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Individualized Gait Trajectory Prediction Based on Fusion LSTM Networks for Robotic Rehabilitation Training

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Abstract— **Robot-assisted gait training is promising to help patients recover from stroke. One key problem is how to design an adaptive and coordinated gait trajectory for each subject. In this paper, we utilize long-short term memory (LSTM) neural network with feature-level fusion, to effectively learn the multi-source motion characteristic data of lower limbs and adapt to the individual gait. Experiments are implemented on healthy subjects with motion capture system to get the joint data and electromyography acquisition equipment to collect the muscle signals simultaneously. The extracted features are input into the adopted neural network for fusion, and then train the model through a large amount of data. This learning-based approach can predict knee joint trajectory in conformity with individual gait patterns by combining kinematic data and biological signals. Experimental results indicate that this model can achieve a superior prediction performance compared with other traditional neural networks and the trained LSTM model also presents better adaptability between individuals.**

I. Introduction

Stroke is a cerebrovascular disease and has a high potential of causing motor dysfunction or even permanent disability in the aged population [1]. Walking abnormality is the major sequela of most stroke survivors, affecting the quality of daily routines. Although physical therapy by physiotherapists can help patients regain their movement capability, with the unceasing expansion of number of stroke patients, physical therapy becomes limited accessible. In order to alleviate the workload of physiotherapists and lengthening the training, lower limb rehabilitation robots have been developed and revealed a natural superiority in rendering physical movement assistance that includes a long-term process of high-intensity repetitive training.

Robot-assisted gait training for hemiparetic stroke patients, has become a research hotspot [2, 3]. Most of the lower limb exoskeleton robots carry out rehabilitation training based on gait tracking. However, every stroke survivor's condition is different, and even during treatment process, the gait pattern of specific patients also varies. Therefore, individualized reference trajectory that effectively reflects the subject's gait characteristics becomes a momentous and challenging issue.

For the sake of obtaining personalized gait trajectories, the strategy of mimicking the healthy side gait to help the affected side restore normal gait was developed[4]. However, due to the gait asymmetry in stroke patients and the different biomechanical properties of bilateral lower limbs[5], the feasibility and safety of this approach remains to be discussed. Another traditional method to obtain individualized gait pattern is to build the complex kinematic and dynamic model from healthy individuals[6]. Unfortunately, the gait of each walking cycle for different users can be diverse. It is impossible to record all the gaits from healthy persons and this strategy would break down in the face of dimensions barriers.

Machine learning technologies have recently gained well-deserved attentions in robot-assisted rehabilitation, and gait prediction is certainly one of the issues that can benefit from it [7]. Plenty of learning-based techniques have been applied to let the robot understand or speculate about human intentions, as well as to learn the regularity of human movements. Some researchers apply artificial neural networks to the trajectory design of lower limb exoskeletons. While others use convolutional neural networks for gait analysis and trajectory reconstruction[8]. Wu et al. predicted an individualized gait pattern by using machine learning techniques based on the wearer's physical characteristics[9].

Long-short term memory (LSTM) is a kind of extensive applied recurrent neural networks that specialize in learning long range relationships of time series data, and show better performance than others[10, 11]. It has been adopted for gait recognition, clinical diagnosis of gait disorder and model-based gait analysis. Quite a few researchers leverage LSTM networks to learn multi-sequence joint data for completing the gait recognition task, while others proposed a prediction technique based on LSTM technology to predict angle trajectories of the damaged lower extremity. For instance, Liu [12] used LSTM to model the intra-limb coordination for generating knee joint trajectory of lower limb exoskeleton.

Gait is a unique walking posture, influenced by mutually independent factors, such as weight, gender and age[13]. Through analyzing various motion characteristic data in different movement states, the kinematic law of human lower limb can be grasped. Electromyography (EMG) signals have an inherent advantage in reflecting the internal activities of the muscle, providing critical information during the onsets of muscle contraction and relaxation[14]. Since the advance prediction of EMG signals can eliminate the time delay

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between human and robot, it is widespread applied to estimate the user's movement intention accurately and quickly[15, 16]. However, due to the uniqueness of gait pattern, the gait prediction method using single sensor information cannot balance accuracy, globality and real-time. Little research on how to generate suitable gait pattern of lower limb exoskeleton robot for the wearer's own physical characteristics is involved.

To overcome these problems, this paper presents an intention prediction model based on personal gait patterns and walking habits. Each hidden layer of the employ neural network has a great quantity of LSTM units, and thus our approach is a prediction model for periodic learning. This study aimed to utilize multiple motion characteristics of lower limbs during walking to estimate knee kinematics trajectories. The rest of this paper is organized as follows: Section II introduces the principle of LSTM internal module and the fusion LSTM model for knee joint. Section III designs materials and experimental setup. In Section IV, the actual gait experiment is carried out and the results are obtained. Then the conclusion is given in Section V.

II. LSTM Model for Gait Prediction

A. Description of LSTM Internal Module

LSTM is a recurrent neural network (RNN) variant for time series modeling and forecasting. By adding two hidden states based on RNN, the LSTM network can better handle the issue of gradient vanishing or explosion while training to capture the long-term dependencies[17]. The structure of an LSTM unit is presented in Figure 1. Three nonlinear gates are located in the LSTM unit, namely input gate, forget gate and output gate. These three gates are designed to control information transmission and final result calculation.

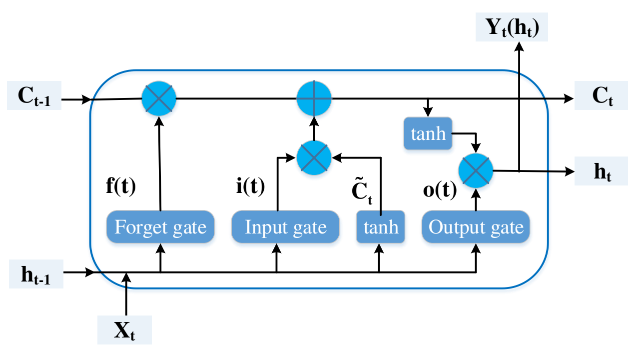

Figure 1. Structure of an LSTM unit

The first gate in the LSTM unit is the forget gate f_t, controlling the extent to which the existing memory information should be erased[18]. The forget gate at time *t* can be calculated as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \qquad (1)$$

where f_t stands for the forget gate vector at time t; W_f and b_f is the weight matrix and bias vector of forgot gate, respectively; $[h_{t-1}, x_t]$ denotes connecting two vectors into a longer vector; σ means the sigmoid activation function. The expansion of $W_f \cdot [h_{t-1}, x_t]$ is as shown below:

$$W_f \cdot [h_{t-1}, x_t] = [W_f] \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} \qquad (2)$$

$$= [W_{fh} \ W_{fx}] \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} = W_{fh}\, h_{t-1} + W_{fx}\, x_t$$

In addition to the intermediate state $\tilde{C}_t$, LSTM also maintain a memory cell C_t, which is updated by partially forgetting the existing memory content and adding new one. The two states are formulated respectively by:

$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c \qquad (3)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad (4)$$

where tanh denotes the nonlinear tanh activation function; W_c and b_c presents the weight and bias vectors of the current gate, separately; and ⊙ stands for the pointwise multiplication operation for two vectors[19].

The input gate i_t is used to decide when to let the activation enter the internal state while the output gate O_t is to calculate how much information can eventually be chosen as the output. The input and output gate can be computed separately as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (5)$$

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \qquad (6)$$

where W_i and W_o are the weight matrices of the corresponding gate; b_i and b_o stand for the bias vectors of the commensurately gate.

As a last step, the final output h_t of the LSTM unit at time step *t* is defined by:

$$h_t = O_t \odot tanh(C_t) \qquad (7)$$

B. LSTM Model for Knee Joint

In gait sequences, the joint angle of current time is associated with the previous angles and also corresponding EMG signals of extensor and flexor muscles. Based on the formula (1) - (7), the unfold LSTM neural network in time-domain is pictured in Figure 2.

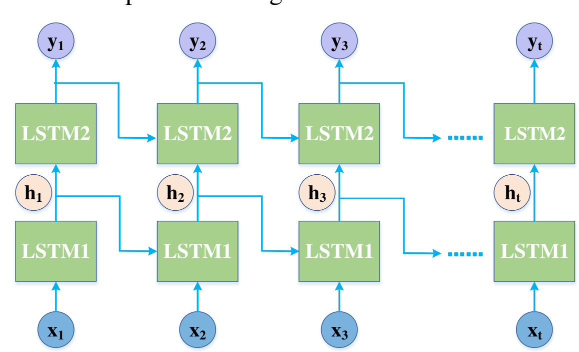

Figure 2. The unrolled LSTM neural network in time-domain

Referring to [20], we established a knee joint model based on the LSTM framework to better predict the knee joint trajectories in real time, as depicted in Figure 3.

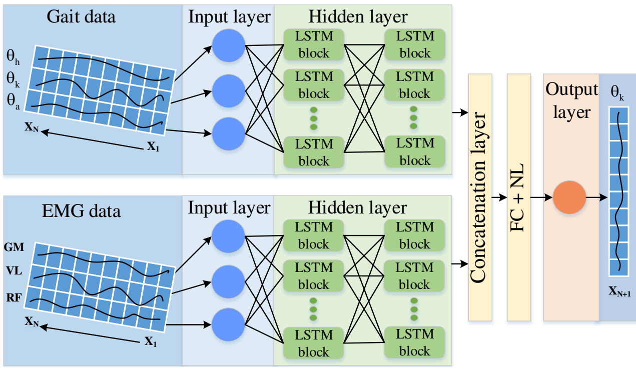

Figure 3. The architecture of LSTM neural network employed (θ=angle, h=hip, k=knee and a=ankle)

Concretely, the applied LSTM model consists of two stages. The first stage is stacked by LSTM units where the inputs are the sequential loads in the order of different timestamps and the output is the hidden state h_t at the last timestamp, corresponding to the encoded characteristics learned from the historical loading. To learn the movement pattern of the subjects efficiently, angles of hip, knee and ankle joints as well as the EMG information related to knee extensor and flexor muscles are included. Gait data and EMG signals pass through each gate function of two LSTM modules respectively. Then key information in input features is retained and transmitted by updating the whole unit state.

The second stage is a fully-connected (FC) network followed by non-linear (NL) activation functions, where the inputs are the concatenated feature vectors generated from the above-mentioned stage. Specifically, the outputs of the two LSTM blocks are further concatenated to generate a high-dimensional feature vector[21]. After the concatenation layer, network trained with one additional fully connected layer with non-linear activation functions. The final output is the forecasted gait trajectory of knee joint after 50ms.

The hyper-parameters of our model include the number of hidden units for each layer (in the range of 20-64), the training batch size (128), and the number of training epochs (200). In order to learn gait characteristics, mean absolute error (MAE) loss function is applied to quantify the loss during training and testing. Adam Optimizer is to adjust the learning rate for every parameter by estimating the first and second moments of the gradients[22]. Finally, the model is evaluated by calculating root mean squared error (RMSE) as well as the correlation coefficient (CC) after each run.

One of the reasons for applying this network structure is that the human walking process is a long time series with a certain periodicity. LSTM neural network has been feasibly applied to learn the intrinsic spatial-temporal correlation of gait features in virtue of the capacity for processing and predicting the time series with prolonged intervals. Furthermore, stacking multiple basic LSTM units can make the gradient flow further backward in time and enhance the ability of the neural network to establish long-term connections. Beyond that, the neural network-based feature fusion could efficiently integrate two sequence features. Therefore, the model is robust and can retain the key information of the historical moment, while avoiding the occurrence of gradient dispersion.

C. Model Training

Our experiments are implemented on the TensorFlow framework using python. The dataset is split into two parts: approximately 70 percent for training set and the remaining 30 percent for testing set. Figure 4 presents the results of the model learning process. It can be seen that the loss of this network is gently decreasing and then obtain a stable convergence during the training process, which indicates the amelioration of model performance.

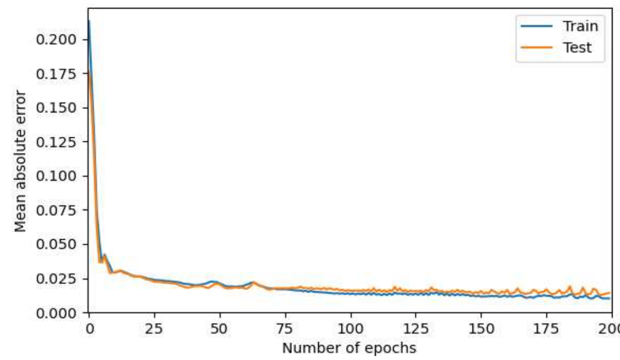

Figure 4. Mean absolute error learning curve for each epoch

III. Materials and Experimental Setup

A. Participants

Four healthy male subjects (age 23.6 ± 1.4 years, height 172.1 ± 5.8 cm, weight 65.2 ± 7.5 kg), with no reported history of gait dysfunction, participated in this study. Each subject was instructed to walk six times at their self-selected walking speeds. We gave no explicit indications about gait speed or posture so as not to induce gait alterations. Subjects signed an informed consent form before participating in the gait experiments.

B. Data Acquisition

The lower limb joints trajectories are recorded by 3D motion capture system (Qualisys, Sweden Qualisys company), which applies an infrared high-speed camera to capture the movement trajectories of reflective markers. Qualisys is capable of supporting both active and passive, indoor and outdoor, delivering high-quality data to users in an accurate, reliable, and real-time manner. The calibration of cameras and platforms locations is performed before each acquisition trial, following the standard procedure described by setup requirements of Qualisys motion capture system. The subject is equipped with nine reflective markers on hip, knee and ankle joints of lower extremities.

Meanwhile, the EMG signals acquisition device is the portable surface electromyography (Trigno™ Wireless EMG, US DELSYS). More channels may decrease the prediction effect due to the crosstalk between different channels of EMG signals. Combining human anatomy and a great quantity of experimental outcomes, rectus femoris (RF), vastus lateralis (VL) in knee extensors and gastrocnemius (GM) in knee flexors are selected based on our trials. Each channel corresponds to one muscle. These muscles are chosen due to its prominence and correlation with the motion state of knee joint muscles, thus providing effective and consistent EMG signals. The electrode pads of three EMG sensors are placed on the muscle belly, paralleling to the muscle spindle. The skin is meticulously shaved and cleaned with alcohol to reduce skin impedance.

The aforementioned two kinds of data are collected synchronously. The synchronous data acquisition is managed by Qualisys Track Manager（QTM）, a motion acquisition software based on Windows platform, which can accurately realize 2D, 3D and 6DOF real-time data browsing. The specific experimental setup are described in Figure 5.

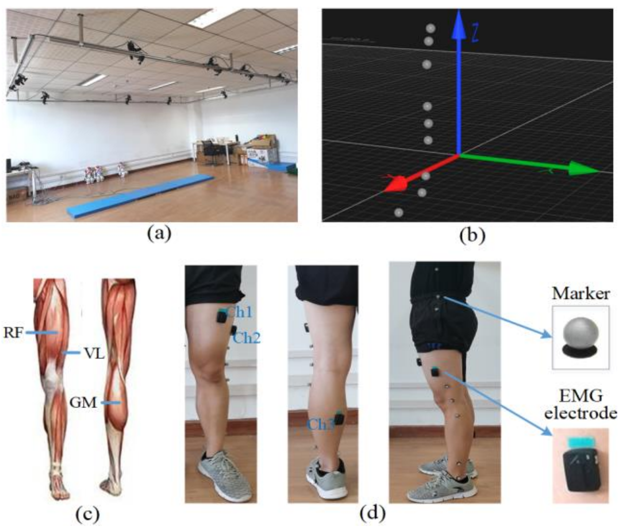

Figure 5. Experimental setup. (a) Qualisys 3D motion capture system. (b) Three-dimensional view of mark points on lower limb. (c)Location of EMG sensors. (d) Photographs of a subject equipped with markers and EMG electrodes during the experiment.

The setup of Qualisys 3D motion capture system is shown in Figure 5(a). This system embodies the analysis and processing software of host computer, eight infrared high-speed cameras and a video camera. Three-dimensional view of the lower limb markers (white dots in Figure 5(b)) is displayed in QTM software, where the markers are named and subsequently processed. Figure 5 (c) and (d) show the mounting positions of nine reflective markers together with three EMG electrodes.

C. Data Process

Raw sensors outputs are synchronized by the software and then exported to a standard mat file format. Subsequently, all the data files are processed under MATLAB (R2018b, The MathWorks, Natick, USA). Gait data and EMG signals are recorded at a sampling rate of 100 Hz and 2000 Hz, respectively. After completing the gait data acquisition experiment. the labels of nine optical marks are indicated in accordance with the actual joint position. The named mark points are wired together, and every three Mark points form a plane, from which a joint angle can be calculated. By connecting the marks of the entire lower limb, a skeleton model of the lower extremity can be constructed to calculate the human motion trajectory.

Since EMG signals are closely related to the knee joint angle, in order to fully and correctly obtain the information in the EMG signal, the raw signal must be preprocessed to extract the features. Step 1: Full-wave rectification. Step 2: EMG signal is filtered to remove the bias and noise. In this step, a 6th-order Butterworth low pass filter with a 30 Hz cut-off frequency is used. Step 3: The sliding window is engaged in extracting the features by setting a time window with an increment window. Finally, the foregoing processed features are used as input signals for the LSTM model. It is worth noting that all data have been normalized before being fed into the neural network.

IV. Results and Discussion

A. Comparison with Traditional Methods

We compare the predicted trajectory of knee joint by our model with that of traditional LSTM, and the performance of traditional RNN without three gates is also tested for comparison. Our approach along with two additional methods is trained and tested with the same dataset. The prediction results of gait trajectory are presented in Figure 6.

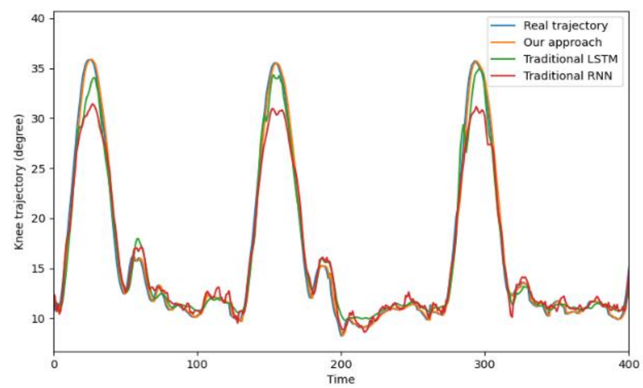

Figure 6. Contrastive results between real and predicted trajectories

Notice that the result of adopted LSTM model is closer to actual trajectory than traditional LSTM, and the capability of smoothing is also better than other methods. This indicates that the LSTM neural network with feature-level fusion can accurately learn various motion characteristic data of lower limbs, which is propitious to gait modeling. Nevertheless, there are some fluctuations in the predicted trajectory. Although the learning-based gait modeling method can quickly obtain spatiotemporal characteristics of gait by training a large amount of diverse data, the produced outcome is a probability distribution, which may lead to a few poor results within error permissibility.

To quantify the validity and stability of the proposed approach, for the same sample dataset, the RMS and CC of the knee angle estimated by different models are calculated (mean, std, max, min derived from thirty experiments). As illustrated in Table I and Table II, the employed adaptive LSTM model exhibited better performance, yielding the best mean, std, min and max RMSE value for all trials, as well as CC. For instance, the applied LSTM shows a mean RMSE error of 0.464°, while the error in traditional RNN model is equal to 2.523°. Although the standard deviation difference between the traditional LSTM and our model is not too big, indicating that both of them have strong stability, it is far worse than our method in terms of prediction accuracy. The predicted trajectory error of our approach changes from 0.348° to 0.713°, and traditional LSTM from 1.359° to 1.729°. Moreover, the average value of CC generated by our method is larger, indicating a stronger correlation and better regression performance of the model. It demonstrates that this approach is superior to traditional neural networks in prediction results and fitting capabilities.

TABLE I. RMSE (°) OF GAIT TRAJECTORY PREDICTION CORRESPONDING TO DIFFERENT METHODS

Type	Mean	Std	Min	Max
Our approach	0.464	0.096	0.348	0.713
Traditional LSTM	1.500	0.098	1.359	1.729
Traditional RNN	2.523	0.373	1.900	3.353

TABLE II. CORRELATION COEFFICIENT (CC) OF GAIT TRAJECTORY PREDICTION CORRESPONDING TO DIFFERENT METHODS

Type	Mean	Std	Min	Max
Our approach	0.999	0.00001	0.998	0.999
Traditional LSTM	0.984	0.00219	0.979	0.987
Traditional RNN	0.963	0.01223	0.927	0.983

The LSTM model we utilized can get the utmost out of the subjects' own multi-source motion data, so that the predicted results can better adapt to the patient's own conditions and avoid rigid gait. It is a promising method to generate adaptive reference trajectory to assist stroke survivors in walking naturally and rhythmically. This method is also applicable to healthy people. Furthermore, the acquired trajectories are capable of being improved with individual's performance during gait rehabilitation process. By encouraging patients to actively participate in the gait training, the central nervous function can be reshaped and the motor ability can be optimized continuously until they can regain normal gait.

B. Data Validation

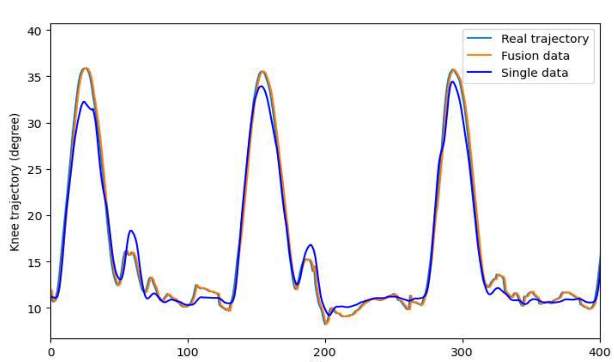

Figure 7. knee angles prediction using fusion data Vs single data

The outcomes of the applied LSTM model with and without EMG signals fusion are sufficiently different. As visualized below in Figure 7, for the fusion data, the error between the predicted trajectory and the original trajectory of knee joint is very low. Our approach can provide more accurate prediction than the model with single signal. The employed knee joint model with fusion data perfectly represents the walking gait characteristics.

In order to comprehensively compare the model performance of two distinct data, the outcomes of RMSE and CC after thirty runs are obtained in the tables below. A better prediction effect can be obtained by our model with the fused features of gait characteristics and EMG features. The RMSE errors of the model with single data range from 1.496° to 2.443°, which is larger and less stable than that of fusion data. The mean RMSE error of single signal is equal to 1.848° compared to the value of 0.464° using fusion signal. Additionally, a high correlation is achieved by our approach (mean CC = 0.999). Even under the worst circumstances, our approach leads to better values with a max RMSE error of 0.713° and a min CC of 0.998.

TABLE III. RMSE (°) OF GAIT TRAJECTORY PREDICTION WITH DIFFERENT DATA

Type	Mean	Std	Min	Max
Fusion signal	0.464	0.096	0.348	0.713
Single signal	1.848	0.277	1.496	2.443

TABLE IV. CORRELATION COEFFICIENT (CC) OF GAIT TRAJECTORY PREDICTION WITH DIFFERENT DATA

Type	Mean	Std	Min	Max
Fusion signal	0.999	0.00001	0.998	0.999
Single signal	0.975	0.00745	0.957	0.984

To validate the performance of inter-individual adaption, we need to prove that the knee joint motion data can be effectively predicted by multiple motion data of randomly selected subjects. Thus, we carry out experiments on all aforementioned models with four able-bodied subjects. Mean value is the average RMSE error of different estimation results based on various subjects. As depicted in Figure 8, our approach's mean error is the smallest among all methods. Not only is the trajectory prediction error per subject much lower than that of other neural networks, but there is little difference of error values between different subjects. It is noticeable that our approach has shown a tremendous advantage over other models.

Consequently, training data from any subjects can be applied to our LSTM model to commendably predict the motion track of the knee joint in the next moment, which is based on the multi-dimensional movement feature data of individuals. It turns out that our approach has good adaptability and universality on different subjects. This model shows excellency in taking advantage of current fusion information to predict next step data through variations over time such as walking.

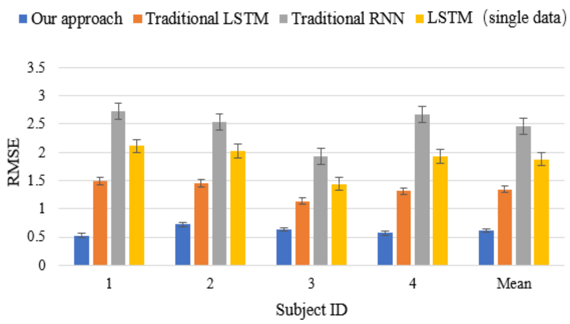

Figure 8. Trajectory RMSE (°) for different subjects

C. Limitations of the Study

This study has a limitation of including only young healthy subjects without any lower extremity motor dysfunction. It would be beneficial to further investigate gait patterns of actual patients, and our strategy will be adopted on the self-developed exoskeleton robot to verify its practical feasibility. Another limitation is the relatively small number and scope of recruits, which limits the universality and prediction effect of the model. In order to obtain complete gait characteristics, we will add larger gait sets with more participants in future work.

V. Conclusion

In this paper, a LSTM neural network are developed to model and predict the suitable knee joint trajectory of subjects. Gait experiments on four fit individuals with different ages, weights and heights are conducted to collect fusion data from motion capture system and EMG sensors. Subsequently, gait data and EMG signals are processed and fused to predict movement trajectory based on individual gait. The effectiveness of the presented approach is demonstrated quantitatively compared with traditional neural network models. Additionally, the comprehensive evaluation method is applied to test the performance. Results indicate that the employed LSTM model has an excellent performance in terms of both prediction performance and generalization ability. The generated gait trajectory is adaptable to different rehabilitation stages, physical fitness and personal gait patterns in real time. Our ultimate goal is to carry out clinical trials to help stroke survivors achieve a more natural, adaptive and stable gait rehabilitation training.

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