Chapter 11
A Vision-Based Posture Monitoring System for the Elderly Using Intelligent Fall Detection Technique

E. Ramanujam and S. Padmavathi

Abstract Elderly monitoring systems are the major applications of care for elderly and the disabled who live alone. Falls are the leading factor to be detected in the elderly monitoring system to avoid serious injuries and even death. The detection systems often use ambient sensors, wearable sensor, and vision-based technologies. In case of sensor-based devices, the elderly are required to wear the detection devices, however, quite often, they forget to wear these or do not wear them correctly. Moreover, the sensors need to be charged and maintained regularly. Also, the ambient sensors need to be installed in all the rooms to cover the whole actuation. The additional difficulty is that they are complex in circuitry and sensitive to temperature. Vision-based devices are the only plausible solution that can replace the aforementioned sensors. Besides, the cost of vision-based implementation is much lower and related devices are better than wearable devices in activity recognition. Much like Ambient sensors, cameras can also be installed in all the rooms; the cost and maintenance of these are less as compared to ambient sensors. This chapter proposes a vision-based posture monitoring system using infrared cameras connected to a digital video recorder and a fall detection mechanism to classify the falls. In the chapter, we observe the behavior of the elderly through the specially designed clothing fabricated with retroreflective radium tape (red in color) for posture identification. The proposed fall detection technique comprises various modules of operations such as image segmentation, rescaling, and classification. The infrared cameras observe the movement of the elderly people and signals are transmitted to a digital video recorder. The digital video recorder snaps only the motion frames from the signal. The motion images are segmented to red band using image segmentation and further rescaled for better classification using k-Nearest Neighbor and decision tree classifiers. The tests have been conducted on 10 different subjects to identify the falls during various motions such as supine, sitting, sitting with knee extension, and standing. We have shown a detection rate of 94% for the proposed model with k-nearest neighbor classifier.

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11.1 Introduction

Fall is one of the major common risks faced by the elderly and disabled individuals. World Health Organization (WHO), in a study conducted in 2007 [1], estimates that 28–35% of people, aged 60 years or above, fall at least once in a year. Fall incidents increase by up to 42% among the people over 70 years of age in which, 50% of elderly patients are hospitalized and remaining half suffer nonnatural mortalities due to fall. In developed countries, mortality of the elderly people who live alone is majorly caused by falls because a significant amount of time can pass before they receive assistance. In European countries, about one-third of the elderly aged over 65 years stay alone, and this figure is expected to increase significantly over the next 20 years [2]. According to Census report, in India, more than 15 million live all alone and close to three-forth of them are women. In some states like Tamil Nadu, the proportion of such "single elders" is even higher with one in eleven of those aged above 60 years living alone.

In the perspective of elderly monitoring system, ambient assistance living [3, 4] plays a significant and vital role in research and development. The core element of ambient assistance living (AAL) is to reduce the assistance time after the fall. AAL aims at applying technology relating to sensors, sensor networks, pervasive computing, and artificial intelligence techniques to make elderly people feel safer and secured to live in their preferred environment.

The availability of AAL optimizes the anticipation of emergencies which can have a practical effect on public and private health services relating to emergencies such as cardiac arrest, fainting, seizures, falls, immobilization, or helplessness. When these emergencies remain unnoticed for a longer time, they lead to severe complications and even death. With the benefits of generous assistance services, chronic diseases like dementia, arthritis, Alzheimer's disease, stroke, and epilepsy can be handled in a proactive and preventive manner.

In view of AAL, emergency conditions and chronic diseases need to be differentiated while monitoring by using automatic systems. The essential requirement of emergency conditions, which may occur unknowingly in a very short period of time is timely notice and detection. In contrast, anomaly or deviation in the normal behavior is the symptom that helps to detect chronic diseases. Research works as in [5–8] suggest wearable and implantable devices for the earlier detection of emergency situations, e.g., by pressing buttons on wearable alarm devices. The success of those devices depends on the user's understanding and involvement in the usage of the devices.

In the case of chronic diseases, the users may lose their consciousness or have poor decision-making capacity. In these scenarios, wearable devices are producing good results in activity recognition [9] but there are many drawbacks as represented by [10] in terms of handling wearable devices. The elderly people have to wear the devices continuously, though, due to aging or age-related diseases like dementia, they may forget to wear them. As a result, any crucial incidents that occur at that time cannot be intimated to the caretakers. Also, the devices need to be charged regularly. Wearing or injecting such devices may cause inconvenience to older people. Hence a noninvasive device [11] is needed to monitor the daily activities of such persons.

Surveillance camera is one plausible solution that can replace many numbers of sensors whose cost of implementation is also much less. Hence, surveillance camera is better than wearable devices in activity recognition. Research papers [5, 12] have suggested a number of automatic vision-based monitoring systems for the elderly. The objective of these studies is to monitor the elderly people in controlled environment and in case of falls, the system will send alert messages to the caretaker or an emergency center. Vibration, location, acoustic, and video sensors are used in these systems.

This chapter aims to develop a vision-based fall detection system to monitor the patient posture behaviors effectively. Unusual behavior is defined as anomaly behavior of the elderly in case of any medical assistance. Various postures such as standing, sitting, supine, and sitting with knee extension from the bed are monitored through the proposed approach. The approach monitors the elderly behaviors at all times (day and night) at low cost by using an infrared camera and digital video recorder with special retroreflective radium red tape [13] which is fabricated within the clothing of the elderly for detecting their movements.

The objective of the proposed chapter is twofold, which are given as follows:

- to use low-cost retroreflective radium red tape for posture detection instead of scanning the entire human body
- to use low-cost infrared cameras with digital video recorder to snap the motion image of the elderly on motion.

The rest of the proposed chapter has been organized as follows. The state of the art in fall detection is discussed in Sect. 11.2. Section 11.3 covers the system setup relating to our study. Section 11.4 describes the methodology of the system; Sect. 11.5 describes the experimental results and Sect. 11.6 concludes of the chapter.

11.2 State of the Art

The fall detection techniques are classified broadly in terms of wearable sensors, ambient sensors, and vision-based technologies. These are now discussed in the following sections.

11.2.1 Wearable Sensors

Accelerometers and gyroscopes are the most commonly used wearable sensors. These sensors are easy to wear. But, they have some drawbacks such as sensitivity to the body movement, power consumption; also the devices rely on user's ability to wear them and manually activate the alarm during the occurrence of fall. Furthermore, these devices have more number of false positives, even if they incorporate fully automated system. In the context of commercial devices, these sensors are fabricated into a pendant, belt or watch. Bagala et al. [5] have collected data for real-world falls among a patient population using accelerometers. They have presented the performance of 13 published fall detection algorithms applied to the database of 29 real-world falls. They have reported an average detection rate of 83% and a fall detection rate of 98% for the well-performing algorithms. The drawback of the typical mechanisms is that the accelerometers generate more false fall warnings in case of abrupt movement of the sensor. To overcome the issues reported in [5], Wang et al. [14] have proposed a technique by placing the accelerometer at the head level to provide highly reliable and sensitive fall detection rates.

Mathie et al. [15] have proposed an advanced wearable device which incorporates multiple sensors with multiple fusion technologies. In this work, they have used gyroscopes and accelerometers in a single waist-mounted system to acquire data about the inclination angle and movement of the subject. The system successfully distinguishes between activity and rest positions. Bianchi et al. in [16] have extended the work presented in [15] by adding barometric sensors to sense the height variations caused by falls and reported 71% success rate. The major advantage of wearable sensors in the context of biometric is that wearables have greater rehabilitation and fall detection.

Ghasemzadeh et al. [17] have presented an array of sensors that can read a patient's posture and obtain muscular activity readings using electromyography (EMG) sensors with a fall detection rate of 98%. The development of Mobile Technologies with the incorporation of sensors implies a very interesting option for home-based fall detection system. Abbate et al. [18] have proposed accelerometer-based algorithm on mobile and reported 100% fall detection rate. Combination of wearable sensors and mobile phones have been considered in [19, 20]. It uses sensors including tri-axis-based accelerometer, gyroscope, and magnetometer with a mobile phone for data processing, fall detection, and messaging.

Many research works suggest that wearable devices are appropriate in case of emergency situations and health monitoring system. Wearable devices are producing good results in activity recognition but there are also many drawbacks in terms of handling wearable devices as follows:

- The elderly are required to wear the devices continuously
- Due to aging or age-related diseases, they may forget to wear the devices
- Devices need to be charged and maintained regularly
- Degree of success depends on the wearers' appropriate use of these, e.g., pressing the button on the device on emergencies

- Costs of the wearable devices are generally high.
- In case of crucial incidents occurring, the time of fall cannot be intimated to the care staff.

Table 11.1 represents the sensors-based fall detection techniques with various considerations of each research work.

Table 11.1 Sensor-based fall detection techniques

Article	Basis	Fall types	Subjects	Declared performance	Positions	Elderly (Yes/No)
Bagala et al. [43]	Triaxial Acceleration Sensor fixed by a belt	9	9 subjects (7 women, 2 men, age: 66.4 ± 6.2)	Average of 13 Algorithms SP: 83.0%	Lower back	Yes
			15 subjects	SP: 83.0 ± 30.3%		
			29 subjects	SE: 57.0%		
			1 subject	SE: 57.0 ± 27.3%		
Wang et al. [13]	6G Triaxial accelerometer	3	5 volunteers	SE: 70.48%	Head	No
Mathie et al. [45]	Triaxial accelerometer	4	NA	NA	Waist	CHF & COPD Patient
Bianchi et al. [14]	Accelerometer-based systems with a barometric pressure sensor	3	20 subjects (12 male, 8 female; mean age: 23.7)	SP: 96.5%	Waist	No
			5 subjects (2 male, 3 female; mean age: 24)	SE: 97.5%		
		2	5 subjects (5 male, mean age: 26.4)	SE: 98.2%		
Ghasemzadeh et al. [15]	Electromyography Sensors + Triaxial accelerometer	9	5 male (Age 25–32)	F—Measure: 0.63	Tibialis anterior, gastrocnemius muscles	No
Abbate et al. [16]	Triaxial Accelerometer	3	7 volunteers (5 male, 2 female, ages 20–67)	SP: 100%, SE: 100%	Waist	No

11.2.2 Ambient Devices

Ambient devices measure various parameters in the environment of the subject under protection using groups of infrared sensing devices, sound, vibrators, and so on. The major drawbacks of the ambient devices are that they need to be installed in several rooms to cover the movement of the elderly to cater for all situations. In commercial fall detection devices, ambient technologies use presence and pressure sensors associated with wearable sensors [21–23]. Zhuang et al. [24] have used acoustics sampling and shown high failure detection rates using an ensemble of machine learning algorithms. Alwan et al. [25] have proposed an automatic system using interesting vibration sensors embedded into the flooring. In this work, authors have reported 100% fall detection ratio with the ability to distinguish activities through vibrations. Rimminen et al. [26] have reported 91% success rate using electromagnetic sensors in the floor plates that create an image of objects which touch the floor. Infrared ceiling sensors are proposed in [27] to know the existence/nonexistence of the persons under the sensor, and consequently it detects falls, if the person remains too long in the same position. It is also interesting to note the system that activates an airbag when a fall is detected, as mentioned in [28]. The proposed airbag inflates to trigger using acceleration and angular velocity signals. Table 11.2 represents the Ambient sensors based fall detection techniques. Ambient sensors also have some major drawbacks, which are given as follows:

Table 11.2 Ambient sensor based fall detection techniques

Article	Basis	Fall types	Subjects	Declared performance	Features	Elderly (Yes/No)
Zhuang et al. [22]	Acoustic Sensors	4	13 subjects	F—Measure: 67%	Single far-field microphone	No
Alwan et al. [23]	Floor Vibration sensor	3	NA	SE:100%	Raw Vibration Signal	No
Rimminen et al. [24]	Floor sensor based on near-field imaging	8	10 subjects	SE: 91%, SP: 91%	Near-field image sensor	No
Tao et al. [25]	Infrared Ceiling Sensor	3	5 subjects	F—Measure: 95.14	Binary responses	No
Tamura et al. [26]	Airbag	4	16 subjects	Acc: 93%	Thresholding technique with accelerometer and gyroscope	Yes

- Sensors need to be installed in several rooms to cover the whole actuation
- These require complex circuitry and are sensitive to temperature
- Lifetime of sensors is limited
- They have poor precision and poor signal-to-noise ratio.

11.2.3 Vision-Based Devices

Most commercial fall detection techniques in the market are based on portable devices as discussed in [29]. It is not easy to find any vision-based commercial devices in the market, but their technical advancements and related literature remain promising. Vision-based devices have similar drawbacks as ambient devices, for example,

- Installation of vision-based devices are required in all rooms to cover the whole area of actuation
- Issues regarding privacy on how to deal with images of a real person's life.

For these reasons, the streaming is controversial. As discussed, in this chapter, the proposed system captures the images of an elderly only when movement takes place and transfers the motion image to the server for processing. Advantages of vision-based systems are that they can run on many computers and the algorithms and libraries are mostly implemented as open source. Varieties of algorithms have been developed for fall detection, of which some are designed to analyze only static images and treat each frame individually. The other concerns are explained in the following subsections.

11.2.4 Cameras

In vision-based systems, the camera is the most important device for fall detection systems. Vision-based approaches are focused on real-time execution of algorithms using standard computing platforms and low-cost cameras. There are several methods that are used to obtain semantic information through video analysis. Many of them use 2D and 3D models, and the others are based on the extraction of some features after the video segmentation. Two types of cameras are often used for fall detection 2D cameras and 3D Time of Flight (TOF) cameras as discussed in [30, 31]. The resolution of TOF cameras is lower than 2D cameras and they are much more expensive. The proposed system uses simple 2D Infrared camera along with the digital video recorder to store the motion images for processing.

11.2.5 Processing Units

Most vision-based fall detectors need high computational processing power and expensive hardware. An active vision system for the automatic detection of falls and recognition of several postures of elderly homecare applications deploys a variety of platforms, for example,

- TOF MESA SwissRander SR3000 as used in [30]
- Intel Core i5 processor (Santa Clara, CA, USA) at 2.6 GHz as used by [32].
- Intel Core i7-2600 3.40 GHz processor and 16 GB of RAM clocked at 1333 MHz.
- Heterogeneous platform Zynq-7000 SoC (System on chip) platform as used by [33], which combines ARM Cortex A9 processor and a FPGA (Field-programmable gate array).

The proposed approach uses Intel Core I3 processor with 4 GB of RAM for processing and classification of the falls.

11.2.6 State Classification

Decision systems are typically required in a fall detection technique. Machine learning algorithms are widely used for computer vision fall detection. Data classification algorithms such as *k*-Nearest Neighbor, Support Vector Machine (SVM), and Decision Trees have been successfully used in computer vision-based fall detection techniques and more advanced machine learning algorithms like artificial Neural Networks, Hidden Markov Model. Deep learning architectures are also used for the classification of falls. Our proposed system uses a simple yet efficient Machine Learning algorithm viz *k*-Nearest Neighbor and Decision Tree classifier. Machine learning algorithms are often well trained using more number of scenarios as in [34] to reduce the misclassification accuracy, however, certain techniques, e.g., those discussed in [35] use cross-validated results to report the detection ratio.

11.3 Controlled Environment

The proposed vision-based posture monitoring technique uses a controlled environment for fall detection. The schematic layout of the experimental setup is shown in Fig. 11.1. The system uses infrared cameras connected to a digital video recorder (DVR). Infrared cameras [36] operating at 25 frames per second are used to obtain an all-round view of coverage of activities of each subject. The digital video recorder [37] automatically snaps the frames with motion and stores the motion image on a built-in hard disk.

Clothing of the elderly are especially designed at a low cost with ordinary cotton cloth and retroreflective radium red tape (referred further as “tape” in the remainder of the chapter) fabricated especially with lamination in the clothing at four different places. The places being bronchium or arm; hip; thighs; and legs. The tapes are originally used in the vehicles for the reflection of lights during night time. The same tape has been used in the elderly dress to identify the posture during motion. The advantage of the system is that the red tape can be easily segmented from the image for classification and the color of the tape does not fade when washing the clothes for any number of times, as it is specially laminated. Image of a person with tapes placed at different positions in the dress is shown in Fig. 11.2.

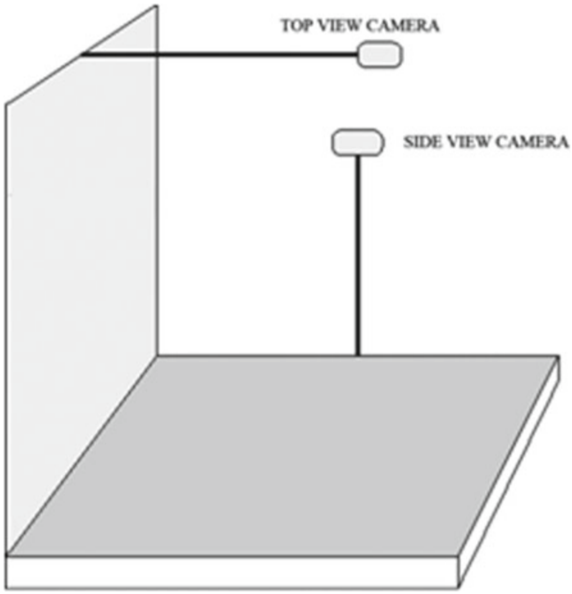


Fig. 11.1 Schematic layout of the elderly living space

11.4 Proposed Methodology

The architecture of the proposed vision-based posture monitoring system is a three-step process as shown in Fig. 11.3. In step 1, the infrared cameras are used to observe the movement of the elderly and the captured signals are transmitted to the digital video recorder (DVR). It step 2, the DVR snaps the motion images and store them in a built-in hard disk. The motion images are also transferred to the server for the fall detection technique as shown in Fig. 11.4. The fall detection technique undergoes various modules of operations such as image segmentation, rescaling, and classification in the server. The captured motion images are segmented to “Red” band for representing the retroreflective radium tape using k-means clustering technique. The segmented images are further rescaled to a numerical vector to undergo better classification. k–NN and decision tree classifiers are used to group the rescaled images as normal images with any fall. If the system classifies any of the motion as fall, then an alert message is passed to medical experts or care persons for emergency actions as step 3 as shown in Fig. 11.3.

The specific advantages of the proposed system are as follows:

- No interruption in the elderly privacy due to motion capture
- Use of the camera will be less depending on the room size or the space used by the elderly
- Tapes are reflective at the night time also, so there is no need for any other specific monitoring facility in the night time

Fig. 11.2 Subject with the dress

- Less communication delay to the server as the cameras capture only the motion images
- No video processing is carried out, instead only image segmentation is carried out to classify the elderly person's posture.

Various modules of the proposed fall detection technique are now discussed in the following section.

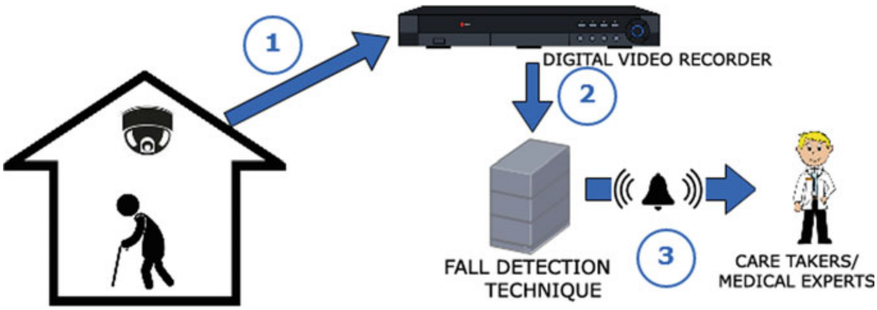
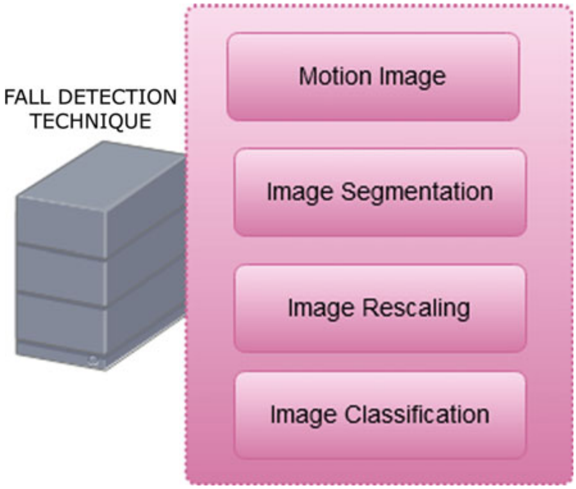


Fig. 11.3 Proposed architecture of the posture monitoring system

Fig. 11.4 Modules of fall detection technique



11.4.1 Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (set of pixels or superpixels). Traditionally, numerous image segmentation algorithms have been proposed by various researchers [38, 39]. Here, the clustering is the familiar technique which groups the pixel values into a specific number of clusters. Clustering works on the principles of high intraclass similarity and less interclass similarity among the pixel values. In the last decade, the algorithms such as Fuzzy C-Means (FCM) clustering [40], k-means clustering [41], subtractive clustering [42] and others have been proposed for image segmentation. The proposed system uses simple yet efficient k-means clustering, an unsupervised algorithm for the process of image segmentation. The general definition of a k-means clustering for image segmentation is as follows.

k-means clustering partitions a collection of data (pixel value) into a k-number of clusters ($k = 3$, k represents three color bands) and classifies into k-number of disjoint clusters. k-means clustering works in two phases. In the first phase, the algorithm calculates the k-centroid and in the second phase, it assigns each data point (pixel value) which has the nearest centroid from the respective data point. The distance between the data point and the centroid are calculated by different distance measures [43] such as Euclidean distance, Manhattan distance, and Minoskwi distance. The proposed system uses the Euclidean distance for the distance measure. Once the grouping of all data points to the centroid has been completed, the algorithm recomputes the new centroid for each k-cluster. For the new centroid, again Euclidean distance is calculated between each new centroid and data points and the data points are assigned to the cluster with minimum Euclidean distance. Each cluster is the partition defined by its member objects and by its centroid. Centroid is the point at which the sum of distances from all the objects in that cluster is minimized. k-means is an iterative algorithm, in which the algorithm minimizes the sum of distances from each object to its cluster centroid.

In the proposed algorithm, the k-means clustering process is used to segment only the retroreflective radium tape which is in red color for further process of image classification. The recorded motion image of any resolution (x, y) is grouped into k number of clusters ($k = 3$) and $p(x, y)$ refer to the input pixels to the cluster and c_k is the cluster center. The algorithm is as follows.

Input:

RGB image with (x, y) as resolution
k—Number of Clusters

Output:

Segmented image with color band as Red

Algorithm:

1. Randomly initialize the cluster center as c_k.
2. For each pixel of an image, calculate the Euclidean distance d between the center and each pixel of an image by using the Eq. (11.1).

$$d = ||p(x, y) - c_k|| \tag{11.1}$$

3. Assign the pixels $p(x, y)$ to the nearest center based on distance d
4. After all the pixels have been assigned, recalculate the new position of the center using the Eq. 11.2

$$c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} p(x, y) \tag{11.2}$$

5. Repeat the process until no new cluster is formed.
6. Reshape the cluster pixels into new image.

Image segmentation is carried out particularly for the tape fabricated in the dress and not for the entire body of the elderly. This may reduce the processing cost on region on interest (ROI) and bounding box issues for the further processing of images. After segmentation, the human posture is displayed through the tape. The segmented image contains only the pixel values of the tape and it is taken for the classification process. Before classification, the segmented image has different resolutions, to avoid the conflicts in classification.

11.4.2 Image Rescaling/Reshaping

The segmented images are rescaled and reshaped into a single numerical vector of size $100X1$ for the classification process. The vector contains numerical value only at the indices of tape and the remaining cells are filled with 0. The target class values are appended to the numerical vector which now becomes $101X1$ for the classification process.

11.4.3 Image Classification

The goal of image classification [44] is to predict the categories of the input image using its features. However, the image classification requires more time to interpret the spectral classes and it may vary across different images. This present chapter proposes the image classification through the traditional data classification, as the image has been rescaled to a numerical vector of size 101X1. Classification is basically grouped as supervised and unsupervised. Numerous supervised classification algorithms have been proposed for data classification as in [45] such as k-nearest neighbor (k-NN), artificial neural network (ANN), decision tree algorithms, support vector machine (SVM) and the like. This section utilizes k–NN, decision tree algorithm and artificial neural network (ANN) for the classification of motion images.

11.4.4 Decision Tree Algorithm

Decision tree learning uses a decision tree to go from observations about an item to conclusions about the items' target values. In decision trees, leaves represent one or more classes and the branches represent conjunctions of the features that lead to the classification process. In decision analysis, decision trees are used to visually and explicitly represent decisions and decisions making. Decision trees can be learned by splitting the source set into subsets on an attribute test value. The process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node has all the same values of the target variable or when splitting no longer adds value to the predictions. Decision tree learning is the construction of a decision tree from class-labeled training tuples. Numerous algorithms have been proposed for decision tree classification [45]. This chapter uses the concept of C4.5 (successor of ID3).

Algorithms for constructing the decision trees usually works as a top-down approach, by choosing a variable at each step that best splits the set of items. Different algorithms use different metrics for measuring the best split. The measures like Gini impurity, information gain and gain ratio, and so on are proposed for the best split measures. C4.5 uses information gain which works on the concept of Entropy and Information Theory. Entropy is defined as in Eq. 11.3 where D represents the tuple to be classified and p_i represents the probability that tuple D belongs to class C_i:

$$Info(D) = -\sum_{i=1}^{m} p_i log_2(p_i) \tag{11.3}$$

11.4.5 k-Nearest Neighbor

In pattern recognition, the k-nearest neighbor algorithm (k-NN) is a nonparametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. In k-NN classification, the output is a class membership. An object is classified by the majority of votes of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all the computations are deferred until classification. The k-NN algorithm is one of the simplest of all machine learning algorithms. Both for classification and regression, a powerful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant neighbors. Closeness is defined in terms of a distance metric such as Euclidean distance between two points or tuples: $X_1 = (x_{11}, x_{12}, \ldots, x_{1n})$ and $X_2 = (x_{21}, x_{22}, \ldots, x_{2n})$, as

$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2} \tag{11.4}$$

11.5 Results and System Evaluation

This section demonstrates the operations and performance of the proposed vision-based fall detection technique. To analyze the performance of the proposed technique, an experiment has been carried out with various subjects of different ages and both genders as shown in Table 11.3. During the experiment in the controlled environment, the subjects are clothed with a special dress fabricated with a retroreflective radium tape. When recording, the subjects are requested to do a variety of motions like sitting, sitting with knee extension, sleeping, supine, standing and some falls during motion. In Motion 1 in Table 11.3, the subject undergoes from the standing position to a sitting position (Motion 1). In Motion 2, the subject undergoes from the sitting position to standing position. Similarly, from the sitting position to sitting with knee extension is referred to as Motion 3. Motion 4 is from the sitting with knee extension to supine position. From supine position to sitting with knee extension is considered as Motion 5. Finally, Motion 6 considers falls from any position. Motion 6 alone is experimented for less number of motions, due to risk in injuries or other health issues. The numerical entries of each Motion represent the number of time the subject has carried out the particular motion during the experiment. In Table 11.3, subject S.No 1 at age 23 Male performs Motion 1 for 80 times (standing to sitting position during record); Motion 2 records for 70 times, i.e., from sitting position to standing position; and so forth.

Figure 11.5 represents various motions of two different subjects detected along with the Tapes. The motion images are processed with various modules as described earlier, i.e., image segmentation using *k*-means clustering and rescaling. Figure 11.6 represents the segmented image that shows only the posture of the subject through the tapes. The pixel value of the stickers is indexed with numeric value and the other

Table 11.3 Elderly attributes with their different Motions

S.no	Gender/Age	Height (cm)/Weight (Kg)	Motion 1	Motion 2	Motion 3	Motion 4	Motion 5	Motion 6
1	23/M	176/74	80	70	85	100	80	28
2	30/M	184/90	70	80	90	100	95	20
3	35/M	170/74	65	80	75	80	90	25
4	19/M	172/70	80	70	80	100	80	30
5	28/F	165/52	90	80	100	80	70	25
6	45/F	170/64	88	90	80	80	85	20
7	70/M	168/59	75	60	55	70	66	20
8	62/F	152/58	80	70	80	90	90	30
9	40/M	174/88	85	80	90	70	80	20
10	34/M	156/70	80	75	95	80	90	22
		Total motions	793	755	830	850	826	240

Fig. 11.5 Various subjects on motion detected

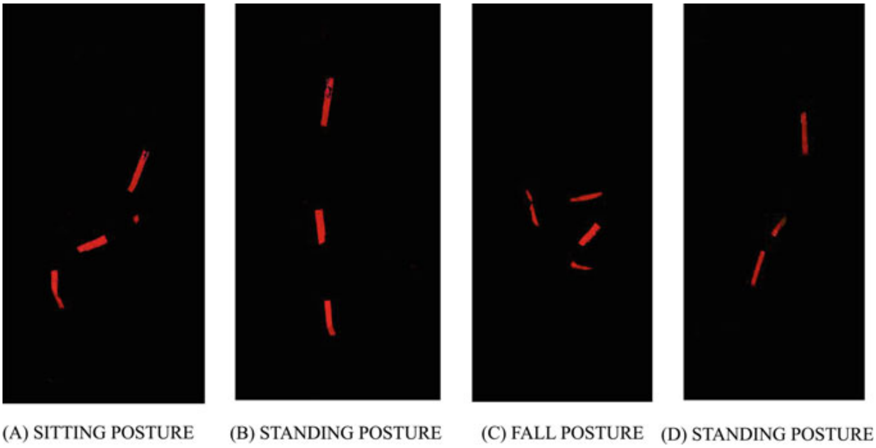


Fig. 11.6 Posture of the elderly visible through tapes after image segmentation

value seems to be zero. On performing rescaling and reshaping of the image, the pixel values are rescaled to a numerical vector for easier classification.

The vector value of each image has been considered for classification process with the target label value. Finally, the 10-fold cross validation is used for classifying the motion images using k-NN and decision tree classifier. For assessing the performance

Table 11.4 10-fold cross-validated result of k-NN classifier

Motions	Motion 1	Motion 2	Motion 3	Motion 4	Motion 5	Motion 6
Motion 1	755	7	8	12	8	7
Motion 2	8	716	9	14	6	8
Motion 3	6	9	789	11	4	8
Motion 4	7	8	7	792	7	9
Motion 5	9	6	8	11	794	6
Motion 6	8	9	9	10	7	202
Accuracy (%)	95.21	94.83	95.06	93.18	96.13	84.17

Table 11.5 10-fold cross-validated result of decision tree classifier

Motions	Motion 1	Motion 2	Motion 3	Motion 4	Motion 5	Motion 6
Motion 1	748	7	10	14	9	10
Motion 2	10	706	12	16	8	9
Motion 3	9	12	773	13	6	8
Motion 4	8	10	10	781	7	10
Motion 5	9	9	12	14	788	9
Motion 6	9	11	13	12	8	194
Accuracy (%)	94.33	93.51	93.13	91.88	95.4	80.83

of the proposed methodology, all the motions from 1 to 6 of all the 10 persons are merged. In total, 4294 motions are used for the assessment. The cross-validated results of k-NN and decision tree are shown in Tables 11.4 and 11.5, respectively. The performances of the classifier are measured using the familiar metrics such as Sensitivity (Sen), Specificity (Spe) and Accuracy (Acc) as given in Eqs. 11.5, 11.6 and 11.7 where M_x and M_y are two motions.

$$Sen = \frac{TP}{TP + FN}, \tag{11.5}$$

$$Spe = \frac{TN}{TN + FP}, \tag{11.6}$$

$$Acc = \frac{TP + TN}{TP + FP + FN + TN}, \tag{11.7}$$

where

TP—Motion M_x identified as M_x
TN—Motion M_x identified as M_y
FP—Motion M_y identified as M_y
FN—Motion M_y identified as M_x

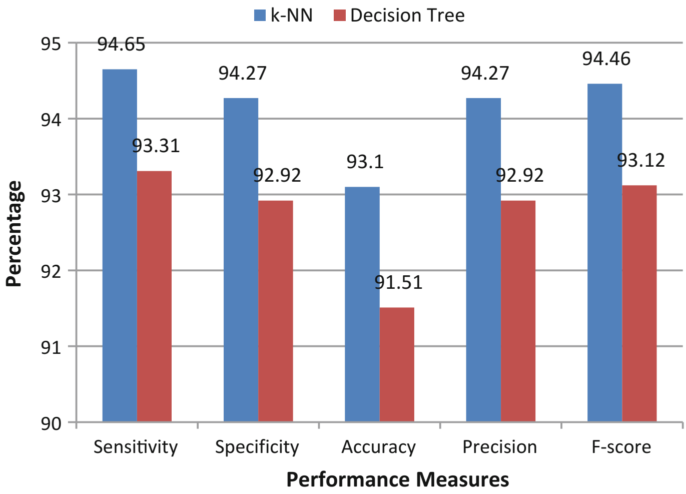


Fig. 11.7 Performance measure of *k*-NN and decision tree classifier

Tables 11.4 and 11.5 represent the 10-fold cross-validated results (Confusion Matrix) of *k*-NN classifier and decision tree, respectively, for the Motions from 1 to 6 for all 10 participants. Table 11.4 shows the performance of *k*-NN classifier, for all Motions 1–6. Accuracy of Motion 1 is 95.21, Motion 2 is 94.83, Motion 3 is 95.06, Motion 4 is 93.18, Motion 5 is 96.13, and Motion 6 is 84.17. The Motions are detected at the scale of 94–95%. However, Motion 6 has the range of 84 due to less number of samples taken for the assessment. The overall average accuracy of *k*-NN classifier for the posture monitoring of all the motions is 93.1%.

Table 11.5 shows a similar performance of decision tree classifier, for all the Motions from 1 to 6. Accuracy of Motion 1 is 94.33, Motion 2 is 93.51, Motion 3 is 93.13, Motion 4 is 91.88, Motion 5 is 95.40, and Motion 6 is 80.83. The overall average accuracy is 91.51. On comparing the performance of both the classifiers, the performance of *k*-NN classifier shows better accuracy than the decision tree classifier. Performance of the system/classifier is measured using different measures like accuracy, sensitivity, and specificity. From Eqs. 11.5 and 11.6, sensitivity and specificity only detect the false positive which is the important factor in determining the performance of the posture monitoring system. Figure 11.7 shows the performance measures of *k*-NN classifier and decision tree. From the performance comparison which is shown in Fig. 11.7, it is clear that sensitivity and specificity show higher value than decision tree in the range of 94–95%. This shows the efficiency of the proposed posture monitoring system. However, in future, the robust monitoring system may be proposed to improve the accuracy, sensitivity and specificity of the system.

11.6 Conclusion

This chapter introduces a low-cost posture monitoring system using retroreflective radium tapes which are fabricated in a loose cotton dress with infrared cameras. The Tapes are fabricated at four different parts of the dress. Although the system presented in this chapter is currently under development, it reliably detects falls in the controlled environments. The system performs with approximately 94% efficiency in the controlled environments. The present system has an enormous advantage in the sense that a person under surveillance is not required to wear any sensory devices. There is no privacy interference for the elderly as it records only the motion images. The cost of the proposed approach is much less when compared to other fall detection techniques, as it requires only a simple infrared camera with digital video recorder. Lifetime of the system is high. The system reliability has been proven with different subjects of different age and genders involved in the experiment. As regards the future, work can be extended in terms of occlusion, state differentiation, and gait recognition.

References

1. World Health Organization (2007) WHO global report on falls prevention in older age. World Health Organization: Geneva, Switzerland, 2007
2. Rodrigues R, Huber M, Lamura G (2012) Facts and figures on healthy ageing and long-term care. European Centre for Social Welfare Policy and Research, Vienna
3. Costa R, Carneiro D, Novais P, Lima L, Machado J, Marques A, Neves J (2009) Ambient assisted living. In: 3rd Symposium of Ubiquitous Computing and Ambient Intelligence 2008. Springer, Berlin, pp 86–94
4. Pieper Michael, Antona Margherita, Cortés Ulises (2011) Ambient assisted living. Ercim News 87(2011):18–19
5. Bagalà F, Becker C, Cappello A, Chiari L, Aminian K, Hausdorff JM, Zijlstra W, Klenk J (2012) Evaluation of accelerometer-based fall detection algorithms on real-world falls. PLoS ONE 2012(7):37062. https://doi.org/10.1371/journal.pone.0037062
6. Wang C-C, Chiang C-Y, Lin P-Y, Chou Y-C, Kuo I-T, Huang C-N, Chan C-T (2008) Development of a fall detecting system for the elderly residents. In: Proceedings of the 2008 2nd International Conference on Bioinformatics and Biomedical Engineering, Shanghai, China, 16–18 May 2008, pp 1359–1362
7. Lindemann U, Hock A, Stuber M, Keck W, Becker C (2008) Evaluation of a fall detector based on accelerometers: a pilot study. Med Biol Eng Comput 2005(43):548–551. https://doi.org/10.1007/BF02351026
8. Mathie MJ, Coster ACF, Lovell NH, Celler BG (2004) Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. Physiol Meas 2004:25. https://doi.org/10.1088/0967-3334/25/2/R01
9. Glaros C, Fotiadis DI (2005) Wearable devices in healthcare. In: Intelligent paradigms for healthcare enterprises. Springer, Berlin, pp 237–264
10. Varshney U (2007) Pervasive healthcare and wireless health monitoring. Mobile Networks and Applications 12(2–3):113–127
11. Rashidi P, Mihailidis A (2013) A survey on ambient-assisted living tools for older adults. IEEE J Biomed Health Inform 17(3):579–590

12. Mubashir M, Shao L, Seed L (2013) A survey on fall detection: principles and approaches. Neurocomputing 2013(100):144–152. https://doi.org/10.1016/j.neucom.2011.09.037
13. Wang C-C, Chiang C-Y, Lin P-Y, Chou Y-C, Kuo I-T, Huang C-N, Chan C-T (2008) Development of a fall detecting system for the elderly residents. In: Proceedings of the 2008 2nd international conference on bioinformatics and biomedical engineering, Shanghai, China, 16–18 May 2008; pp 1359–1362
14. Bianchi F, Redmond SJ, Narayanan MR, Cerutti S, Lovell NH (2010) Barometric pressure and triaxial accelerometry-based falls event detection. IEEE Trans Neural Syst Rehabil Eng 18(6):619–627
15. Ghasemzadeh H, Jafari R, Prabhakaran B (2013) A body sensor network with electromyogram and inertial sensors: multimodal interpretation of muscular activities. IEEE Trans Inf Technol Biomed 2010(14):198–206. https://doi.org/10.1109/TITB.2009.2035050
16. Abbate S, Avvenuti M, Bonatesta F, Cola G, Corsini P, Vecchio A (2012) A smartphone-based fall detection system. Perv Mob Comput J 2012(8):883–899. https://doi.org/10.1016/j.pmcj.2012.08.003
17. Aihua M, Ma X, He Y, Luo J (2017) Highly portable, sensor-based system for human fall monitoring. Sensors 2017:17. https://doi.org/10.3390/s17092096
18. Albert MV, Kording K, Herrmann M, Jayaraman A (2012) Fall classification by machine learning using mobile phones. PLoS ONE 2012(7):e36556. https://doi.org/10.1371/journal.pone.0036556
19. Chaccour K, Darazi R, El Hassani AH, Andrès E (2017) From fall detection to fall prevention: a generic classification of fall-related systems. IEEE Sens J 2017(17):812–822. https://doi.org/10.1109/JSEN.2016.2628099
20. FATE Project (2017). https://fate.webs.upc.edu/project. Accessed 30 Nov 2017
21. Tunstall Products (2017). https://uk.tunstall.com/services/our-products/. Accessed 30 Nov 2017
22. Zhuang X, Huang J, Potamianos G, Hasegawa-Johnson M (2009) Acoustic fall detection using gaussian mixture models and gmm supervectors. In: Proceedings of the IEEE international conference on acoustics, speech and signal processing (2009), Taipei, Taiwan, 19–24 April 2009, pp 69–72
23. Alwan M, Rajendran PJ, Kell S, Mack D, Dalal S, Wolfe M, Felder R (2006) A smart and passive floor-vibration based fall detector for elderly. In: Proceedings of the 2nd information and communication technologies, ICTTA'06, Damascus, Syria, 24–28 April 2006, vol 1, pp 1003–1007
24. Rimminen H, Lindstrom J, Linnavuo M, Sepponen R (2010) Detection of falls among the elderly by a floor sensor using the electric near field. IEEE Trans Inf Technol Biomed 2010(14):1475–1476. https://doi.org/10.1109/TITB.2010.2051956
25. Tao S, Kudo M, Nonaka H (2012) Privacy-preserved behavior analysis and fall detection by an infrared ceiling sensor network. Sensors 2012(12):16920–16936
26. Tamura T, Yoshimura T, Sekine M, Uchida M, Tanaka O (2009) A wearable airbag to prevent fall injuries. IEEE Trans Inf Technol Biomed 2009(13):910–914. https://doi.org/10.1109/TITB.2009.2033673
27. The Top 10 Fall Detectors (2016). http://www.toptenreviews.com. Accessed 30 Nov 2017
28. Diraco G, Leone A, Siciliano P (2010) An active vision system for fall detection and posture recognition in elderly healthcare. In: Proceedings of the 2010 Design, Automation and Test in Europe Conference and Exhibition (DATE 2010), Dresden, Germany, 8–12 Mar 2010, pp 1536–1541
29. Kepski M, Kwolek B (2014). Fall detection using ceiling-mounted 3D depth camera. In: Proceedings of the 2014 international conference on computer vision theory and applications (VISAPP), Lisbon, Portugal, 5–8 Jan 2014, pp 640–647
30. Hsu YW, Perng JW, Liu HL (2015) Development of a vision based pedestrian fall detection system with back propagation neural network. In: Proceedings of the 2015 IEEE/SICE international symposium on system integration (SII), Nagoya, Japan, 11–13 Dec 2015, pp 433–437

31. Nguyen HTK, Fahama H, Belleudy C, Pham TV (2014) Low power architecture exploration for standalone fall detection system based on computer vision. In: Proceedings of the European modelling symposium, Pisa, Italy, 21–23 Oct 2014, pp 169–173
32. de Miguel K, Brunete A, Hernando M, Gambao E (2017) Home camera-based fall detection system for the elderly. Sensors 17(12): 2864
33. Liu CL, Lee CH, Lin PM (2010) A fall detection system using k-nearest neighbor classifier. Expert Syst Appl 37(10):7174–7181
34. Claridge AW, Mifsud G, Dawson J, Saxon MJ (2005) Use of infrared digital cameras to investigate the behaviour of cryptic species. Wildl Res 31(6):645–650
35. Kim M-G, Byun W-G (2006) Digital video recorder. US Patent Application 29/226,437, filed May 2, 2006
36. Haralick RM, Shapiro LG (1985) Image segmentation techniques. Comput Vis Graph Image Process 29(1):100–132
37. Pal NR, Pal SK (1993) A review on image segmentation techniques. Pattern Recognit 26(9):1277–1294
38. Zhang DQ, Chen SC (2004) A novel kernelized fuzzy c-means algorithm with application in medical image segmentation. Artif Intell Med 32(1):37–50
39. Ray S, Turi RH (1999) Determination of number of clusters in k-means clustering and application in colour image segmentation. In: Proceedings of the 4th international conference on advances in pattern recognition and digital techniques, pp. 137–143
40. Dhanachandra N, Manglem K, Chanu YJ (2015) Image segmentation using K-means clustering algorithm and subtractive clustering algorithm. Procedia Comput Sci 54(2015):764–771
41. Davies DL, Bouldin DW (1979) A cluster separation measure. IEEE Trans Pattern Anal Mach Intell 2:224–227
42. Kotsiantis SB, Zaharakis I, Pintelas P (2007) Supervised machine learning: a review of classification techniques. In: Emerging artificial intelligence applications in computer engineering, vol 160, pp 3–24
43. Kotsiantis SB, Zaharakis I, Pintelas P (2007) Supervised machine learning: a review of classification techniques. Emerging artificial intelligence applications in computer engineering 160:3–24
44. Harrison GM (1989) Traffic lane marking device. US Patent 4,875,799, issued October 24, 1989
45. Mathie MJ, Basilakis J, Celler BG (2001) A system for monitoring posture and physical activity using accelerometers. In: Proceedings of the 23rd annual international conference of the Engineering in Medicine and Biology Society, 2001, vol 4. IEEE, pp 3654–3657