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

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***Abstract*—Walking is an easy way to exercise that can maintain and improve health. Quantifying the benefits of walking exercise would make health promotion more effective. The purpose of this study is to estimate lower limb joint moments during daily walking in order to support active healthcare by oneself. Using acceleration data acquired from a large number of wearable sensors, it is not possible to estimate joint moments based on kinetic theory alone. Therefore, this study proposes a method for estimating joint moments using deep learning from measured single-axis acceleration data only, considering the ease of measurement. The accuracy of estimation on the three lower limb joint moments in the stance phase is shown and the benefits of the proposed method are discussed.**

Keywords- Self-healthcare; Gait analysis; Wearable sensing; LSTM.

I. INTRODUCTION

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.

The conventional method for obtaining joint moments during gait with high accuracy is generally to calculate them by inverse dynamic theory using statistical values (e.g., mass, center of gravity position, and moment of inertia, of body part) from ground reaction force data and coordinates, acceleration, and angular velocity of body part. The accuracy is high when multiple large installed force plates and an optical motion capture system are used as measurement devices. However, these devices are limited in installation locations and are expensive, so they are limited to use in specialized institutions such as hospitals and rehabilitation facilities, and are not applicable to measurements in daily life. An alternative to these devices is the use of wearable inertial sensors. Kawamura et al. [2] measured body part acceleration with wearable inertial sensors and calculated lower limb joint moments during running from inverse dynamics theory using statistical values. In our previous report [3][4], we also investigated the use of wearable inertial sensors during walking and obtained some results. However, the method to calculate lower limb joint moments from acceleration as in the previous report can only be applied to the single support phase, because the double support phase, which is not present in running but is present in walking, is a statically indeterminate structure. In addition, to ensure high accuracy, the number of sensors must be 15 in order to include the entire body. Furthermore, the accuracy of joint moment estimation falls as the error in the dynamic acceleration measured accumulates as the number of body parts to be considered increases.

Therefore, this study attempts to estimate joint moments using deep learning from the measurement information of wearable inertial sensors. A previous study [5] used machine learning to predict joint moments and even joint angles. This study used multiple parameters simulated from measured data using optical motion capture systems and multiple inertial sensors as input data, and further expanded the data set by data augmentation. In these cases, it is not easy to prepare a large number of sensor systems and intelligent signal processing. 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 addition, only one wearable inertial sensor is used for estimation. In the future, estimation using only users smartphone is a feasible method. This will help the case of effective active self-health care. In this paper, we describe the proposed method and verify the estimation accuracy. Then, we would like to consider whether it is possible to incorporate easy observation of joint moments into daily life.

The rest of this paper is organized as follows. In Section II, we present the proposed estimation method, then explain the walking experiment to acquire deep learning data and its data processing method, and then describe the method for building deep learning models. Section III shows and discusses the estimated results. Finally, Section IV summarizes this paper and describes future work.

II. METHODS

An outline of the proposed method is shown in Figure 1. In the proposed method, three deep learning models are constructed for each joint by learning the relationship between the time series data of single-axis acceleration acquired from wearable sensor and the correct values of three lower limb joint moments in the sagittal plane, respectively. Untrained single-axis acceleration data not used for learning are input to these learned deep learning models, and the estimated values of the joint moments are the output. For simplicity, the acceleration data is the same single-axis time series data for all three joints.

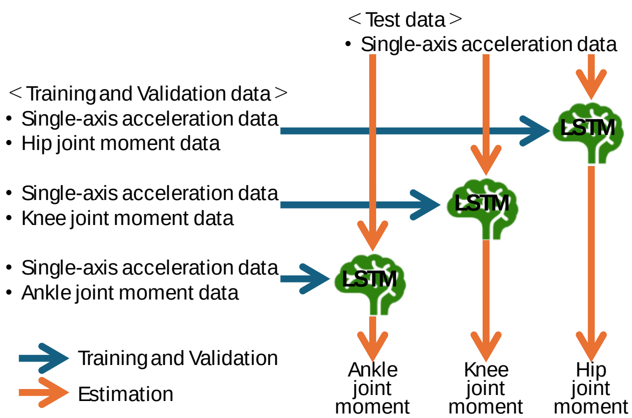

Figure 1. Outline of the proposed method.

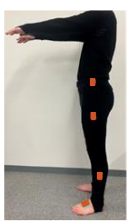

Figure 2. Wearing position of inertial sensors.

The experiment for data acquisition is described next.

Two healthy male subjects (age 22±0 years, height 1.66±0.07 [m], weight 74.0±12.7 [kg]) participated in the experiment. This experiment was conducted after obtaining approval from the University's Ethics Review Committee (No. 176) and after explaining the experiment to the subjects and obtaining their consent.

Three force plates (TF-6090, TF-4060: Tech Giken) and an optical motion capture system (MAC 3D System: Motion Analysis) are used to derive the lower limb joint moments to be used as correct values. In addition, wireless wearable inertial sensors (MTw2: Movella) consisting of 3-axis accelerometer, 3-axis gyro sensor, and 3-axis magnetometer are used to acquire acceleration data to be used as training and validation data and test data. Ultimately, only one inertial sensor common to all three joints is used during estimation, and only that one axis is used. Therefore, in order to determine the suitable inertial sensor mounting position, the inertial sensors are mounted at four locations (Figure 2): pelvis, thigh, lower leg, and dorsal foot during the data acquisition experiment.

The experimental subject walks on the walking path; 50 trials of 10 steps per trial are performed. Three force plates are placed on the 5th to 7th step (steady walking) of the walking path, and the subject is required to take only one step on each of these force plates. The sampling frequency of each device is uniform at 100 Hz.

After the walking experiment, lower limb joint moments are derived using inverse dynamics analysis software (KinTools RT: Motion Analysis) based on a total of 29 three-dimensional coordinate positions on the whole body obtained from the optical motion capture system and three-dimensional ground reaction forces from the force plates. The obtained lower limb joint moments are values in the world coordinate system. On the other hand, the acceleration output from the wearable inertial sensor is data in a local coordinate system that has been corrected for the motion caused by wearing the sensor. Therefore, using the angular velocity data obtained from the inertial sensor, the acceleration was also prepared as data converted from the local coordinate system to the world coordinate system. When using acceleration in the world coordinate system, high estimation accuracy can be expected because the coordinate system is unified with the joint moments. On the other hand, when using acceleration in the local coordinate system, estimation can be realized with acceleration sensors alone, without using inertial sensors, because angular velocity data used only for coordinate conversion is unnecessary. In general, acceleration sensors are less expensive and easier to obtain than inertial sensors. We believe that this is an advantage.

All data obtained were smoothed by low-pass processing with a cutoff frequency of 9 Hz.

In the present study, only the stance phase, which causes ground reaction forces and places a high burden on the joints, is considered in the range of estimation. The left leg is the target. Vertical ground reaction force data obtained from the force plate were used to determine the ground and release times during the stance phase of the left leg. Based on these times, joint moments and acceleration data for the stance phase of the left leg only were extracted and combined, respectively. Since the number of data differs from trial to trial, the acceleration data and the respective lower limb joint moments for approximately 40 of the 50 trials are used as training data, and those from the 41st trial are used as validation data. For the remaining nine trials, the acceleration data is used as test data and the lower limb joint moments are used as correct values for accuracy verification. As an example, Figure 3 shows the acceleration in the walking direction in the world coordinate system at the dorsal foot of subject A and the hip joint moment of the left leg. The green dashed box is the training data.

The learning algorithm for deep learning is Long Short-Term Memory (LSTM), which is suitable for time series waveform estimation. This decision is the result of comparing LSTM, Recurrent Neural Network (RNN), and Gated Recurrent Unit (GRU) in prior experiments. The hyperparameters determined by trial and error are shown in

Table I. The number of input data was set for each subject based on the estimated correlation coefficients for nine trials. The appropriate values for subjects A and B were 65 and 62, respectively.

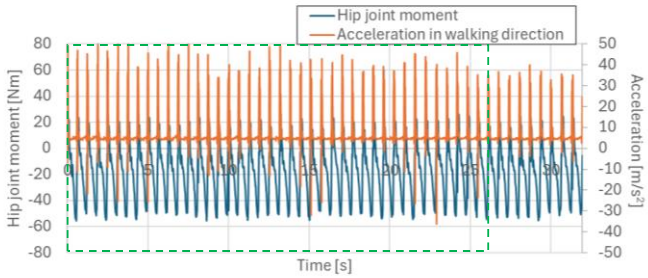

Figure 3. 50 trials of single-axis acceleration measurement data and joint moment calculation data.

TABLE I. LEARNING CONDITIONS.

Number of hidden layers	50
Number of epochs	50
Batch size	32
Learning rate	0.001

III. RESULTS

To determine the mounting position of the inertial sensor that obtains single-axis acceleration data, we performed individual learning for subject A with all 3-axis acceleration data in the world coordinate system obtained from 4 inertial sensors for each of the three joints. Then, we estimated with unknown test data for subject A. As results, the dorsal foot acceleration in the walking direction was selected from the twelve data points. This is because a balanced and high estimation accuracy was obtained for all three lower limb joint moments in subject A. In this section, the results are presented.

The trained deep learning models for each subject were created using training and validation data, which were acceleration in the walking direction obtained from the wearable inertial sensor attached to the dorsal foot. Subsequently, the joint moments of the left leg were estimated three times for nine trials using each test data for each subject. Table II shows the correlation coefficients and mean absolute errors with the joint moments calculated

TABLE II. ESTIMATION RESULTS.

Subject	*CS*[a]	*Joint moment*	*Correlation coefficient*	*MAE*[b] *[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 b. Mean Absolute Error

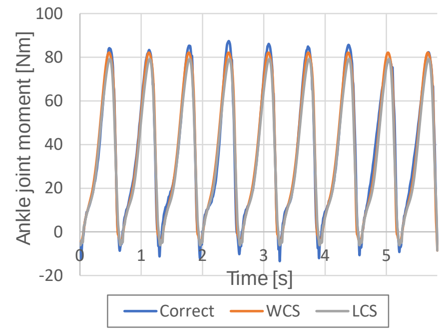

Figure 4. Estimated and measured ankle joint moments for subject A in nine trials.

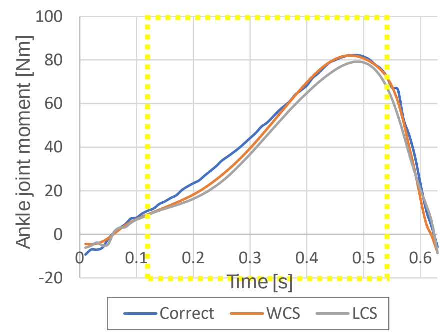

Figure 5. Estimated and measured ankle joint moments for subject A in one trial.

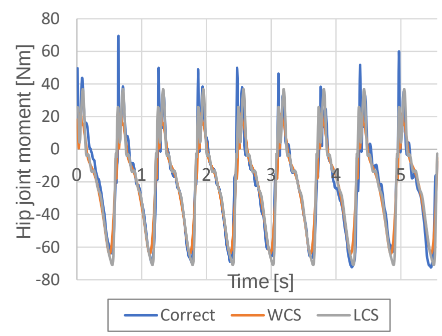

Figure 6. Estimated and measured hip joint moments for subject B in nine trials.

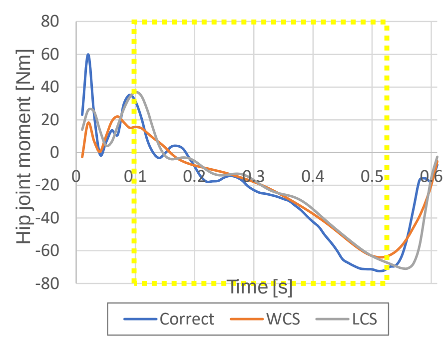

Figure 7. Estimated and measured hip joint moments for subject B in one trial.

based on actual measurements as the correct values. Figure 4 shows the results of nine trials of ankle joint moments for subject A, and Figure 5 shows only the ninth trial of Figure 4. From Table II, this was generally the highest correlation coefficient among all the estimations. Figure 6 shows the results of nine trials of hip moments for subject B, and Figure 7 shows only the ninth trial of Figure 6. From Table II, this was generally the lowest correlation coefficient among all the estimations. In these figures, the blue line shows the estimated values using acceleration in the world coordinate system, the gray line shows the estimated values using acceleration in the local coordinate system, and the orange line shows the correct values. The stance phase begins with the double support phase, passes through the single support phase in which the other leg (the right leg in this case) is in the free leg phase, and ends with the double support phase in which the other leg is grounded again. In Figures 5 and 7, the yellow dashed box indicates the single support phase, and the others indicate the double support phase.

In Table II, the correlation coefficients between the correct and estimated values are all above 0.9, indicating the presence of a relatively strong positive correlation. Furthermore, the strength of the correlation can be observed in Figures 4 and 6. The mean value of MAE presented in Table II 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, Table II and Figures 4 and 6 demonstrate that the results for nine trials were highly accurate. Figures 5 and 7, which show one trial, indicate 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, as shown in Figure 5, vary gently, so errors in the double support phase are not a problem. However, for the hip joint moments, as shown in Figure 7, the failure to capture the peak values in the initial double support phase may have implications. This is because, as previously stated, 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. 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.

Besides, from Table II, both the correlation coefficient and MAE are slightly less accurate for subject B than for subject A. As mentioned earlier, 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 values, 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.

In addition, 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.

IV. 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 a 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.

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. Furthermore, we will apply the proposed method to other gaits.

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