Design of Intelligent Shoes Based on Multi-sensor

Hao Wang¹ and Yawei Song²,* Tao Pan³

¹Graduate School Of Nanjing Institute Of Physical Education, Nan jing China
²Institute Of Competitive Sports, Nanjing Institute of Physical Education, Nan jing China
³Graduate School Of Nanjing Institute Of Physical Education, Nan jing China

*Corresponding author email: 516805946@qq.com

Abstract. To collect and analyze movement data of human foot, an intelligent shoe system was developed to collect foot pressure, foot acceleration and angular velocity data. Intelligent shoes include pressure insole module, wireless transmission module and sports data receiving software in addition to the shoe body. The foot movement data is collected by the intelligent shoes, which is sent to the receiving software through Bluetooth, and displayed and stored. Three basic movement behaviors including sitting, standing and walking were identified through the multi-layer long short-term memory (LSTM) network, and the accuracy of motion behavior recognition model based on LSTM and the validity of motion data collected by intelligent shoes were verified. The intelligent shoes can be used in the study of human motion behavior recognition.

1. Introduction

Human motion behavior recognition records human motion by certain detection methods, which is used to study human behavior characteristics. The characteristics recognition of motion behavior can be used in many fields, such as medical health, safety certification, sports competition, etc. It can be used in disease diagnosis and health monitoring [1-3], athletes' body movement analysis [4], identity recognition [5], human-computer interaction [6,7], etc, which has very important value of research and application. The acquisition of human motion behavior data can be divided into two categories including image-based and sensor-based acquisition. Compared with the image-based method, the sensor-based acquisition has advantages in low requirements for environment light and hardware equipment performance, and low power consumption and cost of equipment. Hsu Y, et al. [4] implemented a wearable inertial sensor network, which could be worn at the wrist and ankle to collect the motion data generated in daily activities and sports. Hegde N, et al. [8] designed a kind of children's intelligent shoe for measuring body movement and gait, which was equipped with a pressure sensor in the insole, and placed a box containing an acceleration sensor at the heel of the shoe; Jiahui Zhang, et al. [9] implemented a plantar pressure acquisition device, which collected plantar pressure data by installing multiple pressure sensors in the insole, but the circuit placed in the heel of the shoe was too large. Ruohong Huan, et al. [10] collected human motion data directly through the inertial sensor built in the mobile phone. Most of the above sensor based motion data collection can only collect a single type of data, and there are many problems such as cumbersome use or wearing process, and too large device volume. Regarding to the above issues, we designed an intelligent shoe based on multi-sensor in the present study. By building a recognition model based on long short-term memory (LSTM), we verified that the data collected by this intelligent shoe could be used for basic research of motion behavior recognition.
2. Motion Behavior Recognition Based on LSTM
Comparing with the traditional method of motion behavior recognition, the data of neural network method only needs a little or none preprocessing. Meanwhile, the method of motion behavior recognition based on neural network does not need to construct feature vector, which makes investigators focus more on how to build an effective recognition network model.

2.1. LSTM Introduction
The common human movement behaviors in daily life include standing, walking, running, up and down stairs, etc. The essence of human motion data collected by sensors is a time series of correlation between before and after. LSTM was proposed by Hochreiter S \(^{11}\), which was a kind of neural network introducing memory cell into RNN (recurrent neural networks). On this basis, Gers FA et al. \(^{12}\) obtained the most common LSTM by adding the forget gate. As an improved RNN, LSTM is very suitable to deal with long-term dependent time series.

2.2. Behavior Recognition Model Based on LSTM
Keras \(^{13}\) is an advanced deep learning library API that can quickly build neural network model. It is Python programmed and support multiple back ends. In the present study, Tensorflow of GPU version was used as the back end. The training sample data with dimension (S, T, C) and the label data with dimension (S, L) were obtained after segmenting and labelling the original data. Of which, S represented the number of samples, T represented the length of time, C represented the number of channels of data at the same time and L represented the number of categories of classification labels. As shown in Figure 1, it is the frame diagram of the behavior recognition model based on LSTM in the present study. In the last layer of the model, LSTM takes the output of the last time T of the output sequence as the input data of the full connected network, and finally obtains the classification results of L categories.

![Figure 1. Behavior recognition model based on LSTM.](image)

3. Design of Data Acquisition System
In the present study, the intelligent shoe based on multi sensor was developed to collect human motion data, and the structure of system design was shown in Figure 2. The intelligent shoe is composed of shoe body and data acquisition system which includes wireless micro control module (integrated with inertial measurement unit and power module), pressure insole.
3.1. Realization of Pressure Insole
Self-made pressure insoles were used in intelligent shoes to measure the pressure distribution of the plantar. Single point film pressure sensor is a common sensor for acquisition of plantar pressure data [9, 14]. A total of 8 single point film pressure sensors was used to collect pressure data in the pressure insole of the intelligent shoe. The film pressure sensor has certain flexibility, its diameter is 16 mm, and the diameter of pressure sensing area is 10 mm. The film pressure sensor can bear a maximum pressure of about 500N in the sensing area, and the larger the pressure is, the smaller the resistance value is. According to the force on the foot when walking [15] the 1-8 film pressure sensors were respectively installed at the corresponding positions on the back of the insole to collect the pressure changes of 8 positions including the first phalanx of foot, the first metatarsal joint, the second metatarsal joint, the fifth metatarsal bone, the inside of the arch, the outside of the arch, the inside of the heel and the outside of the heel. The distribution of the pressure sensor on the self-made pressure insole was shown in Figure 3. There is a single point membrane pressure sensor in each of the eight boxes.

3.2. Wireless Transmission Module
The wireless transmission module of intelligent shoes mainly composed of wireless microcontroller, inertial sensor, low-voltage differential linear regulator, etc, which is about 30mm × 20mm in size and 4g in weight. The module can be carried out easily by making square grooves in the sole. The practical installing the wireless transmission module in the shoe body is shown in Figure 4.
The CC2640R2F instrument (Texas, USA), a kind of wireless micro controller, which has a general Cortex-M3 micro control core, a special Cortex-M0 radio frequency (RF) core and a sensor controller core, was used as the core device of wireless transmission module. Mpu6050 six axis inertial sensor with I2C interface was used in intelligent shoes to collect acceleration and angular velocity data of foot. Mpu6050 is a low-cost, low-power, high-performance micro electro-mechanical system (MEMS) device, which can measure the data of three-axis acceleration and angular velocity. The maximum angular velocity range can reach ± 35rad / s, and the maximum acceleration range can reach ± 16G.

3.3. Program Design of Data Acquisition
The data acquisition program of intelligent shoes is based on TI—RTOS real-time operating system, and its main functions include sampling and converting analog signals of 8 pressure sensors in the pressure insole, controlling mpu6050 to collect the data of three-axis acceleration and angular velocity, using Bluetooth to connect the mobile terminal for data transmission. The flow chart of data acquisition program is shown in Figure 5 (a). The frequency of data collection was set to 50Hz, and the collected motion data was needed processing to facilitate transmission through Bluetooth. Here, all the data will be sent out after caching the data collected five times. The wireless transmission module can actively send data to the mobile phone by setting the Bluetooth service attribute to Notify.

3.4. Application of Mobile Phone Receiving
The mobile phone application is used to receive the motion data sent by the wireless transmission module through Bluetooth. After receiving the data of the pressure, three-axis acceleration and angular velocity, the phone displays the data in the form of curve chart and saves it locally. The flow chart of the mobile phone receiving application is shown in Fig. 5 (b).

Figure 4. Wireless transmission module in shoe body.

Figure 5. Program flow.
4. Experimental Test

4.1 Acquisition of Motion Data

Three healthy adults were selected for the motion data collection experiment to verify the accuracy of the LSTM model and the reliability of the sports data collected by the intelligent shoes. The subjects wore the intelligent shoes developed in the present study, and completed three kinds of behaviors including sitting, standing and walking with about 2 minutes lasting, respectively. According to the collected motion data, it is found that the duration of three kinds of motion behaviors to be identified is within 3s, which is taken as the intercept time length of a single data sample. The changes during 3s walking of the No. 1 pressure sensor, acceleration perpendicular to the sole direction and angular velocity were shown in Figure 6 curves (a), (b) and (c), respectively. The measured pressure value output is relatively small, but the change trend of pressure is consistent with the actual walking situation (Figure 6a). This is because the material used in shoe insole is a soft foam, which will disperse a great deal of pressure to ensure comfort. The acceleration measured in Figure 6(b) reflects the process of the foot lifting and stepping in the vertical direction. The angular velocity measured in Figure 6(c) reflects the external and internal rotation of the foot during walking.

![Figure 6. Motion data curve.](image)

After data acquisition, a total of 300 groups of motion data samples are finally extracted from the raw data to train and test the behavior recognition model. The label data corresponding to the sample data can be obtained by manually marking the type of motion behavior. 80% of all samples were randomly selected as training samples and the remaining 20% as test samples. The actual sample data dimension is $300 \times 150 \times 14$, indicating that the number of samples is 300, the time step is 150, i.e. 3s, and the data channel is 14. The label data dimension is $300 \times 3$, indicating that the number of sample labels is 300, and there are three types of motion behavior categories.

4.2 Test Results

The above motion data was used to train and test the LSTM motion recognition model, and to recognize three simple motion behaviors including sitting, standing and walking. The accuracy of the model is 96.7%. The result of classification recognition test set is shown in Table 1. There were 60 groups in the test set, including 23 groups of sitting, 19 groups of standing and 18 groups of walking. The results revealed that only two groups of standing were mistakenly classified as sitting. The evaluation of corresponding classification results is shown in Table 2. The accuracy rate in identifying one motion category is the ratio of the number of samples correctly classified to the number of all samples identified in a category by the model. The recall rate is the ratio of the number of samples correctly classified to the total number of samples in a category when identifying a movement. F1 value is the harmonic mean value of accuracy rate and recall rate. Finally, the macro average can be calculated, including macro accuracy rate, macro recall rate and macro F value. The results indicated that the trained LSTM model has a good performance in classification, which can make good use of intelligent shoes collected data for motion behavior recognition.
Table 1. Identification results of test set.

| Label   | Sitting | Standing | Walking |
|---------|---------|----------|---------|
| Sitting | 23      | 0        | 0       |
| Standing| 2       | 17       | 0       |
| Walking | 0       | 0        | 18      |

Table 2. Evaluation of identification results.

| Behavior category | accuracy rate | recall rate | F1 value |
|-------------------|---------------|-------------|----------|
| Sitting            | 0.92          | 1.00        | 0.96     |
| Standing           | 1.00          | 0.89        | 0.95     |
| Walking            | 1.00          | 1.00        | 1.00     |
| Macro-avg          | 0.97          | 0.96        | 0.97     |

5. Conclusion

The movement data collected by the intelligent shoes were tested through the construction of the movement behavior recognition model based on LSTM. The results indicated that the model of motion behavior recognition based on LSTM could well identify the three basic motion behaviors of sitting, standing and walking. Meanwhile, it verified that the motion data collected by the intelligent shoes developed in the present study could be used for motion behavior recognition study.

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