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Human Fall Detection Based on Motion Tracking and Shape Aspect Ratio

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Abstract

Automatic human fall detection based on video monitoring plays an important role in protecting vulnerable people especially the seniors whose falls could cause severe injuries and need attentions from others immediately. In this paper, an automatic human fall detection method based on human motion tracking and shape aspect ratio in real-time video is proposed. While most existing methods detect falls in homes, the proposed method is suitable for both outdoor and indoor environments. The method first detects human objects in general environment, then tracks their motions, meanwhile calculating and recording the motion characteristics of each person. Comparing with the existing fall detection method using shape aspect ratio, the proposed method has advantages of employing the shape aspect ratio together with the moving speed and direction to better detect human falls, as well as being able to detect falls toward different directions. Experiment results demonstrate that the proposed method can effectively detect human falls in general environments including outdoor places.

***Keywords**: Human fall detection, Video surveillance, Motion tracking, Shape aspect ratio, Real-time*

1. Introduction

With the extensive deployment of video camera, video surveillance technology has been widely used to ensure safety in public locations such as banks, railway stations, airports, schools, and numerous other business places. The traditional passive video surveillance method which involves lots of human efforts to do analysis after the event as an assisting tool to check video for evidence has lots of shortcomings and becomes the bottleneck of automatic video surveillance. Automatic and intelligent video analysis and recognition has been becoming a tendency in recent years because of its advantages of detecting abnormal events and abnormal human behaviors in real-time which can help avoid further damages. Automatic human fall detection based on video monitoring, as an example of abnormal behavior detection, plays an important role in protecting vulnerable people whose falls could cause severe injuries and need attentions from others and measures to be taken immediately. Especially in the rapidly aging population nowadays, seniors' falls in nursing houses, at home, and in public places, sometimes means a matter of life and death, and may request medical care rescue promptly. Falls are the second leading cause of unintentional-injury death for people of all ages and the leading cause of death for elders 79 years and older. Studies have shown that the medical outcome of a fall is largely dependent upon the response and rescue time [1].

There are several kinds of methods currently available for detecting human falls. Fall detection methods can be roughly classified into three major categories: methods based on wearable sensors to monitor body movements, methods based on sensors to monitor

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environment changes, and methods based on video to detect changes of body pose and movements status. Some of them used human shape information for fall detection [2-6].

The following are some methods based on wearable sensors. Angular rate sensors were employed to distinguish fall activities from normal activities [7]. The authors also researched on pre-impact fall detection using sensors [8]. Literature [9] used an asynchronous temporal contrast vision sensor to detect falls at home. Falls were also detected using location sensors and accelerometers [10-12], some of which worked together with a wireless network [13-14]. These wearable sensors methods require users to wear equipments which might be either inconvenient or intrusive. The reliability of sensors has not been completed solved.

The methods based on sensors to monitor environment changes mainly use technologies to detect floor vibration caused by human falls [1, 15-16]. Floor vibration based detectors could be a promising solution but they depend upon the floor dynamics and are still in their infancy. Apparently this type of method might be impacted by other factors which could cause floor vibrations.

To alleviate the above issues, many researches have been conducted on video based fall detection methods. The video based fall detection methods don't need to wear or install any equipment. Apparently this kind of methods is an economical solution to monitor many people in the same time and more suitable for monitoring falls in general public environments.

The following video based methods used human shape for fall detection. A fall detection method based on 3D head tracking using a single calibrated camera was proposed [2]. The head was represented as a 3D ellipsoid, which was tracked with a hierarchical particle filter based on color histograms and shape information. A fall detection method based on analyzing human shape deformation during a video sequence was proposed [3]. A shape matching technique was used to track the person's silhouette along the video sequence. Falls in home environment were detected from normal activities using a Gaussian mixture model. The fall detection method aiming at detecting fall incidents in unobserved home situations in literature [4] used two fixed, uncalibrated, perpendicular cameras. The literature [5] proposed to fit an ellipse on the foreground object, using a ceiling-placed, wide-angle camera. The motion-history image and the standard deviations of the angle and aspect ratio of the ellipse were used to check large motion and detect in home environment. The disadvantage is that fast sitting down can be seen also as a fall, and slow falls can even be missed. Aspect ratio of human shape was used to detect falls in literature [6]. However, falling toward different directions were not discussed, and other conditions of falling such as speed changes were not considered either.

The following are more fall detection methods based on video to detect changes of body pose and movements status. A fall detection method for vulnerable people in home used a particle filter to track the silhouette in the scene and discriminated the person posture to detect falls [17]. A method was proposed for monitoring falls in a home surveillance scenario by using the best-fit approximated ellipse around the human body, projection histograms of the segmented silhouette and temporal changes of head position [18]. The author also studied the human fall detection based on combination of integrated time motion images and eigenspace technique [19]. Both methods were developed for home environment and did not research on the enclosing ellipse for different fall directions. The fall detection method in [20] extracted human objects from omni-camera images, then used human shape only to detect falls. A fall detection method was proposed using a Hierarchical Hidden Markov Model (HHMM) whose first layer states were related to the orientation of the tracked person [21]. Elementary motion patterns were generated by a sequence of states representing human 3D pose. A fall detection method based on depth image analysis was proposed [22], which is different from the conventional methods. Literature [23] presented a method using silhouettes from multiple cameras to build a three-dimensional approximation of the human, *i.e.* voxel person, and extracted features from the voxel person along with fuzzy inference to determine the state of the resident. The method involved complicated computation and the assistance from nurse gerontology experts in the design of the rules for fall detection.

Most fall detection research discussed above focused on fall detection for home environment. However, fall detection for outdoor public places is the same important as for indoor places. Fall detection in outdoor environment is more general and more complicated because the background is complex and dynamically changing frequently, such as flickering screens and meadow, the change of illumination from day to night. The method proposed in this paper handles fall detection in both indoor and outdoor environment.

The human shape information and aspect ratio were already used in several previous work for fall detection as reviewed in the above [2-6]. Comparing with the existing work, the proposed method in this paper has the following advantages. It employs the shape aspect ratio together with the moving speed and direction to better detect human falls. It also handles the detections of falling toward different directions.

In this paper, an automatic human fall detection method based on human motion track and shape aspect ratio in real-time video is proposed. The method is designed to be suitable for both outdoor and indoor environments. The human object detection algorithm in this paper is capable of handling dynamically changing background while the human tracking algorithm is efficient for tracking non-rigid objects and capable of handling partial occlusions.

This paper is organized as follows. The overview of the proposed method as well as the human object detection and motion tracking are discussed in Section 2. Section 3 presents human fall detection based on shape aspect ratio in details. Experiment results and discussions are described in Section 4. Finally, conclusions are drawn in Section 5.

2. The Proposed Method

2.1. Overview of the Fall Detection Method

The human fall detection method proposed in this paper is based on the motion tracking of persons and shape aspect ratio in real video monitoring. The method detects people appearing in the video scene, then tracks the motion of the persons, in the meanwhile collects the motion characteristics and shape changes of the persons and does the analysis whether a human fall happens. The method is suitable for both outdoor and indoor environments.

Figure 1 depicts the overview of the proposed fall detection method. The method captures video and detect human falls in real-time. First the foreground of each video frame is detected using a fast and efficient foreground detection algorithm, followed by the human object segmentation from the background. Then an object tracking algorithm based on mean shift iterations is employed to find the most probable target position in the current video frame and track the detected human object. The algorithm is quite suitable for human fall detection in the real-time video monitoring because it is fast, efficient for tracking non-rigid objects and capable of handling partial occlusions. Each human object detected above is tracked while the motion characteristics of each person including the moving trajectory of the centroid of the persons, the moving speed history, the rectangles enclosing the human shapes, are calculated and recorded. These characteristics provide important information for analyzing the feature of human motion and performing further judgment and detection of human falls. The proposed method employs the shape aspect ratio which will be discussed in details later together with the moving speed and direction to detect human falls.

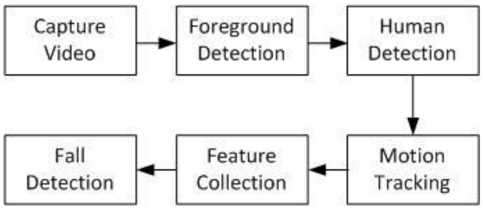


Figure 1. The Proposed Human Fall Detection Method Based on Motion Tracking and Shape Aspect Ratio

2.2. Human Object Detection

The major roles involved in human fall detection are human beings in a video scene. Human fall is a special movement of a person whose centroid of his/her body falls toward the ground. Therefore, the fall detection method first needs to detect the moving objects from video sequences. Only persons moving around will be selected for fall detection. A person who stands still or even already falls and stays still in the ground is not detected by the method. In other words, the method proposed in the paper only detects actively moving persons and judges whether their movements meet the conditions of human falls.

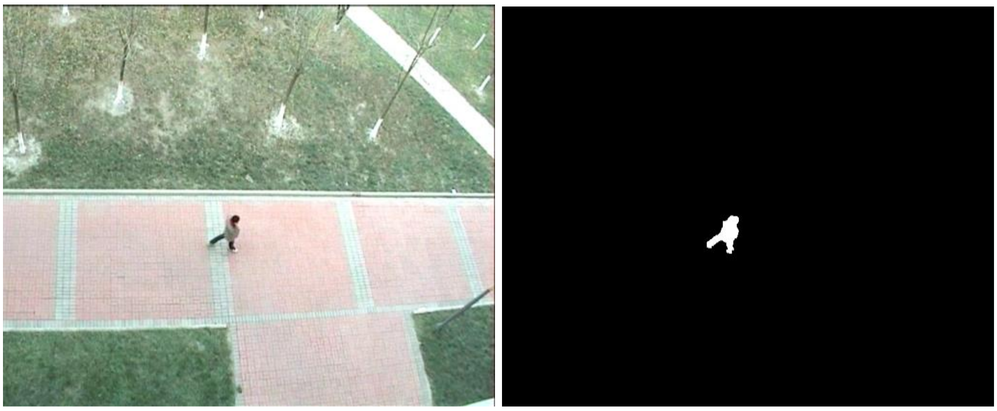
The algorithm of human object detection in the method is designed according to the above considerations. It detects the foreground of a video and then segments the foreground images as human objects. The human object detection algorithm is based on the algorithm in literature [24] with some improvements. The algorithm contains four major steps: background difference detection, difference classification, foreground object extraction, and reference background image updating.

The foreground object detection algorithm uses a Bayes decision rule to classify background and foreground from selected feature vectors. Under this rule, different types of background objects will be classified from foreground objects by choosing a proper feature vector. The stationary background object is described by the color feature, and the moving background object is represented by the color co-occurrence feature. Foreground objects are extracted by fusing the classification results from both stationary and moving pixels. [24]

For the general purpose of video processing, the background is usually considered as the scene without the presence of objects of interest, such as human objects or moving vehicles. Background is usually composed of non-living objects that remain passively in the scene. However, in the video scene for detecting human falls, it is a general environment and contains both stationary and moving background objects and undergoes both gradual and sudden “once-off” changes. The stationary background objects can be walls, doors, floors and furniture in an indoor scene, as well as buildings, road, meadow, trees and ground surfaces in an outdoor scene. Many factors introduced by the moving background objects make background complex and dynamically changing frequently, such as wavering tree branches, flickering screens and meadow, the change of illumination from day to night, shadows of moving objects, vehicles entering the video scene and stopping. A reference background image that represents the most recent appearance of the background is maintained to adapt to various changes in background through the video to make the background difference accurate. Through this learning strategy the algorithm can successfully detect and segment foreground objects from video sequences.

After the foreground objects are segmented, these human being candidates are further judged whether they are moving persons. The judgment is done using the size of the objects. The size of human being in a video scene should be within a threshold. Small objects in the detection caused by some environment changes are removed successfully. Objects much larger then a person are removed as well.

The algorithm can efficiently detect human objects in a general environment in experiments. As an example, Figure 2 shows a video frame and the corresponding human object detected by the algorithm. While the person walked from left to right in the video scene, he was detected correctly in the whole walk process. Only the person was recognized as a human object while those small foreground objects caused by complex meadow background were ruled out.



(a) (b)

Figure 2. Human Object Detection (a) A Video Frame (b) A Human Object Detected Using Foreground Detection

2.3. Motion Tracking

After the human objects are detected through foreground detection and size judgment, they are tracked to both further confirm whether they are persons of our interests and to collect movement features including the moving trajectory, the moving speed history and the rectangles enclosing the human shapes.

The object tracking algorithm in this paper is based on the algorithm in literature [25], using the mean shift iterations to find the most probable target position in the current video frame. The dissimilarity between the target model (its color distribution) and the target candidate is expressed by a metric derived from the Bhattacharyya coefficient. The algorithm is quite suitable for human fall detection in the real-time video monitoring because it is fast, efficient for tracking non-rigid objects and capable of handling partial occlusions.

In the initial video frame, first a rectangle window is defined for the area of the target object to be tracked. Then the mean shift method is used in the color space to separate the target object from the background. The search for the new target location in the current frame starts at the estimated location of the target in the previous frame. The Bhattacharyya coefficient is used as a similarity measure for color distributions of the target. When the object moves, the algorithm calculates and estimates the most probable location of the target in the current frame through maximizing the Bhattacharyya coefficient which is equivalent to minimizing the distance between two color distributions of the target in the current and previous frames [25].

The Bhattacharyya coefficient is define in the following formula (1) where $p(x)$ and $q(x)$ are the relative density functions for the discrete location and the target model, respectively.

$$\rho = \int \sqrt{p(x)q(x)}dx \tag{1}$$

Using the mean shift algorithm discussed above, a human object is tracked through continuous tracking of the most probable location from the previous frame to the current frame when the person walks. The method of human fall detection in this paper successfully tracked human objects in experiments. Figure 3 is an example of human object tracking result when a person walked from left to right in a video scene. In a video frame shown in Figure 3, the green rectangle is the target human object recognized by the object detection algorithm discussed above. The blue line records the walking path of the body centroid when the person walk from the left to right.

Figure 3. Human Motion Tracking

3. Fall Detection

3.1. Shape Aspect Ratio and Fall Detection Criteria

In the human shape detection and motion tracking discussed above, a human is detected and enclosed in a rectangle. In other words, the video image inside the enclosing rectangle is a human. When a person falls, apparently the shape of the rectangle changes correspondingly. However, even when a person moves normally instead of falling, the shape of the rectangle changes as well because of the moves of parts of the human body such as hands and legs. Telling the difference between the normal movement and fall will depend on shape aspect ratio to be defined in the following.

The height of the rectangle divided by the width of the rectangle is defined as the shape aspect ratio of a human. When a person falls, apparently the shape aspect ratio changes substantially, which is quite different from the small aspect ratio change in the normal walk.

When a person falls, the speed of a person decreases as well. In some cases, a falling person even stays still for a while.

To summarize, a human falling is detected if the following conditions are met.

(1) $f > F_H$, or $f < F_L$

(2) $dV < V_0$

Where f is the shape aspect ratio of a human, F_H and F_L are the high threshold and low threshold of the shape aspect ratio, respectively. Variable dV stands for the speed change, and V_0 is the speed change threshold.

When a person falls, the centroid of his body moves toward the ground. A human may fall toward different directions. If the centroid of a person moves toward a direction when falling, then that direction is called the falling direction. The falling toward the four major falling directions of a video scene, *i.e*. Upward, Downward, Leftward and Rightward as shown in Figure 4, will be discussed first.

In the following in this section, a video example of a person walking from left to right is used for fall detection. For this case, falling rightward is also called as falling forward because the right direction of the video scene is the same as the walking direction. For the similar reason, falling leftward is also called as falling backward.

More falling directions and falling examples will be discussed later in the paper.

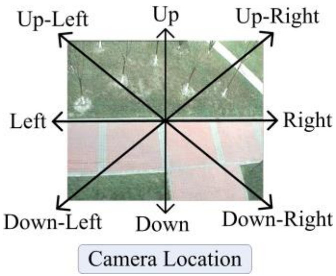


Figure 4. Direction Definition in a Video Scene

Figure 5 demonstrates that the shape aspect ratio of a person changed when a person fell backward. In Figure 5(a) a person walked normally. In Figure 5(b) the person fell backward. From the Figure 5, apparently the shape aspect ratio of the person decreased substantially because the height of the human shape rectangle decreased while the width of the human shape rectangle increased. The method proposed in this paper successfully detected the person falling backward in Figure 5.

(a) (b)

Figure 5. The Shape Aspect Ratio Changed when a Person Fell Backward (a) A Video Frame of Normal Walk (b) The Person Fell Backward

3.2. Using Shape Aspect Ratio for Fall Detection

In the above subsection, a human falling backward was detected using the shape aspect ratio. For falling toward other three falling directions, the shape aspect ratio also changes substantially.

Figure 6 demonstrates that the shape aspect ratio of a person changed when a person fell forward. In Figure 6 a person fell forward whose shape aspect ratio decreased substantially because the height of the human shape rectangle decreased while the width of the human shape rectangle increased. The method proposed in this paper successfully detected the person falling forward in Figure 6.

Figure 6. The Shape Aspect Ratio Changed when a Person Fell Forward

Figure 7 demonstrates that the shape aspect ratio of a person changed when a person fell upward. In Figure 7 a person fell upward whose shape aspect ratio increased substantially because the height of the human shape rectangle increased while the width of the human shape rectangle kept almost the same. The method proposed in this paper successfully detected the person falling upward in Figure 7.

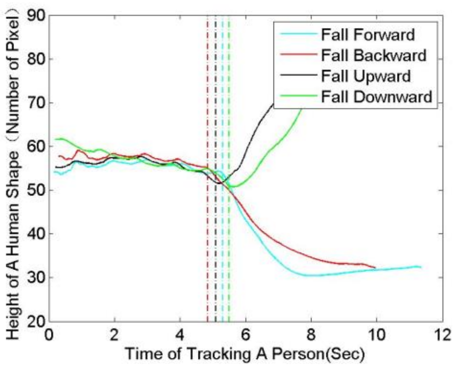
Figure 7. The Shape Aspect Ratio Changed when a Person Fell Upward

Figure 8 demonstrates that the shape aspect ratio of a person changed when a person fell downward. In Figure 8 a person fell downward whose shape aspect ratio increased substantially because the height of the human shape rectangle increased while the width of the human shape rectangle kept almost the same. The method proposed in this paper successfully detected the person falling downward in Figure 8.

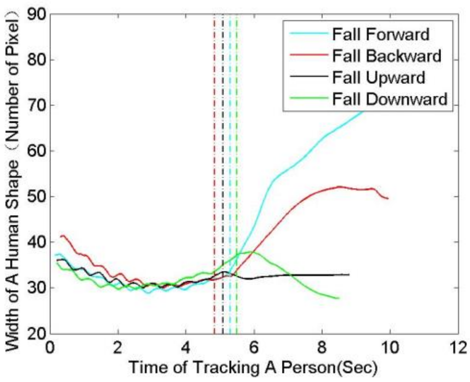
Figure 8. The Shape Aspect Ratio Changed when a Person Fell Downward

Figure 9 shows the changes of the height, width and the shape aspect ratio of a human shape when a person walked from the left to right and fell. There are four solid lines of different color in each of Figure 9(a), Figure 9(b) and Figure 9(c), recording the changes of the height, width and shape aspect ratio when the person walked and then fell forward, backward, upward and downward, respectively. The four dash-dot lines of different colors marks the four falling time detected by the algorithm. Each dash-dot line corresponds to the falling time of the solid line of the same color. For example, red solid lines are for the walk involving falling backward. Correspondingly red dash-dot lines marks the falling time of falling backward.

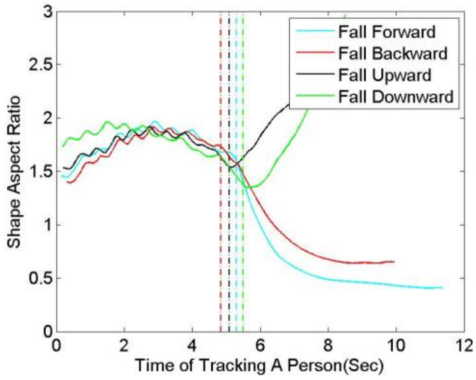
From Figure 9(c), apparently from the falling time, the shape aspect ratio started to change substantially. The shape aspect ratio of falling upward and falling downward increased dramatically while the shape aspect ratio of falling forward and falling backward decreased dramatically. The method proposed in this paper successfully detected the human falls toward these four directions using the detection of the shape aspect ratio changes. The method further distinguished the four falling directions using the moving directions of the human body centroid. The shape aspect ratio decreased in both falling forward and falling backward, while the body centroid moved forward and backward, respectively. The shape aspect ratio increased in both falling upward and falling downward, while the body centroid moved upward and downward, respectively.



(a)



(b)



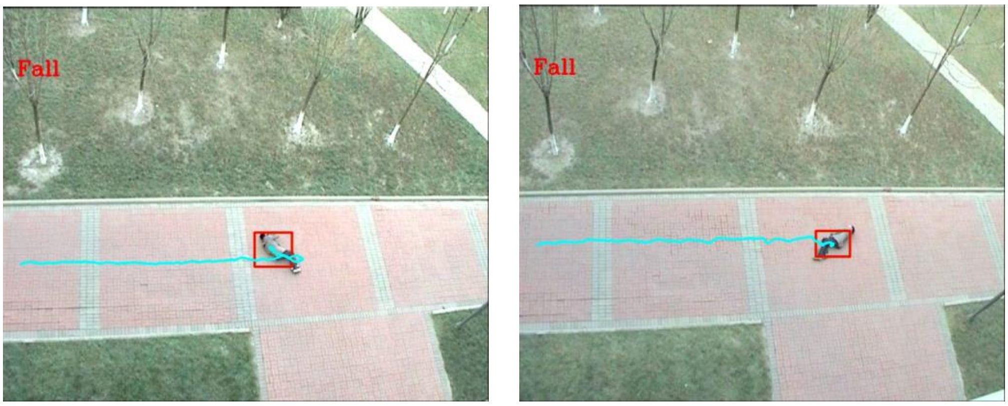
(c)

Figure 9. The Height and Width of a Human Shape and the Shape Aspect Ratio Changed when a Person Walked from Left to Right and Fell. The Four Dash-Dot Lines of Different Colors Marks the Four Falling Time Detected by the Algorithm

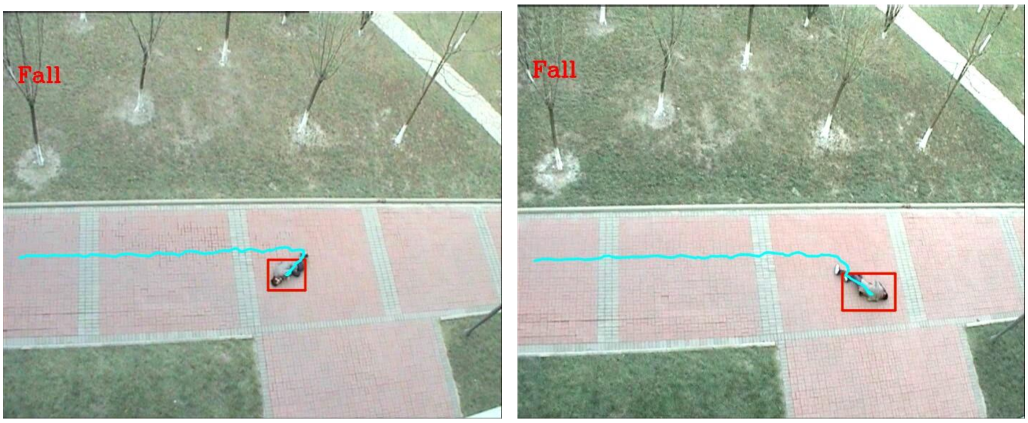
4. Experimental Results

In the above, the shape aspect ratio has been used to detect human falls for the cases that a person walked from left to right and fell forward, backward, upward and downward. In the following, more experiment results of falling toward different directions are presented.

In Figure 10, a person walked from left to right and fell toward the following four directions: Up-Left, Up-Right, Down-Left and Down-Right.



(a) (b)



(c) (d)

Figure 10. A Person Walked from Left to Right and Fell the Following Four Directions: Up-Left, Up-Right, Down-Left and Down-Right

Figure 11 shows the changes of the shape aspect ratio when a person walked from left to right and fell. There are four solid lines of different color in Figure 11, recording the changes of the shape aspect ratio when the person walked and then fell Up-Left, Up-Right, Down-Left and Down-Right, respectively. The four dash-dot lines of different colors marks the four falling time. Each dash-dot line corresponds to the falling time of the solid line of the same color. For example, red solid lines are for the walk involving falling Up-Left. Correspondingly the red dash-dot lines marks the falling time of falling Up-Left.

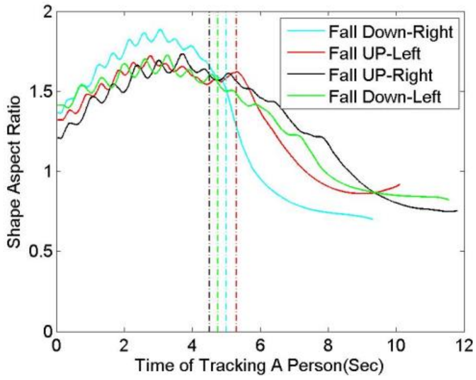


Figure 11. The Shape Aspect Ratio Changed Substantially Walked from Left to Right and Fell the Following Four Directions: Up-Left, Up-Right, Down-Left and Down-Right. The Four Dash-Dot Lines of Different Colors Marks the Four Falling Time Detected by the Algorithm

5. Conclusions

In this paper, an automatic human fall detection method based on human motion tracking and shape aspect ratio in real-time video is proposed. While most existing methods detect falls in homes, the proposed method is suitable for both outdoor and indoor environments. The method first detects human objects in general environment, then tracks their motions using mean shift iterations, meanwhile calculating and recording the motion characteristics of each person. Comparing with the existing fall detection method using shape aspect ratio, the proposed method has advantages of employing the shape aspect ratio together with the moving speed and direction to better detect human falls, as well as being able to detect falls toward different directions. Experiment results demonstrate that the proposed method can effectively detect human falls in general environments including outdoor places. The method proposed in this paper can potentially be used in applications such as monitoring human falls of seniors at nursing houses and little kids at daycare centers, and detecting human falls in general public places. In the future, more research needs to be conducted in the areas of gesture recognition using machine learning methods to future distinguish human falls and normal daily behaviors such as bending, crouching and sitting down, *etc.*

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References

[1] M. Alwan, P. J. Rajendran, S. Kell, D. Mack, S. Dalal, M. Wolfe and R. Felder, "A Smart and Passive Floor-Vibration Based Fall Detector for Elderly", Proceedings of the 2006 International Conference on Information & Communication Technologies: from Theory to Applications, **(2006)**, pp. 1003-1007.
[2] C. Rougier, J. Meunier, A. St-Arnaud and J. Rousseau, "3D Head Tracking for Fall Detection Using a Single Calibrated Camera", Image and Vision Computing, vol. 31, no. 3, **(2013)**, pp. 246-254.
[3] C. Rougier, J. Meunier, A. St-Arnaud and J. Rousseau, "Robust Video Surveillance for Fall Detection Based on Human Shape Deformation", IEEE Transactions on Circuits and Systems for Video Technology, vol. 21, no. 5, **(2011)**, pp. 611-622.
[4] L. Hazelhoff, J. Han and P. H. N. de With "Video-based Fall Detection in the Home Using Principal Component Analysis", Proceeding of the 10th International Conference on Advanced Concepts for Intelligent Vision Systems, **(2008)**, pp. 298-309.
[5] C. Rougier, J. Meunier, A. St-Arnaud and J. Rousseau, "Fall Detection from Human Shape and Motion History Using Video Surveillance", Proceedings of the 21st International Conference on Advanced Information Networking and Applications Workshops/Symposia, **(2007)**, pp. 875-880.
[6] J. Tao, M. Turjo, M. F. Wong, M. Wang and Y.P. Tan, "Fall Incidents Detection for Intelligent Video Surveillance", Proceedings of the 5th IEEE International Conference on Information, Communications and Signal Processing, **(2005)**, pp. 1590-1594.
[7] M. N. Nyan, F. E. H. Tay, A. W. Y. Tan and K. H. W. Seah, "Distinguishing Fall Activities from Normal Activities by Angular Rate Characteristics and High-speed Camera Characterization", Medical Engineering & Physics, vol. 28, no. 8, **(2006)**, pp. 842-849.
[8] M. N. Nyan, F. E. H. Tay and M. Z. E. Mah, "Application of Motion Analysis System in Pre-impact Fall Detection", Journal of Biomechanics, vol. 41, no. 10, **(2008)**, pp. 2297-2304.
[9] Z. Fu, E. Culurciello, P. Lichtsteiner and T. Delbruck, "Fall Detection Using an Address-event Temporal Contrast Vision Sensor", Proceedings of the 2008 IEEE International Symposium on Circuits and Systems, **(2008)**, pp. 424-427.
[10] M. Lustrek, H. Gjoreski, S. Kozina, B. Cvetkovic, V. Mirchevska and M. Gams, "Detecting Falls with Location Sensors and Accelerometers", Proceedings of the 25th AAAI Conference on Artificial Intelligence and the 23rd Innovative Applications of Artificial Intelligence Conference, **(2011)**, pp. 1662-1667.
[11] M. Kangas, A. Konttila, I. Winblad and T. Jämsä, "Determination of Simple Thresholds for Accelerometry-based Parameters for Fall Detection", Proceedings of the 29th Annual International Conference of IEEE-EMBS, Engineering in Medicine and Biology Society, **(2007)**, pp. 1367-1370.
[12] S. Luo and Q. Hu, "A Dynamic Motion Pattern Analysis Approach to Fall Detection", Proceedings of the 2004 IEEE International Workshop on Biomedical Circuits and Systems, **(2004)**, pp. S2.1-5-S2.1-8.
[13] C. Doukas, I. Maglogiannis, F. Tragkas, D. Liapis and G. Yovanof, "Patient Fall Detection Using Support Vector Machines", Proceedings of 4th IFIP International Conference on Artificial Intelligence Applications and Innovations, **(2007)**, pp. 147-156.
[14] J. Chen, K. Kwong, D. Chang, J. Luk and R. Bajcsy, "Wearable Sensors For Reliable Fall Detection", Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society, **(2005)**, pp. 3551-3554.
[15] H. Rimminen, J. Lindstrom, M. Linnavuo and R. Sepponen, "Detection of Falls among the Elderly by a Floor Sensor Using the Electric Near Field", IEEE transactions on Information Technology in Biomedicine, vol. 14, no. 6, **(2010)**, pp. 1475-1476.
[16] Y. Zigel, D. Litvak and I. Gannot, "A Method for Automatic Fall Detection of Elderly People Using Floor Vibrations and Sound - Proof of Concept on Human Mimicking Doll Falls", IEEE Transactions on Biomedical Engineering, vol. 56, no. 12, **(2009)**, pp.2858-2867.

[17] Q. C. Pham, Y. Dhome, L. Gond and P. Sayd, "Video Monitoring of Vulnerable People in Home Environment", Proceedings of the 6th International Conference on Smart Homes and Health Telematics, **(2008)**, pp. 90-98.
[18] H. Foroughi, B. S. Aski and H. Pourreza, "Intelligent Video Surveillance for Monitoring Fall Detection of Elderly in Home Environments", Proceedings of the 11th International Conference on Computer and Information Technology, **(2008)**, pp. 219-224.
[19] H. Foroughi, A. Naseri, A. Saberi and H. S. Yazdi, "An Eigenspace-Based Approach for Human Fall Detection Using Integrated Time Motion Image and Neural Network", Proceedings of the 9th International Conference on Signal Processing, **(2008)**, pp. 1499-1503.
[20] S. G. Miaou, P. H. Sung and C. Y. Huang, "A Customized Human Fall Detection System Using Omni-camera Images and Personal Information", Proceedings of the 1st Transdisciplinary Conference on Distributed Diagnosis and Home Healthcare, **(2006)**, pp. 39-42.
[21] N. Thome and S. Miguet, "A HHMM-Based Approach for Robust Fall Detection", Proceedings of the 9th International Conference on Control, Automation, Robotics and Vision, **(2006)**, pp. 1-8.
[22] S. W. Yang and S. K. Lin, "Fall Detection for Multiple Pedestrians Using Depth Image Processing Technique", Computer Methods and Programs in Biomedicine, vol. 114, no. 2, **(2014)**, pp. 172-182.
[23] D. Anderson, R. H. Luke, J. M. Keller, M. Skubic, M. Rantz and M. Aud, "Linguistic Summarization of Video for Fall Detection Using Voxel Person and Fuzzy Logic", Computer Vision and Image Understanding, vol. 113, no. 1, **(2009)**, pp. 80-89.
[24] L. Li, W. Huang, I. Y. H. Gu and Q. Tian, Foreground Object Detection from Videos Containing Complex Background, Proceedings of the 11th ACM International Conference on Multimedia, **(2003)**, pp. 2-10.
[25] D. Comaniciu, V. Ramesh and P. Meer, "Real-time Tracking of Non-rigid Objects Using Mean Shift", Proceedings of the 2000 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, **(2000)**, pp. 142-149.

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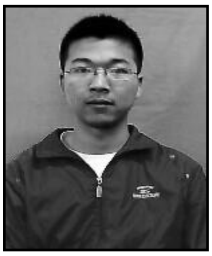

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