Geometric Kinect Joints Computing for Human Fall Recognition

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Abstract

This paper proposes an computing analysis on human geometric shape features to detect a fall behavior. The system mainly computes the changes on human orientation (torso angle) and centroid height via the human skeleton joints extracted by Kinect sensor. The system computes and tracks the spatial changes of these human orientation and centroid height and distinguishs a fall behavior among other daily activities by using a thresholding algorithm. The main objective of this computation is to minize the computational time and to increase the true alarms in developing a fall detection. The system works the feature extraction on our collected fall detection dataset containing the fall data along with daily activities such as sitting down, lying, combing. Standing, etc., are collected by Microsoft Kinect sensor.

Keywords: *Fall Detection, Image Processing, Skeleton Joint Extraction, Geometric Computing, Microsoft Kinect Sensor.*

1. Introduction

It is difficult for immediately assisting and supporting medical attention to a falling victim in a very short time. Therefore, the automatic fall detection systems are essential as health care application and the most important research topic leading with the low cost and low false alarms during the recent year. There are still very few problems which elderly people are facing just because there is no one to look after.

There are many fall detection systems by using video-based technologies or wearable-based technologies like smartphones, force sensors, smart watches or tri-accelerometers. Through weareable devices, fall or other activities information of person can be analyzed. Falls were identified by using the built-in accelerometer in smartphone [1] or by embedding the force sensor in the shoes [2], or by analyzing the changes of human posture with the help of the tri-axial accelerator sensor [3]. Howere, the main disadvantage focusing on wearable sensors, the users need to wear and carry various uncomfortable devices and their fall will not be recognized if they forget to bring or weare these sensors. Although the existing technology has been reaching quite high performance of fall detection as mentioned above, there are many requirements of the users with special needs.

On the other, non-invasive alternatives for the problem of automatic fall detection is video-based systems through surveillance cameras. Video-cameras have largely been used for falls detection on the basis of various single or multiple cameras. Video cameras offer low intrusiveness and the possibility of remote verification of fall events. Analyzing human shape variances over a short period is one explore for fall detection approximating human silhouettes in a regular bounding box or an ellipse, and geometric attributes like human orientation, aspect ratio in [4] and [5]. Some detection system judged whether a fall occure by analyzing on video combining with audio in [6, 7]. However, these such methods have still low accuracy with high false alarm rate due to the proximity of shape attributes and the various human motion motions.

This approach proposes an analysis on geometric computing to detect the human falls based on video surveilliance. The system extracts and detect the target object from depth video sequence. Then, object's skeleton joints are extracted and computed torso angle and centroid height of the object. To judge whether a fall event occures against from other daily activites or similar fall activities, the system detects the changes in the human's cyclic angle and centroid height based on thresholding algorithm. The proposed system can monitor a fall everytime as well as Kinect sensor can work at nighttime. The main advantage of the proposed system is that it can distinguish a fall from other fall-like activities as well as implementing the real-time processing requirements with low false alarms and computational cost.

2. Related Work

A wide variety of fall detection applications has been carried out over a wide range of technologies and methods. Some methods of fall detection algorithm are discussed in this section.

Kuan Wen and Feng Wang reviewed some fall detection methods: surrounding environment based methods and wearable devices based methods in 2015. Rougier et al. [5] used a shape matching technique to detect falls in motion history image (MHI), human shape variations and orientation of an object's elliptical boundary without the motion of fall. In [8], it used MHI and detected the human fall based on aspect ratio and their changes. Wang also analysed the changes of human height and width ratio to detect a fall in [9]. Priys Kumar in [10] presented an identification of human fall events from using RGB-D videos and Histogram of Oriented Gradients, optical flow and shape feaures are analyzed and determined the fall by SVM-based classifier on these features. Olivieri et al. also recognized human fall and other activities by using optical flow in [11].

Rainer Planinc and Matin Kampel in [12] introduced a new fall detection technologies by the use of audio, 2D camera sensors and 3D depth Kinect sensor. Samuele Gasparrini in [13] proposed an automatic fall detection method which extracts the elements, classify all the blobs in the scene by analyzing the depth data in an *Ad-Hoc* segmentation algorithm. It used Anthropometric relationships, features and a reference depth frame to extract one interest object among other objects After detecting and tracking a person by a tracking algorithm between different frames, it detected a fall if the human blob is near to the floor.

Bogdan Kwolek in [14] presented the detection of the fall on the basis of accelerometric data, depth maps and orphological skeleton. Ziyun Cai in [15] surved RGB-D datasets using microsoft kinect or similar sensors to give a comprehensive description about the available RGB-D datasets and to guide researchers in the selection of suitable datasets for evaluating their algorithms.

3. Proposed Fall Detection Approach

The proposed fall dectection system is illustrated in Figure 1.The works in this proposed system architecture are as follows. Firstly, the system reads the depth frames to segment the moving object with the help of Adaptive Gaussian Mixture Model and detects the object with some fuzzy morphological operations. Next, system extracts human joint skeletons by the Kinect sensor image space as shown in Figure 2.

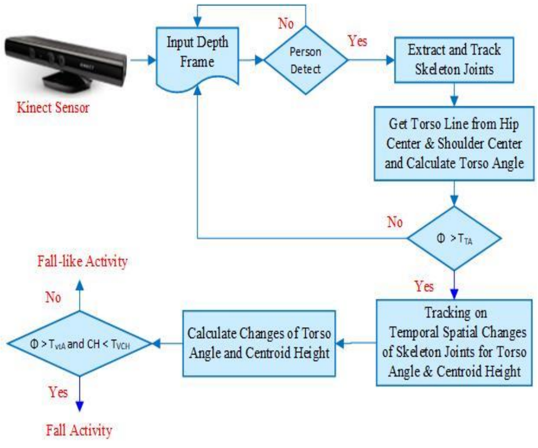

Figure 1. Proposed System Architecture

Next, the system extracts two feature values: human torso inclination (torso angle) and human centroid height. On the basis of the data acquired by geometric shape analysis, a threshold based algorithm is used to analyze the torso angle in T_{TA} to distinguish fall-like activities from others daily activites such as picking up an object, and sitting down-standing up.

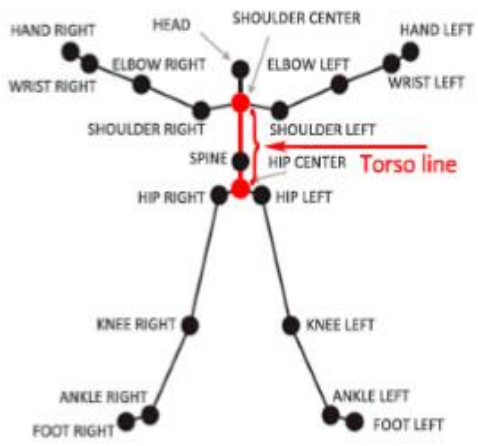

Figure 2. 3D Image Space viewed by Kinect Sensor.

Next, the algorithm further tracks the angle and centroid height, and judges whether a fall occur by analyzing on T_{VTA} and T_{VCH} via the identified lowest threshold reached all the falls from recorded data falls. To do algorithm, the all data during falls are recorded and choose the lowest threshold that catches all the falls. Detail processes are described in the next sections.

3.1. Human Segmentation and Detection

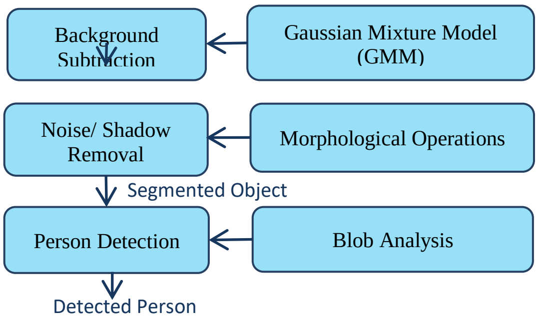

Figure 3. Pre-processing Steps of the System.

In the first pre processing step of the system as shown in Figure 3, we remove background pixels from depth image by Kinect sensor based on the Adaptive Gaussian Mixture Model. Then, we remove noise or shadow, the false detected objects, and fill the gaps in the object by morphological and regionprops Matlab methods. And then, we lable the object by detecting the objects by using blob analysis.

3.2. Torso Angle and Centroid Height Computing

To analyze whether a person falls or not, this system used the twenty skeleton joints of a person in 3D depth map supported by Kinect Sensor as shown in Figure 4. The computation of the torso angle $\emptyset$ and centroid height will help detecting the fall among its similar daily acitvities as shown in Figure 5.

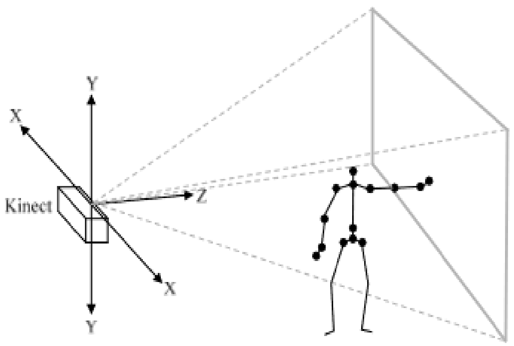

Figure 4. Twenty Human-Skeleton Joints extracted by means of Kinect.

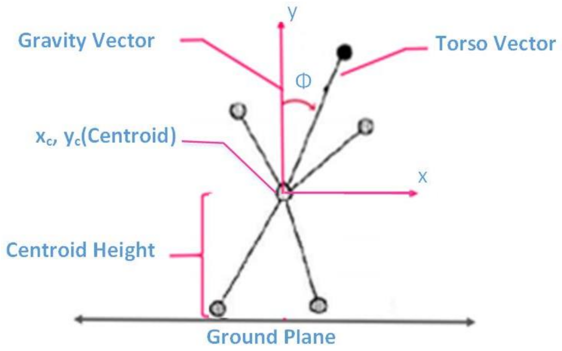

Figure 5. The Torso Angle and Centroid Height Configuration Model.

To obtain this angle, a vector line between the shoulder center joint, SC (X_{sc}, Y_{sc}, Z_{sc}) and the hip center joint, HC (X_{hc}, Y_{hc}, Z_{hc}) is marked in red and used as a torso line by calculating as follow:

$$\overrightarrow{TSO} = (X_{hc} - X_{sc}, Y_{hc} - Y_{sc}, Z_{hc} - Z_{sc}) \quad (1)$$

where, $\overrightarrow{TSO}$ is the torso vector line. $SC(X_{sc}, Y_{sc}, Z_{sc})$ is the shoulder center skeleton joint coordinate, and $HC(X_{hc}, Y_{hc}, Z_{hc})$ is the hip center skeleton joint coordinate.

Next, the system computes the body inclination between the torso line and the gravity y-axis line from the hip joint (GL) based on the cosine law as follow by equation (2) or (3):

$$\cos(\emptyset) = cos\left(\overrightarrow{TSO}, \overrightarrow{GL}\right) \quad (2)$$

$$\cos(\emptyset) = \frac{Y_{hc} - Y_{sc}}{\sqrt{(X_{sc} - X_{hc})^2 + (Y_{sc} - Y_{hc})^2 + (Z_{sc} - Z_{hc})^2}} \quad (3)$$

where, $\emptyset$ is the torso angle between the torso vector and the gravity vector.

Next, to estimate the centroid height (CH), the distance from the human centric point to the ground, the system uses the ground points (A, B, C, D) provided by Kinect is given by:

$$A_x + B_y + C_z + D = 0 \quad (4)$$

where, A_x, B_y, C_z, and are the of ground plane in 3D coordinates, and D is the distance between the plane and the sensor.

And the hip center joint is also used. Next, the centroid height (CH) of the person from the ground is calculated by:

$$CH = \frac{|AX_{hc} + BY_{hc} + CZ_{hc} + D|}{\sqrt{A^2 + B^2 + C^2}} \quad (5)$$

where, CH is the human centroid height from gravity line, and are hip-center joint coordinates from gravity unit.

When the system can estimate the ground plane due to the too high of Kinect, the centroid height can be computed by using one foot joint as follow:

$$CH = \sqrt{(X_{hc} - X_{rf})^2 + (Y_{hc} - Y_{rf})^2 + (Z_{hc} - Z_{rf})^2} \quad (6)$$

where, $RF(X_{rf}, Y_{rf}, Z_{rf})$ is the right foot skeleton joint coordinate.

3.3. Threshold-based Fall Detection

In our threshold-based fall detection system, there are three threshold values. The first one is T_{TA} to distinguish between fall and fall like activities, and other daily activities. The rest ones are T_{VTA} and T_{VCH} for the temporal variance rates of torso angle and centroid height in maximum respectively. The system firstly detect whether the current torso angle exceed the threshold T_{TA} and if it exceed, the system further detect the temporal changes of T_{VTA} and T_{VCH}. When T_{VTA} exceed its maximum threshold and T_{VCH} is less than its maximum threshold, the system will recognize the event as a fall and will alert a ring for emergency to assist a fallen person.

4. Data Collection for Fall Detection

Kinect is a hand-free motion sensor to control by using both body movements and spoken instructions or only each one. It has a range of 0.4m to 4 m and can capture the RGB frame, depth frame and skeleton joints of a body in 30 frames per second with beautiful 1080p video. In our data collection, fall and ADL events are collected with Microsoft Kinect cameras at our lab. This dataset contains 70 (30 falls along with 40 activities of daily living like picking up an object, and sitting down-standing up, lying, etc.) sequences.

5. Experimental Results

Firstly, we mounted the Kinect sensor on a table with the height of about 0.8128m and the system detected the background by the Kinect sensor in Figure 6.

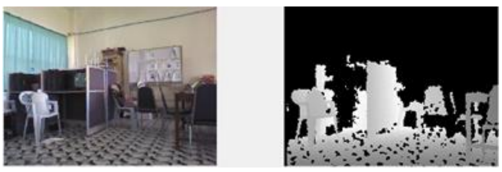

Figure 6: Background Detection by Kinect Sensor.

Next, the proposed system collected RGB-Depth and extracted their temporal joint locations in vector to calculate the temporal torso angle over hip-center and shoulder-cneter joints, and the temporal centroid height of the human from gravity line. Therefore, the system continued to configure the human torso vector and computed the torso angle and centroid height parameters. Then, the system determines whether a fall has happened based on these geometric computing using the threshold based algorithm. The human detection and geometric skeletons tracking are shown in Figure 7.

Left Fall ($\emptyset = 59°, CH = 0.1016m$)

Right Fall ($\emptyset = 57°, CH = 0.1014m$)

Forward Fall ($\emptyset = 27°, CH = 0.635m$)

Backward Fall ($\emptyset = 55°, CH = 0.0762m$)

Figure 7. Sample Humman Skeleton Joints Extraction and Tracking .

Next, we lined out the torso vector for calculating the torso angle of detected object to apply in further detecting a fall event. Sample configuration results of torso angle and centroid height of a falling person with their cooresponding geometric absolute magnitudes as shown in Figure 8.

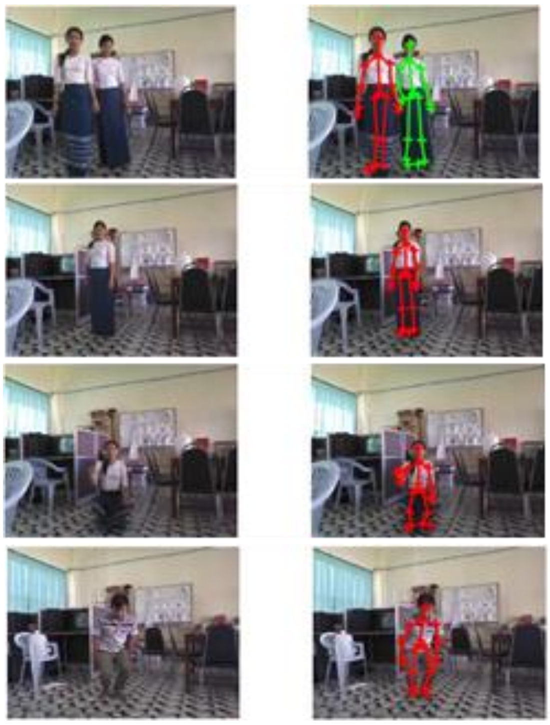

Figure 8. Torso Angle Configuration with Geometric Computation for Four Fall Activities.

In our experimentation, we used a Microsoft Kinect infrared sensor, so the system can also work in more effectively at night time. Unlike other systems, this system is not based on the computation of only on the inclination of the whole body, the big changes of aspect ratio as the big variance conditions of target and camera, the big prediction time of machine learning systems. Moreover, this calculated only the changing rates of the torso angle and centroid height unless difficult and complex ground plane finding. Therefore, the propsed system can reduce the confusion between a fall and other fall-like behaviours in more high computational effeicency.

6. Conclusion and Future Work

Fall detection are essential assistive model in order to prevent fear of falling. We extract spatial depth skeleton data to develop a reliable fall detection system in video approach. Our proposed system can be applied for the elderly, disabled or children to alert and assist a medical attention to their fall accidence in time and place with high computing efficiency and low false alarms. Currently, we experienced this work collected fall detection dataset using the temporal changes of human torso angle and centroid height. In future, we will develop a more robust fall detection system using more parameters: human motion monuments and fall prevention system by surveying the fall issues: human physical behavior or environmental condiions. our more simulated falls and ADL, position of a detector, sampling frequency, temporal length of signal, extracted features, etc.

References

[1] V. Vo quang, L. Gueesang, and C. deokjai, "Fall Detection Based on Movement and Smart Phone Technology, pp. 1-4, 2012.

[2] L. Tong, W. Chen, et al, A research on automatic Human Fall Detection Method Based on Wearable Inertial Force Information Acquisition System," pp. 949-953, 2009.

[3] P. Sagado, and P. Afonso, "Fall Body Detection Algorithm Based on Tri-accelerometer Sensors," pp. 355-358, 2013.

[4] V. Vishwakarma, C.Mandal, and S.Sural, "Automatic detection of human fall in video," in *Proc. Int. Conf. Pattern Recogn, Mach, Intell., 2007, pp. 616-623.*

[5] C. Rougier, J. Meunier, A. St-Amaud, and J. Rousseau, "Fall detection from human shape and motion history using video surveillance," in *Proc. 21st Int. Conf. Adv. Inf. Netw. Apl. Workshops*, 2007, vol. 2, pp. 875-880.

[6] B. Ugur Toreyin, Yigithan Dedeoglu, A. Enis Cetin, " HMM Based Faling Person Detection Using Both Audio and Video", Computer Cision in Human-Computer Interaction Lecture Notes in Computer Science N. sebe, M. Lew and T. Huand eds., pp 211-220: Springer Berlin Heidelberg, 2005.

[7] X. Zhuang, J. Huand, G. Potamanos, M. Hasegawa-Johnson, "Acoustic Fall Detection using Gausssian Mixture Models and GMM super Vectors", In Proceedings of the IEEE International Conference on Acoustics, Speech and Singnal Processing, Taipei, Taiwan, 19-24 April 2009.

[8] Xin Ma, Haibo Wang, "Depth-Based Human Fall Detection via Shape Features and Improved Extreme Learning Machine," *IEEE, Journal of Biomedical and Health Informatics*, vol. 18, no. 6, November, 2014.

[9] Chih-Yan Lin, Shang-Ming Wang, "Vision Based Fall Detection through Shape Feature," *IEEE Second International Conference on Multimedia Big Data*, 2016.

[10] Durga Priya Kumar, "Identificaton of human fall events from using RGB-D videos, *Dpet. Of Signals and Systems, 2015.*

[11] D.N. Olivieri, I. Mez Conde, X. Vila sobrino, "Eigenspae-Based Fall Detection and Activity Recognition From Motion Templates and Machine Learning," *Expert syst. Appl. 2012, 39, 5935-5945.*

[12] Rainer Planinc, Martin Kampel, “Introducing the Use of Depth Data for Fall Detection,” *European Union under grant AAL 2010-3-020*.

[13] Samuele Gasparrini, “A Depth-Based Fall Detection System Using a Kinect ® Sensor”, Sensors 2014, 14, 2756-2775; doi:10.3390/s140202756.

[14] Bogdan Kwolek and Michal Kepski, “Human fall detection on embedded platform using depth maps and wireless accelerometer”.

[15] Ziyun Cai, Jungong Han, Li Liu, Ling Shao RGB-D datasets using microsoft kinect or similar sensors: a survey, *Multimedia Tools and Applications*,February 2017, Volume 76, Issue 3, pp 4313–4355.