On-line Dynamic Gait Generation Model for Wearable Robot with User's Motion Intention

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***Abstract*—In this paper, an on-line dynamic gait generation model is proposed, which makes it possible to plan real-time gait trajectories in continuous motion process online. The model enables wearers to perform complex movements in different scenes with the help of an exoskeleton robot. Meanwhile, based on multi-sensor fusion, a method is designed to detect the wearers' movement intention. The gait trajectories generated by the proposed algorithm are applied to the lightweight lower-limb exoskeleton robot (LLEX). The experimental results show that the algorithm can accurately and effectively plan wearers' movement trajectories of lower limbs, and freely perform various gait patterns, indicating the described algorithm is credible enough to generate dynamic gait patterns for wearable exoskeleton robots.**

***Index Terms*—lower-limb exoskeleton robot, on-line gait generation, intention detection.**

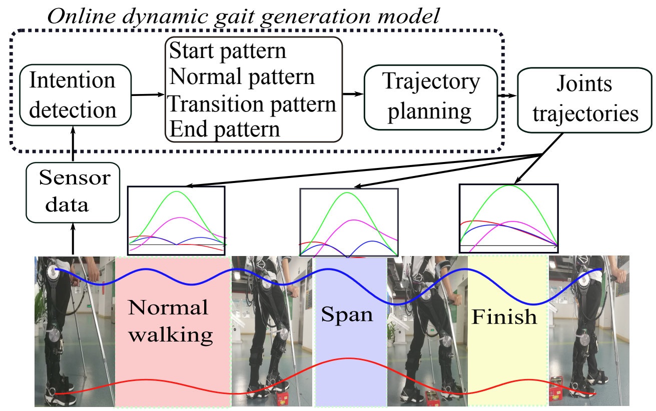

Fig. 1. The framework of on-line dynamic gait generation model

I. INTRODUCTION

It has been a long time since humans attempted to use robotics to assist themselves in daily activities. In recent years, robotics technology has been increasingly applied in the field of assisting the disabled and the elderly[1]. After years of development, wearable exoskeleton robots are now able to enhance wearers' athletic ability or to compensate wearers' loss of athletic ability due to illness or injury[2]. Wearable exoskeleton robots are mainly divided into two types depending on their functions. One is to enhance the exercise ability of people who have active exercise ability, and help healthy wearers bear the weight and reduce the muscle force during walking. The other is for people who lose their athletic ability. In that case, exoskeleton robot fully assumes its weight and plays the role of supporting the body. It serves to restore the exercise capacity and alleviate the problems of paraplegic patients' muscle atrophy and metabolic function degradation caused by long-term stay on wheelchairs. And significant achievements have been made recorded in the development of prototypes such as LOPES [3], Lokomat[4]. At the same time, some mature products have been put in place to the market, such as Ekso[5], ReWalk[6], HAL[7].

The emphasis of this paper is to build an on-line dynamic gait planning model, which can plan various gait patterns in real time according to the wearer's intentions (shown in figure1). Firstly, according to the characteristics of different gait patterns, the walking process is divided into four patterns. Then, the motion intention of wearers are detected by a method based on multi-sensor fusion. Finally, gait trajectories based on motion intention are generated.

The major contributions of this study are as follows:(1) This paper proposes a motion intent detection method based on multi-sensor fusion, which can detect the motion intentions of wears. (2) A more accurate gait generation method with various stride lengths is proposed. (3) The continuous walking process can be dynamically programmed online, so that wearable robot can have richer and more complex application scenarios.

The rest of this article is organized as follows. Second II discusses related work. Section III gives the definition of the problem and assumptions. Section IV proposes an on-line dynamic gait generation method. Section V gives experimental results and analysis. The conclusion of this paper is given in section VI.

II. RELATED WORK

Gait planning is a fundamental problem in the automatic control strategy of lower-limb exoskeleton robot. In general, the control strategy of the preset gait data is used to drive the wearable robot to walk. Initial preset gait data is from normal people's walking data or clinical databases [8]. However, it is difficult to adjust the stride height and the stride length according to the user's preference and actual exercise requirements. In addition, because the gait angle data are collected from a particular individual, such data cannot be implemented to wearers with different physical parameters. Sanz-Merodio et al. [9] used two finite state machines to adjust the hip and knee trajectories of ATLAS robots based on records of healthy individuals. Suzuki et al. [10] used a real-time intention estimator to control an exoskeleton robot based on a desired joint pattern recorded from a healthy subject. However, these gait patterns are relatively single and cannot meet the need of continuous movement with different gait patterns. Vallery et al. [11] proposed an on-line trajectory generation method called complementary limb motion estimation method that can be applied to patients with Hemiplegic patients. Kagwa et al.[12]proposed a gait planning method for a wearable robot with variable strides and walking speeds in the joint space. This method can change the stride length and velocity in the normal sport mode, but does not consider other gait patterns. And this method assumes that the knee joint remains in a non-flexed state during support. All these methods simplify the motion process, or only consider a specific gait pattern. In fact, everyone has his/her own unique gait, and there are different motion characteristics under different gait patterns.

We have developed several types of exoskeleton robots for rehabilitation walking. Initially, a motion capture system was used to collect normal people's joint angle data. These data were used to control exoskeleton robots through interpolation and simple data processing. The generated gait is continuous but not natural enough. Later, we directly planned the joint angle curve and optimized the optimal joint angle trajectory through some constraints. The improved gait generation method can generate gait with variable pace, but it cannot quantify the gait trajectory for a specific stride length. In order to study the personalized dynamic gait generation model, we developed a more lightweight robot for rehabilitation walking, called the lightweight exoskeleton robot (LLEX). At the same time, the algorithm proposed in this paper will also be verified on LLEX.

III. PROBLEM DEFINITION

The purpose of this paper is to provide a dynamic gait planning model based on different wearer preferences and physical parameters. The model can detect the wearer's motion intentions during walking, and plan the corresponding gait trajectories for LLEX. Considering the gait characteristics of walking process and the requirements for practical application, this paper makes the following assumptions:

1. The algorithm is based on the kinematic characteristics of different motion patterns, regardless of the dynamics.

2. The wearer and LLEX robot maintain balance through upper limbs and two crutches that do not affect gait.

3. Considering that gait is a cyclical process, so this study is concentrated on generation of a single gait cycle

In this paper, the walking process is divided into four different patterns according to actual conditions. Different gait patterns have different motion characteristics, so we give different constraint conditions for each gait pattern. The gait pattern is related to body parameters and step lengths, so the gait trajectories can be expressed by formula (1). Wearer's motion intention can be judged by multi-sensor fusion result.

$$P_i = [\theta_{hl}, \theta_{kl}, \theta_{hr}, \theta_{kr}]^T = \Gamma(Q, L, H, T, i) \tag{1}$$

$$Q = [l_1, l_2] \tag{2}$$

$$[i, L, H] = \zeta(\theta, \theta_{hl}, \theta_{kl}, \theta_{hr}, \theta_{kr}, \dot{\theta}_{hl}, \dot{\theta}_{kl}, \dot{\theta}_{hr}, \dot{\theta}_{kr}) \tag{3}$$

Where P_i is the gait trajectories of the i-th gait pattern. Q is the physical parameters, which includes the length of thigh l_1 and the length of shank l_2. And L, H are the target stride length and height respectively, i represents the i-th pattern. $\zeta(\cdot)$ is the motion intention detection function, its input includes the inclination angle of user's upper body, the angular displacement and the angular velocity of each joint of LLEX, while the output contains the i-th gait pattern and the target stride length L. The ultimate goal of this paper is to establish a relationship $\Gamma(\cdot)$ that proposes an on-line dynamic gait generation algorithm.

IV. ON-LINE GAIT GENERATION MODEL

A. The lightweight lower-limb exoskeleton robot (LLEX)

The lightweight lower-limb exoskeleton robot (LLEX), as shown in Figure 2(b), used in experiments to verify the proposed algorithm, as well to collect the angle data of each joint and the data of the back inertial measurement unit (IMU) in the backpack. These data will be used to determine the posture of the robot and users motion intention, and also be recorded as actual gait data.

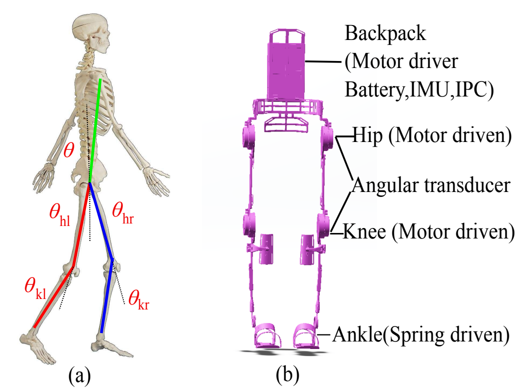

Fig. 2. The lightweight lower-limb exoskeleton robot (LLEX).

In order to facilitate kinematic analysis, the exoskeleton robot is abstracted by the linkage model shown in Figure 2(a). Among them, θ is the angle between the upper body and the vertical direction. θ_{hl} and θ_{hr} are the angles between the left right hip joint and the vertical direction, respectively. θ_{kl} and θ_{kr} the angles between the left right knee joint and the extension line of the thighs, respectively.

B. Dynamic gait generation algorithm

In order to meet the need for more flexible and accurate gait path planning with variable stride lengths, this paper adopts a strategy based on real-time spatial position planning of each joint and then uses inverse kinematics to solve the joint angle trajectory.

According to the relevant research and OPENSIM software simulation of human walking, gait is a cyclical process. A non-linear equation that satisfies the conditions is used to represent the spatial position trajectories of the hip joints and the ankle joints. The definition is as follows:

$$y = \mathrm{G}(L, l_1, l_2, H, T, x) = \sum_{i=0}^{n} \mathrm{C}_i x^i \tag{4}$$

$$x = \mathrm{f}(L, T, H, t) = \sum_{i=0}^{3} \lambda_i t^i \tag{5}$$

Where x is the horizontal position of each joint, while y is vertical height of each joint. And T is gait cycle. C_i and λ_i are parameters to be optimized, so the corresponding constraints are required to solve the optimal solution satisfying the constraints. The walking process is divided into four gait patterns (the tart pattern, the normal gait pattern, the transition patten and the end pattern), and the constraints of different motion modes are given as follows.

The normal gait pattern is from the two legs cross-support state to the two legs cross-support state. The constraints are given by equations (6) and (7).

$$\begin{aligned} & y(0) = y_{\min}, y'(0) = 0, y(\frac{s}{2}) = y_{\max} \\ & y'(\frac{s}{2}) = 0, y(s) = y_{\min}, y'(s) = 0 \end{aligned} \tag{6}$$

$$\begin{aligned} & \mathrm{x}(0) = x_{\min}, x'(0) = 0, x(\frac{T}{2}) = \frac{x_{\min} + x_{\max}}{2} \\ & x(\mathrm{T}) = x_{\max}, x'(\mathrm{T}) = 0 \end{aligned} \tag{7}$$

Where $y_{\max}$ and $y_{\min}$ represent the values of the highest and lowest position of each joint, while $x_{\min}$ and $x_{\max}$ represent the start and end position of each joint in the horizontal direction. And s represents the period length.

The start pattern is swung to the two legs cross-support state from two legs erect-support state, and its constraint conditions are given by equations (8) and (9).

$$\begin{aligned} & y(0) = y_{\max}, y'(0) = 0, y(\frac{L}{2}) = \frac{y_{\max} + y_{\min}}{2} \\ & y(\mathrm{L}) = y_{\min}, y'(\mathrm{L}) = 0 \end{aligned} \tag{8}$$

$$\mathrm{x}(0) = x_{\min}, x'(0) = 0, x(\frac{T}{2}) = \frac{s}{4}, x(\mathrm{T}) = \frac{\mathrm{s}}{2}, x'(\mathrm{T}) = 0 \tag{9}$$

The end pattern is from two legs cross-support state to the two legs erect-support state. The constraints are given by equations (10) and (11).

$$\begin{aligned} & y(0) = y_{\min}, y'(0) = 0, y(\frac{L}{2}) = \frac{y_{\max} + y_{\min}}{2} \\ & y(\mathrm{L}) = y_{\max}, y'(\mathrm{L}) = 0 \end{aligned} \tag{10}$$

$$\mathrm{x}(0) = x_{\min}, x'(0) = 0, x(\frac{T}{2}) = \frac{\mathrm{s}}{4}, x(T) = \frac{s}{2}, x'(T) = 0 \tag{11}$$

The transition pattern is from two legs cross-support (the initial distance between two foots) to the two legs cross-support state (the distance between two foots after changing the stride length). The constraints are given by equations (12) and (13).

$$\begin{aligned} & y(0) = y_{\min-\mathrm{normal}}, y'(0) = 0, y(\frac{s_{normal}}{4} + \frac{s_{new}}{4}) \\ & = y_{\max}, y'(\frac{s}{2}) = 0, y(s) = y_{\min-new}, y'(s) = 0 \end{aligned} \tag{12}$$

$$\begin{aligned} & \mathrm{x}(0) = x_{\min}, x'(0) = 0, x(\frac{T}{2}) = \frac{x_{\min} + x_{\max}}{2} \\ & x(\mathrm{T}) = x_{\max}, x'(\mathrm{T}) = 0, x_{\max} = \frac{s_{normal} + s_{new}}{2} \end{aligned} \tag{13}$$

Where $y_{\min-\mathrm{normal}}$ and s_{normal} are the parameter values in the normal walking pattern of previous cycle, s_{new} is the new parameter value after changing the stride length.

Hip joints and knee joints have different parameter values, includes $y_{\max}$, $y_{\min}$, $x_{\min}$, $x_{\min}$ and s. They are given by (14) and (15) respectively.

$$\begin{aligned} & y_{\max} = \mathrm{l}_1 + l_2, y_{min} = \sqrt{(l_1 + l_2)^2 - (\frac{L}{4})^2} \\ & x_{\max} = \frac{3L}{4}, x_{\min} = \frac{L}{4}, s = \frac{L}{2} \end{aligned} \tag{14}$$

$$y_{\max} = H, y_{\min} = 0, x_{\max} = L, x_{\min} = 0, s = L \tag{15}$$

According to the leg length constraints, the spatial trajectories of knee joints can be obtained. The constraint conditions are presented by formulas (16) and (17), where (x_{kl}, y_{kl}) represents the spatial position coordinate of left knee joint, and (x_{kr}, y_{kr}) represents the spatial position coordinate of right knee joint. (x_{hl}, y_{hl}) is the spatial coordinate of left hip joint, and (x_{hr}, y_{hr}) is the spatial coordinate of right hip joint. (x_{al},y_{al}) is the spatial coordinate of left ankle joint, and (x_{ar},y_{ar}) is the spatial coordinate of right ankle joint.

$$\begin{aligned} (y_{kl} - y_{hl})^2 + (x_{kl} - x_{hl})^2 = \mathrm{l}_1{}^2 \\ (y_{kl} - y_{al})^2 + (x_{kl} - x_{al})^2 = \mathrm{l}_2{}^2 \end{aligned} \tag{16}$$

$$\begin{aligned} (y_{kr} - y_{hr})^2 + (x_{kr} - x_{hr})^2 = \mathrm{l}_1{}^2 \\ (y_{kr} - y_{ar})^2 + (x_{kr} - x_{ar})^2 = \mathrm{l}_2{}^2 \end{aligned} \tag{17}$$

According to the planned spatial position trajectory of each joint, the corresponding joint angle trajectory can be obtained by inverse kinematics solution.

$$\theta_{hl} = \tan^{-1}(\frac{y_{hl} - y_{kl}}{x_{kl} - x_{hl}}) \tag{18}$$

$$\theta_{kl} = \theta_{hl} - \tan^{-1}(\frac{y_{kl} - y_{al}}{x_{al} - x_{kl}}) \tag{19}$$

$$\theta_{hr} = \tan^{-1}(\frac{y_{hr} - y_{kr}}{x_{kr} - x_{hr}}) \tag{20}$$

$$\theta_{kr} = \theta_{hr} - \tan^{-1}(\frac{y_{kr} - y_{ar}}{x_{ar} - x_{kr}}) \tag{21}$$

C. Motion intention prediction

Based on multi-sensor fusion, a method is used to detect intention of wearer's movement. In order to reliably obtain the intention of the wearer, this method determines the intention of wearer's movement only in the phase of two legs support.

This paper uses a two-state state machine to distinguish the two-leg support phase and other phases to meet the dynamic gait generation algorithm requirements, as shown in Figure 3.

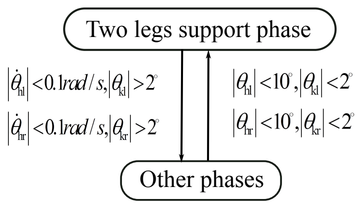

Fig. 3. State machines.

The wearer's intention is detected through the combination of information output from the IMU module mounted on the backpack and the angle sensor of each joint. Rules of determine different motion intentions are as follows.

1. Intent to keep normal pattern with the previous stride length: $0 < \theta < 5^\circ, |\theta_{\mathrm{hl}}| < 10^\circ, |\theta_{\mathrm{hr}}| < 10^\circ, |\theta_{kl}| < 2^\circ, |\theta_{kr}| < 2^\circ$

2. Intent to enter transitional pattern to change stride length: $5^\circ < \theta < 10^\circ, |\theta_{\mathrm{hl}}| < 10^\circ, |\theta_{\mathrm{hr}}| < 10^\circ, |\theta_{kl}| < 2^\circ, |\theta_{kr}| < 2^\circ$

3. Intent to enter end pattern: $-2^\circ < \theta < 0^\circ, |\theta_{\mathrm{hl}}| < 10^\circ, |\theta_{\mathrm{hr}}| < 10^\circ, |\theta_{kl}| < 2^\circ, |\theta_{kr}| < 2^\circ$

The upper body inclination angle θ is not the absolute angle value between the upper body and the vertical direction, but the relative angle value determined by the wearer at the start of experiment with a comfortable standing posture. To prevent the wearer losing balance due to excessive tilt, we set the range of tilt angle to be -2° to 10°.

When the wearer intends to enter the transition pattern of changing stride length, in order to quantitatively determine a new stride length, a linear mapping relationship between the tilt angle of the upper body and the stride length is proposed, as shown in formula (22). Where θ_0 is the initial inclination angle of the upper body, L_0 is the Minimum stride length.

$$L = f(\theta) = k(\theta - \theta_0) + L_0 \tag{22}$$

V. EXPERIMENTS

To verify the feasibility of the proposed dynamic gait model generation algorithm, a healthy male (21 years old, the length of the thigh is 40cm and the length of the shank is 41.5cm) was recruited to join experiments(*approved with IRB No. SIAT-IRB-170315-H0142*). To ensure the safety of the volunteer, simulation experiments are carried out first. After the results of the simulation experiments are strictly consistent with the joint data constraint in human movement process, the volunteer can then wear the exoskeleton robot to conduct experiments.

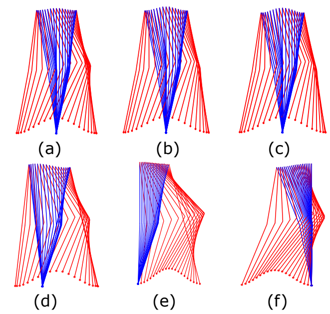

Fig. 4. Movement process of various stride length and different gait patterns. (a) The normal gait pattern with a 60 cm stride length; (b) The normal gait pattern with a 80 cm stride length; (c) The normal gait pattern with a 90 cm stride length; (d) The transition pattern, where the stride length changes from 60cm to 80cm. (e) The start pattern. (f) The end pattern.

A. Algorithm simulation

The algorithm is implemented in MATLAB(2014a). The gait period T is set to 1 s, the sampling frequency is 200 Hz. Figure 4 (a)-(c) denote the motion process of three different step lengths in normal gait mode (L=60, 80, 90cm). The blue lines represent the supporting leg, and the red lines represent the swinging leg. Because the sampling time of each state is the same, the thinner lines in the graph represent faster motion speed, while the denser lines represent slower motion speed. The speed is set to a small value at the moment when in the heel-off and heel-strike states. It can prevent the human body from receiving a large reaction force by the ground, which is beneficial to the balance of human body. At the same time, the large speed when the foot is at highest position makes up for the impact of the small speeds of heel-off and hell-strike on average speed. So the whole movement process still has a high average speed. Figure 4(d)-4(f) show the motion process of the transitional pattern, the start pattern, and the end pattern, respectively. Simulation results show that gait trajectories generated by the algorithm are consistent with human walking characteristics.

B. Experimental method

The subject was healthy without any medical history of lower limb nerves, muscles and bones. The width of hip, thigh length and shank length of the LLEX were adjusted to match the body parameters of the subject.

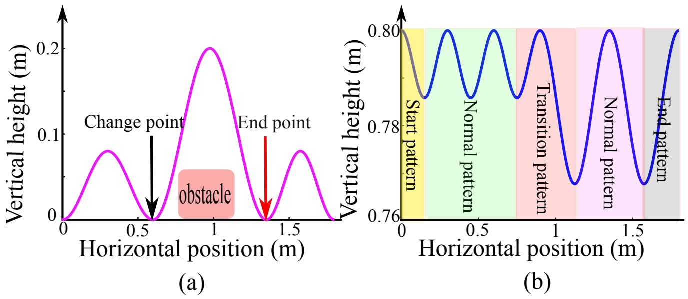

Fig. 5. The position of ankle joint during continuous movement.

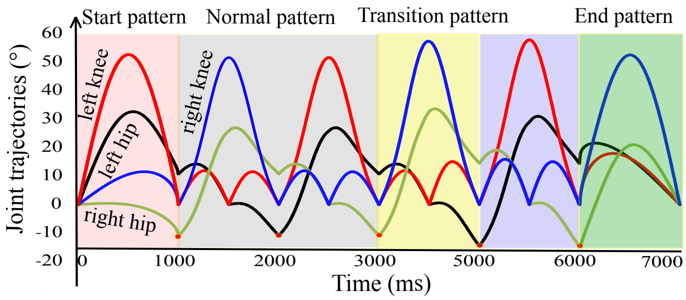

Fig. 6. Joints trajectories during continuous movement.

The subject was required to carry out the continuous walking process including 4 different patterns of motion. For eliminating the experimental error caused by the subjects' subjective reasons, the subject agreed to carry out 8 groups of repetitive experiments. And the actual joint trajectories and actual step lengths in each experiment were recorded.

Figure 5 represents the spatial position of the ankle joint and the hip joint during the experiment. It can be seen that the trajectory of ankle joint changed significantly in the transition pattern. For example, there is an obstacle ahead, which can increase stride length and stride height to complete the crossing. Figure 6 shows the angle trajectory of each joint. When the four gait patterns are continuously converted, the angle trajectories are always smooth and continuous. This shows that the algorithm can effectively plan the continuous dynamic gait trajectories online.

C. The Evaluation of Model Performance

Accuracy and naturalness are used to evaluate the proposed gait generation algorithm.

$$\delta = \frac{\tilde{L} - L}{L} * 100\% \tag{23}$$

$\tilde{L}$ represents the actual stride length measured in each experiment, while L represents the stride length of corresponding planned gait.

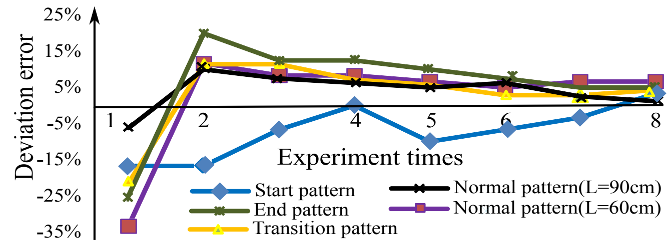

Fig. 7. Deviation error of stride length of different patterns in eight experiments.

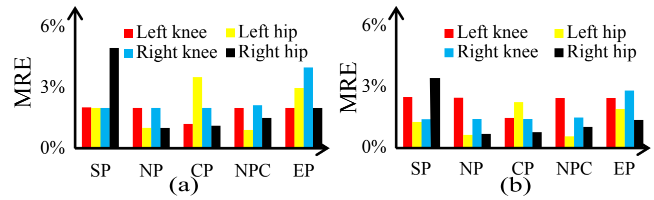

Fig. 8. Mean relative error of different gait trajectories. (a) Mean relative error between generated trajectories and actual trajectories. (b) Mean relative error between generated trajectories and natural gait trajectories. Note: SP: Start pattern. NP: Normal gait pattern. CP: Transition pattern. NPC: Normal gait pattern after changing stride length. EP: End pattern.

The mean relative error (MRE) is used to evaluate the comfort and accuracy of the generated gait, the planned gait trajectories are marked as $\tilde{\theta}$, the actual gait trajectories during experiments are marked as θ and the natural gait trajectories without wearing LLEX (collected by NEURON motion capture system) are marked as θ_0. The gait trajectories length is n, so the mean relative error is:

$$MRE = \frac{\sum_{k=1}^{n} \frac{\left|\tilde{\theta} - \theta_0\right|}{\theta_0}}{n} * 100\% \tag{24}$$

Figure 7 represents the error between actual stride length and planned length in eight experiments. The overall deviation is around 10%. It can be seen that after four experiments, the subject is already familiar with LLEX, and the deviation is basically maintained below 5%. It is demonstrated that the proposed dynamic gait generation algorithm can accurately plan the stride length in different gait patterns. Figure 8(a) shows the mean relative error between generated trajectories and actual trajectories under different gait patterns. The error of each gait pattern is less than 6%. Meanwhile, the error value is relatively large in start pattern and end pattern. The reason may be that the amplitude of the angle of motor is larger in those patterns, and the angular velocity is also large, resulting in a large back electromotive force of the motor and affecting the response speed of motor. However, the error value is still at a low level. Figure 8(b) shows the mean relative error of the driving joints between generated gait and natural gait under different gait patterns. The overall error is also below 5%. This indicates that the gait formed basically accords with the natural gait. It shows that the dynamic gait generation algorithm proposed in this paper has a good naturalness.

D. Comparison with existing algorithms

Since each robot's size, driving mode and sensor configuration are different, it is difficult to compare under the same standards. The algorithm proposed in the searchable literatures will be compared with the dynamic gait generation algorithm proposed in this paper. Kagawa [13] presented a method of gait generation with variable stride length based on joint spatial position planning. The accuracy of planning stride length is compared, the result is shown in Figure 11. And in Table 1, we concentrate on comparing the existing algorithms with the dynamic gait generation algorithm described in this paper. By comparison, it can be seen that the proposed algorithm has higher accuracy, comfort and continuity. This means that the proposed dynamic gait planning algorithm is feasible and can provide more accurate and natural gait for exoskeleton robots.

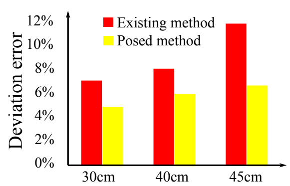

Fig. 9. Comparison of two algorithms in stride length planning accuracy.

TABLE I
COMPARISON WITH EXISTING ALGORITHMS

Method	Continuity	Accuracy	Comfort
Posed method	high	high	high
Previous spatial position planning method[14]	high	low	low
Direct joint angle planning method[13]	-	-	high
Collect natural gait data method[9,10]	high	-	high

VI. DISCUSSION

In this study, a dynamic gait planning method combined with wearer's intention is proposed, which can generate continuous gait trajectories. First, the motion processes are divided into four gait patterns, and the constraint conditions of the trajectory equation are given according to the characteristics of each pattern. Secondly, a multi-sensor fusion method is used to detect the pose of LLEX and wearers intention. Finally, joint trajectories are optimized. In order to verify the feasibility of the algorithm, theoretical simulation and experimental evaluation are carried out. The experimental results show that this method has good accuracy, naturalness, and continuity.

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