Fuzzy Inference-Based Reliable Fall Detection Using Kinect and Accelerometer

Michal Kepski[1*], Bogdan Kwolek[1], and Ivar Austvoll[2]

[1] Rzeszów University of Technology, 35-959 Rzeszów, Poland
bkwolek@prz.edu.pl
[2] University of Stavanger, N-4036 Stavanger, Norway
ivar.austvoll@uis.no

Abstract. Falls are major causes of mortality and morbidity in the elderly. However, prevalent methods only utilize accelerometers or both accelerometers and gyroscopes to separate falls from activities of daily living. This makes it not easy to distinguish real falls from fall-like activities. The existing CCD-camera based solutions require time for installation, camera calibration and are not generally cheap. In this paper we show how to achieve reliable fall detection. The detection is done by a fuzzy inference system using low-cost Kinect and a device consisting of an accelerometer and a gyroscope. The experimental results indicate high accuracy of the detection and effectiveness of the system.

1 Introduction

In developed countries the segment of the elderly population over 65 years of age is growing quickly. About one third of people aged over 65 years are failing once a year at least. This rate increases to one half for the segment of people aged over 80 years. 20 up to 30% of 65+ adults who fall suffer moderate to severe injuries, and 2% of such falls result in broken hips [4]. Approximately 30% of people older than 60 years live alone. Considerable portion of the elderly population is also willing to accept new technologies to increase safety and the quality of life. The above mentioned issues stimulated a great interest in fall detection systems.

Most proposed systems to fall detection are based on a wearable device that monitor the movements of an individual, recognize a fall and trigger an alarm. Body attached accelerometers [2][5] and gyroscopes [8] are widely used in monitoring human movement and detecting falls. Fall detection methods can be divided into two groups of methods in relation to how kinetic data is utilized to distinguish activities of daily living (ADLs) from falls. To the first group belong methods that are based on a fixed threshold. In [2] a system based on magnitude of acceleration values has been proposed, whereas in [1] an algorithm using measures of angular velocity obtained from gyroscopes has been presented. The critical issue in such algorithms is to determine proper threshold. However, several ADLs like fast sitting have similar kinematic motion patterns to those of

* M. Kepski is currently a student, doing his MSc thesis on fall detection.

real falls and in consequence the methods belonging to this group might trigger many false alarms. In the second group of approaches are methods that combine kinematic thresholds with posture. The method proposed in [8] assumes that a fall always ends in a lying position. The assumption that a fall always ends in a lying pose permits to separate out some fall-like ADLs like sitting, running and jumps. However, such an assumption might also lead to both false positive alarms when a person lies quickly on a bed or false negatives in case of remaining in a sitting position after a harmless fall. According to the experimental evaluation of the method its sensitivity is 91%, while specificity is 92%. In general, the solutions mentioned above are somehow intrusive for people as they require wearing continuously at least one device or smart sensor.

Several attempts were made to amend the limitations mentioned above. Some of them propose the use of two or more wearable devices [10]. However, such methods can be uncomfortable for elderly people. Moreover, body attached devices might be uncomfortable when sleeping, during change of clothes, wash, etc. Some approaches focus on ambient devices, which are installed in the places to be monitored. Common examples of such sensors are pressure sensors on the floor, bed exit detectors, etc. However, pressure sensitive mats have unavoidable edges that can cause falls. In addition, the installation of such multiple sensors is time consuming and monitoring is strictly limited to the places with the sensors.

There have also been several attempts to achieve reliable human fall detection using single CCD cameras [11], multiple cameras [3] or specialized omnidirectional ones [9]. A vision system [7], which uses a camera mounted on the ceiling was tested on 21 volunteers who carried out simulated falls. The fall detection ratio was 77%. There are several advantages of using video cameras, among others the ability to detect various events. Another advantage is low intrusiveness. In some circumstances, the possibility of remote verification of fall events might be very important. Internet network IP cameras, including GigE vision cameras can be used to achieve such capability easily. However, the existing solutions require time for installation and/or camera calibration and are not generally cheap. Moreover, in monocular camera based approaches the lack of depth information may lead to false alarms. The shortcomings mentioned above motivated us to develop a low-cost and reliable system to trigger a fall alarm.

Our system employs both an accelerometer and a video camera, which complement each other. The system is based on expert knowledge and demonstrates high generalization abilities. The main part of the algorithm is based on a fuzzy inference system (FIS). We show that low-cost Kinect contribute toward reliable fall detections. The disadvantage of Kinect is that it only can monitor restricted areas. In such areas we utilized an accelerometer. On the other hand, in some ADLs during which the use of this wearable sensor might not be comfortable, for instance during changing clothes, wash, etc., the system relies on Kinect camera only. An advantage of Kinect is that it can be put in certain places according to the user requirements. Moreover, the system operates on depth images and thus preserves privacy for people being monitored. In this context, it is worth noting that Kinect uses infrared light and therefore it is able to extract depth images in a room that is dark to our eyes. Using both devices, our system can reliably distinguish the falls from activities of daily living, and thus the number of false alarms is reduced.

2 The system

Our fall detection system uses both data from Kinect and motion data from a wearable smart device containing accelerometer and gyroscope sensors. Data from the smart device (Sony PlayStation Move) are transmitted wirelessly via Bluetooth to a notebook computer on which the signal processing is done, whereas Kinect is connected via USB, see Fig. 1. The device contains one tri-axial accelerometer and a tri-axial gyroscope consisting of a dual-axis gyroscope and a Z-axis gyroscope. The fall alarm is triggered by a fuzzy inference engine based on expert knowledge, which is declared explicitly by fuzzy rules and sets. As inputs the engine takes the acceleration, the angular velocity and the distance of the person's gravity center to the altitude at which the Kinect is placed. The acceleration's vector length is calculated using data provided by the tri-axial accelerometer, whereas the angular velocity is provided by the gyroscope.

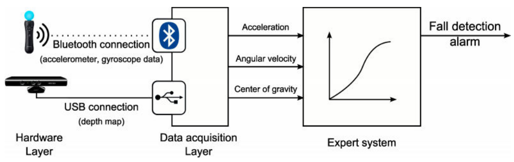

Fig. 1. The system architecture.

A tri-axial accelerometer is a sensor that returns a real valued estimate of acceleration along x, y and z axes. Data from an accelerometer contains time and acceleration along three axes. Figure 2 depicts the plots of acceleration and angular velocities readings vs. time for walking and simulated falling. The sampling rate of both sensors is equal to 60 Hz. The measured acceleration signals were median filtered with a window length of three samples to suppress the noise and then used to calculate the acceleration's vector length. When people fall, acceleration and angular velocity are rapidly changed, as demonstrated at right plots at Fig. 2. A lot of attention to the optimal sensor placement on the body has been done until now [5]. The attachment of the sensor to trunk or lower back is recommended because such body parts represent the major component of body mass and move with most activities. The depicted plots were obtained for the device that was worn at the waist or near the pelvis region.

Kinect is a motion sensing input device for the Xbox 360 video game console. The Kinect device has two cameras and one laser-based IR projector. The IR camera and the IR projector form a stereo pair with a baseline of approximately

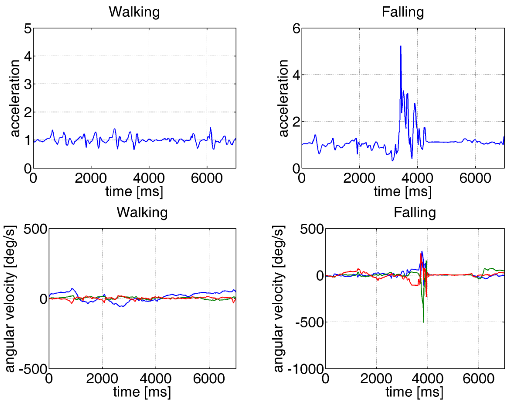

Fig. 2. Acceleration and angular velocity for walking and a real fall.

75 mm. The IR projector sends out a fixed pattern and dark speckles. The depth is determined by triangulation against a known pattern. Then the pattern is remembered at known depth. Given the known depth of such a plane and the disparity, the depth for each pixel is calculated by the triangulation. In Fig. 3 color and depth images that were acquired by Kinect are depicted. The depth image was then segmented using OpenNI library. Finally, on the basis of the segmented objects the center of gravity of the object of interest was calculated.

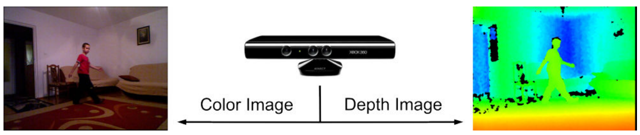

Fig. 3. Color and depth images provided by Kinect.

Figure 4 illustrates the architecture of the fall detection system. A fuzzy inference system proposed by Takagi and Sugeno (TS) [12] is used to generate the fall alarm. It expresses human expert knowledge and experience by using fuzzy inference rules represented in $if - then$ statements. In such an inference system the linear submodels associated with TS rules are combined to describe the global behavior of the nonlinear system.

When input data is fed into the TS type fuzzy inference system, each feature value of the unknown input vector is fuzzified, i.e., converted to a fuzzy number, through their membership functions (MFs), see Fig. 4. The common types of membership functions are singletons, triangles, trapezoids, Gaussians, etc. Every kind of membership function has its advantages and disadvantages. For example,

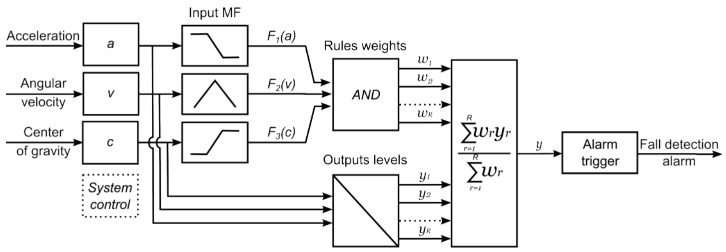

Fig. 4. The fuzzy inference system.

triangular membership function is very easy to implement and it can be calculated fast. Figure 5 shows the membership functions (MFs), which were designed by an expert. The acceleration is proportional to the gravitational acceleration g, angular velocity is expressed in degrees, whereas the center of gravity is the difference between the estimated persons gravity center to the floor level and the Kinect altitude.

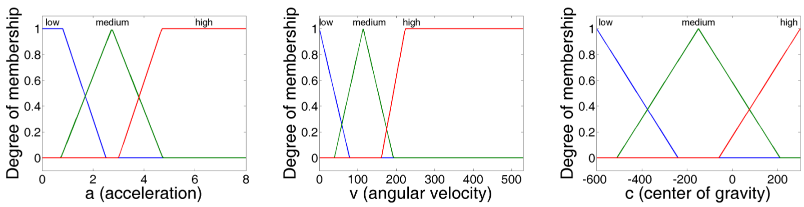

Fig. 5. Membership functions.

The inference is done by the TS fuzzy system consisting of R rules of the following form: $if\ x_1\ is\ A_{1r}\ and \ldots and\ x_i\ is\ A_{ir}\ and \ldots and\ x_N\ is\ A_{Nr}\ then\ y_r = p_{0r} + p_{1r}x_1 + \cdots + p_{Nr}x_N$, where A_{ir} denotes the linguistic labels of the ith input variable ($i = 1, \ldots, N$), associated with the rth rule ($r = 1, \ldots, R$), p_{0r}, p_{ir} are the parameters of the rth rule, whereas x_i stands for the numerical value of the ith input variable. The inference function is given by the following expression:

$$y = \frac{\sum_{r=1}^{R} w_r y_r}{\sum_{r=1}^{R} w_r} \tag{1}$$

The twenty seven rules in the system produce a decision surface. The decision surfaces of our fall detection system for the two inputs are illustrated in Fig. 6. The filtered data from the accelerometer and the gyroscope were interpolated and decimated as well as synchronized with the data from Kinect, i.e. the center of gravity of the moving person. The output y that is generated with 30 Hz is fed into the alarm trigger module, see also Fig. 4, which makes the final decision. The alarm is triggered if a specified number of samples in a predefined period of time is above a predefined value.

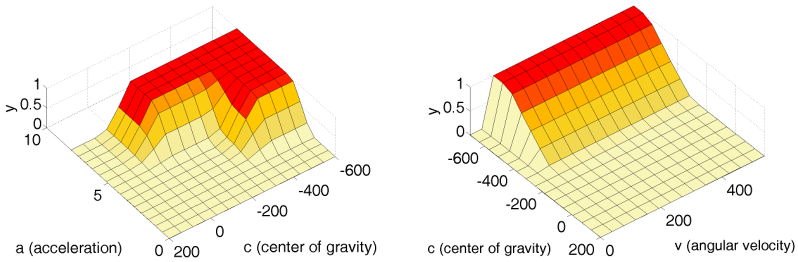

Fig. 6. Decision surfaces of the fuzzy inference engine.

3 Experimental Results

Three volunteers with age over 26 years attended in evaluation of our developed algorithm and system. Intentional falls were performed towards carpets of various thicknesses ranging from 2 cm to 5 cm. During the simulation of falls, it was paid attention to falling not too heavily. The accelerometer was worn near the pelvis. Each individual performed three types of falls, namely forward, backward and lateral at least three times. Each individual performed also ADLs like walking, sitting, crouching down, leaning down/picking up objects from the floor, lying on a bed. Figure 7 depicts some example images with selected ADLs.

Fig. 7. Images with activities of daily living: walking, crouching down, lying on a bed, leaning down/picking up objects from the floor, sitting and falling (from left to right and from top to bottom), which were shot by Kinect.

The corresponding depth images, which were extracted by Kinect, are depicted in Fig. 8. As we can observe, one of the disadvantages of Kinect is a blind spot that cannot be directly observed. Kinect's field of view is fifty-seven degrees horizontally and forty-three degrees vertically and in consequence some areas at the floor close to Kinect are not observable, see also the right-down image at Fig. 8. The minimum range for the Kinect is about 0.6 m and the maximum range is somewhere between 4-5 m.

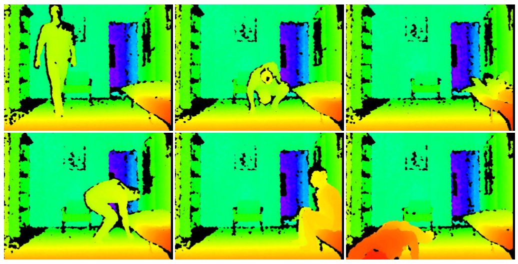

Fig. 8. Depth images corresponding to images from Fig. 7, extracted by Kinect.

Figure 9 demonstrates some example outputs of our fall detection system, that were generated during performing some ADLs, including a fall simulated by a volunteer. These plots show that a single accelerometer with gyroscope and Kinect are completely sufficient to implement a reliable fall detection system. All intentional falls performed by three volunteers were detected correctly. In particular, sitting down fast, which is not easily distinguishable from a typical fall when only accelerometer or even accelerometer and gyroscope are used, was detected reliably by our system. One activity consisting in seating on a sofa was wrongly classified as a fall using only Kinect. The false alarm was altered because on the depth image acquired by Kinect the legs were merged with the sofa bottom part. In consequence, the gravity center extracted by the OpenNI library was situated at a relatively small distance to the floor. It is worth noting that in the near future the modern mobile devices will be equipped with some fall detection capabilities, but in some daily activities their helpfulness can still

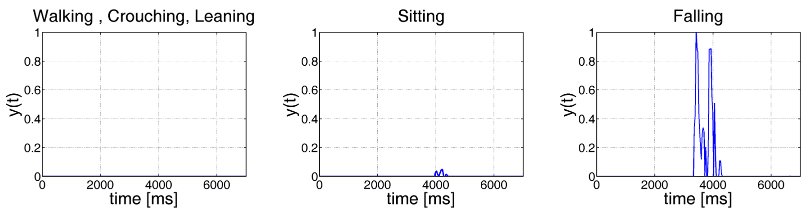

Fig. 9. FIS output smoothed with a moving average filter. Person fall is easily recognizable.

be reduced. Our results demonstrate that the use of low-cost Kinect will make it possible to construct unobtrusive and reliable fall detection systems. Moreover, using Kinect it will be possible to recognize simultaneously some daily activities, which is an important and challenging problem [6].

4 Conclusions

In this paper we demonstrate how to achieve reliable fall detection. The detection was done by fuzzy inference system using Kinect, accelerometer and gyroscope. The results show that a single accelerometer with gyroscope and Kinect are completely sufficient to implement a reliable fall detection system.

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