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A Human Fall Detection Method based on Machine Learning and TRIZ Theory

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Abstract. The paper proposes a human fall detection method using a Kinect sensor with a TRIZ tool to analyze and improve the existing problem solutions. The used Kinect sensor captures the human point cloud data and Back Propagation Neural Network (BPNN) algorithm detects different human behavior states. By analyzing and processing the human-body point cloud data, the gained height change acceleration of the human body point cloud is used as the feature value. The BPNN algorithm is used to classify activities from the sensor acquired data from sample data. The human-body point cloud image is extracted and the human-body attitude after falling is recognized by a trained Convolutional Neural Network (CNN) model. The experimental results show that the CNN model is capable of a precise recognition for the human-body attitude, thus providing a basis for creating an innovative, reliable and practical fall detection method.

Keywords: Kinect; Back propagation neural network; Point cloud; Centroid; TRIZ theory

Raziskava metode za ugotavljanje padcev na osnovi strojnega učenja in teorije TRIZ

V članku je predstavljen sistem za ugotavljanje padcev na osnovi senzorske naprave Kinect in teorije TRIZ za analizo in izboljšavo obstoječih pristopov. Z napravo Kinect zajamemo gibanje oseb in na osnovi algoritma vzvratnega razširjanja, izvedenega z nevronskimi mrežami, ugotovimo in klasificiramo različna stanja gibanja s poudarkom na spremembi višine opazovane osebe. Dogodek, da oseba pade, ugotovimo z naučeno konvolucijsko nevronsko mrežo. Eksperimentalni rezultati potrjujejo, da lahko z nevronsko mrežo natančno ugotovimo spremembo višine osebe, ki je osnova za izdelavo inovativnega, zanesljivega in praktičnega sistema za ugotavljanje padcev oseb.

1 INTRODUCTION

At present, China has become the country with the largest population of the elderly in the world, and one of the countries with the fastest population aging. The high incidence and serious consequences of falls in the elderly are a serious threat to the health and even life of the elderly. Every year, a large number of elderly people miss the best time to seek help because they have not been rescued in time, resulting in frequent life safety accidents. Therefore, it is of a great practical significance to automatically detect and send out on alarm information for the accidents of the elderly living alone.

At present, the research on the human fall detection has really become a focus， there have been several detection methods proposed and used. The detection method [1-5] is based on a kind of a wearing sensor to monitor postures of human bodies from which the fall detection judgment can made. The commonly used sensors are like acceleration sensor, gyroscope sensor, and pressure sensor. Besides being capable of completing a multi-sensor joint detection, they also use ECG, pulse and other devices. However, the wearable fall detection equipment needs a long-term wear, considerable experience and should be convenient for being used for daily activities. In the process of long-time wearing, there are inevitable occurrences of certain losses and errors of the equipment. Moreover, the false alarm rate is very high, which altogether minimize the accuracy; The human fall detection method [6-9] uses a vision sensor. One or more cameras are installed in a certain area to collect human motion images, extract the feature vectors of fall motions, and match how to realize the fall detection. In [5], a fall detection system is designed and implemented based on static human image features by using cameras. The fall is assessed by extracting the aspect ratio and tilt angle of the human body. The calculation capacity of the system is small, and can only detect the static state of the target, not the dynamic falling process of the moving target in a

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real time. A considerable drawback of such video fall detection is exposing the privacy of the elderly.

The TRIZ theory, is an innovative method which integrated several systematic, scientific and operable creative thinking and analysis methods for solving inventive problems [10]. It provides a reliable guidance when constructing solutions. The paper reveals a combination of using the TRIZ theory, causal analyzing of two existing solutions, abstracting the root of the problem and using the IFR (ideal final result) model to get a new solution [11-12]. Using the Kinect sensors provides the user depth images [13-20]. For instance, in [21], the fall is detected by determining the human body 3D (height, width, depth) bounding box as well as by calculating the bounding box height and the depth-width direction of the velocity. In [15], using the developed color depth images, a method is proposed to recognize the human body and detect the fall by using the Kinect overlooking angle which detects and tracks multiple human bodies. In [22], the human body image is divided from the foreground map, the centroid height is extracted, and the human body falling is determined from the distance between the human centroid and the ground and the speed of the human centroid. These methods may trigger a false alarm when the users after their falling by themselves.

To reduce the false alarm rate and improve the user efficiency, the provided fall detection method uses a Kinect sensor to acquire the human point cloud data and to determine whether there is a potential fall activity by identifying two stages of the human point cloud altitude change acceleration and attitude recognition after the fall. In the first stage, the height change acceleration and centroid height of the human point cloud are used as features and are imported into a pre-trained classifier to identify a potential recognition activity. Then the second-stage, an assessment is made. A pre-trained convolution neural network model is used to identify the point cloud postures of a human body after a fall, and a timer is used to record the hold time of the fall posture to finally determine the true fall activity. The innovative optimization of our paper are: users wear no equipment, which make it easier for them; the point cloud data is displayed in a form of a spectrum which protects the user privacy, and highly efficiently during the night; recording time of a fall, reduces the false alarm rate, which altogether ensures good market prospects.

2 THE TRIZ THEORY

2.1 General

Fig. 1. shows the root cause of the problem when using the TRIZ theory.

The detected deficiencies using TRIZ theory are due to the misjudgment from miscalculations caused algorithm and data errors. The algorithm is inadequate that the problem is non-linear and complex, which make it difficult to obtain accurate parameters from a limited testing. This is due to find differences in the body and their movement habits.

From the data source, the more equipment one wears, the less easer one moves, which increases the equipment error rate. In a low-light environment, the camera accuracy is greatly reduced. And when a human is obscured by some items, the recognition accuracy decreases too, leading to a miscalculation.

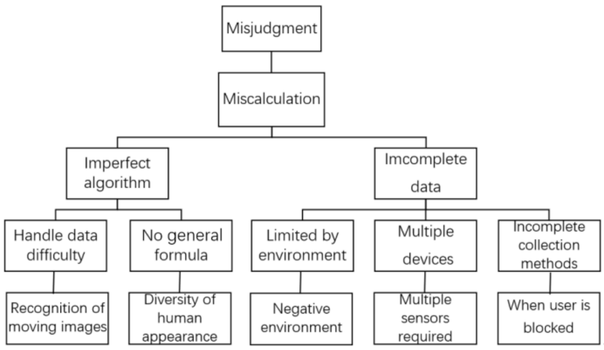


Figure 1. Analysis of the existing technology

2.2 IFR (Ideal Final Result)

The analysis revolves the root cause of the problem. IFR is shown in Table. 1.

Table 1. IFR table of causal analysis

Ultimate purpose of design	Change collecting device, optimize judgment algorithm
IFR in this problem	Accurate and safe fall detection system
Obstacles to reaching IFR	Data collecting device is limited by the environment, and the algorithm is not general
What causes this obstacle	The fall detection based on user actions can only be judged based on image data, which loses the generality of action judgment
Conditions under which this obstacle does not occur	Change the design idea, abstract the common points from the action of the human body, and update the algorithm at the same time, so that the algorithm can use the existing information to judge
Available resources to create these conditions	Kinect equipment collects and generates point cloud images, and uses neural network algorithms to process point cloud data for fall detection

Judging from IFR, the solution is to employee hardware equipment, such as the Kinect sensor, to collect and generate the human point cloud images, use a neural network algorithm to make a fall judgment and try displaying the point cloud image on the spectrum to protect the user privacy.

3 FALL DETECTION SYSTEM

3.1 System design process

Using our fall detection system based on the point cloud data employing a machine learning algorithm, the depth images in the scene are obtained by combining the software Processing and the Kinect sensor and generating 3D point cloud images. The algorithm extracts the human data and image features assigned to a trained classifier to recognize attitude recognition and, finally, to determine whether the fall is an activity. The system structure is shown in Fig. 2.

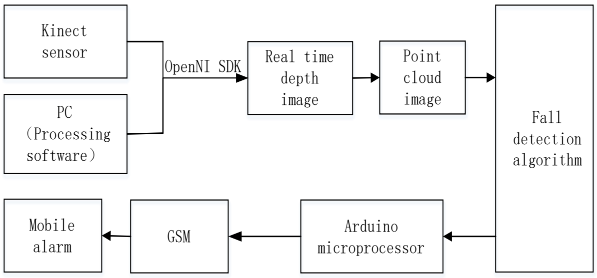


Figure 2. System structure diagram.

3.2 Kinect sensor

The body sensing device applied in our method is a motion-sensitive Kinect sensor produced by Microsoft. The sensor is composed of color cameras, infrared devices, microphone arrays, logic circuits and motors. It has three cameras, the middle one is a RGB color camera and the left and the right side ones are 3D deep sensors made of infrared transmitters and CMOS infrared cameras to acquire the color and depth images at the same time. The microphone unit consists of four microphones.

Our Depth Image method acquisition is to extract 3D data from a human body by using an open source image processing software developed in the Java language and a Kinect sensor. The method is easy to operate and only needs to export the SimpleOpenNI library. The depth map in the Kinect object is enabled in processing, and the pixels in the real spatial coordinates are drawn by using the function through the depth map. First, the depth map is stored in an integer array and the processing image is composed of a linear array of pixels. Next, the PVector that contains the X, Y, Z coordinates want to be drawn on the screen are initialized and then two loop sets to get the pixels of the depth map. First, the index associated with the X and Y coordinates in the depth map is found. If the index of the pixel point in the current depth map is not zero, the depthMapRealWorld() [index] function is returned to the 3D coordinates of the current point and is displayed with the point () function of processing[23]. The 3D data obtained with our method is shown in Fig. 3.

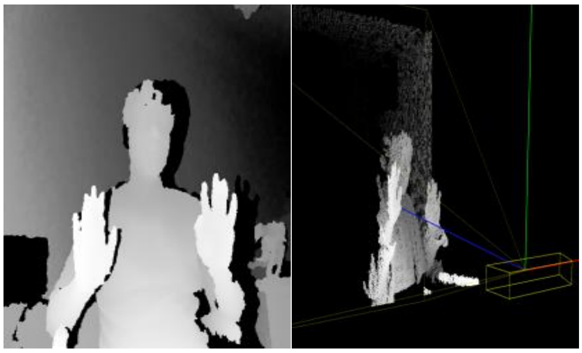


Figure 3. Point cloud image in a depth image and a real world coordinate system.

3.3 Arduino microprocessor

The Arduino microprocessor mainly consists of two parts. The hardware part is on Arduino circuit board and the other part is on Arduino IDE which is a program development environment stored in the computer. The Arduino microprocessor is an open source hardware development platform with an eight bit ATMEGA328 microprocessor as the core. The circuit diagram is shown in Fig. 4. It supports a USB data transmission. Different electronic devices are connected on the I/O port[24]. The Arduino microprocessor realizes the alarm function of the system by carrying a GSM module.

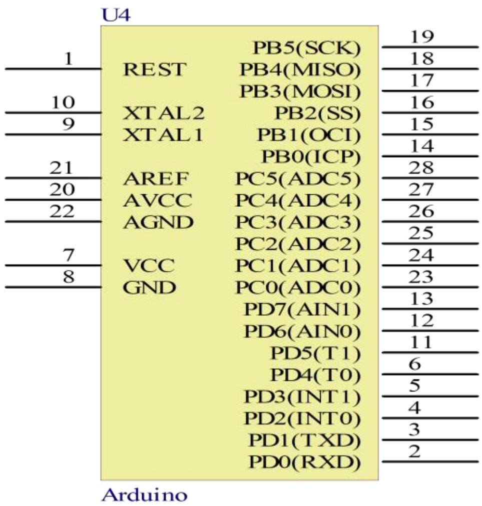


Figure 4. Arduino circuit diagram.

3.4 Back propagation neural network

The BPNN algorithm is the core algorithm of the neural network training. It optimizes the parameter values in a neural network according to the defined loss function. The loss function of the neural network model in the training data set them reaches a small value. The topology structure and generation process of the standard BPNN algorithm are shown in Fig. 5. The major steps of the BPNN algorithm are shown in Fig. 6.

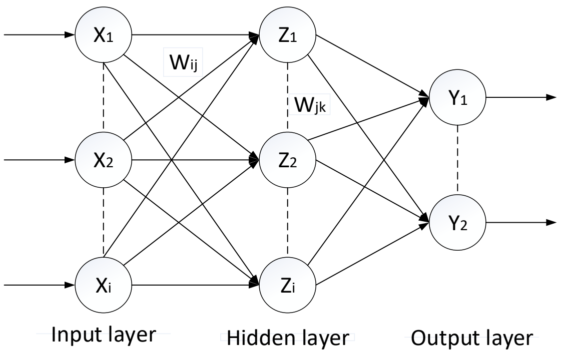


Figure 5. Three-layer neural networks.

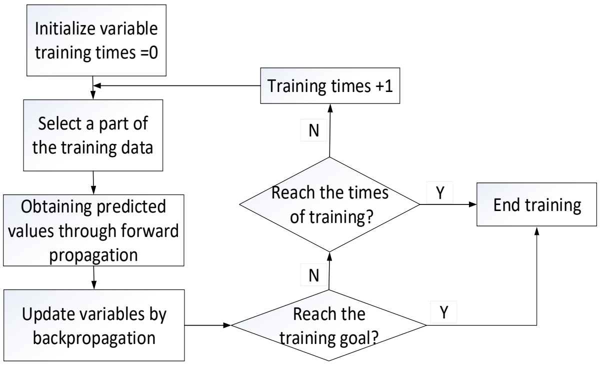


Figure 6. Optimization flow chart.

3.5 Convolutional neural network(CNN)

CNN is a kind of a feedforward artificial neural network, developed on the basis of a traditional neural network. Nowadays, CNN has been widely used in image and video recognition and has been an appropriate and effective method for many computer vision problems.

In the first few CNN layers, each node is organized into a three-dimensional matrix. Each node in the first several CNN layers is only connected with some nodes in the upper layer. Plus, CNN is comattituded of the input layer, convolutional layer, pooling layer, full-connection layer and softmax layer. The CNN recognition model designed in this paper has a total of seven layers (See Fig. 7).

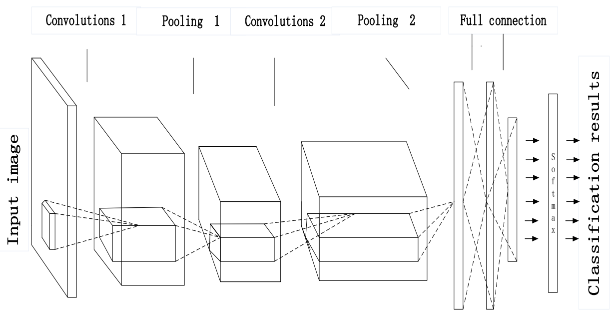
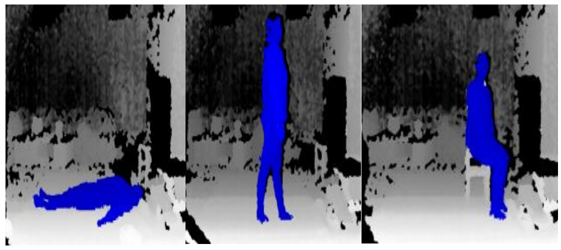


Figure 7. CNN architecture for an image classification problem.

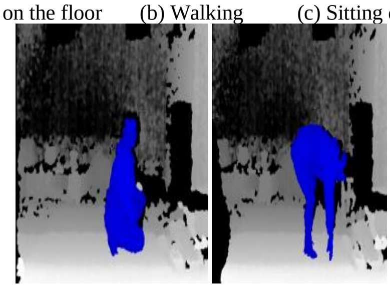
3.6 Dataset

The paper creates a dataset consisting of various activity data, such as falling, walking, picking up objects, sitting down, squatting and lying down. To get the height change acceleration and centroid height of the point cloud in various activities, it is used to train classifiers to verify whether a human has a fall behavior. Our model is trained and tested using the feature values of 240 fall activities and 360 typical ADLs.

Five hundred pictures of five attitudes of five human are observed are taken to set up an attitude training database. The five attitudes are walking, sitting, squatting, picking up things and lying down. The collected images are grouped. The lying down is divided into a sub-group and the rest of the pictures are taken as a group. The partial image effect of the point cloud image captured by the human body is shown in Fig. 8.



(a) Lying on the floor (b) Walking (c) Sitting down



(d) Squatting (e) Picking up objects from the floor

Figure 8. Human action point cloud image.

4 DESIGN AND IMPLEMENTATION OF THE SYSTEM ALGORITHM

In this section, the extraction process of the point cloud height acceleration variation and the centroid height of the human body point cloud are discussed. The BPNN and CNN designs are described, the model training and testing process is shown. Finally, the realization process of the system algorithm is demonstrated.

4.1 Extraction of features from the point cloud images

4.1.1 Human segmentation

The 3D scene data is collected and the scene images are obtained and converted into 3D point cloud images. In a continuous frame, a mixed Gaussian model of the pixel points in the point cloud images is built in the simple viewer application programming interface NITE. Each pixel in the model is regarded as an independent random variable. After modeling each random variable, each pixel in the depth image is described by the M Gaussian distribution. The threshold is set in advance and the threshold is used as a dividing point. The former P distribution in the Gaussian distribution is defined as the background model, $M-P$ distribution is defined as the foreground model and the 3D human point cloud foreground map is generated by segmentation.

A Kinect camera is used to collect the 3D data of the scene, and the scene image is obtained and converted into a 3D point cloud image. In the algorithm, each pixel of the depth reference image is assumed to be the median of several pixels in the preceding image. At the beginning, multiple images are collected for each pixel. A list of pixels is assembled from the previous image and then sorted to extract the median. The depth reference image is quickly updated by removing the previous pixels. A 3D human point cloud foreground map is generated by segmentation(See Fig. 8). The human body point cloud image is obtained by point cloud segmentation, and a function is set, subordinately to the human body point cloud image. The highest and the lowest point clouds are found. And the difference value between them is the height of the point cloud of a human body.

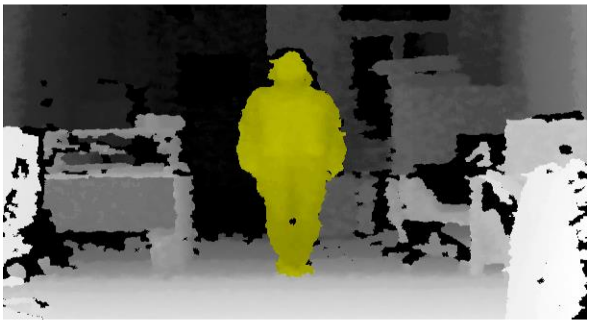
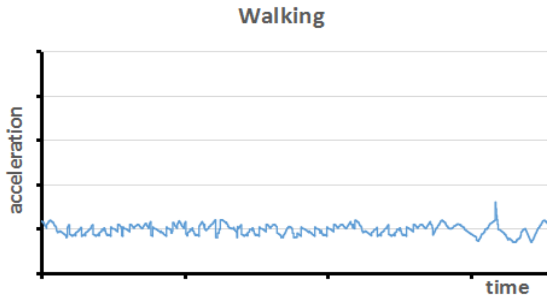


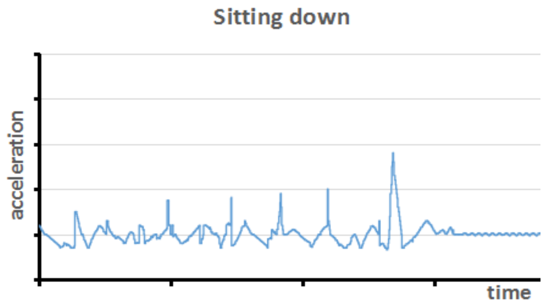
Figure 9. Point cloud image of a human body.

4.1.2 Extraction of the feature values under different actions

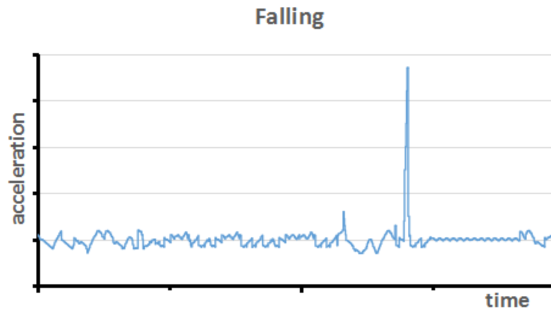
Based on the results of the extraction of the point cloud height of the human body, the real-time motion trajectory curve of the feature value is obtained under different human actions[25], such as walking, sitting down and falling (See Fig. 10).



a. Motion trajectory curve of a walking acceleration



b. Motion trajectory curve of a sitting-down acceleration



c. Motion trajectory curve of a falling acceleration

Figure 10. Motion trajectory curve of a walking, sitting-down and falling motion acceleration.

The abscissa coordinate of a curve graph is the number of frames (times) when the height of the user point cloud is obtained, while the vertical coordinate of the curve graph is the acceleration of the point cloud height. As seen from the falling curve, the acceleration increases at the time of falling. Based on this, the acceleration is selected as the feature analysis, feature extraction is made for the acceleration curves of the human point cloud under different actions.

A V-disparity is used to extract the ground-plane position and get the distance from the centroid of the 3D point cloud of a human to the ground plane. The line corresponding to the floor pixels is extracted using the Hough Transform. The plane described by $ax+by+cx+d$ is recovered. The centroid height (D) is calculated by the following equation (1):

$$D = \frac{|aX_c + bY_c + cZ_c + d|}{\sqrt{a^2 + b^2 + c^2}} \qquad (1)$$

where X_c , Y_c and Z_c are the coordinates of a human centroid. The centroid height of each activity is shown in Fig. 11.

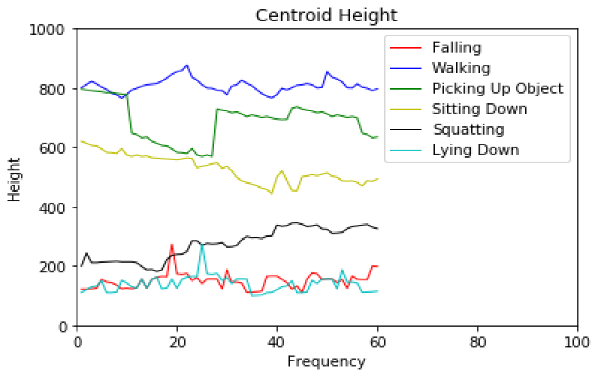


Figure 11. Centroid height of each activity.

4.2 The fall detection classifier

4.2.1 CNN design

Our CNN recognition model has seven layers. Two are convolutional layers, two are pooling layers and three are full-connection layers (See Fig. 12)[26]. Firstly, it comes to the input of the network. The CNN network learns the features of a two-dimensional image independently. The original image is a point cloud image used as a direct input of the network. The convolutional layer mainly extracts the low-level features of the image and the pooling layer reduces the amount of information processing on the premise of preserving useful information pursuant to the local correlation principle of the image. After several rounds of stacking and pool treatment, the final classification results are given by three fully-connected layers ultimately.

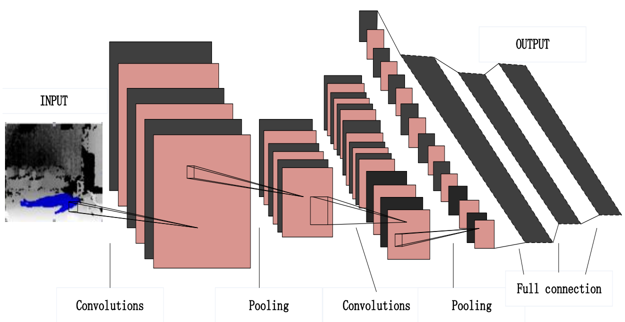


Figure 12. Convolutional neural network architecture diagram.

4.2.2 Implementation of the machine learning algorithm

The BPNN model is used to classify the activities and identify a potential fall. Conducting the dataset into the neural network models and the dataset fitting image are shown in Fig. 13. The process of training the neural networks can be divided into three steps:

1. Defining the structure of the neural network and the output result of forward propagation.
2. Defining the loss function and selecting the back-propagation optimization algorithm.
3. Generating sessions and running back the propagation optimization algorithm on the training data repeatedly.

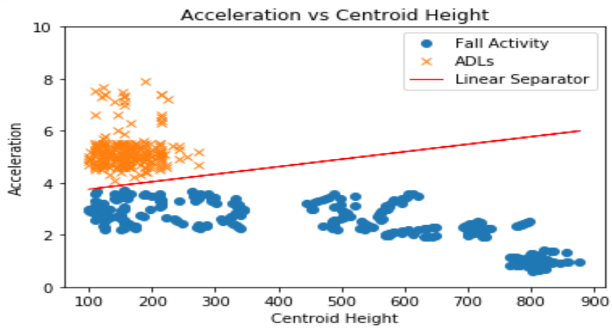


Figure 13. Dataset fitting image.

In order to evaluate the effect of the neural network model under different parameters, a part of the training data is extracted as a validation data. Fig. 14 shows the accuracy curve for every 1000 generations on different datasets. The red curve shows that as the number of generations increases, the accuracy of the model on the validation data; the blue curve demonstrates the accuracy of the test data. The more similar is the trend of the two curves, the much better will be the performance of the model. The validation data reflect the performance of the model on a test data.

To guide the dataset into a CNN model for training and testing, the network is initialized and each group of the attitude samples in the dataset is the input into the CNN network model, whereby one attitude is trained in one round. With the increase in the number of iteration rounds, the training and testing accuracy of the model is improved. The loss function value is then reduced, and it converges and tends to be stable after 600 iterations(See Fig. 15), whereby the parameter values of the network are determined.

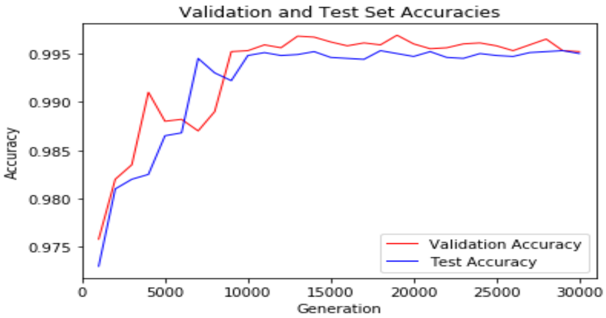
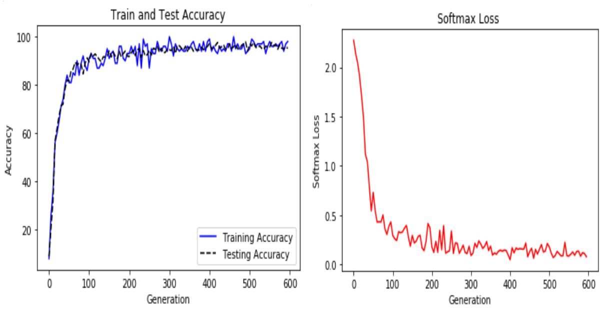


Figure 14. Accuracy of the validation dataset and test dataset on models under different generations.



(a) Train and test accuracy (b) Softmax loss

Figure 15. Accuracy and the Softmax loss function of 600 generations of a training set and test set.

4.3 System algorithm implementation

When the BPNN classifier determines that an activity is a potential fall activity, the system automatically triggers the timing device. After ten seconds, the system will extract the current scene point cloud image and imports the CNN model to judge whether the user is lying down or not. If the hypothesis is established, it is judged as a fall activity, the system will turn off the timer and sends an alarm to Arduino. The algorithm ensures the detection efficiency and avoids the false positives caused by the human ability to stand up after falling down. The flow chart of the fall detection algorithm is shown in Fig. 16.

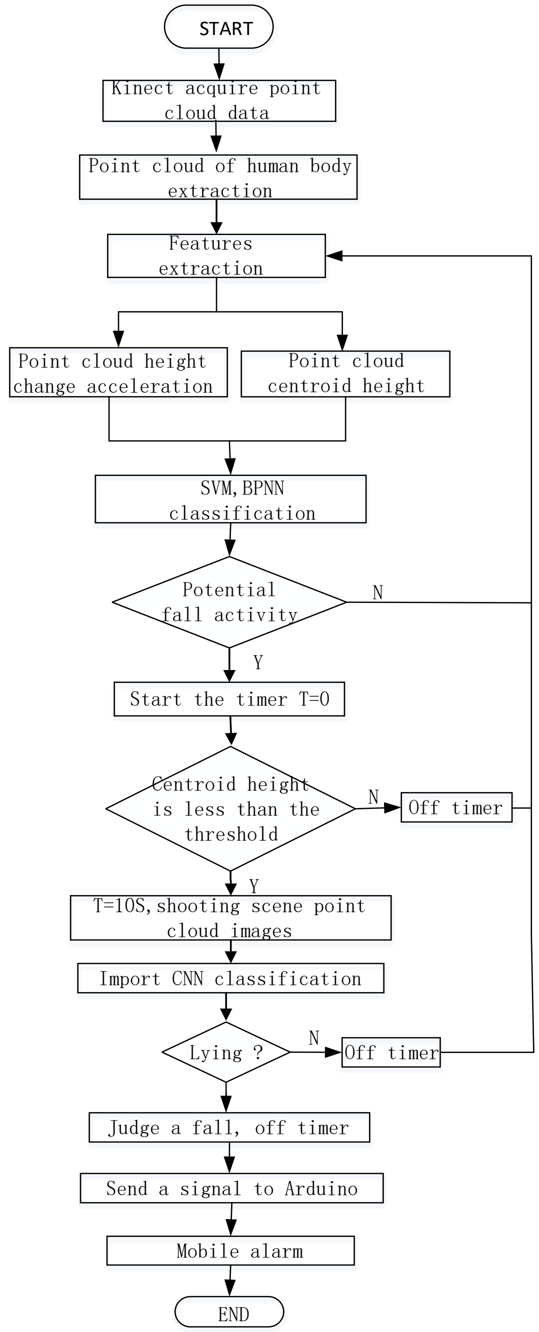


Figure 16. System algorithm flow chart.

5 Experimental result

5.1 Experimental analysis

Experimenting with the fall detection system is made in a real home environment scenario. The Kinect sensor is installed in a suitable location to cover the whole home detection environment.

The fall detection system processes is the collected information and displays results simultaneously without causing the processing speed to decrease or the performance to degrade. When a human enters the field of vision of the Kinect sensor, the system starts automatically. The system displays the collected information and processing results, and the point cloud image protects the privacy of the human as shown in Fig. 16. When the classifier identified a potential fall, the system automatically triggers the timing device. After ten seconds, the system will extract the current scene point cloud image and imports the CNN model to judge whether the user is lying down or not. If the hypothesis is established, it is judged as a fall activity and notify the guardian is modified.

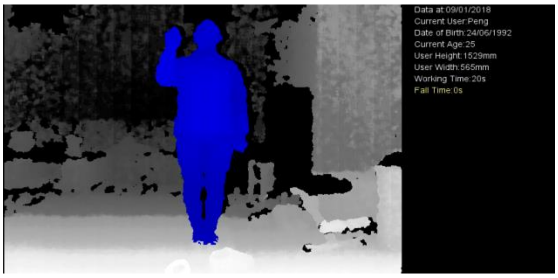


Figure 17. System running image.

5.2 Classifier evaluation

The BPNN-based classifier is evaluated and compared with a support vector machine (SVM) classifier. The classifiers are evaluated in a ten-fold cross-validation. To examine the classification performance, the sensitivity, specificity, precision and classification accuracy are calculated. Table 2 shows the classifier ability to avoid false alarms and its exactness in assuming perfect values.

Table 2. Performance of a potential fall classification

BPNN	**Fall**	**ADLs**	
Fall	238	0	Accuracy 99,7%
ADLs	2	360	Precision 100%
	Sensitivity 99.2%	Specificity 100%	
SVM			
Fall	238	0	Accuracy 99,7%
ADLs	2	360	Precision 100%
	Sensitivity 99.2%	Specificity 100%	

The recognition of the human attitude is evaluated by CNN. Four volunteers complete the attitudes such as lying or walking, squatting and other non-lying attitudes in front of the system, and the system takes the images and conducts the classification and recognition. As seen from Table 3, the CNN model achieves a high recognition accuracy.

Table 3. Accuracy of the attitude recognition

Human attitude	**Test times**	**Recognition results**	**Accuracy**
Lying	100	99	99%
No lying	200	199	99.5%

The overall functioning of the system is assessed with five volunteers doing deliberate falls or daily activities on a mat. A total of 540 experiments are conducted, including 240 falls and 300 daily activities.

5.3 Data analysis

The effectiveness of the classifiers is evaluated by testing. When a human activity is judged by a classifier as a potential fall activity, the system judges its recovery time, whereby effectively avoiding the occurrence of alerts caused by the human activity being too fast or when they are able to stand up after falling on their own. The system test data is shown in Table 4. Using only the BPNN model, 238 out of 240 fall activities are considered a potential fall activity, five out of 300 ADLs are considered the potential fall activity. The accuracy of the model is 98.7%. Using the BPNN model and assessing the recovery time, 238 out of 240 fall activities are considered a potential fall activity, one out of 300 ADLs are considered a potential fall activity. The accuracy of the model is 99.5%. Our experiment shows that adding the assessed recovery time achieves good results. The results of using only classifier algorithm are slightly worse than the results of classifier and the recovery time algorithm. The reason is that they might trigger a false alarm when a human has the ability to stand up after falling. The activity that is not considered to be a potential fall is because the volunteers subconsciously support the ground with arms or hands when simulating backward falls. In fact, the humans fall into weightlessness when they are falling, and the data characteristics to be more obvious and increases the accuracy. In the ADLs test, the volunteers are squatting or lying down too fast, which is considered a potential fall activity.

Table 4. Performance of a fall detection

BPNN only	**Fall**	**Non-fall**	
Fall	238	5	Accuracy 98,7%
Non-fall	2 Sensitivity 99.2%	295 Specificity 98.3%	
BPNN+recovery time (CNN)			
Fall	238	1	Accuracy 99,5%
ADLs	2 Sensitivity 99.2%	299 Specificity 99.7%	

Our method of the fall detection meets the real-time requirement and realizes the 24h continuous real-time detection of a human body. The detection accuracy is higher than the Kinect skeleton tracking method used in [14], and it solves the problem that the data of the human skeleton joint point is unstable and easy to be lost. Compared with the wearable sensor and the camera detection technology [1-8], the detection accuracy is definitely improved, the human comfort and detection efficiency are enhanced, and the human privacy is protected.

6 CONCLUSIONS

The paper proposes a human fall detection method. By analyzing and processing the point cloud data of a human body, the feature values such as the height change acceleration and centroid height of the point cloud are extracted from different human activities. After calculating the features and executing the BPNN classifier, a potential fall activity is verified. The features of different human attitude images are extracted and a CNN model is built to recognize the human attitude accurately and efficiently. Increasing the recovery time assessment and reducing the false alarm rate show a good market prospect.

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