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Natural Gait Parameters Prediction for Gait Rehabilitation via Artificial Neural Network

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Abstract—**Gait pattern planning is an important issue in robotic gait rehabilitation. Gait pattern is known to be related to gait parameters, such as cadence, stride length, and walking speed. Thus, prior before the discussion of gait pattern planning, the planning of gait parameters for natural walking should be addressed. This work utilizes multi-layer perceptron neural network (MLPNN) to predict natural gait parameters for a given subject. The inputs of the MLPNN are age, gender, body height, and body weight of the targeted subject. The MLPNN is trained to output a suitable walking speed and cadence for given subject. Two MLPNNs are trained to study the efficiency and accuracy in predicting the desired outputs, for two different setups. First setup is that the MLPNN is trained specifically for slow speed condition only. In second setup, the MLPNN is trained for both slow and normal speed conditions. The results of the MLPNNs are presented in this paper. The efficiency and accuracy of the MLPNNs are discussed.**

I. Introduction

SPINAL cord injury (SCI) and stroke are the leading cause of permanent disability around the world. In United States, there are 795,000 new stroke cases [1], and an estimated 12,000 new spinal cord injury cases [2] occurring each year. Loss of walking ability is a debilitating outcome in post-stroke and spinal cord injury, with more than 50% of the post-stroke patients demonstrating persistent walking deficits, and more than 90% of the SCI patients lose their sensory and motor control of the lower limbs.

The method of suspending a human over a treadmill for gait rehabilitation was first reported by Barbeau *et al.* in year 1987 [3]. The method is commonly referred to as body weight supported (BWS) treadmill training. This is a relatively new method that originated from basic science research on the neural control of the vertebrate locomotion. The method is developed based on the observation of a spinalized cat that can be trained to step with their hind limbs on a treadmill when its weight is partially supported [4, 5].

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Studies have shown that SCI and stroke patients who receive BWS treadmill training demonstrate improved EMG activation patterns, more natural walking characteristics, increment in weight bearing on their legs, and demonstrate functional improvement in walking ability. The review of the evidences can be found in [6, 7].

To maximize therapeutic outcome, it is crucial to induce a gait pattern that resembles natural human gait pattern during gait rehabilitation [5, 8]. In the context of practicing correct kinematic gait patterns in a repetitive manner, little attention has been diverted to the study of gait pattern used in 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 [9].

In comparison, robotic orthosis found in gait rehabilitation systems adopt simplified approach to replicate the leg kinematics [10, 11]. 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 joints [12]. The BWS apparatus restricted pelvic motion, causes the modification of pelvic motion planning. The restricted pelvic motion are planned according to the lower limb motions and desired foot trajectory [13]. 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 collection, which is not efficient.

This work aims to generate a gait pattern for patient, without the need of a matching template. In this paper, the efficiency and accuracy of using multi-layer perceptron neural network (MLPNN) in predicting walking speed and stride length for given subject, whereby walking speed can be specified by doctor, or physiotherapist is studied.

The objective of this study is to generate walking speed, cadence, and stride length resembling to natural walking, and facilitate the gait pattern generation in the context of gait rehabilitation. Walking speed, cadence, and stride length are crucial parameters to be investigated, as these parameters affect gait pattern. The prediction of walking speed, cadence, and stride length shall be addressed, prior to the gait pattern generation for lower limb and pelvic for our developed robotic gait rehabilitation. This work could be useful for other researches that need to plan these gait parameters.

The structure of this paper is as follows. Section II gives the overview for the developed robotic gait rehabilitation system, *NaTUre-gaits*, and the details of gait planning for rehabilitation. Section III gives the details on the design of MLPNN and design of gait experiment. Section IV presents the results of the designed MLPNNs. Section V summarizes the key points discussed in this paper and suggest future work that will further enhance the current work.

II. Gait Planning for Robotic Gait Rehabilitation

There is no proper definition for natural human walking. However, there is a common understanding of how walking should appear for human. Every individual displays a certain personal peculiarities superimposed on the basic pattern of bipedal locomotion during walking. There is no definite indication of how human walking has to be, but it would be able to tell instantly, if someone is not walking naturally. The variation between different individuals or within the same individual arises from individual personal peculiarities, anatomy parameters, changes in the walking speed, and even alterations in footwear.

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 provides 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.

To provide an overview for this work, this section is dedicated to the introduction of the robotic gait rehabilitation system and the concept of gait pattern generation.

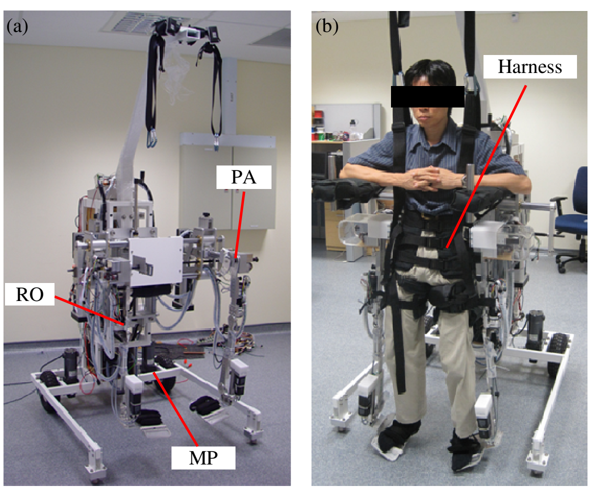

Fig. 1. *NaTUre-gaits*-II (a) Assembled prototype (b) Trial with therapist

A. Introduction to NaTUre-gaits

Targeted to provide natural walking in gait rehabilitation, *NaTUre-gaits* was prototyped in 2006. The gait rehabilitation system (prototype shown in Fig. 1a) is developed to provide pelvic and lower limb motion assistance, in the context of over ground walking for BWS gait rehabilitation. Four main functions outlined for gait rehabilitation: pelvic control, active assistance to lower limb, BWS (with minimum restriction on pelvic motion during walking), and functional over-ground walking have been incorporated in the developed prototype. These functions are realized by Robotic Orthosis (RO), Mobile Platform (MP), and Parallelogram Arm (PA), whereby gait locomotion assistance is provided by RO, pelvic motion assistance and BWS is provided by PA, and lastly, the functional over-ground walking is achieved with MP.

NaTUre-gaits prototype II has been developed and the modules have been tested on healthy human subject and preliminary assessed by therapist and doctor (Fig. 1b). *NaTUre-gaits* prototype II is modified to provide the complete 3D pelvic motion (prototype I is only capable of sagittal plane pelvic motion provision), and redesign the mechanism to enhance the safety, rigidity, and functionality.

B. 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 [8]. Although it is known that normal gait pattern is preferred, a proper method to plan normal gait pattern is missing.

In the author's knowledge, there is no other work focused on the predicting/planning of natural gait parameters for human. The most relevant research work in this area is normalized gait parameters formula highlighted by Inman *et al.* [14]. The formula described a linear relationship between stride length, cadence, and body height. The normalized gait parameters is given by

$$\frac{stride\_length}{cadence \times body\_height} = 0.008 \qquad (1)$$

Equation (1) is derived by fitting a straight line to the experimental data. The relationship of these parameters may not be represented by a simple linear function. The linear regression of the experimental data provides a general perception towards the relationship.

GaitGen has been introduced in previous work [15], to provide a systematic approach of gait pattern generation for robotic gait rehabilitation. The overview of GaitGen is depicted in Fig. 2. With the understanding of clinical requirement, GaitGen is designed to facilitate the gait pattern generation in clinical setting. A gait pattern specifically tailored for the patient can be generated with parameters obtained from the patient, and with walking speed specified by doctor or physiotherapist. Two states of walking speed, slow or normal walking speed, are made available for selection, since they reflect the actual scenario, as human will have their preferences of slow, normal, and fast mode of walking. 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.

In this work, the stage-I of GaitGen is explored. Stage-I is designed to predict natural walking speed, stride length and cadence for a given subject, whereby the parameters of the subject and a specified walking speed state (slow or normal) are provided to MLPNN. The stage-II of GaitGen uses the stride length and cadence generated, and maps a gait pattern accordingly.

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.

Doctor or physiotherapist selects the desired walking speed from the suggested walking speed given by neural network. In the second process, gait parameters calculator computes cadence by

$$cadence = \frac{2 \times walking\_velocity}{stride\_length} \quad (2)$$

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

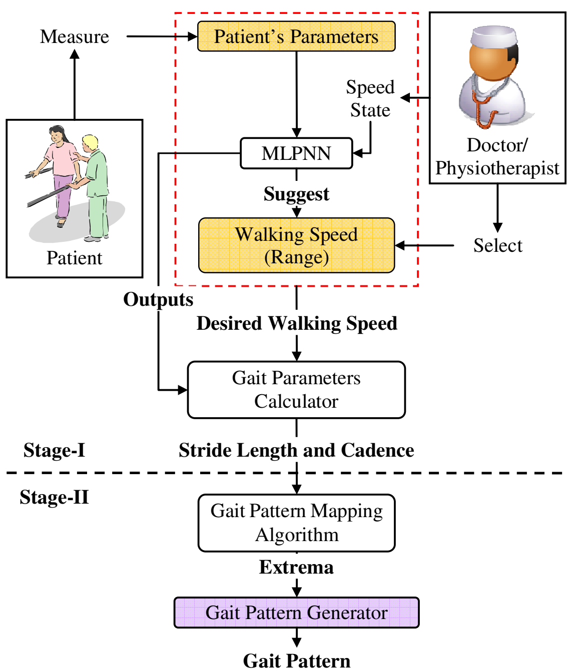

Fig. 2. Overview of GaitGen

III. Design of MLPNN and Experiment

Neural network is an analysis tool commonly used in gait data studies over the past 10 years [16], whereby it can extract the functional relationship between inputs and outputs. In this work, MLPNN is proposed to investigate the relationship between the inputs and outputs. Two MLPNNS are created, one is trained specifically for slow walking speed, and the other is trained for both slow and normal walking speeds in one neural network. Subsequently, it is refers to as MLPNN-I for the slow speed set, and MLPNN-II for the slow and normal speeds set. Two MLPNNs are created to study the accuracy of the gait parameters prediction for MLPNN trained specifically for slow speed and MLPNN trained for combination of slow and normal speed.

A. *Design of Experiment*

Experiment is designed to obtain the required gait parameters for the training of the MLPNN. Fifty healthy subjects (26 male and 24 female) with no known gait deficit are recruited for gait experiment. GAITRite [17] (subsequently refers to as mat) is used to record walking speed, stride length and cadence of the recruited subjects.

TABLE I
Division of Experimental Data for MLPNN

Set	Number of Subject
Training Set	30 subjects
Validation Set	10 subjects
Test Set	10 subjects

Subjects are instructed to walk on the mat at two self paced walking speeds: normal walking speed, and slow walking speed. The subjects are instructed to walk barefoot, to prevent the influence of footwear on the gait parameters. The subjects walk six times on the mat, three times for each walking speeds. An additional space of 2.5 m is 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 are randomly divided into the subsets as shown in Table I. Subjects in the training set are used to train the MLPNNs and the trained MLPNNs are validated with subjects in the validation set. Finally, the subjects in the test set are used to test the performance of the validated MLPNNs.

B. *Selection of MLPNN Inputs*

The objective of this work is to facilitate the gait pattern planning for clinical practitioner, the selected parameters (inputs) for the MLPNN have to be those parameters, which can be measured or can be obtained without much trouble.

Tall, slender people walk differently from short, stocky people. People also alter their manner of walking when wearing shoes with different heel heights. A person walks differently when exhilarated than when mentally depressed [18]. All the above statements described the factors that would affect gaits.

The relationship of gait parameters and human anatomical parameters is emphasized by the introduction of the normalized gait parameters formula [14]. The formula correlates stride length, cadence, and body height with a constant index (0.008). Age is also one of the factors affecting gait parameters, as older people walk slower than young adults [19]. In our previous study, we found out that gender, and body height are factors that affect cadence and stride length [15].

Based on literature review and preliminary analysis, 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. The effect of shoe is eliminated by having all the subjects to walk barefoot during experiment.

C. Design of MLPNN

The MLPNNs are designed to have one input layer, one hidden layer, and one output layer in this work. The optimized number of neurons in the hidden layer is determined based on the success rate of the MLPNN.

The activation function of each neuron in the MLPNNs uses the hyperbolic tangent sigmoid transfer function, which is a derivative and provides the output to lie in the range of ($-1 \le y_l(n) \le 1$). The activation function is given by

$$y_j(n) = \varphi_j\left[\gamma_j(n)\right] = a\frac{e^{b\gamma_j(n)} - e^{-b\gamma_j(n)}}{e^{b\gamma_j(n)} + e^{-b\gamma_j(n)}} \quad (3)$$

where

$y_j(n)$: Desired output at n iteration

φ_j : Activation function of neuron j

γ_j : Activation signal of neuron j

a,b : Constant (1, 1)

The learning algorithm applied in the MLPNNs is Lavenberg-Marquardt (LM) algorithm.

The inputs of the MLPNNs are age, gender, body height, and weight of the subjects. MLPNN-II has one additional input, which is state of walking speed (slow or normal). The outputs of both MLPNNs are range of walking speed and range of stride length. The outputs and the denotation for the outputs are summarized in Table II.

TABLE II
DENOTATION OF MLPNNs OUTPUTS

Output	Denotation (MLPNN-I) Max	Denotation (MLPNN-I) Min	Denotation (MLPNN-II) Max	Denotation (MLPNN-II) Min
Cadence	C-I$_{max}$	C-I$_{min}$	C-II$_{max}$	C-II$_{min}$
Stride length	S-I$_{max}$	S-I$_{min}$	S-II$_{max}$	S-II$_{min}$
Walking speed	v-I$_{max}$	v-I$_{min}$	v-II$_{max}$	v-II$_{min}$

The success rate of the MLPNN is determined by comparing the output of the neural network in each test to the corresponding experimental data. If the predicted outputs for all subjects in the test set fall within the maximum and minimum value of the corresponding parameter of the experimental data (acceptable deviation for MLPNN output is 5% from the maximum and minimum value of the respective experimental result), the MLPNN is considered as success for that test.

Both MLPNNs are tested to obtain the optimized number of neurons required in the hidden layer. The MLPNNs are tested with a variation of 10 to 70 neurons in the hidden layer. The tests are carried out with the input parameters taken from the subjects in the test set. A total of 122 set of MLPNNs (61 for each MLPNN) are tested with random starting weight factor. The test provides a general indication of the optimized number of neurons in the hidden layer.

The overall success rate of each MLPNN set versus number of neurons of the hidden layer in MLPNN is depicted in Fig. 3. The success rate converges at approximately 40 neurons for MLPNN-I and 50 neurons for MLPNN-II. Based on the result, the hidden layer of the MLPNN is designed to contain 44 and 63 neurons for MLPNN-I and MLPNN-II respectively. The neural networks have the highest success rate with this number of neurons.

From the success rate shown in Fig. 3, it is noticeable that MLPNN-I has higher success rate compared to MLPNN-II. MLPNN-I has four inputs and MLPNN-II has five inputs. The additional input in MLPNN-II requires a more complicated neural network, thus more neurons in the hidden layer are required in order to achieve a high success rate.

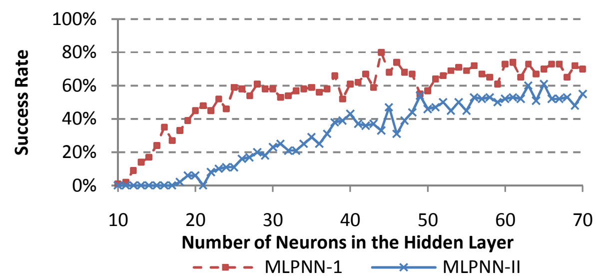

Fig. 3. The success rate of MLPNN for different number of neurons in the hidden layer

TABLE III
INFORMATION OF SELECTED FIVE SUBJECTS IN TEST SET

Subject	Age	Gender	Body Height	Weight
Subject 1	22	Female	164	49
Subject 2	48	Male	168	75
Subject 3	50	Female	150	44
Subject 4	21	Male	180	75
Subject 5	17	Male	167	65

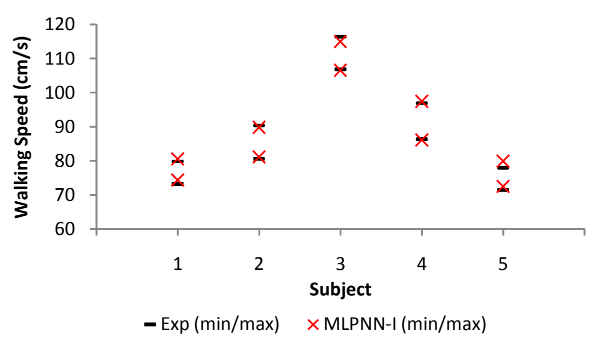

Fig. 4. v-I$_{min}$, v-I$_{max}$ predicted by MLPNN-I for five subjects in the test set, denote by MLPNN-I (min/max). 'Experimental (min/max)' refers to v_{min} and v_{max} listed in Table IV

IV. Result and Discussion

The MLPNNs are designed and trained with the training set, and validated with the validation set. The subjects in the test set are used to study the prediction performance of the two MLPNNs. The MLPNNs predicted the range for the walking speed and stride length. These two desired outputs are compared to experimental data, to study the accuracy of the MLPNNs. In this session, the results for five subjects from the test set will be presented. The results present in this work are focused on slow walking speed state. The MLPNNs inputs of the five subjects are available in Table III.

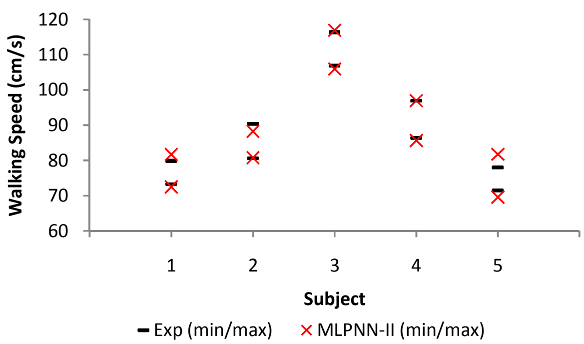

Fig. 5. v-II$_{min}$, v-II$_{max}$ predicted by MLPNN-II for five subjects in the test set, denote by MLPNN-I (min/max). 'Experimental (min/max)' refers to v_{min} and v_{max} listed in Table IV

TABLE IV
Walking Velocity Predicted by MLPNNs

Subject	v_{min} (cm/s)	v_{max} (cm/s)	v-I$_{min}$ (cm/s)	v-I$_{max}$ (cm/s)	v-II$_{min}$ (cm/s)	v-II$_{max}$ (cm/s)
Subject 1	73.25	79.86	74.37	80.57	72.47	81.70
Subject 2	80.60	90.40	81.13	89.84	80.75	88.24
Subject 3	106.90	116.40	106.57	115.00	105.94	116.97
Subject 4	86.35	96.94	86.14	97.47	85.64	96.97
Subject 5	71.50	78.00	72.53	79.96	69.56	81.74

A. *Walking Speed Prediction of MLPNNs*

The MLPNNs provide the range of walking speed as one of the outputs. Maximum and minimum values are predicted by the MLPNNs for given subject and form the range for suggested walking speed. The predicted range of walking speed serves as 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 speed by the MLPNNs for the subjects in the test set are plotted in Figs. 4 and 5 with the maximum and minimum walking speed acquired by gait experiment for the subjects.

B. *Stride Length Prediction of MLPNNs*

Stride length generated by MLPNN is used to calculate cadence with a selected value of walking speed from the suggested range. The stride length predicted by the MLPNNs is depicted in Figs. 6 and 7. The stride length outputs are plotted with experimental data, S_{min} and S_{max} for comparison.

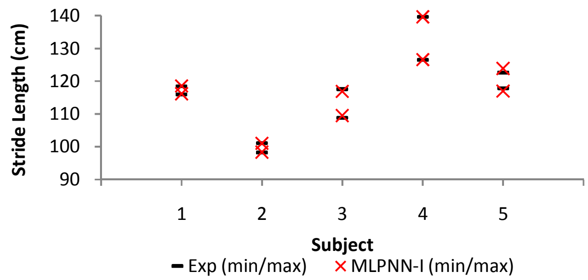

Fig. 6. S-I$_{min}$, S-I$_{max}$ predicted by MLPNN-I for five subjects in the test set, Exp. Min and Exp. Max refers to S_{min} and S_{max} listed in Table V

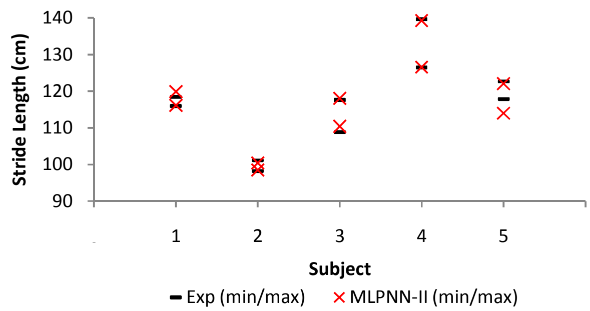

Fig. 7. S-II$_{min}$, S-II$_{max}$ predicted by MLPNN-II for five subjects in the test set, Exp. Min and Exp. Max refers to S_{min} and S_{max} listed in Table V

TABLE V
Stride Length Predicted by MLPNNs

Subject	S_{min} (cm/s)	S_{max} (cm/s)	S-I$_{min}$ (cm/s)	S-I$_{max}$ (cm/s)	S-II$_{min}$ (cm/s)	S-II$_{max}$ (cm/s)
Subject 1	115.96	118.46	116.15	118.58	116.13	119.88
Subject 2	98.21	101.11	98.38	101.04	98.49	100.43
Subject 3	108.85	117.60	109.50	116.91	110.40	118.07
Subject 4	126.50	139.65	126.59	139.65	126.56	139.28
Subject 5	117.86	122.67	116.96	123.87	113.99	122.05

TABLE VI
Maximum Percentage of Deviation for Predicted Outputs

Subject	Walking speed		Stride length	
	MLPNN-I	MLPNN-II	MLPNN-I	MLPNN-II
Subject 1	1.53%	2.31%	0.17%	1.20%
Subject 2	0.66%	2.38%	0.17%	0.67%
Subject 3	1.20%	0.89%	0.60%	1.42%
Subject 4	0.55%	0.83%	0.07%	0.27%
Subject 5	2.51%	4.80%	0.98%	3.28%

C. *Discussion on the Accuracy of MLPNNs*

With the selected number of neurons in the hidden layer, MLPNN-I and MLPNN-II are able to predict acceptable value for the desired outputs. The maximum percentages of deviation from the experimental value are presented in Table VI. In general, MLPNN-II exhibits higher percentage of deviation compared to MLPNN-I. The finding shows that MLPNN-I is capable of a much accurate outputs prediction compared to MLPNN-II.

D. Comparison to Experimental Data

For the purpose of comparison, walking speed and stride length are selected from the outputs recommended by MLPNNs. Cadence is calculated with (2) using the selected walking speed and stride length (average value of the predicted maximum and minimum for respective output). The computed cadence values are presented in Table VII.

TABLE VII
COMPUTED CADENCE WITH SELECTED OUTPUTS VALUE FROM MLPNNS

Subject	Experimental		MLPNN	
	Cad_{min}	Cad_{max}	MLPNN-I	MLPNN-II
Subject 1	75.80	80.90	79.21	78.39
Subject 2	98.90	108.50	102.88	101.94
Subject 3	117.20	119.00	117.44	117.09
Subject 4	80.90	83.80	82.76	82.43
Subject 5	72.80	76.90	75.98	76.92

The cadence computed based on MLPNN-I outputs falls within the experimental maximum and minimum value. Using the MLPNN-II predicted outputs to compute cadence resulted in two computed values (subjects 3 and 5) fall out of the maximum and minimum value of experimental data. However, the deviations are 0.09% and 0.03% respectively. It is insignificant, if compared to the standard deviation of the experimental data for the subjects.

V. CONCLUDING REMARKS

This work utilizes MLPNN to predict the gait parameters required for gait pattern planning. Two MLPNNs have been designed and trained to predict the desired output for gait pattern generation purpose. We have shown that the trained MLPNNs have acceptable accuracy in predicting natural gait parameters for given subjects, for selected walking speed. The naturalness of the gait parameters is confirmed by making a comparison to the actual gait parameters recorded from the subjects during natural walking.

This work aims to compare the efficiency and accuracy of MLPNNs, specifically trained for one walking speed state, and trained for two walking speed states. It has hypothesized that MLPNN trained for one walking speed state should be more accurate. From the predicted output, we have shown that the MLPNN-I is more accurate in the output prediction compared to MLPNN-II. It is also noticed that MLPNN-II requires more number of neurons in the hidden layer to achieve acceptable accuracy in predicting the desired output.

The developed MLPNNs can be further optimized to increase the accuracy of the predicted outputs. The existing initial weight factor for MLPNN training is randomly selected. The selection of initial weight factor influences the accuracy of predicted outputs. Future work is suggested to investigate the effects of the initial weight factor.

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