Research on the prediction model of elderly fall

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Abstract. As the world's aging process accelerates, the issue of elderly safety is about to become a serious social problem. The elderly are prone to falls due to physiological reasons such as decreased physical function, weakened balance and coordination ability, and poor vision. The study of fall prediction models can predict the impending fall behavior in time before the fall, and have enough time to remind the elderly to adjust or take corresponding protective measures. Reduce the damage caused by falls to the human body, reduce the medical expenses caused by falls, and enhance the confidence of the elderly to live independently. This article gives a detailed overview of the research on the wearable device-based fall prediction system, and introduces the entire process of falling. According to the work flow of the wearable device fall detection system, it includes data collection, data preprocessing, feature extraction, and discrimination algorithms. Several aspects of the current research work are introduced, and the existing research results are classified, compared and statistically analyzed to provide meaningful reference and reference for subsequent research work. Finally, a fall prediction model based on an improved ConvLSTM is proposed.

1 Introduction

WHO reports that an estimated 646,000 people die every year due to falls without timely treatment, with the largest proportion of people over 60 years old. Therefore, fall detection has practical significance. In terms of time, falls can be divided into pre-detection and post-detection. Currently, most studies are post-mortem detection of falls.

At present, most fall detection methods are highly accurate, but there are few studies on prediction. However, the fall prediction has more research significance. Due to the need to take corresponding protective measures, the earlier you predict, the better.

This article introduces the research of the fall prediction model based on wearable devices, introduces the current research work from multiple aspects of the model process, and compares and analyzes the existing research results. Finally, a fall prediction model based on improved ConvLSTM is proposed.

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2 Fall behavior analysis

The fall process of the human body can be divided into four stages: before falling, falling instability, crashing on the ground, and recovering. Generally, the duration of the human body falling process is about 1.5 seconds to 2.5 seconds. After analysis, fall prediction is the detection of the characteristics of the instability stage, and the pre-impact phase feature is the key stage of fall prediction.

3 Wearable fall prediction analysis

The fall prediction process based on wearable devices mainly includes data collection and preprocessing, feature extraction, model training, fall classification, etc., as shown in Fig.1. The following will introduce the latest progress of related research work according to the work flow of wearable fall prediction, and compare and analyze existing research results.

Fig.1. Flow chart of fall prediction

3.1 Data collection

The data collection module collects human behavior activity data through the worn sensor device. The researchers studied the data acquisition module from two aspects: sensor type and wearing position. Studies have shown that the difference in sensor equipment and wearing position will affect the performance of the fall detection system.

Fall prediction needs to consider speed issues, so there are certain requirements for sensors. Miao [1] designed a MEMS-based fall detection, the airbag can be fully opened before falling. Multi-sensor fusion improves accuracy, but it affects speed. Therefore, 1-3 sensors are usually selected. On the sensor's market, choose WIT's multi-level attitude sensor which integrated high-precision gyroscope, accelerometer and geomagnetic field sensor. Ozdemii [2] used the same algorithm to verify the effect of placing sensor modules on different parts of the human body. It was found that the waist is the best place to place the sensor. And this wearing position has little interference with daily activities.

3.2 Data preprocessing

The actual collected data is "dirty" and needs to be preprocessed to avoid problems in the original data from affecting the detection results.

Table 1. Comparison of noise reduction methods.

Method	Advantage	Disadvantage	Literature
Low pass filter	Suppress periodic interference	It is difficult to reduce the noise	[3]
Moving average filter	Small calculation, high smoothness	Sensitivity is not high, with hysteresis	[4]
Kalman filter	Fast calculation speed and good real-time performance	the model does not match will cause filtering divergence	[5][6]

After comparison, the Kalman filter method is chosen. The normalization of sensor data signals helps to find the global optimal solution after training [4]. Due to the diverse sample data, the maximum and minimum methods will be used in the data preprocessing stage of fall prediction. According to the requirements of the model for the data input format, the standardized data is templated to apply the model.

3.3 Feature extraction

Feature is to extract data that can express its characteristics after preprocessing the original data. In the classification algorithm, the choice of features has a great impact on it, so it is very important to choose the right features. This article analyzes the transformation of feature extraction from machine learning to deep learning.

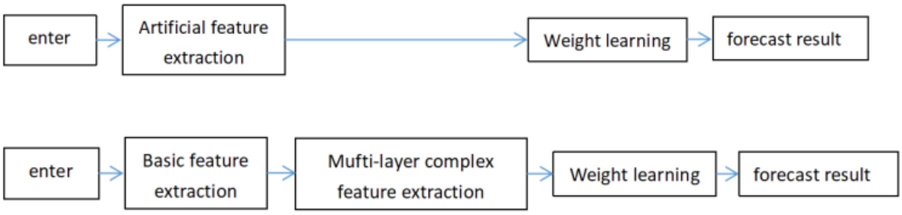

Fig. 2. Comparison of traditional machine learning and deep learning processes.

Traditional machine learning technology has great limitations in processing raw data. Deep learning is developed on the basis of machine learning to realize automatic feature extraction. The process comparison between them is shown in Figure 2.

Traditional feature extraction uses manual extraction, which requires personnel with professional knowledge. The early features of a fall are weak and complex, which results in time-consuming and laborious feature extraction, which reduces the accuracy and speed of classification and recognition. Therefore, a neural network algorithm was selected to automatically extract features. Deep learning methods can actively learn and identify features from the original data to obtain more accurate prediction results. Taking into account the time requirement of fall prediction, manual feature extraction combined with automatic feature extraction is adopted.

Table 3. Common feature set for fall detection.

Features	Description	Formula	Literature
mean(s)	Arithmetic mean	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$	[7][8]
std(s)	Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$	[8][9]
max(s)/min(s)	The largest/smallest value	$\max_i(x_i) / \min_i(x_i)$	[7]

3.4 Time series classification algorithm

Due to the large number of data variables and temporal and spatial correlation, a classification algorithm based on time series is used. This section conducts research and comparative analysis on the classification algorithms of time series.

Before deep learning was widely used, the combination of DTW and KNN was a very useful time series classification method. DTW is used to obtain measurement results, and then clustering is performed by KNN. Xia [10] uses KNN and DTW algorithms for gesture recognition, with a high success rate. The feature-based method is a method of extracting relevant features through a certain measurement relationship. Xu [11] extracted 14 features from different dimensions, and used the normalized features as the input of the deep learning model. This method has good robustness, but the classification effect is not good. LSTM_FCN has achieved better results than FCN. In some other competition programs, there are also other combinations. You have to try to find out which one is better for different problems. Xu [12] proposed a combined model of time series prediction based on convolutional neural network and Markov chain. This method has better prediction accuracy than existing algorithms. MCNN integrates multi-scale concepts in image processing into time series processing, and outputs different feature maps for prediction and classification. Liu [13] proposed an EMG signal classification method based on ConvLSTM. It has better performance. LSTM has strong ability to process time series data. It has the time-series modeling ability of LSTM and describe local features like CNN.

Table 4. Comparative analysis of time series classification algorithms.

Algorithm	Advantage	Disadvantage	Literature
DTW&KNN	Simple method	Slow prediction	[10][14]
MLP	Simple and fast	Unused contextual information	[17]
FCN	Arbitrary input, efficient	Lack of spatial consistency	[15]
LSTM_FCN	Excellent classification task	Individual accuracy differences	[16]
MC-CNN	High recognition accuracy	Slow recognition	[12]
ConvLSTM	Possess time and space features	Affect the time information	[4][13]

In summary, first, use the Kalman filter to reduce the noise of the original data. Since the length of the collected data is different, the maximum and minimum methods are used for normalization. Templated normalized data. Then, the preprocessed original signal is directly put into the neural network for training and weight update. The feature set is obtained through multiple training. Finally used to effectively predict fall.

4 Summary and outlook

There are still some challenges and problems in the fall prediction model based, as follows:

On the sensor devices:Fall prediction is an application that needs to provide long-term, real-time, accurate and efficient services. How to effectively control the calculation and storage consumption of the model without losing speed and accuracy is very critical.

(1)Fall prediction model training: The fall situation is different between the elderly and the young. How to obtain fall data of the elderly in the actual environment is very important.

(2)Fall prediction algorithm design: How to design an algorithm to ensure speed while still having high accuracy is very important. Adjusting the algorithm adaptively according to different external factors to make the system more stable is also worth considering.

(3)This paper studies and analyzes the algorithms involved in the fall prediction model, which provides a meaningful reference for future work.

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