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Elders' fall detection based on biomechanical features using depth camera

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An accidental fall poses a serious threat to the health of the elderly. With the advances of technology, an increased number of surveillance systems have been installed in the elderly home to help medical staffs find the elderly at risk. Based on the study of human biomechanical equilibrium, we proposed a fall detection method based on 3D skeleton data obtained from the Microsoft Kinect. This method leverages the accelerated velocity of Center of Mass (COM) of different body segments and the skeleton data as main biomechanical features, and adopts Long Short-Term Memory networks (LSTM) for fall detection. Compared with other fall detection methods, it does not require older people to wear any other sensors and can protect the privacy of the elderly. According to the experiment to validate our method using the existing database, we found that it could efficiently detect the fall behaviors. Our method provides a feasible solution for the fall detection that can be applied at homes of the elderly.

Keywords: Fall detection; skeleton data; biomechanics equilibrium; video surveillance-oriented.

AMS Subject Classification: 22E46, 53C35, 57S20

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1. Introduction

Falls in biomechanical research can be seen as an uncontrolled imbalanced movement of the human body. The frequency of falls increases year by year with age and physical debility.[14] Vellas *et al.*[24] conducted a follow-up study of 482 elderly people who lived independently in the community for 24 months. The study showed that the accidental fall was the leading cause of accidental death in elderly people over 85 years of age, 61% of participants (53.7% of men and 65.7% of women) experienced at least one fall during a two-year study. The WHO Global Report on Falls Prevention in Older Age[27] indicated that about 28–35% of the 65-year-old fell every year, and for the 70-year-old, this number would rise to 32–42%. Fall is one of the main threats to elders' health.[20] If an application can detect a fall accurately, it can effectively reduce lay time of the fallen elders and reduce risk of injury for the elders. It will be one of the most important infrastructures for the elders' healthy living at home.

Fall is hard to detect due to its similarity with some types of normal actions, such as sitting and laying. In the early works, researchers let users wear specific sensors to detect a fall based on changes in the acceleration. Then, some researchers proposed fall detection methods based on computer vision technologies. Due to inconvenience and inaccuracy, these methods have not been widely used in reality. Kinect, a three-dimensional somatosensory vision sensor, provides a new possibility for the study of fall behavior. It can dynamically capture the motion of human body in three-dimensional space so that researchers can analyze human posture more accurately, which greatly improves the ability of human behavior analysis. In addition, differing from the traditional vision sensor, Kinect provides dynamic position information of skeleton nodes in the three dimension. Due to the use of three-dimensional skeleton data instead of original image data, it could effectively protect users' private image information while analyzing behaviors.

A loss of balance or instability possibly causes an old individual to fall ending up on the floor. Based on the theory of the biomechanical balance, an uncontrollable imbalance behavior would result in a fall while the controllable will not, like sitting or lying. The posture and the speed of body movement are the key factors to distinguish the imbalance between the controllable and the uncontrollable. We propose a fall detection method based on the change of states of human balance using the skeleton data. The main idea of this method is shown in Fig. 1. First, we build a human bionic dynamic mass model using skeleton joints data collecting from Kinect and dynamic positions of Center of Mass (COM) computed from the human mass distribution. Then, the balance state is determined by calculating the region of Base of Support (BOS) and Line of Gravity (LOG). Then, we choose the accelerated velocity of COM of five kinematic chains and skeleton data as biomechanical features. Finally, the Long Short-Term Memory networks (LSTM) is used to detect fall based on these features. We have evaluated our fall detection method on the existing database.[9] Results showed that our fall detection method based on human

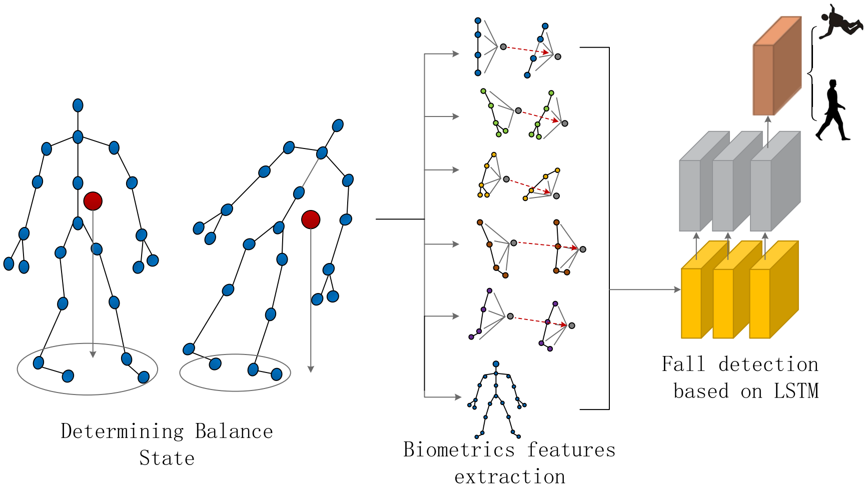

Fig. 1. An illustration of the proposed fall detection method based on 3D skeleton data.

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biomechanics equilibrium and posture recognition can detect a fall (97.41%). This method has been proved to be efficient and has three advantages: First, it is a non-contact fall detection method not requiring users to wear any equipment; Second, it detects fall only based on 3D skeleton data, the amount of which is in small size and easily transmitted; Third, since the skeleton data only contains the basic information of human behaviors, it can protect the privacy of the elders and be applied to elders' home.

The remainder of the paper is organized as follows: First, we introduce the related work on fall detection in Sec. 2. Second, the definition of balance is provided, presented with the investigation of biomechanical equilibrium of humans in Sec. 3. Following these discussions, we propose a fall detection method by studying human biomechanics equilibrium and posture recognition, including biometrics features extraction and LSTM, in Sec. 4. Experimental results and discussion are described in Sec. 5. Finally, the paper ends with a conclusion and future work on fall detection in Sec. 6.

2. Related Work

In this section, we outline the relevant research work that helps inspire this study on fall detection. At first, we start with a definition of fall.

Fall has a widely accepted definition by scholars: non-deliberate movements towards the ground or lower (except for continuous blows, loss of consciousness, paralysis, and epileptic consequences).[15] There are many researchers' attempts to separate the fall behavior from normal daily behaviors. This is a daunting task, because many normal daily behaviors, such as sitting down, lying down, are similar to fall.[14]

In recent years, with the advances of sensor technology, increased scholars explored the fall detection problems. Initially, researchers used wearable acceleration sensor to distinguish a fall from different behaviors based on change of acceleration.[5,22,32] These methods could effectively identify some kinds of fall behaviors. But it was not convenient in that it requires elders' always wearing equipment. Then many scholars detected falls using image processing technology according to different falling-ending posture features.[12,21,26] Due to limitations of two-dimensional image data, the accuracy of detection has been affected by different kinds of issues like how to distinguish between foreground and background, and how to accurately track human behavior.

The emergence of depth camera, such as Kinect, provides more opportunity to study human action. It can improve the robustness of object recognition and can offer some useful information about the relationship between humans and their environments, such as the human hitting the floor.[4] It can distinguish human actions using the trajectories of skeleton joints, which provides a good representation for describing actions.[33]

Currently, more and more researchers employ 3D human skeleton data to analyze human action. Raviteja Vemulapalli *et al.* proposed a new skeletal representation that explicitly modeled the 3D geometric relationships between various body parts using rotations and translations in 3D space to achieve skeleton-based human action recognition.[25] Chen *et al.* first extracted frame-level features from the skeletal data and built a recognition system based on the extreme learning machine.[7] Zhu *et al.* proposed an end-to-end fully connected deep LSTM network for skeleton-based action recognition.[33] Du *et al.*[8] proposed an end-to-end hierarchical RNN for skeleton-based action recognition instead of taking the whole skeleton as the input. It could handle skeleton-based action recognition very well without sophisticated pre-processing. These methods achieve the state-of-the-art performance on action recognition with high computational efficiency, however, they can just recognize normal activity and cannot detect a fall. Xu *et al.*[30] designed an intelligent elder care system based on context-aware middleware, which employed Kinect to detect fall.[29] It focused on system design, so the fall detection method was a preliminary study. Bian *et al.*[4] proposed a fall detection based on the Support Vector Machine (SVM) classifier to determine whether a fall occurred. Compared with the state-of-the-art methods, it was more accurate and robust. However, its input was depth image with the 3D trajectory of the head joint, which could not protect users' privacy.

Inspired by these works, we investigate the fall from biomechanical balance via 3D skeleton data. The recurrent neural networks with LSTM are adopted to learn biomechanical features and to detect a fall.

3. Biomechanical Principles on Balance and Stability

Based on the detailed above-mentioned analysis of the current fall detection methods, this paper proposes a fall detection method based on skeleton data by studying

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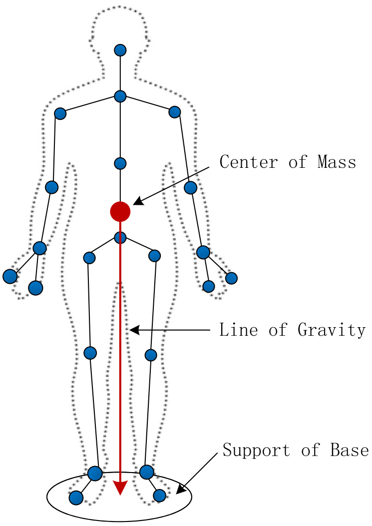

Fig. 2. The critical characters of body balance.

states of human body balance. In this section, we start from the definition of human balance.

3.1. *The definition of balance*

Body balance refers to the ability of an individual to maintain the Center of Mass (COM)'s Line of Gravity (LOG) within the body's Base of Support (BOS) region as shown in Fig. 2. A fall would occur caused by imbalance of the body. Imbalance is an important signal to fall. If imbalance of human body can be detected, the fall might be detected. The basic idea of our fall detection is to determine whether the body is balanced by relative position of LOG and BOS (most of the actions in daily life, such as standing and walking, belonging to a state of equilibrium). If the body is found to be imbalanced (the fall is an imbalance action, sitting down and lying down are also imbalanced behaviors), we will try to figure out whether the human will fall or not by LSTM.

We adopt Demspter's body segment parameters[28] and collect skeleton data from Kinect to estimate the position of COM of human body segments. Kinect is a line of motion sensing input device made by Microsoft, which can detect up to six users at the same time and compute their skeletons in 3D with 25 joints representing body junctions like the head, feet, knees, hips, shoulders, elbows, wrists. The COM of body segment can be determined based on the ratio of the proximal and distal point coordinates to the segment length. All the parameters mentioned above can be obtained from Table 1.[28]

We improve the method[31] to obtain the COM of the human body of three-dimensions from skeleton data. This improved method can be summarized in

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Table 1. Mass and coefficient of human segment.[28]

Body segment	Segment mass/ Total body mass	COM/Segment proximal	Length distal
Head and neck	0.081	1.000	N/A
Thorax and abdomen	0.355	0.500	0.500
Upper arms	0.028	0.436	0.564
Forearms	0.016	0.430	0.570
Hands	0.006	0.506	0.494
Pelvis	0.142	0.105	0.895
Thighs	0.100	0.433	0.567
Legs	0.0465	0.433	0.567
Feet	0.0145	0.500	0.500

equations by two main steps:

(1) Compute the COM of each body's segment by the following formulas:

$$x_{s\mathrm{COM}} = x_p l_p + x_d l_d, \tag{3.1}$$

$$y_{s\mathrm{COM}} = y_p l_p + y_d l_d, \tag{3.2}$$

$$z_{ss\mathrm{COM}} = z_p l_p + z_d l_d, \tag{3.3}$$

where $x_{s\mathrm{COM}}$, $y_{s\mathrm{COM}}$, $z_{s\mathrm{COM}}$ are coordinates of COM of segmental body; x_p, y_p, z_p are coordinates of proximal ends; x_d, y_d, z_d are coordinates of distal ends; and the percentage of segmental length from the proximal and distal ends are represented by l_p, l_d.

(2) Calculate COM of the whole body by the following formulas:

$$x_{\mathrm{COM}} = \frac{\sum m_i x_{s_i\mathrm{COM}}}{M} \tag{3.4}$$

$$y_{\mathrm{COM}} = \frac{\sum m_i y_{s_i\mathrm{COM}}}{M} \tag{3.5}$$

$$z_{\mathrm{COM}} = \frac{\sum m_i z_{s_i\mathrm{COM}}}{M} \tag{3.6}$$

where x_{COM}, y_{COM}, z_{COM} are coordinates of body; m_i is the mass of the ith segment; M is the whole mass of body.

3.2. *Calculating LOG and BOS*

LOG is an essential feature to determine whether the body is off balance. When LOG in BOS, the person keeps the balance. When LOG falls outside BOS, the person is considered to lose the balance.[6] Since the direction of the force of gravity through COM is downward, towards the earth, LOG can be computed by vertical projection of COM.

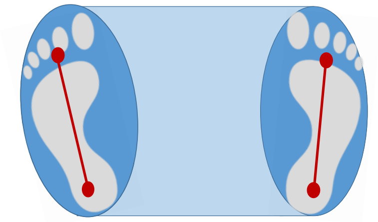

Fig. 3. Estimation for support of base.

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BOS refers to the area beneath a person that includes every point of the contact that the person makes with the supporting surface.[2] We estimate BOS according to the simulation of human feet by ellipse shape based on the skeleton as shown in Fig. 3.

We use the positional relationship to determine the state of human balance. Once human lacks balance, a LTSM model with biomechanical features is employed to detect a fall. The detail will be introduced in the next section.

4. Elders' Fall Detection Method

In the field of machine learning, fall detection can be considered as a sequential data classification problem. RNN is a new powerful method to classify sequential data. However, training has proved to be problematic. The back-propagated gradients either grow or shrink at each time step, therefore, over many time steps they typically explode or vanish.[17] LSTM is an advanced RNN architecture that can avoid these shortcomings.[11] We propose a fall detection method based on LSTM. When human body's state of imbalance occurs, it employs biomechanical balance theory and machine learning method to detect a fall based on balance features extracted from 3D skeleton data.

4.1. *Balance features extraction*

The feature selection plays an important role in the establishment of learning models. An appropriate feature selection can greatly enhance the performance of the algorithm. Every human action can be modeled in spatial and temporal aspects. Our method extracts biomechanical features from 3D skeleton data based on this idea. According to the body structure, the skeleton data of the humans can be divided into five kinematic chains: the trunk, the left arm, the right arm, the left leg and the right leg. Different kinds of actions compose the different positions of five kinematic chains. In other words, using five kinematic chains can represent different kinds of actions. Accelerated velocity is a key feature to distinguish different kinds of imbalance actions based on previous research. To trade off between robustness and computation, we choose the accelerated velocity of COM of kinematic chains as a temporal feature, which can indicate the tendency of human action. Skeleton

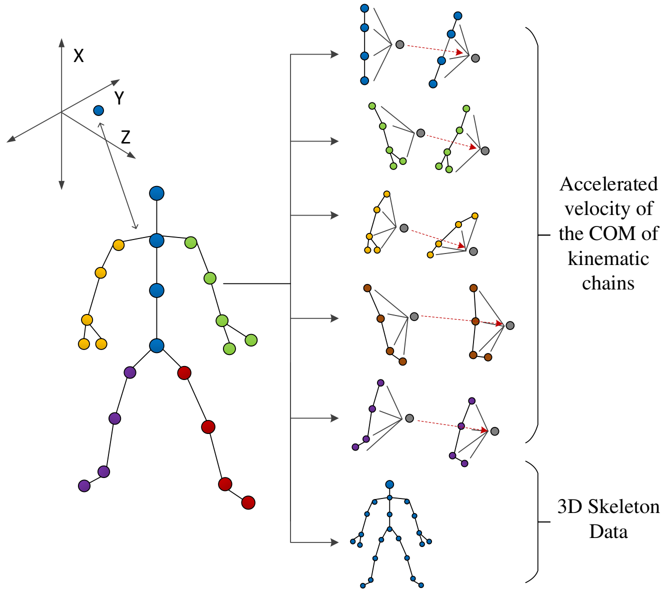

Fig. 4. Balance features from skeleton data.

data in each frame is considered as a spatial feature to model human's actions, as shown in Fig. 4. From the viewpoint of action modeling, these features extracted from 3D skeleton data sequence can represent not only the tendency of action but also the position of action.

4.2. *Fall detection-based on LSTM*

RNN is a popular model that has shown great promise for many sequential data analysis tasks. LSTM has been introduced[13] and has become a crucial ingredient in recent advances with RNN since it is good at learning long-range dependencies[17] and not affected by vanishing and exploding gradient problems. The structure of LSTM is shown in Fig. 5. It introduces a new structure called a memory cell, which

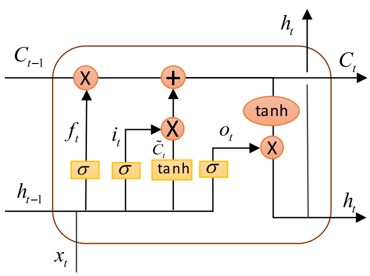

Fig. 5. The structure of LSTM in sequence.[23]

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is composed of four main elements: an input gate, a forget gate, an output gate and cell activation vectors. The gates serve to modulate interactions between the memory cell itself and its environment. The input gate allows incoming signal to alter the state of the memory cell or block it. The output gate allows the state of the memory cell to have an effect on other neurons or prevent it. The forget gate modulates the memory cell's self-recurrent connection, allowing the cell to remember or forget its previous state.[18]

The formulas 4.1 to 4.6 describe how a model of LSTM works, shown as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \tag{4.1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{4.2}$$

$$\widetilde{C_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c), \tag{4.3}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t}, \tag{4.4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \tag{4.5}$$

$$h_t = o_t * \tanh(C_t), \tag{4.6}$$

where i, j, o and C denote input gate, forget gate, output gate, and cell activation vectors respectively, and σ denotes the logistic sigmoid function.

In our fall detection method, we employ the accelerated velocity of the COM of kinematic chains and skeleton data per frame as biomechanical input features of LSTM. According to several testings, our model is composed of three layers of LSTM, which is the trade-off between enhancing the ability of modeling and avoiding overfitting. Optimizer is implemented by the RMSProp algorithm, which can keep a moving average of the squared gradient of each weight by the following formula:

$$\mathrm{MeanSquare}(w,t) = 0.9\ \mathrm{MeanSquare}(w,t-1) + 0.1\left(\frac{\partial E}{\partial w(t)}\right)^2. \tag{4.7}$$

It makes the learning work efficient and provides a good performance. When imbalance occurs, the learned LSTM model is employed to classify human's actions based on biomechanical input features.

5. Experimental Results and Analysis

We employ TST Fall detection database v2[9] to evaluate our method. In this database, Kinect is employed to record different kinds of human actions, which are grouped into two main categories: Activity of Daily Living (ADL) and the fall. The category of ADL has four types of actions: sit, grasp, walk, and lay; the category of fall has four types of actions depending on direction: front, back, side, and end-up-sit. It contains the data of 11 healthy volunteers from 22 to 39 years old with different height and weight. Every action is recorded three times from

11 health volunteers in database. Our method is built on TensorFlow. The work environment is as follows: OS: Ubuntu 16.04, CPU: Intel Xeon E3-1241v3, Graphic Card: NVIDIA Quadro K1200 4 GB, RAM: 32 G.

5.1. *Evaluation*

We adopt two kinds of different biomechanical features to evaluate our method, respectively: the first method (Method One) only adopts the skeleton data as the feature, while the second method (Method Two) uses the accelerated velocity of COM of different body segments and the skeleton data as the features. In order to obtain reliable results, we evaluate our two methods four times with different train-test runs. At each time, 216 actions belonging to nine different persons have been chosen as training set; the remain of actions, belonging to the other two persons, are the testing set. The results are shown in Fig. 6. Method Two is the fall detection method with the two biomechanical features. Its mean of accuracy achieves 97.41%, especially, it detects all the fall actions in case two. While Method One is a method with only skeleton joints data, which performs weaker than Method Two, and its mean of accuracy is 95.84%. It shows that our method achieves a good performance on fall detection. The method using spatial and temporal biomechanical features is more accurate than only using spatial biomechanical features, since the data

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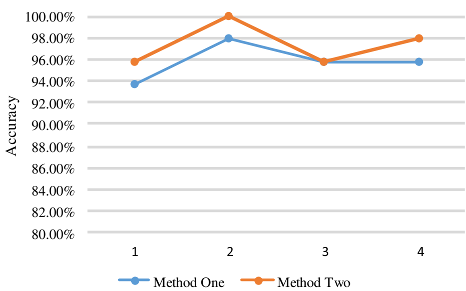
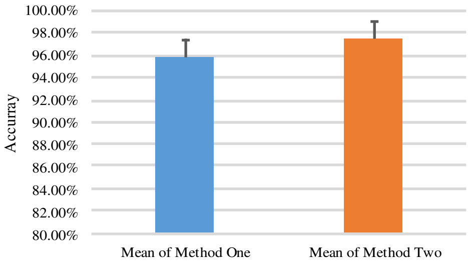


(a) Accuracy with different train-test runs



(b) Mean and standard deviation of our methods

Fig. 6. Experiment results on skeleton database.

contains more temporal information of human action. The standard deviation of these two methods are 1.47 and 1.51, indicating that our method is stable and reliable.

5.2. *Comparison and analysis*

We compare our two methods with the three methods proposed by the work[9] of Gasparrini *et al.* They used two sensors: Kinect and the accelerometer which was put on different parts of body including the wrist and the waist, and provided three algorithms based on different data sources. The first one (Algorithm One) used the variation in the skeleton joint position from Kinect and acceleration of the wrist accelerometer. The second one (Algorithm Two) used the same parameters as the first one, but it collected data from the accelerometer placed on the waist. The third one (Algorithm Three) added a parameter: the distance of the spine base joint from the floor.

According to the performance, the accuracy of our method with accelerated velocity of COM of different body segment and skeleton data is much better than Algorithm One and Algorithm Two, a little weaker than Algorithm Three, as shown in Fig. 7. It indicates that our two methods with the spatial and temporal feature from 3D skeleton data achieve good result for fall detection. Compared with them, the advantage of our methods lie in only using one sensor: Kinect to detect falls, which does not require humans to wear any other sensors on the body. It increases convenience and the possibility of practical applications.

According to the results of the study, we find an interesting phenomenon that all the faults are related to one type of fall action, that is, falling backward and end-up-sitting. It is inaccurately recognized as lying down on the mattress, sitting on a chair or walking. The largest proportion of the total errors is in that the model misidentifies it as the action of sitting on the chair, as shown in Fig. 8.

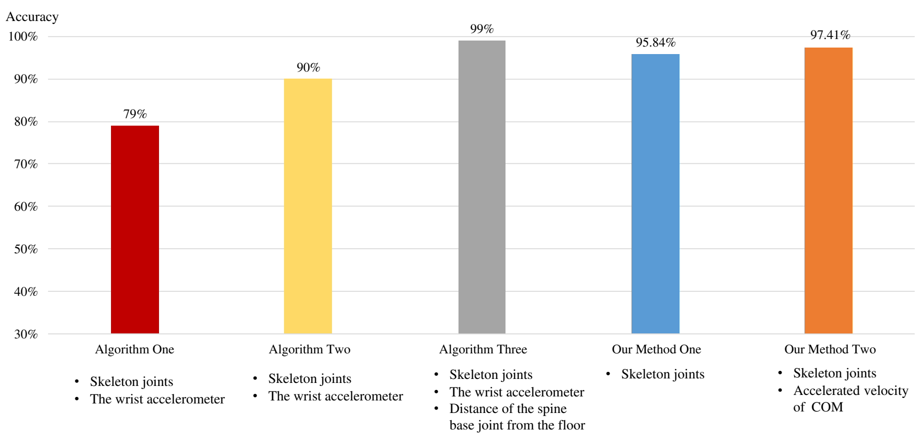


Fig. 7. Comparison of other results on skeleton database.

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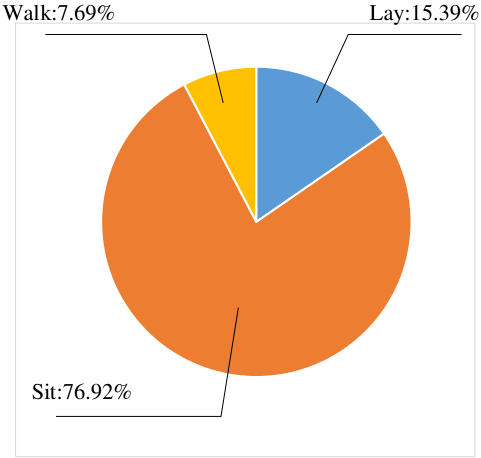
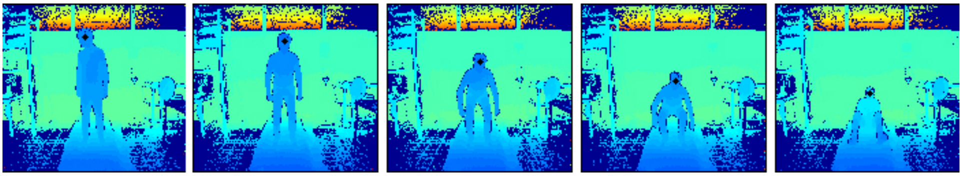


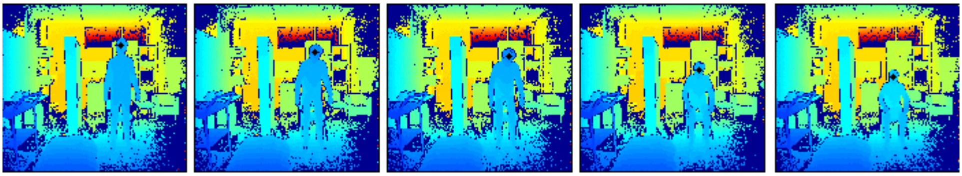
Fig. 8. Error rates of different actions related to falling backward and end-up-sitting.

We investigated original action videos. These four actions are similar, especially two actions: falling backward with end-up-sitting, as shown in Fig. 9(a) and sit on a chair, as shown in Fig. 9(b). We believe that the cause of the error is that these two actions begin with imbalance action and the ending up action is similar. Thus, our method would not work in some cases, which will be explored and improved in our future work.

To evaluate our method profoundly, we compare other methods which used Kinect to detect the fall in the indoor environment additionally, which are based



(a) Fall backward with ending up sitting



(b) Sit on a chair

Fig. 9. Two original vedio sequences for two actions.

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Table 2. Accuracy of different methods on fall detection.

References	Device	Data type	Main method	Accuracy
Bevilacqua *et al.*[3]	Kinect	Depth images	Change of 3D human bounding box	84.43%
Akagndz *et al.*[1]	Kinect	Depth images	Silhouette orientation volume	91.89%
Kepski *et al.*[16]	Kinect	Depth images, the acceleration and the angular velocity	Fuzzy inference	96.77%
Our method	Kinect, accelerometer and gyroscope	Skeleton joints data	Biomechanics equilibrium and RNN	97.41%

on different data sources (depth images) or different angles of view (top angle of view setting Kinect on the roof). Some of them[10,19] focused on the system design, which did not provide the accuracy of fall detection. We compare our method with the rest of them, as shown in Table 2, results indicate that our method employed less data (skeleton joints data) and achieved better performance in the similar experimental condition.

6. Conclusion and Future Work

In this paper, we propose a fall detection method based on 3D skeleton data that can be applied to the elders' home. Based on analyzing human's biomechanics equilibrium, our method is to determine the state of human balance at first, then to extract the spatial and temporal biomechanical features from skeleton data. Finally, the LSTM is adopted to distinguish the fall from other kinds of actions. Results of the evaluation showed good performance of fall detection. Since our method uses only skeleton data from Kinect, it does not require the elders to wear any other sensors and protects their privacy. It increases convenience and the possibility of practical applications.

In this work, we use an existing database to test our method of fall detection, which does not take into account practical problems involved in reality. And it does not have perfect performance in distinguishing falling from sitting in some cases. In the nearer future, we are going to improve the method following this direction and test it in a real environment.

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