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AI-based Estimation of Lower Limb Joint Moments in Stance Phase using a Single Wearable Inertial Sensor

Kyoko Shibata[1)], Kohei Watanabe

Kochi University of Technology

1) shibata.kyoko＠kochi-tech.ac.jp

Presenter’s short resume

Kyoko Shibata, PhD

- 1998-2002, Research Associate, Department of Applied Physics, Seikei University, Tokyo Japan.
- 2003-, Associate Professor, Department of Mechanical Engineering, Kochi University of Technology, Kochi Japan.
- 2022-, Professor, Department of Mechanical Engineering, Kochi University of Technology, Kochi Japan.

Research interests:

- human dynamics in healthcare, medical and welfare
- self healthcare engineering
- sensor system for gait analysis
- energy-regenerative welfare orthoses

1. Introduction

[1] S. Yamamoto, 2003

One of the quantitative parameters to validate the load of exercise is the lower limb joint moment (joint torque). This is because muscle activity can be estimated from joint moments [1]. Therefore, joint moment is also a parameter used for diagnosis in orthopedic and rehabilitation clinics.

In this study, we propose a method to easily obtain joint moments in daily life. If this method can be systematized, we believe that it will contribute to enhancing the effectiveness of exercise by quantitatively and visually confirming the effects of daily health care exercises by oneself. In other words, **support for active self-healthcare** can be realized.

In this study, first, we will estimate the lower limb joint moments during the stance phase of walking exercise in a simplified manner.

[2] S. Kawamura, 2016
[3] H. Kotani, K. Shibata, 2018
[4] H. Kotani, K. Shibata, 2020
[5] M. Mundt, 2020

1. Introduction

The conventional methods for obtaining joint moments during gait with high accuracy are inadequate in terms of simplicity

× to calculate by inverse dynamic theory using statistical values from ground reaction force data and coordinates, acceleration, and angular velocity of body part which measured with multiple large installed force plates and an optical motion capture system.

× to calculate by inverse dynamic theory using statistical values from ground reaction force data and coordinates, acceleration, and angular velocity of body part which measured with 15 wearable inertial sensors[2][3][4].

× to use machine learning used multiple parameters simulated from measured data using optical motion capture systems and multiple inertial sensors, and further expanded the data set by data augmentation[5].

← unsuitable for use in practice.

1. Introduction

Therefore, this proposal uses only one wearable inertial sensor for measurement when the user estimates, even if errors are introduced, and only actual measured data. The creation of a pre-prepared trained deep learning model requires a high degree of accuracy, so force plates and optical motion capture system must be used, but again, only calculated values from actual measured data are used.

In the future, estimation using only users smartphone is a feasible method. This will lead to help **effective active self-health care**.

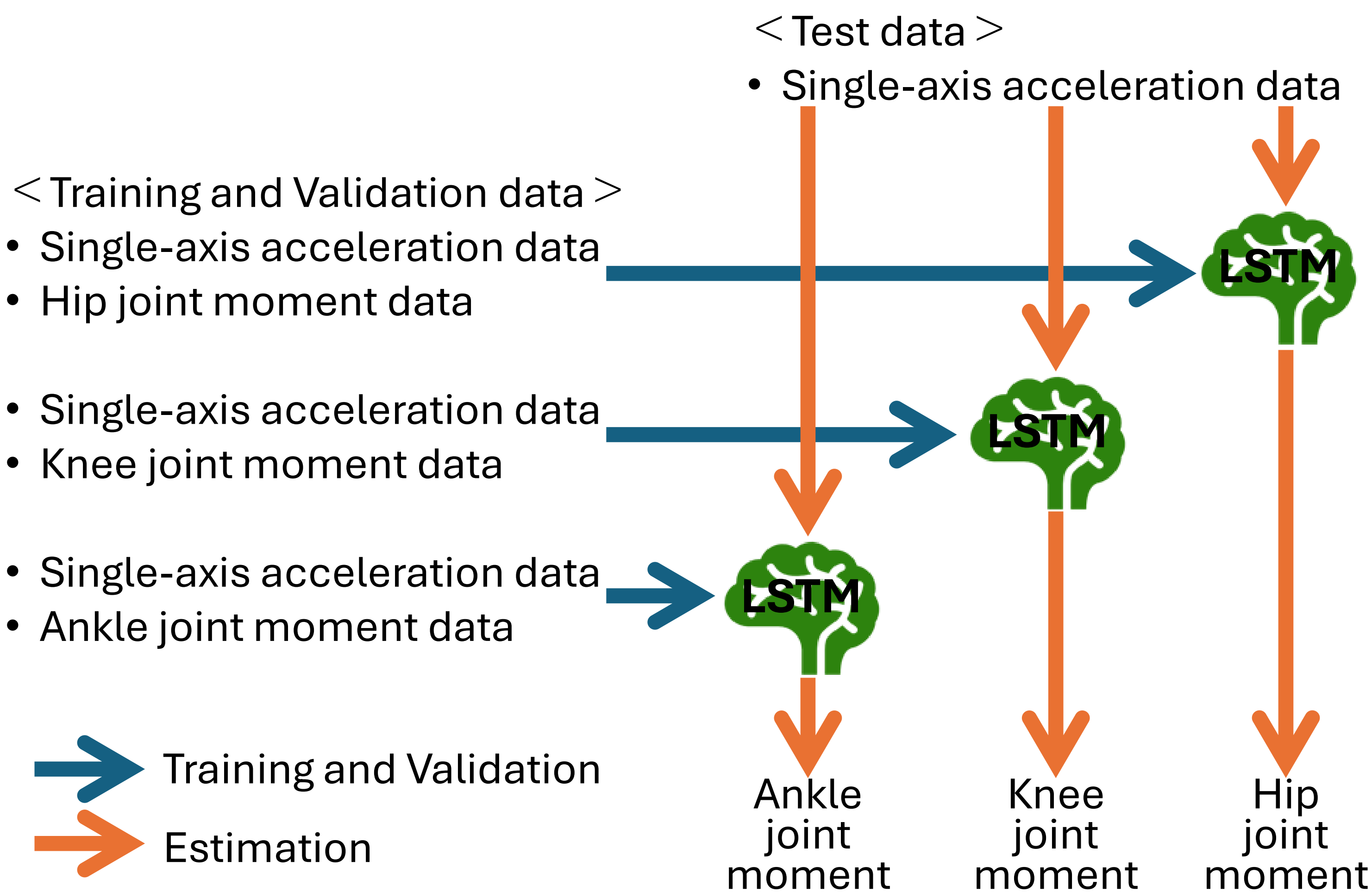
In this presentation,

- the proposed method is described.
- the estimation accuracy is verified.

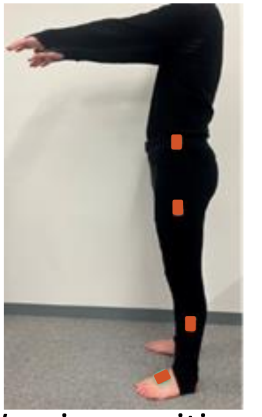
→ to consider whether it is possible to incorporate easy observation of joint moments into daily life.

2. Method

Outline of the proposed method



2. Method



Wearing position of inertial sensors.

Walking experiments and data processing

- Two healthy Japanese male subjects (age 22 $\pm$ 0 years, height 1.66 $\pm$ 0.07 [m], weight 74.0 $\pm$ 12.7 [kg]).
- Devices
    - Three FPs (one TF-6090 and two TF-4060, Tec Gihan); for acquiring three-dimensional ground reaction forces
    - Motion Capture (MC, MAC3D, Motion Analysis) ; for acquiring 29 three-dimensional coordinate positions

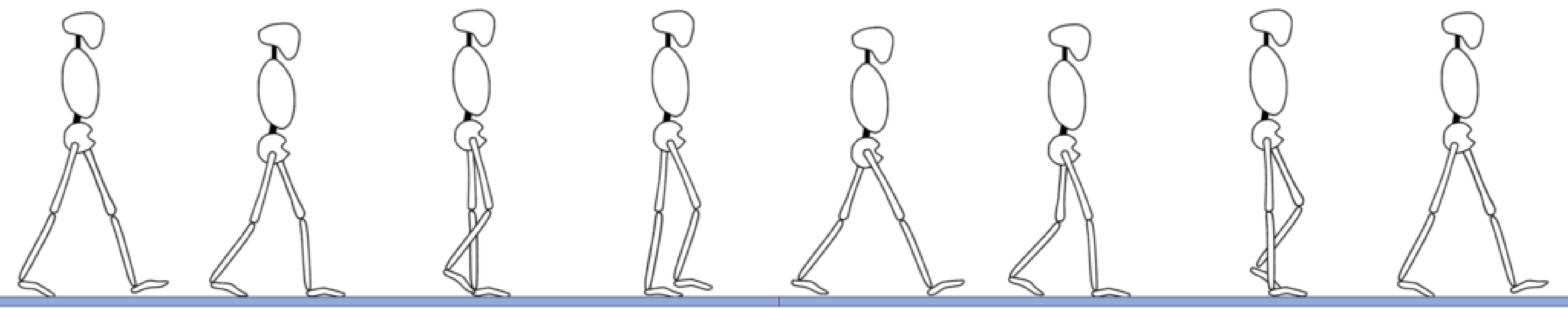
  As training/validation data and test data.

    - 4 Inertial sensors (MTw2,Movella), they are wireless 3-axis sensor; For acquiring acceleration data <Nevertheless, estimation is based on a single-axis acceleration of a single sensor.>
- Software

  As training/validation data and correct values.

    - Inverse dynamics analysis software (KinTools RT, Motion Analysis); For deriving the lower limb joint moments
- For each subject, 50 trials of 10 steps of natural walking are measured.
- The sampling frequency is 100[Hz], and the cutoff frequency of the low pass filter for smoothing is 9[Hz].
- This experiment is approved by the Kochi University of Technology Ethics Review Committee.

2. Method



One gait cycle（2steps）

Target period: The stance phase of the left leg in a steady gait

Double support phase

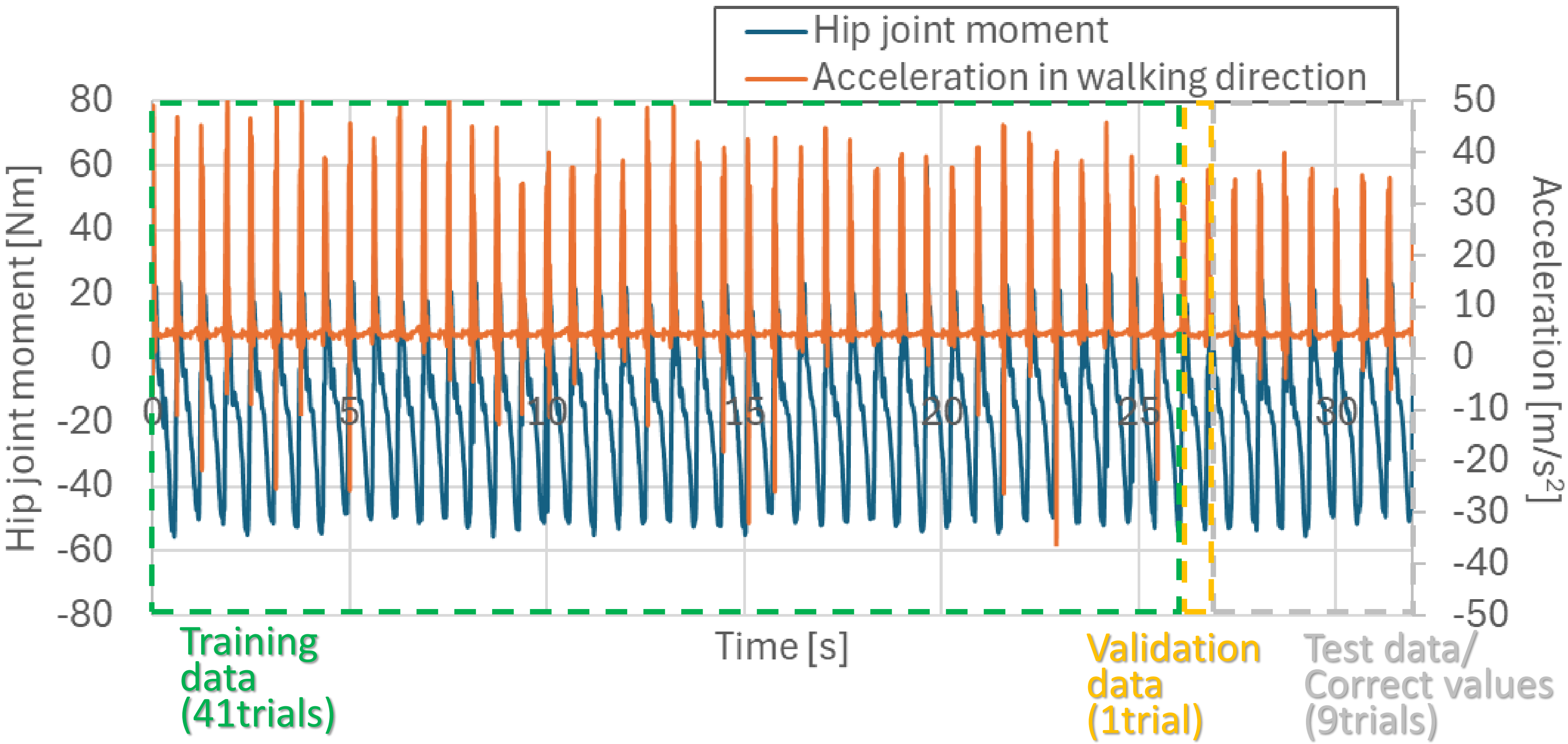
Single support phase

Double support phase

（Determined by ground and release times based on the vertical ground reaction force values output from the force plate.）

2. Method

50 trials of single-axis acceleration measurement data and joint moment calculation data.



2. Method

Prior comparative experiments have shown that the learning algorithm for deep learning is **LSTM**.

Learning conditions

Number of hidden layers		50
Number of epochs		50
Batch size		32
Learning rate		0.001
Appropriate values	Sub. A	65
	Sub. B	62

3. Results

Prior estimation experiments were carried out and then **the dorsal foot acceleration in the walking direction** was selected from 4 inertial sensors x 3 axes = 12 acceleration data as a single-axis acceleration which is used AI data.

This is because a **balanced and high estimation accuracy was obtained for all three lower limb joint moments** in subject A.

3. Results

Estimation results on Individual learning using the dorsal foot acceleration in the walking direction

Subject	CS[a]	Joint moment	Correlation coefficient	MAE [Nm]
A	World	Hip	0.948±0.0066	4.47±0.375
		Knee	0.972±0.0020	3.53±0.253
		Ankle	**0.985±0.0055**	**3.82±0.665**
	Local	Hip	0.946±0.0035	4.53±0.313
		Knee	0.969±0.0038	3.97±0.541
		Ankle	**0.987±0.0044**	**3.85±0.505**
B	World	Hip	**0.943±0.0006**	**6.88±0.205**
		Knee	0.948±0.0032	4.76±0.296
		Ankle	0.975±0.0064	7.48±0.821
	Local	Hip	**0.938±0.0090**	**7.70±0.798**
		Knee	0.939±0.0084	5.23±0.538
		Ankle	0.975±0.0050	9.44±1.225

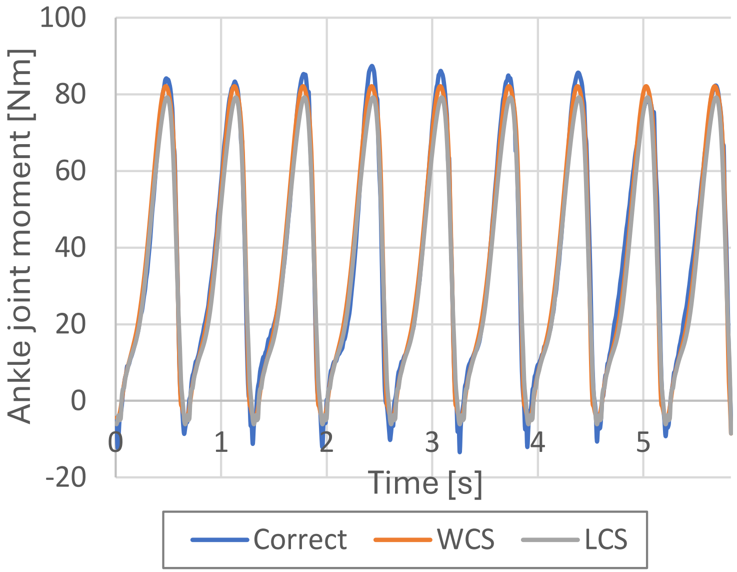
a. Coordinate System

3. Results :Ankle joint moment

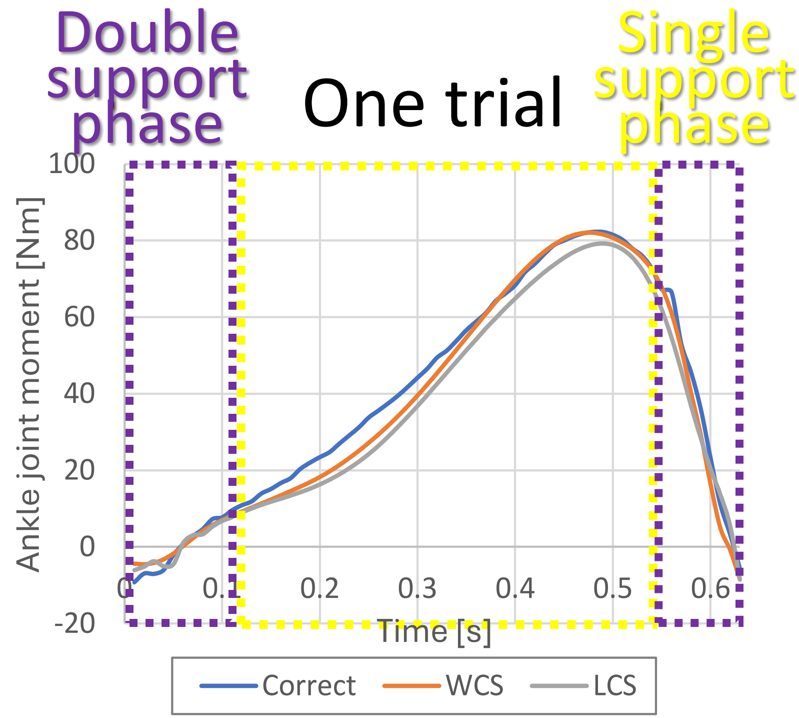
Estimated (World CS and Local CS) and measured (Correct) ankle joint moments for subject A.

This was generally the **highest** correlation coefficient among all the estimations (From Table II).

Nine trials



One trial

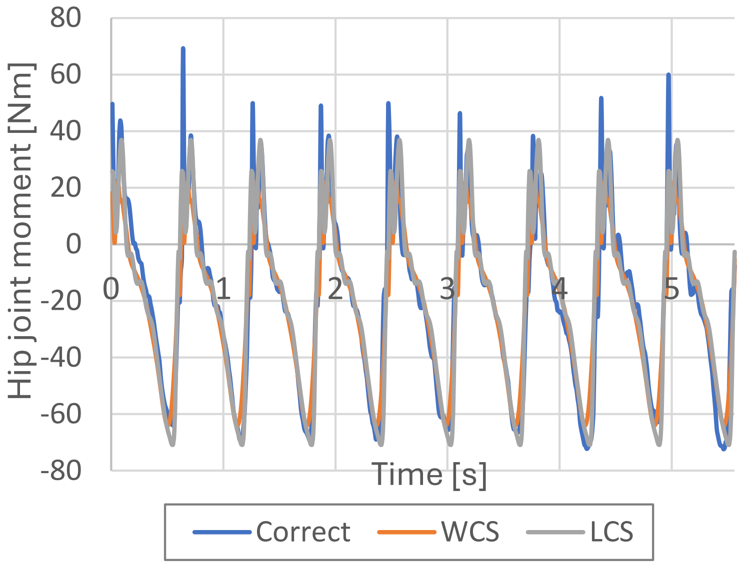


3. Results :Hip joint moment

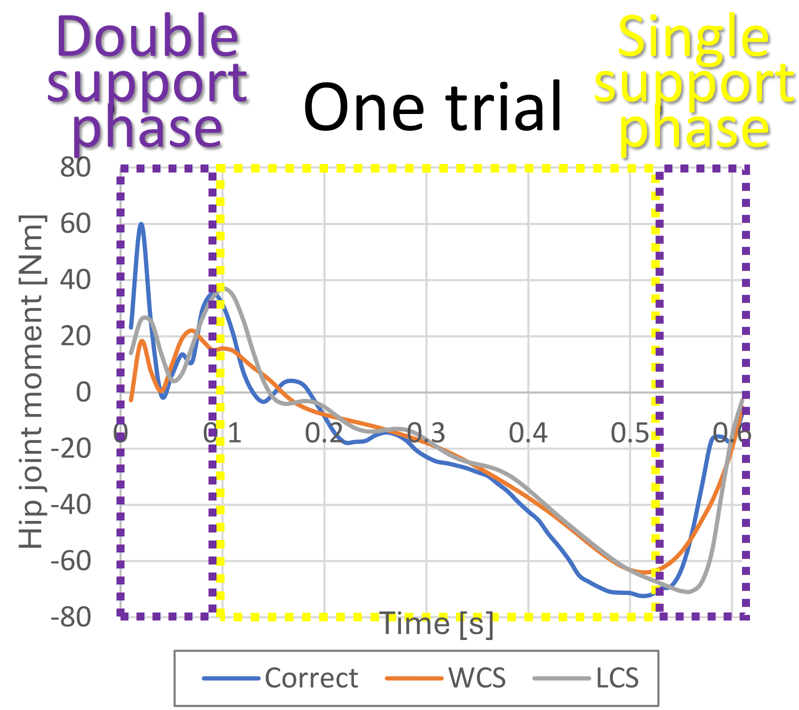
Estimated (World CS and Local CS) and measured (Correct) hip joint moments for subject B.

This was generally the **lowest** correlation coefficient among all the estimations (From Table II).

Nine trials



One trial



3. Results :Consideration1

The correlation coefficients between the correct and estimated values are all above 0.9, indicating the presence of a relatively strong positive correlation.

The mean value of MAE is 7.4% of the mean body mass, which is small, and the standard deviation is 0.74%, which is also small. In other words, the results for nine trials were highly accurate.

3. Results :Consideration2

For one trial, the result for the single support phase is generally consistent, but there are steady-state errors and errors that do not follow minor changes in the double support phase.

As the double support phase in one gait cycle is short and the ankle joint moments vary gently, so errors in the double support phase are not a problem.

However, for the hip joint moments, the failure to capture the peak values in the initial double support phase may have implications.

This is because, joint moments can be used to represent muscle activity, with the peak value representing the maximum load on the joint.

Therefore, two sources of error and suggestions for improvement are listed below.

The first is that most of the stance phase is during the single support phase, and there are no large moment fluctuations during this phase at any joint, so the number of input data determined from the overall correlation coefficient was biased toward the larger values. We believe that changing the evaluation index and changing the number of input data to a size small enough to capture the fine variation in the double support phase will lead to a reduction in errors.

Second, because only the stance phase was extracted and combined, there were discontinuities at the trial junctions. We believe that by setting the estimation range to one gait cycle that includes not only the stance phase but also the swing phase, in which the moment is zero, continuity will be maintained and errors will be reduced.

3. Results :Consideration3

Both the correlation coefficient and MAE are slightly less accurate for subject B than for subject A.

This is due to the fact that the hyperparameters were set and the sensor mounting positions were determined using data from subject A.

In addition, early stopping was not used in the present study.

Therefore, there is a possibility of overfitting in the learning of both subjects, especially in subject B.

Optimization of hyperparameters and sensor position, in addition to incorporation of early stopping into individual learning for subject B would have yielded better results.

However, the results for subject B also showed good results, which means that even if the parameters were optimized for other subjects to save time and effort, good results could be obtained with a healthy gait.

3. Results :Consideration4

Comparing the results in the world coordinate system with those in the local coordinate system, there is no significant difference.

Therefore, this study adopts estimation using a local coordinate system, which requires only one sensor for measurement and no coordinate transformation during estimation.

4. Conclusion

This study examines a convenient method for estimating quantitative parameters useful for self-healthcare.

Therefore, in this paper, the three lower limb joint moments were considered as effective parameters, and a convenient method was proposed to estimate them using trained LSTM model by measuring only the actual single-axis acceleration data.

As its acceleration data, we decided to use the dorsal foot acceleration in the walking direction, which provided high estimation results for all three joint moments simultaneously.

From the estimation results of individual learning for each of the two subjects, although some errors remained during the double support phase, the overall estimation in each of the two subjects was highly accurate, regardless of whether a world or local coordinate system was used for the acceleration data.

Thus, it is expected to be **possible to verify the effect of exercise by simply installing a small and lightweight acceleration sensor during daily walking exercise, without restrictions on time and place**.

4. Conclusion

In the future,

- the generalization performance will be evaluated with an increased number of subjects in order to improve the practical relevance of this study.
- it will apply the proposed method to other gaits.