Walking Speed Learning and Generalization Using Seq2Seq Gated and Adaptive Continuous-Time Recurrent Neural Network (S2S-GACTRNN) for a Hip Exoskeleton

Wuxiang Zhang, Zhitao Ling, Stefan Heinrich, Xilun Ding and Yanggang Feng*

***Abstract*—An appropriate method to deal with walking gaits is required to realize the adaptive control of the exoskeleton for the wearer's walking at different speeds. In this study, we presented a novel neural network model called S2S-GACTRNN and showed the potential of S2S-GACTRNN in learning and generalization of walking speeds. First, S2S-GACTRNN was used to process sinusoidal signals in the simulation experiments to evaluate the learning and generalization capabilities of periodic signals with different frequencies. Second, S2S-GACTRNN was applied to deal with walking gait signals in the offline experiments to evaluate the capabilities of learning and generalization of walking speeds. Third, the online walking gait prediction experiments were conducted to further evaluate the trained model's performance in walking speed generalization. From the online experiments of three subjects, the average generalization errors of S2S-GACTRNN trained using walking data at different speeds were reduced by 24%, 38% and 24% respectively compared to that trained using the walking data at one specific speed. Results show that the model has the potential of learning and generalization for gait signals of different walking speeds, which may be used as a new approach to the adaptive control of the wearer's different walking speeds in the field of the exoskeleton in the future.**

***Index Terms*—Recurrent neural network, learning and generalization, hip exoskeleton.**

I. INTRODUCTION

AS a wearable robot device, the lower limb exoskeleton robot can not only be used for the rehabilitation treatment of patients with lower limb motor dysfunction such as paralysis, but also be used to provide motor assistance for the elderly whose physical function declines with age [1]–[4]. The performance of the exoskeleton depends on the control system as well as the matching degree between the assistance strategies and the users. For users with weak lower limb motor function, one control method of the exoskeleton is to drive the users' legs along a predefined trajectory [5]–[7]. Although the exoskeleton using predefined trajectories could assist people with fully lost walking ability (*e.g* the hemiplegia), the exoskeleton faced some challenges while dealing with the people with walking ability or partially with (*e.g* the elderly), *e.g*, reducing the activity of muscles and resulting in abnormal muscle activity patterns [8].

For users with partially lower limb movement ability, such as the elderly with decreased physical function and the patients during the late recovery after stroke, the role of the exoskeleton is to provide partial assistance for lower limb movement in their daily life. In this case, the users do not always follow a fixed gait trajectory but adjust their gaits (*e.g.* the walking speed) according to their own needs. For example, the users may walk at a relatively high speed, and while fatigued, begin to slow down to a lower speed. While facing an emergency, the walking speed will encounter a sudden stop and in this situation, the exoskeleton is needed to be adjusted dramatically. Consequently, a robust and adaptive method is required to enable self-dominated gaits for users to move at different speeds [9] [10].

A simple approach to achieving speed regulation is that the exoskeleton obtains speed information via the state of other healthy parts of the human body. Based on virtual constraints, hybrid zero dynamics and gait optimization, a nonlinear decentralized control scheme for a lower-limb exoskeleton was developed [11]. By changing the torso pitch angle, the wearer is able to stabilize the walking speed to the desired value. The simulation experiments show that the overall controller is stabilizing as well as tracking the human's desired velocity. However, the optimization progress needs a lot of computing resources, leading to real-time control loop difficulties [12]. Vallery $et\ al.$ proposed a method for online trajectory generation called Complementary Limb Motion Estimation (CLME) [13]. By exploiting physiological inter-joint couplings, the reference trajectory of the affected leg can be generated online by that of the healthy leg. Although this method allows the subjects to generate the reference motion autonomously, it may be more suitable for hemiparetic subjects. In addition to the above methods using the information of healthy parts of the body as the reference, the exoskeleton can also directly process the gaits of the assisted leg for trajectory planning or generation. Based on the adaptive oscillator which is a mathematical tool capable of learning the features such as the frequency and envelope of a periodic input signal, another method was proposed to estimate the users' intended movement while performing a cyclical motion task [14]. The method was extended by putting several oscillators in parallel which is similar to a real-time Fourier decomposition, to deal with the non-sinusoidal input gait signals. One premise of this method is that the gait trajectory can achieve the required accuracy through finite synthesis. Also, dynamic movement primitives theory (DMPs) was deployed as a generator for trajectory

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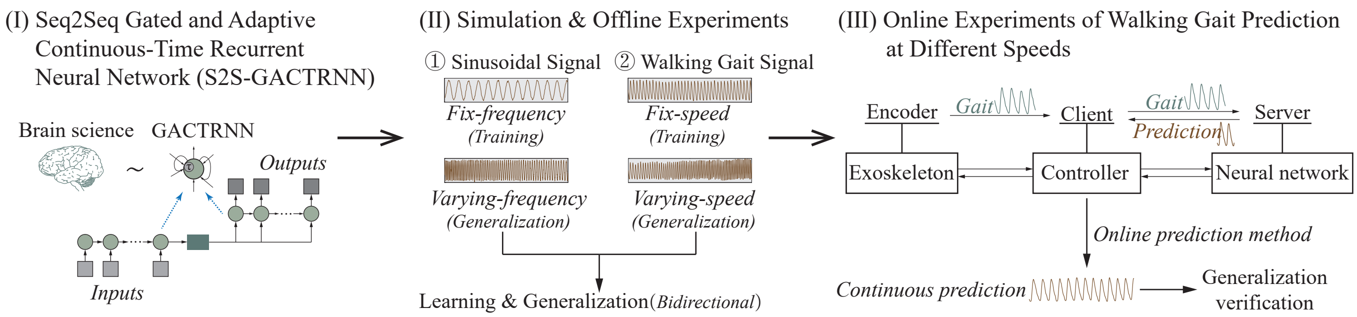

Fig. 1. The overview of this study. (I) S2S-GACTRNN model inspired by brain science. (II) Simulation and offline experiments using sinusoidal signals and walking data from three subjects to evaluate S2S-GACTRNN's learning and generalization capabilities. (III) Online walking experiments to further verify the trained model's generalization capability.

planning during sit-to-stand motion based on a previously collected database of trajectories as training samples [15]. The parameters in the DMPs gait model are learned and updated online to describe the new gait motion curve of the wearer and the human-exoskeleton interaction force is used as the feedback to modify the parameters, to synchronize the DMPs trajectory speed with the user's intended speed. One challenge of DMPs is that a complete motion gait cycle or segment is required to relearn a new DMPs model in the process of modeling and learning the users' motion gaits.

Essentially, the walking gaits change alongside time change, which can be regarded as the signals with the features of time series and can be processed by time-series-related neural networks [16]. The state-of-the-art work focused on using neural networks to extract any information from the gaits [17], [18]. Kang $et\ al.$ used a convolutional neural network to construct a gait phase estimator that can modulate the exoskeleton assistance through different locomotion mode settings [17]. Also, Graph convolutional network model has been applied to recognize four phases of one leg gait during walking, which solves the problem of gait phase classification from the non-Euclidean domain [18]. Inspired by brain science and cognitive model research, a novel continuous-time recurrent neural network (CTRNN) model was proposed to originally help humans understand how our brains deal with time-series signals and make a prediction [19]. For instance, based on stochastic CTRNN (S-CTRNN), a variant of CTRNN, the robot was able to reproduce latent stochastic structures hidden in fluctuating tutoring trajectories from humans [20]. In [21], S-CTRNN and Bayesian inference were utilized in dealing with drawings of different shapes which can be regarded as multidimensional time series to investigate the underlying cognitive mechanisms between humans and chimpanzees. Moreover, by steering the timescale parameters of CTRNN based on learnable weights, the Gated and Adaptive CTRNN (GACTRNN) model was proposed [22], [23]. The GACTRNN is able to learn general patterns on multiple timescales that could temporally notable vary because the neurons in the models adapt and modulate their inherent timescale characteristics. The experiment results show the performance of the GACTRNN in learning and reproducing the general characteristic of seven different Lissajous curves with Gaussian noise is better than that of the Simple Recurrent Network (SRN) or Gated Recurrent Unit (GRU). All these studies related to CTRNN indicate that the CTRNN may have the potential in processing and predicting periodic signals.

To realize multi-step prediction of gaits in the time domain, a widely used recurrent neural network (RNN) form—the "sequence to sequence" (seq2seq) structure is employed. The seq2seq model, including an encoder and a decoder, is a form of processing while using RNN, whose input sequence and output sequence are not required to have the same length [24]. The seq2seq has been widely used in machine translation, speech recognition, etc [25]. By combining GACTRNN and seq2seq, the seq2seq GACTNN (S2S-GACTRNN) model was constructed to process time series in this study.

This paper is organized as follows (see Fig. 1). First, the S2S-GACTRNN model is described in detail. Second, simulation experiments of sinusoidal signals with different frequencies and offline experiments of walking gait signals at different speeds are carried out to evaluate the model's capabilities and potential for learning and generalization for periodic signals. Third, online prediction experiments are conducted to further verify the trained model's generalization capabilities of walking gaits at different speeds. Last, discussion and conclusion are demonstrated.

II. S2S-GACTRNN AND EXPERIMENTAL PLATFORM

In terms of gait prediction, the GACTRNN model is required to process the gaits from the previous period and predict the gaits in the subsequent period. To make the sequence prediction more reasonable, the input and prediction sequence of the model should retain their time sequence information, and both the input and generation processes must be in order. Therefore, the seq2seq model is used to combine GACTRNN to build the network model in this paper. Moreover, the experimental platform was described in this section.

A. S2S-GACTRNN

1) Model:

The hybrid, S2S-GACTRNN model, unfolded by time steps is shown in Fig. 2. The input sequence $\{\boldsymbol{x}_i\}$ is fed chronologically and encoded into a context vector $\boldsymbol{c}$, which contains the input sequence information. The vector $\boldsymbol{c}$ is taken as inputs

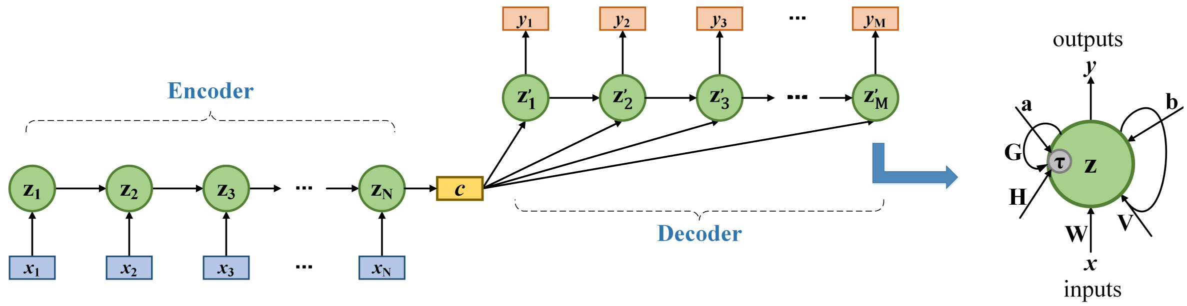

Fig. 2. The S2S-GACTRNN model includes an encoder and a decoder. $\{\boldsymbol{x}_i\}$ and $\{\boldsymbol{y}_i\}$ are the input and output sequences, respectively. $\mathbf{z}_t$ and $\mathbf{z}'_t$ are the internal states of the encoder and decoder, respectively. $\boldsymbol{c}$ represents the context vector that contains the information of the input sequence. Each unit (green circles) is a GACTRNN unit whose computational mechanism is shown on the right.

of the decoder at each time step in the decoding process and the output sequence $\{\boldsymbol{y}_i\}$ can be obtained afterward. N and M represent the lengths of input and output sequences, respectively. Since the context vector $\boldsymbol{c}$ contains the hidden feature information of the input sequence and is used in each time step of the decoding process, the generated sequence can be considered as the comprehensive prediction of the input sequence.

Each unit in the S2S-GACTRNN model is a GACTRNN unit mentioned above whose characteristic is shown on the right of Fig. 2. In tasks with discrete numbers of time steps, the GACTRNN can get employed as a discrete model. As a result, the activation $\mathbf{y}$ of GACTRNN units is defined as follows:

$$\mathbf{y}_t = f\left(\mathbf{z}_t\right) \tag{1}$$

$$\mathbf{z}_t = \left(1 - \frac{1}{\boldsymbol{\tau}_t}\right)\mathbf{z}_{t-1} + \frac{1}{\boldsymbol{\tau}_t}\left(\mathbf{W}\mathbf{x} + \mathbf{V}\mathbf{y}_{t-1} + \mathbf{b}\right) \tag{2}$$

$$\boldsymbol{\tau}_t = 1 + \exp\left(\mathbf{H}\mathbf{x} + \mathbf{G}\mathbf{y}_{t-1} + \mathbf{a} + \boldsymbol{\tau}_0\right) \tag{3}$$

for inputs $\mathbf{x}$, internal states $\mathbf{z}_t$ at time step t and previous internal states $\mathbf{z}_{t-1}$, weights $\mathbf{W}$ and $\mathbf{V}$, and a bias $\mathbf{b}$. f represents the activation function used in neural network (tanh, sigmoid, etc). The *timescale* parameter $\boldsymbol{\tau}_t$, which expresses the leakage of neurons, can be a scalar or vector. $\boldsymbol{\tau}_0$ can be computed by the initial value of the *timescale* parameter $\boldsymbol{\tau}$ before training and remains constant during the training process: $\boldsymbol{\tau}_0 = log(\boldsymbol{\tau} - 1)$. The trainable parameters $\mathbf{H}$, $\mathbf{G}$ and $\mathbf{a}$ are the input weights, the recurrent weights and the bias on the timescale, respectively.

The GACTRNN neurons can be grouped into several *modules* and share the same timescale in each module [23]. All these modules are interconnected recurrently using a *dense* strategy in this study. For example, an encoder with (m_1, m_2, m_3, m_4) neurons with timescales (τ_1, τ_2, τ_3, τ_4) means that the encoder has four modules in different size with their own initial values of timescales. In this study, to simplify the model, both encoder and decoder share the same numbers of modules and neurons as well as the timescales.

2) Proactive Loop&Reactive Loop:

After being trained by data sets, the network is able to generate the output sequence as predictions of the previous input sequence. To evaluate the model's characteristics, there are two different ways (see Fig. 3) to generate the predictions depending on the input sequence $\{\boldsymbol{x}_i\}$:

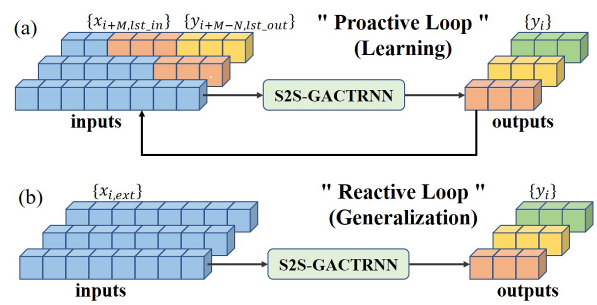

Fig. 3. Two generation methods. (a) Proactive loop related to learning capability. The last prediction output sequence (the orange and yellow cubes) is used to combine with the latter part of the input sequence to form a new sequence to be fed into the network (like a closed loop). (b) Reactive loop related to generalization capability. The external signals are the current inputs to be fed into the network.

- Proactive loop:

$$\boldsymbol{x}_i = \begin{cases} \boldsymbol{x}_{i+\mathrm{M},lst\_in}, 1 \leq i \leq \mathrm{N} - \mathrm{M} \\ \boldsymbol{y}_{i+\mathrm{M}-\mathrm{N},lst\_out}, \mathrm{N} - \mathrm{M} + 1 \leq i \leq \mathrm{N} \end{cases} \tag{4}$$

  where N and M represent the lengths of input and output sequences respectively, and $\boldsymbol{x}_{i+\mathrm{M},lst\_in}$, $\boldsymbol{y}_{i+\mathrm{M}-\mathrm{N},lst\_out}$ represents the input at time step $i + \mathrm{M}$ and the output at timestep $i + \mathrm{M} - \mathrm{N}$ of the last prediction, respectively.
- Reactive loop:

$$\boldsymbol{x}_i = \boldsymbol{x}_{i,ext}, 1 \leq i \leq \mathrm{N} \tag{5}$$

  where $\boldsymbol{x}_{i,ext}$ represents the input at time step $\boldsymbol{i}$ from the external.

In "proactive loop", the whole output sequence of the last prediction is used to combine with the latter part of its input sequence to form a new sequence to be fed into the network and make a new prediction. In short, the last output of the network will be part of the next input, similar to a closed loop. This means that no external inputs will be required in subsequent predictions except for the first prediction. This method is related to the learning capability evaluation in the following experiments.

The ”reactive loop” is the most commonly used prediction method in neural networks, that is, the current external signals are fed into the network as current inputs to make a prediction. This method is related to the generalization capability evaluation in the following experiments.

B. Experimental Platform

A hip joint exoskeleton is used in the following experiments. The exoskeleton consists of a 3-DOF concentric series mechanism, a novel Series Elastic Actuator (SEA), a thigh bar and a 3D-printed component, with an active flexion-extension degree of freedom on the sagittal plane and two passive degrees of freedom on the axial and coronal planes (see Fig. 4). The thigh bar is driven by the SEA and can be bundled to the wearer's thigh with the 3D-printed component and bandages. The SEA, as a drive unit, includes a frameless motor, a harmonic reducer and a constant-stiffness torsion spring on either side of which a rotary magnetic encoder is installed for angle measurement (motor encoder and joint encoder). Based on the above sensors and SEA mechanical structure, the hip joint angle can be obtained and the output torque of the SEA can be calculated by Hooke's law.

An experimental platform is built for the subsequent exoskeleton experiments, as shown in Fig. 5. The hip joint exoskeleton is fixed to a supporting frame with a treadmill below it. The supporting frame is equipped with a ball screw mechanism, which allows subjects to adjust the exoskeleton to the heights corresponding to their leg lengths. The control system hardware is integrated into a box and installed behind the exoskeleton. The speed of the treadmill can be regulated from 0.1 to 10.0km/h with a minimum speed interval of 0.1km/h. There is a clock on the treadmill control panel for timing during the experiments.

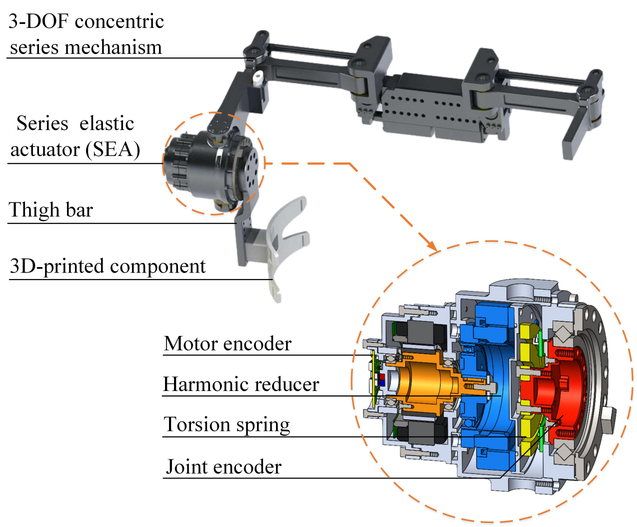

Fig. 4. Hip joint exoskeleton and series elastic actuator (SEA).

III. SIMULATION AND OFFLINE EXPERIMENTS

On the one hand, the GACTRNN model is inspired by brain science and has been verified to capture patterns and

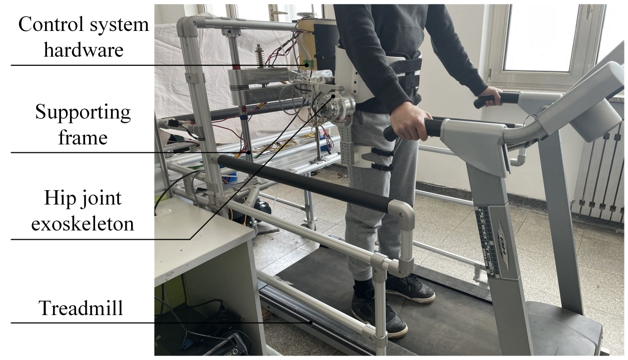

Fig. 5. The experimental platform includes a hip exoskeleton, a frame for supporting, a box with integrated control system hardware and a treadmill.

underlying temporal characteristics from input sequences. For example, the model is able to generate different whole Lissajous shapes according to only their initial curves [23]. Therefore, a trained model can learn some characteristics of the training data, or in other words, contain a prior experience with the training data. Similarly, as a variant, it is necessary to evaluate this ”learning capability” of the S2S-GACTRNN model. The ”proactive loop” mode of the model will be employed to generate continuous sequence prediction and the learning capability of the model will be verified by the reproduction of the characteristics of the training signals.

On the other hand, the generalization capability of the neural network is worthy of attention when building and training a network, which essentially refers to the ability of the model to learn from given data and apply what the model has learned elsewhere. Generalization is one of the features most useful and specific to neural networks [26]. Similarly, for the S2S-GACTRNN model built in this paper, we use the trained model to make predictions for the external inputs with different signal characteristics (in ”reactive loop” mode) and investigate the prediction and generalization errors of S2S-GACTRNN to verify the generalization capability.

Generally speaking, the performance of neural networks is related to the scale and the amount of training data. In this study, using the data from simulation and real-world walking for training, the S2S-GACTRNN model's learning and generalization capabilities of periodic signals on small-scale data sets were investigated. First, simulation experiments with sinusoidal signals were carried out to verify S2S-GACTRNN's ability to process periodic signals with different frequencies. Subsequently, the model was used to deal with a more complex period signal—the walking gait signal, which may have varying frequency and amplitude with walking speed. The offline experiments using real-world walking data were carried out to evaluate the model's learning and generalization capabilities of walking gait signals at different speeds, to show S2S-GACTRNN's potential for adaptive speed control.

A. Simulation Experiments of Sinusoidal Signals

1) Data Acquisition:

The sinusoidal signals include fixed-frequency signals (FFS) for network training and learning evaluation, and varying-frequency signals (VFS) for generalization evaluation. Both kinds of sinusoidal signals are generated in accordance with:

$$y = 2\sin\left(\frac{2\pi}{\mathrm{T}}t\right) + \mathrm{N}(0, 0.1^2) \tag{6}$$

where T is the signal period, $\mathrm{N}(0, 0.1^2)$ is Gaussian noise with the mean value of 0 and standard deviation of 0.1, and t is the time length. The signal sampling time is set to 50 milliseconds. For FFS and VFS, parameter T is set to:

- FFS (for training and learning evaluation): T=$\mathrm{T_1}$, $\mathrm{T_2}$, $\mathrm{T_3}$, $\cdots$. A data set of training data is generated for each $\mathrm{T_i}$. In this way, several data sets of different fixed periods are obtained for model training as well as for learning capability evaluation in "proactive loop".
- VFS (for generalization evaluation): T=1.2s, 1.3s, $\cdots$, 2.4s. By generating a five-cycle signal for each T (setting t=5T) and splicing them in order of ascending period, a data set of sinusoidal signals with different frequencies is obtained for model generalization in "reactive loop".

2) Learning Capability:

We used four data sets of FFS with T=1.0s, 1.5s, 2.0s and 2.5s (all the time lengths were set to t=60s) to train a model with (6, 6, 6, 6) neurons and timescales (1, 3, 9, 27). The lengths of the input and output sequences were set to N=25 and M=3, respectively. Subsequently, the initial values of another four sinusoidal signals with the above signal periods were fed into the trained model respectively and the predictions were generated in "proactive loop". Results showed that the trained model was able to reproduce the whole sinusoidal signals with different periods via the initial values of signals (see Fig. 6), which meant that the model gained some prior knowledge from the training sets. This indicated that the S2S-GACTRNN model had a certain capability of learning characteristics of sinusoidal signals with different periods. In addition, due to the prediction errors, the accumulation of errors would cause the generated curve to deviate from the actual curve more and more significantly as time steps went on.

3) Generalization Capability:

To evaluate the generalization capability, two S2S-GACTRNN models were obtained by using different training data—one model was trained by only a data set of FFS with T=1.8s (set t=60s), while the other one was trained by three data sets of FFS with T=1.7s, 1.8s and 1.9s (also set t=60s). The lengths of the input and output sequences were set to N=25 and M=3, respectively. Both models shared the same hyper-parameters: (6, 6, 6, 6) neurons with timescales (1, 5, 25, 125) and 15% of the training data were split for model validating during training.

The trained models were then applied for the prediction of VFS. The errors between the prediction and the ground truth were calculated to evaluate the prediction accuracy, as shown in Fig. 7. Both models performed better in predicting the sinusoidal signals at the periods of their own training signals (T=1.8s and T=1.7, 1.8&1.9s, respectively) compared to other periods. At the same time, with the increase of signal period deviation, the prediction errors of the two models also increased gradually (both increasing and decreasing direction),

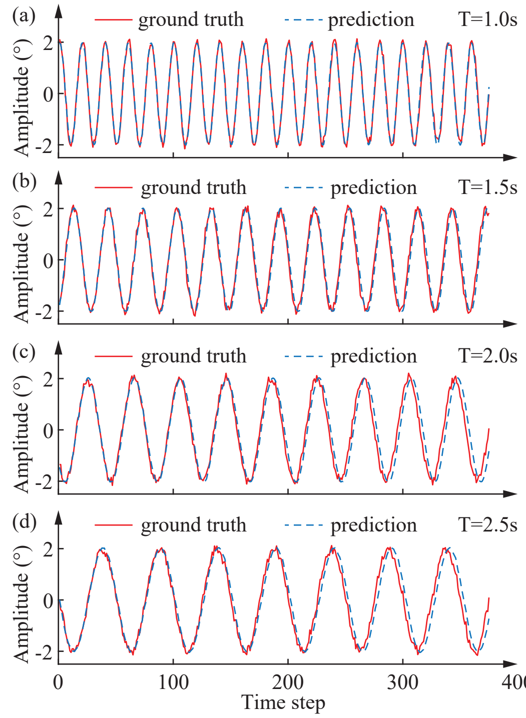

Fig. 6. Predictions of sinusoidal signals with different periods in "proactive loop": $y = 2\sin\left(\frac{2\pi}{\mathrm{T}}t\right) + \mathrm{N}(0, 0.1^2)$. (a) T=1.0s. (b) T=1.5s. (c) T=2.0s. (d) T=2.5s.

meaning that the generalization capability of the model declined. Moreover, by comparing the two error curves, the generalization errors of the model trained by three data sets of FFS were significantly smaller than that trained by only one data set. Results indicate that the S2S-GACTRNN model has potential capability in the prediction task of sinusoidal signals with different frequencies, and the generalization capability can be improved by using more data sets in model training.

B. Offline Experiments of Walking Gait Signals

1) Data Acquisition:

To obtain the data on human walking gaits, we carried out the experiments in which the subjects walked on the treadmill wearing the exoskeleton. The exoskeleton worked under the transparent mode based on the PD controller with the joint torque τ_o calculated for feedback (see Fig. 8), which had minimum output impedance allowing the user to move freely while walking [27]. Gravity compensation was not employed for control due to the small quality of the thigh bar. The other two passive degrees of freedom of the hip joint exoskeleton were restricted in case of disturbance. The data from the encoder were collected at a frequency of 100Hz and the hip joint angle values were calculated and recorded. There are two types of gait signals collected:

- fixed-speed signals (FSS, for training and learning evaluation): The subject walked on the treadmill for 60 seconds at a fixed speed during one data acquisition experiment. Several data sets of walking gaits at different fixed walking speeds were obtained for model training as

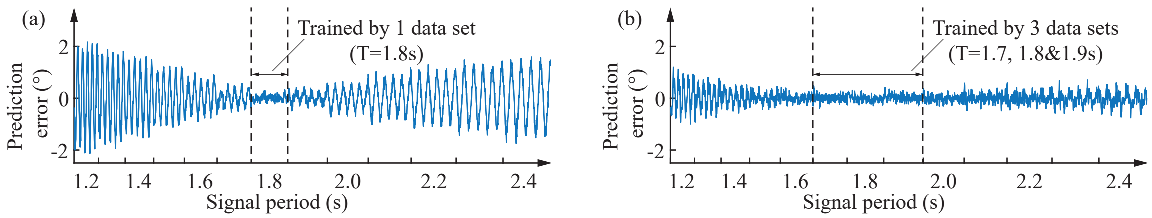

Fig. 7. Prediction error of the simulation experiments of varying-frequency signals. (a) Model is trained by 1 data set. (b) Model is trained by 3 data sets.

well as for learning capability evaluation in "proactive loop".

- varying-speed signals (VSS, for generalization): The subject walked at an initial speed of v=1.0km/h, and subsequently the speed would be increased by 0.2km/h until 3.0km/h every 10 seconds manually via the control panel. One data set of walking gaits at varying walking speeds was obtained for model generalization in "reactive loop".

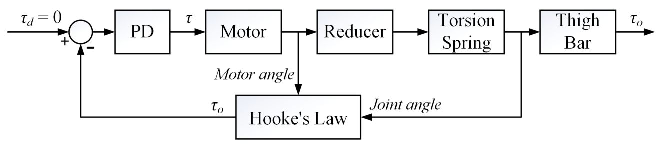

Fig. 8. Block diagram of the transparent mode based on the PD controller.

2) Learning Capability:

Two data sets of FSS with v=1.0km/h and 3.0km/h were used in this experiment and both time lengths were set to t=600s. The step size of the sliding window for data set constructions was set to 10 to simplify training. These two data sets were used to train a network with (16, 16, 16, 16) neurons and timescales (1, 6, 36, 216). The lengths of the input and output sequences were set to N=100 and M=10, respectively. After training, the initial values of another two walking gait signals at the above walking speeds were input into the model to generate the prediction in "proactive loop". As shown in Fig. 9, both prediction curves reproduced the characteristics of their own gait signals to a certain extent including amplitude and frequency. Similar to the sinusoidal simulation experiments, the prediction value deviated more and more from the ground truth, which may be due to the accumulation of errors as well as the instability of gaits in the process of walking.

Overall, by comparing the prediction curves of the above two signals, we can find two noteworthy things. On the one hand, the model effectively learned the frequencies of the two walking gait signals. On the other hand, the model reproduced the corresponding valley values to a certain extent for the two signals, which indicates that the model also has a certain capability of learning the amplitude of walking gait signals.

3) Generalization Capability:

Similar to the sinusoidal signal experiments, two S2S-GACTRNN models were trained by different data for generalization capability evaluation—one by FSS at a speed of v=2.0km/h and the other one by FSS of v=1.8, 2.0 and 2.2km/h (3 data sets in total). Considering that the sampling time of the walking gait signals was 10 milliseconds, we set the lengths of the input and output sequences to N=100 and M=10, respectively, meaning that the trained models were intended to predict the walking gaits of the next 0.1 seconds via the gaits of previous 1 second. The hyper-parameters were set to: (20, 16, 12, 8) neurons with timescales (1, 6, 36, 216).

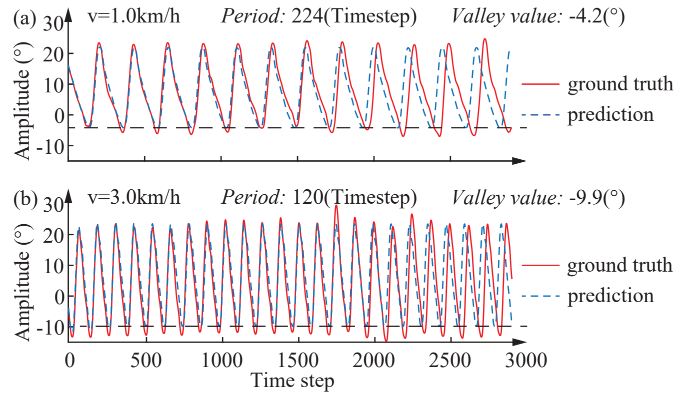

Fig. 9. Predictions of walking gait signals at v=1.0km/h and 3.0km/h in "proactive loop". The trained model reproduced the corresponding frequencies (or periods) and valley values of walking gaits.

TABLE I
PARTICIPANT INFORMATION

Subject	A	B	C
Age (years)	23	24	23
Height (cm)	175	180	177
Weight (kg)	68	70	65
Length of Leg (cm)	91	103	99

After training, both models were then applied for the prediction of VSS. We conducted the same experiments on different subjects (represented by A, B and C, see Table I). The experiments were approved by the Local Ethics Committee of Beihang University. All the subjects read and signed informed consent before the experiments.

The prediction error curves were shown in Fig. 10. Both models performed better in predicting the walking gait signals at the speeds of their own training signals (v=2.0km/h and v=1.8, 2.0&2.2km/h, respectively) compared to other speeds. What's more, although VSS (varying-speed signals) is more complex than VFS (varying-frequency signals) due to the varying frequency and amplitude with varying walking speeds, by comparing these two models' performance on VSS we can understand the S2S-GACTRNN model's capability and the implications of the amount of the training data sets. The sum of absolute values of prediction errors at each speed was calculated for analysis (see Fig. 11). Both models' errors

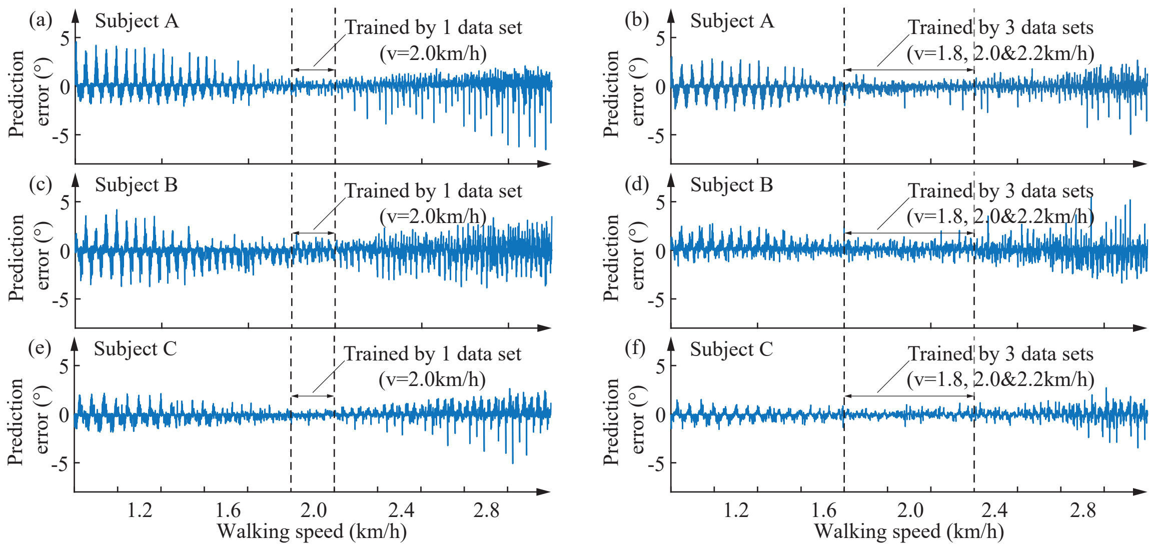

Fig. 10. Prediction error of the offline experiments of varying-speed signals. (a)(c)(e) Model is trained by 1 data set. (b)(d)(f) Model is trained by 3 data sets. (a)&(b), (c)&(d), (e)&(f) are the online results of subject A, B, C, respectively.

increased with the increase of the speed deviation (both increasing and decreasing directions). Additionally, compared to those trained just by only one data set of FSS, the average generalization errors of the model trained by three data sets of FSS were reduced respectively by 24.51%, 28.35% and 24.61%, indicating that the generalization capability of the S2S-GACTRNN model can be improved by more training data.

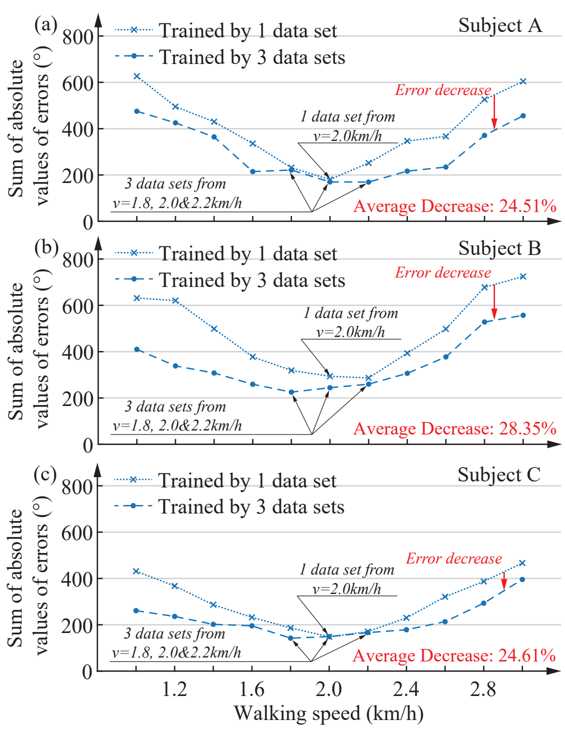

Fig. 11. Sum of absolute values of prediction errors of "the offline experiments of varying-speed signals" at each speed (calculated according to Fig. 10).

IV. ONLINE WALKING GAIT PREDICTION EXPERIMENTS

In the above offline experiments, the walking gait signals of each subject were used for model training. The S2S-GACTRNN model's generalization capability of dealing with the walking gait signals at different speeds was verified. In this section, the online prediction experiments were conducted using the models trained above (2 models for each subject) to further verify the trained model's generalization capability.

A. System Architecture&Online Prediction Method

Since the neural network and motion controller ran on different devices, a problem to be solved was the transmission of the real-time and prediction gait data. A client-server system was constructed to solve this problem (see Fig. 12). A server was deployed on the upper computer (PC), on which the neural network ran in an infinite loop awaiting requests from the client. The lower computer, which worked as a motion controller for the exoskeleton with the transparent mode controller mentioned above employed on it, deployed a client in charge of acquiring gait signals from the joint encoder and transmitting them to the server. The transmissions between the server and client, between the controller and driver were based on TCP/IP, EtherCAT protocol, respectively. A complete prediction process was as follows:

1) Signal acquisition: When the subject was walking on the treadmill wearing the exoskeleton, the motion controller always computed and recorded the last 100 hip-joint-angle values from the joint encoder at a sampling time of 10 milliseconds as gait signals for transmission.
2) Data transmission: While making a prediction (the timing was described below), the motion controller would pack and transmit the 100-angle-value data from the client to the server via TCP/IP protocol.
3) Gait Prediction: Once the server received data, an unpacking and predicting process would be conducted by

the neural network, and subsequently 10 prediction gait angle values would be generated. These 10 values would be packed and transmitted back to the client. Then the motion controller obtained the prediction gaits by unpacking the received data.

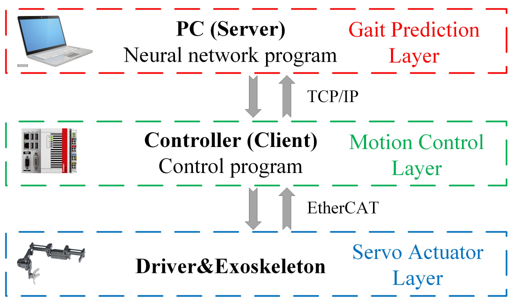

Fig. 12. System Architecture: A client-server system was constructed to realize the transmission of the real-time and prediction gait data.

Considering that it took some time for both data transmission and forward propagation of neural network prediction, the sequence obtained from each prediction was segmented and spliced to generate a continuous sequence, as depicted in Fig. 13. Since the sampling time was 10 milliseconds, the client was set to transmit data (the blue lines) to the server every 50 milliseconds and simultaneously received the last prediction values (10 red dots after each blue line) from the server. The moment is marked with asterisks. All the last 5 prediction values generated in each prediction process were used to form a time-continuous sequence.

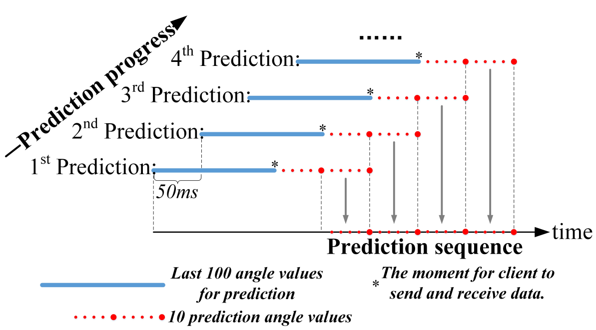

Fig. 13. Online Prediction Method: All the prediction sequences (red dots) were segmented and spliced to generate a continuous sequence.

B. Experimental Process

The same three subjects were recruited to participate in the online walking gait prediction experiments to further verify the generalization capability of the trained models. Similar to the offline experiments, in each subject's online experiments, two neural network models were used for data prediction trained by their respective walking data—one by FSS at a speed of v=2.0km/h and the other one by FSS of v=1.8, 2.0&2.2km/h. First, the server and client started and the exoskeleton was set to the PD-controller-based transparent mode. Subsequently, the subject walked on the treadmill wearing the exoskeleton at an initial speed of v=1.0km/h. When the walking became smooth, we sent a request from the client to the server for connection establishment. After a short wait for the connection to become stable, the client started to send real-time gait data and receive prediction values every 50ms. We used the treadmill clock to time the walking and increased the speed of the treadmill by 0.2km/h every 10s by pressing the acceleration button on the control panel. After the subject walked at a speed of 3.0km/h for 10s, the client was terminated manually and one experiment was finished. During the experiment, the motion controller generated a continuous sequence of predictions via the above method and saved all the required data via the data storage channel. After each experiment, a transmitted and received data comparison was carried out to check whether there was data packet loss and ensure the effectiveness of the data.

C. Results

The generalization capability of S2S-GACTRNN was evaluated by the errors (see Fig. 14) between the prediction value and ground truth. We calculated the sum of absolute errors at each speed, as shown in Fig. 15. The error curves of the online experiments are similar to that of the offline experiments. When walking at the speeds corresponding to that of the gaits used in model training (v=2.0km/h and v=1.8, 2.0&2.2km/h, respectively), the prediction errors were lower than the prediction errors that occurred at other speeds. As the walking speed gradually deviated from the training speed, the prediction error gradually increased. Moreover, from the comparison of the results, the overall generalization errors of the model trained by three data sets of gait signals with different speeds were reduced respectively by 24.08%, 37.99% and 24.04% compared to that trained by one data set of gait signals, indicating that the generalization capability of S2S-GACTRNN was improved with the increase of training data. Overall, the trained model's generalization capability of gait signals was verified by the online experiments, indicating that the S2S-GACTRNN model has the potential in processing walking gaits with different speeds.

V. DISCUSSION

A. Similarities Between Brain and S2S-GACTRNN

The development of brain science is of great significance to the study of biological behaviors [28]. In the process of perception of the outside world, biological individuals constantly collect and learn from the information to form their cognition of the environment, which will be stored in brains as prior knowledge to guide similar movements henceforth [29]. The neural activities of individuals reflect the integration of signals from the outside world with prior knowledge stored in the brains [30]. The brain seems to do this by learning from perception and actions on different timescales and adapting well to changing temporal variance [31]. In particular, the brain exhibits temporal abstraction and compositionality characteristics that seem to emerge from intrinsic timescale properties in neuro-modulation as well mode coupling between neurons across the cortex [32], [33]. This combination of prior experience and sensory inputs has been used to explain key

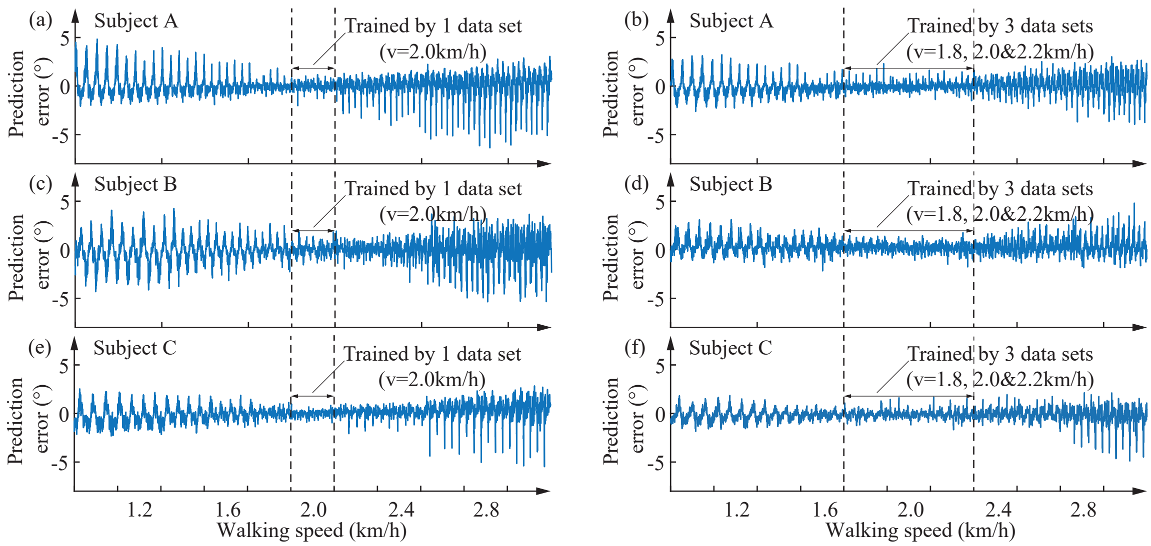

Fig. 14. Prediction error of the online experiments of varying-speed signals (VSS). (a)(c)(e) Model is trained by 1 data set. (b)(d)(f) Model is trained by 3 data sets. (a)&(b), (c)&(d), (e)&(f) are the online results of subject A, B, C,respectively.

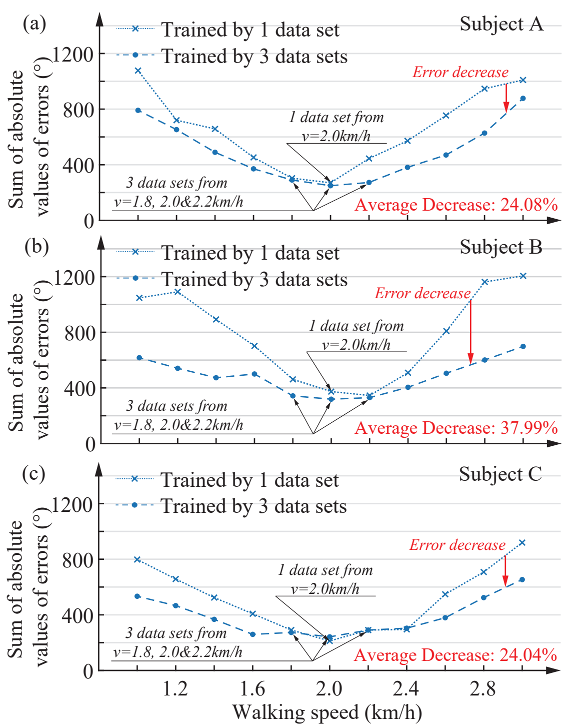

Fig. 15. Sum of absolute values of prediction errors of ”the online experiments of varying-speed signals” at each speed (calculated according to Fig. 14).

features of autism [34]. To some extent, the application of the proposed S2S-GACTRNN model to walking gait processing draws lessons from brain science research. Similar to the brain, S2S-GACTRNN learns certain characteristics of signals and obtains prior experience through model training. Specifically, it learns to represent components of those signals and, at the same time, learns to flexibly vary the temporal extent of such components by modulating the timescales. This way, the model is able to recognize differences in the timescales of the perceived signal and adapt its activation dynamically. When applied to a prediction task, a trained model makes inferences about the external input signals with the help of the learned knowledge. This mechanism of prior experience and external inputs provides S2S-GACTRNN the generalization capability of processing biological signal, *e.g.*, walking speed generalization.

B. Methods Comparison

The DMPs method is one way for trajectory generation mentioned before [15]. While using DMPs, a complete cycle or segment of the signals is required for parameter learning. However, the proposed S2S-GACTRNN is able to make predictions for walking gaits of the next 0.1 seconds via the gaits of the previous 1 second, which allows it to be employed more flexibly. Another way to generate trajectories is the adaptive oscillator [14] which is similar to a real-time Fourier decomposition. Both S2S-GACTRNN and the adaptive oscillator are tools for data fitting. However, a trained S2S-GACTRNN makes predictions based on prior experience and external inputs similar to the brain, while the adaptive oscillator is based on only external inputs. Therefore, compared to the adaptive oscillator, S2S-GACTRNN may have some characteristics of the brain and may be biologically reasonable.

C. Characteristics of S2S-GACTRNN

The experiment results show that the proposed model has potential in generalization while processing human walking gaits at different speeds, which may be improved by using more training data. Considering that only the walking gaits are required, this generalization method just needs to use an encoder for angle measurement without using other sensors (EMG, EEG, IMU, *et al.*) [35], which may bring convenience to the application of exoskeleton and avoid difficulties in multi-sensor fusion algorithm design [36]. Meanwhile, since the results showed the potential of S2S-GACTRNN in walking speed generalization, the proposed model may be used as a new approach to the adaptive control of the wearer's different walking speeds in the field of the exoskeleton. For example, it can be employed to design a speed adaptive controller to provide suitable assistance for the elderly or patients with lower limb motor dysfunction to walk at different speeds. Secondly, in addition to studying the generalization capability of the flat-ground walking gaits at different speeds, by optimizing the structure and parameters, the application scenarios of the model may be extended. For example, the proposed model may be used to process the walking gaits of different terrains.

D. Discrepancy between offline and online experiments

The overall prediction errors of online experiments are higher than that of offline experiments, which may be explained by two aspects. First, the prediction sequence of the offline experiment is obtained by predicting a series of external inputs, while in the online experiment, the prediction sequence is composed of the last 5 of the 10 prediction values generated in each prediction process. This online prediction method may eventually lead to an increase in the overall prediction errors. Second, due to the limited training data, the slight changes in exoskeleton wearing status and human walking gaits will inevitably cause additional angle errors, which may degrade the prediction performance of the models.

E. Limitations

The limitations are listed as follows.

- The constructed network only used the gaits of a single hip joint, while using gaits of more lower limb joints may make this study more comprehensive.
- Due to the variability of walking gaits, more gait data sets may be acquired for training and the complexity of the network may be increased to allow the model to learn more prior experience.
- The length of the output sequence or the sampling time of the gaits may be changed to study whether a longer gait in the time domain can be predicted, to facilitate the design of the controller.

VI. Conclusions

In this study, we proposed a novel neural network model called S2S-GACTRNN combining sequence to sequence and gated and adaptive continuous-time recurrent neural network to deal with walking speed learning and generalization. Simulation experiments of sinusoidal signals with different frequencies and offline experiments of walking gaits at different speeds were carried out to evaluate S2S-GACTRNN's learning and generalization capabilities of periodic signals. Subsequently, the online prediction experiments were carried out to further verify the generalization performance of walking gaits. Results show that the average generalization errors of the model trained using walking data at versatile speeds were reduced by 24.51%, 28.35%, 24.61% in the offline experiments and by 24.08%, 37.99%, 24.04% in the online experiments respectively compared to that trained using the walking data at one specific speed, indicating that there is a certain potential of S2S-GACTRNN in dealing with the walking gait signals whose frequency and amplitude are varying at different speeds, and the generalization performance may be improved by using more training data. The S2S-GACTRNN could pave a new way for the adaptive control of exoskeletons to provide users with corresponding assistance while walking at different speeds in some cases in their daily life.

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