FALL DETECTION AND ACTIVITY RECOGNITION METHODS FOR THE CONFIDENCE PROJECT: A SURVEY

Boštjan Kaluža, Mitja Luštrek
Department of Intelligent Systems
Jožef Stefan Institute
Jamova cesta 39, 1000 Ljubljana, Slovenia
Tel: +386 1 4773944; fax: +386 1 4251038
E-mail: bostjan.kaluza@ijs.si

ABSTRACT

The Confidence project is designed to support independent living of the elderly. The main goal of the project is reconstructing the user's posture to detect falls in real time and to detect other abnormalities in behavior. This paper presents a survey of methods for fall detection and activity recognition and discusses how suitable they are for the Confidence project. The presented methods use accelerometers, velocity profiles and visual markers.

1 INTRODUCTION

While the expected lifetime in Europe is increasing, the population growth is negative. The over-65 population is anticipated to rise from 17.9 % in 2007 to 53.5 % by 2060 [5] as shown in Figure 1. Thus an effort needs to be made to ensure that elderly people could live longer independently with minimal support of working-age population.

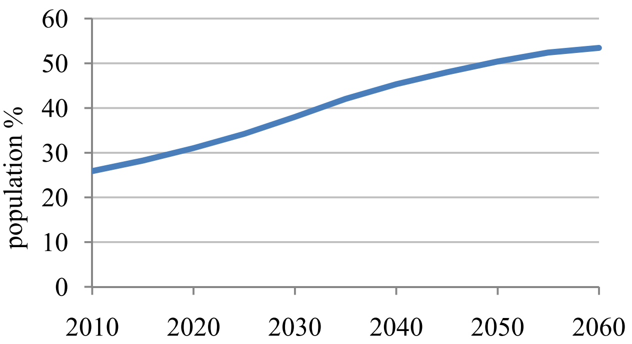

Figure 1: *Projected dependency ratio of persons aged 65 and over in EU (27 countries).*

The Confidence project will develop a ubiquitous care system to support independent living of the elderly. The system will be able to reconstruct the user's posture and detect abnormal situations, such as falls, loss of consciousness or behaviors indicating a disease.

This paper surveys fall detection and activity recognition methods that could be used in the project. They are mostly based on the data from accelerometers, gyroscopes or cameras, which will not be employed in Confidence, so they cannot be used directly. Nevertheless, some may be adapted to the system to be developed in the project.

Section 2 presents the hardware architecture of the Confidence system and the basic ideas of the project. Section 3 is dedicated to fall detection using acceleration-based methods, velocity profiles and computer vision. In Section 4 are presented some systems and methods for activity and posture recognition. Section 5 summarizes the survey.

2 CONFIDENCE SYSTEM DESCRIPTION

The user will wear small low-cost wireless tags placed on the significant places on the body such as wrists, elbows, shoulders, ankles, knees and hips. The precise number and placement of tags will be defined during development. The tags may be sewn into the clothes. The location of the tags will be detected by a base station located in the apartment or a portable device carried outside. This will make it possible to reconstruct the user's posture as shown in Figure 2.

Some tags will be placed in the user's environment at specific positions, such as bed, chair, sofa, table, etc. These tags will enable the recognition of situations such as the user lying in the bed or sitting in a chair.

Intelligent modules in the Confidence system will process and analyze the data and raise the alarm if the user's behavior indicates a hazardous situation such as a fall, stroke, epileptic attack etc. First, the system will make a phone call to the user and verify the user's state by requiring the user to press a sequence of buttons or say a certain word. If the user does not pick up the phone, the system will make a phone call to relatives, friends and even the emergency services if nobody answers.

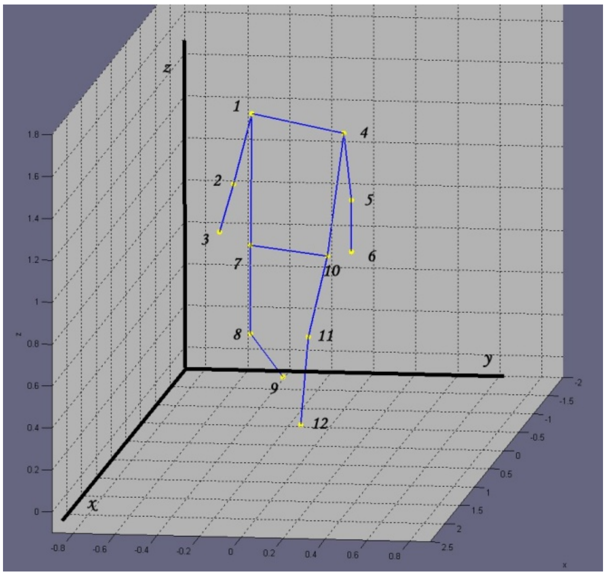

Figure 2: *3D locations of body tags obtained by motion capture system.*

3 FALL DETECTION

Falls among the elderly are the leading cause of injury, even death, and the loss of independent living. Detection and prevention of falls is consequently an important issue in the Confidence project. Figure 3 shows simulation of a fall during the capturing of training data in the laboratory.

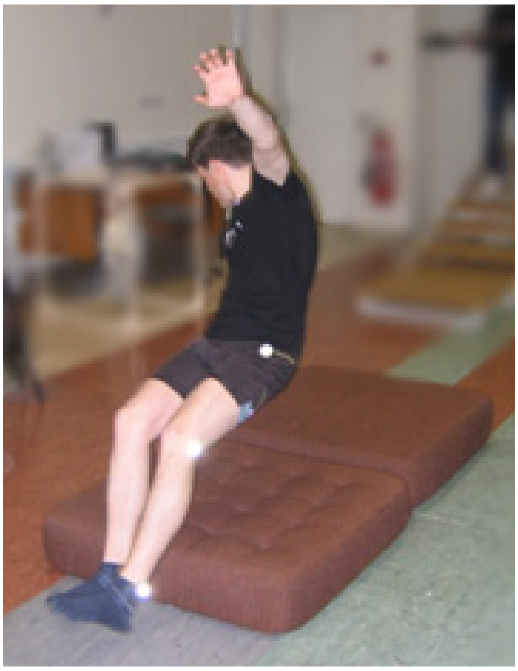

Figure 3: *A simulation of a fall.*

3.1 Accelerometer-based methods

The most common and simple methodology for fall detection is using a tri-axial accelerometer with quite simple threshold-based algorithms [3, 7]. Such algorithms simply raise the alarm when the threshold value of acceleration is reached. There are several sensors with hardware built-in fall detection [1, 4, 9].

D. J. Willis [12] developed a more complex fall detection system based on dynamic belief network models, which can be used to model and produce conclusions about the state of complex temporal environments. He used pressure transducers besides accelerometers.

T. Zhang et al. [15] designed fall detector based on support vector machine algorithm. Their method detected falls with 96.7 % success rate. Researches embedded an accelerometer in a cell phone [14] and detected falls with the proposed method. The cell phone was put in the pocket of clothes or hanged around the neck. The system correctly raised the alarm in 93.3 % of the cases.

Researchers using accelerometers give a lot of attention to the optimal sensor placement on the body [3, 7]. A head-worn accelerometer provides excellent impact detection sensitivity, but its limitations are usability and user acceptance. A better option is a waist-worn accelerometer. The wrist did not appear to be an optimal site for fall detection. Some researchers made a step further and used accelerometers for trying to recognize the impact and the posture after the fall [8].

In Confidence we will be able to derive accelerations from the movement of the tags and use one of the threshold algorithms if the localization precision is sufficient. Using more complex algorithms such are dynamic belief networks and support vector machine may be considered if threshold algorithms do not achieve the desired accuracy. Posture after the fall can be obtained from the locations of the body tags rather than from accelerations. Studies of the sensor placement may be valuable for deciding where to place tags in Confidence.

3.2 Velocity profile

A. K. Bourke and G. M. Lyons [2] introduced a threshold algorithm to distinguish between normal activities and falls. The ability to discriminate was achieved using a bi-axial gyroscope sensor mounted on the trunk, measuring pitch and roll angular velocities. They constructed a threshold algorithm based on the investigation of peaks in the angular velocity signal, angular acceleration and trunk angle change. System proved 100 % successful in fall detection.

In Confidence we may use the proposed method. Having sufficiently precise tag localization would enable us to compute the required signals. Decreased precision may cause problems when defining the threshold values.

G. Wu [13] studied unique features of the velocity profile during normal and abnormal (i.e. fall) activities so as to make the automatic detection of falls during the descending phase of a fall possible. Normal activities included walking, rising from a chair and sitting down, descending stairs, picking up an object from the floor, transferring in and out of a tub and lying down on a bed.

The study provides exhaustive velocity parameters for fall detection, which could be very useful in Confidence.

Supposing that we have sufficiently precise tag localization, we could simply extract those velocities and detect falls extremely quickly.

3.3 Computer vision

Z. Fu et al. [6] described a vision system designed to detect accidental falls in elderly home care applications. The system raised the alarm when a fall hazard was detected. They used an asynchronous temporal contrast vision sensor, which extracts changing pixels from the background and reports temporal contrast. A lightweight algorithm computed an instantaneous motion vector and reported fall events. They were able to distinguish fall events from normal human behavior, such as walking, crouching down and sitting down.

Temporal contrast vision sensor gives a similar human body contour as the Confidence human body model derived from tag locations. Z. Fu et al. defined a centroid event as the average of the motion events, which was used for fall detection. This method could be potentially useful when localization precision is reduced.

4 ACTIVITY AND POSTURE RECOGNITION

E. M. Tapia et al. [11] presented a real-time algorithm for automatic recognition of not only physical activities, but also, in some cases, their intensities, using five wireless accelerometers and a wireless heart rate monitor. Features were extracted from time and frequency domains using a predefined window size on the signal. The classification of activity was done with C4.5 and Naïve Bayes classifiers.

The algorithm was evaluated using datasets consisting of 30 physical gymnasium activities collected from a total of 21 people. On these activities, they obtained a recognition accuracy of 94.6 % using subject-dependent training and 56.3 % using subject-independent training.

Although the researchers were using a different monitoring system, the presented system successfully dealt with real-time activity recognition, which could be useful in Confidence.

G. Qian et al. [10] introduced a gesture-driven interactive dance system capable of real-time feedback for performing arts. They used 41 markers on the body measured by 8 cameras with the frame rate of 120 Hz. They developed data cleaning algorithm to tackle missing markers and constructed a human body model. The model was used to extract features such as torso orientation, joint angles between adjacent body parts etc., which was used to represent different gestures. Each gesture was statistically modeled with a Gaussian random vector. Gesture matching was performed to determine whether a new pose is inside the gesture space and if it is, the likelihoods of the feature vector given different gestures were computed.

Experimental results with two dancers performing 21 different gestures achieved gesture recognition rate of 99.3 %.

The markers in the proposed system have the same role as tags in the Confidence system. The presented methods could be directly used for posture recognition. The Confidence system will avoid data cleaning due to wireless transmission of 3D coordinates instead of detecting them with a camera.

A lot of researches investigated fall detection and posture recognition using video surveillance. They extracted features from image signal and used one of the abovementioned methods. Such feature extraction is not applicable to Confidence and consecutively not discussed.

5 CONCLUSION

The presented systems and methods are successful in detecting falls and activities. Falls are mainly detected with accelerometers and gyroscopes. In the Confidence system, the derivation of accelerations is questionable due to tag sampling rate. Methods using velocity profiles are more appropriate. In combination with furniture tags to detect the location of the fall, they may give very reliable results.

Activity recognition is mainly based on processing video images. System based on markers detected with a camera give promising results.

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