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Gait Training Robot with Intermittent Force Application based on Prediction of Minimum Toe Clearance

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***Abstract*—Adaptive assistance of gait training robots has been determined to improve gait performance through motion assistance. An important control role during walking is to avoid tripping by controlling minimum toe clearance (MTC), which is an indicator of tripping risk, to avoid its decrease among gait cycles. No conventional gait training robots can adjust assistance timing based on MTC. In this paper, we propose a system that applies force intermittently based on the MTC prediction algorithm to encourage people to avoid lowering the MTC. This prediction algorithm is based on a radial basis function network, the input data of which include the angles, angular velocities, and angular accelerations of the hip, knee, and ankle joints in the sagittal and coronal planes at toe-off. The cable-driven system that can switch between assistance and non-assistance modes applies force when the predicted MTC is lower than the mean value. Nine participants were asked to walk on a treadmill, and we tested the effect of the system. The MTC data before, during, and after the assistance phase were analyzed for 120 s. The results showed that the minimum and first quartile values of MTC could be increased after the assistance phase.**

I. INTRODUCTION

Robotics dealing with physical human–robot interaction techniques has been proposed to enhance an ability of walking. The instinctive somatosensory feeling of body motion provided through robotic guidance is beneficial because training with instinctive modification is more effective than that with conscious modification [1]. People can rely on robotic assistance, and thus reduce their own exertion when the robot moves human legs. Robot-aided training must be designed to encourage humans to move their bodies actively with an interaction only when the assistance is needed because the ability of movement decreases when people do not use their own ability actively [2].

Assistance-as-needed control strategy of the gait-training robots is actively being studied to adjust the assistance level or mechanical impedance modes based on human ability [3–7]. Control of the interaction force between a robot and human allows the user to walk in a different way from the desired predetermined trajectory using force-field control. As the trajectory-based control is mainly targeted at severely affected patients, multiple degrees of freedom are used to recover motor function for joint-angular trajectory generation. Another adaptive approach of assistive technology is torque optimization using a cable-driven robot based on the estimation of metabolic cost for improving human's energy efficiency while walking [8, 9]. The cable-driven mechanism is used mainly for people who can walk by themselves. The conventional algorithms are adaptive based on human ability by evaluating a human state after human action. Conversely, assistance-based methods that decide the robotic parameters by predicting the gait motion beforehand have not yet been established.

Falling is one of the most serious problems that people must avoid during walking, and is mainly caused by tripping, which result from a toe hitting the ground or the person taking small steps [10, 11]. Therefore, the ability of controlling toe movement must be improved. The variability of minimum toe clearance (MTC) in the middle swing phase is a critical tripping parameter, and can be reduced by controlling MTC [12]. The possibility of tripping occurs if the toe approaches the ground at an arbitrary point among gait cycles. The robot based on an evaluation of a human motion after human action cannot modify the motion in real-time. Prediction of MTC is important for modifying the toe motion in real-time to encourage people to walk with more precise MTC control. Therefore, an assistance-as-needed approach based on MTC prediction is necessary.

Our hypothesis is that robotic assistance along with the MTC prediction algorithm can modify human control to inhibit the reduction of MTC. We developed the MTC prediction algorithm based on the radial basis function network (RBFN) by using angles of lower limb joints [13].

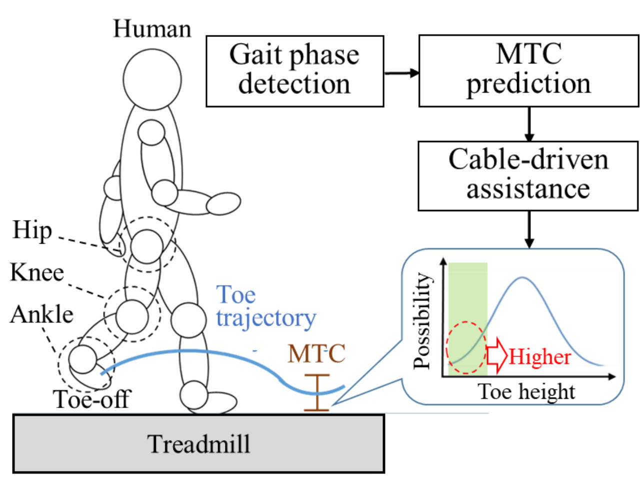

Fig. 1. The scheme of intermittent force application based on MTC prediction.

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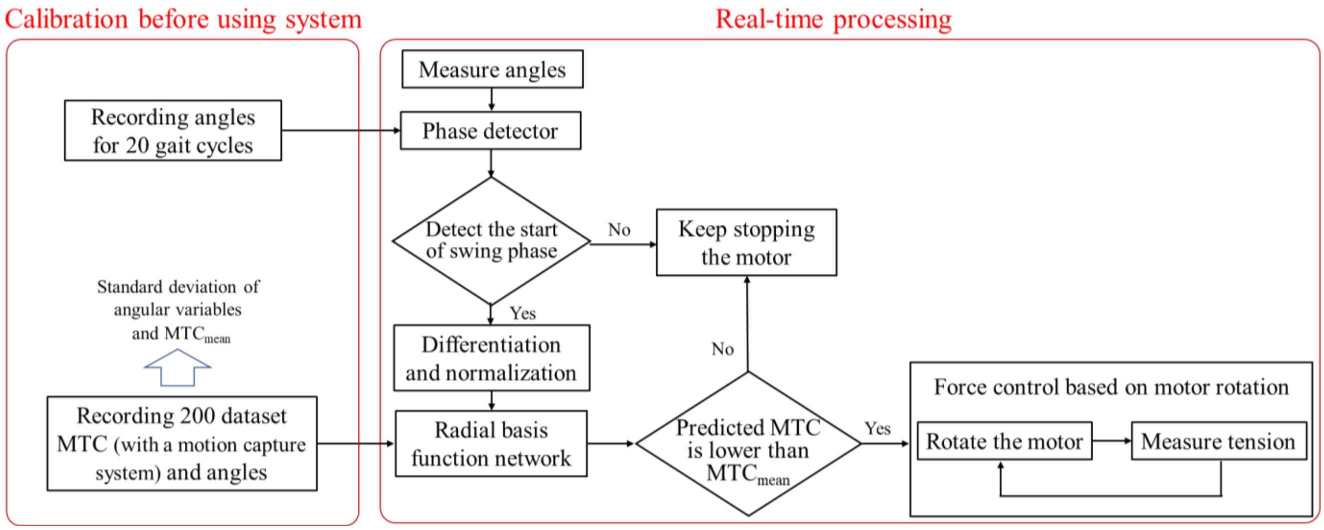


Fig.2 Flowchart of the proposed system. The controller detects the start of the swing phase based on the gait phase detection algorithm with angular information of hip, knee, and ankle joints, and the system with the MTC prediction algorithm and a hardware for cable-driven assistance tries to increase lower values of MTC distribution.

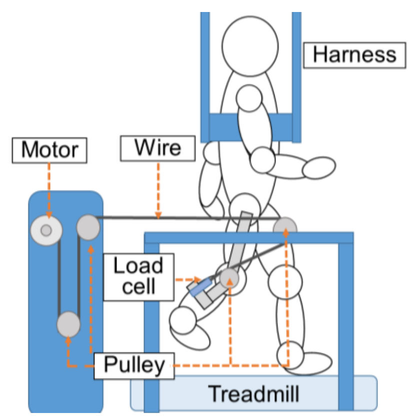
The results showed that the prediction error was lower than that obtained in previous studies on the estimation or prediction of MTC [14-17]. No research has yet investigated the effect of robotic assistance using MTC prediction on the modification of MTC control. We assumed that people could modify their MTC control through training, in which a robot detects the lower values of MTC distribution beforehand and increases it.

In this work, we established robotic assistance based on MTC prediction to inhibit the reduction of MTC, as shown in Fig. 1. We implemented the MTC prediction algorithm on the cable-driven system that could switch between the assistance and non-assistance modes. Force application at a part of the lower leg around toe-off could increase MTC without decreasing range of joint motion [18]. We investigated whether the lower values of MTC distribution increased with robotic assistance using the proposed prediction algorithm. Moreover, we evaluated whether a person modifies his/her MTC distribution even after the assistance is withdrawn. The contribution is an implementation of the intermittent force application based on MTC prediction in gait training and investigation of the after-effects.

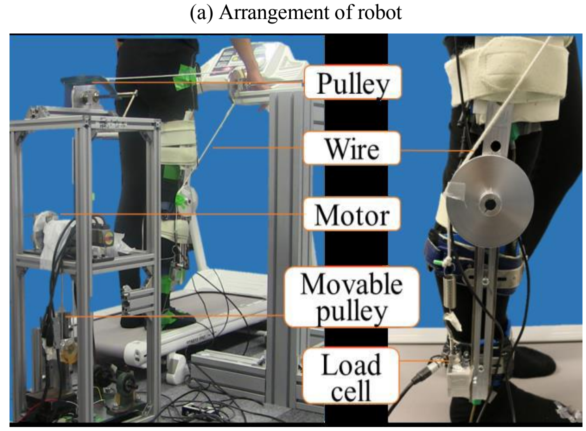
II. MTC PREDICTION-BASED ASSISTANCE

The proposed system applies the force to human intermittently for increasing MTC based on prediction result. The system consists of cable-driven system that we developed [18] and MTC prediction algorithm [13]. Intermittency of force application could be achieved based on control of the cable tension in gait phase. Fig. 2 shows the flowchart of the proposed system.

The cable-driven system could switch between modes in which force is applied and not applied [18]. Force is applied to a part of the shank to apply knee flexion torque, and thus lift toe because knee flexion motion has the largest contribution to toe clearance. The motor (NX610MA-PS25; Oriental Motor Co., Tokyo, Japan) is connected with the frame the user wore through nylon cable and spring (E659; stiffness of 0.040 N/mm). The loadcell (LUX-B-200N-ID; Kyowa Electronic Instruments Co., Tokyo, Japan) is attached between the frame and cable to obtain feedback information of the cable tension to apply force. The strength of the flexion torque to the knee is determined solely based on the tensile force because the moment arm is a constant, at 0.05 m. The constitution of the cable-driven system is indicted in Fig. 3.



(a) Arrangement of robot



(b) Photograph

Fig. 3. Overview of cable-driven gait-training robot.

The analog I/O board (ADA16-32/2(PCI)F, CONTEC, Osaka, Japan) is connected to the main controller (Windows) via the PCI Express bus. Electrical goniometers (SG110, SG150, Biometrics Ltd., Newport, UK), which can sense joint angles in sagittal and coronal planes, are attached to the leg under the frame with a tape for sensing the hip, knee, and ankle joints' angles. The input values from the goniometer and the load cell are collected by the analog I/O boards and processed by the main controller.

MTC prediction algorithm consists of phase detection and regression of MTC on variables related to the joint angles. The start of swing phase is detected by the gait phase detection method using the plane structure in a space consisting of the hip, knee, and ankle joints' angles in sagittal plane based on [13], as shown in Fig. 4. The change of phases can be detected more clearly with angles using planes in the angular space, whereas the change detection according to angle readings is difficult because angle range was noisy and fluctuating. The controller detects the switching points from the stance phase to the swing phase in real-time by detecting a timing at which the measured angular point passes through the section plane of the angular trajectory, which is derived previously from 20 gait cycles.

After detecting the start of the swing phase, the MTC prediction algorithm is performed [13]. MTC is predicted using the RBFN which is a machine learning algorithm with the Gaussian function, as shown in Fig. 5. The output of RBFN is an inner product of a weight vector and a vector of Gaussian functions which is calculated based on the Euclidean distance between the vector of the input data and the centroids of each Gaussian. The RBFN structure is defined as:

$$\boldsymbol{y} = \sum_{k=1}^{N} \boldsymbol{w_k} \exp\left(-\frac{\| \boldsymbol{x} - \boldsymbol{c_k} \|^2}{\sigma}\right), \quad (1)$$

where $\boldsymbol{y}$ denotes the output vector, $\boldsymbol{w_k}$ is the weight vector, $\boldsymbol{x}$ is the input vector, $\boldsymbol{c_k}$ is the centroid vector, N is the number of Gaussian functions, and σ is a variable related to the standard deviation of the Gaussian function. σ was derived as [19]:

$$\sigma = \frac{d_{max}}{\sqrt[m]{Nm}}, \quad (2)$$

where d_{max} denotes the maximum distance among the data and m is the dimension of the data. The parameters of the RBFN can be calculated rapidly (less than 1 s in this work). The centroids of the gaussian functions are derived through the K-means clustering algorithm, which classifies the input dataset into a predetermined number of groups (2 to 20 units) according to the Euclidean distance. The weight vectors are derived by solving the least squares problem of example input-output pairs (training dataset).

In this study, the input data included 18 variables: angles, angular velocity, and angular acceleration of the hip, knee, and ankle joints in the sagittal and coronal planes. The angular velocity and angular acceleration of these joints were calculated by differentiating the angles with a pseudo differential. The angles were smoothed with a low pass filter (cutoff frequency was 6 Hz) because noise frequency was more than 6 Hz. All input values were normalized to reduce the effect of the range of values of each variable because the range of variance affects the output value of the RBFN. If one variable has a much larger range of values, the output value

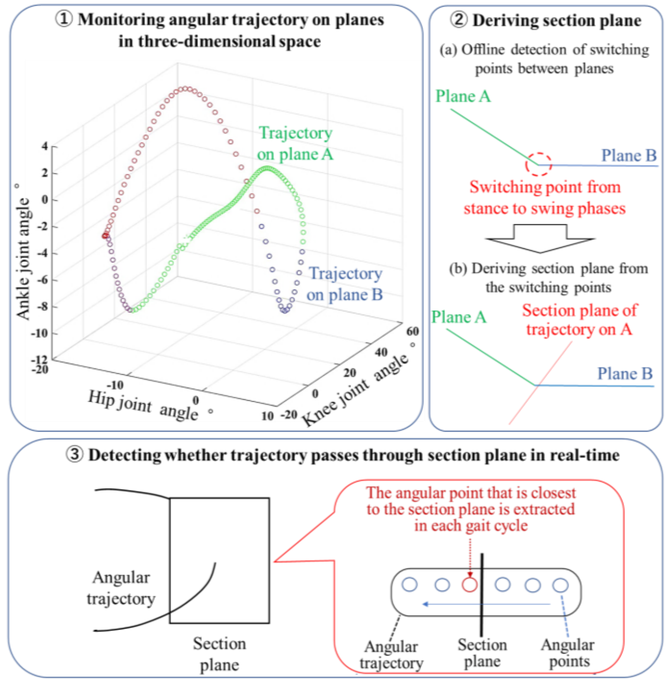


Fig. 4. Detection of start of swing phase. The system detects the angular point that is the closest to the section plane when the gait state changes from the stance phase to the swing phase. The section plane is derived in the calibration phase.

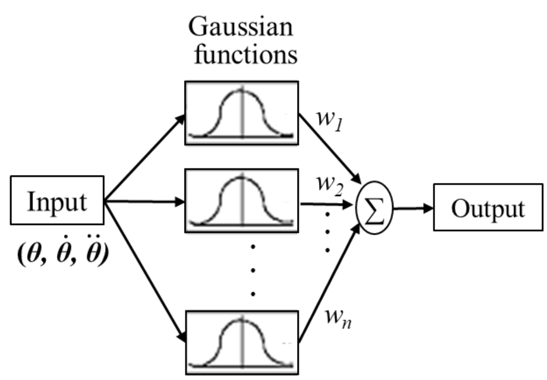


Fig. 5. Structure of the radial basis function network (RBFN). Output was calculated by the sum of Gaussian functions,

relies on this variable. First, the standard deviation of each variable in the training dataset was derived. Next, each measured input value was divided by each standard deviation, that is, measured input vector was divided by the vector of standard deviation.

After detecting that the predicted MTC is lower than the mean value calculated when the RBFN is trained, the motor pulls the cable and applied force while the knee joint is flexing. Applying force to assist knee flexion around start of the swing phase can increase MTC [18]. A ratchet mechanism stopped the movement of the movable pulley when the motor rotated and pulled the cable. The rotational position of the motor was controlled for control of the pulled cable tension. However, the motor is not activated for a predicted MTC higher than the mean value. The force is not applied when the motor stops and the force is applied when the motor is activated [20], as shown in Fig. 6.

III. Human Walking Experiment

Because it was reported that function of adapting to a new gait pattern in older people was same as younger people [21], we evaluated whether the proposed system could modify the lower values of MTC after training with young adults. Nine younger adults (five men and four women; mean age was approximately 25 years, standard deviation of age was approximately 5 years, mean weight was approximately 58 kg, standard deviation of weight was approximately 16 kg, mean height was approximately 1.65 m, standard deviation of height was approximately 0.09 m) with no neurological injuries or gait disorders participated in the study. Before the experiment, we provided the subjects with a detailed account of our study goal (we did not explain the objectives of this experiment), explained that they could withdraw from the experiment whenever they desired, and obtained their consent. We asked them only to continue to walk during experiment. This experiment was approved by the institutional review board at Waseda University (No. 2017-085).

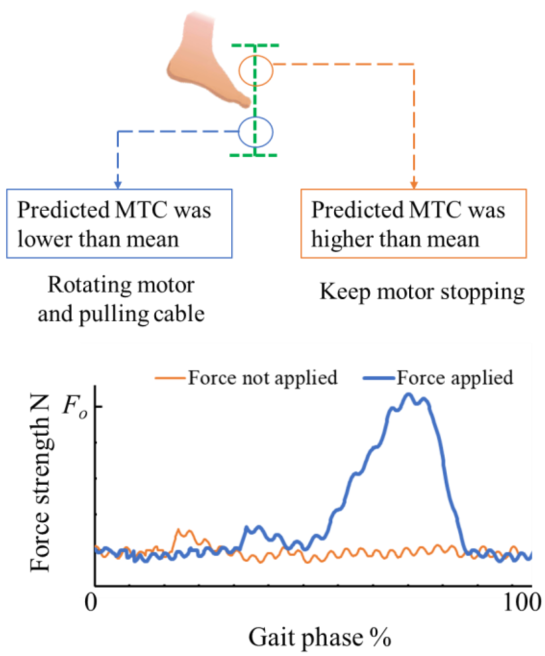


Fig. 6 Intermittent force application method. The force was not applied if the predicted MTC was higher than mean, while the force was applied in case where the predicted MTC was lower than mean.

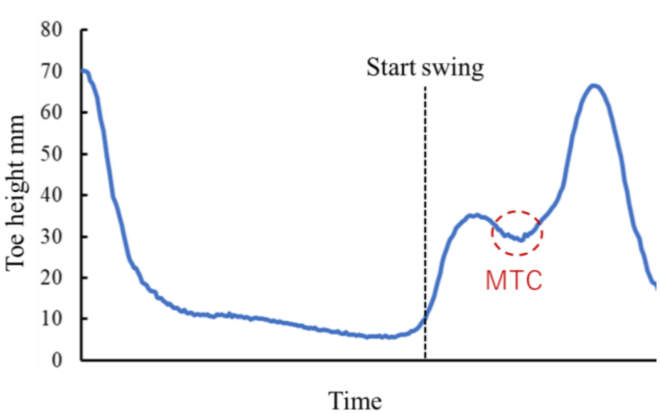


Fig. 7 Extraction of MTC from toe height data obtained by the motion capture system.

The toe coordinates of the right foot were measured using a motion capture system (Raptor-E; Motion Analysis, Santa Rosa, CA, USA) that could measure a marker coordinates with an error of 0.1 mm or less. The marker for the measurement was attached to the first metatarsophalangeal joint of the foot. The participants wore the cable-driven system and the sensors on their right leg. To evaluate results of MTC prediction and after-effect caused by the robotic assistance, ground-truth MTC data were extracted by detecting the second smallest local minimum of the toe clearance in each gait cycle, as shown in Fig. 7.

The experiment task consisted of mainly the measurement of gait data for training the RBFN and testing the robotic assistance by using the prediction algorithm. At first, the experimental participants were guided to continue walking on a treadmill for 5 min, where they decided their preferred walking speed (2.5 ± 0.27 km/h). Next, they walked for 400 s; this was considered the measurement phase. Approximately 200 datasets were used for training and 100 datasets were used for check of the result of training. The measured toe height data obtained from the motion capture system and the measured angular data at toe-off obtained from the robotic system were used for the machine learning of the RBFN. After training of the parameters of the RBFN using 2-20 Gaussian functions, the participants were asked to walk on the treadmill for 270 s. After 30 s, the robot applied the force intermittently for 120 s. The timing of the force application was when the predicted MTC would be lower than the mean of MTCs obtained in the RBFN training phase. The duration of applying the tensile force was approximately 0.18 s, and the desired force value was 16 N based on a previous research [18]. The robot stopped the intermittent assistance for the last 120 s of walking.

MTC prediction algorithm was evaluated using 100 datasets after training of the RBFN parameters. The root mean square error (RMSE) between ground truth MTC data and predicted MTC data was calculated. Furthermore, the rate of detecting MTC negative values was calculated by dividing the number of negative values of the predicted MTC when the ground truth MTC was negative by the number of negative values of the ground truth MTC.

We analyzed how the MTC changed according to the intermittent force application and whether the change of MTC remained after the assistance phase. Approximately 90 gait data during steady locomotion in each phase (before, during, and after assistance) were analyzed for each participant. The first quartile, mean, third quartile, and maximum values of the MTC were derived to analyze the change of the MTC distribution. These values of MTC were analyzed to evaluate whether the lower MTC values could be increased as the after-effect after robotic intermittent assistance. The first and third quartiles showed the values of the lowest and highest 25% of the data, respectively. Significant test was performed to investigate whether the MTC parameters increased significantly after the assistance using the Wilcoxon rank sum test which is a non-parametric statistical hypothesis test comparing two related samples (a pair of MTC parameters before and after assistance). Furthermore, the after-effect of the minimum and first quartile values of MTC was evaluated in case where the force was applied every gait cycle without the prediction algorithm to consider the effect of the prediction algorithm. Data were collected before this experiment from other nine people (eight men; aged 22.5 ± 2.9 years, body weight 61 ± 8 kg, height 1.67 ± 0.07 cm).

IV. Results and Discussion

As shown in Table 1, the mean RMSE between ground truth and predicted MTC was 2.31 mm. Moreover, the mean rate of detecting MTC negative values was approximately 80%. Input variables for this test of the algorithm were extracted in the start of the swing phase every gait cycle in real-time. Although the noise might increase comparing to the offline prediction method due to real-time processing (sampling frequency varied) and electrical signals emitted by the robotic system, we concluded that the prediction was accurate enough to affect lower values of MTC because the error was smaller than the range of lower values of MTC.

The force application of the cable-driven robot used in this experiment increased the knee flexion angle [18]. Increase in ratio of the knee flexion angle to the hip flexion angle while people flex the hip joint and maintain the ankle joint angle leads to the increase in MTC. The system could switch the force strength based on the prediction result because the maximum force strength was 15.9 and -0.4 N when the predicted MTC was higher and lower than the mean MTC, respectively. Therefore, the cable-driven robot was controlled based on the prediction results.

Fig. 8 shows that the minimum value before, during, and after intermittent-force application. Further, Figs. 9, 10, 11, and 12 show the first quartile, mean, third quartile, and maximum values of the MTC in each phase, respectively. The minimum and first-quartile values of the MTC tended to increase with the intermittent-force application as shown in Figs. 8 and 9. The minimum value of the MTC during the application of intermittent force was lower than the mean MTC before the force was applied intermittently. The original difference between the minimum and mean MTC values before the intermittent force application was approximately 5.1 mm. The difference between minimum MTC during the application of intermittent force and the mean MTC before the application was approximately 3.5 mm. This implies that the system could inhibit the participants from producing the toe motion around the minimum value of the original MTC distribution. In the experiment, the proposed algorithm was able to predict MTC within an error of approximately 2.3 mm. As a result, approximately 84% of the MTC values during the force application were higher than the mean MTC before the intermittent force application.

TABLE I. MTC prediction results

	Mean	*Standard deviation*
RMSE mm	2.3	0.57
Rate of detecting negative values of MTC %	80	13

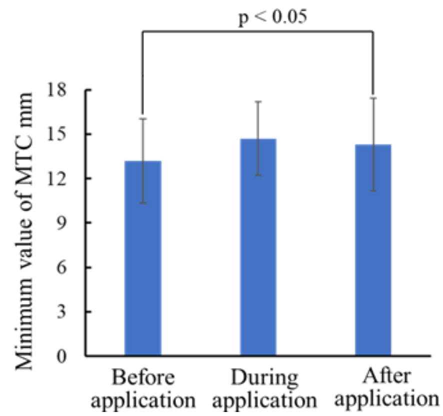


Fig. 8 Minimum value of MTC. Value p indicates the result of Wilcoxon rank sum test. The change was significant if the p was lower than 0.05.

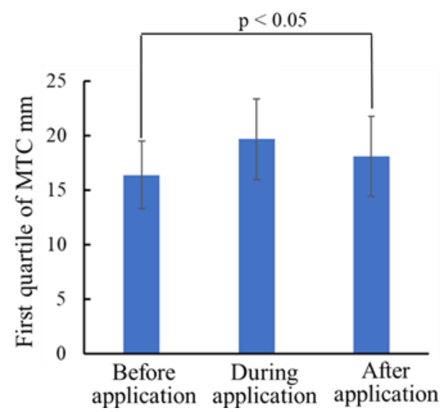


Fig. 9 First quartile of MTC. Value p indicates the result of Wilcoxon rank sum test. The change was significant if the p was lower than 0.05.

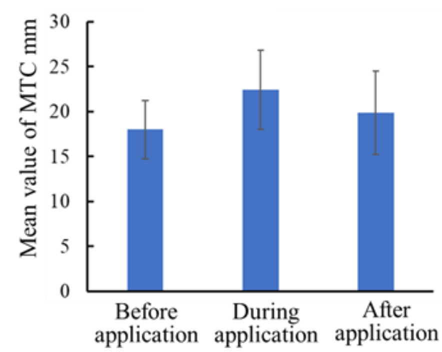


Fig. 10 Mean value of MTC. The change was significant if the p was lower than 0.05.

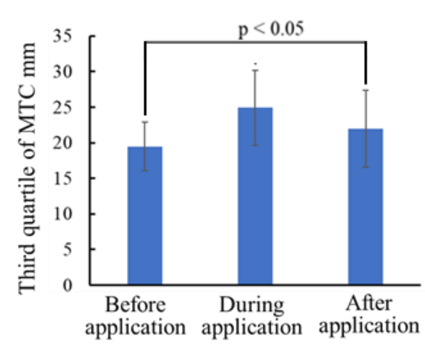


Fig. 11 Third quartile of MTC. Value p indicates the result of Wilcoxon rank sum test. The change was significant if the p was lower than 0.05.

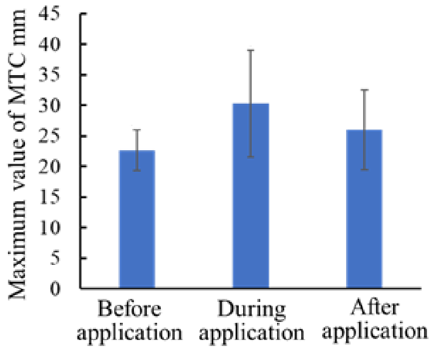


Fig. 12 Maximum value of MTC. The change was significant if the p was lower than 0.05.

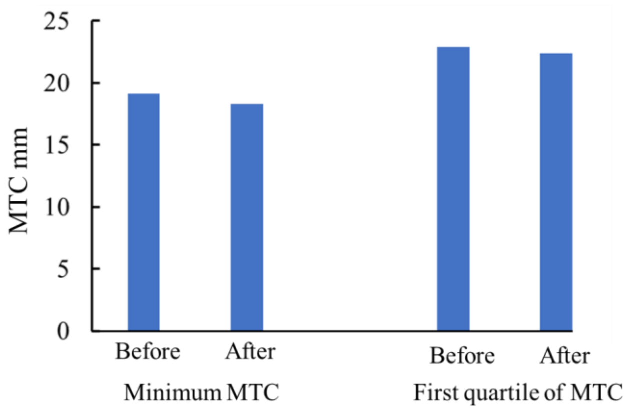


Fig. 13 Minimum and First quartile values of MTC when the force was applied without prediction algorithm.

The minimum and first quartile values of MTC increased significantly after the intermittent force application comparing to before the application as shown in Figs. 8 and 9. Fig. 13 shows minimum and first quartile values of MTC after force application was not different significantly than before application in case where the force was applied without prediction algorithm. Consequently, the intermittent force application based on MTC prediction could encourage the participants to increase the lower values of MTC.

We assumed that the reason why the motion modification was observed when avoiding relying on the robot to complete the task was that active motor behavior encouraged them to relearn the motion pattern. The after-effect is generally produced by the predictive adjustment, i.e., the feedforward altered motion pattern according to the cerebellum [22]. The first reaction of people is the reactive adjustment with lower level of central nervous system. The proprioceptive sense related to motion pattern is transmitted to the cerebellum through trial-and-error repetition, leading to predictive adjustment [23]. Therefore, people do not learn the new motion pattern if they are moved fully by the robot. The robotic assistance that inhibits MTC from decreasing provides proprioceptive sense to avoid the reduction. Although the participants did not know the objective of this experiment (increasing the lower values of MTC distribution), they automatically modified their motion to increase the lower values of MTC distribution. As this training system did not enhance the muscle strength, the altered factor of human body might be related to the central nervous system. We assume that the proposed intermittent force application based on prediction involved modification by encouraging the participants to try to avoid reducing MTC unconsciously thorough proprioceptive stimulation to avoid the reduction of MTC.

The increased MTC at the gait cycle when the force was applied was higher than the original MTC. We observed that the higher the third-quartile or maximum values of MTC, the lesser was the increase in MTC after intermittent-force application (after-effect). Considering the interquartile change rate was approximately -47% (decrease) in male and 200% (increase) in female, the degree of the MTC change when the force was applied influenced the after-effect. In addition, the physical difference affects the degree of the movement change. The increase of interquartile range was related to the significant increase in the third quartile values of MTC from before to after the intermittent force application, which was our unexpected changes. The force strength was constant in this experiment because the effect of the difference in force strength was not the focus of this study. If the force strength is appropriate for individual, only lower values of MTC distribution might increase and be modified as the after-effect. As a future work, it would be beneficial to ensure the adaptive adjustment of force strength corresponding to the user's physique.

Although the participants modified their MTC control using the proposed robotic assistance, further investigation about long-term after-effects (MTC modification, change in spatiotemporal parameters of both legs, etc.) would be beneficial. There is a limitation that the system is affected easily by the shift of the angular sensors. The gait phase detection and MTC prediction algorithms rely on the angular information. We assume that the angular sensors might shift thorough the long-term use of the system. Therefore, ensuring the calibration method of angular information during walking would be needed. Moreover, we focused on only increasing the toe height to avoid tripping in this work. We assume that the proposed prediction-based assistance method will be used for other training systems to improve control ability.

V. Conclusion

We have presented an intermittent force application method of gait training robot based on MTC prediction. As results of the experiment of human subjects, the proposed system could increase lower values of MTC distribution and encouraged the participants to modify their MTC control to inhibit from reduction significantly.

Force parameters of the robotic controller were constant in the experiment. The adjustment of force parameters corresponding to the user's physique would be beneficial as a future work. Moreover, the long-term investigation of gait training effect with the proposed system would be also beneficial as a future work. We assume that the automatic calibration method of angular sensors would be required for long-term use in case where the sensors shift.

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