Classification of Human Fall from Activities of Daily Life using Joint Measurements

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***Abstract*—Falls are a major health concern to most of communities with aging population. There are different approaches used in developing fall detection system such as some sort of wearable, non-wearable ambient sensor and vision based systems. This paper proposes a fall detection system using Kinect for Windows to generate depth stream which is used to classify human fall from other activities of daily life. From the experimental results our system was able to achieve an average accuracy of 94.43% with a sensitivity of 94.44% and specificity of 68.18%. The results also showed that brutally sitting on floor has a higher acceleration, which is very close to the acceleration shown by fall. Even then the system was able to achieve a high accuracy in determining brutal movements with the use of joint positions, this is an indication that further improvements to the algorithm can make the system more robust.**

***Index Terms*— Depth Image; Depth Sensor; Fall Detection.**

I. INTRODUCTION

Human fall detection systems are the most frequent research being carried out in the field of assistive technology, because fall is the main obstacle for elderly people to live independently. More over statistics [1, 2] has also shown that falls are the main reasons of injury related deaths for seniors aged 79. Fall detection systems such as wearable based devices, non-wearable sensors (ambient sensors) and vision based devices use various approaches to distinguish human fall from other Activities of Daily Life.

Most of the previous researches conducted on fall detection is based on some sort of wearing devices such as belts, embedded sensors on garments etc. The recent trend is now going towards non-wearable devices due to the difficulty of wearing devices and its high false alarm ratio. Due to these reasons, fall detection systems based on vision or depth images are in high demand. One of the sensors that generate depth images and which can track human skeleton is Kinect for windows. This paper proposes a vision based fall detection system, which uses Kinect sensor to capture depth image.

II. RELATED WORK

In recent years, vision based fall detection approaches are more popular. Vision based sensors [3, 4] for human detection and identification are important sensors among the researchers as they tend to base their fall detection on non-wearable devices [5]. Among the vision based sensors, those that generate depth images are more accurate in human shape and movement identification. Since this paper focuses on the use of the depth information to recognize fall, we will review only a set of selected papers that had based their fall detection on depth sensors.

Kepski and Kwolek used a Kinect sensor as a ceiling mounted depth camera for capturing the depth images [6]. They used k-NN classifier to separate lying pose from normal daily activities and applies distance between head to floor to identify fall. In order to distinguish between intentional lying postures and accidental fall they also used motion between static postures.

Combination of a wearable wireless accelerometer and a depth sensor based fall detection were conducted in [7, 8] which used distance between the person center of gravity and floor to confirm fall. The authentication of fall after potential fall indication from the accelerometer is accomplished from a Kinect sensor depth images.

Yang et al proposed a robust method based on Spatio temporal context (STC) tracking of depth images from a Kinect sensor. In the pre-processing, the parameters of the single Gauss Model (SGM) are estimated and the coefficients of the floor plane are extracted. Foreground coefficient of ellipses is used to determine the head position and STC algorithm is used to track head position. The distance from head to floor plane is calculated in every following frame and a fall indicated if an adaptive threshold is reached [9].

Bian et al presented a method for fall detection based on two features: distance between human skeleton joints and the floor, and the joint velocity. A fall is detected if the distance between the joints and the floor is close. Then the velocity of the joint hitting the floor is used to distinguish the event from a fall accident or a sitting/lying down on the floor [5].

A fall detection and reporting system using Microsoft Kinect sensor presented in [10], uses two algorithms. The first uses only a single frame to determine a fall and the second uses time series data to distinguish between fall and slow lying down on the floor. For these algorithms they use the joint position and the joint velocities. The reporting can be sent as emails or text messages and can include pictures during & after the fall.

Gasparrini et al proposed an automatic, privacy-preserving, fall detection method for indoor that uses Microsoft Kinect sensor on ceiling configuration. Ad-Hoc segmentation algorithm is used recognize the elements captured in the depth scene. Then blobs in the scene are classified and anthropometric relationships and features are exploited to recognize one or more human subjects among the blobs. Once a person is detected, he is followed by a tracking algorithm and a fall is detected if the blob associated to a person is near to the floor [11].

In another work a mobile robot system is introduced, which follows a person and detects when the person has fallen using a Kinect sensor. They used the distance between the body joints and the floor plane to detect fall [12].

Rougier et al presented a method for fall detection that uses human centroid height relative to the ground and body velocity. They have also dealt with occlusions, which was a weakness of previous works and claimed to have a really good fall detection results with an overall success rate of 98.7% [13].

III. METHODOLOGY

A. *Overview of the system*

The proposed system setup uses Kinect for windows (v1 sensor) for capturing depth images at a frame rate of 30 frames per second (FPS), with Microsoft SDK v1.7. The methodology applied in this system uses, the floor plane equation and the joint coordinates from the skeleton data generated by the Kinect runtime. These data are then used to compute the velocity & acceleration of the body, the distance between the head to floor plane and the position of the other joints to identify an unintentional fall movement from other activities of daily life.

B. *Floor plane and human detection*

As discussed this system uses Kinect for capturing depth images. It has three types of sensors: a standard RGB camera, an IR camera and a microphone array. The depth images are generated from the IR sensor stream, which can work both day and night.

The Kinect sensor used here, can detect 3D location of 21 joints for two people in 'default' mode (10 joints in 'seated' mode) using Kinect SDK. This capability to track the skeleton image of one or two people within the Kinect's field of view is processed by the Kinect Runtime from the generated depth images.

The detected skeleton joints data are stored as (x, y, z) coordinates, which is expressed in meters. In this coordinate system, the positive y-axis extends vertical upwards from the depth sensor, the positive x-axis extends to the left placing the Kinect sensor on a surface level and the positive z-axis extending in the direction in which the Kinect is pointed. The z value gives the distance of the object to the sensor (objects close to sensor will have a small depth value and object far away will have larger depth value). Using these joint coordinate data, the movement of any joint, velocity and acceleration can be computed along with the direction respective to the previous joint position.

The floor plane provided by the Kinect is used for the calculation of distance between the joints and the floor. The skeleton frame generated from depth image also contains floor-clipping-plane vector, which has the coefficients of an estimated floor-plane equation as shown below. This clipping plane was used for removing the background and segmenting players.

$$Ax + By + Cz + D = 0 \tag{1}$$

where:

A = vFloorClipPlane.x
B = vFloorClipPlane.y
C = vFloorClipPlane.z
D = vFloorClipPlane.w

The equation is normalized such that D is the height of the camera from the floor in meters. Using this equation we can detect the floor plane or even stair plane at the same time. To calculate the distance between any joint and the floor, the joint coordinates and floor plane equation can be applied to the following equation.

$$D\text{ (distance - joint to floor)} = \frac{|\mathbf{Ax+By+Cz+D}|}{\sqrt{\mathbf{A^2+B^2+C^2}}}) \tag{2}$$

where: x, y, z are the coordinates of the joint.

C. *Fall detection algorithm*

For fall detection, we use the distance between head to floor, which was calculated using the formula shown in previous section and the velocity of joints together with the acceleration of head joint coordinates. We also use the position of the joints for fall confirmation.

Fall detection in the proposed system is accomplished in two stages. In stage one, the system will be sensing for any abnormal change in the velocity or acceleration of head joint coordinates or its distance to floor. If the system senses any abnormal change it will go to stage two, where the direction of the change of velocity that led to the increased acceleration will be identified and the change of the head coordinates. A positive indication from any data will trigger an alarm called "a Potential fall movement detected". At the same time the system, will now check the position of the joints, especially the head, hip center and shoulder center to confirm that the subject is on the floor. If the subject remains on the floor without any movement for 5 seconds a fall alarm will be generated. The following section will discuss on the acceleration calculation and the fall detection flow.

The flow graph for fall detection starts with the calculation of the velocity and acceleration from the generated skeleton of the detected person in the view of the sensor. If the calculated velocity or acceleration is not high enough to generate a "potential fall activity", then it will check the distance between head to floor. If either of them is high, it will proceed to fall detection process. At the beginning of this process the microphone array of the Kinect will be activated to listen to any voice from the detected person. Then the system will compute the position of the skeleton joints to identify the location of the person. If the position of the joints are close to the floor, the fall alarm will be generated, else it will display the joint coordinates and starts the process all over for the next frames as shown in Figure 1.

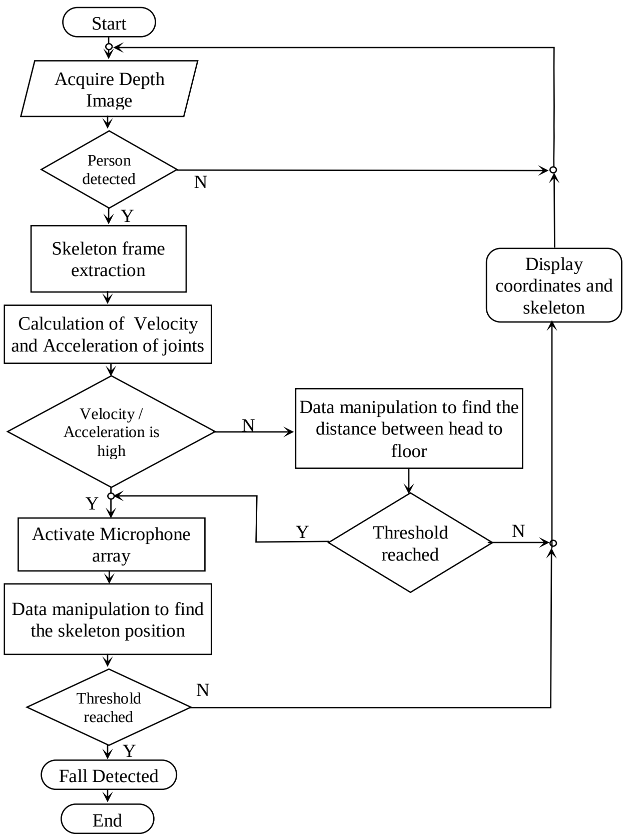

Figure 1: Flowchart for proposed fall detection

D. Velocity and Acceleration

For velocity calculation, joint coordinates are extracted after every 5 frames. The difference of current frame and previous frame is divided by the change of time (0.1667 seconds) as shown in equation in 3, to compute the magnitude part for the velocity of right, left, up, down, coming close to sensor and going far to sensor movement. Since these movements are just straight on to any of the axis as shown in Figure 2, therefore the subtraction of current location from previous location will give the distance.

$$\text{Velocity (V)} = \frac{\mathbf{D_c - D_p}}{\mathbf{t_c - t_p}} \text{ Meter/second} \tag{3}$$

where: Dc is the Current Distance (current joint coordinate), Dp is the Previous Distance (previous joint coordinate), tc is the current time in second and tp is the previous time in second.

The velocity for the other movements, the required distances are calculated using the formula shown in equation 4, according to the description in right side of Figure 2. Here we use the simple trigonometry formula: square of hypotenuse is equal to square of opposite plus the square of adjacent. Opposite and adjacent is calculated by using the current and the previous coordinates of x-axis and y-axis respectively. Once the distance is calculated the equation in 3, is used to find the velocity.

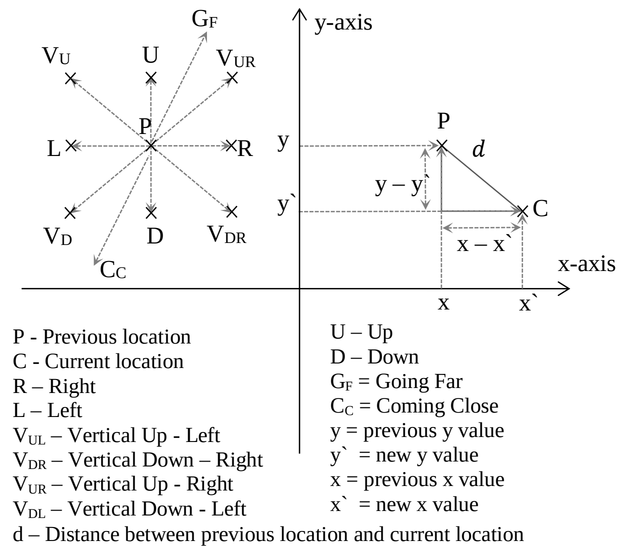

Figure 2: Coordinate system and velocity calculation description

$$\boldsymbol{d} = \sqrt{(\boldsymbol{y} - \boldsymbol{y}`)^{2} + (\boldsymbol{x} - \boldsymbol{x}`)^{2}} \tag{4}$$

The direction is obtained using the coordinate system of the Kinect. As per the coordinate system shown in Figure 2, any movement to the right or top or going far (to any axis) gives a positive value for the distance difference. Similarly any movement to left or down or coming close gives a negative value for the distance difference. Using this concept, the direction is determined to all the movements shown in left side of Figure 2. From the calculated velocity, acceleration can also be derived using the below equation (5). Acceleration calculation are sometimes important because for some activities where the distance changes are similar, acceleration shows the difference more clearly than velocity.

$$\text{Acceleration (a)} = \frac{\boldsymbol{V_c - V_p}}{\boldsymbol{t_c - t_p}} \text{ Meter/second square} \tag{5}$$

where: V_c is the Current Velocity, V_p is the Previous Velocity, t_c is the current time in second and t_p is the previous time in second.

IV. Results And Discussion

Our methods have been tested on simulated falls and some normal daily activities indoor. The activities that have been tested are walking, running, sitting on chair, standing from chair, falling, standing after a fall and bending etc. Figure 3, shows screenshot of some of the activities performed

The following Figure 4 and Figure 5 shows the distance between the head center to floor and changes in velocity & acceleration for some of the daily activities. The section ‘a’ in Figure 4, shows the fluctuation of distance from head to floor while standing in front of the sensor. Similarly the ‘b’ part represents the changes to the same distance for walking across the camera. Likewise the parts from ‘c’ until ‘l’ shows the distances changes for the activities such as sitting down, stand from sitting, falling, standing up from falling, bending down, falling from chair and stand from falling on chair. Figure 5 shows the velocity and acceleration changes for the activities mentioned in left part of the same figure.

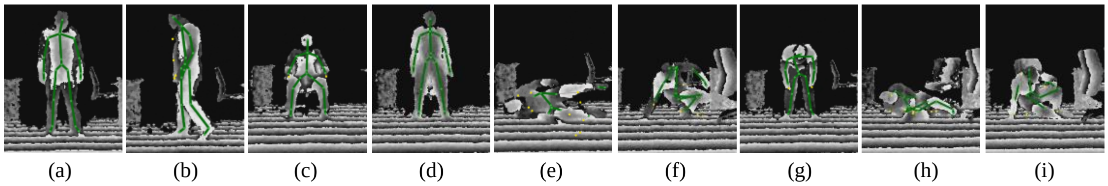

Figure 3 Screenshot of activities performed in depth images (a) Standing; (b) Walking; (c) Sitting down; (d) Standing up; (e) falling; (f) Standing up; (g) bending down; (h) falling from sitting on chair; (i) stand from falling on chair

[a] Standing
[b] Walking
[c] Sitting on Floor
[d] Stand up
[e] Fall from standing
[f] Stand up
[g] Bend down and stand up
[h] Sitting on Chair
[i] Fall from chair
[j] Stand up
[k] Walking around
[l] Vertical fall and stand up

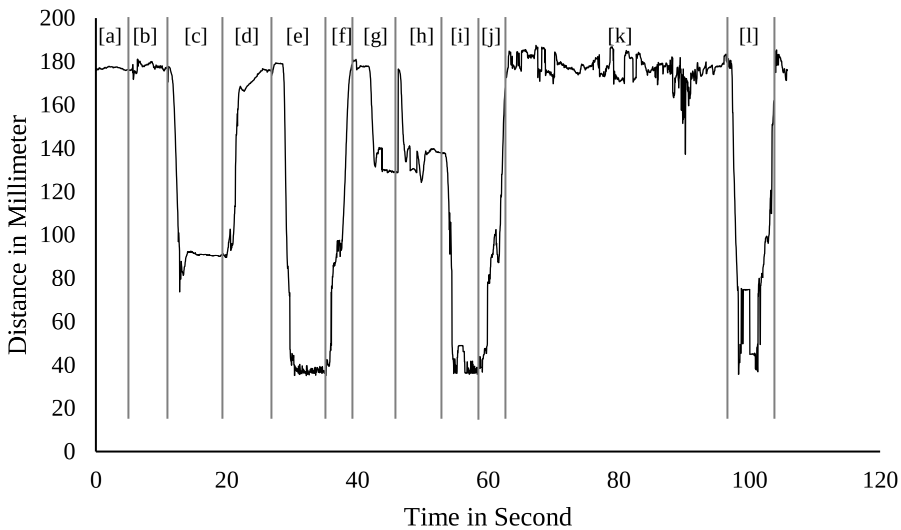

Figure 4 Distance from head center to floor

W - Walking
R - Running
S_f - Sit on floor
S_{up} – Stand up
F - Fall
B - Bend
S_c – Sit on Chair
F_c – Fall from chair

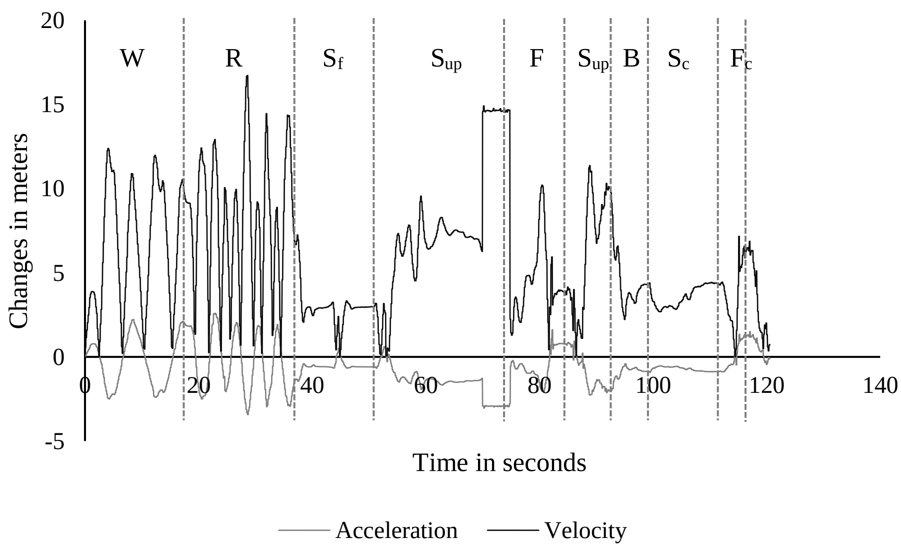

Figure 5 Velocity and Acceleration of the activities

V. CONCLUSION

In this paper we were able to propose a human fall detection system using depth images generated by the Kinect infrared sensor. The experimental results show that the algorithm used on the system can accurately distinguish fall movements from other daily activities with an average accuracy of 94.43%. It also showed that the distance from head to floor calculation was more accurate in distinguishing the activities than the acceleration of the joints alone. With the combination of joint position, acceleration of head and distance from head to floor, the system can more accurately distinguish a fall from other daily activities. The system was also very accurate in identifying brutal movements with the use of joint position; this is an indication that the further improvements to the algorithm can make the system more robust.

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