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Personalized single support trajectory generation with preferred walking speed for lower limb exoskeletons

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***Abstract*—This paper presents an algorithm to generate the single support phase trajectory in each step for exoskeleton users with low strength in their lower body. This method generates the trajectory of the single support phase according to the patient's body parameters and enables the patients to voluntarily change their walking speed. In this method, the body parameters of the exoskeleton user and the information of the double support phase are taken as input. A multi-layer perceptron neural network, human kinematic model, and cubic spline interpolation are used to generate the single support phase trajectory for the hip and knee joints. To evaluate the performance of this algorithm, a healthy person walked on the ground at three different speeds, and the walking data was recorded. Then the knee and hip joints trajectory of the single support phase for one step was generated by the proposed algorithm. Then the generated Trajectories were compared with the actual trajectories. The experimental results reveal that the proposed algorithm is able to generate a smooth personalized trajectory according to the preferred walking speed.**

Keywords— Exoskeleton trajectory, Personalized trajectory generation, Body parameters, Neural network

I. INTRODUCTION

Nowadays, the number of people with movement disorders in the lower body, due to spinal cord injury, stroke, etc. is increasing. There are about 250,000 to 500,000 people worldwide who suffer from a spinal cord injury each year [1]. Surveys of patients with stroke or spinal cord injury show that their most common concern is the full or partial disability in some activities like walking and standing [2]. Moreover, such individuals are at risk of decreased motivation to adhere to a long-term exercise program. Exoskeleton robots have shown promising results in motivating people with spinal cord injuries to follow long-term exercises and improve their physical activity level [3]. Furthermore, traditional rehabilitation that helps patients to stand and walk is based on manual work. Exoskeleton robots can help with this repetitive and exhausting treatment [2]. When a patient with movement disorders in the lower body walks with the help of an exoskeleton robot, the ground reaction forces stimulate the sensory and musculoskeletal system [4]. Until now, various lower body exoskeletons have been made and developed to assist or rehabilitate the walking ability of patients with spinal cord injury, stroke, etc. Among the well-known examples of these exoskeleton robots, can refer to Rewalk [5], HAL [4], and EksoNR [6].

A key requirement for exoskeleton robots to work efficiently is to generate suitable gait patterns and joint trajectories. It is important that the trajectory is generated in such a way that the user feels comfortable during the walking. Chen et al. [1] presented an offline design and online optimization algorithm for the CUHK-EXO exoskeleton. First, they generated an offline reference trajectory by recording motion data. Then, with an online correction method, the angle of the hip joint was adjusted based on the center of pressure position to maintain the balance of the person while walking. Tsukahara et al. [4] proposed an algorithm to estimate the gait intention for the HAL robot. In this algorithm, the center of ground reaction force is used to discover the patient's intention to start the swing. This method also allows the user to adjust the swing speed by getting feedback from the double support phase. Huang et al. [7] presented an algorithm to generate a reference gait trajectory based on the kinematic model of human gait. In their proposed algorithm, the trajectory of the knee joint is obtained using the trajectory of the hip joint. He et al. [2] proposed an algorithm to generate a walking trajectory corresponding to the body features of the exoskeleton user. For this purpose, they designed a neural network and trained it using the walking trajectories of healthy people. The inputs of this neural network are body features and walking speed. The outputs of this neural network are the trajectories of hip and knee joints. Wu et al. [8] presented an algorithm for generating personalized gait patterns for the SLEX robot. In their proposed algorithm, 21 body parameters and walking speed are considered as input, and the sagittal joint trajectories are the output of the algorithm. Kagawa et al. [9] used an inverted pendulum model to develop a joint space motion planning algorithm with adjustable step length and walking speed for an exoskeleton robot. Lim et al. [10] presented an algorithm to estimate natural gait parameters for a specific subject using a neural network. The inputs of this neural network are body height, body weight, age, and gender. The outputs of this neural network are the gait parameters, including cadence, stride length, and walking speed. Li et al. [11] presented an algorithm that can generate dynamically stable and tunable gait patterns. Ren et al. [12]

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presented an individualized gait generation method based on anthropometric data. In this way, 14 body parameters are used to generate the individualized gait trajectory.

Generating the trajectory in a way that is individualized for each person and making it possible for the exoskeleton user to change the speed while walking, makes the user comfortable.

In all the aforementioned works, except [4], the patients are not able to voluntarily change their walking speed. On the other hand, in the research [4], the generated swing trajectory has not been personalized for each patient.

This paper presents a method for generating the single support phase trajectory with both features of being personalized according to the patient's body parameters and enabling the patients to change their walking speed voluntarily.

The outline of the paper is as follows; Section II introduces the proposed algorithm by describing the structure of the neural network, the kinematic model, and the interpolation method. This section also discusses the parameters that affect the gait pattern. Analysis and discussion of the experimental results are presented in Section III and the summary and conclusion of the paper are provided in Section IV.

II. PROPOSED ALGORITHM

A complete gait cycle is the sequence of the swing and stance phases. In this definition, one gait cycle is considered for one leg. The swing phase begins when the foot lifts off the ground and ends when the heel hits the ground. In the stance phase, the foot is in contact with the ground. The swing phase comprises around 40% of a gait cycle and the stance phase includes around 60% of the cycle [13].

In another definition, a gait cycle includes the sequences of single and double support phases. In this definition, one gait cycle is considered for both legs. If one leg is in contact with the ground and the other leg is swinging, the gait is in the single support phase. If both feet are in contact with the ground, the gait is in the double support phase. In a complete gait cycle, each of these phases occurs twice.

In the proposed method, the joint angles and their angular velocities, at the end of the double support phase, and the body parameters are used to generate the single support trajectory at each step.

For this purpose, we need to have the following trajectory parameters: 1) step length, 2) foot clearance at the relay point, 3) single support duration, and 4) duration of the ankle reaching the relay point. These parameters are obtained by a neural network. The input of this neural network is the body parameters and double support duration, and the output is the trajectory parameters. This neural network is trained using walking data of healthy people. Finally, we calculate the angle of the joints and time at the end and relay points of the single support phase, using the trajectory parameters. Then we obtain the trajectory equation of each joint with a cubic spline interpolation on the initial, relay, and end points of the single support phase. Fig. 1 illustrates the overall architecture of the proposed algorithm.

A. Neural Network and Data Collection

An MLP neural network with a single hidden layer is applied to estimate the trajectory parameters for a specific exoskeleton wearer. This neural network has four inputs and outputs. The hidden layer of this neural network has four neurons. The activation functions for hidden and output layers are sigmoid and identity, respectively. The gradient descent algorithm is used to train this neural network. According to [8], the gait pattern depends on body parameters and walking speed. From [4], it can be concluded that the walking speed has a direct relationship with the double support duration.

Therefore, the inputs to this neural network are the double support duration and body parameters. First, we selected the six most important body parameters related to human gait according to [8], and we encountered a high error in the neural network. After different tests on the neural network, out of the six body parameters mentioned, three body parameters that have the most impact on gait pattern were selected. These three parameters are body weight, waist circumference, and body height. The outputs of this neural network are the trajectory parameters.

To get training set for training this neural network, six healthy male subjects (70.71 ± 15.31 kg body weight, 84.86 ± 10.11 waist circumference, 175.86 ± 6.82 body height) walked on the ground at three different speeds: very slow (19.8 ± 5.19 cm/s), medium (36.80 ± 4.95 cm/s) and normal (81.43 ± 15.22 cm/s), while their walking data were recorded by two cameras located on both sides of the subjects. Then, three one-step normal gait trajectories were selected for each speed of each subject for training the neural network. A schematic of this neural network is shown in Fig. 2.

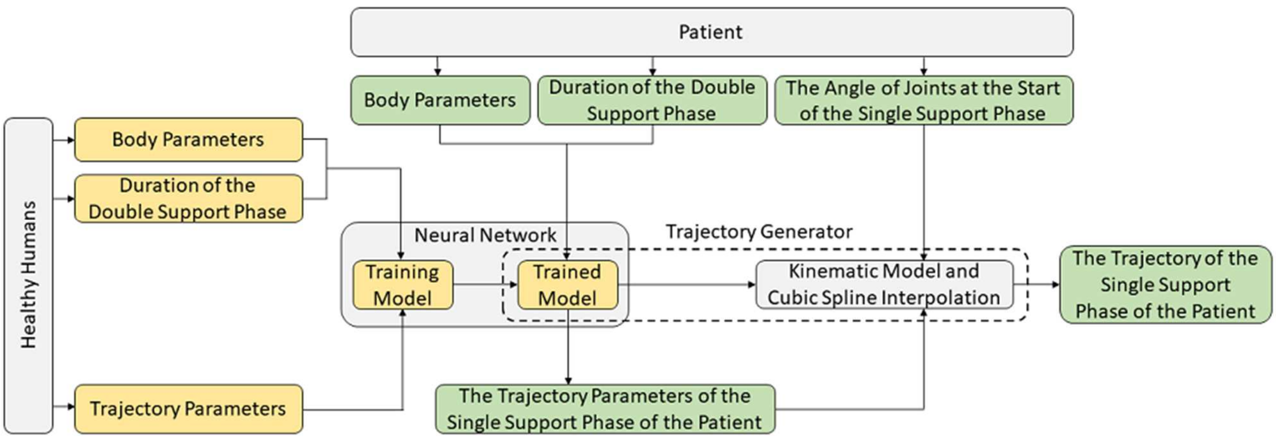


Fig. 1. Overall architecture of the proposed algorithm

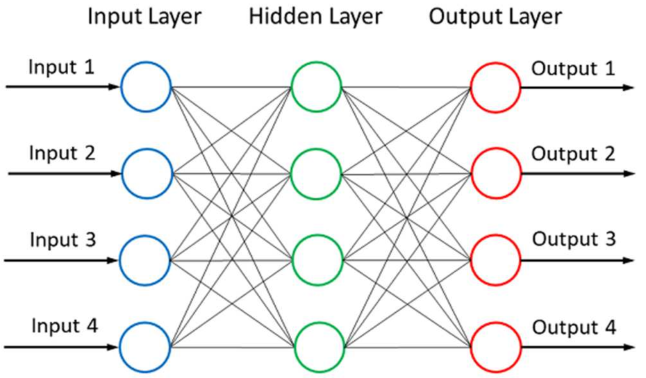


Fig. 2. Structure of the proposed neural network. Input 1: weight, Input 2: waist circumference, Input 3: body height, Input 4: double support duration, Output 1: step length, Output 2: foot clearance at the relay point, Output 3: single support duration, Output 4: duration of the ankle reaching the relay point

B. Kinematic Model

As shown in Fig. 3, three specific points of the single support phase are considered to generate the trajectory. These points are:

1) Initial point: This is the initial point of the single support phase and it is coincident with the end point of the double support phase. Therefore, we have the hip and knee angles at this point for both legs.

2) Relay point: This is the moment when the ankle that is doing the swing motion is raised up to the height of h and passes by the other ankle that is on the ground and doing the stance motion. At this point, the angle of the hip and knee joints, for the leg that performs stance motion, is assumed to be zero. The angles of the hip and knee joints, for the leg that performs the swing motion, are obtained by inverse kinematics.

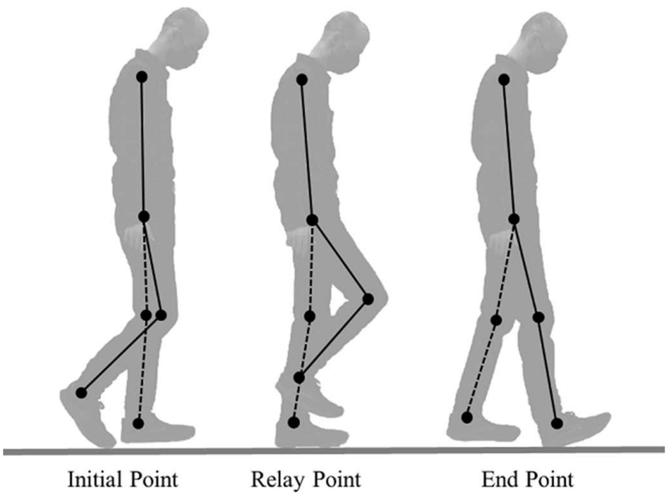


Fig. 3. Schematic of the single support

Fig. 4 shows the kinematic model of the body. The reference coordinate O is placed on the hip joint. The inverse kinematics equations for the swing leg is as follows:

$$\begin{cases} \theta_{k_{sw}} = atan2(\sin(\theta_{k_{sw}}), \cos(\theta_{k_{sw}})) \\ \theta_{h_{sw}} = \theta_{t_{sw}} - \theta_u \\ \theta_{t_{sw}} = atan2(y_{a_{sw}}, x_{a_{sw}}) - atan2(k_1, k_2) \end{cases} \quad (1)$$

$$\begin{cases} cos(\theta_{k_{sw}}) = \frac{{x_{a_{sw}}}^2 + {y_{a_{sw}}}^2 - (L_1 + L_2)}{2L_1L_2} \\ sin(\theta_{k_{sw}}) = \pm\sqrt{1 - cos(\theta_{k_{sw}})} \\ k_1 = L_1 + L_2\cos(\theta_{k_{sw}}) \\ k_2 = L_2\sin(\theta_{k_{sw}}) \end{cases} \quad (2)$$

where L_1 and L_2 are thigh length and shank length, $\theta_{h_{sw}}$ and $\theta_{k_{sw}}$ are the angles of the hip and knee joints of the swing leg, $\theta_{t_{sw}}$ is the angle of the thigh of the swing leg, θ_u is the angle of the upper body, and $(x_{a_{sw}}, y_{a_{sw}})$ is the position of the ankle of the swing leg. In the relay point, the swing leg is raised up to the height of h and is placed next to the ankle of the stance leg. Moreover, for simplicity, the angle of the upper body (θ_u) is assumed to be zero. Therefore we have:

$$\begin{cases} x_{a_{sw}} = x_{a_{st}} - H \\ y_{a_{sw}} = 0 \\ H = h \\ \theta_u = 0 \end{cases} \quad (3)$$

The x position of the ankle of the stance leg ($x_{a_{st}}$) is calculated as:

$$\begin{cases} x_{a_{st}} = L_1\cos(\theta_{t_{st}}) + L_2\cos(\theta_{t_{st}} + \theta_{k_{st}}) \\ \theta_{t_{st}} = \theta_{h_{st}} + \theta_u \end{cases} \quad (4)$$

where $\theta_{t_{st}}$ is the angle of the thigh of the stance leg. According to the assumption, the angle of the hip and knee joints for the stance leg and the angle of the upper body is zero.

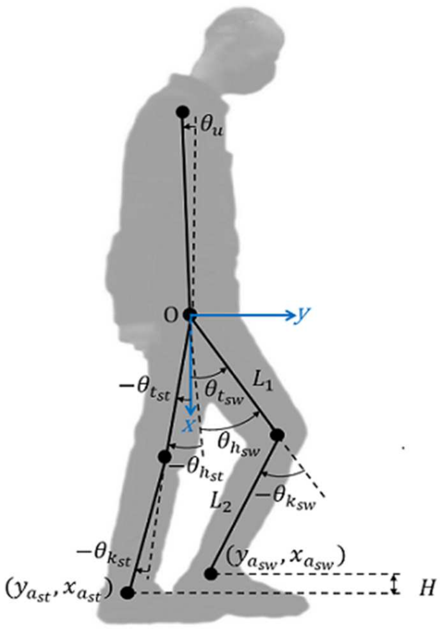


Fig. 4. Kinematics parameters of the human body

Therefore, by substituting equation (4) in (3) and considering the assumptions, equation (3) is rewritten as follows:

$$\begin{cases} x_{a_{sw}} = L_1 + L_2 - h \\ y_{a_{sw}} = 0 \end{cases} \quad (5)$$

Substitution of equation (5) in equation (2) and then in equation (1) gives the knee and hip angles of the swing leg ($\theta_{k_{sw}}$ and $\theta_{h_{sw}}$) at the relay point. There are two solutions for $\theta_{k_{sw}}$ in equation (1) that the minus solution is acceptable.

3) End point: This point is the end of the single support phase. At this point we consider three assumptions as shown in Fig. 5. These assumptions are: 1) The angle of the knee joint of both legs is zero ($\theta_{k_{sw}} = \theta_{k_{st}} = 0$). 2) The hip and ankle joints constitute an equilateral triangle. 3) For simplicity, the angle of the upper body (θ_u) is zero. Therefore, by having the step length, the angle of the hip joint for both legs is calculated as follows:

$$\theta_{h_{sw}} = -\theta_{h_{st}} = sin^{-1}\left(\frac{0.5L_s}{L_1+L_2}\right) \tag{6}$$

In which L_s is the step length.

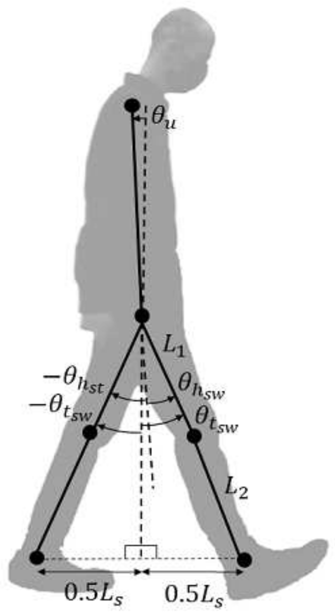


Fig. 5. Human posture at the end of the single support phase

Cubic Spline Interpolation

To obtain the single support phase trajectory equation for each joint, a cubic spline interpolation is performed between the initial, relay, and end points of this phase. Therefore, the generated trajectory equation is obtained by the interpolation method as follows:

$$\begin{cases} \theta_i = a_{1_i} + b_{1_i}(t-t_0) + c_{1_i}(t-t_0)^2 + d_{1_i}(t-t_0)^3 \\ \qquad t_0 \le t \le t_m \\ \theta_i = a_{2_i} + b_{2_i}(t-t_m) + c_{2_i}(t-t_m)^2 + d_{2_i}(t-t_m)^3 \\ \qquad t_m < t \le t_f \end{cases} \tag{7}$$

where $i = 1,2,3,4$ with $i = 1$ for the hip joint of the swing leg, $i = 2$ for the knee joint of the swing leg, $i = 3$ for the hip joint of the stance leg, and $i = 4$ for the knee joint of the stance leg. t_0, t_m and t_f are the times at the initial, relay, and end points.

Cubic spline coefficients (a_{1_i}, a_{2_i}, b_{1_i}, b_{2_i}, c_{1_i}, c_{2_i}, d_{1_i}, and d_{2_i}) in equation (7) are obtained according to [14] by applying angles at initial, relay, and end points and boundary conditions including angular velocity at the initial and end points.

The angular velocity of all joints at the initial point comes from double support data. Therefore, the trajectories are continuous with respect to the velocity at the initial point. The angular velocity of all joints at the end point is assumed to be zero.

III. Result and Discussion

To evaluate the performance of the proposed algorithm, a healthy person walked on the ground at three different speeds: slow (34.09 cm/s), medium (64.71 cm/s), and normal (92.26 cm/s), and the trajectory of the knee and hip joints was recorded by two simple cameras located on both sides of the subject. Then, one step was selected from each speed and the trajectory of the single support phase was generated for each step using the proposed algorithm corresponding to the duration of the double support and body parameters of the person.

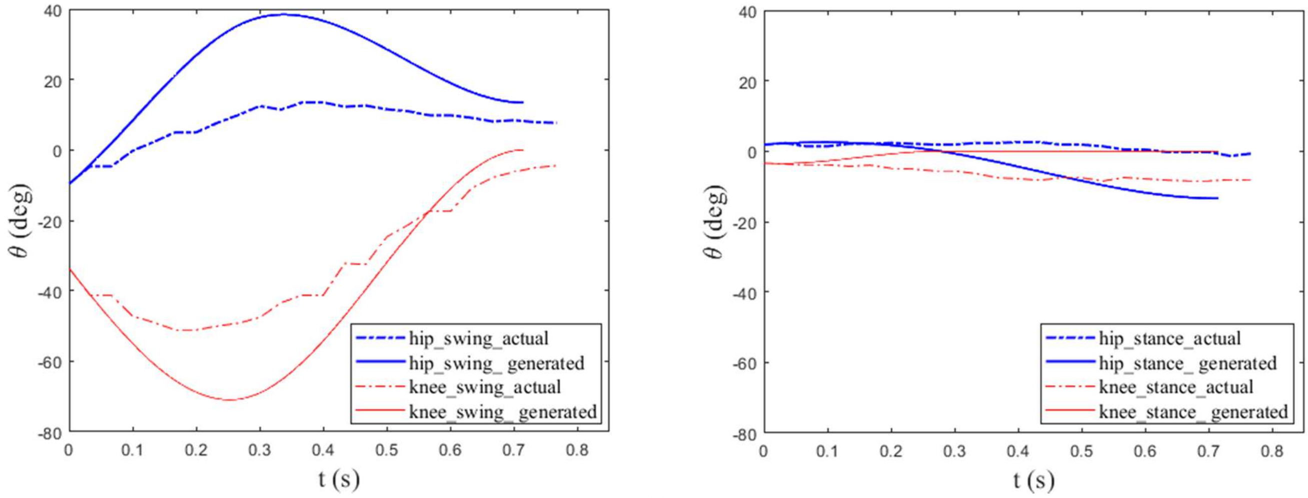
For this purpose, first, the values of the trajectory parameters were obtained by the neural network and compared with the actual which is shown in Table 1. Then the trajectory of the hip and knee joints for the swing and stance of the single support phase was generated and compared with the actual trajectories, which are shown in Fig. 6.

The actual data in Table 1 show that with the increase in the walking speed, the double support duration decreases.

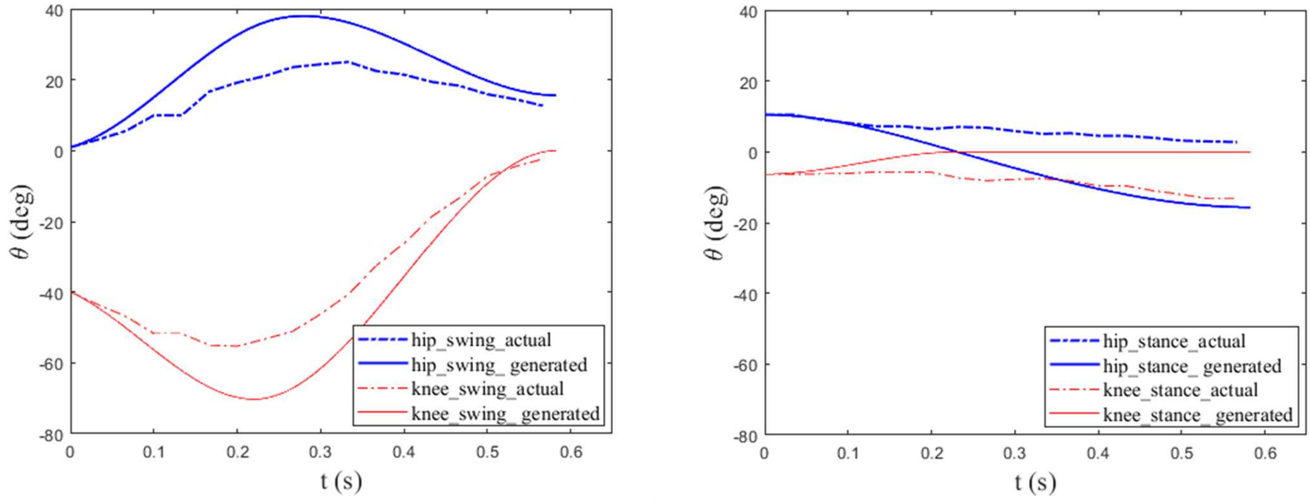
On the other hand, the actual trajectory parameters show that with the increase in walking speed, the single support duration decreases, and the step length increases. The trajectory parameters predicted by the neural network also show the same thing.

Table 1: Comparison of the trajectory parameters obtained from the proposed method with the actual values of the experimental test

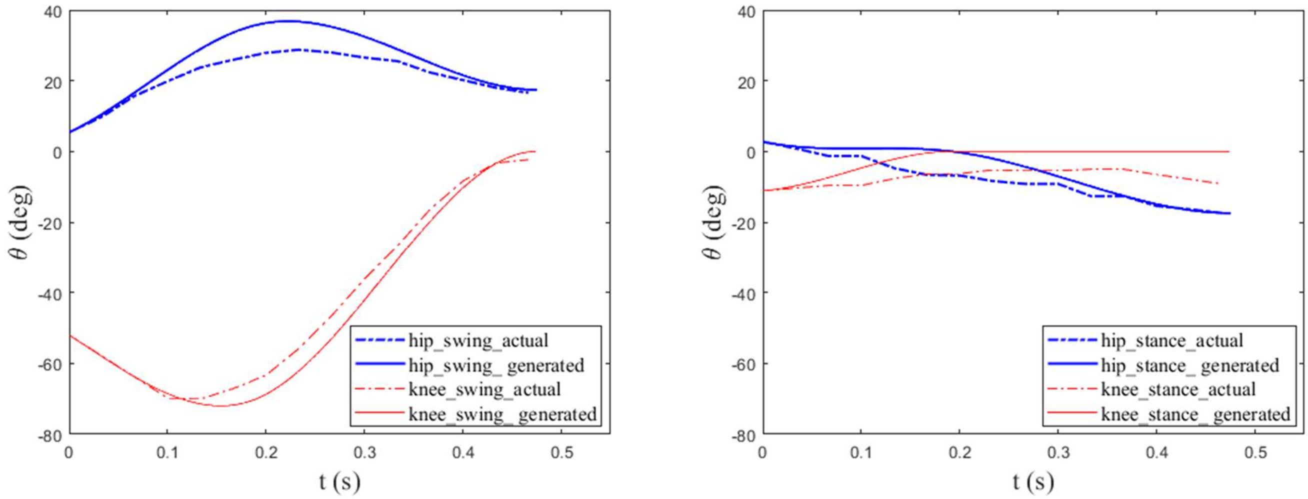
Trajectory Parameters	Speed					
	Slow (34.09 cm/s)		Medium (64.71 cm/s)		Normal (92.26 cm/s)	
	actual	predicted	actual	predicted	actual	predicted
double support duration (sec)	0.5000	-	0.3333	-	0.2000	-
single support duration (sec)	0.7667	0.7146	0.5667	0.5831	0.4667	0.4750
duration of the ankle reaching the relay point (sec)	0.3000	0.2773	0.2000	0.2306	0.2000	0.1922
foot clearance at the relay point (cm)	11.7200	14.9988	19.0440	14.8541	18.6150	14.7324
step length (cm)	35.1760	38.0658	44.5600	44.1560	53.8710	49.1555



(a)



(b)



(c)

Fig. 6. Comparison of the trajectory designed using the proposed algorithm with the actual data for the swing and stance phase of one step of experimental tests at three different speeds. (a): Slow speed, (b): Medium speed, (c): Normal speed

Therefore, if an exoskeleton robot wearer who walks using the proposed algorithm wants to walk more slowly, just needs to perform the double support phase in a longer time. In this case, the speed of the generated trajectory for the single support phase will decrease corresponding to the double support duration. On the other hand, If the wearer wants to walk faster, just needs to perform the double support phase in a shorter time. In this case, the speed of the generated trajectory for the single support phase will increase corresponding to the double support duration. The results in

Fig. 6 reveal that the generated trajectory using the proposed algorithm is smooth.

IV. CONCLUSION

This paper proposed a trajectory generation method for the single support phase, which is personalized according to the patient's body parameters and enables the patient to change the walking speed voluntarily. First, we created a neural network to obtain trajectory parameters. Then, we derived the trajectory equations of the hip and knee joints using the kinematic model of human gait and cubic spline interpolation.

Finally, the single support trajectory for a healthy person who walked on the ground at three different speeds was generated using the proposed algorithm and compared with the actual trajectory. The results indicate that the proposed method successfully detects the preferred walking speed of the exoskeleton user and generates a smooth single support trajectory according to the detected walking speed and the body parameters of the user.

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