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A Healthy Monitor System for Fall and Balance Detection of Elderly

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ABSTRACT: This paper presents a non wearable health monitor system for elderly fall detection and balance ability evaluation. To protect the privacy of the elderly, the system uses a Microsoft Kinect depth camera to capture the depth images and then construct the human 3D action box. Different features extracted from the 3D action box are used as input to a BP neural network classifier for fall detection. This system can monitor the daily life of the elderly. When the elderly fall, the system will alarm. Meanwhile it can detect the balance ability for the elderly to prevent them from getting senile dementia. Experiments show that the system's accuracy has reached 90% which is robust and reliable.

KEYWORDS: Fall detection; Balancing; Kinect; BP neural network.

INTRODUCTION

Aging has become a worldwide phenomenon. The healthcare expenditure for elderly is increasing every year.Homemonitoring technology has become a hot research topic since about 28–35% of people who are 65 or older are dead due to the fall reported by the World Health Organization [1]. Therefore it is importantto build a health monitor system to detectfall and balance for the elderly. The existing health monitoring systems can be broadly categorized into wearable-sensor based approach and non-wearable sensor-based approach (e.g., vision-based approach).

Wearable sensor-based systems have been used extensively for healthcare monitoring.Wearable sensor-based system can directly obtain data from the human body. Inertial measurement units (IMUs) are low-cost and low power consumption devices with many potential applications. Now it can be put on clothes or shoes [2]. Inertial tracking has become a popular method in health monitor systems [3]. In the past few years, many different approachesbased on inertial tracking has been developed to detect the fall due to its advantages of low-cost, portable, small size and ease to use.

A common fall detection method is touse acceleration signalsfrom accelerometers.When the accelerations are larger than some thresholds, the system alarms [4]. This algorithm requires high sampling rate. However the method may not distinguish between the fall and the activities of daily living (ADLs). One reason of this may be the high false rate.There are some fall-like activities throughout the daily living, use the acceleration data may not work well. Some researchers combined the accelerometer and gyroscope together to detect fall [5,6]. However some fall-like activities, such as sit down and lie down, also make the system generate false alarms. Moreover, the elderly may not want to wear the sensor or forget to wear it. [7] has pointed out that, the fall detectors may not be worn on body during sleep so that it cannot detect falls when the elderly get up from the bed.

Non-wearable sensor does not need to be worn by the elderly. There are several non-wearable systems to detect falls such as acoustic and ambience systems. They use microphones or vibration sensors to detect the loudness of the sound[8] or the floor vibration[9] to recognize falls. Another type of non-wearable system is to use the cameras. Algorithms based on cameras have been used to detect falls by using different types of vision cameras such as single CCD camera [10,11], multiple cameras [12], specialized omni-directional cameras [13] and stereo-pair cameras[14].These systems can work independently without any interference with a person's daily lift. However, they have some shortcomings. First of all, they may not work wellwith the environmental change. The lighting condition of the environment may have directly impact onmonitoring performance and they cannot work at night. Secondly, these cameras are relatively expensive. In addition, these cameras capture the RGB image, which posesprivacy issues of the elderly.

Recently, Microsoft has developed a depth camera called Kinect which can provide depth images. Since the release of Kinect, many methods have been developedto detect the falls [15,16,17]. Kinect is the first low-cost camera that

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combines a RGB camera and a depth sensor. It can track the human body in 3D so that it can offer more features of the human body. Moreover, by using the infrared light, Kinect can work in total darkness. Compare with conventionalcameras, depth images are insensitive to lighting conditions and therefore provide a new solution for developing fall detection algorithms based on depth information.

Kinect can not only capture the depth data, but also capture the skeletons of a human body. In the paper, we propose a 3D box algorithm for the fall and balance detection. According to the 20 skeletons captured by Kinect, we turn the human action into a 3D box. This 3D box can effectively track the activity region. Unlike the traditional cameras that track a personin a 2D box, our 3D box contains more action information such as depth.Different features are extracted from a 3D box such as the acceleration in three axis, the distance between the gravity center of the human body and the slope of the body. Accelerations can detecta sudden stop of ahuman motion. When a fall occurs, the 3D box changesdramaticallywhich leads to large changes inthe features extracted from the 3D box.Instead of using a simple threshold to detect falls, we use the features as input to a BP neural network classifier to detect falls.We also use the BP neural network to detect the balance ability of the elderly according to a balance standard. The standard contains two parts. One is the projects including 14 projects for the elderly. While the elderly are doing these projects, the system give them scores. Another is the Evaluation Standards. The system will give the detector some suggestions for their balance ability according to their scores, therefore, the elderly can know their balance health condition. All above, our system can not only detect the fall of the elderly effectively, but also detect the balance ability of the elderly. It can alarm when a fall occurs without invading their privacy.Experiment results show that the proposed system achievesgood detection accuracy and is of practical use.

PROPOSED METHOD

Fall detection

In our developed system, it is assumed that when the velocity suddenly slow down, human body may be hurt. Therefore, we suppose that a fall is occurred when the velocity suddenly increasedat a low distance from the ground.The lack of balance is the direct cause to falls. The walking swayamplitude can reflect the balance ability of the elderly.In our proposed algorithm, wecalculate the distance from the body center to the ground, acceleration velocity and the body's slope.

First, the human 3D box is located as shown in Figure 1.The human body is fixed to a cube and 20 skeleton points of a human body are obtained. In the Kinect coordinate system, we obtain the most left point Pl, the most right point Pr, the most top point Pt,the most bottom point Pb, the nearest point Pn, the farthest point Pf and the head point Phead. These points form a 3D projectionbox.

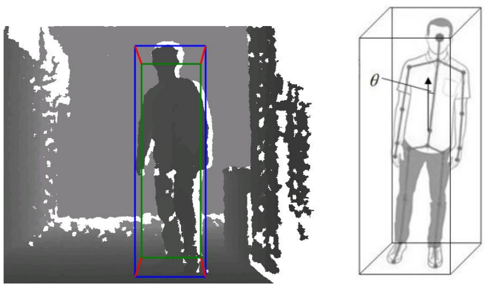

Figure 1. 3D projection box and the angle between the body and the ground.

The normal vector of the ground denote h, the vector of the head and the trunk p are calculated. At the ith frame, the length, weight, height and the distance from the ground are computed as follows:

$width_i = |Pl - \mathrm{Pr}|$, $height_i = |Pt - Pb|$, $depth_i = |Pn - Pf|$, $dis_i = |Pc - Pb|$

At theith frame, the velocity and angles are calculates as

$$V_{\mathrm{w}} = \left|\frac{width_i - width_{i-1}}{t_i - t_{i-1}}\right| \tag{1}$$

$$V_h = \left| \frac{height_i - height_{i-1}}{t_i - t_{i-1}} \right| \tag{2}$$

$$V_d = \left| \frac{depth_i - depth_{i-1}}{t_i - t_{i-1}} \right| \tag{3}$$

$$\cos < \theta >= \cos < \vec{p}, \vec{h} >= \frac{\vec{p} \cdot \vec{h}}{|\vec{p}||\vec{h}|} \tag{4}$$

It is unable to detect the balance or fall by using only the speed since the velocity can only represent the state of ahuman action. It cannot show the trend. Sometimes the velocity may be very high, but it does not necessaryindicating a fall. Therefore, we calculate the accelerationvelocity and the angle change to show the trend.

$$a_w = \left| \frac{V_{wi} - V_{wi-1}}{t_i - t_{i-1}} \right| \tag{5}$$

$$a_h = \left| \frac{V_{hi} - V_{hi-1}}{t_i - t_{i-1}} \right| \tag{6}$$

$$a_d = \left| \frac{V_{di} - V_{di-1}}{t_i - t_{i-1}} \right|, \ \Delta\cos < \theta, i >= abs(\cos < \theta, i > - \cos < \theta, i-1 >) \tag{7}$$

When a fall isoccurred, due to different fall direction, these three accelerated velocity won't have a big change at the same time. Under the condition of low dis, any big accelerated velocity's change can be presented as a fall.

The data features of the behavior recognition can be expressed as

$$D = \{a_w, a_h, a_d, dis, \Delta\cos\}.$$

Use the BP neural network to train the weights, The process is as follows:

Initialize the BP neural network, set the weights w_{ij}, v_{jt}, θ_j, γ_t within [0,1].

Calculate the input u_j and the output u_j of BP neural network hidden layer nodes:

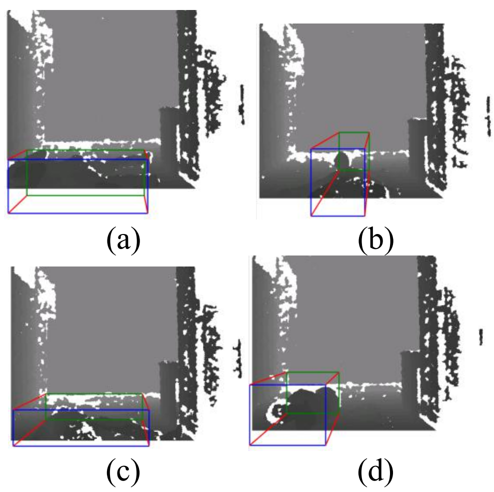

Figure 2. (a) is the parallel fall. (b) is the vertical fall. (c) (d) are fall with any angle.

$$u_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \tag{8}$$

$$h_j = f(u_j) = \frac{1}{1 + \exp(-u_j)} \tag{9}$$

Calculate the input l_t and the output y_t of BP neural network input layer:

$$l_t = \sum v_{jt} h_j - \gamma_t \tag{10}$$

$$y_t = \frac{1}{1+\exp(-l_t)} \tag{11}$$

Calculate the weight error ε_i of the output layer node t of BP neural network connection:

$$\varepsilon_i = (c_t - y_t) y_t (1 - y_t) \tag{12}$$

Calculate the weight error ε_j of the hidden layer node j:

$$\varepsilon_j = \sum_{t=1}^{q} \varepsilon_i v_{jt} h_j (1 - h_j) \tag{13}$$

Update the weight v_{jt} and γ_t :

$$w_{jt}(N+1) = w_{jt}(N) + \partial \varepsilon_j x_i \tag{14}$$

$$\theta_j(N+1) = \theta_j(N) + \beta \varepsilon_j \tag{15}$$

Calculate the error between the output and expectation. If the error meets the precision, the training end. If not, turn to step 2.

Balance detection

At present there is no unified definition of balance. Mechanics balance refers to a state in which the force is zero. In the category of medical balance refers to a body posture or a stable stateand an ability to automatically adjust and maintain posture by the external force. According to the balance standard, use BP neural network to mark, finally evaluate according to the evaluation standard.

put the walking data D of the patients with the loss of balance into the BP neural network and train. Mark according to the projects table and get the total scores of the ability of the balance and then get the result by the evaluation standards table.

Table 1. Evaluation standards.

total	Evaluation
0-20	Poor balance and need wheelchair
21-41	A certain balance ability and can be assisted to walk
41-56	Good balance ability and can walk independently

Table 2. Projects.

projects	
1、 Stand up 2、 Stand alone 3、 Sit alone 4、 Sit down 5、 Move to chair from bed 6、 Stand with eyes closed 7、 Stand with legs put together 8、 Stand and outstretch	9、 Pick up 10、 Turn around and look back 11、 Turn a circle 12、 The feet alternately step 13、 Stand with two legs before and after 14、 Stand with one leg
Scores：1/2/3/4	

EXPERIMENTAL RESULTS

Experimental data

Collect 150 sets training data including 100 sets of the normal action data and 50 sets of the fall data. The 100 normal sets contains 25 sets of normal standing, 25 sets of quick bending, 25 sets of quick get down, 25 sets of lying. At the same time , collect another same 150 sets data for testing and collect 50 sets of walking data of the patients with lack of balance.

The data is divided into some groups as the table 3.

Table 3. Data groups.

Sign	Action
C1	Normal stand and work
C2	Quick bend
C3	Quick get down
C4	Lie down
C5	fall
C6	Walk without balance

Fall detection results

Take the data set $C = \{C1, C2, C3, C4, C5\}$ as input. C1 is the data of normal walking. C2, C3, C4 are the data like to fall. C5 is the data of fall. Take C2, C3, C4 into the training set can make the system more robust and Integrity. As the figure shown that the correct rate of the normal walking can be 100%. Quick bend and quick pick up are familiar, so there will be a little wrong Classification but both of them are not classified to the fall. It is the most like for lying down to be confused with the fall class. As the results shown, the accuracy of lying can be up to 92%, so it nearly can distinguish between lying down and fall. The accuracy of the fall is 90%. The remaining 10% is divided to bending, getting down and lying because they are much familiar with the fall.

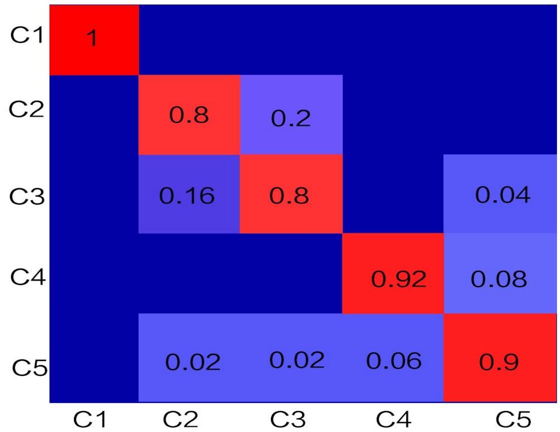

Figure 3. The accuracy rate.

Balance detection results

Take the data set $C = \{C1, \ C6\}$ as input. Because C1 set is the data of normal walking and standing and C6 set is the data of the walking patients without balance, mixing up C1 and C6 can make the system robust. As the figure shown that the normal data C1 most distribute in 41-56 and C6 most distribute in 0-20 or 21-41 which is realistic.

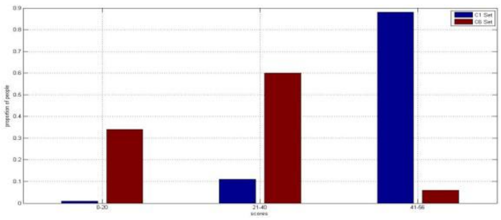

Figure 4. Balance distribution.

DISCUSSION

Stability of the feature

Between the fall and the non fall, ah, aw, ad and dis change sharply, so use these as the fall and the balance feature. Put the normal data and the fall data together, as the figure shown below, blue line denotes the normal data, red line denotes the fall data. When the fall occurs, the data changes a lot.

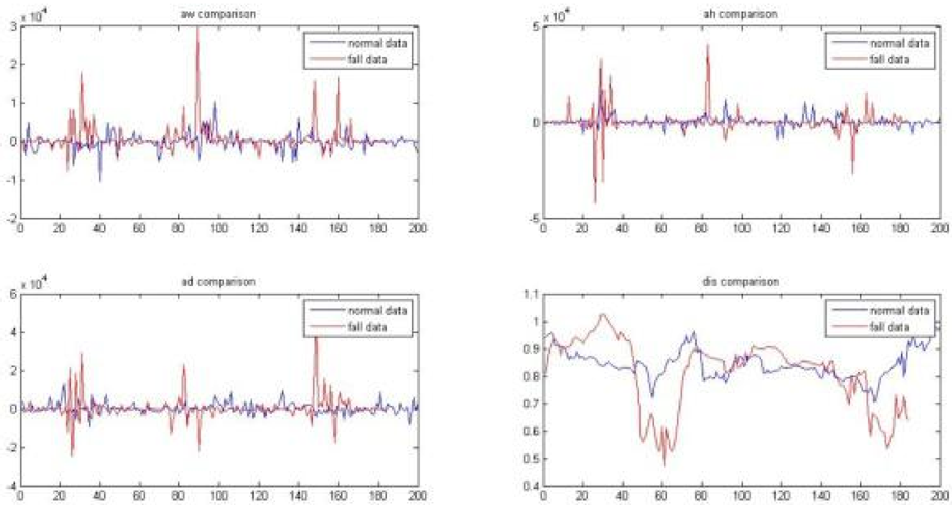

Figure 5. Comparison of each feature.

Fall-Like action

In daily life, we maybe do some action like fall, the system can distinguish between the fall and the fall-like action.

Quick Bend

Quick bending to pick up something is the common action like the fall. The confusion is that when quick bending, the velocity of getting down is very high which can cause the fault classification. In the system, when quick bending, the center of the human body does not change a lot. As the figure shown, when falling, the center of the human body changed sharply while quick bending don't.

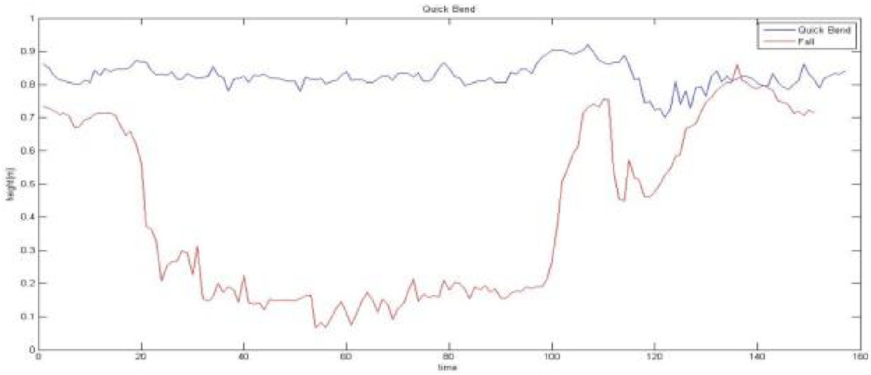

Figure 6. Comparison of quick bending and falling.

Quick get down and up

Quick get down and up is also a common action that is similar with the fall. In the system, when getting down and up, the center maybe change, but compare with the fall, the difference is obvious so that the system can make a distinction between them.

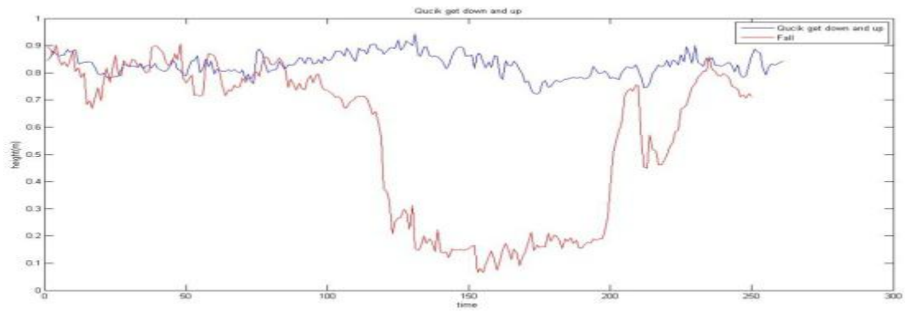

Figure 7. Comparison of quick get down up and falling.

Lie down

Lie down is the most similar with the fall. In the experiment, as the figure shown, we recorded the change of the features when lying down.

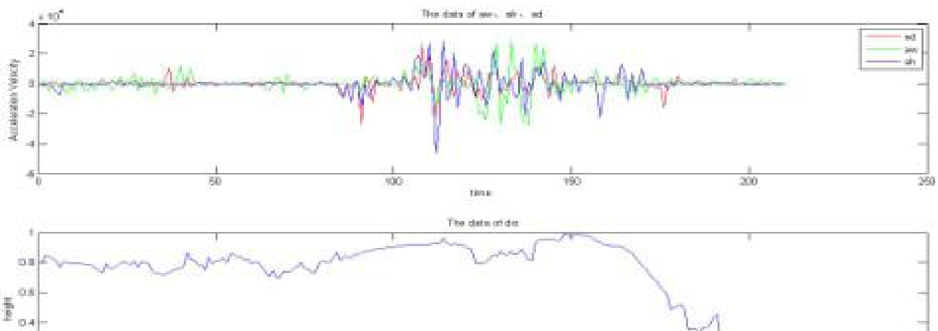

Figure 8. Comparison of lying data.

At the start of lying down, some irregular movements of the human body lead to the instable change of ah, ad, aw. While lying down, the center of the human body will be closed to the ground and the features will be stable that the system can make a great distinction.

The shade of the fall

When falling, it is easily to be shaded by something like sofa which is a difficult problem to the former solution. In the system, if the shade occurs while falling, the number of the captured skeleton points will decline, which will lead to make the 3D projection box smaller. The smaller the 3D projection box is, the more sensitive the features are.

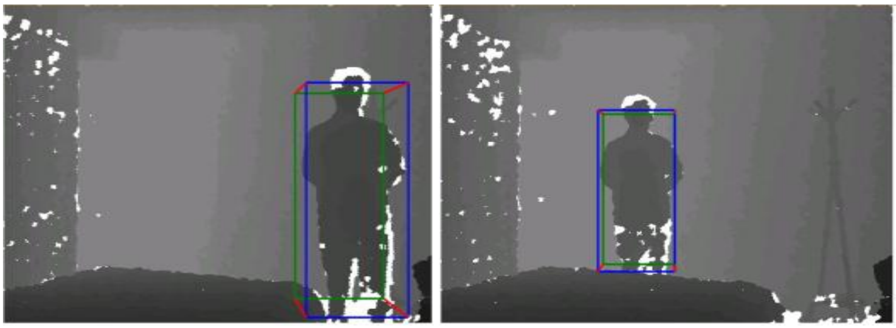

Figure 9. The shade of the human body.

CONCLUSION

This paper proposed a fall and balance detection system for the elderly. We use the Micorsoft Kinect sensor to capture the depth data and construct a 3D projection box. We extract the features from the 3D projection box and use the features as input to the BP neural network classifier.The BP neural network is used to train the weight of each feature to recognize falls. Mark the balance ability by the projects and some reasonable suggestion can be put forward according to the scores. The proposed system achieve high fall detection accuracy and is of practical use.

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