Survey of fall detection techniques based on computer vision

Nuth Otanasap and Poonpong Boonbrahm
School of Informatics, Walailak University, Nakornsi Thammarat, Thailand
auisuke@gmail.com, poonpong@gmail.com

Abstract

Falls affect tens of millions of elderly people throughout the world, approximately 28-35% of people over the age of 65 falls each year. That means falls are the primary cause of injury related to death for elderly and the second leading cause of injury related death and set of symptoms after fall. Falling, the rapid movement from standing or sitting to lying position can be classified in to four phases as pre-fall, critical fall, post-fall and recovery phases. In this paper, we have reviewed and compared different fall detection techniques based on computer vision in four phases of fall. Examples of techniques founded are Bayesian network, Centroid, Eigen-space, Gaussian mixture model, Hidden Markov model, Neural network, Support vector machine and Velocity. Most of techniques are focused on critical phase and post-fall phase which mean that the falling person had been fallen already and may be injured. Some new sensor technologies included multi-camera systems were used to improve the results in pre-fall and early critical fall phase by combining information from several cameras and sensors to make decision and determine the direction of the signal from multiple sources that may track many people at the same time.

Keywords: Fall detection; Fall activities

1. Introduction

Statistics in Global brief for World Health Day 2012 [26] show that approximately 28-42% of elderly people fall each year. That means falls are the primary reason of injury related death for seniors and the second leading cause of symptoms after fall, which includes loss of autonomy, confusion, increased dependence, immobilization and depression. The fall therefore raises the interest of researchers, particularly preventive detection of the fall because there are inappropriately defined processes and can be approached using various methods. To reduce the risk of falling, the early detection of fall in pre-fall or critical fall phase therefore advances the interest of researchers. Several of research has been done in this area to develop algorithms and systems of preventive fall detection. The goals of this study were to classify the computer vision based approaches to prevented fall and to comparing the results of these studies.

2. Fall detection definition

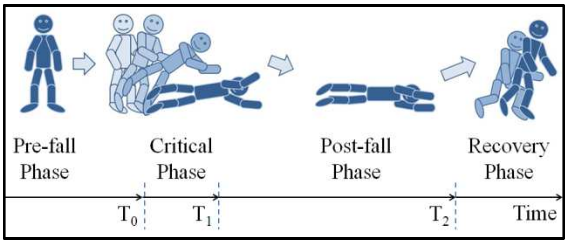

Fig. 1: Four phases of a fall event. [15, 19]

Firstly, as Fig. 1 the pre-fall phase is sudden movements directed to the ground as sitting or crouching down occasionally. The second phase is critical phase that very short period and most important of fall event. This phase can be detected by the body movement toward on the ground or by the impact shock with the floor. Next phase is the post fall phase which can be detected by motionless of human body after lying on the ground, lying position or by a motion absence significantly. Last phase is the recovery phase that faller get up from falling dawn. Explicitly, fall event in human can be described as the rapid movement from standing or sitting to lying position. During the critical fall phase there is free fall temporal time that continuous vertical speed increasingly.

3. Classification of fall detection techniques

As Fig. 2 [14] wearable device based, vision based and ambience sensor based are the three categories of existing fall detection methods as a hierarchy. Most of wearable sensors are based on accelerometers or based on gyroscopes which track the body movement automatically, not need intervention by human.

However, these kinds of sensors are often embarrassing to wear, and require batteries which need to be replaced or recharged frequently, that are important hindrance of these technologies.

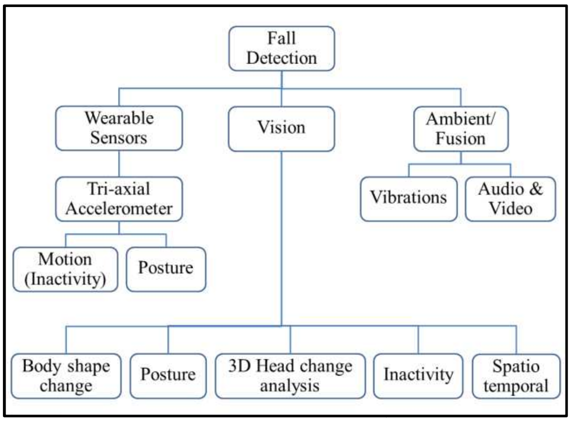

Fig. 2 Classification of techniques [14]

According to vision based device there are several techniques that are useful for detecting falling down of elderly people. As the following details, we have reviewed and compared different human motion tracking based on computer vision for understanding of fall detection techniques.

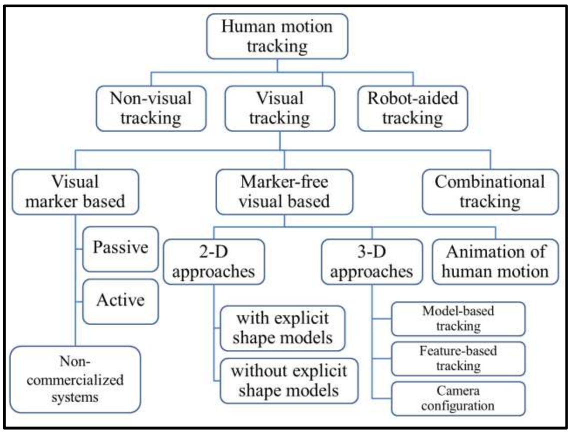

Fig. 3 Classification of motion tracking [29]

As Fig.3 [29], a tracking system can be non-visual, visual based or a combination of both. Visual tracking systems can be classified as either visual marker based or marker-free visual based as following details. Firstly, visual marker based tracking is a technique where cameras are adapted to track human movements, with identifiers position upon the human body. Consequently, each body part controls an unpredictable and complex motion trajectory, which may lead to contradictory and unreliable motion estimation. Moreover, disordered scenes or various lighting most likely divert visual attention from the real position of a marker. Visual marker based tracking is preferred to these kind of conditions that are frequently used as a human motion analysis standard due to their correct position information. One weakness of marker based using optical sensors is unable to detect joint rotation or body part overlapping and unable to render 3-D [21]. Secondly, marker-free visual based tracking systems utilize optical sensors (camera) that can produce continuous high resolution image to detect movements of body. Currently cameras are popularly used in surveillance applications with low cost and flexible to configure by user. However this technique requires complicated computation to error reduction, 3-D rendering, decreasing of data latency [4] and high speed camera [2] for high bandwidth. Lastly, Combination tracking systems take advantage of marker based and marker-free based technologies to reduce errors coming from using individual technology [23].

4. Related works

Generally, several kinds of techniques were used to detect falling down event in pre-fall, critical-fall or post fall phases. Some of them can only been used in one phase but some were used in several phases. Following details are briefly example of techniques that were used.

Cucchiara et al. [5] and Rimminen et al. [17] proposed a human posture classifier using Bayesian technique to detect falling in critical through post-fall phases. Both use shape, size and magnitude of the patterns or postures as an input for classification. Furthermore, centroids [8, 9, 10] are an effective way to measure object motion in space and can be computed as temporal averages of series of events. Researchers use a temporal moderate of the centroid motion events as an input to track fall risks and evaluate its dynamics in critical and post-fall phase.

An efficient method for activity recognition based on fusion of integrated spatio-temporal motion images and eigen-space techniques, mainly dedicated to fall detection in critical fall phase was proposed by Foroughi et al. [7] and Olivieri et al. [16]. The technique is used for accurate classification of motions and definition of a fall event in critical fall phase.

Silhouettes from multiple cameras [1] are used to build a 3-D estimation of the human by extracting feature from voxel person and used together with fuzzy inference to specify the state of fall in critical through post-fall phases. The resulting fuzzy rule base outputs are used to generate temporal linguistic summarizations and then temporally processed.

An automatically learning context-specific spatial model [12] in terms of semantic regions, particularly inactivity zones and entry zones, uses maximum a posteriori assessment of Gaussian mixtures (GM). Results of contextual model are presented using overhead camera sequences tracked using a particle filter that can be produced and unusual inactivity in post-fall phase to be detected. Rougier et al. [19] also presented a GM model (GMM) classification method to detect falls in critical through post-fall phases by analyzing human shape contortion during a video sequence. The silhouette of human along the video sequence was tracked by using a shape matching technique. The peak of fall is an important feature to indicate a fall in critical phase, but the lack of significant movement after the fall is also important for robustness when obstructions occur.

Hierarchical Hidden Markov Model (HHMM) and 3D human postures was proposed by Thome and Miguet [24] whose first layer states are related to the orientation of the tracked person in critical and post fall phase. They also proposed a multi-view method to achieve automatic detection of a falling person in video sequences, where motion is modeled using a layered hidden Markov model (LHMM) [25]. The posture classification is accomplished by a fusion unit that integrates the decision provided by the independently processing cameras in a fuzzy logic context.

The development of a vision system to detect natural events in a low-resolution image stream [3] concerns the assessment of algorithmic design decisions to increase detection reliability. As the approach of calculating vertical velocities from the infrared images and using a neural network to classify fall or non-fall in critical through post fall phase is sufficient to produce an actually fall detector. A comparison of the basic physics of falls to the ground that event can be explained in terms of the distributions of vertical velocities they generate, and the performance of the nearest neighbor classifier, an honest classifier.

A MEMS-based human airbag system [20] detects the complicated human motions and the recognition of a falling down motion in critical phase, which can be used to release an airbags. The system records human motion information using a high-speed camera then set up a human motion database that includes falls and normal motions, and use a support vector machine training process to classify. Moreover, a network of overlapping smart cameras [27] uses a decentralized process for computing inter-image homographies by calibrating only one camera. To evaluate fall detection procedure in post fall phase by both the Cyclops' algorithm and support vector machine (SVM) classifier, it uses a 3^{rd} degree polynomial kernel along with three features which are extracted from the Cyclops' images.

The study of identify unique features of the velocity profile during normal and abnormal activities [28] made the automatic detection of falls during the critical phase of fall. Additionally the horizontal and vertical velocities of the trunk during normal activities [11] are within a well controlled distances, when the velocity in one direction increase, the velocity in the other direction normally did not. These two velocity characteristics could be used to differentiate fall movements from normal activities during the critical phase of the fall.

As the new hardware technologies and in particular digital cameras are now affordable and popularly used as tools for automatically assuring the human safety. Omni camera [13] and multi camera [6] vision system are proposed for detecting and tracking human and recognizing risk behaviors and events using posture based technique. Some posture methods to detect falls are based on a combination of motion history, human shape variation, event-inference, human aspect ratio and effective area ratio [11, 18, 22] that algorithm provides promising results on video sequences and simulated falls which can effectively prevent misjudgments and greatly increase the accuracy of detection results.

5. Summarization of phase detection

As Table 1, summarization of phase detection using several techniques has been presented.

There are 18 items of critical phase detection and 15 items of post-fall phase detection which several techniques. Most of them detect falling in critical and post fall phases sequentially that means pre-fall and early critical fall phase should be considered.

Table 1: Classification of Phase Detection

Detection Techniques	Critical Phase	Post-fall Phase	Input
Bayesian	[5, 17]	[5, 17]	posture
Centroid	[8, 9]	[9, 10]	centroid motion
Eigen-space	[7, 16]	-	saptio-temporal
Fuzzy	[1]	[1]	voxel person
GMM	[19]	[12, 19]	human motion
HMM	[25, 26]	[25, 26]	posture
Neural Network	[3]	[3]	velocity
SVM	[21]	[29]	human motion
Velocity	[11, 30]	-	human motion
Combination	[6, 11, 13, 18, 23]	[6, 11, 13, 18, 23]	posture

6. Conclusion and future work

We have reviewed different fall detection techniques as Bayesian, Centroid, Context Aware, Eigen-space, Fuzzy Logic, GMM, HMM, Neural Network, Posture, SVM, and Velocity. Several fall detection techniques are good solution for fall detection with high rates but mostly detect on lately critical phase or post-fall phase that mean fall person had been injured already. To reduce the risk of falling, the early detection of fall in pre-fall or critical fall phase therefore advances the interest of researchers. Some new sensor technologies could also be used to improve the recognition results in pre fall and early critical fall phase by combining information from several cameras and sensors by time synchronization like PrimeSence, Kinect or Xtion sensors that can provide color, depth, audio and video stream. Moreover, it features a microphone array that is possible to determine the direction of the audio source and optimizes skeleton tracking to recognize users as six people can be detected and one or two human can be tracked at one time.

References

[1] Anderson, D., Luke, R. H., Keller, J. M., Skubic, M., Rantz, M., & Aud, M. (2009). Linguistic summarization of video for fall detection using voxel person and fuzzy logic. *Computer Vision and Image Understanding*, *113*(1), 80-89.

[2] Bhatnagar, D. K. (1993). Position trackers for Head Mounted Display systems: A survey. *University of North Carolina, Chapel Hill TR93, 10.*

[3] Bromiley, P. A., Courtney, P., & Thacker, N. A. (2002). Design of a visual system for detecting natural events by the use of an independent visual estimate: a human fall detector. *Empirical Evaluation Methods in Computer Vision, 50.*

[4] Bryson, S. (1996). Virtual reality in scientific visualization. *Communications of the ACM*, *39*(5), 62-71.

[5] Cucchiara, R., Grana, C., Prati, A., & Vezzani, R. (2005). Probabilistic posture classification for human-behavior analysis. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, *35*(1), 42-54.

[6] Cucchiara, R., Prati, A., & Vezzani, R. (2007). A multi-camera vision system for fall detection and alarm generation. *Expert Systems*, *24*(5), 334-345.

[7] Foroughi, H., Naseri, A., Saberi, A., & Yazdi, H. S. (2008, October). An eigenspace-based approach for human fall detection using integrated time motion image and neural network. In *Signal Processing, 2008. ICSP 2008. 9th International Conference on* (pp. 1499-1503). IEEE.

[8] Fu, Z., Culurciello, E., Lichtsteiner, P., & Delbruck, T. (2008, May). Fall detection using an address-event temporal contrast vision sensor. In *Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on* (pp. 424-427). IEEE.

[9] Leone, A., Diraco, G., & Siciliano, P. (2011). Detecting falls with 3D range camera in ambient assisted living applications: A preliminary study. *Medical engineering & physics*, *33*(6), 770-781.

[10] Lin, C. W., & Ling, Z. H. (2007, August). Automatic fall incident detection in compressed video for intelligent homecare. In *Computer Communications and*

Networks, 2007. ICCCN 2007. Proceedings of 16th International Conference on (pp. 1172-1177). IEEE.

[11] Liu, H., & Zuo, C. (2012). An Improved Algorithm of Automatic Fall Detection. *AASRI Procedia*, *1*, 353-358.

[12] McKenna, S. J., & Charif, H. N. (2004). Summarising contextual activity and detecting unusual inactivity in a supportive home environment. *Pattern Analysis and Applications*, *7*(4), 386-401.

[13] Miaou, S. G., Sung, P. H., & Huang, C. Y. (2006, April). A customized human fall detection system using omni-camera images and personal information. In *Distributed Diagnosis and Home Healthcare, 2006. D2H2. 1st Transdisciplinary Conference on* (pp. 39-42). IEEE.

[14] Mubashir, M., Shao, L., & Seed, L. (2013). A survey on fall detection: Principles and approaches. *Neurocomputing*, *100*, 144-152.

[15] Noury, N., Rumeau, P., Bourke, A. K., ÓLaighin, G., & Lundy, J. E. (2008). A proposal for the classification and evaluation of fall detectors. *Irbm*, *29*(6), 340-349.

[16] Olivieri, D. N., Gómez Conde, I., & Vila Sobrino, X. A. (2012). Eigenspace-based fall detection and activity recognition from motion templates and machine learning. *Expert Systems with Applications*, *39*(5), 5935-5945.

[17] Rimminen, H., Lindström, J., Linnavuo, M., & Sepponen, R. (2010). Detection of falls among the elderly by a floor sensor using the electric near field. *Information Technology in Biomedicine, IEEE Transactions on*, *14*(6), 1475-1476.

[18] Rougier, C., Meunier, J., St-Arnaud, A., & Rousseau, J. (2007, May). Fall detection from human shape and motion history using video surveillance. In *Advanced Information Networking and Applications Workshops, 2007, AINAW'07. 21st International Conference on* (Vol. 2, pp. 875-880). IEEE.

[19] Rougier, C., Meunier, J., St-Arnaud, A., & Rousseau, J. (2011). Robust video surveillance for fall detection based on human shape deformation. *Circuits and Systems for Video Technology, IEEE Transactions on*, *21*(5), 611-622.

[20] Shi, G., Chan, C. S., Li, W. J., Leung, K. S., Zou, Y., & Jin, Y. (2009). Mobile human airbag system for fall protection using MEMS sensors and embedded SVM classifier. *Sensors Journal, IEEE*, *9*(5), 495-503.

[21] Sturman, D. J., & Zeltzer, D. (1994). A survey of glove-based input. *Computer Graphics and Applications, IEEE*, *14*(1), 30-39.

[22] Tao, J., Turjo, M., Wong, M. F., Wang, M., & Tan, Y. P. (2005, December). Fall incidents detection for intelligent video surveillance. In *Information, Communications and Signal Processing, 2005 Fifth International Conference on* (pp. 1590-1594). IEEE.

[23] Tao, Y., & Hu, H. (2003, September). Building a visual tracking system for home-based rehabilitation. In *Proc. of the 9th Chinese Automation and Computing Society Conf. In the UK*.

[24] Thome, N., & Miguet, S. (2006, December). A HHMM-based approach for robust fall detection. In *Control, Automation, Robotics and Vision, 2006. ICARCV'06. 9th International Conference on* (pp. 1-8). IEEE.

[25] Thome, N., Miguet, S., & Ambellouis, S. (2008). A real-time, multiview fall detection system: A LHMM-based approach. *Circuits and Systems for Video Technology, IEEE Transactions on*, *18*(11), 1522-1532.

[26] World Health Organization. (2012). Good health adds life to years. Global brief for World Health Day 2012. *Geneva, Switzerland: World Health Organization. Accessed July*, *1*, 2012.

[27] Williams, A., Ganesan, D., & Hanson, A. (2007, September). Aging in place: fall detection and localization in a distributed smart camera network. In *Proceedings of the 15th international conference on Multimedia* (pp. 892-901). ACM.

[28] Wu, G. (2000). Distinguishing fall activities from normal activities by velocity characteristics. *Journal of biomechanics*, *33*(11), 1497-1500.

[29] Zhou, H., & Hu, H. (2008). Human motion tracking for rehabilitation—A survey. *Biomedical Signal Processing and Control*, *3*(1), 1-18.