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A survey on fall detection: Principles and approaches

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ABSTRACT

Fall detection is a major challenge in the public health care domain, especially for the elderly, and reliable surveillance is a necessity to mitigate the effects of falls. The technology and products related to fall detection have always been in high demand within the security and the health-care industries. An effective fall detection system is required to provide urgent support and to significantly reduce the medical care costs associated with falls. In this paper, we give a comprehensive survey of different systems for fall detection and their underlying algorithms. Fall detection approaches are divided into three main categories: wearable device based, ambience device based and vision based. These approaches are summarised and compared with each other and a conclusion is derived with some discussions on possible future work.

1. Introduction

Falls are a major cause of fatal injury especially for the elderly and create a serious obstruction for independent living. Statistics [57] show that falls are the primary reason of injury related death for seniors aged 79 or more and the second leading cause of injury related (unintentional) death for all ages. The demand for surveillance systems, especially for fall detection, has increased within the healthcare industry with the rapid growth of the population of the elderly in the world. It has become very important to develop intelligent surveillance systems, especially vision-based systems, which can automatically monitor and detect falls. It has been proved that the medical consequences of a fall are highly contingent upon the response and rescue time. Thus, a highly-accurate automatic fall detection system is likely to be a significant part of the living environment for the elderly to expedite and improve the medical care provided whilst allowing people to retain autonomy for longer.

The quality of an individual's life is significantly affected by the levels of functional ability. Plenty of research has been done in this area to develop systems and algorithms for enhancing the functional ability of the elderly and patients. The maturity of cameras, sensors and computer technologies make such systems feasible. Such systems cannot only increase the independent living ability of the elderly, by raising the confidence levels in a supportive care environment within the public sector, but also save on manual labour in terms of the presence of nurses or support staff at all times.

The rest of the paper is organised as follows. In Section 2, different types of fall are introduced, followed by the classification of fall detection methods. We review three different categories of fall detection approaches in Sections 3–5. Finally, we conclude and discuss future directions of research in Section 6.

2. Classification of falls and fall detection techniques

In this section, different kinds of falls are first identified. Specifying different types of falls help towards an understanding of the existing approaches. It also guides and contributes towards the design of new algorithms.

Different scenarios should be considered when identifying different kinds of falls: falls from walking or standing, falls from standing on supports, e.g., ladders etc., falls from sleeping or lying in the bed and falls from sitting on a chair. There are some common characteristics among these falls as well as significant different characteristics. It is also interesting to note that some characteristics of fall also exist in normal actions, e.g., a crouch also demonstrates a rapid downward motion. Noury et al. [56] and Yu [55] reviewed principles and methods used in existing fall detection approaches. These are the only review papers on fall detection and their scope is limited, which prompts us to write a comprehensive survey of recent fall detection techniques.

Existing fall detection approaches can be explained and categorised into three different classes to build a hierarchy of fall detection methods. Different methods under these categories are discussed further in the following sections. Fall detection

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Fig. 1. A typical fall from Sitting on a chair (frames from a simulated fall sequence).

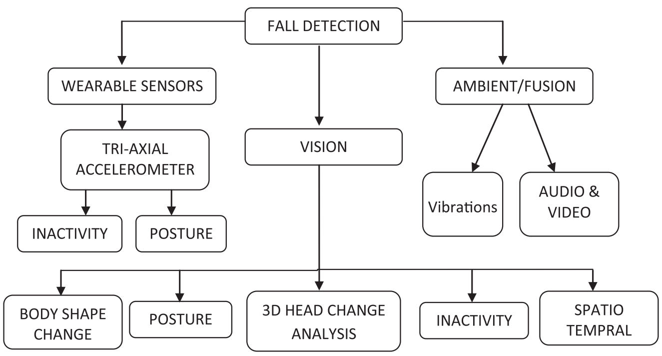

Fig. 2. Classification of fall detection methods.

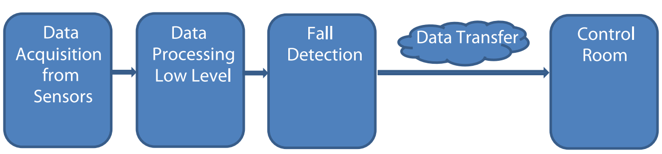

Fig. 3. Framework for existing wearable sensor and ambience based approaches.

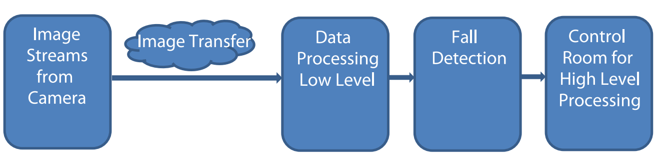

Fig. 4. Framework for existing vision based approaches.

methods can be divided roughly into three categories: wearable device based, ambience sensor based and camera (vision) based. A typical fall in a video sequence is illustrated in Fig. 1. Fig. 2 depicts the classification of fall detection techniques.

Wearable devices can be further divided into posture based and motion based devices. Ambience devices can be further classified into presence and posture based sensors. And the camera (vision) based systems can be further categorised into three classes as shape change, inactivity and 3D head motion. Most of the existing approaches share the same general framework. Data acquisition varies from one sensor to multiple sensors and from one fixed camera to multiple cameras and moving cameras. Figs. 3 and 4 illustrate the general framework for a fall detection system based on Wearable and Ambient and Vision based approaches, respectively.

3. Wearable device based approaches

Wearable device based approaches rely on garments with embedded sensors to detect the motion and location of the body of the subject. In the following we summarise the different methods.

3.1. Accelerometery

Technological developments have yielded devices that can measure activity using accelerometers. Accelerometry is composed of measure of acceleration of the body or parts of the body. It is one of the most extensively-used methods implemented for measuring physical activities to monitor activity patterns. Mathie et al. [38] used an integrated approach of waist-mounted accelerometry. A fall is detected when the negative acceleration is suddenly increased due to the change in orientation from upright to lying position. A barometric pressure sensor was introduced by Bianchi et al. in [36], as a surrogate measure for altitude to improve upon existing accelerometer-based fall event detection techniques. The acceleration and air pressure data are recorded using a wearable device attached to the subject's waist and analysed offline. A heuristically trained decision tree classifier is used to label suspected falls. Estudillo-Valderrama et al. [31] analysed results related to a fall detection system through data acquisition from multiple biomedical sensors, then processed the data with a personal server. The hardware and software design issues are clearly discussed when processing of bio-signals is involved during analysis. A wearable airbag was incorporated by Tamura et al. in [32] for fall detection by triggering airbag inflation when acceleration and angular velocity thresholds are exceeded. The system design consists of an accelerometer and a gyro sensor. Such a fall detection system can be very useful, especially at construction sites etc., for reducing fall related injuries.

Chen et al. [8] created a wireless, low-power sensor network by utilising small, non-invasive, low power motes (sensor nodes). The on-board device performs the sampling of acceleration sequentially, thus reduces the burden on the network. The dot product of acceleration vectors, from the orientation information, produces the angle of change during the fall event. The acceleration vectors are calculated using the average across a one-second window. The accelerometric data were analysed by Narayanan et al. in [19] and a platform based on the "PreventaFall" ambulatory monitor (PFAM) and MiiLink data portal (MiiLink) can be used to monitor the accelerometric data. In [20], Wang et al. applied reference velocities and developed a system that uses an accelerometer placed on the head. The reference velocity is calculated using the backward integration of accelerations. By using the reference velocity and a predefined threshold, falls are distinguished from normal daily activities.

3.2. Fusion of accelerometry and posture sensors

Physiological responses such as varying heart rate or blood pressure may result from physical activity and changes in body position. That makes the assessment of motion and posture a key factor in an ambulatory monitoring environment. Acceleration vectors were represented in a 3D space in [6] when Luo et al. implemented a group of sensors on a belt that filter noisy components with a Gaussian filter and generate a three dimensional body motion model that can be related to various body postures and the accelerometer's outputs. A two-axis accelerometer with a posture sensor was used in [25] for fall detection. The authors developed a wrist-worn prototype that integrates a health monitoring device with tele-reporting functionality for emergency telemedicine that contains a fall detector. The measured bio-signals have limited fidelity because the wrist area has limited body contact. This shortcoming could be overcome with further development in the posture sensor.

Ghasemzadeh et al. analysed machine learning and statistical techniques in [33] to create a physiological monitoring system that collects acceleration and muscle activity signals and performs analysis on those signals during standing balance. The objective of this system is to assess the behaviour of the electromyogram (EMG) signals to interpret the activity of postural control systems in terms of balance control.

3.3. Inactivity with accelerometry

Accelerometry provides detailed information on behaviour such as physical activity and inactivity. This information can be used to measure more comprehensive relationships among movement frequency, intensity and duration. An array of relatively cheap infrared detectors was used by Sixsmith et al. in [23] for the design of a wearable system called Smart Inactivity Monitor using Array-Based Detectors (SIMBAD). The target motion was analysed to detect characteristic dynamics of falls. Inactivity periods were also monitored and compared within the viewing field with a map of acceptable periods of inactivity in different locations. Ghasemzadeh et al. in [34] implemented a similar approach for inertial sensor nodes that constructs motion transcripts from biomedical signals and identifies movements by taking collaboration between the nodes into consideration. The system relies on motion transcripts that are built using mobile wearable inertial sensors.

Srinivasan et al. [17] and Lee et al. [18] both used motion sensors along with wireless accelerometer sensor modules to monitor general presence or absence of motion. A smart fall sensor was designed by Noury et al. for fall detection in [3]. The software application transmits the data remotely through the network as well as exploiting data locally. The data are further analysed to determine the current state such as lying after a fall, sleeping, walking, etc.

3.4. Tri-axial accelerometry

Tri-axial accelerometers are designed for simultaneous detection of acceleration in three axial directions. Lai et al. in [37] combined several tri-axial acceleration sensor devices for joint sensing of injured body parts, when an accidental fall occurs. The model transmits the information fed by the sensors which are distributed over various body parts. The system can determine the possible occurrence of a fall when the acceleration significantly exceeds the usual acceleration range. The impact acceleration and normal acceleration can be compared to determine the level of injury. Inertial sensors and the data logging unit are combined by Wu et al. in [27] to develop a portable pre-impact fall detection system. The inertial sensor unit consists of accelerometers and tri-axial angular rate sensors. The inertial frame vertical velocity is the key variable that detects the fall prior impact and is applied using a threshold detection algorithm. Adaptive thresholding has been quite successful for the reduction of false positives.

Embedded intelligence was employed in [7] for the design of a system that performs the vast majority of signal processing onboard the wearable unit. The tri-axial accelerometer output is acquired from the portable unit containing an embedded microcontroller and the tracking information regarding the user's motion is transmitted to a local receiver unit. The analysis of acceleration thresholds in [16] was carried out where Kangas et al. used acceleration thresholds to detect falls using tri-axial accelerometric measurements taken at the waist, wrist, and head. The threshold values for different parameters are adjusted to optimise the detection of falls.

The trunk angle change was observed in [41] when Boissy et al. applied motion sensors on objects to derive impact magnitudes and trunk angle changes. Motion sensors were placed on the front and side of the trunk along with three dimensional accelerometers. The deceleration as hitting the ground and trunk angle change in relation to hitting the ground represent two separate events. The fall detection algorithm is able to identify these two events as they are common to most falls. Wolf et al. [42] followed a popular low cost approach of a tri-axial accelerometer with a wireless transceiver. The algorithm is very similar to other accelerometric approaches discussed in this survey as data acquired from accelerometers are transmitted through a wireless transceiver for further sophisticated analysis. The algorithm applies acceleration thresholds to detect falls.

Zhang et al. [45] applied a similar idea of wearable tri-axial accelerometers for fall detection but with the introduction of non-negative matrix factorisation (NMF). The method uses the vertical axis of the human body and acceleration sequences as input vectors. Vector decomposition is performed through NMF. Finally a fall occurrence is determined via the k-nearest neighbour algorithm. Interestingly, as opposed to [45], Zhang et al. in [47] used a cell phone with a tri-axial accelerometer embedded in it. Data pre-processing is performed using 1-class support vector machine (SVM) and the wireless channel for Internet connection. Classification is achieved through the k-nearest neighbour (k-NN) algorithm and kernel fisher discriminant (KFD) analysis.

3.5. Posture based

Multichannel accelerometry can be used to distinguish between posture and basic motion patterns. Body orientation as posture is measured to detect falls. Kaluza et al. [48] presented a posture-based fall detection algorithm. Falls along with abnormal behaviours are detected based on the ideology of reconstruction of an object's posture. Small inexpensive wireless tags are placed on body parts, such as hips, ankles, knees, wrists, shoulders and elbows, identifying them as significant places. The locations of the tags are detected by the motion capture system. The posture is reconstructed in a 3D plane after locating the tags. Acceleration thresholds along with velocity profiles are applied in the fall detection algorithm.

Kangas et al. carried out study with the aim of developing a new fall detector prototype in [51] based on fall associated impact and end posture. A waist-worn tri-axial accelerometer, transceiver and microcontroller unit is used for data acquisition, transmission and processing. Sensitivity and specificity are also defined with respect to different fall detection algorithms. Sensitivity and specificity are achieved based on fall associated impact and end postures. Some backward falls cannot be detected by impact monitoring. This may partly be caused by the study set-up with intentional falls.

3.6. Discussion on wearable devices

Wearable devices have their advantages as well as disadvantages. The biggest advantage remains the cost efficiency of wearable devices. Installation and setup of the design is also not very complicated. Therefore, the devices are relatively easy to operate. The disadvantages include intrusion and fixed relative relations with the object, which could cause the device to be easily disconnected. Such disadvantages make wearable devices an unfavourable choice for the elderly.

4. Ambient device based approaches

Ambience based devices attempt to fuse audio and visual data and event sensing through vibrational data.

4.1. Audio & video

Image sensing and vision-based reasoning were presented in [2] by Tabar et al. for verification and further analysis of sensor-transmitted events. A bridge like operation via a wireless badge node is created between the user and the network. The badge node detects falls through event sensing functions. Along with fall detection it also creates a voice communication medium between the user and the Monitoring Control when the system detects a problem and alerts the control. The monitoring control continuously tracks the approximate location of the user using signal strength measurements via the network nodes. A fusion of image sensing and network nodes is created for further analysis of the field-of-view and the user's status during fall detection.

Zhuang et al. [50] proposed a different approach to the method in [44] using the audio signal from a single far-field microphone. A Gaussian mixture model (GMM) super vector is created to model each fall as a noise segment. The pairwise difference between audio segments is measured using the Euclidean distance. The kernel between GMM super vectors constitutes the support vector machine employed for the classification of various types of noise and audio segments into falls. Accelerometric data with video streams are used in the algorithm in [52]. Wearable sensors transmit the motion data wirelessly. Classification is achieved from acquired data using support vector machines (SVM) to detect fall events. Finally video streams are transmitted from a context-aware server. The image sequences are coded according to both the patient and the network status.

4.2. Event sensing using vibrational data

The detection of events and changes using vibrational date can be useful in many ways such as monitoring, tracking and localisation etc. A completely passive and unobtrusive system was introduced by Alwan et al. in [10] that developed the working principle and the design of a floor vibration-based fall detector. Detection of human falls is estimated by monitoring the floor vibration patterns. The principle is based on the vibration signature of the floor. The floor's vibration signature generated by the human fall is different from normal activities, such as walking. A special piezoelectric sensor is used which is coupled to the floor surface. A battery powered pre-processing circuit alongside is employed to analyse the vibration patterns. A binary fall signal can be generated in the case of a fall event.

A slip-fall detection system, using the sliding linear investigative platform, was proposed in [22] by Robinson et al. Classification of acceleration thresholds has been used to identify true slip-falls. Data such as tri-axial head accelerations and the centre of pressure in terms of psychophysical response are measured. Slip-fall vibrations are distinguished easily due to noticeable small vibration translations. The movement parameters require precise control and its advantages are discussed in terms of usefulness. The concept of floor vibrations with sound sensing is unique in its own way in [30]. Pattern recognition is applied to differentiate between falls and other events. Shock response spectrum is one of the key special features used in classification. The system is unique in the detection of falls in critical cases, such as an object being unconscious or in a stressful condition. The algorithm can be further developed with the calibration of the floor

Rimminen et al. in [35] proposed to use a floor sensor based on near-field imaging. The shape, size, and magnitude of the patterns are collected for classification. A set of features is computed from the cluster of observations. The postural estimation is implemented using Bayesian filtering instead of the features being classified directly. The system has problems with test subjects falling onto their knees as this produces a pattern very similar to a standing person. Toreyin et al. [44] fused the multitude of sound, vibration and passive infrared (PIR) sensors inside an intelligent environment equipped with the above fusion elements. Wavelet based feature extraction is performed on data received from raw sensor outputs. Regular and unusual activities, such as falls, are used for training the Hidden Markov Models (HMM). The process of fusion is applied to all outputs from sensors to detect falls.

Nyan et al. in [54] distinguished backward and sideway falls from normal activities using gyroscopes (angular rate sensors). The gyroscopes are securely placed on different positions, such as underarm and waist. The angular rate is measured for normal activities and falls in lateral and sagittal body planes. A high speed camera is used to capture video image sequences of motion for body configuration analysis in the event of a fall. High speed cameras have the frame rate of 250 frames per second. The fusion of high speed camera images and gyroscope data is synchronised. Gyroscopes rely on the idea of acceleration thresholds to differentiate fall events from normal activities.

4.3. Discussion on ambient devices

Most ambient device based approaches use pressure sensors for object detection and tracking. The pressure sensor is based on the principle of sensing high pressure of the object due to the object's weight for detection and tracking. It is very cost effective and less intrusive for the implementation of surveillance systems. However, it has a big disadvantage of sensing pressure of everything in and around the object and generating false alarms in the case of fall detection, which leads to a low detection accuracy.

5. Camera (vision) based approaches

Cameras are increasingly included, these days, in in-home assistive/care systems as they convey multiple advantages over other sensor based systems. Cameras can be used to detect multiple events simultaneously with less intrusion.

5.1. Spatiotemporal

Shape modelling using spatiotemporal features provides crucial information of human activities which is used to detect different events. Image analysis requires efficient and accurate shape modelling methods. Foroughi et al. [4] developed a method for detecting falls using a combination of the Eigen space approach and integrated time motion images (ITMI). ITMI can be described as a spatiotemporal database that contains motion information and time stamps of motion occurrence with an emphasis on the final action. Feature reduction is performed using the Eigen space technique. Feature vectors obtained from the feature reduction process are then fed to the Motion Recognition and Classification Neural Network classifier that can deal with motion data robustly. In [29], a mobile human airbag release system was designed for fall protection for the elderly. The system consists of 3D MEMS accelerometers, gyroscopes, a Micro

Controller Unit and a blue-tooth module. The object's motion information is recorded by the accelerometers. A high speed camera is used for the analysis of falls. Gyro thresholding is applied to detect a lateral fall. The classification of falls is performed by using a support vector machine (SVM) classifier. The real time fall detection system contains an embedded digital signal processor.

An asynchronous temporal contrast vision sensor was developed for fall detection in [21]. The method extracts changing pixels from the background and reports temporal contrast (compared to a threshold), which is equivalent to the change in image reflectance in the presence of constant lighting and finally an instantaneous motion vector computation reports fall events. The device requires a power socket nearby that makes the deployment of the system very simple. The motion detector protects the patient's privacy because no data are communicated until an emergency is detected.

5.2. Inactivity/change of shape

In this section, we describe algorithms based on shape change analysis as well as inactivity detection. From tracking data, McKenna et al. in [1] automatically obtained spatial context models by using the combination of Bayesian Gaussian mixture estimation and minimum description length model for the selection of Gaussian mixture components through semantic regions (zones) of interest. Ceiling-mounted visual sensors are used to reduce the influence of occlusion. Human-readable summaries of activity are produced and unusual inactivity is detected through the resulting contextual model. The contextual model can differentiate unusual activities, such as falls, from normal activities. Foroughi in [5] applied an approximated ellipse around the human body for shape change. Projection histograms after segmentation are evaluated and any temporal changes of the head position are noted. Segmentation of moving objects is obtained initially, and the next step involves extracting features by carrying out shape change analysis in the video sequence through an approximated ellipse around the human body. Further analysis of projection histograms (both horizontal and vertical) and temporal changes of the head position are carried out to extract feature vectors with optimised information. Extracted feature vectors are then fed to a MLP Neural Network similar to the earlier approach of Foroughi in [4] for classification of motions and fall events. Miaou et al. [9] captured images using an omni-camera called MapCam for fall detection. The personal information of each individual, such as weight, height and electronic health history, is also considered in the image processing task. Object segmentation is performed by using methods such as background subtraction. Noise reduction is applied during and after segmentation for accuracy. A bounding-box like approach is used by creating a rectangle enclosing the object. The ratio of height to width of the object is calculated at each frame. The ratios are then analysed by considering the last six consecutive image frames and result, in total, in five ratio changes between two adjacent frames. The occurrence of fall becomes likely if the first three ratios are all greater than 1 and the last three ratios are all less than 1. The system's decision of fall detection is based on the last two ratio changes with respect to a threshold. Each individual, due to different body figures, has different ratio changes between normal and fall states, and the Body Mass Index (BMI) value is used to adjust the threshold. Therefore, the system is flexible enough to adjust the detection sensitivity on individual basis.

Tao et al. [11] developed a detection system based on Miaou et al.'s [9] approach of using background subtraction (another approach based on the shape change analysis algorithm) but with an addition of foreground extraction, extracting the aspect ratio (height over width) as one of the features for analysis, and an event-inference module which uses data parsing on image sequences. A simple two-state machine in combination with falling motion inference is implemented. The two states are "standing/walking" and "falling down". Rougier et al.'s [14] approach is based on a combination of motion history image (MHI) and human shape variation. The MHI is an image projected from multiple motion images. The recent information of motion in an image sequence is represented by the pixel intensity and the most recent motion is more emphasised than that happened in the past. Shape change analysis in combination with inactivity analysis is performed using the approximated ellipse.

Fall incident detection in a compressed-domain is discussed in [15]. Object segmentation within the compressed domain is applied for the extraction of moving objects using the combination of global motion estimation and local motion clustering. The three extracted features used are: short time period range of fall occurrence, significant and rapid centroid change of the falling human, and the vertical projection histogram of the falling human. Fleck et al. [28] proposed a very unique idea of processing the stream at the point of sight and transmitting the processed stream to the control leaving no further processing to be done except for the higher level abstraction. The system design consists of a distributed network that contains smart cameras. Geo-referenced tracking and activity recognition are performed simultaneously, embedding in each camera node. An FPGA module and a Power PC processor are used for low level computations. The efficiency of the automated video analysis algorithm plays an important role towards the performance of the system. The proposed system could be further developed with self-diagnostic tools. Further improvements such as comprehensive processing and better decision making could be used as one of the major research directions for future development.

Rougier et al. in [59] proposed a classification method for fall detection by analysing human shape deformation. Segmentation is performed to extract the silhouette and additional edge points inside the silhouette are extracted using a Canny edge detector for matching two consecutive human shapes using the shape context. The mean matching cost and Procrustes analysis are applied for shape analysis. Both of these methods contribute in quantifying the abnormal shape deformation. "*A fall is characterised by a peak on the smoothed full Procrustes distance curve or mean matching cost curve followed by a lack of significative movement of the person just after the fall.* [59]" A Gaussian Mixture Model (GMM) classifier is implemented to detect falls. Further computation of the sensitivity, specificity, accuracy and the error rate obtained from the GMM classifier is performed for the analysis. Ensemble classifier is used later to combine the results of all cameras. The mean matching cost and the Procrustes analysis reduce the error rate to 4.6% and 3.8%, respectively. Further development can be made by the introduction of a remotely activated method which learns the inactivity zones automatically to improve the recognition results.

Wu et al. [39] uniquely identified velocity profile features between normal and abnormal activities, such as falls, for automatic detection. The fall activities contain forward and backward falls from standing and tripping, etc. Horizontal and vertical velocities are measured at different locations of the trunk. The trend of velocity increase shows an interesting pattern as it increases in one direction but does not in another. Two different characteristic patterns for falls are exhibited by the horizontal and vertical velocities. Differentiating falls from normal activities during the descending phase of falls heavily depends on these characteristics, i.e., the change in magnitude and timing when the change in magnitude occurs in both velocities.

Willimas et al. [60] detected and localised falls through distributed network of overlapping smart cameras. The system design is composed of battery powered camera sensor nodes of the same type on a single tier. Each node contains a camera sensor, an on-board processor with RAM, wireless radio communication and flash memory. The system design works on a principle assumption of at least one leader node with calibrated camera to the world that has known homography between its image coordinates and the world coordinates of the 2D ground plane. Human detection is performed through background subtraction. Planar homography is estimated through the normalised Direct Linear Transform that gathers point correspondences between the two images of interest. Fall is detected through the feature of aspect ratio (width of the person divided by height) extracted from segmentation. Simple thresholding is used to classify the fall. Localisation is achieved via a method estimated from pairwise camera homographies. Transformation of fall points into the destination node's image coordinates is performed before every hop, until it reaches the leader and transformation into world coordinates is achieved through intelligent weighting procedure (the inverse of the cumulative mean squared transformation). The system works under an assumption of at most one moving person about the environment and fairly stable lighting conditions due to the processor and RAM constraints. The idea of simplistic algorithmic design on low power devices is appealing to an extent but it is prone to false positives although the evaluation results show very low false positive rate due to the data set used.

Vishwakarma in [40] followed an adaptive approach for the detection of moving objects by using background subtraction as well as bounding boxes. The described fall model is based on feature extraction analysis, detection and classification. Features extracted include horizontal and vertical gradients, aspect ratio and the centroid angle to the horizontal axis of the bounding box. Falls are confirmed when the angle reaches a value less than 45 degrees. The image stream from the thermal detector is monitored by the fall detector proposed in [43]. The analysis is focused on measuring vertical velocities of the object using the coloured segmentation algorithm and identifying features in the pattern of velocities over time. These velocity estimates are then fed into a neural network-based fall detector that identifies the characteristic patterns of velocities present during a fall. Cucchiara et al. [49] instead applied a multi-camera system for image stream processing. The processing includes recognition of hazardous events and behaviours, such as falls, through tracking and detection. The cameras are partially overlapped and exchange visual data during the camera handover through a novel idea of warping ''*people's silhouettes*''. The video server (multi-client, multi-threaded transcoding) transmits sequences for further processing to confirm the validity of received data. The bandwidth usage is optimised through event-based transcoding and semantic methods. Anderson et al. [53] used a multi-camera system, similar to Nyan et al. [54], and applied silhouettes to form a 3D model of the human object. The membership degree of the object is measured using fuzzy logic to a pre-determined number of states at each image. The fall detection method consists of two levels. The first level deduces the number of states for the object at each image. The second level deals with linguistic summaries of the object's states called ''*Voxel Person*''. Further derivations are performed regarding the activity.

5.3. Posture

The use of posture information contributes towards accurate fall detection. Different body positions are used to calculate postures. Specific types of postures are identified and localised in image sequences. Cucchiara et al. [24] carried out analysis of human behaviours by classifying the posture of the monitored person and consequently detecting falls. Projection histograms are calculated and compared with the stored posture maps (training). The tracking also deals with occlusions. Accuracy levels achieved are up to 95%. A different posture classification approach based on a neural fuzzy network was introduced in [28] by Juang et al. Standing, bending, sitting, and lying are the postures used for classification. After segmentation (background subtraction and extraction), projection histograms are used and discrete Fourier transform is applied. A neural fuzzy network is used for classification. The results could be improved with better segmentation, such as better elimination of shadows and filtering the illumination influence.

Thome et al. [12] developed a Hierarchical Hidden Markov Model (HHMM) with two layers for modelling motion. The first layer has two states, an upright standing pose and lying. Fall detection, in terms of sudden change, has dedicated motion features from the first layer. 3D angle relationships and their image plane projections have been carefully observed. After performing an initial image metric rectification, theoretical properties are derived from binding the error angle for a standing posture during the image formation process. This simply differentiates other poses as ''non-standing'' ones. Thus falls can be accurately detected from other actions, such as walking or sitting. Computer vision systems typically use cameras only for recording and capturing video signals. Once transmission of the stream of images is completed, data processing is performed.

A support vector machine (SVM) approach is applied in [26] by Khandoker et al. for the classification of balance impairments, such as risks of fall for the elderly, based on the minimum foot clearance (MFC) principle which is used on the samples taken while walking on treadmill during training. Foot clearance data was collected using a 2D Motion Analysis system. Unobstructed walking sequences were recorded for foot motion using a high speed camera. The SVM model builds on the effectiveness of multi-scale analysis of a gait variable which is based on a wavelet in comparison to histogram plot analysis during feature extraction. There is a clear indication of better performance of the SVM model based on multi-scale exponents (by wavelet analysis) in the results than the model based on MFC statistical features.

5.4. 3D head position analysis

Head position analysis is based on head tracking that determines the occurrence of large movement within the video sequence. Different state models are used to track the head based on the magnitude of the movement information. Rougier and Meunier in [46] obtained image streams from a monocular camera. This methodology of fall detection is based on 3D head trajectories and the idea that the object's head remains visible in the image sequence and undergoes a large movement when a fall occurs. The 3D ellipsoid is used for bounding around the head. The 3D ellipse is a projection of ellipses in 2D image planes. A particle filter extracts the 3D head trajectory for tracking. The 3D head trajectory also contains features, such as 3D velocities, which are applied for fall detection.

Hazelhoff et al. in [58] aimed at incidents involving falls in unobserved home situations by presenting the design and real time implementation of a fall detection system. The design involves segmentation of foreground objects in the image streams obtained from two fixed, uncalibrated, perpendicular cameras. The direction of the main axis of the body and the ratio of the variances in x and y directions are calculated through principal component analysis (PCA). A head tracking module is used for human detection as well as increasing the robustness of the system. Head position is estimated as a blob using the Gaussian skin-colour model and is tracked by searching for skin-coloured blobs nearby the head position. The classification is performed through a Gaussian multi-frame classier. The system shows accuracy of 100% on un-occluded video sequences. The addition of occlusion only reduces the accuracy to 90%. Non perfect segmentations with the addition of occlusions reduces the accuracy to 44%. The system can be improved with further development of an advanced tracker.

In 3D head motion based analysis, the principle involving faster vertical motion than horizontal motion in a fall was proposed by Jansen and Deklerck in [13]. The method uses information extracted from images obtained using three dimensional visual approaches in combination with a context model. The contextual model interprets the fall occurrence differently. It depends on the time, location and duration of the fall event.

5.5. Discussion on vision based approaches

Vision based systems tend to deal with intrusion better than other approaches. Recent research in computer vision on surveillance indeed provides a practical and complex framework. Most of the emphasis in the context of surveillance in computer vision is dedicated to methods with the ability of real time execution using standard computing platforms and low cost cameras. The methods with capability of dealing with robustness still leave a wide open area for further research and development. Video analysis of human behaviour containing semantic description of the activities belongs to higher level abstraction and lower level represents the segmentation of motion along with feature extraction in computer vision.

Current posture related methods are classified depending on the use of a model. 3D techniques are not mostly automatic and usually require manual initialisation. Generally, model dependent methods obtain postures relatively easily and are robust to occlusion to an extent after labelling the body parts. Many of the body modelling techniques are 2D models. Comparatively, other non model based techniques compute the posture using features.

Models, learned through extended observation such as the interpretation of human activities in a scene, provide contextual representation of the activities. These models provide recognition and summary of the events and activities. Several techniques have been developed to learn these models automatically as manual techniques are useful to an extent. The range involved dealing with the complexity and abstraction of comprehensive activity and event analysis to fall detection automatically. However, interpreting human behaviours and the further pattern analysis depends on the choice of level of abstraction.

In 3D head motion analysis methods, the principle of faster vertical motion than horizontal motion during a fall is applied. The head is initially located and then the 3D head position is estimated using filters. The idea of using appropriate thresholds to distinguish a fall from other actions is applied by computing vertical and horizontal velocities of the head [55].

Though some of the implementations discussed earlier have shown a diverse pattern when it comes to dealing with image sequences, still there is plenty of room for further development in this area. Fall detection has still not been implemented using the total optical flow of the image sequence or specifically analysing the optical flow of the object after the object has been tracked and located. Further higher level abstraction can be applied on calculated optical flow to achieve higher levels of accuracy and robustness.

6. Conclusion and future work

We have reviewed different techniques for the detection of a fall event. Table 1 lists various characteristics of those approaches. A comprehensive and robust fall detection system should possess both high sensitivity and good specificity. The existing approaches have not comprehensively satisfied the accuracy as well as robustness of a fall detection system. However, the existing approaches do provide a framework to further develop techniques as well as modify the existing algorithms to achieve better performance.

As discussed earlier, sensor based approaches lack consistency when it comes to providing highly accurate automatic fall detection systems. Higher accuracy levels have been achieved to an extent using multi-dimensional combination of physiological and kinematic parameters. Further research and development should continue in terms of making the design more automatic and without much intervention.

Vision based approaches in comparison to others are certainly the area to look forward to. Most of the existing vision based approaches lack flexibility. These approaches are often case specific and dependent on different scenarios. There is a need for a reliable and robust generic fall detection algorithm. Both ambience and sensor based approaches share a common disadvantage, generally, of object data not being visually verified by the control or care service provider for accuracy.

Continuous surveillance through vision/camera and sensor based systems also introduces some ethical issues concerning the respect of confidentiality and privacy and also the risk of dependency of the subject on the technology. A common definition of a fall and of a fall detection system would certainly benefit the research community as well as the healthcare industry for the evaluation of fall detection systems. From a research perspective, there are issues relating to the availability of data sets of falls for training as well as evaluation. A comprehensive data set containing different scenarios of falls with different camera angles and

Table 1
Brief comparison of different categories of fall detection approaches.

Approach	Category	Cost	Intrusion	Accuracy	Setup	Robust
Wearable devices	Tri-axial	Cheap	Yes	Scenario dependent	Easy	No
	Posture	Cheap	Yes	Scenario dependent	Easy	No
	Inactivity	Cheap	Yes	Scenario dependent	Easy	No
Ambient	Audio	Cheap to medium	Yes	Scenario dependent	Easy/medium	No
	Video	Cheap to medium	Yes	Scenario dependent	Easy/medium	No
Vision based	Body shape change	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Posture	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Inactivity	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Spatiotemporal	Medium	Low/dependent	Higher/non specific	Medium	Yes
	3D head change	Medium	Low/dependent	Higher/non specific	Medium	Yes

with both static and moving cameras should be publicly available for the scientific community for the development and research purposes.

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