Robust Fall Detection by Combining 3D Data and Fuzzy Logic

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Abstract. Falls are a major risk for the elderly and where immediate help is needed. The elderly, especially when suffering from dementia, are not able to react to emergency situations properly, thus falls need to be detected automatically. An overview of different classes of fall detection approaches is presented and a vision-based approach is introduced. We propose the use of a Kinect to obtain 3D data in combination with fuzzy logic for robust fall detection and show that our approach outperforms current state-of-the-art algorithms. Our approach is evaluated on 72 video sequences, containing 40 falls and 32 activities of daily living.

1 Introduction

Wild et al. [1] show that the mortality of fallers is higher compared to other elderly. Moreover, if elderly are not able to get up on their own again they may lie on the floor for hours, until help is provided [1]. Noury et al. [2] have shown that getting help quickly after a fall reduces the risk of death by over 80% and the risk of hospilization by 26%. Furthermore, elderly suffering from dementia are not able to react to emergency situations properly [3]. Hence, the aim of assistive systems is not only to assist, but also to reduce the cognitive load on the user [4]. This motivates the introduction of a fall detection system, which is able to detect falls and raise alarms automatically. Moreover, these systems boost the confidence of elderly in living independently [5]. The contribution of this paper is to present an overview of current state-of-the-art fall detection approaches and to introduce a robust vision-based fall detection system using 3D data obtained by the Kinect in combination with fuzzy logic.

Fall detection systems can be divided into three major approaches [5]: wearable devices, ambient devices and camera-based (or vision-based) approaches. Figure 1 shows an overview of the three major approaches including divisions for each of these approaches into smaller and thus more specific approaches.

Wearable devices broadly used to assist elderly are panic buttons, which need to be worn (e.g. on the wrist) by the elderly and pressed if an emergency situation occurs and help is needed [6]. These devices have the main drawback that elderly need to push the button actively - if they are not able to push the button (e.g. due to the lost of consciousness), help can not be provided. Hence, wearable sensors

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detecting falls automatically have been developed (e.g. [7–11]). These wearable sensors detect the body orientation, the impact of falling (using accelerometers) or the amount of activity/movement. Särelä et al. [11] combine a panic button (i.e. button on the wrist) together with a movement sensor to detect emergency situations automatically if the user is not able to push the button any more. Noury et al. [10] combine the measurement of the impact together with the measurement of the body orientation and the vibrations on the body surface to build a fall detection device which they called "actimeter". The main advantage of wearable devices are costs, as such systems are cheap - the main disadvantage is that sensors need to be worn, which is very intrusive [5].

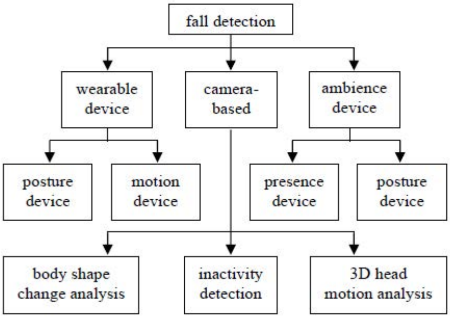

Fig. 1. Classification of fall detection approaches taken from [5]

Ambient devices are multiple sensors which are installed within the flat [5], turning the flat into a smart home [12] being able to support elderly living alone at home [13]. Approaches and sensors used in this field are very broad, including measuring the vibration of the floor to detect falls [14, 15], detecting falls by using pressure mats [6, 16] or motion sensors [16]. Ambient sensors are not intrusive, as they can be hidden within a smart home, but have the drawback of a high false alarm rate [5].

Vision-based systems are able to overcome limitations of other sensor types [17], but raise privacy issues. Hence, in contrast to Xinguo [5], we propose to not record any video data in order to respect concerns about privacy. Vision-based systems can be distinguished between systems using 2D images and systems using 3D data (e.g. obtained by multiple cameras [18] or 3D sensors [19]). To overcome limitations of multiple cameras (e.g. calibration is needed) and 3D sensors (e.g. availability and costs) we propose to use the Kinect as a vision-based 3D sensor for fall detection.

In contrast to the focus on the fall event mentioned by Xinguo [5], we neither focus on the fall event nor do we constrict a fall to time constraints (i.e. the fall process lasts from x to y seconds). Hence we propose to automatically raise an alarm if a person is detected to be on the ground and is not able to get up any more, as this is the situation where help is needed - independently of the reason for being on the floor (falling or lying down on purpose). Hence, if a person lies down on the floor on purpose and is not able to get up again, an alarm will be raised since help is needed anyway. Furthermore our approach combines and benefits from all sub categories of vision-based approaches defined by Xinguo [5]: body shape change analysis is done by analysing the major orientation of the person, whereas a person lying on the ground is seen as inactivity analysis, since the person is not moving or getting up. Furthermore, 3D motion analysis is done by tracking the person's skeleton position in a 3D environment over time.

The rest of this document is structured as follows: Section 2 provides an overview of state-of-the-art approaches in the field of vision-based fall detection. The methodology of our fall detection approach is introduced in Section 3, an empirical evaluation is presented in Section 4. Finally, a conclusion is drawn in Section 5.

2 State-of-the-Art

2.1 Body Shape Change Analysis

The shape of a person implies the orientation and thus is used to distinguish whether a person is in an upright position or not. The use of the bounding box aspect ratio (width to height ratio) to detect falls is proposed by Anderson et al. [20]. If people are in an upright position, the bounding box aspect ratio is bigger than one (i.e. $height > width$). In case of a fall, the ratio changes to a value smaller than one (i.e. $height < width$). Another approach presented by Rougier et al. uses information of an approximated ellipse instead of a bounding box [21]. Falls are detected by analyzing the orientation of the ellipse as well as the ratio of the major axis of the ellipse. Figure 2 illustrates these two approaches and depicts the shape of a person during a normal activity and during a fall. Furthermore, the corresponding bounding boxes and ellipses to analyze the bounding box aspect ratio and the orientation of the ellipse are illustrated. The use of a bounding box and an approximate ellipse for fall detection is feasible, but depends on the quality of the background segmentation. Assuming that the background segmentation yields in robust results, the fall detection also yields in robust results. A fall into the direction of the camera only using 2D images cannot be recognized by both approaches, as the change of orientation of the person cannot be detected.

Approaches not using 3D sensors reconstruct 3D information for humans from silhouettes gained by different camera views [22]. The human is represented by the use of voxels allowing to identify different states (upright, on–the–ground and in–between), depending on the shape of the person. The quality of this approach also depends on the quality of background segmentation, but it has the main drawback of needing a calibrated camera setup.

Zambanini et al. [18] propose a method to detect falls by using multiple cameras, and they distinguish between an uncalibrated camera-setup and a calibrated camera-setup. When using an uncalibrated camera-setup, scene analysis is performed on each camera individually. Afterwards, the individual results are combined to get an overall decision. In contrast, if information from multiple cameras using a calibrated camera-setup is combined to reconstruct the person in 3D space, the combination takes place at an early stage. Feature extraction is done on the 3D reconstruction of the person and a decision whether a fall occurred or not is made afterwards. Compared to other works (e.g. [23]), their system is not vulnerable to low-quality images (e.g. high noise and low resolution) as only basic information (i.e. silhouettes) are extracted from the image anyway. Using a calibrated camera-setup results in a higher accuracy than using an uncalibrated camera-setup, but it is practically not possible to calibrate the cameras if they are installed in an elderly person's flat or house.

Time-of-Flight cameras [24] are generating depth maps and can be used for fall detection [25]. Jansen et al. [19] mention the higher accuracy in contrast to stereo vision and propose a system for pose recognition discriminating the poses standing, sitting or lying by thresholding the height of the centroid. They state that their approach works in nursing homes reliably, but not in real homes due to false alarms.

2.2 Inactivity Detection

Unusual inactivity can be determined by tracking people from an overhead position [26, 27]. Therefore, zones with low activity (and little motion) are identified automatically and marked as an inactivity zones (e.g. sofa). Unusual inactivities are detected by analyzing the motion. If the amount of motion is below a threshold and occurred outside of the learned inactivity zones, this event is defined to be an unusual inactivity (e.g. person is lying on the floor). Inactivity detection is only able to detect falls indirectly by the lack of motion. Therefore it is important to ensure that the system is able to handle new situations (e.g. a chair is moved to a new position, thus moving the inactivity zone) properly.

A combination of applying a statistical model of inactivity zones and shape-based fall detection is introduced by Zweng et al. [28]. A so called accumulated hitmap models areas with low and high activities. In combination with their shape-based fall detection, the robustness of their approach is enhanced.

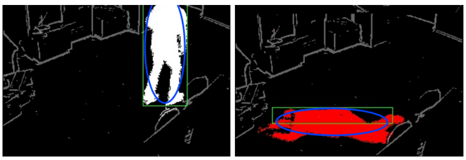

Fig. 2. Analysis of the bounding box aspect ratio and the orientation of the ellipse to detect falls

2.3 3D Motion Analysis

3D head motion analysis by using stereo vision sensors to detect falls is used by Belbachir et al. [29]. These biologically-inspired sensors feature a massively parallel pre-processing and reduce the amount of data in comparison to stereo vision cameras as they are not frame-based, but event-based. Hence, the motion of people can be determined and the position of the person can be extracted. A fall is detected by tracking the position and velocity of the head, as they assume the position of the head changes rapidly during a fall. Another approach by Rougier et al. [30] uses 3D information obtained by one single camera to track the head of the person and to obtain its trajectory. Not only the head position but also the motion speed is taken as an indicator for falls as the motion speed is assumed to be higher during a fall than during activities of daily living.

The approaches of Zambanini et al. [18], Belbachir et al. [29] and Rougier et al. [30] consider motion speed to detect falls, as they assume that the velocity is higher during a fall than during activities of daily living. From our point of view this assumption should not be made, as falls can also occur slowly and thus are not detected using these approaches.

In contrast to the definition introduced by Xinguo [5], we do not restrict 3D motion analysis to the head of a person, as other body parts (e.g. centroid) are analyzed as well. An approach using Time-of-Flight cameras detects moving regions within the 3D points cloud in a first step [25]. The person (foreground) is segmented from the background and - in contrast to other works analyzing the head position - the distance of the person's centroid to the ground floor is analyzed. This results in an efficiency of 80% and a reliability of 97.3% when using a centroid-ground floor distance of 0.4 meters as threshold [25]. Furthermore they propose to extract the skeleton from the depth data to analyse the orientation of the person's spine.

Since the introduction of the Kinect sensor in 2010, a new 3D sensor is available. Smisek et al. [31] analyzed the depth resolution and accuracy of the Kinect. Evaluation shows that regarding multi-view reconstruction the Kinect overperforms a Time-of-Flight sensor (SwissRanger SR-4000) and the quality is almost equal to a reconstruction using a 3.5 Mega Pixel SLR Stereo approach. Using the Kinect sensor for fall detection is proposed by Rougier et al. [32], but they focus on low level vision tasks like foreground / background segmentation and detecting the ground plane. Their proposed fall detection algorithm analyzes the distance between the centroid of the body and the ground floor as well as motion speed. Mastorakis et al. [33] use the Kinect and the 3D bounding box to detect falls. Falls are detected by analyzing the velocity of the person (i.e. falls occur if the velocity is higher than a threshold) as well as by assuming that a fall is followed by an inactivity period (i.e. no motion after a fall). Motion speed is not a suitable feature for fall detection as the motion speed is not necessarily high during a fall. Furthermore motion can occur after a fall since elderly might be able to crawl on the floor.

3 Methodology

Zweng et al. [28] show that the accuracy of their fall detection approach is higher when using a 3D reconstruction of the person, but having the main drawback of needing a calibrated camera setup. Therefore we propose to use a 3D reconstruction of a person, but using the Kinect instead of multiple cameras. Due to the use of infrared light, the Kinect also works during the night, when falls of elderly occur (e.g. when going to the bathroom in the dark). Furthermore, changing lighting conditions (e.g. switching the lights on and off) does not affect the results of the Kinect. Hence, the results (e.g. foreground/background segmentation, tracking) are more robust when using the Kinect than using standard IP cameras.

Our fall detection approach combines body shape analysis together with inactivity detection and 3D motion analysis. A fall is detected by analyzing the body orientation and the height of the spine. If a person is detected to be on the floor and is not able to get up on her/his own within a specified time, an alarm is triggered (inactivity detection).

The workflow of our approach is shown in Figure 3. Starting with a depth image obtained by the Kinect, skeleton information is extracted and the ground plane is estimated by OpenNI [34]. The skeleton information provided by OpenNI is optimized for being in an upright position (since it was developed for the use with the Xbox), but also works in different positions (e.g. lying on the floor). Based on the coordinate data of the skeleton, features to determine the pose of the person (i.e. orientation of the body and distance to the ground) are extracted. A final decision about the pose of the person is made by applying fuzzy logic. This simplistic approach is chosen to reduce the computational load of our algorithm and therefore there is no need for special system requirements when running our approach. The evaluation shows that our approach already yields in reasonable results.

Fig. 3. Workflow

3.1 Feature Extraction

The depth image of a person includes the skeleton information of the shoulder (center), spine and hip (center). Since the coordinates are not in 2D but in 3D space and the ground plane equation is known, the pose of the person can be illustrated relative to the ground floor, depicted in Figure 4. Therefore the major axis of the person is estimated by approximating the coordinates of the shoulder, spine and hip by a line. This line is approximated by calculating the mean slope between these three skeleton coordinates. Afterwards the following features are calculated:

– *Similarity between the body orientation and the ground plane:* the pose is estimated by calculating the similarity of the person's orientation and the ground floor. If the orientation of the person is parallel to the ground floor, the person is defined to be "lying" (either on the floor or on the bed). If the major orientation is orthogonal to the ground floor, the person is in the position "upright". Although this is only an approximate approach, experimental results show that this is already sufficient to detect falls with a high accuracy.
– *Spine distance to the ground floor:* the distance between the spine and the ground floor is calculated, allowing to determine whether the person is lying on the floor or e.g. on the bed. The integration of this feature is essential, since otherwise it is not possible to determine if a person is lying on the bed or on the floor, which results in false alarms.

The use of the similarity of the body orientation and the ground floor is illustrated in Figure 4a and Figure 4b: in contrast to a person being in an upright position (shown in Figure 4a), a person lying on the floor is shown in Figure 4b. Therefore the similarity of the body orientation can be used as a feature to distinguish between these poses. The need for analyzing the spine distance is illustrated in Figure 4c and Figure 4d: Figure 4c shows a person sitting on a chair, whereas a person is sitting on the floor is illustrated in Figure 4d.

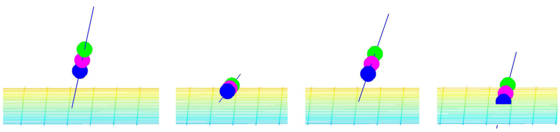

Fig. 4. Person (a) being in an upright position, (b) lying on the floor, (c) sitting on a chair and (d) sitting on the floor

3.2 Pose Estimation Based on Fuzzy Logic

Similar to Anderson et al. [22] and Zweng et al. [28], pose estimation is based on confidence values for the poses "upright", "in between" and "lying on the floor". In contrast to Zweng et al., our pose estimation and fall detection is only based on features introduced in Section 3.1 and motion speed is not taken into consideration. This is done in order not to constrain the fall event, but to be able to detect a variety of falls - even those, which occur slowly. To be able to differentiate between our three defined poses, trapezoidal functions [35] for the poses are created by finding thresholds empirically. Figure 5a depicts the trapezoidal function of the posture confidence depending on the body orientation. The posture confidence with respect to the ground plane distance is shown in Figure 5b.

Posture confidences for the orientation and the height of the body are calculated independently in the first step. To get an overall decision whether a fall occurred, the confidence values are combined by calculating the arithmetic average. This combination results in three confidence values for the poses "upright", "in between" and "lying on the floor". The final decision whether a fall occurred is made by thresholding the confidence values. Eliminating outliers is achieved by analyzing the average of pose confidences over time (e.g. 50 frames).

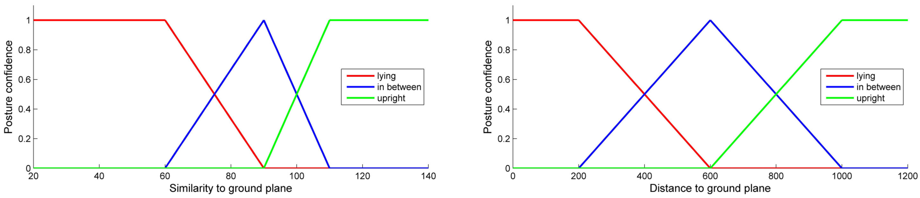

Fig. 5. Definition of fuzzy boundaries for the (a) orientation similarity and (b) spine-ground distance

4 Evaluation

Falls are simulated in a way that is similar to the definition of falls by Noury et al. [2], but using an extended version of scenarios, depicted in Table 1. The additionally added scenarios are "sitting down on a chair and falling while getting up", "lying down to a bed and falling out of the bed" and "falling into camera direction". These scenarios are added to enhance the quality of evaluation. Furthermore two scenarios are taken out of the original definition of Noury et al. since we do not agree with the uniqueness of the outcome. The modification results in 18 different sequences, containing ten falls and eight no-falls. These scenarios are simulated by two subjects, simulating each scenario twice. This results in an overall set of 72 videos, containing 40 falls and 32 no-falls.

Experiments have shown that the pose "in between" is not necessarily needed for evaluation, as analyzing only two poses is sufficient. We present our results using a precision-recall curve alternatively to the ROC curve [36] since it is not possible to specify the number of negative samples as the overall number of negative samples is not known in advance (a negative sample in our dataset is specified as a "no fall" event). Since our algorithm is frame-based, "no fall" events occur in each sequence (even if it is a sequence containing a fall event), since most of the frames are "no falls" and only a few frames show the fall respectively a person lying on the floor. Hence we cannot define all frames not containing a fall as "negative samples", but we cannot define only 32 negative samples either. The precision-recall curve in Figure 6 is generated by varying the thresholds $t_{upright}$ and t_{lying}.

Table 1. Definition of scenarios, similar to Noury et al. [2]

Category	Description	Outcome
Backward fall	Ending sitting	Positive
	Ending lying	Positive
	Ending in lateral position	Positive
	With recovery	Negative
Forward fall	With forward arm protection	Positive
	Ending lying flat	Positive
	With rotation, ending in lateral position (left or right)	Positive
	With recovery	Negative
Lateral fall (to the left or right)	Ending lying	Positive
	With recovery	Negative
Neutral	To sit down on a chair, then to stand up	Negative
	To lie down on the bed, then to stand up	Negative
	Walking	Negative
	To bend down, pick something up, then to rise up	Negative
	To cough or sneeze	Negative
Additional sequences	To sit down on a chair, then fall while getting up	Positive
	To lie down on the bed, then to fall out of the bed	Positive
	Fall into camera direction	Positive

Our approach results in an accuracy of 98.6% on 72 videos, resulting in one FP in the whole dataset. This FP occurs due to a tracking error after a fall, since the person is not tracked correctly while getting up again. Hence, a second fall is detected within the same sequence but as this fall does not occur in the time interval specified in the ground truth annotation, it is marked as a FP.

These results show that our approach outperforms other state-of-the-art approaches (e.g. [25],[28]). Although the evaluation is not based on the same dataset (due to the lack of dataset/code availability), the evaluation setting is similar (laboratory setting is similar to Zweng et al.[28]). Furthermore, similar to

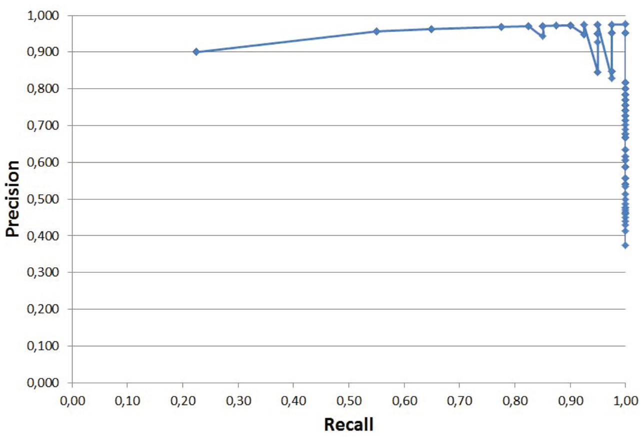

Fig. 6. Precision-recall curve of our fuzzy fall detection approach

Zweng et al.[28] the fall scenarios defined by Noury et al.[2] are used. Our approach results in only one FP on the whole dataset whereas the ROC curve from Zweng et al.[28] indicates a higher number of FP. Furthermore, the use of the Kinect offers practical advantages: it is robust to changing lighting conditions, also works also during the night and the installation in real homes is simplified by using only one sensor without the need for a complex calibration.

5 Conclusion

This article discussed state-of-the-art approaches based on different classes of fall detection. We introduced the combination of 3D tracking data obtained by the Kinect together with fuzzy logic for fall detection. Evaluation showed that this approach results in a high accuracy, being able to detect falls robustly. Our proposed approach was evaluated on a dataset of 72 video sequences and outperformed other state-of-the-art approaches. The fall dataset was recorded in cooperation with medical scientists and care taker organizations and is publicly available[1].

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References

1. Wild, D., Nayak, U.S., Isaacs, B.: How dangerous are falls in old people at home? British Medical Journal (Clinical Research Ed.) 282, 266–268 (1981)
2. Noury, N., Rumeau, P., Bourke, A.K., OLaighin, G., Lundy, J.E.: A proposal for the classification and evaluation of fall detectors. Biomedical Engineering and Research IRBM 29, 340–349 (2008)
3. Leikas, J., Salo, J., Poramo, R.: Security Alarm System Supports Independent Living of Demented Persons. Gerontechnology: A Sustainable Investment in the Future. Technology and Informatics 48, 402–405 (1998)
4. Lubinski, R.: Dementia and Communication. B.C. Decker, Inc. (1991)
5. Yu, X.: Approaches and principles of fall detection for elderly and patient. In: 10th International Conference on e-health Networking, Applications and Services (HealthCom 2008), pp. 42–47 (2008)
6. Miskelly, F.G.: Assistive technology in elderly care. Age and Ageing 30, 455–458 (2001)
7. Boissy, P., Choquette, S., Hamel, M., Noury, N.: User-based motion sensing and fuzzy logic for automated fall detection in older adults. Telemedicine Journal and e-Health: the Official Journal of the American Telemedicine Association 13, 683–693 (2007)
8. Doukas, C., Maglogiannis, I., Tragas, P., Liapis, D., Yovanof, G.: Patient Fall Detection using Support Vector Machines. In: Boukis, C., Pnevmatikakis, A., Polymenakos, L. (eds.) Artificial Intelligence and Innovations 2007: From Theory to Applications. IFIP, vol. 247, pp. 147–156. Springer, Boston (2007)

[1] `http://fall.fearless-project.eu`

9. Lin, C., Hsu, H., Lay, Y., Chiu, C., Chao, C.: Wearable device for real-time monitoring of human falls. Measurement 40, 831–840 (2007)
10. Noury, N., Barralon, P., Virone, G., Boissy, P., Hamel, M., Rumeau, P.: A smart sensor based on rules and its evaluation in daily routines. In: Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 4, pp. 3286–3289 (2003)
11. Sarela, A., Korhonen, I., Lotjonen, J., Sola, M., Myllymaki, M.: Ist vivago reg; - an intelligent social and remote wellness monitoring system for the elderly. In: Proceedings of the 4th International IEEE EMBS Special Topic Conference on Information Technology Applications in Biomedicine, pp. 362–365 (2003)
12. Scanaill, C., Carew, S., Barralon, P., Noury, N., Lyons, D., Lyons, G.: A Review of Approaches to Mobility Telemonitoring of the Elderly in Their Living Environment. Annals of Biomedical Engineering 34, 547–563 (2006)
13. Chan, M., Campo, E., Estève, D., Fourniols, J.Y.: Smart homes - current features and future perspectives. Maturitas 64, 90–97 (2009)
14. Alwan, M., Rajendran, P.J., Kell, S., Mack, D., Dalal, S., Wolfe, M., Felder, R.: A Smart and Passive Floor-Vibration Based Fall Detector for Elderly. In: IEEE International Conference on Information & Communication Technologies: from Theory to Applications, ICTTA, vol. 1, pp. 1003–1007 (2006)
15. Litvak, D., Zigel, Y., Gannot, I.: Fall detection of elderly through floor vibrations and sound. In: 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2008, vol. 2008, pp. 4632–4635 (2008)
16. Zhang, Z., Kapoor, U., Narayanan, M., Lovell, N.H., Redmond, S.J.: Design of an Unobtrusive Wireless Sensor Network for Nighttime Falls Detection. In: Annual International Conference of the IEEE in Engineering in Medicine and Biology Society, EMBC, pp. 5275–5278 (2011)
17. Mihailidis, A., Carmichael, B., Boger, J.: The Use of Computer Vision in an Intelligent Environment to Support Aging-in-Place, Safety, and Independence in the Home. Gerontechnology 2, 173–189 (2002)
18. Zambanini, S., Machajdik, J., Kampel, M.: Early versus Late Fusion in a Multiple Camera Network for Fall Detection. In: 34th Annual Workshop of the Austrian Association for Pattern Recognition (ÖAGM 2010), Zwettl, Austria, vol. 819862, pp. 15–22 (2010)
19. Jansen, B., Temmermans, F., Deklerck, R.: 3D human pose recognition for home monitoring of elderly. In: Conference of the IEEE on Engineering in Medicine and Biology Society, Lyon, pp. 4049–4051 (2007)
20. Anderson, D., Keller, J., Skubic, M., Chen, X., He, Z.: Recognizing falls from silhouettes. In: 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2006, New York, pp. 6388–6391 (2006)
21. Rougier, C., Meunier, J., St-Arnaud, A., Rousseau, J.: Fall detection from human shape and motion history using video surveillance. In: 21st International Conference on Advanced Information Networking and Applications Workshops, AINAW 2007, Niagara Falls, vol. 2, pp. 875–880 (2007)
22. Anderson, D., Luke, R.H., Keller, J.M., Skubic, M., Rantz, M., Aud, M.: Linguistic Summarization of Video for Fall Detection Using Voxel Person and Fuzzy Logic. Computer Vision and Image Understanding 113, 80–89 (2009)
23. Aghajan, H., Wu, C., Kleihorst, R.: Distributed Vision Networks for Human Pose Analysis. In: Mandic, D., Golz, M., Kuh, A., Obradovic, D., Tanaka, T. (eds.) Signal Processing Techniques for Knowledge Extraction and Information Fusion, pp. 181–200. Springer, US (2008)

24. Oggier, T., Lehmann, M., Kaufmann, R., Schweizer, M., Richter, M., Metzler, P., Lang, G., Lustenberger, F., Blanc, N.: An all-solid-state optical range camera for 3D real-time imaging with sub-centimeter depth resolution (SwissRanger). In: Proceedings of SPIE, vol. 5249, pp. 534–545. SPIE (2004)
25. Diraco, G., Leone, A., Siciliano, P.: An active vision system for fall detection and posture recognition in elderly healthcare. In: Design, Automation Test in Europe Conference Exhibition (DATE), Dresden, pp. 1536–1541 (2010)
26. McKenna, S.J., Charif, H.N.: Summarising contextual activity and detecting unusual inactivity in a supportive home environment. Pattern Analysis and Applications 7, 386–401 (2005)
27. Nait-Charif, H., McKenna, S.: Activity summarisation and fall detection in a supportive home environment. In: Proceedings of the 17th International Conference on Pattern Recognition, ICPR, vol. 4, pp. 323–326. IEEE (2004)
28. Zweng, A., Zambanini, S., Kampel, M.: Introducing a Statistical Behavior Model into Camera-Based Fall Detection. In: Bebis, G., Boyle, R., Parvin, B., Koracin, D., Chung, R., Hammoud, R., Hussain, M., Kar-Han, T., Crawfis, R., Thalmann, D., Kao, D., Avila, L. (eds.) ISVC 2010, Part I. LNCS, vol. 6453, pp. 163–172. Springer, Heidelberg (2010)
29. Belbachir, A.N., Lunden, T., Hanák, P., Markus, F., Böttcher, M., Mannersola, T.: Biologically-inspired stereo vision for elderly safety at home. e & i Elektrotechnik und Informationstechnik 127, 216–222 (2010)
30. Rougier, C., Meunier, J., St-Arnaud, A., Rousseau, J.: Monocular 3d head tracking to detect falls of elderly people. In: 28th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society, EMBS 2006, New York, pp. 6384–6387 (2006)
31. Smisek, J., Jancosek, M., Pajdla, T.: 3D with Kinect. In: IEEE International Conference on Computer Vision Workshops, ICCV Workshops, pp. 1154–1160. IEEE Computer Society Press, Los Alamitos (2011)
32. Rougier, C., Auvinet, E., Rousseau, J., Mignotte, M., Meunier, J.: Fall Detection from Depth Map Video Sequences. In: Abdulrazak, B., Giroux, S., Bouchard, B., Pigot, H., Mokhtari, M. (eds.) ICOST 2011. LNCS, vol. 6719, pp. 121–128. Springer, Heidelberg (2011)
33. Mastorakis, G., Makris, D.: Fall detection system using Kinects infrared sensor. Journal of Real-Time Image Processing (2012)
34. Shotton, J., Fitzgibbon, A., Cook, M., Sharp, T., Finocchio, M., Moore, R., Kipman, A., Blake, A.: Real-time human pose recognition in parts from single depth images. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR, pp. 1297–1304 (2011)
35. Zadeh, L.: Fuzzy sets. Information and Control 8, 338–353 (1965)
36. Davis, J., Goadrich, M.: The relationship between Precision-Recall and ROC curves. In: Proceedings of the 23rd International Conference on Machine Learning, ICML 2006, pp. 233–240. ACM Press, New York (2006)