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Subject-Specific Gait Parameters Prediction for Robotic Gait Rehabilitation via Generalized Regression Neural Network

Trieu Phat Luu, H. B. Lim, K. H. Hoon, Xingda Qu, and K. H. Low

Abstract— **Gait pattern planning is important in robotic gait rehabilitation, whereby patients learned the pattern provided to them Gait pattern is related to gait parameters, such as cadence, stride length, and walking speed. Therefore, the planning of gait parameters for natural walking should be addressed in order to generate gait pattern for specific subjects. The present work utilizes generalized regression neural networks (GRNNs) to predict natural gait parameters for a given subject. The inputs of GRNNs are age, gender, body height, and body weight of the targeted subject. First of all, speed mode (normal/slow) must be chosen by the therapist. When speed mode is specified, the trained "Walking Speed" GRNN (WS-GRNN) outputs a selectable range of walking speed for a given subject. Subsequently, the therapist can select and recommend a walking speed, which will be used as an input to "Stride Length" GRNN (SL-GRNN) for the generation of stride length in the next step. Finally, cadence is calculated from walking speed and stride length. This model is easy to use to obtain gait parameters, since the therapist only needs to predefine the speed mode and select a walking speed from the range that is recommended by WS-GRNN. Results and t-test shows that outputs predicted by the GRNNs are closed to the experimental data. The efficiency and accuracy of the GRNNs are discussed in the conclusion.**

I. Introduction

A gait pattern is required for robotic system to define the correct motion, which will be induced by the system to the patient during rehabilitation. However, the acquisition of gait patterns catering different combinations of walking speed, cadence, and stride length specifically for all targeted subjects is not practical.

The importance of gait pattern planning is clearly to maximize therapeutic outcome and it is crucial to induce a gait pattern that resembles natural human gait pattern during gait rehabilitation [1, 2]. In the context of practicing correct kinematic gait patterns in a repetitive manner, little attention has been paid to the study of gait pattern generation for various gait rehabilitation systems. In manual assisted BWS treadmill gait rehabilitation, the therapist moves the patient leg and pelvic using visual feedback and "feel". The assistance provided can vary greatly between therapists and between training sessions [3].

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Trieu Phat Luu is PhD student of School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. (phone: +65-6790-5568; fax: +65-67935921; e-mail: luut0004@ntu.edu.sg).
H. B. Lim is PhD student of School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. (phone: +65-6790-5568; fax: +65-67935921; e-mail: limh0048@ntu.edu.sg).
K. H. Hoon is Associate Professor of School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. (e-mail: mkhhoon@ntu.edu.sg).
Xingda Qu is Assistant Professor of School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. (e-mail: XDQU@ntu.edu.sg).
K. H. Low is Professor with the School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. He is the principal investigator of the project. (phone: 65-67905755; e-mail: mkhlow@ ntu.edu.sg).

In comparison, robotic orthosis from those robotic gait rehabilitation systems adopt simplified approach to replicate the leg kinematics [4, 5]. Lokomat took a step further by allowing the gait pattern to be set according to the patient's height and range of motion of the lower limb joint [6]. In another research work, the BWS apparatus restricts pelvic motion, and causes the modification of pelvic motion planning. The restricted pelvic motion are planned according to the lower limb motions and desired foot trajectory [7]. Apparently, most of the motion planning is template based, whereby a motion template of subject with anatomy parameters similar to the targeted subject is required. Template-based planning needs a wide range of template collections, which is not practically feasible.

Every individual has a certain amount of peculiarities superimposed on the basic pattern of bipedal locomotion during walking. Hence, gait pattern generation plays an important role in robotic gait rehabilitation. The importance of subject specific gait pattern is obvious, as the patients learn the gait pattern imposed to them during the gait rehabilitation session. Improper gait pattern imposed by the robotic system during gait rehabilitation session could result in unwanted actual gait pattern learning outcome. In view of the issue, a methodology is developed to systematically generate a desired gait pattern for robotic gait rehabilitation.

A methodology, which addresses the need of gait pattern generation for robotic assisted gait rehabilitation has been presented [8]. This methodology facilitates the generation of gait pattern for a patient, without the need of a matching template. The objective of the proposed methodology is to generate a pattern in the context of gait rehabilitation specifically for each subject, based on anthropometric data of the subject. The methodology can generate the gait pattern corresponding to a given walking speed, stride length, and cadence, as long as it is physically feasible for the targeted subject. This work could be useful for other researches that need to plan gait pattern. The gait pattern generation methodology aims to generate a gait pattern for a given subject resembling to the pattern obtained from motion capture experiment, for the same gait parameters.

The work presented in this paper enhances the concept presented in previous work [9]. *GaitGen* stage-I has been introduced earlier for the prediction of walking speed and stride length specifically for a targeted human subject [9]. Previous work has two limitations: (1) Walking speed and

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stride length are generated for a range of values, which resulted in infinite combination of computed cadence; and (2) The stride length neural network is not trained with walking speed as input, which could be inaccurate. This work aims to eliminate the two mentioned limitations.

II. Gait Planning for Robotic Gait Rehabilitation

Since every individual displays variation in gait pattern, gait pattern planning plays an important role in robotic gait rehabilitation. Patients learn the gait pattern imposed to them during the gait rehabilitation. The improper gait pattern provided by robot during gait rehabilitation could result in unwanted rehabilitation outcome. Thus, it is important that a tailored gait pattern is planned for the patient with a systematic and logical approach.

A. Overview of Gait Pattern Generation

Patients re-learn the ability of walking through the process of gait rehabilitation. One of the key sensory cues for gait rehabilitation is to approximate normal hip, knee, and ankle kinematics for walking [2]. Although it is known that normal gait pattern is preferred, a proper method to plan normal gait pattern is missing.

To the authors' knowledge, there is no other work focused on the predicting/planning of natural gait parameters for humans. The most relevant research work in this area is normalized gait parameters formula highlighted by Inman [10]. The formula described a linear relationship between stride length, cadence, and body height. The normalized gait parameters is given by

$$\frac{stride\_length}{cadence \cdot body\_height} = 0.008 \tag{1}$$

Equation (1) is derived by fitting a straight line to the experimental data. However, the relationship of these parameters may not be represented by a simple linear function and the constant value 0.008 is not the same for all population [8]. This work conducted experiments with a small group of students in Singapore and showed that the normalized gait parameters are varied from 0.006 to 0.0098 for different subjects.

A methodology of gait pattern generation, *GaitGen,* was introduced to provide a systematic approach to generate gait pattern for robotic gait rehabilitation [8]. The overview of *GaitGen* is depicted in Fig. 1. With the understanding of clinical requirement, *GaitGen* is designed to facilitate the gait pattern generation in clinical settings. A gait pattern specifically tailored for the patient can be generated with anatomical parameters obtained from the patient, and with walking speed specified by doctors or physiotherapists (subsequently also refers to as users). Two states of walking speed, slow or normal, are made available for selection, since they reflect the actual scenarios. Fast walking speed is not considered, as gait rehabilitation usually starts with slow walking speed, then progress to normal walking speed. Patient will be discharged after rehabilitated to walk at normal walking speed.

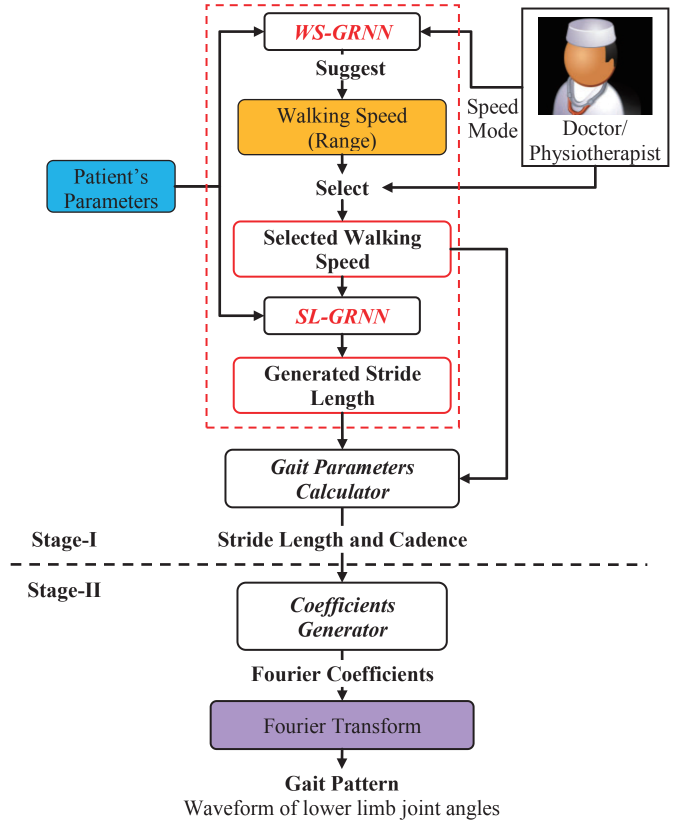

Fig. 1. Overview of *GaitGen*

GaitGen is designed with two stages. Stage-I of *GaitGen* is to predict natural walking speed, stride length, and cadence for a specific subject, given anatomical parameters of the subject and desired walking speed state (slow or normal). The prediction of stride length and cadence is achieved by two processes. First process utilizes artificial neural network to predict the desired outputs with the given inputs. The desired outputs consist of suitable walking speed and stride length (maximum and minimum values are given for these outputs) for the targeted subject.

User selects the desired walking speed from a range of walking speeds suggested by the neural network. In the second process, the gait parameters calculator computes cadence by

$$cadence = \frac{120 \cdot walking\_speed}{stride\_length} \tag{2}$$

with the walking speed selected. Stride length will be selected from the suggested range by *GaitGen* if it is not specifically specified.

The function of *GaitGen* stage-II is to generate lower limb joint angle waveforms for walking, with the stride length and cadence predicted in Stage-I. Previous works on *GaitGen* stage-II have been presented in [11, 12].

III. Design of Experiment and GRNN

A. Design of Experiment

Experiment was carried out to obtain the required gait

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parameters for the training of the GRNNs. Fifty healthy subjects (26 male and 24 female) with ages ranging 17 to 51 years (mean 28 $\pm$10 years), height 150- 189 cm (mean 166.2$\pm$9.22 cm) and weight 37- 85 kg (mean 59.6$\pm$11.5 kg), were recruited from the local population of the Nanyang Technological University (NTU), Singapore. These subjects have neither neurological injury nor gait disorder. Each subject was instructed to walk three times at their slow and self-paced walking speed. GAITRite [13] (subsequently refers to as mat) was used to record walking speed, stride length, and cadence of the recruited subjects. The general information of the subjects and number of walks is shown in Table I.

TABLE I
INFORMATION OF SUBJECTS AND NUMBER OF WALKS

Numbers of subjects	Age	Height (cm)	Weight (kg)	Numbers of normal walks	Numbers of slow walks
50	17-51	150-189	37-85	150	150

Subjects were instructed to walk on the mat at two self paced walking speeds: normal walking speed, and slow walking speed. The subjects were instructed to walk barefoot, to prevent the influence of footwear on the gait parameters. An additional space of 2.5 m was provided at the two ends of the mat, to ensure the subject enters the mat at rhythmic walking stage.

The experimental data of the fifty subjects was randomly divided into the subsets, as depicted in Table II. Subjects in the training set were used to train the neural networks. Subsequently, the subjects in the test set were used to test the performance of the trained networks.

TABLE II
DIVISION OF EXPERIMENTAL DATA FOR MLPNN

Set	Number of Subjects
Training Set	45 subjects
Test Set	5 subjects

B. Gait Parameters Prediction using GRNN

In this work, Generalized Regression Neural Network (GRNN) is proposed to predict the value for gait parameters (walking speed, stride length, cadence). Neural network is a prevalent analysis tool used in gait data studies in the last 10 years [14]. Neural network allows gait data analysis with a highly flexible, non-linear modeling ability.

The process of gait parameters calculation using Generalized Regression Neural Networks (GRNN) is illustrated in Fig. 2. First of all, speed mode (normal/slow) must be chosen by the doctor/therapist. If the patient is needed to be trained at normal walking speed, WS-GRNN-N will be applied to produce a range of normal walking speeds. From the recommended values, the therapist will select a walking speed to be used as an input to SL-GRNN-N to generate value of stride length in the next step. Finally, cadence is calculated from walking speed and stride length using (1). Similarly, WS-GRNN-S and SL-GRNN-S will be applied to generate gait parameters if the slow speed mode is selected. By using *GaitGen-I* model, doctor/therapist needs only to specify value of walking speed. The proposed model is easier to use and more efficient, if compared to the previous model that provides two ranges of walking speeds and stride lengths [9].

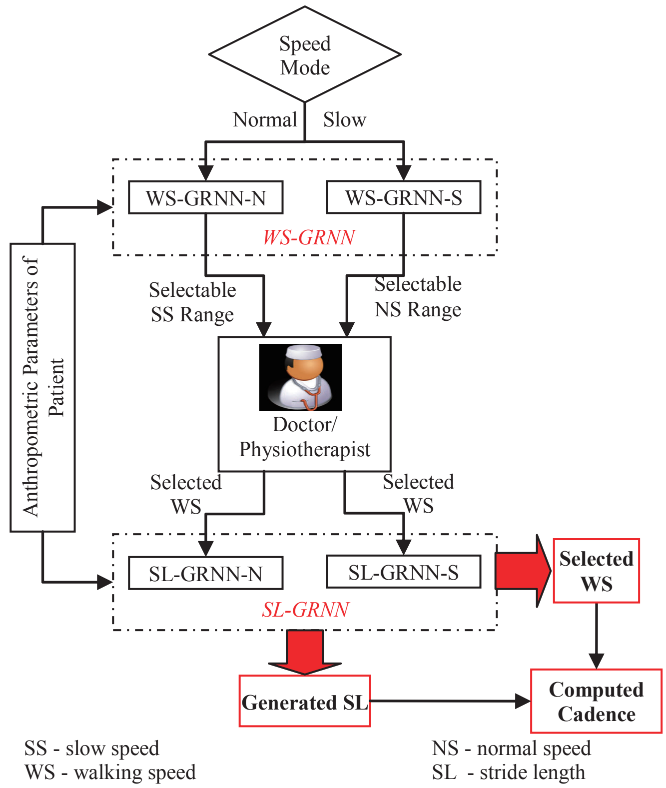

Fig. 2. Gait parameters generation using GRNN (*GaitGen-I*)

C. Selection of Inputs for GRNN

Based on literature review and preliminary analysis [9, 15], we hypothesized that these factors: age, body height, weight, and walking speed are significantly affecting cadence and stride length. For this study, we consider only factors that can be defined quantitatively. Age, gender, body height, and weight can be acquired through measurement and questionnaire. The walking speed is specified by doctor or physiotherapist in term of state of walking speed: slow or normal mode of walking. Descriptive factor (for example, mood) is not considered in this work. Design of GRNN

Generalized Regression Neural Network (GRNN) is often used as a powerful regression tool because it has a high training speed and a strong non-linear mapping capability [16]. A typical architecture of GRNN is shown in Fig. 3. The network consists of a radial basis layer and a linear output layer in addition to the input layer. Each neuron in hidden layer has a radial basis function to perform the nonlinear transformation from the input space to the hidden space. The Gaussian function is the common choice for the radial basis neurons and it is given by

$$g(d) = \exp\left(-\frac{d^2}{2\cdot\sigma^2}\right) \tag{3}$$

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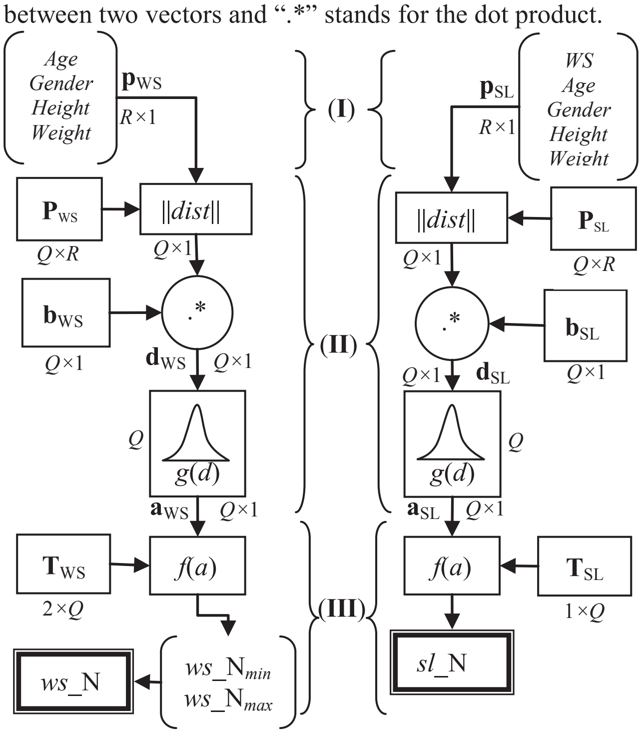
where d is the distance between two vectors and σ is the spread of Gaussian function.

The linear output layer adopts the linear weighted sum of hidden layers as the mapping mode as follows:

$$f(a) = \frac{T \cdot a}{\sum a} \tag{4}$$

in which T is the matrix of target vectors and a is the output vector from Gaussian function.

In Fig. 3, R is the number of elements in input vector. In WS-GRNN-N network, these elements are age, gender, body height, and weight. SL-GRNN-N has one additional element which is walking speed. Q is the number of input/target pairs in training set. **p** and **b** is new input and bias vector. **P** is matrix of input vectors in training set. ws_N and sl_N are predicted values from WS-GRNN-N and SL-GRNN-N, respectively. $\|dist\|$ is applied to calculate the distance between two vectors and ".*" stands for the dot product.



WS, **SL**-Walking Speed and Stride Length
(**I**)- Input layer, (**II**)- Radial basis layer, (**III**)- Linear output layer.

Fig. 3. Architecture of GRNN

The spread of radial basis function of neurons in hidden layer plays an important role in function approximation [16, 17]. The function is very steep if spread is small; therefore, the neuron with the weight vector closest to the input vector will give a much larger output and other neurons. The radial basis function becomes smoother as spread becomes larger so that several neurons can respond to an input vector. The network then provides the output by taking a weight average between target vectors whose design input vectors are closest to the new input vector. In this work, trial and error method is applied to extract the optimal value of spread parameter.

The success rate of the WS-GRNN-N is calculated using (5). It is determined by comparing the output of the neural network in each test to the corresponding experimental data. If the predicted outputs $ws\_N_{i,min}$ and $ws\_N_{i,max}$ fall within the allowed deviation of the corresponding minimum and maximum walking speed from the experimental data, the WS-GRNN-N is taken as "success" for the test.

$$\mathrm{ws\_ssr} = \sum_{i=1}^{100} \mathrm{ws\_ss}_i$$
$$\mathrm{ws\_ss}_i = \begin{cases} 1, \text{ if } \begin{cases} ws\_\mathrm{N}_{i,\min} \in [(1\pm\gamma)\cdot ws_{i,\min}] \\ ws\_\mathrm{N}_{i,\max} \in [(1\pm\gamma)\cdot ws_{i,\max}] \end{cases} \\ 0, \text{ otherwise} \end{cases} \tag{5}$$

where i is the test subject and γ is the allowed deviation (γ=5% in this work)

On the other hand, SL-GRNN-N is considered as "success" for one subject when predicted value sl_N falls within the minimum and maximum value of stride length from experimental data.

$$\mathrm{sl\_ssr} = \sum_{i=1}^{100} \mathrm{sl\_ss}_i$$
$$\mathrm{sl\_ss}_i = \begin{cases} 1, & \text{if } sl\_\mathrm{N} \in [sl_{\min}, sl_{\max}] \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Both GRNNs are tested to obtain the optimized spread value σ of radial basis function. The GRNNs are tested with the spread values varying from 0.2 to 10 at step size 0.2. Each GRNN is tested 20 times with five subjects (test set) randomly selected from the experimental database. The test provides a general indication of the optimized spread value σ of radial basis function. The overall success rate of each GRNN set versus the spread value is depicted in Fig. 4.

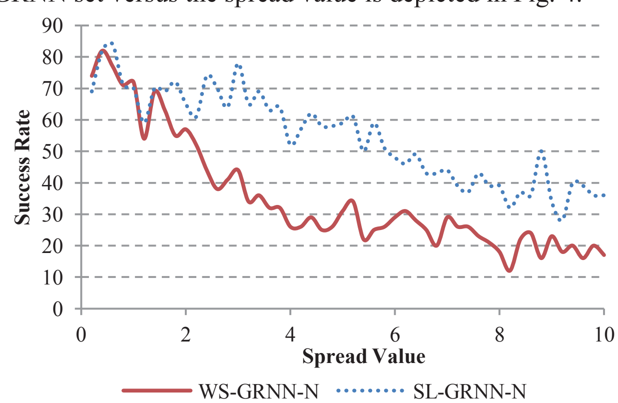


Fig. 4. Success rate of GRNNs for different spread values of radial basis function

Based on the result, the radial basis functions of the WS-GRNN-N and SL-GRNN-N are designed with spread values 0.4 and 0.6, respectively. The success rate at 82% and 84% can be obtained respectively for WS-GRNN-N and SL-GRNN-N with these spread values.

IV. Results and Discussion

The subjects in the test set were used to study the prediction performance of the two trained GRNNs. WS-GRNN-N was applied to predict the range for the walking

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speed. When a walking speed was selected, SL-GRNN-N was applied to predict stride length. These outputs were compared to experimental data to study the accuracy of the GRNNs. In this session, the results for five subjects from the test set will be presented. The results present in this work are focused on normal walking speed state. The information of the five subjects is available in Table III.

TABLE III
INFORMATION OF SELECTED FIVE SUBJECTS IN TEST SET

Subject	Age	Gender	Body Height	Weight
Subject 1	48	Female	158	50
Subject 2	22	Female	163	54
Subject 3	27	Male	174	76
Subject 4	23	Male	168	60
Subject 5	22	Female	164	49

The inputs of WS-GRNN-N are age, gender, body height, and weight of the subjects. SL-MLPNN-I has one additional input which is walking speed. Output of WS-GRNN-N is the range of walking speed and output of SL-GRNN-N is stride length. The denotation for the outputs is summarized in Table IV.

TABLE IV
DENOTATION OF GRNNS OUTPUTS

Output	Denotation (Exp data)		Denotation (WS-GRNN-N)		Denotation (SL-GRNN-N)
	Max	Min			
Walking speed	$ws_{\max}$	$ws_{\min}$	$ws\_N_{\max}$	$ws\_N_{\min}$	–
Stride length	$sl_{\max}$	$sl_{\min}$	–		sl_N
Cadence	Cad_{max}	$Cad_{\min}$	Cad_N		

A. Walking Speed Prediction of WS-GRNN-N

The WS-GRNN-N provides the range of walking speed as the output. Maximum and minimum values are predicted by the WS-GRNN-N for a given subject. The values form the range for suggested normal walking speed. The predicted range of walking speed serves as a suggestion for the doctor or therapist. A suitable walking speed for the subject can be selected from the suggested range. The predicted range of walking speeds given by the WS-GRNN-N for the subjects in the test set is listed in Table V with the maximum and minimum walking speed acquired by gait experiment for the subjects.

TABLE V
WALKING VELOCITY PREDICTED BY MLPNNS

Subject	Experimental $ws_{\min}$	Experimental $ws_{\max}$	WS-GRNN-N ws_N_{min}	WS-GRNN-N ws_N_{max}
Subject 1	114.5	121.9	113.3	125.6
Subject 2	103.0	108.4	95.8	106.1
Subject 3	115.7	116.7	108.6	120.3
Subject 4	96.5	105.3	95	105.3
Subject 5	117.2	127.6	118.7	131.4

B. Stride Length Prediction of SL-GRNN-N

After the therapist selected the walking speed from the range suggested by WS-GRNN-N, the predicted stride length will be generated by SL-GRNN-N and denoted as *sl*_N. Stride length generated by SL-GRNN-N is used to calculate cadence with a selected value of walking speed from the suggested range.

Stride length is also calculated by using normalized gait parameters equation (1) for comparison. The index of 0.0071 is used instead of 0.008, since 0.0071 is found to be more appropriate for the population we studied [8]. Given the walking speed and index, stride length and cadence can be calculated as follows:

$$stride\_length = \sqrt{120 \cdot index \cdot height \cdot walking\_speed}$$
$$cadence = \frac{120 \cdot walking\_speed}{stride\_length} \tag{7}$$

The stride length calculated by using (7) is denoted as *sl*_Index. The stride lengths *sl*_N and *sl*_Index are shown in Table VI.

TABLE VI
STRIDE LENGTH PREDICTED BY GRNNS

Subject	Experimental $sl_{\min}$	Experimental $sl_{\max}$	Experimental sl_targ	GRNNs sl_N	Using Index sl-Index
Subject 1	114.1	118.5	116.17	118.5	126.9
Subject 2	118.4	122.9	119.34	118.4	118.6
Subject 3	128.3	134.8	134.79	134.3	130.2
Subject 4	126.2	130.6	126.24	129.4	118.2
Subject 5	128.9	135.1	132.78	135.1	129.3

C. Comparison of Cadence

Cadence calculated with (2) using the selected walking speed suggested by WS-GRNN-N and stride length predicted by SL-GRNN-N is denoted as *Cad*_N. Cadence computed by (7) with the same selected walking speed and index is denoted as *Cad*_Index. *Cad*_N and *Cad*_Index for five subjects in the test set are shown in Table VII. These cadence values are displayed and compared with experimental data $Cad_{\min}$ and $Cad_{\max}$.

TABLE VII
COMPUTED CADENCE WITH SELECTED OUTPUTS VALUE FROM GRNNS

Subject	Experimental $Cad_{\min}$	Experimental $Cad_{\max}$	GRNNs Cad-N	Index Cad-Index
Subject 1	120.5	123.5	121.1	113.1
Subject 2	104.2	106.8	108.0	107.8
Subject 3	103.0	109.1	103.3	106.6
Subject 4	91.2	96.8	89.5	97.9
Subject 5	109.1	113.7	106.9	111.7

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D. *Discussion on the Accuracy of MLPNNs*

As compared to the normalized gait parameters equation, Tables VI and VII show the values of stride length and cadence found using these two concepts. It is shown that the predicted values of stride length and cadence calculated by using normalized gait parameters equation do not fall within the range of values found with gait experiment for several subjects. This outcome of comparison showed that the proposed concept is more accurate in gait parameters prediction, compared to the normalized gait parameters equation.

The data presented in Tables V and VI are t-tested with 95% confidence level. Matlab toolbox is used to perform a t-test of the null hypothesis that data in the experimental data and simulation results are independent random samples from normal distributions with equal means and equal but unknown variances, against the alternative that the means are not equal. The result of the test is returned in h, in which h = 1 indicates a rejection of the null hypothesis at the 5% significance level, while h = 0 indicates a failure to reject the null hypothesis at the 5% significance level.

The results of t-test are h = 0 for walking speed data set: (1) $ws_{\min}$ and $ws\_N_{\min}$; (2) $ws_{\max}$ and $ws\_N_{\max}$. T-test is also carried out for data presented in Table VI. The result of t-test is h = 0 for the data set: 1. *sl_targ* and *sl*_N. The t-test results suggest that outputs of GRNNs and experimental data are equal at a 95% confidence level.

V. Concluding Remarks

This work utilized Generalized Regression Neural Network (GRNN) to enhance the concept introduced in previous work [9]. The enhanced concept allows the generation of gait parameters for clinical rehabilitation setting by specific only the walking speed. The trained GRNNs shows more accurate results compared to normalized gait parameters equation.

Based on t-test analysis, the gait parameters predicted by trained GRNNs are equal to gait experimental result. Nevertheless, the error is relatively larger for certain subjects presented in the test set. This could be due to inadequate samples to train the GRNNs.

Future work will be carried out to acquire extensive amount of samples for the training of GRNNs.

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