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HUMAN PHYSICAL ACTIVITY RECOGNITION ALGORITHM BASED ON SMARTPHONE DATA AND LONG SHORT TIME MEMORY NEURAL NETWORK

CHEN Z.Y., YANG Z.X., LI H.

Belarusian State University of Informatics and Radioelectronics[1], Minsk, Republic of Belarus

BARYSKIEVIC I.A. – PhD in Digital signal processing algorithm, Image Compression

Annotation. The continuous advancement of smartphone sensors has brought more opportunities for the universal application of human motion recognition technology. Based on the data of the mobile phone's three-axis acceleration sensor, using combining a double-layer Long Short Time Memory (LSTM) and full connected layers allow us to improve human actions recognition accuracy, including walking, jogging, sitting, standing, and going up and down stairs. This is helpful for smart assistive technology. It is shown that physical activity classification accuracy is equal to 98.4 %.

Keywords. Mobile acceleration sensor, long short time memory, action recognition and classification accuracy

Traditional sensor devices are bulky and expensive. With the continuous development of smart phones in recent years, the acceleration sensors of mobile phones have also continued to improve. It has the obvious advantages of small size, high penetration rate and lower price, which provides a new idea for the application of intelligent assistance technology and so on. Recognition of human activities from sensor data is at the core of intelligent assistive technologies, such as smart home, rehabilitation, health support, skills assessment or industrial environments [1]. For example, the project of Inooka et al. predicts the energy consumption of users by recognizing their activities [2], and Mathie et al. judges whether users are safe or not by recognizing their actions [3]. This work is motivated by two requirements of activity recognition: improving recognition accuracy and reducing reliance on engineered features to address increasingly complex recognition problems.

Human Activity Recognition (HAR) is based on the assumption that specific body movements translate into characteristic sensor signal patterns, which can be sensed and classified using machine learning techniques. We use data collected from accelerometer sensors. Almost every modern smartphone has a three-axis accelerometer that measures acceleration in all three spatial dimensions.

We selected the data set from the Wireless Sensor Data Mining (WISDM) project, which collected 1,098,207 experimental data generated from 29 volunteers carrying smartphones to perform specified actions every 50 ms, and each piece of data consists of 6 parts: Username, specified action, timestamp and accelerometer values for x, y and z axis.

Before feeding the raw data into the network model, we need to perform preprocessing and feature generation operations on it. Due to the impact of environmental changes in the data collection process, the data from the mobile phone accelerometer inevitably has a lot of measurement noise. The main method to eliminate these noises is to filter the original data with a low-pass filter, which helps to improve the accuracy of model recognition. The reason why the low-pass filter can be used is based on the following two conditions: 1. The noise is mainly concentrated in the high-frequency band; 2. When the human body is moving, the accelerometer measurement value is only related to gravity and human body acceleration, both of which are of small magnitude.

As a low-pass filter with a maximum flat amplitude response, the Butterworth filter has been widely used in the field of communication and electronic measurement, and can be used as a filter for detecting signals. The first-order Butterworth filter has an attenuation rate of 6 dB per octave and 20 dB per decade. A second-order Butterworth filter has an attenuation rate of 12 dB per octave, a third-order Butterworth filter has an attenuation rate of 18 dB per octave, and so on. The Butterworth low-pass filter can be expressed as the square of the amplitude $|H(jw)|$ and the frequency w as formula (1):

$$|H(jw)|^2 = \frac{1}{1+\left(\frac{w}{w_c}\right)^{2n}} = \frac{1}{1+\varepsilon^2\left(\frac{w}{w_p}\right)^{2n}}, \quad (1)$$

where w_c - cutoff frequency, that is, the frequency at which the amplitude drops to -3db, w_p - passband edge frequency, ε - damping ratio.

We experimented with Butterworth filters of different orders and cut-off frequencies. The Butterworth filter with a third-order cut-off frequency of 4 performed best. The graphs before and after filtering the raw data of 200 three-axis accelerometers with label of sitting in the dataset using a Butterworth filter with a third-order cutoff frequency of 4 are shown in Fig. 1 and Fig. 2. After filtering, the graph is visibly flattened.

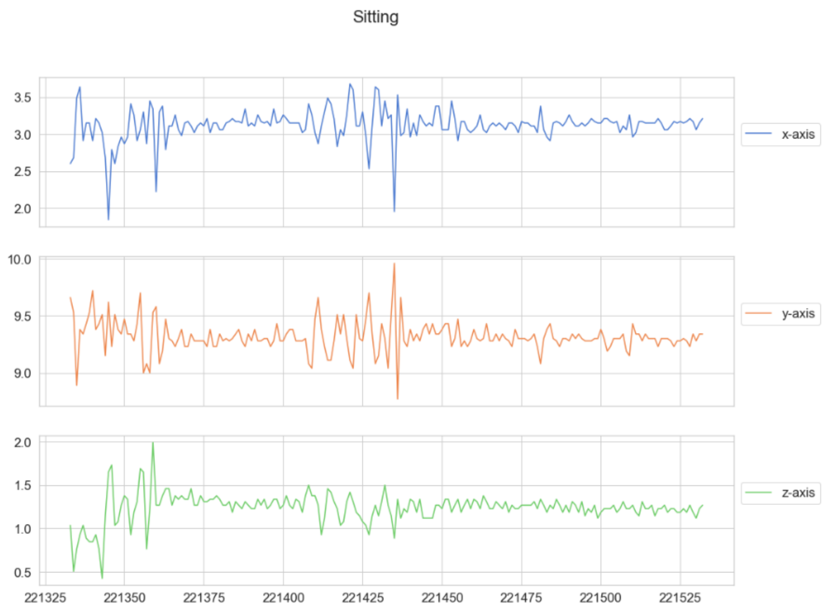

Figure 1 - Three-axis accelerometer plot labeled as sitting before filtering using a third-order 4 Hz Butterworth filter

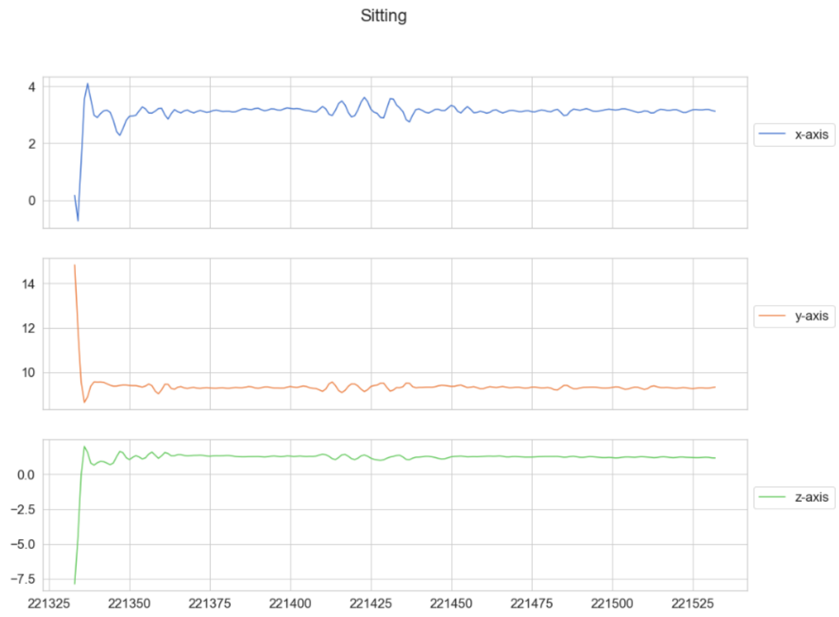

Figure 2 - Three-axis accelerometer plot labeled as sitting after filtering using a third-order 4 Hz Butterworth filter

We use a window of size 200 with an overlap of 90 % to divide the x, y and z axis accelerometer and label part in the original data, store them as acceleration data and label data respectively for preprocessing. We get 54901 windows and split both data into a training set (80 %) and a test set (20 %).

We trained a double layer LSTM neural network (implemented in TensorFlow) for HAR from accelerometer data with the purpose of providing an algorithm with higher recognition accuracy. The trained model will be exported/saved and added to the Android app. The network model consists of double layer

LSTM network layers and double fully connected layer (FCL), and predicts the corresponding human actions from the x, y and z axis acceleration count values from the data set. The proposed algorithm achieved 98,4 % accuracy and a loss of 0,2 on the test set.

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