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Generation of gait data less prone to stumbling considering the physical differences among trainees

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Abstract

Several training methods have been developed to obtain motion information during real-time walking and feed it back to trainees who adjust their gait to ensure that the measured gait parameters approach target value, which may not always be suitable for every trainee owing to physical differences between individuals. This paper proposes a method of setting this target value considering these physical differences and discusses the usefulness of the gait training method, wherein a multichannel deep convolutional neural network (MC-DCNN) gait classification model constructed by learning ideal or non-ideal gait features beforehand is used for trainee gait classification. Activation maximization is applied to the MC-DCNN model; data wherein the ideal walking features are activated are generated based on trainee gait data. However, the amounts of features to be activated to generate a possible and natural gait are restricted. The original trainee gait, beyond individual physical differences, and gait data generated based on the original gait data seem to yield the target value considering the physical differences among individuals. This study focused on gait related to stumbling. To verify its usefulness, a multivariate gait dataset consisting of kinematic and kinetic indices labeled as “gait rarely associated with stumbling” or “gait frequently associated with stumbling” was divided into a training set, validation set, and test set. The MC-DCNN model learned gait features for multivariate gait data classification in the training set. It classified the gait with $96.04 \pm 0.12\%$ accuracy against the validation set. Finally, by applying the proposed method to the multivariate gait data contained in the test set, we generated multivariate gait data classified as “gait rarely associated with stumbling” based on the input data. In addition, the generated multivariate gait data include motion that increases the thumb-to-ground distance and describe possible and natural gait considering the physical differences among individuals.

Keywords : Healthcare, Gait training, Motion analysis, Walking factor, Neural network, Activation maximization

1. Introduction

In Japan's super-aging society, the increase in the number of people requiring nursing care has become a problem. According to a survey by the Ministry of Health, Labour and Welfare of Japan, falls and fractures accounted for 12.5% of the total cases, and old age-related weakness accounted for 13.8%, which is the second highest after stroke and dementia (Japanese Ministry of Health, Labour and Welfare, 2016). Therefore, the prevention of falls is an issue for not only those who require nursing care but also active seniors. In the field of physical therapy, gait training is conducted under the guidance and supervision of a physical therapist, but since the guidance is based on subjective observation by the physical therapist, it requires specialized knowledge and experience, and the contents of guidance may differ among physical therapists. In response to these problems, feedback training methods have been proposed that acquire gait indicators while the trainee is walking and present them to the trainee in real time as visual and auditory information. It has been confirmed that these feedback training methods have a greater effect on gait improvement than training under

the guidance of a physical therapist and that the effect is sustained over a long period of time (Stanton et al., 2011). However, most of these studies were conducted on stroke patients. Montoya et al. (1994) proposed a feedback method that measures the stride length during walking and presents it to the trainee in real time for stroke patients. Since it is known that stroke patients have a smaller stride length (Sashika et al., 1986), the trainee should adjust the stride length to a larger value when the stride length is the target of training. However, when targeting active seniors, their symptoms are not limited; the gait components and their directions and extents of adjustments are unclear. Therefore, target values for each gait component are necessary. A representative value, such as the average value of each gait variant of a young healthy person, can be considered a target value, but the optimal value differs for each trainee owing to individual physical differences among trainees (e.g., range of motion of joints and muscle strength). Therefore, it is necessary to set the target values considering the individual physical characteristics of each trainee. Further, previous studies have not addressed specific joints or muscles strength that should be adjusted to increase the stride length. Thus, it is considered that the adjustments differ among the trainees. Therefore, it is desirable for gait training methods to present multiple gait variables, such as joint angle and muscle strength, that should be adjusted by the trainee.

To address these problems, we developed the multivariate gait feedback training system shown in Fig. 1, which considers the individual physical differences among trainees (Osawa et al., 2020). As it has been reported that many falls in the elderly are caused by stumbling while walking (Blake et al., 1988), this study was focused on stumbling as an object of gait training. This system consists of an optical motion capture system (Natural Point Inc., OptiTrack), a dual belt treadmill with two force plates (Tec Gihan Co., Ltd., HPT-2200D), a computer, and a display. The developed system measures kinetic and kinematic data during walking and generates multivariate gait data consisting of joint angles (the trunk, hips, knees, and ankles) and ground reaction forces. In addition, the gait of the trainee is classified as “gait rarely associated with stumbling” or “gait frequently associated with stumbling” using a gait classification model that learned features of gait related with stumbling through a multi-channel convolutional neural network (MC-DCNN) (Zheng et al., 2014). Then, gradient-weighted class activation mapping (Grad-CAM) (Selvaraju et al., 2017) is applied to the multivariate gait data and gait classification model to visualize the parts of the multivariate gait data with considerable effects on the classification of gait related with stumbling, as well as their relative strengths. The gait classification model considers individual differences. In addition, as multivariate gait data are composed of time-series data of multiple gait variables, trainees can visually understand the body parts and timings to be adjusted by feeding back the output of Grad-CAM in real time.

In the previously developed method, the body parts and timings to be adjusted by trainees could be visualized, but target values indicating how and to what extent to adjust each component were not set. To address this issue, we proposed a method of setting target values considering the physical differences among trainees. Specifically, activation maximization (Mahendran and Vedardi, 2015; Nguyen et al., 2016; Simonyan et al., 2014), which optimizes input data and activates features learned in the CNN classification model based on arbitrary input data, is applied to the gait classification model and multivariate gait data. In addition, target multivariate gait data are generated by activating features of “gait rarely associated with stumbling” based on the multivariate gait data of trainees, which describe a “gait frequently associated with stumbling.” However, as the multivariate gait data generated by activation maximization are not considered to correspond to human motion, they may describe an impossible or unnatural gait. To address this issue, a target value setting method was developed that considers individual differences by generating multivariate gait data

Fig. 1 Outline of gait training system considering physical differences among individuals.

corresponding to the “gait rarely associated with stumbling” class with restrictions on the activation amounts of features by activation maximization. We also discussed the usefulness of the multivariate gait data generated by the proposed method as a target value for feedback training. First, the multivariate gait dataset, which consists of kinematic and kinetic indices generated in previous studies and which were labeled as “gait rarely associated with stumbling” or “gait frequently associated with stumbling,” was divided into a training set, a validation set, and a test set. Using the multivariate gait data in the training set as input and the corresponding class as output, MC-DCNN learned the gait features related to stumbling, and a gait classification model was constructed. We also evaluated the accuracy of classification of the data contained in the validation set of the model. Finally, the data of the “gait frequently associated with stumbling” class included in the test set were input to the gait classification model, and the proposed method (with restriction and without restriction) was applied. Then, we compared the multivariate gait data generated by the proposed method (unconstrained and constrained) with the mean values of each gait variable in the “gait rarely associated with stumbling” class and confirmed the usefulness of the multivariate gait data generated by the proposed method with restriction for gait training.

This paper is organized as follows. Chapter 2 presents an overview of the proposed method, Chapter 3 describes the experiment of multivariate gait data generation by the proposed method. Chapter 4 discusses the usefulness of the proposed method, and Chapter 5 presents the conclusions of the study.

2. Generation of “gait rarely associated with stumbling” data considering physical differences among trainees

Activation maximization is used to visualize the features on which a learned model is based for classification and is often utilized as a classification model for image data. In this approach, an arbitrary image or random noise is input into a learned classification model and the input is adjusted and optimized so that the output of an arbitrary layer of the model becomes large, that is, the feature is activated. The simplest method of activation maximization is as follows. Firstly, the gradient for the output of any intermediate or output layer in each element of the input matrix data is calculated, and the gradient matrix is obtained. The value of this gradient matrix is normalized; multiplied times weight w , which determines the degree to be adjusted by one update; and added to the original input data to update the input data. Repeatedly updating these input data activates the learned features, and the matrix data in which the output of the arbitrary layer increases is generated based on the original input data. As the learning is performed to extract the feature quantity by filtering in the convolution layer of the CNN, the feature quantity learned by the convolution layer can be understood by targeting the convolution layer as a layer to which activation maximization is applied. By using the output in an arbitrary class of the output layer as the target, it is possible to generate the data so that the features of the class are activated with the input data as a basis.

In this study, we developed a method of setting target values for gait parameters considering the physical differences among trainees by applying activation maximization to a gait classification model and multivariate gait data (Fig. 2). Firstly, we constructed a gait classification model that learned the features of “gait rarely associated with stumbling” and “gait frequently associated with stumbling” using an MC-DCNN with multivariate gait data as input. MC-DCNNs learn feature quantities individually for each variable of multivariate time series data, learn suitable convolutional layer filters for each variate of multivariate time series data, and combine the output of the convolutional layer for each variate in the fully connected layer. During training, the gait of the trainee is classified using the MC-DCNN model, and activation maximization is applied when the “gait frequently associated with stumbling” class is identified. However, the softmax function represented by Eq. (1) is used as the activation function of the output layer of the MC-DCNN model:

$$\mathbf{o}_k^{softmax} = \frac{\exp(x_k)}{\sum_{i=1}^n \exp(x_i)} \quad (1)$$

The output $\mathbf{o}^{softmax}$ of the softmax function represents the ratio of the output of the exponential function of each element of the input vector $\mathbf{x}$, and their indices represent the classes used for classification. In this paper, the classes are “gait rarely associated with stumbling” and “gait frequently associated with stumbling.” Then, the outputs of the softmax function for the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes are expressed as $\mathbf{o}_{rarely}^{softmax}$ and $\mathbf{o}_{frequently}^{softmax}$, respectively. The input vector of the softmax function is the output of the fully connected layer and represents the strength of the learned features of each class of the input data. Therefore, by using the

output $O_{rarely}^{softmax}$, the generated multivariate gait data have the features of the “gait rarely associated with stumbling” class activated and those of the “gait frequently associated with stumbling” class deactivated. As the multivariate gait data generated by this method are based on the original multivariate gait data of the trainee, the gait characteristics corresponding to the physical differences among trainees (that is, differences in muscle strength and joint mobility) are considered. However, when original Activation Maximization is applied, the optimum target value for the trainee cannot be set. Figure 3 shows $O_{rarely}^{softmax}$ for the other elements and its derivatives when the input vector has two elements, one of which is constant at zero. As the data are repeatedly updated and the input approaches zero, the absolute value of the gradient for the output becomes larger. Therefore, the normalized values of elements with large gradients are larger than those of elements with small gradients. As the original activation maximization normalizes the gradient for the output of any layer, multiplies it times the weight, and adds it to the input, the adjustment amount of the element with a large gradient increases with every update, and consequently, the element is extremely adjusted. Considering that the multivariate gait data used in this study are human movements, extreme adjustments to certain gait variables may result in an impossible or unnatural gait. Then, it is necessary to perform natural adjustment of the walking motion by restricting the amount of adjustment of each gait variable. To set the restriction, a method of adjusting within the range each gait variable can take is considered. For example, as the multivariate gait data have the joint angle as a gait variable, the range of motion of the ankle joint is made to be within the physical limits of the amount of adjustment. However, even within the range of motion of the joint, unnatural gait could occur. Thus, in the proposed method, after normalizing each element of the gradient matrix, it is input into the tanh function represented by Eq. (2) as a restriction, and its output matrix is multiplied times w and added to the input:

$$f(x) = \frac{\exp(ax) - \exp(-ax)}{\exp(ax) + \exp(-ax)} \quad (2)$$

Figure 4 shows the relationship between the input and output of the tanh function. By increasing parameter a , the gradient near the origin becomes large, and the absolute value of the input whose output asymptotically approaches 1 becomes small. When the element of the input matrix whose absolute value of the normalized gradient is sufficiently large is input into the tanh function, the output asymptotically approaches 1, and the adjustment amount becomes relatively small, whereas the adjustment amount of the element whose absolute value of the normalized gradient is small becomes relatively large. Therefore, it is considered that this method can be used to set the natural target value for the gait motion by suppressing the adjustment amount of each gait variable at a certain time, which is sufficiently adjusted in the data update process and by increasing the adjustment amounts of the other gait variables.

Fig. 2 Proposed target setting method considering physical differences among trainees.

Fig. 3 Softmax function output $O^{softmax}$ versus input and its derivatives. The number of elements of the input vector was 2, and if one element was set to 0, the output of the other element was used.

Fig. 4 Tanh function output versus input.

3. Generation of multivariate gait data

3.1 Multivariate gait data for learning

When a classification model for arbitrary kinds of data is constructed using a CNN, which is employed in supervised learning, input data for learning and corresponding classes are necessary. In this study, we used a dataset of gaits related to stumbling that was generated in a previous study (Osawa et al., 2020). The dataset contained 1,548 multivariate gait data divided by the stride of the target leg as input data. The experiment was performed on eight participants (male, mean age 23.9 ± 1.0 years) under conditions of “normal walking” and “restricted walking (walking with muscle load and limited joint motion by the simulated elderly orthosis (Sanwa Manufacturing Co., Ltd, Expert set III of teaching materials for simulating elderly)).” In each condition, the belt speed of the treadmill was automatically controlled to keep the experiment participant in the center of the treadmill such that the participant could walk at a comfortable speed. The multivariate gait data consisted of the normalized joint angles (those of the trunk, target and non-target hip, knee, and ankle joints) on the YZ and XZ planes in global coordinates and three components of the normalized ground reaction forces (X, Y, and Z for the target and non-target legs) as gait variables, as shown in Figs. 5 and 6. However, the joint angle was measured by the motion capture system, and the ground reaction forces were measured by a force plate built into the treadmill (The rated capacity of the x and y components is ± 3000 N and that of the z component is 10000 N. The analog output scale is ± 10 V, and the resolution of the AD conversion is 16 bits). The sampling frequencies were 250 Hz. Each multivariate gait datum was assigned to the “gait rarely associated with stumbling” or “gait frequently associated with stumbling” class, which contained 790 and 758 data points, respectively. The labeling was performed based on the results of clustering by the nearest neighbor method using the dynamic time warping (Sakoe and Chiba, 1978) and the elbow method (Bholowalia and Kumar, 2014) for the thumb-to-ground distance corresponding to each multivariate gait datum, regardless of the experimental conditions. Since the thumb-to-ground distance is considered a cause of stumbling (Nishizawa et al., 1998), a person is less prone to stumble if the thumb-to-ground distance is high during the swing phase. Therefore, multivariate gait data included in the cluster with a high thumb-to-ground distance during the swing phase were defined as “gait rarely associated with stumbling”, whereas multivariate gait data included in the cluster with low thumb-to-ground distance were defined as “gait frequently associated with stumbling”.

Fig. 5 Definitions of gait variables for multivariate gait data used in this study.

	Initial contact with the ground of the target leg					End of terminal swing				
Normalized change in trunk angle in the YZ	0.25	0.34	0.35	0.27	...	0.18				
Normalized change in trunk angle in the XZ	0.10	0.86	0.03	0.72	...	0.53				
Normalized change in hip joint angle of the target leg in the YZ	0.43	0.53	0.64	0.62	...	0.45				
Normalized change in hip joint angle of the target leg in the XZ	0.12	0.78	0.34	0.26	...	0.87				
Normalized change in hip joint angle of the non-target leg in the YZ	0.62	0.60	0.52	0.46	...	0.53				
Normalized change in hip joint angle of the non-target leg in the XZ	0.26	0.34	0.52	0.10	...	0.34				
	:	:	:	:		:				
Normalized ground reaction force Z component of the non-target leg	0.26	0.18	0.54	0.72	...	0.54				
	0					100				
	Walking cycle [%]									

Fig. 6 Structure of multivariate gait data used in this study.

3.2 Learning multivariate gait data using MC-DCNN

In addition to the joint angles and floor reaction forces included in multivariate gait data, angular velocity, angular acceleration, and acceleration are considered as factors that generate motion. In the Newton-Euler method for solving the equations of motion of a mechanism with an open-loop structure, angular velocity, angular acceleration, and acceleration are required as elements to obtain the force to be applied at each joint to achieve the target motion. Therefore, their features (i.e., time-series features) should be considered. The MC-DCNN used in this study sets up a convolutional layer for each variable of the input data and learns the parameters of each convolutional layer. The convolutional layer extracts the features of the input matrix by the same action as the filter process. Since the joint angles and floor reaction forces contained in the multivariate gait data are time-series data, these convolution layers are also expected to learn to extract the features in the time direction that each variable has (e.g., the features of the derivative). In addition, the gait training method proposed in this study assumes that the target value and the actual measured value are fed back to the trainee, and the trainee adjusts the gait through repeated trial and error. Therefore, it is not necessary for the trainee to uniquely determine in advance the force to be generated at each joint. If the variables to be fed back are subdivided and increased, it will be difficult for the trainee to understand them, and even if they do understand them, it will be difficult to control them correctly. Therefore, in this study, only joint angles and floor reaction forces were used as gait variables for learning. Using the multivariate gait data as input and the labeled classes as output, gait classification models were constructed by learning the features of the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes using an MC-DCNN. The model structure of the MC-DCNN is shown in Fig. 7 and summarized in Table 1. The number of epochs was 4,000, batch size was 64, optimization function was stochastic gradient descent, and error function was

categorical cross-entropy. In the classification model constructed previously, the ReLU function was used as the activation function of the intermediate layer, but in this study, the tanh function, which is said to be suitable for feature extraction from time series data, was used. As a test set for usefulness verification, 10 data points were randomly selected for each class from a total of 1,548 data points, and 80% and 20% of the remaining 1,528 data points were used as the training set and validation set, respectively. The model with the lowest loss for the validation set among 4,000 epochs was saved using the model check point function.

Learning was performed 10 times, and the average classification accuracy of gait related to stumbling for the validation set in the 10 gait classification models generated was $96.04\% \pm 0.12\%$. Table 2 shows the classification results for the 20 data points in the test set based on the gait classification model with the lowest loss for the validation set of the 10 learning models and their $\mathbf{O}^{softmax}$. Data points 3 and 16 have the largest outputs for the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes (0.999870 and 0.999841, respectively). In addition, data points 10 and 13 have the smallest outputs for the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes among the data of the respective classes (0.610133 and 0.996495, respectively). Figure 8 shows the thumb-to-ground distances of the target leg corresponding to these four multivariate

Fig. 7 Structure of the MC-DCNN model for gait classification.

Table 1 Description of the layers in the MC-DCNN model for gait classification.

Layer name	Layer description
Input	$20 \times 400 \times 1$ Two-dimensional data
Conv1d n_1	Filters: 32, kernel size: 25, stride: 1, padding: causal
Activation	Activation function: tanh
Max pooling1d n_1	pool size: 2, padding: valid
Conv1d n_2	Filters: 64, kernel size: 10, stride: 1, padding: causal
Activation	Activation function: tanh
Max pooling1d n_2	pool size: 2, padding: valid
Flatten	-
Dense 1	Units: 256
Activation	Activation function: tanh
Dense 2	Units: 64
Activation	Activation function: tanh
Dense 3	Units: 16
Activation	Activation function: tanh
Dense 4	Units: 2
Output	Activation function: softmax

gait data, and Table 3 shows the peak value of the non-normalized thumb-to-ground distance of the target leg in the range from 80% to 100%. However, the Z coordinate of the first metatarsal head was defined as the thumb-to-ground distance. In the range from 80% to 100%, data points 3 and 16 have the highest and lowest thumb-to-ground distances (with pre-normalized maximum values of 141.14 mm and 59.84 mm, respectively). Data points 10 and 13 are intermediate between data points 3 and 16 (with pre-normalized maximum values of 93.91 mm and 80.01 mm, respectively).

Table 2 Classification results of multivariate gait data and output $\mathbf{O}^{softmax}$ of softmax function using the MC-DCNN model for gait classification.

Class of input data	Data point number	Classification result	$\mathbf{O}^{softmax}_{rarely}$	$\mathbf{O}^{softmax}_{frequently}$
“Gait rarely associated with stumbling”	1	Correct	0.999844	0.000156
	2	Correct	0.999867	0.000133
	3	Correct	0.999870	0.000130
	4	Correct	0.999792	0.000208
	5	Correct	0.999854	0.000146
	6	Correct	0.998480	0.001520
	7	Correct	0.999794	0.000206
	8	Correct	0.999506	0.000494
	9	Correct	0.998228	0.001772
	10	Correct	0.610133	0.389867
“Gait frequently associated with stumbling”	11	Correct	0.001384	0.998616
	12	Correct	0.000224	0.999776
	13	Correct	0.003505	0.996495
	14	Correct	0.000206	0.999794
	15	Correct	0.000281	0.999719
	16	Correct	0.000159	0.999841
	17	Correct	0.000349	0.999651
	18	Correct	0.000455	0.999545
	19	Correct	0.000378	0.999622
	20	Correct	0.003183	0.996817

Fig. 8 Normalized thumb-to-ground distance corresponding to multivariate gait data included in test set (red, orange, green, and blue represent data points 3, 10, 13, and 16)

Table 3 Maximum non-normalized thumb-to-ground distance of the target leg during the terminal swing.

Class of input data	Data point number	Non-normalized thumb-to-ground distance of the peak in the range from 80% to 100% [mm]	Class of input data	Data point number	Non-normalized thumb-to-ground distance of the peak in the range from 80% to 100% [mm]
“Gait rarely associated with stumbling”	3	141.14	“Gait frequently associated with stumbling”	13	80.01
	10	93.91		16	59.84

3.3. Generation of “gait rarely associated with stumbling” using optimization with activation maximization

Activation maximization (with and without restriction) was applied to data point 16, which has the largest output for the “gait frequently associated with stumbling” class and has a low thumb-to-ground distance during the terminal swing. Using original data point 16 as a basis, multivariate gait data were generated that activated the features of the “gait rarely associated with stumbling” class. However, the gradient matrix was normalized using the average of the absolute values of each element of the gradient matrix. The weight w for determining the degree of adjustment in one update was set to 5×10^{-4} , and the restriction parameter a was set to 4×10^{-1} . The data update by Activation Maximization ended when the classification result of the data generated for each update switched to the “gait rarely associated with stumbling” class.

Figure 9 shows each gait variable of original data point 16, each multivariate gait datum (with and without restriction) that activated the features of the “gait rarely associated with stumbling” class based on data point 16, and the mean of each gait variable of each class. Table 4 lists the maximum and minimum values of each non-normalized gait variable, minimum non-normalized ankle joint angle on the YZ plane of the target leg in the range of 80% to 100%, and minimum non-normalized ankle joint angle on the YZ plane of the non-target leg in the range of 40% to 60%. In the multivariate gait data generated without restriction, the adjustment amount of the knee joint angle on the YZ plane of the target leg and the ankle joint angle on the YZ plane of the target leg from data point 16 is large. In particular, the maximum non-normalized knee angle on the YZ plane of the target leg of original data point 16 is 36.34° , whereas that of the multivariate gait data generated without restriction is 43.04° . Also, the minimum non-normalized knee joint angle on the YZ plane of the target leg of original data point 16 is -0.40° , whereas that of the multivariate gait data generated without restriction is -13.27° . The maximum non-normalized ankle joint angle on the YZ plane of the target leg of original data point 16 is 14.43° , whereas that of the multivariate gait data generated without restriction is 19.83° . In addition, the minimum non-normalized ankle angle on the YZ plane of the target leg in the range from 80% to 100% of original data point 16 is 1.86° , whereas that of the multivariate gait data generated without restriction is -16.15° . For the other gait variables, the adjustments are small. On the other hand, in the multivariate gait data generated with restriction, the minimum non-normalized knee joint angle on the YZ plane of the target leg is -7.15° , and the maximum non-normalized ankle joint angle on the YZ plane of the target leg is 19.49° . In addition, the minimum non-normalized ankle angle on the YZ plane of the target leg in the range from 80% to 100% is -3.32° . For the other gait variables, the adjustments are larger than those of the multivariate gait data generated without restriction.

Fig. 9 Mean of each variate of each class (dotted red and blue lines are means of “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes, respectively), each variate of original data point 16 (blue line), and each variate data generated with and without restriction based on data point 16 (red and green lines are data generated without and with restriction, respectively).

Table 4 Maximum and minimum values of each non-normalized gait variable, minimum non-normalized ankle joint angle on the YZ plane of the target leg in the range of 80% to 100% and minimum non-normalized ankle joint angle on the YZ plane of the non-target leg in the range of 40% to 60%.

Gait variable	Original multivariate gait data of data point 16		Mean of the multivariate data of “gait rarely associated with stumbling”	
	Non-normalized maximum value	Non-normalized minimum value	Non-normalized maximum value	Non-normalized minimum value
Trunk angle on the YZ plane [°]	9.40	2.71	3.22	2.29
Trunk angle on the XZ plane [°]	12.70	-0.17	2.85	-3.19
Hip angle on the YZ plane of the target leg [°]	3.66	-24.49	7.84	-20.12
Hip angle on the XZ plane of the target leg [°]	15.68	-4.03	3.43	-7.67
Hip angle on the YZ plane of the non-target leg [°]	0.78	-28.32	8.28	-19.82
Hip angle on the XZ plane of the non-target leg [°]	6.14	-10.92	7.50	-3.49
Knee angle on the YZ plane of the target leg [°]	36.34	-0.40	59.19	-0.32
Knee angle on the XZ plane of the target leg [°]	-9.97	-34.12	3.26	-6.39
Knee angle on the YZ plane of the non-target leg [°]	47.20	8.77	58.43	-0.74
Knee angle on the XZ plane of the non-target leg [°]	19.55	3.51	6.53	-0.41
Ankle angle on the YZ plane of the target leg [°]	14.43	-10.49	16.72	-8.84
Ankle angle on the XZ plane of the target leg [°]	152.40	75.18	43.58	-71.20
Ankle angle on the YZ plane of the non-target leg [°]	12.05	-12.04	17.24	-8.32
Ankle angle on the XZ plane of the non-target leg [°]	-48.02	-145.09	72.38	-42.00
Ground reaction force X component of the target leg [%]	20.12	-8.42	8.89	-6.26
Ground reaction force Y component of the target leg [%]	16.98	-8.44	18.22	-18.26
Ground reaction force Z component of the target leg [%]	127.18	-4.15	123.39	-2.90
Ground reaction force X component of the non-target leg [%]	10.61	-20.82	6.18	-8.59
Ground reaction force Y component of the non-target leg [%]	11.27	-13.09	17.78	-19.22
Ground reaction force Z component of the non-target leg [%]	128.27	-3.06	123.04	-2.75
Ankle angle on the YZ plane of the target leg in the range from 80% to 100% [°]	-	1.86	-	-2.21
Ankle angle on the YZ plane of the non-target leg in the range from 80% to 100% [°]	-	0.59	-	-1.20

Gait variable	Multivariate gait data generated without limitation		Multivariate gait data generated with limitation	
	Non-normalized maximum value	Non-normalized minimum value	Non-normalized maximum value	Non-normalized minimum value
Trunk angle on the YZ plane [°]	9.77	2.75	9.96	2.77
Trunk angle on the XZ plane [°]	12.67	0.27	12.58	0.78
Hip angle on the YZ plane of the target leg [°]	4.07	-24.68	4.45	-25.03
Hip angle on the XZ plane of the target leg [°]	15.73	-4.94	15.78	-5.81
Hip angle on the YZ plane of the non-target leg [°]	0.78	-28.32	0.76	-28.31
Hip angle on the XZ plane of the non-target leg [°]	6.22	-11.03	6.85	-11.10

Knee angle on the YZ plane of the target leg [°]	43.04	-13.27	42.84	-7.15
Knee angle on the XZ plane of the target leg [°]	-9.98	-32.55	-9.94	-31.39
Knee angle on the YZ plane of the non-target leg [°]	48.88	-4.22	50.34	3.03
Knee angle on the XZ plane of the non-target leg [°]	18.86	3.67	18.39	3.71
Ankle angle on the YZ plane of the target leg [°]	19.83	-16.15	19.49	-14.17
Ankle angle on the XZ plane of the target leg [°]	143.36	73.16	143.49	64.52
Ankle angle on the YZ plane of the non-target leg [°]	11.68	-11.42	11.14	-11.46
Ankle angle on the XZ plane of the non-target leg [°]	-45.16	-138.63	-39.28	-132.58
Ground reaction force X component of the target leg [%]	20.09	-8.75	20.09	-9.06
Ground reaction force Y component of the target leg [%]	17.48	-8.61	18.18	-8.82
Ground reaction force Z component of the target leg [%]	128.31	-4.04	129.63	-4.54
Ground reaction force X component of the non-target leg [%]	10.75	-20.67	10.92	-20.62
Ground reaction force Y component of the non-target leg [%]	11.36	-13.32	11.52	-13.88
Ground reaction force Z component of the non-target leg [%]	125.33	-5.00	122.17	-8.01
Ankle angle on the YZ plane of the target leg in the range from 80% to 100% [°]	-	-16.15	-	-3.32
Ankle angle on the YZ plane of the non-target leg in the range from 80% to 100% [°]	-	-0.55	-	-1.61

4. Discussion

4.1. Results of learning gait related to stumbling using MC-DCNN

The gait classification model constructed in this study exhibited a high classification accuracy of $96.04\% \pm 0.12\%$ for the validation set. As the output $\mathbf{O}^{softmax}$ of the softmax function represents the ratio of the output of the exponential function describing the strength of the features of each class included in the input data, it can be seen that data points 3 and 16, which have the largest outputs for the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes, respectively, are the gaits that have the largest features in the respective classes. In addition, data points 10 and 13 have the smallest outputs for the “gait rarely associated with stumbling” and “gait frequently associated with stumbling” classes, respectively, among the data of these classes and thus can be regarded as intermediate gaits between the two classes. Data points 3 and 16, which have the highest $\mathbf{O}_{rarely}^{softmax}$ and $\mathbf{O}_{frequently}^{softmax}$, respectively, have the highest and lowest thumb-to-ground distances of the target leg during the terminal swing. Further, data points 10 and 13 with intermediate $\mathbf{O}^{softmax}$ values between the classes have intermediate thumb-to-ground distances during the terminal swing. Although learning was performed using only multivariate gait data consisting of joint angles and ground reaction forces with binary values of 0 and 1 as outputs, $\mathbf{O}^{softmax}$ was correlated with the actual thumb-to-ground distance of the target leg during the terminal swing. These results suggest that the CNN model learned the features of the multivariate gait data that determine the thumb-to-ground distance, similar to previous studies (Osawa et al., 2020).

4.2. Usefulness of gait training by generating multivariate gait data in “gait rarely associated with stumbling” class

Multivariate gait data are divided for each stride of the target leg. Around 60%, the thumb-to-ground distance of the target leg increased, and the ground reaction force Z component of the target leg decreased. Thus, the range of 0% to 60% represents the phase of standing on the target leg, and the range of 60% to 100% represents the phase of swinging the leg. In addition, as the ground reaction force Z component of the non-target leg decreased at around 20% and increased at around 50%, the range from 20% to around 50% represents the phase of standing on the non-target leg, and the range of 0% to 20% and 50% to 100% represents the phase of swinging the non-target leg. According to Fig. 9 and Table 4, data point 16 has a small knee joint angle on the YZ plane of the target leg during the mid-swing and a large ankle joint angle on the YZ plane of the target leg during the terminal swing. In addition, the absolute values of the Y component of the ground reaction forces are large in the terminal stance. In addition, the changes of the angles on the XZ plane of the trunk, hip joint, and knee joint are large throughout the walking cycle, and the ankle joint on the XZ plane angle is inverted. In

addition, X components of the ground reaction forces in the stance phase are large. The gait of data point 16 shows that the knee joint flexion during the mid-swing and ankle joint dorsiflexion during the terminal swing are insufficient. In addition, the hip joint was abducted and externally rotated, and the ankle joint was abducted, which means that the experimental participant who generated data point 16 performed “circumduction.” It is possible to present the mean of the “gait rarely associated with stumbling” class shown in Fig. 9 as a target value during the training. In this case, the experimental participant who generated data point 16 needs to perform adjustment so that the knee joint angle on the YZ plane is large during the mid-swing, the ankle joint angle on the YZ plane is small during the terminal swing, and the absolute value of the Y component of the ground reaction force during the terminal swing is large. In addition, it is necessary to perform large adjustment of each joint angle on the XZ plane and the X component of the ground reaction force. However, the “circumduction” observed in the gait of data point 16 is an alternative action during the mid-swing in the case in which the knee joint cannot be fully flexed when the leg is swung forward, and this action increases the thumb-to-ground distance. Therefore, in setting the mean value of the “gait rarely associated with stumbling” class as a target value for the experimental participant who generated the data point 16, the muscular strength of the trainee and the mobility of the joint are not considered, and the gait can be said not to be suitable for the experimental participant.

On the other hand, as shown in Fig. 9, when the target is the multivariate gait data adjusted to activate the features of the “gait rarely associated with stumbling” class without restriction based on the multivariate gait data of data point 16, the change of the knee joint angle on the XZ plane during the mid-swing of each leg is adjusted to be small, but the adjustment amount is small. These results indicate that the multivariate gait data generated by activation maximization without restriction allowed “circumduction” (abduction of the ankle joint and abduction and external rotation of the hip joint) as a suitable gait for the participant who generated data point 16. In addition, in the multivariate gait data generated without restriction based on data point 16, the knee joint and ankle angles on the YZ plane of the target leg during the terminal swing were adjusted to be smaller. As a decrease in the knee joint angle on the YZ plane represents knee joint extension and a decrease in the ankle joint angle on the YZ plane represents ankle joint dorsiflexion, these adjustments increase the thumb-to-ground distance during the terminal swing. However, their adjustment amount is large; in particular, the minimum the non-normalized knee joint angle on the YZ plane of the target leg is -13.27° , and the normalized value is smaller than 0. The normalization was performed using the maximum and minimum values of each gait variable among all the multivariate gait data. Therefore, the minimum knee joint angle on the YZ plane generated without restriction is impossible as a human joint movement. In addition, the ankle joint angle on the YZ plane of the target leg, which is generated without restriction, is within the range of joint movement but indicates excessive dorsiflexion during the terminal swing. Therefore, the gait is impossible or unnatural, when multivariate gait data generated without restriction are used to set the target values of the gait parameters.

Comparing the multivariate gait data generated with restriction to those generated without restriction, which are shown in Fig. 9 and Table 4, the multivariate gait data generated with restriction have a larger knee joint angle on the YZ plane of the target leg during the terminal swing, and the amount of adjustment from original data point 16 is smaller. The ankle joint angle on the YZ plane of the target leg during the terminal swing is large, and the adjustment from original data point 16 is small. However, the adjustments of the other gait variables are large. For example, the hip angle on the YZ plane of the target leg during the terminal swing phase is small. As a decrease in the hip angle on the YZ plane represents hip flexion, this adjustment increases the thumb-to-ground distance during the swing phase. Therefore, when multivariate gait data generated without restriction based on data point 16 are used to set the target values of the gait parameters, the gait training system presents the participant with an adjustment to increase the thumb-to-ground distance by extending the knee joint beyond the range of joint motion and excessively dorsiflexing the ankle joint at the terminal swing. On the other hand, when the multivariable gait data generated with restriction are used to set the target values, the adjustment amount is restricted to the possible range as a gait and ensures an appropriate thumb-to-ground distance by bending the hip joint instead. Therefore, by using the proposed method, which is based on the original multivariate gait data of trainees and generates the target multivariate gait data by activating the features of the “gait rarely associated with stumbling” class with restriction, the gait characteristics resulting from the physical differences among trainees (in term of muscle strength and joint mobility) can be considered, and natural gait motion can be taught to trainees (Fig. 10).

Fig. 10 Comparison between target values that are the mean of the “gait rarely associated with stumbling” class, multivariate gait data generated without restriction, and multivariate gait data generated with restriction (proposed method)

4.3. Limitations

In this study, restriction parameter a was set to 4×10^{-1} . This setting enabled the adjustment of each element of the input matrix whose gradient became sufficiently large as the update was repeated to be decreased and that of each element whose gradient was small to be increased. However, by adjusting a , the threshold magnitude of the restricted gradient can be adjusted. As the magnitude of the gradient of the input matrix to the output depends on the structure of the classification model and learned weights, a should be determined appropriately according to the constructed classification model. Therefore, it is necessary to examine the method of determining the restriction parameter according to the classification model.

As we measured the multivariate gait data of young people during normal and restricted walking, the developed gait classification model is not necessarily applicable to the gait of elderly people. Therefore, in actual training, it is necessary to use a model constructed by measuring the gait of the elderly for gait classification. In addition, the classification model was constructed using the multivariate gait data of only men. Although the number of participants in the experiment was artificially increased by investigating two conditions, only eight individuals actually participated in the experiment. As gait is known to be affected by age, gender, etc., it is necessary to measure the multivariate gait data of various experimental participants, to learn the features of stumbling, and to construct a gait classification model to develop a more general gait training system. The classification model learned from the multivariate gait data of various individuals seems to enable gait training to prevent stumbling considering various individual differences.

5. Conclusion

The purpose of this study was to examine a method of setting target values of various gait parameters in gait training considering the physical differences among trainees. This paper proposed a method of generating target multivariate gait data by applying activation maximization with restriction of the amount of adjustment to the gait classification model and multivariate gait data of a trainee. Further, this approach activates the features of a “gait rarely associated with stumbling” class based on the original multivariate gait data of the trainee. To verify the usefulness of the proposed method for gait training, a multivariate gait dataset, consisting of joint angles and ground reaction forces that were measured and generated in a previous study and labeled with classes related to stumbling, was used and divided into a training set, a validation set, and a test set. The gait classification model was constructed by learning gait features related to stumbling using MC-DCNN with the multivariate gait data in the training set as input and the corresponding classes as output. In addition, we evaluated the accuracy of gait classification against the validation set of the gait classification model. Finally, we generated multivariate gait data (with restriction and without restriction) that activated the features of the “gait rarely associated with stumbling” class based on the original input data by inputting the multivariate gait data that had the most features of the “gait frequently associated with stumbling” class, included the test set, and compared the generated results. The MC-DCNN model learned the features that determined the thumb-to-ground distance with multivariate gait data and classified the gait related to stumbling with high accuracy ($96.04\% \pm 0.12\%$). In addition, the multivariate gait data, generated with restriction were adjusted to increase the angles of the hip joint flexion, knee joint extension, and ankle joint dorsiflexion during the terminal swing compared with the original input data. These

adjustments increased the thumb-to-ground distance. The gait training system considers the physical differences among trainees and presents possible and natural target values of the gait parameters to the trainee when the multivariate gait data generated with restriction are used to set the training targets, rather than using with the mean parameter values for the “gait rarely associated with stumbling” class or the multivariate gait data generated without restriction.

In the future, we will measure multivariate gait data of the elderly and construct a model to classify gaits from the data. In addition, the training effects of the proposed method and the gait training method using general motion information feedback will be compared. Further, we aim to develop a training system for various abnormal gaits (e.g., hemiplegic gait) by constructing a model for symptoms other than stumbling. It is expected that the proposed method can be used not only in nursing but also in sports, with appropriate training.

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