN:1348-711

Introduction (Image-based gait analysis)

Skeletal information can be acquired using OpenPose [6], a skeletal information detection AI, to obtain stride length and walking speed [5].



Using of skeletal information detection AI affects the accuracy of gait analysis in its accuracy

Estimates ground reaction force for each foot without skeletal information detection AI

[5] K. Yagi, Y. Sugiura, K. Hasegawa, and H. Saito, "Gait Measurement at Home Using a Single RGB Camera," Gait&Posture Volume 76, February 2020, Pages 136-140
 [6]OpenPose, https://cmu-perceptual-computing-lab.github.io/openpose/web/html/doc/, 2023.10.13

Introduction (Method for estimating ground reaction forces in our research group [7])

Ground reaction force estimation method using deep learning from walking images [7]



During system development

By creating a deep learning model in advance, the system can estimate the ground reaction force simply by capturing images of the user walking.

[7] T. Mochizuki, and K. Shibata, "Estimation of Floor Reaction Forces by Convolutional Neural Network Using Walking Image without Depth Information : Evaluation of Generalization Ability," 2023 JSME Information, Intelligence and Precision Equipment Division, IIPB-4-12, 2023, (in Japanese) 6

Introduction (Estimated accuracy in the previous report [7])

Table I. RESULTS ESTIMATED OF VERTICAL GROUND REACTION FORCEOF THE CONVENTIONAL PROPOSED METHOD DEEP LEARNING MODELS

Deep learning models number	Ι	II	III	IV	V	Average
Pearson's correlation coefficient	0.68	0.63	0.94	0.82	0.92	0.80
Mean absolute error for body mass [%]	14	16	7	12	8	12

* Laboratory environment results

Vertical ground reaction force estimated from a single image using a deep learning model.

Vertical ground reaction forces can be estimated with an error of approximately 12% of body mass, with an average Pearson's correlation coefficient of 0.80.

Estimation accuracy is not sufficient

[7] T. Mochizuki, and K. Shibata, "Estimation of Floor Reaction Forces by Convolutional Neural Network Using Walking Image without Depth Information : Evaluation of Generalization Ability," 2023 JSME Information, Intelligence and Precision Equipment Division, IIPB-4-12, 2023, (in Japanese) 7

Research Objective

Improve the accuracy of our estimation methods



Propose a new ways to create training and input data

Estimation object : Vertical ground reaction force per foot

Accuracy target : 5% of body mass

Proposal Method

Include a time factor in the training and input data

Image at a time before the estimated walking image



Estimated walking image



Create voxel data

The size of the voxel data was chosen to be $40 \times 40 \times 5$, which gave the best estimation accuracy after much trial and error.

Prepare the estimated walking image and the image at a time before the estimated walking image, and create voxel data, that will be used as training data.

Experimental Methods

Using the same experimental data as in the previous study [7]

- iPad Pro (manufactured by Apple Inc., 1080p/60fps, 1 unit)
- Force plate(manufactured by Tec Gihan Co., Ltd., TF-6090-C 1 unit)
 * Not used during estimation
- 5 male volunteers (age 22 ± 1 , height 1.73 ± 0.05 [m], weight 61 ± 13 [kg])
- Ten steps were measured from the beginning of the walk and the analysis area was the sixth steps
- 50 trials per volunteers



Camera position

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How to Create Deep Learning Model



The voxel data is then labeled with the normalized ground reaction force values at the time of the image to be estimated and input into a deep learning model for training.



Create 5 deep learning models so that all volunteers are validation data for cross-validation.

Deep learning models number	Ι	II	III	IV	V
Training data	B,C,D,E	A,C,D,E	A,B,D,E	A,B,C,E	A,B,C,D
Number of voxel data for the training data	8252	8046	8255	8152	8366
Validation data	А	В	С	D	Е
Number of voxel data for the validation data	2016	2222	2013	2115	1902

TABLE II. NUMBER OF TRAINING AND VALIDATION DATA

The number of voxel data that could be create varied from one volunteer to another

Learning Condition

Estimation uses 3D Convolutional Neural Network which is a three-dimensional extension of the convolutional neural network used in previous reports.

 Table III. CNN LEARNING CONDITIONS

		Set value
	Filter size	$5 \times 5 \times 2$
Convolution layer	Stride	1
	Channels	256
Dooling lover	Filter size	$5 \times 5 \times 2$
	Stride	1
Drop	0.3	
Fully conne	128	
Batch	100	
Еро	500	

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

All models have been successfully trained

Results \sim Deep learning model III \sim



Fig.3 Normalized ground reaction force estimates versus true values

Some voxel data are estimated with good accuracy when the true value is larger than 0.70, but not when the value is smaller than 0.70.

Results \sim All deep learning models \sim

Table IV. RESULTS FOR ALL DEEP LEARNING MODELS.

Deep learning models number	Ι	II	III	IV	V	Average
Pearson's correlation coefficient	0.65	0.78	0.85	0.02	0.63	0.59
Mean absolute error [N]	105.5	101.5	63.5	120.3	69.2	92.0
Mean absolute error for body mass [%]	16	14	10	19	15	15

The target estimation accuracy was set at 5% error of body mass, but the target was not met as the accuracy was 15% of body mass.

Discussion

Discussion on why accuracy was not good



Fig.4 Accuracy rates of training and validation data for deep learning model III

- The figure 4 shows that the accuracy rate for the training data improves with each successive training, but the accuracy rate for the validation data does not.
- This trend was observed for all deep learning models.

Thought to be caused by overlearning

Discussion

The bias in the training data to be the cause of the overlearning.

	Estimation in	ion interval 0.01~0.10		0.11~0.20		0.2	0.21~0.30		0.31~0.40		0.41~0.50		0.51~0.60		0.61~0.70		
	Deep learning r	nodel I	5.7%		2.2%		2.1%		2.3%		2.8%		2.9%		3.3%		
	Deep learning n	rning model II 6.1%		5.1%	2.0%		1.9%		2.1%		3.2%		3.0%		3.2%		
	Deep learning m	learning model III		5.7%	2.1%		2.0%		2.2%		3.0%		2.7%		3.4%		
	Deep learning m	learning model IV 6.3%		5.3%	2	2.0%		1.7%	7% 2.0%		3.0%		2.9%		3.2%		
	Deep learning n	nodel V	6	5.0%	2	2.1%	2.2%		2.3%		3.4%		2.6%		2.7%		
Estimation interval 0.71~0.		.80	0.81~0	0.90 0.91~1		.00	1.01~1.1		1.11~1.20		1.21~1	1.30 1.31~1		.40	1.41~1	.50	
Deep learning model I 11.2%		, 0	26.4%	% 17.19		6	11.19	% 11.89		% 1.0%		ю́ 0.0%)	0.0%	ý D	
Deep learning model II 11.6%		⁄0	21.9%	% 16.0		6	12.49	6	15.3%		1.4%		0.0%		0.0%		
Deep learning model III 11.19		ó	25.9%	% 17.49		6	11.89	6	12.2%		0.6%		0.0%		0.0%		
Deep learning model IV		12.6%	6	23.4%	6 14.69		6	13.0%	6	14.3%		1.1%		0.0%		0.0%	ó
Deep learning model V		9.0%		26.79	5 16.89		6	11.0%		13.9%		1.3%		0.0%		0.0%	ó 0

Table V. PERCENTAGE OF TRAINING DATA PER ESTIMATION INTERVAL

The proportion of training data in the interval of 0.70 to 1.20 estimates accounts for about 80%, indicating that the training data is biased.

We suppose that accuracy can be improved by creating a large amount of unbiased training data.

Conclusion

- In this report, we examined how to improve the accuracy of the ground reaction force estimation algorithm using only the RGB camera for sensing, which is the proposed method.
- The method of creating training data was changed to include a time factor.
- No improvement in accuracy was found.
- It is suggested that overlearning occurs during the training of any deep learning models. We suppose that the overlearning is due to the small amount of training data and bias.
- Therefore, creating a large amount of unbiased training data is expected to eliminate overlearning and improve accuracy.

Future Work

- In the future, our aim is to develop a system that can capture images and estimate three directions ground reaction forces using only a tablet device.
- If this is realized, it will be possible to evaluate gait on a daily by observing ground reaction force waveforms, which will support people to be aware of gait improvement and contribute to extending healthy life expectancy.

- THANK YOU -





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