Proceedings of the 2018 IEEE
International Conference on Robotics and Biomimetics
December 12-15, 2018, Kuala Lumpur, Malaysia

Online Adaptive and LSTM-based Trajectory Generation of Lower Limb Exoskeletons for Stroke Rehabilitation

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Abstract— **Lower Limb Exoskeletons (LLEs) are promising in stroke rehabilitation, but the challenge is how to design an adaptive and appropriate trajectory for each stroke survivor to encourage active engagement. To achieve this, online adaptive trajectory generation based on synergies is proposed. In neurology, a gait involves not only the movement of lower limbs but also the rhythmic interjoint coordination (i.e., synergies) among different limbs. Studies also showed the promising applications of synergies in stroke rehabilitation. In this paper, Long Short-Term Memory (LSTM) network is adopted for the first time to interpret and exploit inter-limb synergy for trajectory generation of rehabilitative LLEs. The reference trajectory is generated online for the leg of the paretic side of stroke patients based on the motion data of their upper and lower limbs by LSTM-based synergy extracted from healthy people. Gait experiments on healthy subjects are conducted using a wearable motion capture system to get motion data. One side's hip and knee angle data of a randomly selected subject are estimated, based on the other side's motion data by an LSTM model trained by motion data of other healthy subjects. The estimation results are compared with estimation based on other methods. Results indicate that LSTM has better estimation performance and stability over statistical regression methods such as PCA, which has been widely adopted to analyze human motion synergy. In addition, LSTM shows better inter-individual adaption. The feasibility of the proposed trajectory generation based on LSTM has been validated, although the therapeutic effects or possible benefits of applying synergies into rehabilitation need further exploration.**

Keywords—exoskeletons; stroke rehabilitation; LSTM; synergy.

I. INTRODUCTION

Stroke is a leading cause of hemiparesis and hemiplegia. New therapeutic methods using robotic assistive devices such as Lower Limb Exoskeletons (LLEs) to help patients restore impaired mobility in rehabilitation are under extensive research. LEE has been proved promising to provide intensive rehabilitation training for stroke survivors, while reducing labor-intensive physical therapy and cost.

Weaker strength or inability to generate proper voluntary muscle activities lead to pathological gait in stroke patients. They may have spasticity and altered muscular mechanical properties in lower limbs, causing increased resistance to extending the muscles [1]. Situations vary from each stroke patient, and even the gait of a specific stroke subject can change during rehabilitation. Thus, adaptive trajectory generation for rehabilitative LLE has become an important and challenging issue.

In general, there are three approaches for the trajectory generation of rehabilitative exoskeleton. The first approach is to record gait data from a representative able-bodied subject and then let the exoskeleton echo the obtained trajectory after tuning or adjustment [2]. Some researchers tried to build models from healthy gait data to generate or resemble reference trajectory at given walking speed, gait cycle and amplitude. But, this would limit the natural variability in self-intended gait and cannot avoid safety problems, considering altered biomechanical properties of stroke survivors. The second approach suggested by Kazuo and Yokomine [2] copies the trajectory of the sound limb of the wearer as the reference trajectory for the paretic side in real time. However, the safety and feasibility of this approach are questionable, since stroke patients exhibit asymmetric gait and lower limbs of two sides share different biomechanical properties. Currently, this approach is rarely be used.

The last but most promising approach is calculating the reference trajectory utilizing the data of the wearer's sound side based on the inter-joint coupling relationship named synergy. In neurology, different human motions are considered as combinations of different synergies (coupling movements) which are controlled by the central nervous system [3]. During walking, synergies exist not only between two legs but also among upper and lower limbs. Also, altered synergies are found in stroke patients, but they can be improved along the rehabilitation procedure [4]. These findings reveal that adopting synergy in rehabilitation is promising. We can use synergies extracted from healthy people to guide stroke patients how to walk properly, and then positive feedback can be sent to their nervous system during walking, contributing to the recovery of the brain, not only of the muscles. The famous theory in stroke rehabilitation named "motor relearning theory" shares similar ideas. Principal Components Analysis (PCA) is the most commonly used tool to reduce the dimensionality of joint data and help derive the synergy. Many researchers adopt PCA to analyze synergies in different human motions, but some information may be lost during the reduction.

A few researchers studied on the third approach. Vallery and Buss [5] firstly adopted synergy into trajectory generation

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978-1-7281-0377-8/18/$31.00 © 2018 IEEE

using PCA and regression. They have conducted controlled experiments on healthy subjects and results showed that trajectory generated based on synergies tend to reduce electrical motor consumption and make less interference on the wearers, encouraging the participation. But they only considered the synergy between two legs and the performance of estimation in knee joints was not good, although they tried two different statistical methods to extract synergy. Hassan from HAL (Hybrid Assistive Limb) group added the tilting angle of a cane to investigate the synergy among upper limbs and lower limbs based on PCA. They conducted clinical trials on three stroke subjects, proving the feasibility of adopting inter-limb coordination on trajectory generation for stroke patients [6].

Artificial Neural Networks (ANNs) are state-of-the-art powerful learning tools without any prior knowledge. Long Short-Term Memory (LSTM) networks are the widely used recurrent neural networks that are good at learning long range relationships. ANN has drawn wide attention in exoskeleton areas. It has been adopted for gait recognition, assessment of motor rehabilitation, building healthy gait model based on different gait features. Some researchers [7] [8] utilized ANN to model the intra-limb coordination, such as the trajectory design of knee angle based on hip and ankle angle of the same lower limb. But the application of intra-limb coordination in knee joint rehabilitation is controversial, because the abnormality in knee joint may alter the feature of other joints, and finally output a deficient reference trajectory of knee joint.

The mechanism of inter-limb synergy or coordination is still unknown, although there are many hypotheses proposed. Biologically-inspired ANN is somewhat like human neural networks. Both of them are powerful but difficult to interpret. Thus, we consider using LSTM to model inter-limb synergy.

In this paper, we propose a trajectory generation strategy of rehabilitation LLEs, which is online adaptive to different stroke patients by synergy extracted from healthy subjects using LSTM to encourage active engagement and provide advisable therapeutic effects. The adaptivity here includes not only inter-subject adaptivity, but also intra-subject adaptivity. Because the reference trajectory is generated based on the motion data of patients' sound side by synergy. Hopefully, when the patients receive much rehabilitative training and are in better conditions, they can walk more like those with healthy gait pattern. To better interpret synergy, motion data here cover not only the joint angle and angular velocity data of hip and knee, but also the upper limb information (angle and angular velocity of shoulder and elbow) with the help of wearable motion capture system. The wearable system can be easily attached to the LLE in the real application.

To the best of our knowledge, main contributions of this work are:

1. LSTM is adopted for the first time to interpret and exploit inter-limb synergy for trajectory generation of rehabilitative LLEs.
2. Capturing motion of upper limbs by a wearable motion capture system to better interpret synergy and improve the accuracy. The system can also be equipped on LLEs for application.
3. Highly improving the estimation performance and stability of trajectory based on the synergies, compared with statistic regression methods such as PCA.

This paper contains an introduction of characteristics of stroke gait, LLE CUHK-EXO 3.0 and gait data, followed by application of PCA and LSTM. Then, estimation and results comparison of different methods are shown and discussed.

II. Preparation Work

A. Stroke gait data

Stroke patients exhibit pathological gait. It is reported that stroke patients have lower walking speed, longer stance phase and tend to rely more on the sound side, compared with healthy people, because of the fear of lateral instability. For kinematics, noteworthy are the reduction in hip, knee flexion and also in ankle plantarflexion. In Fig. 1, it is clear that the range of motion of knee joint and hip joint stroke patients' sound side, paretic side and healthy people's varies from each other. Deviations between stroke gait and normal gait call for suitable reference trajectory for LLE. In a 30 subjects stroke database [9], the patients are generally divided into three groups based on their comfortable walking speed: slow (mean = 0.25±0.05 m/sec), medium (mean = 0.41±0.08 m/sec), fast (mean = 0.63±0.08 m/sec). Since this database contains enough variability on stroke gait, we adopted this stroke database in analysis at the current stage.

B. CUHK-EXO 3.0

Previously, our group has developed a lower limb exoskeleton named CUHK-EXO and conducted clinical trials on polio subjects [11]. It has 6 degrees of freedom in total with 3 in each leg. Equipped with more powerful motors and having lighter weight but more robust structures, CUHK-EXO 3.0 (shown in Fig. 2) is more promising for the rehabilitation of stroke patients, in particular those in acute and sub-acute phases, compared with former prototypes [12].

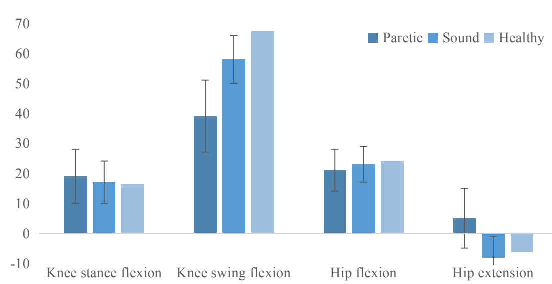

Fig. 1 Stroke gait data from [9] and healthy gait data from Winter's [10]. Paretic and sound stand for the paretic and sound side of stroke patients, respectively. Maximum knee flexion in stance and swing phase are shown in "knee stance flexion" and "knee swing flexion", respectively.

Fig. 2 Prototype of CUHK-EXO 3.0

C. Healthy gait data

To obtain enough training data, gait experiments on able-bodied subjects are conducted with the help of a wearable motion capture system (Noitom® Perception Neural, shown in Fig. 3). Sixteen Inertial Measurement Unit (IMU) nodes are placed at the corresponding parts of the skeleton on the wearer by sticky straps according to the instruction. The wearable motion capture system is free of spatial constraint, thus it has been employed to continuously record the motion of upper and lower limb. Another advantage is that IMU nodes can be easily installed on the exoskeleton in the real application, and the number of IMUs can be reduced.

Four able-bodied male subjects without gait-related pathology (shown in Table I) are recruited and asked to walk on a 17m hallway at two different speed (self-selected and slow). 10 trials in total for each subject. It is noted that all the subjects swing their arms naturally during walking.

TABLE I. SUBJECT INFORMATION

Subject	Height (cm)	Weight (kg)	Age
A	175	62	25
B	165	55	29
C	180	60	25
D	170	68	28

Fig. 3 Wearable motion capture system.

The wearable system can output quaternion and filtered angular velocity of body segments. The joint angle of knee, ankle, hip, shoulder, arm of right side and left knee, left hip in the sagittal plane were calculated based on the quaternion. After omitting the unrhythmic data, the angular velocity of right shank, thigh in 3 axes, right arm in x, z and right forearm in z-direction are also collected. The data of first several accommodation steps of each trial are dismissed. Thus, 7 angular data and 9 angular velocities of more than 1000 gait cycles (about 95 data points in each cycle) from 4 subjects are obtained (given in Table).

TABLE II. GAIT DATA ACQUISITION

Angle		Angluar velocity	
Right	***Left***	***Lower limb***	***Upper limb***
RHip RKnee RAnkle RArm RShoulder	LHip LKnee	$RThighW_{x/y/z}$ $RShankW_{x/y/z}$	$RArmW_{x/z}$ $RForearmW_{z}$

III. PCA-BASED ESTIMATION

A. Data processing

PCA is the mostly employed approach to analyze motion synergies. To make a fair comparison, we firstly use PCA and regression to extract inter-limb synergy and perform estimation. Detailed PCA procedure to get synergy is introduced in [5].

Firstly, 7 angular data from 3 subjects were normalized by (1). PCA was performed among θ^*_{RK}, θ^*_{RH}, θ^*_{RA}, θ^*_{RS} and θ^*_{RE} to reduce the dimensionality. According to the scree plot, four principal components ($F_1 \sim F_4$) were selected to meet the contribution rate over 95%. So we have the relationship among PCs, the eigenvalues ($E_1 \sim E_4$) and right angle data as (2). a ~ e are coefficients.

$$\theta^* = \frac{\theta - \bar{\theta}}{\sigma_\theta} \tag{1}$$

$$F_n = (a_n / \sqrt{E_n})\theta^*_{RH} + (b_n / \sqrt{E_n})\theta^*_{RK} + \ldots + (e_n / \sqrt{E_n})\theta^*_{RE} \tag{2}$$

And then linear regression was completed among dependent variables $\theta^*_{LH} / \theta^*_{LK}$ and independent variables $F_1 \sim F_4$. Combining regression result with (2), we can finally have the relationship of left hip, knee angle with respect to right angular data of upper and lower limbs (shown in (3)).

$$\begin{cases} \theta_{LH} = n_1\theta_{RK} + n_2\theta_{RH} + n_3\theta_{RA} + n_4\theta_{RAR} + n_5\theta_{RFA} \\ \theta_{LK} = n_1'\theta_{RK} + n_2'\theta_{RH} + n_3'\theta_{RA} + n_4'\theta_{RAR} + n_5'\theta_{RFA} \end{cases} \tag{3}$$

B. Estimation results

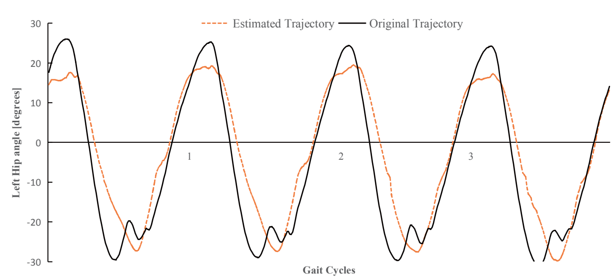

Fig. 4 Estimated left hip angle from synergy by PCA vs. original hip angle.

To test its feasibility and accuracy, we employ synergy (3) calculated from one subject's gait data into motion data of right side from another data set of the trials (as testing data) to calculate the left knee and hip joint angles. And then the calculated joint angle based on the testing data were compared with the original ones. The results of the estimated hip angles and the original left hip angle are shown in Fig. 4.

In Fig. 4, there are some deviations in the amplitude and also time delays between estimated hip trajectory and the original ones. For knee angle estimation based on PCA and regression, the result is worse. Vallery [5] also confirmed this finding. To improve the estimation accuracy, one way is to add angular velocity into training data and get a more detailed synergy. But it will make redundancy and reduce the stability and continuity of the trajectory. Vallery thus designed a Kalman filter to model the errors and integrate estimated angle and angular velocity, but the results were still not desirable and may violate the naturality of human gait. We then set other subjects' motion data as the testing data and followed the same PCA procedure to calculate the estimation error. The result indicates that PCA-based synergy does not have good inter-subject feasibility (shown in Fig. 9).

According to the results, PCA-based estimation does not show good performance, especially on knee angle data. Maybe it is because knee angle data do not have a very strong linear relationship with upper and lower limb motion data of the other side. PCA cannot well exploit inter-limb synergy. It reduces the data dimensionality, while it increases the uncertainty and instability. Also, it is controversial to adopt some filters to modify the trajectory. Although many neurologic researchers employ PCA to analyze synergy of many human motions, applying PCA-based synergy to robotic gait rehabilitation is another issue. Deviations, time delay and bad inter-subject universality will lead to safety problems. Thus, it is advisable to find another tool to better exploit the inter-limb synergy and make the reference trajectory more adaptive.

IV. LSTM-BASED TRAJECTORY GENERATION

The proposed approach of trajectory generation is to apply the inter-limb synergy extracted from healthy subjects by LSTM on stroke patients to generate an ideal trajectory for the paretic side based on the motion data of the sound side. Before that, we need to validate the method on healthy subjects. And also, we need to prove our extracted "healthy" synergy have universality on different subjects.

A. LSTM

LSTM is popular for its ability to regain information from inputs long time ago, while standard recurrent neural networks can traceback only a limited number of steps [13] to filter the information of the internal state and also solve the problem of vanishing gradients. The internal state $s^{(t)}$ is then influenced by the forget gate $f^{(t)}$ (where σ stands for sigmoid function):

$$f^{(t)} = \sigma(W_1^f x^{(t)} + W_2^f h^{(t-1)} + b_f) \quad (4)$$

$$s^{(t)} = g^{(t)} \odot i^{(t)} + s^{(t-1)} \odot f^{(t)} \quad (5)$$

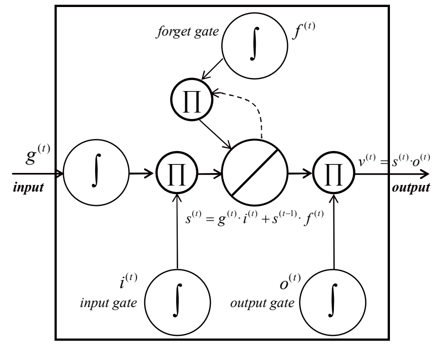

Fig. 5 LSTM memory block with one forget gate.

A block diagram of LSTM with a forget gate by Gers et al. [14] is shown in Fig. 5.

The input $i^{(f)}$ and output $o^{(t)}$ gate decide when to let the activation enter or exit from of the internal state:

$$i^{(t)} = \sigma(W_1^i x^{(t)} + W_2^i h^{(t-1)} + b_i) \quad (6)$$

$$o^{(t)} = \sigma(W_1^o x^{(t)} + W_2^o h^{(t-1)} + b_o) \quad (7)$$

where W_1, W_2 and b are corresponding weight matrices and bias parameters, respectively. $h^{(t-1)}$ stands for the values output by each neuron in the hidden layer before $h^{(t)}$, the present value, which is decided by the internal state $s^{(t)}$ and output gate $o^{(t)}$:

$$h^{(t)} = tanh(s^{(t)}) \odot o^{(t)} \quad (8)$$

It is noted that normally, the forget gate $f^{(t)}$ in simpler LSTM without forget gates is set 1 for all *t*. All the parameters in (4)~(8) are determined during training with enough training data set.

B. LSTM data preparation

To validate the feasibility of LSTM-based synergy, we need to prove that for any randomly selected motion data of a subject, we are able to estimate one side's data using the other side's data based on the synergy from all the other subjects. We already have 16 gait feature data (7 angles and 9 angular velocities) of upper and lower limbs from 4 healthy subjects. Firstly, several gait cycles of subject A (8574 × 15) are randomly selected as testing data, while all of the motion data of other subjects are set as training data (77166 × 15). Note that the input shape of the LSTM model is 15 features in each step, since the knee and hip angular data of the target side are supposed to be trained in different LSTM program.

C. *LSTM training and results*

An LSTM model with 50 neurons in the first hidden layer and 1 in the output layer is adopted. There are 50 training epochs in total, and the internal state is updated after each epoch. We firstly trained the model with the training data and then calculated the estimated left knee and hip data of subject A, based on the other side's motion data by the LSTM model. Mean absolute error loss function is employed to quantify the loss during training and testing, and Root Mean Squared Error (RMSE) is calculated after each run to evaluate the model.

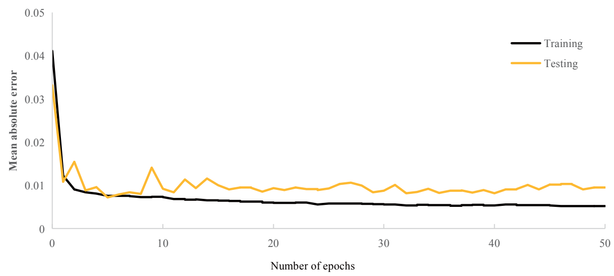

Fig. 6 Mean absolute error during each training and testing.

From Fig. 6, we can find that the loss decreases in the training procedure, which indicates the improvement of model performance. Thus, 50 epochs were selected to get a lower error at reasonable time cost.

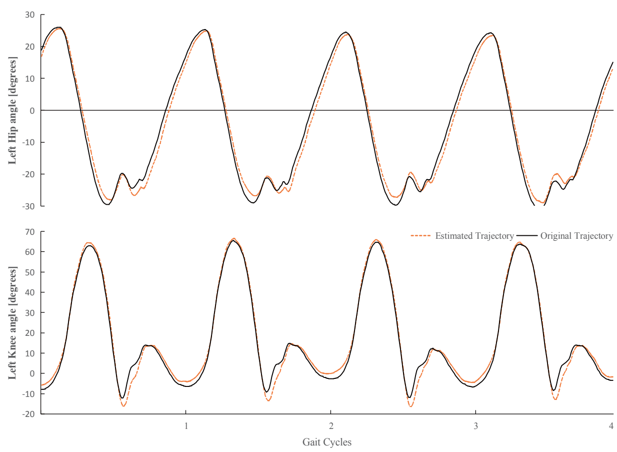

Fig. 7 Estimated left knee and hip trajectories vs. original trajectories.

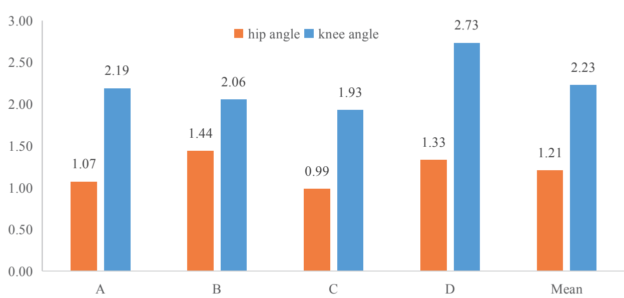

Fig. 8 RMSE of LSTM-based estimation on hip and knee angles when motion data of subjects A, B, C, D are selected, respectively (synergy is extracted from alien data). For example, when estimating the hip and knee angles of subject A, motion data of subjects B, C, D are set as the training data. "Mean" is the average RMSE of different estimation results based on different training data.

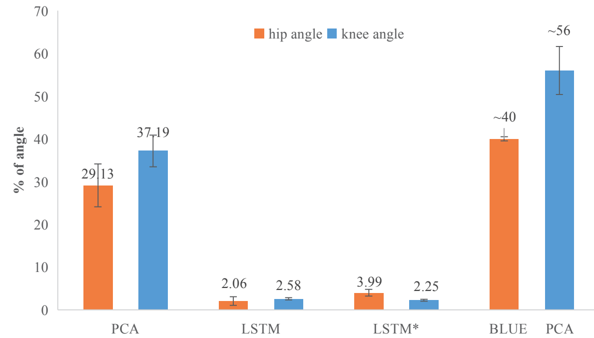

Fig. 9 Mean distortion rate (%) of the angle by different methods. LSTM* stands for adopting LSTM using training data without upper limb angle data. The latter BLUE and PCA data are Vallery's data [15].

Fig. 7 shows the estimated results by LSTM. The error rate between the estimated trajectory and the original trajectory of the left hip and knee joints is very low (1.21% and 2.23%, respectively). Thus, LSTM has good performance on synergy extraction and interpretation. To validate the universality of this approach, we set motion data of subject B, C, D as the testing data set and conduct estimation following the same procedure, respectively. Here, to make a fair comparison, we calculate RMSE between the estimated angle and the original data. Lower RMSE means better estimation performance. The result is shown in Fig. 8.

Results indicate that LSTM-based synergy has good universality on different subjects for various walking speed. With the LSTM model, training data from any of the three subjects can well estimate another subject's trajectory based on his motion data of one side. Also, knee angle estimation seems harder than hip angle, which agrees with the finding in PCA-based estimation. Maybe this is due to the weaker relationship among knee angle and the other side's motion data.

V. DISCUSSION

To compare inter-subject estimation performance, we also adopted PCA-based synergy (derived from other subjects) to estimate an alien subject's knee and hip trajectory. PCA and regression procedure have been introduced above. Mean distortion rate of each group of comparison was then calculated. The results from Vallery et al. [15] are also included. Other than PCA, they also proposed using Best Linear Unbiased Estimation (BLUE) to extract inter-limb synergy and it was shown having better performance than PCA. Average distortions of several methods for synergy extraction are plotted in Fig. 9.

We can see that LSTM has obvious better estimation accuracy over statistical regression methods such as PCA. LSTM can better exploit human inter-limb synergy. Although Vallery's results are based on different gait data, the difference is reasonable, since we also consider the motion of upper limbs.

Normally, the sound side's upper limb of stroke patients can still function well. Considering the synergy among upper and lower limbs is a promising way to guide patients to walk rhythmically. Rehabilitative exoskeletons embedded with wearable motion capture system can help to realize it. But for those patients who have difficulty walking with hands or cannot use crutches properly, LSTM-based synergy is still feasible. In Fig. 9, the synergy based only on lower limb motion data still has good estimation performance. That is because LSTM can fully exploit gait features and obtain synergy. Also, LSTM-based synergy can have better stability over statistical regression methods, since the LSTM model is merely interfered by missing data or outliers.

VI. Conclusion

In this paper, a reference trajectory generation strategy based on human synergies is proposed for rehabilitative LLE. Thus, the ideal reference trajectory designed can be online adaptive to different rehabilitation stages, body conditions and individual gait pattern. LSTM is adopted for the first time to interpret human inter-limb synergy and then generate the reference trajectory of one side based on the motion data of wearer's upper and lower limbs. Thus, inter- and intra-individual adaption can be realized. The trajectory can be improved along with wearers' performance during rehabilitation to encourage active engagement, until they can regain healthy gait. Many neurological findings reveal synergy's promising application in rehabilitation. We aim to use synergy from healthy people to guide hemiplegic patients to walk properly and provide therapeutic effects.

To obtain healthy synergy, gait experiments on four able-bodied subjects from different height, weight and age are conducted. Many researchers use PCA to analyze synergy in human motions. In this paper, we use PCA and LSTM to extract synergy from same data groups and then a comparison was made between estimation results by different methods. Results indicate that LSTM has better estimation performance and stability than statistical regression methods such as PCA. Also, LSTM shows better inter-individual adaption since our subjects have varieties in height, weight and age. The feasibility of the proposed trajectory generation strategy based on LSTM has been validated. But the therapeutic effects or benefits of applying synergies into rehabilitation needs further exploration, although some researchers already provided experimental evidence of some advantages of this approach.

One limitation of this work is the lack of subjects of gait data, although we have enough gait cycles of data for training. We also need to prove that the extracted "healthy" synergy have universality on various able-bodied subjects. Therefore, more subjects will be recruited in our future work. When the simulation results show good adaptivity on a larger group of subjects, we will adopt the proposed strategy on our self-developed exoskeleton and conduct experiments on able-bodied subjects.

Acknowledgments

This work was supported by the Innovation and Technology Commission (Project No. ITS/296/14), Research Grants Council (Project No. CUHK 14201615) of the Hong Kong Special Administrative Region, China, and Vice-Chancellor's Discretionary Fund / CUHK T Stone Robotics Institute (Project ID: 4930762).

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