RESEARCH ON GAIT PREDICTION BASED ON LSTM

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ABSTRACT

With an aging population that continues to grow, the protection and assistance of the older persons has become a very important issue. Falls are the main safety problems of the elderly people, so it is very important to predict the falls. In this paper, a gait prediction method is proposed. Firstly, the lumbar posture of the human body is measured by the acceleration gyroscope as the gait feature, and then the gait is predicted by the LSTM network. The experimental results show that the RMSE between the gait trend predicted by the method and the actual gait trend can be reached a level of 0.06 ± 0.01. The proposed method can predict the gait trend well.

KEYWORDS

Elderly people fall, Acceleration gyro, Lumbar posture, Gait prediction, LSTM

1. INTRODUCTION

If the elderly people are unable to help themselves after falling, they will remain in a prone position for a long time, with aftereffects. In serious cases, it will threat to their lives. In the United States, for example, the older persons who are over the age of 65 fall at least once a year, but only 1/40 people will be taken to the hospital, and only half of them will still be alive after a year [1]. There is some device which can detect the falls and provide an alarm, however, their functions are limited, because the fall has happened and caused the injury, despite it worked out. Even after the rescue, their trauma was restored, but the shadow left by the fall was lingering, leading to depression and other mental illness. Therefore, when the post fall detection is combined with the pre-fall prediction, the serious consequences caused by the fall can be minimized as much as possible [2].

At present, elderly person fall detection research is focused on fall detection, but there are few studies on fall prediction. However, there are not many researches on fall prediction, and most of them are based on wearable devices to predict falls. The key to fall prediction is how to improve accuracy and achieve early prediction. Many scholars have conducted related research on fall prediction: Wu used the threshold algorithm based on the horizontal and vertical speeds of the torso to predict the fall in [3], the results show that it can be predicted 300 to 400ms before the fall. A. K. Bourke et al. used the threshold algorithm to perform the fall prediction in [4], fixed the acceleration sensor and the gyroscope to the chest, used the acceleration and the angular

velocity to calculate the vertical velocity of the trunk, and tested the set speed threshold -1.3 m/s2 for the fall prediction. It achieved 100% accuracy and was able to predict a fall 322ms before a torso collision or 140ms before a knee collision. Nyan used a three-axis accelerometer and a two-axis gyroscope to obtain the angle of the leg and torso in [5] . Using the threshold algorithm to determine whether the leg angle exceeded the threshold (±10), if it exceeded, then determine the torso and leg whether the correlation coefficient exceeds the correlation coefficient threshold (0.99), and if it is exceeded, it is judged to be falling. The method achieved 95.2% sensitivity and 100% specificity, and the pre-fall time averaged 700ms. Li Na Tong propose a time series method to predict the fall and established a hidden Markov model (HMM) to describe the human body to assess the risk of human fall at the current moment in [6]. The output probability thresholds of acceleration time series in different motion processes are get based on the SVM, and the prediction of human fall can be realized within 200-300ms before the impact. Guangyi Shi et al. used a nine-axis inertial sensor placed at the waist and a pressure sensor placed on the sole of the foot to perform a fall prediction. It was found that the combination of the waist and the foot has higher accuracy than the use of only the waist nine-axis sensor. The accuracy of the fall prediction is 98.565%. Chenchao et al. [8] used SAE and LSTM to predict the gait of lower extremity exoskeleton. According to the gait sequence of the previous period, the gait information of the next moment was effectively predicted. The average accuracy rate was over 92.9%. ZENG M [9] used convolutional neural network to recognize gait. Xu Fan et al. [10] used CNN and LSTM to classify gait and get a good prediction. Thus, it can get a good fall prediction results using sensor data, but the sequence of gait is neglected in references [2] ~ [4], [6], and [8]. The gait recognition and prediction in references [7], [9], and [10] are carried out by using neural network, and the sequence of gait is taken into account, and get better accuracy. For this reason, a gait prediction method based on LSTM and a time series prediction model is established in this paper, which is used to predict the human gait. Nine-axis accelerometer gyroscope angle sensor is used to collect gait sequence data and the LSTM network is used to predict gait sequence.

The organization of the paper is as follows. Section 1 presents the related work, analyses their progressiveness and limitations and describes he objective of the paper. Section 2 introduces LSTM neural network. Section 3 shows the model of gait prediction. Section 4 describes data collection. Section 5 presents experiments of prediction and shows the results. Final section concludes this paper.

2.   LONG AND SHORT TIME MEMORY NEURAL NETWORK (LSTM)

LSTM is a special type of RNN that can learn long-term dependency information. The LSTM has three gates to protect and control the state of the cells: the input gate, the forget gate, and the output gate. First, the forget gate reads the output of the previous cell h_{t-1} and input of current cell x_t and decides to discard and retain information from the cell state.

First, the forgetting gate reads the output h_{t-1} and input $x_t$of the previous cell and decides to discard and retain information from the cell state. Next, the input gate determines whether the value is updated or not, then a new candidate vector $\tilde{C}_t$ for storage state is created through a tanh layer, then the cell state is updated to C_t: Finally, the output gate outputs a value. They can be calculated using equations (1) ~ (6). LSTM structure as shown in Fig. 1 [11]

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \qquad (1)$$
$$i_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_i\right) \qquad (2)$$
$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \qquad (3)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \qquad (5)$$
$$h_t = o_t * \tanh(C_t) \qquad (6)$$

Figure 1. LSTM structure

3. GAIT PREDICTION MODEL ESTABLISHMENT

There are two gait prediction models, one is single gait feature prediction model, the other is multi-feature gait prediction model.

For single gait feature prediction, the modle was build to predict the following features of gait one by one. For every model the input of data is one of the features at time t, the output of data is this feature at the time t+1. So, the input unit is one, the output unit is one. The LSTM network is created based on the keras framework.

The features of the gait are the characteristic data of human lumbar posture collected by sensors, which are (1) the acceleration of x, y and z axes in terms of (g), which are ax, ay and az; (2) the angular acceleration of x, y and z axes in terms of (deg/s), which are wx, wy and wz; (3) the angular acceleration of x, y and z axes in terms of (deg), which are anglex, angley and anglez.
For multi-feature gait prediction, the input of data is as following features at time t, the output of data are those features at the time t+1. So, the input units are three, the output units are three. The LSTM network is created based on the keras framework.

The data used in multi-feature gait prediction experiments are the acceleration of x, y and z axes, the angular acceleration of x, y and z axes, the angular acceleration of x, y and z axes, and the angular acceleration of x, y and z axes. The three matrices are [ax ay az], [wx wy wz], [anglex angley anglez]. The three matrices are respectively used as input variables for prediction.
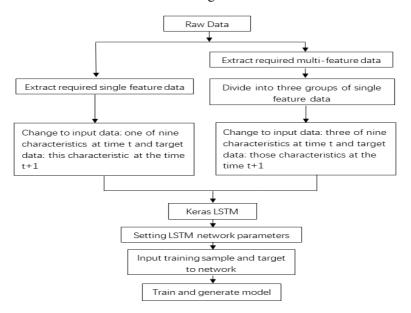The process of model establishment is shown in Figure 2.

Figure 2. The flowchart of model establishment

4. EXPERIMENTAL DATA COLLECTION

The experimental data is collected by the BWT901 nine-axis acceleration gyro angle sensor. The acquisition process is as follows:

(1) Connect the sensor to the PC through USB-HID. After the connection is successful, open the data receiving software MiniIMU on the PC side for data recording, as shown in Figure 3.

(2) When collecting data, fix the sensor to the waist of the human body, collect data for walking, walking and sitting, and record the data through software, as shown in Figure 4.

(3) In order to record the human gait data more smoothly, at the time of recording, each time after the end of the action, the stagnation time is used as the buffer time, and then the buffer time data will be cut off as the final data input. See figure 5 for an example of experimental data.

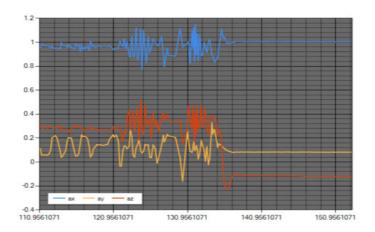Figure 3. The connection between sensor and pc

Figure 4. The UI of Recording software

Time(s)	ax(g)	ay(g)	az(g)	wx(deg/s)	wy(deg/s)	wz(deg/s)	AngleX(deg)	AngleY(deg)	AngleZ(deg)
68.432	0.0435	-0.9819	-0.1401	-1.4648	-0.1221	-0.061	105.1392	60.2271	-153.095
68.633	0.0425	-0.9819	-0.1406	-1.77	-0.061	-0.1221	104.892	60.2545	-153.193
68.842	0.0449	-0.98	-0.1406	-1.5869	-0.061	-0.1221	104.6777	60.282	-153.254
69.066	0.0454	-0.9785	-0.1436	-1.5869	-0.061	0.061	104.5294	60.2985	-153.259
69.232	0.0415	-0.978	-0.1465	-2.7466	0.4883	0.4883	104.3866	60.26	-153.204
69.45	0.0356	-0.9829	-0.1597	-3.479	1.5869	0.061	104.2877	60.1776	-152.952
69.64	0.0527	-0.9839	-0.1802	-2.5635	0.1831	-1.0986	104.1229	60.1996	-152.721

Figure 5. Example of experimental data

5. EXPERIMENTS AND RESULTS

There are two part of experiments: collection of data and prediction experiment. The prediction experiment is divided into two parts. The first part is a single variable prediction experiment, and the second part is a multi-variable prediction experiment.

In data collection experiment, we use the sensor which collects a value every 0.2 seconds to collect 365s time series data totalling 1825 values. The 67% of them are used to train the model, and the rest are used to test.

In prediction experiment, we create LSTM neural network with one input layer, one hidden layer, and one input layer. The hidden layer has 4 neurons, the hidden layer uses the sigmoid activation function, the number of iterations is 100, the batch size is 1 and the loss function is mean square error, the optimization algorithm uses the adam algorithm. We use the LSTM to build models. The model establishment is in section 4.

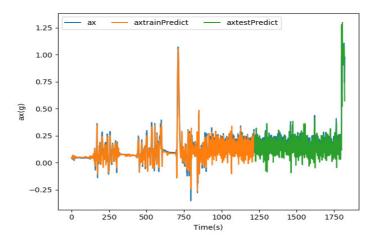The predict results show in Figure 6 and Figure 7.

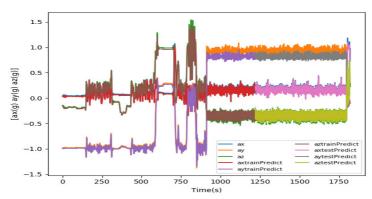Figure 6. Example of univariate prediction experiment

Figure 7. Example of multivariate prediction experiments

The score of predicted results corresponding to univariate input is shown in Table 1, the score of predicted results corresponding to multivariate input is shown in Table 2.

Table 1.   Score of predicted results corresponding to univariate input

input score	ax	ay	az	wx	wy	wz	anglex	angley	anglez
Train score	0.05	0.08	0.08	7.72	12.87	8.45	22.47	2.69	23.03
Test score	0.08	0.09	0.12	8.83	19.43	14.89	6.93	3.77	32.83

Table 2.   Score of predicted results corresponding to multivariate input

input score	[ax ay az]	[wx wy wz]	[anglex angley anglez]
Train score	0.04	0.05	0.07
Test score	0.05	0.07	0.06

Scoring result analysis: The predicted result score is determined by RMSE. The RMSE stands for the distance between the predicted result and the original data, it means that the distance is shorter, the result is better. From the data in the table, it can be seen that the prediction result of single variable input is better than that of x, y and z axis acceleration, while that of multi-variable input is better. As a whole, LSTM network has ideal prediction results and good prediction results for different human postures. Therefore, it is of practical significance to use LSTM to predict gait sequence to predict falls.

6. CONCLUSIONS

Experiments show that the prediction results of multi-variable input are better than that of single-variable input, which indicates that human gait or posture needs three-dimensional data to predict or detect better. However, there are still some shortcomings in this paper. Firstly, when estimating, modelling and forecasting gait data, the collected data types are relatively single, and various gait types should be collected to predict. This analysis from many aspects can improve the accuracy and feasibility of gait forecasting analysis and is more efficient and effective in practical application. Secondly, the gait sequence with very short time interval is analysed in this paper, and the gait span in real situation is not considered. At the same time, this paper only introduces one method of prediction, without comparing many methods, which fails to reflect the superiority of this method very well. Moreover, I have not applied this method further.

The next research includes the following aspects:(1) Increasing the number of layers of neural networks and combining two or more kinds of neural networks to optimize the network structure [12] and improve the accuracy of prediction. (2) Combining gait prediction with gait recognition to enhance the practicability of the model.

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