

Effects of Individualized Gait Rehabilitation Robotics for Gait Training on Hemiplegic Patients: Before-After Study in The Same Person

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Research

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RESEARCH

Effects of individualized gait rehabilitation robotics for gait training on hemiplegic patients: before-after study in the same person

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Abstract

Background: Lower-limb exoskeleton robots are being widely used in gait rehabilitation training for stroke patients. However, most of the current rehabilitation robots are guided by predestined gait trajectories, which are often different from the actual gait trajectories of specific patients. One solution is to train patients using individualized gait trajectories generated from the physical parameters of patients. Hence, we aimed to explore the effect of individual gaits on energy consumption situation during gait rehabilitation training for hemiplegic patient with low-limb exoskeleton robot.

Methods: 9 unilateral-hemiplegic patients were recruited. On the first day of the experiment, the 9 patients were guided by a low-limb exoskeleton robot, walking on a flat ground for 15 minutes in general gait trajectory, which was gained by CGA (clinical gait analysis) method. On the other day, the same 9 patients wore the identical robot and walked on the same flat ground for 15 minutes in individualized gait trajectory. The main physiological parameters including heart rate (HR) and peripheral capillary oxygen saturation (SpO₂) were acquired via cardiometer and oximeter before and after the walking training. The energy consumption situation was indicated by the variation of the value of HR and SpO₂ after walking training compared to before.

Results: Between-group comparison shows that the individualized gait trajectory training results in lower increase in HR levels and decrease in SpO₂ levels in experimenters compared to general gait trajectory training. Difference has statistical significance ($p < 0.05$).

Conclusions: Using individualized gait guidance in rehabilitation walking training can significantly improve energy efficiency for hemiplegic patient with stroke. Trial registration: Registered on 29 July 2021 at Chinese Clinical Trial Registry (ChiCTR2100049310). <https://www.chictr.org.cn/edit.aspx?pid=130960&htm=4>

Keywords: individualized gait; hemiplegic patient; gait rehabilitation; exoskeleton robot

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Introduction

Globally, stroke is a major cause of functional disabilities of limbs and one of the diseases with the highest disability rate (80%-90%). In recent years, stroke continues to grow at a rate of nearly 9 every year [1], and shows a trend of younger, which is a persistent serious harm to the health of patients and brings a heavy burden to the family and society.

In recent years, more and more attention has been paid to the application of exoskeleton robot in the field of rehabilitation, in particular neurorehabilitation. The rehabilitation robot, such as LOPES [2], Lokomat [3], WalkTrainer [4], ALEX [5], Indego [6], HAL [7], ReWalk [8], Ekso [9], replaces the rehabilitation physician to provide physical therapy for patients and provides safe and reliable repetitive training for patients, which helps to reduce the workload of rehabilitation physician in physical therapy and improve the effect of rehabilitation treatment [10].

In the above devices, gait control strategy based on finite state or predetermined gait trajectory is adopted. These general gait trajectories of hip joint, knee joint and ankle joint are the statistical results of many healthy people [11, 12, 13]. However, many studies have shown that physical factors - walking speed, gender, age and other anthropometric parameters - lead to different gait patterns in different groups [14] [15]. The existing wearable exoskeleton control strategy cannot meet the individual differences of different users [16]. In order to provide specific gait guidance for exoskeleton wearers, gait prediction has become a popular research branch [17] [18]. Valley et al. [19] proposed a complementary limb motion estimation algorithm, which can generate real-time trajectory to provide compensation for hemiplegic patients, but its goal is the symmetry between legs, rather than periodic gait sequence. Kagawa et al. [20] proposed the method of motion planning control in joint space to provide variable step length and speed for

exoskeleton, but the gait mode is not natural, because the limited fixed joint angle is predefined for trajectory planning. However, these studies lack of clinical verification. Rajasekaran et al. [21] applied machine and brain computer interface to exoskeleton control, and conducted clinical trials on 4 patients with spinal cord injury. But if there is no additional trajectory guidance, it is difficult for patients to walk normally after rehabilitation.

We combined Fast Fourier Transformation (FFT) and Gaussian process regression (GPR) to generate individualized gait trajectory, which can be adjusted according to different patients. Finally apply it to a new lower extremity exoskeleton BEAR-H1 to train patients [22] [23]. Nine stroke patients with different morphological parameters are recruited for clinical trial, which is helpful to observe the diversified behaviors of rehabilitation strategies. The results show that after walking training, both the increase of HR and the decrease of SpO₂ was smaller when the robot was control by individualized gait trajectory compared to general gait trajectory, which indicates that individualized gait strategy is energy friendly for hemiplegic patients.

Exoskeleton BEAR-H1 platform

BEAR-H1 is a wearable, battery-powered lower limb rehabilitation robot with active assisting technology and the gait events are detected when the subjects are wearing the BEAR-H1, shown in (Fig. 1a). The robot, which has three active degree of freedoms and a passive degree of freedom in each leg, is self-developed to help patients with hemiplegia conduct rehabilitation training. The three degrees of freedoms are rotations along the hip joint, the knee joint and the ankle joint in the sagittal plane and they are actuated by motors [24]. The adduction and abduction of the hip joint is the passive degree of freedom [25]. There is a rotary encoder in each joint of BEAR-H1, shown in (Fig. 1a), which is used to measure the real-time angle of each joint [26].

In addition, the actuator can accurately control the joint angle by the feedback of the encoder. The gait trajectories, shown in (Fig. 1b), can be changed easily by modifying the program of the robot.

For the purpose of the present study, we embedded different individualized gait trajectories in advance into the internal storage in the micro-controller unit and selected the corresponding trajectory for the specific patient. The control process is executed at 1000 Hz. The time that wear the BEAR-H1 is about 5 minutes. The level of assistance is able to be varied according to the patient's actual ability level while walking.

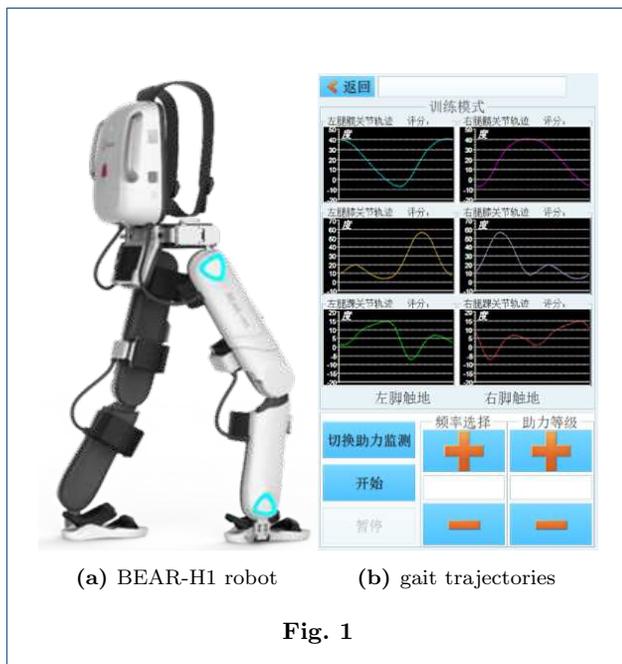


Fig. 1

Individualized gait reconstruction

The generation process for individualized gait reconstruction includes four components. As shown in (Fig. 2), the input component is consisted by body parameters only. Gait data is divided into various sets according to different walking speed. A certain walking speed is selected, linking to a specific set for feature extraction. During the feature extraction, encoding process employs an explicable model for apprehensible processing which is Fourier Transform. Correspondingly, decoding

and reconstruction for generating the final individualized gait pattern is finished by Fourier Inversion at the output component.

In order to establish the mapping relationships between the body parameters and the gait pattern, the gait pattern is firstly extracted into Fourier Coefficients to reduce the computational cost from numerous data points to handful coefficients [27]. The Fourier Coefficients can be predicted through GPR with body parameters. Finally, the individualized gait pattern is reconstructed based on predictive Fourier Coefficients.

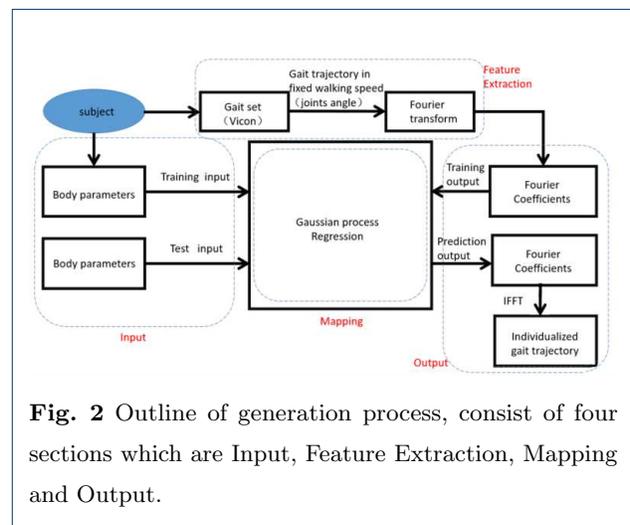


Fig. 2 Outline of generation process, consist of four sections which are Input, Feature Extraction, Mapping and Output.

Gait feature extraction and anthropometry

Gait patterns are represented as the trajectories of low-limb joints, which are joints of hips, knees and ankles [28]. Although gait pattern determined various gait features, they are time-sequence signal with the periodic pattern [29], which is the most often domain applied with Fourier Transform [30].

Fourier transform is a traditional spectral analysis method to describe any periodic signal in its harmonic components [31]. Since walking is periodic and the power for walking is supplied rhythmically with temporal consistency [31], Fourier transform is often used to describe the frequency content of gait [32] [33]. In our study, each joint angle waveform was analyzed in frequency

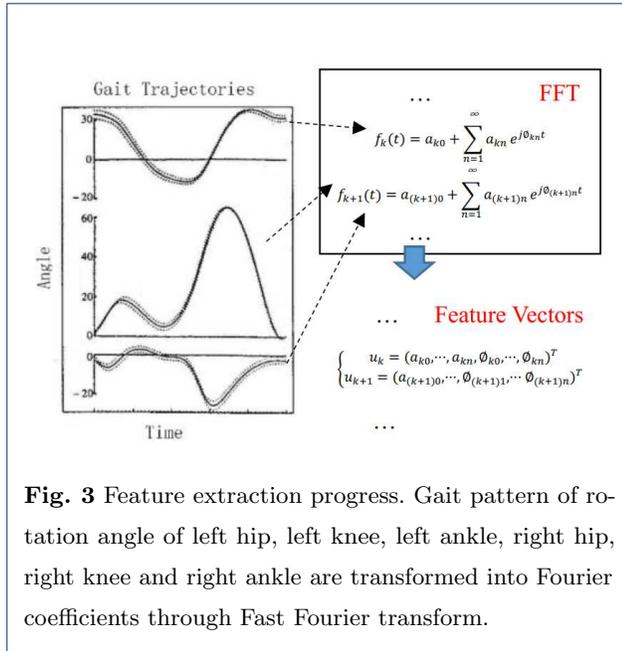


Fig. 3 Feature extraction progress. Gait pattern of rotation angle of left hip, left knee, left ankle, right hip, right knee and right ankle are transformed into Fourier coefficients through Fast Fourier transform.

domain and decomposed into one Fourier coefficient and frequency vector as the gait features:

$$\mu_k = (a_{k0}, \dots, a_{kn}, \phi_{k1}, \dots, \phi_{kn})^T \quad (1)$$

where a_{kn} is the Fourier coefficients, ϕ_{kn} is the frequency of harmonic wave, k is the number of walking trials. Note that $\phi_0 = 0$. In this paper we take $n = 3$. Shown in (Fig.3).

Gait patterns are determined by various factors. To fully study the influence of different parameters to the gait pattern, a total of 28 body parameters are considered in this paper, as shown in (Fig.4). Then, the vector of body parameters for the i^{th} human subject can be formulated as

$$B_i = (b_1, \dots, b_{28})^T \quad (2)$$

Gaussian process regression

In order to obtain the mapping relationship between each gait feature μ and human body parameters B . We implemented the GPR algorithm for achieving our goal since gait feature prediction is regarded as a nonlinear

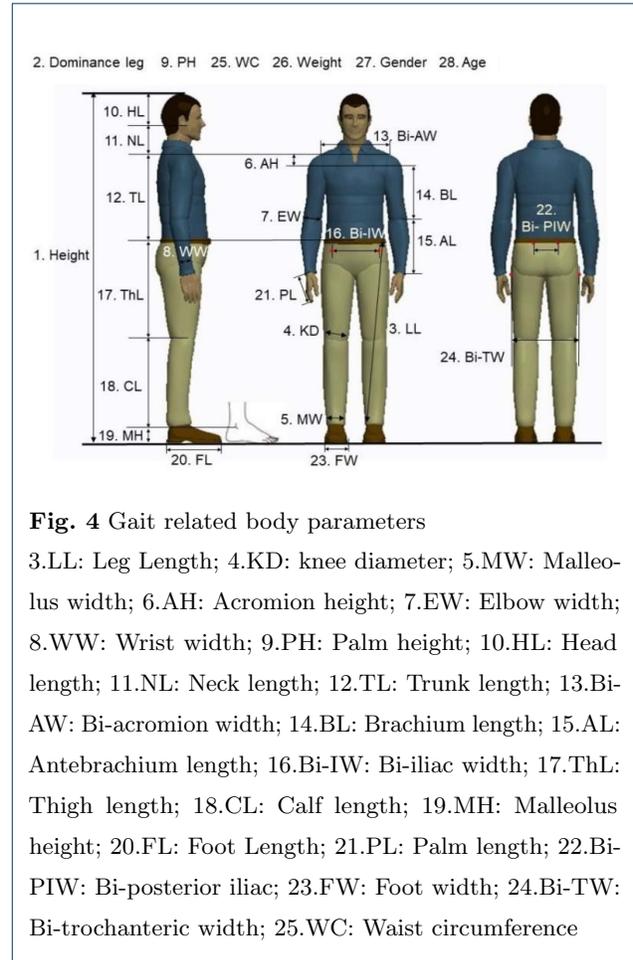


Fig. 4 Gait related body parameters

3.LL: Leg Length; 4.KD: knee diameter; 5.MW: Malleolus width; 6.AH: Acromion height; 7.EW: Elbow width; 8.WW: Wrist width; 9.PH: Palm height; 10.HL: Head length; 11.NL: Neck length; 12.TL: Trunk length; 13.Bi-AW: Bi-acromion width; 14.BL: Brachium length; 15.AL: Antebrachium length; 16.Bi-IW: Bi-iliac width; 17.ThL: Thigh length; 18.CL: Calf length; 19.MH: Malleolus height; 20.FL: Foot Length; 21.PL: Palm length; 22.Bi-PIW: Bi-posterior iliac; 23.FW: Foot width; 24.Bi-TW: Bi-trochanteric width; 25.WC: Waist circumference

regression task. As a kernel-based statistical learning method, GPR is with advantages for solving the small sample learning problem [34], which suits to the scenario that limited human subjects are included in the database. A detailed description about GPR can be studied in [35].

The performance of the proposed scheme can be assessed by comparing the difference between the generated gait and the actual gait of the subject (i.e. measured by the sensor), in terms of the correlation coefficient (3) and the Mean Absolute Error (MAE) (4). A higher correlation coefficient between the predicted and actual and smaller values of MAE implies a better performance of the proposed scheme, and vice versa

[36][37].

$$\rho = \frac{\text{cov}(\tilde{\theta}, \hat{\theta})}{\sqrt{\text{var}(\tilde{\theta})\text{var}(\hat{\theta})}} \quad (3)$$

$$e_{MAE} = \sum_{i=1}^{L_0} \frac{|\hat{\theta}_i - \tilde{\theta}_i|}{L_0} \quad (4)$$

Where L_0 is the fixed length which gait cycle is resampled to. $\tilde{\theta}_i$ is the i^{th} actual angle of joint after resampling. $\hat{\theta}_i$ is the i^{th} predicted angle of joint.

Algorithm Performance

The performance of the proposed algorithm was validated by cross validation using the training set. Due to the limited data and to make full use of it, leave-one-out method was chosen to validate this algorithm's robustness [38][39]. The formula (4) defines the MAE to measure the degree of deviation of the predicted gait trajectory from the real trajectory. The average MAEs of each joint for all subjects with leave-one-out method are presented in Table 1. For comparison, the mean and standard deviation for each joint are also given, as well as the mean and standard deviations obtained by the clinical gait analysis (CGA) [34] methods. It is obvious that the means and standard deviations of MAEs obtained by GPR are both smaller than those obtained by the CGA (no data of ankle are provided by CGA). This also suggests that the trajectory predicted by GPR is closer to the real trajectory, and the MAEs of different subjects have fewer fluctuations. In Table 2, the correlation coefficients for each joint of five subjects at different WSS, and the means (standard deviations) of correlation coefficients, as well as the results from CGA. By comparison, the correlation coefficients obtained by GPR are also better than those obtained by CGA. Therefore, according to the correlation analysis, the GPR method gives a better prediction with strong correlation.

Table 1 Maes of subjects results from CGA for comparison

Joints	GPR(deg)	CGA(deg)
Hip(L)	3.36(1.03)	7.66(1.78)
Knee(L)	4.21(1.64)	9.28(3.07)
Ankle(L)	3.35(1.42)	
Hip(R)	3.47(1.18)	7.66(1.78)
Knee(R)	4.51(1.11)	9.28(3.07)
Ankle(R)	3.40(1.25)	

L - left side, R - right side

Table 2 Correlation coefficients of subjects and results from CGA for comparison

Joints	GPR(deg)	CGA(deg)
Hip(L)	0.99(0.01)	0.87(0.07)
Knee(L)	0.97(0.02)	0.85(0.11)
Ankle(L)	0.92(0.04)	
Hip(R)	0.98(0.01)	0.87(0.07)
Knee(R)	0.95(0.02)	0.85(0.11)
Ankle(R)	0.94(0.04)	

L - left side, R - right side

Subjects and methods

Experiment criteria

The participants were nine patients (eight men and one woman with mean age=48.22 years) with hemiplegia status-post stroke, who resided in a convalescent rehabilitation ward. Participants' average time since last stroke was within 12 months. Both of them had residual right hemiplegia. Participant demographics are presented in Table 3.

Inclusion criteria were as follows:

- First stroke with hemiplegia.
- Functional ambulation category (FAC) of III or IV for the leg.
- Independent or supervision-only walking ability with quad cane or T cane or no support tool.
- Participant provided written informed consent after the purpose of the study was explained.

Participants were excluded if they were:

- Unable to understand study-related procedures.

- Exhibited serious hypertension on walking.
- With circulatory disease, respiratory disease or extreme weakness.
- Failed to receive physical clearance to participate.

Experiment protocol

The experiment was conducted for a total of two days.

On the first day of experiment, 9 patients wore the exoskeleton robot, guided by general gait trajectory which reflects the motion of hip, knee and ankle joint on healthy people [11] [13], and received walking training for 15 minutes at a fixed frequency(Fig. 5).

On the second day of experiment, the individualized gait which was generalized by our method, was applied into the exoskeleton robot to train the same 9 patients with the same method.

Dependent variables are heart rate (HR) and peripheral capillary oxygen saturation (SpO2). Dependent variables were sampled four times for each patient: prior to and after the last individualized-gait exercise treatment, prior to and after the last general-gait exercise treatment. The effectiveness of the algorithm was verified by comparing patients’ decrease of SpO2 and the increase of HR when they were guided by individualized gait trajectory and general gait trajectory respectively (Fig. 6).

The purpose of the experiment is explained to each patient and written informed consents are required to be signed by patients.

RESULT

Experiments were administered over 2 days totally, during which the patients were trained by general gait trajectory and individualized gait trajectory sequentially. Results are presented in Table 4 and Table 5.

- Changes after walking training with exoskeleton robot — We observed changes in SpO2 and HR between the prior to treatment and after treatment in two days respectively. Specifically, changes in

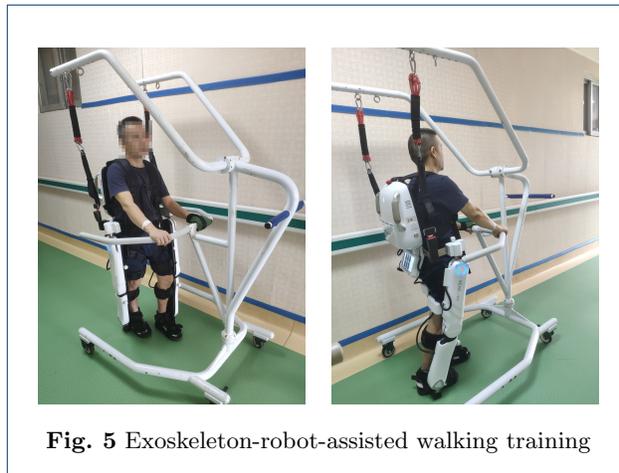


Fig. 5 Exoskeleton-robot-assisted walking training

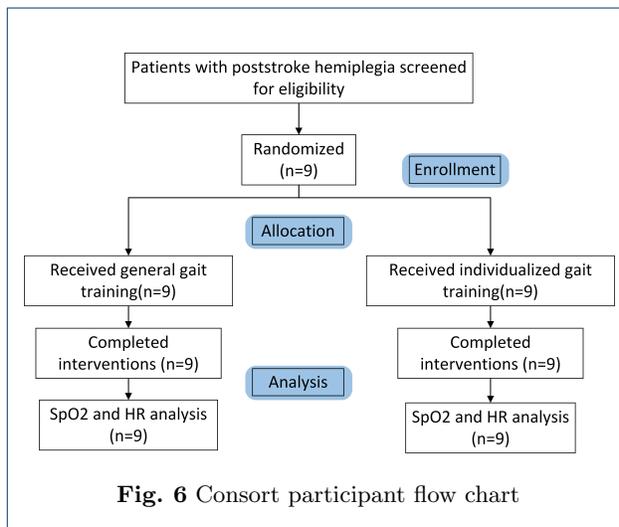


Fig. 6 Consort participant flow chart

Table 3 Participant demographics(N=9)

Subject	Age	Gender	Paretic side	FAC	Diagnosis
1	42	Male	Left	IV	The cerebral thrombosis
2	40	Male	Left	IV	The putamen hemorrhage
3	47	Male	Right	III	The putamen hemorrhage
4	56	Female	Right	IV	The putamen hemorrhage
5	65	Male	Left	III	The cerebral thrombosis
6	40	Male	Left	IV	The cerebral thrombosis
7	33	Male	Right	III	The putamen hemorrhage
8	69	Male	Right	III	The putamen hemorrhage
9	42	Male	Left	IV	The cerebral thrombosis

Table 4 Result of general-gait-guided treatment

	Evaluation items	Prior to treatment	After treatment	variation
Subject 1	SpO2 (%)	96	91	-5
	HR(bpm)	80	88	8
Subject 2	SpO2 (%)	97	96	-1
	HR(bpm)	82	104	22
Subject 3	SpO2 (%)	98	96	-2
	HR(bpm)	105	120	15
Subject 4	SpO2 (%)	97	96	-1
	HR(bpm)	96	109	13
Subject 5	SpO2 (%)	97	95	-2
	HR(bpm)	82	89	7
Subject 6	SpO2 (%)	98	97	-1
	HR(bpm)	77	89	12
Subject 7	SpO2 (%)	99	96	-3
	HR(bpm)	82	91	9
Subject 8	SpO2 (%)	98	94	-4
	HR(bpm)	76	89	13
Subject 9	SpO2 (%)	98	96	-2
	HR(bpm)	81	79	-2

Table 5 Result of individualized-gait-guided treatment

	Evaluation items	Prior to treatment	After treatment	variation
Subject 1	SpO2 (%)	97	95	-2
	HR(bpm)	80	74	-6
Subject 2	SpO2 (%)	96	96	0
	HR(bpm)	90	105	15
Subject 3	SpO2 (%)	97	96	-1
	HR(bpm)	107	113	6
Subject 4	SpO2 (%)	97	98	1
	HR(bpm)	103	113	10
Subject 5	SpO2 (%)	98	97	-1
	HR(bpm)	83	87	4
Subject 6	SpO2 (%)	98	97	-1
	HR(bpm)	75	84	9
Subject 7	SpO2 (%)	99	98	-1
	HR(bpm)	80	88	8
Subject 8	SpO2 (%)	98	96	-2
	HR(bpm)	79	83	4
Subject 9	SpO2 (%)	98	98	0
	HR(bpm)	78	79	1

heart rate are more significant. On the contrary, changes in SpO2 are much smaller.

- Differences between two rehabilitation training — From the data collected in the two training sessions, we observed a common trend in SpO2 and HR between the prior to treatment and after treatment. In both groups, the levels of SpO2 decreased and the levels of HR increased (except in rare cases, the levels of HR decreases and the level of SpO2 increases or remains unchanged. As shown in (Fig. 7) and (Fig. 8), there is a significant difference in the degree of changes in the levels of SpO2 and HR between two rehabilitation training. Patients have a smaller SpO2 reduction and HR increase when they are guided by the individualized gait trajectory.
- Differences between patients — In both training sessions, the SpO2 levels of different patients before receiving the treatment is roughly the same, but start to have slight differences after patients receiving the treatment, while the HR levels of

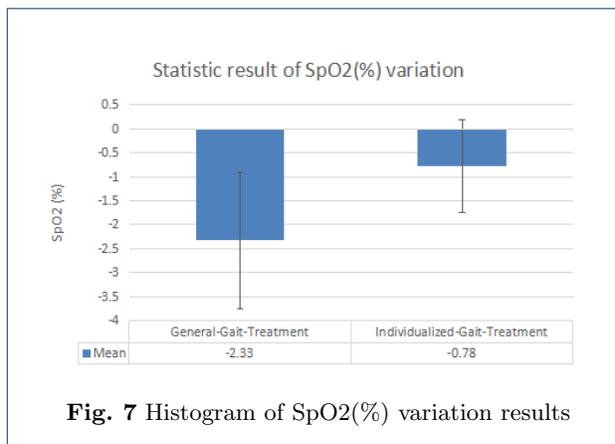


Fig. 7 Histogram of SpO2(%) variation results

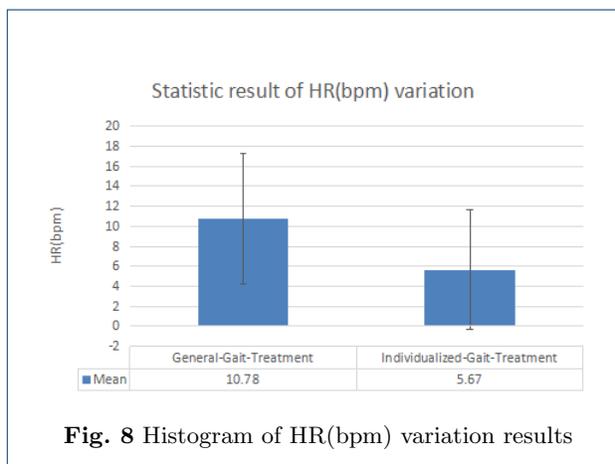


Fig. 8 Histogram of HR(bpm) variation results

different patients before and after receiving the treatment is quite different. Besides, the degree of dispersion of changes in HR and SpO₂ shown by patients under the guidance of those two gait trajectories is different. When patients are guided by the individualized gait trajectory, they have a smaller standard deviation value of the change values of HR and SpO₂ levels.

Discussion and conclusions

Lower extremity robotic exoskeletal devices perform the repetitive practice of specific functional tasks in rehabilitation therapy, such as walking training. For each hemiplegic patient, we generalize individualized gaits for their specific training.

This study is to examine the energy consumption effects of individualized gait in walking training among nine patients with hemiplegia status-post stroke with the help of a low-limb exoskeleton robot. Heart rate (HR) and peripheral capillary oxygen saturation (SpO₂) are selected as the independent variables to reflect energy consumption level [40] [41]. Table 4 and Table 5 show that SpO₂ decreased and HR increased during the walking training. It reveals that our measurement result is acceptable because the internal oxygen is consumed and the heart beats have higher frequency to provide blood where the oxygen is stored during the training process. For all patients, the levels of SpO₂ are similar but the values of HR are various, showing that the physiological condition are different among patients. Different heart rates are needed to maintain a required blood oxygen level to support their physiological activity. In Table 5, compared to Table 4, the decrease of SpO₂ is generally smaller and the HR is also with a tinier change. Table 7 and Table 6 express the same view precisely. From the aspect of SpO₂, the decrease is 2.33 percent in general-gait-treatment which is larger than that in individualized-gait treatment, 0.78 percent in average. The heart rate increase by 10.78

beats per minutes in general-gait treatment but it just with 5.67 beats-per-minute growth in individualized-gait treatment. SpO₂ and HR are related to the extent of effort the patients made during walking training period [42, 43, 44]. The more effort they made, the bigger SpO₂ decrease and HR increase. The human gaits are specific pattern for each individual. Walking with a general gait means the mismatching to original walking habit and therefore patients have to make more effort to overcome the inconformity to follow the gait pattern of exoskeleton robot. On the other hand, an individualized gait reduce the inconformity between patients and exoskeleton robot then patients can follow the robot easier while having walking rehabilitation training. Thus, individualized gait save the energy consumption and therefore the training time for hemiplegic patients can be expanded since more energy remains.

In the future, more metabolic parameters, i.e. the CO₂ and O₂ content in exhaled gas, more patients and more algorithm for gait generalizing will be investigated to find out the energy consumption situation. On the other hand, a formal clinical will be conducted to verify that the individualized-gait exoskeleton robot has positive effects on rehabilitation for hemiplegic patients.

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Abbreviations

FFT: Fourier transform; CGA: clinical analysis; GPR: Gaussian Process Regression;

Availability of data and materials

The data collected and/or analyzed in this study are available from the corresponding author on reasonable request.

Table 6 Statistic result of SpO₂(%) variation

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6
general-gait-treatment	-5	-1	-2	-1	-2	-1
individualized-gait treatment	-2	0	-1	1	-1	-1
	Subject 7	Subject 8	Subject 9	Mean	STD	
general-gait-treatment	-3	-4	-2	-2.33	1.1414	
individualized-gait treatment	-1	-2	0	-0.78	0.972	

Table 7 Statistic result of HR(%) variation

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6
general-gait-treatment	8	22	15	13	7	12
individualized-gait treatment	-6	15	6	10	4	9
	Subject 7	Subject 8	Subject 9	Mean	STD	
general-gait-treatment	9	13	-2	10.78	6.553	
individualized-gait treatment	8	4	1	5.67	5.979	

Ethics approval and consent to participate

This study was approved by the Scientific research ethics committee of Qilu Hospital of Shandong University (No. KYLL-202011-131). This trial was designed following the principle of the Declaration of Helsinki. All recruited subjects read and signed consent form before participation. This study protocol is registered at the Chinese Clinical Trial Registry with the following identifier: ChiCTR2100049310.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

The person with stroke problem in Fig.5 has consented to the publication of the photograph.

Authors' Contributions

JY, ZG and GC made substantial contributions to experimental design, SSZ and LSX are in charge of data collection, data analysis and drafting the manuscript. YGL, ZMZ and XG offered their expertise advice in screening the subjects, supervising the clinical trial and interpreting the results. All authors read and approved the final manuscript.

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