Ubiquitous Care System to Support Independent Living: Preliminary Results

Boštjan Kaluža[1], Violeta Mirčevska[1], Mitja Luštrek[1], Igone Vélez[2], and Matjaž Gams[1]

[1] Department of Intelligent Systems, Jožef Stefan Institute,
Jamova cesta 39, SI-1000 Ljubljana, Slovenia
{bosjtan.kaluza,violeta.mircevska,mitja.lustrek,matjaz.gams}@ijs.si
http://dis.ijs.si/

[2] Centro de Estudios e Investigaciones Técnicas de Gipuzkoa,
Paseo de Manuel Lardizabal, N° 15, Donostia – San Sebastián, 20.018, Spain
ivelez@ceit.es
http://www.ceit.es

Abstract. The European FP7 project CONFIDENCE – Ubiquitous Care System to Support Independent Living is developing a system that will monitor the health conditions of the elderly in real-time based on radio tags placed on the human body. In case of health problems, the system will issue a warning to the user and an alarm to the caregiver if necessary. This way the elderly should gain the needed confidence and security to continue their independent participation in society, thus reducing costs for medical services and burden to the working age population. The paper describes work in progress of the reconstruction and interpretation subsystem and presents encouraging results in complex fall detection scenario.

1 Introduction

Falls account for 40% of the nursing home admissions. Moreover, the fear of falling decreases quality of life and increases the decline in the ability to perform daily activities. Several FP7 and FP6 systems were devoted to this subject, since Europe is the continent with the highest percentage of the elderly. However, the system have to be cost effective, non-intrusive and reliable with aim to increase the quality of life and security of the elderly and, thus, prolong their personal autonomy and participation in society. Moreover, not only the elderly will profit from the system, but also their families and caregivers, since the burden on them will be substantially reduced. The system will decrease the need of institutionalization of the elderly and, thus, there will be a significant cut down in healthcare expenditure.

In this paper we present the CONFIDENCE system. Its main objective is the development and integration of innovative technologies for the detection of abnormal events (such as falls) or unexpected behaviors that may be related to a health problem of the elderly people. The main focus of this paper is on the reconstruction and interpretation subsystem. The reconstruction part receives the estimates of the positions of the tags attached to a user and generates a model of the user and the environment, while the interpretation part interprets the data to make a decision about the situation. This subsystem is provided with "intelligence", so that it can learn from the user's habits and help to detect early symptoms of illness, such as Parkinson, spine cancer etc.

The paper is structured as follows. The CONFIDENCE project is presented in Section 2. Next, a detailed look at reconstruction and interpretation subsystem is described in Section 3. Section 4 is dedicated to the evaluation results of complex scenario for fall detection. The paper concludes with conclusion and discussion in Section 5.

2 The CONFIDENCE Project

The primary goal is to create a care system that will be able to detect abnormal situations in short-term behavior, such as falls and loss of consciousness. The second goal is to detect changes in behavior over longer periods of time. Gait disorders, for example, are an important indicator of a number of health problems: joint and muscular diseases, neurological disorders such as Parkinson's disease etc. Moreover, the system will also notify an increased danger of falling which may appear with time, so that the user can start walking with a cane or a walker. Detection of anomalous behavior will utilize prior expert knowledge as well as learned movement patterns of particular users.

The system consists of a central device, which plays the role of a base station, and several tags as shown in Figure 1. A user will wear small tags, either in the form of bracelets/necklaces or sewed into the clothes. Additionally, some tags can be placed in specific positions such as bed, chairs or some other pieces of furniture. These tags make it possible to distinguish situations such as the user lying in bed or on the sofa.

The base station will be able to determine the position of each tag. Based on this information, the system will reconstruct the posture of the body and decide if the user has either suffered a fall or is acting abnormally. When a fall or an atypical situation is detected, the system will raise an alarm.

3 Reconstruction and Interpretation Subsystem

The reconstruction and interpretation subsystem is structured as shown in Figure 2. The figure identifies various software modules which process data as follows. Firstly, tag coordinates are assembled as they come from the location subsystem. When a whole snapshot of the body tags is available (i.e., the current coordinates of all the body tags), it is first preprocessed, which mainly means that the noise is filtered. Next, the filtered data is transformed in various ways useful for further analysis. Basic data representations describe each snapshot (details in Section 3.2), whereas complex data representations describe actions spanning multiple snapshots (details in Section 3.3).

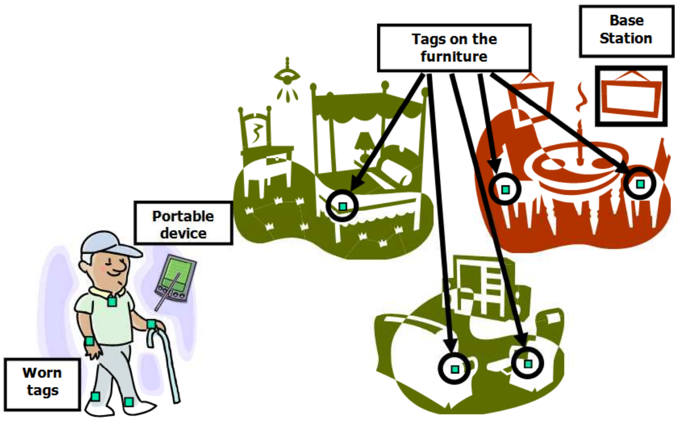

Fig. 1. The CONFIDENCE system.

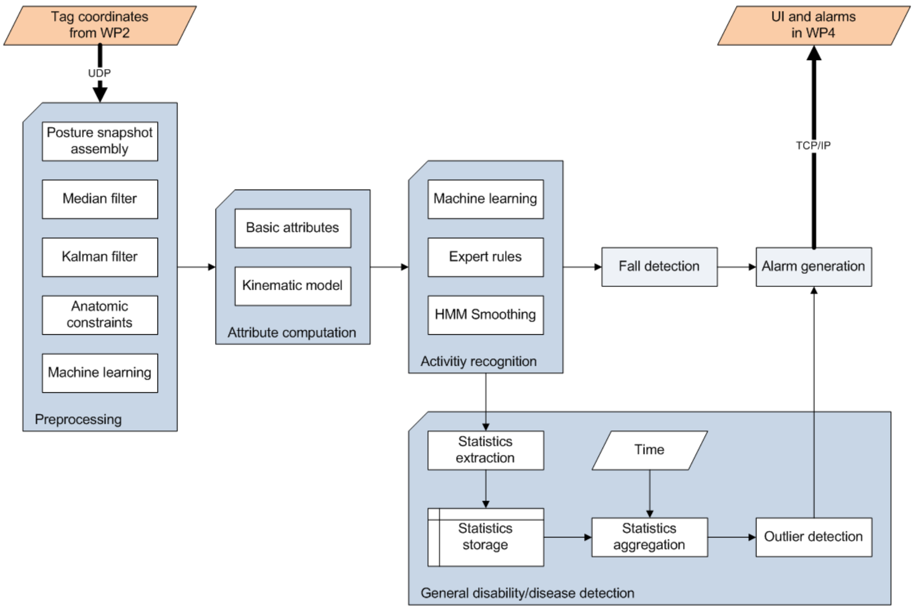

Fig. 2. Architecture of the reconstruction and interpretation subsystem.

The next step is activity recognition. Machine learning algorithms and expert rules classify basic data representations into activities. Since the classifiers are not perfect, the classification error is smoothed with Hiden Markov models, which eliminates spurious activities. The output is used by fall detection inference engine and general disability/disease detection.

General disability/disease detection is based on statistics collected over different periods of time. Some of them are derived directly from the data representations and some need dedicated extraction. A special statistics-gathering module is based on outlier detection. Finally criteria are applied to the statistics to determine whether their values warrant raising a warning. This decision is forwarded to the interface subsystem.

All the data regarding the current state of the user and his/her environment are stored in the internal state, from which they can be retrieved by all methods that need them. After a time they are moved to the log.

3.1 Preprocessing

The location information from the CONFIDENCE hardware is noisy. The noise of a tag location is reduced it three steps. It the first step, the median filter is applied. It successfully removes outliers, but it introduces some time delay in the filtered signals. The second step applies anatomic constraints, which ensure that the body is in valid position. The final step uses Kalman filtering, which optimally estimates the non-measurable states of a dynamic system (e.g. velocity, acceleration) and smoothes the measured position.

3.2 Basic Data Representation

Basic Attributes. These attributes are the coordinates of the body tags and the quantities derived directly from them. Three coordinate systems are considered:

1. Reference coordinate system is fixed relative to the environment. It captures properties such as the location in the apartment, whether the user is lying on the floor or on the bed etc.
2. Body coordinate system is fixed relative to the body of the user. Its purpose is to unify the instances of recurring movements that only differ in the location and direction of the user.
3. Body coordinate system belonging to the first set of coordinates in the interval under observation. Its purpose is also to unify the instances of recurring movements that only differ by the location and direction of the user. However, unlike in the previous coordinate system, the changes in position in the interval are also captured (relative to the location and direction at the beginning of the interval).

Kinematic Model. If sufficient number of tags is available, the kinematic model of a user is constructed. We use reference coordinate system and compute the following attributes: the angles of the left and right elbow, left and right knee, left and right shoulder, and left and right hip. The angles are represented by quaternions, which provide a convenient mathematical notation for representing orientations and rotations of objects in three dimensions.

3.3 Complex Data Representation

Activity Recognition and Fall Detection. Activities are defined as the periods of time the user has a common characteristic posture or a set of postures occurring in a certain order. The activities we consider are walking (standing, running), sitting, lying (conscious and moving, sleeping, unconscious, dead), on all fours, going up, going down, and falling as a special activity. Each activity has a number of parameters: duration, speed and angle of movement, smoothness of movement, flexibility, symmetry, straightness of posture and movement, the height of lifting the feet (when walking), and general movement and posture signature.

Simple attributes derived from consecutive snapshots of body tags are captured in the time interval of T seconds. N sets of attributes are captured, one after every update $1/T$. The concatenation of these N sets forms the attribute vector. A new attribute vector is obtained after every update (thus overlapping with the previous one).

Two approaches were examined for activity recognition. In the first approach, a machine learning algorithm was used. In [1] we examined various machine learning algorithms and selected random forest as the most accurate. The second approach uses expert rules [2], which were extracted by combining decision tree induction with expert knowledge. For example, activity is *lying* if z coordinates are less than 0.3 m and on approximately the same height. The final decision is based on both outputs using voting, weighted by the methods' certainty.

Detection of Critical Situations. Critical situations that arise from injuries or sudden health problems are reflected mainly by a user sitting or lying at an inappropriate place (mainly on the ground) since it is hard to distinguish these problems from normal sleeping. At this moment we consider three critical situations due to the injuries or sudden health problems - tripping, fainting and falling from a chair. Tripping and fainting consist of standing, falling and lying on the ground. When tripping, the person moves while lying on the ground, whereas with fainting the person is immovable. An important fact for their detection is prolonged lying on the ground, which indicates inability of the person to stand up and, therefore, injury or health problem. Falling from a chair consists of sitting on a chair, falling and sitting on the ground. This is a situation in which a person is not able to stand up from the chair because of weakness due to health problems. Again, the health problem is reflected by prolonged sitting on the ground.

The detection of critical situations is done by means of expert rules. Conclusions are made based on information about the place and length of lying/sitting and detection of falls. Therefore, an appropriate activity recognition is essential for accurate detection of the critical situations due to injuries and health problems.

General Disability/Disease Detection. Whether the user has developed some sort of disability, has fallen ill or is otherwise unwell will be detected from a number of statistics of daily life activities. These statistics were selected in cooperation with medical experts. In addition to the parameters of the activities, the statistics consist of the speed of: standing up from a sitting position, sitting down, standing up from a lying position, lying down; the number of times the user gets up at night; time spent: sitting or lying still, in motion, during recognizable activities, etc.

Some of the statistics are straightforward to measure, whereas others require dedicated methods, some of them quite complex. For the listed statistics, the following aggregate values are computed (where applicable): the average value over some period of time, the maximum value, the standard deviation of the values, the number of occurrences. These values are aggregated over multiple time periods, because multiple time periods are needed to detect both rapid changes (hours to detect the onset of a disease and go to the doctor) and long-terms disabilities (months to detect weakening of leg muscles and start using a cane).

4 Evaluation

4.1 Prototype

We have set up a prototype environment which consists of a single room equipped with the Ubisense real-time location system [6], similar to the equipment planned for the CONFIDENCE project, and a PC running the software. The reconstruction and interpretation subsystem was developed in Java environment and displayed in a control panel as shown in Figure 3.

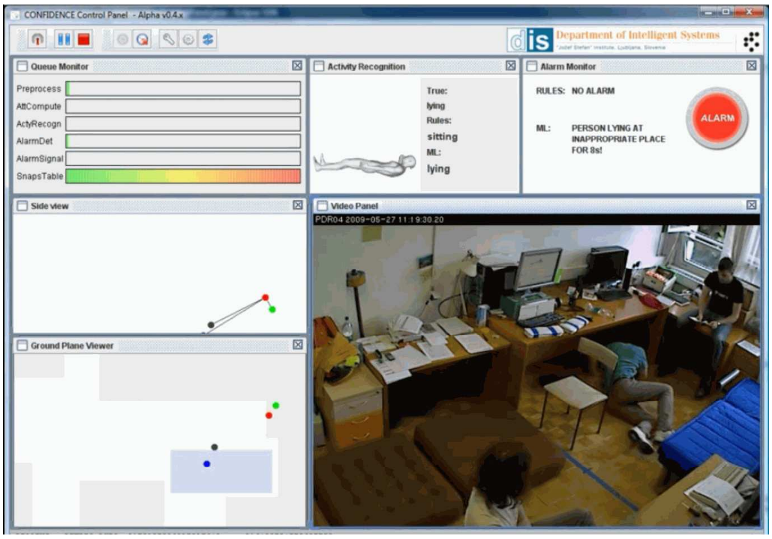

Fig. 3. CONFIDENCE prototype control panel.

4.2 Scenarios

For the testing purposes, a complex scenario including three cases when alarm must be raised and three possibilities for false alarm were designed. Cases in which alarm must be raised are tripping, fainting and falling from the chair, as presented in Section 3.3.

Cases which may cause false alarm, but which do not represent alarming situation, are jumping in a bed, sitting down quickly and searching under the table/bed. Both jumping in a bed and sitting down quickly contain falling. Falls may be misleading to the system, since they are fundamental indication of alarm situation. For systems based on accelerometers [3, 4] this is the primary problem. These two test cases basically reveal the ability of the system for context dependent reasoning, i.e. distinction between alarm situation and normal behavior consisting of same user activities based on the circumstances in which they are done. Searching under the table/bed may be mistaken as prolonged lying on the ground since the person is very low on the ground in such case. Beside this, searching differs from lying on the ground by the amount of user movement and length of time the user is on the ground.

4.3 Results

In this paper we present abilities of the interpretation and reconstruction subsystem of the CONFIDENCE system with respect to detection of critical situations due to injuries and health problems. The CONFIDENCE prototype were tested on recordings of five people, each performing the abovementioned test scenario five times. The recordings were performed[3] in the prototype environment (see Section 4.1). System evaluation was performed with *leave-one-person-out* methodology.

Detection of critical situations is performed in two phases. In the first phase, activity recognition is based on two proposed techniques - machine learning and expert rules for activity recognition. In the second phase, critical situations due to injuries and health problems are detected by means of expert rules. This reasoning uses information about the activity of the user determined in the first phase.

Table 1 presents the achieved accuracy for critical situation detection for each alarm situation and possibility for false alarm recorded in the proposed scenario. Results when the activity recognition is performed with machine learning is shown in the second column, whereas the third column shows the results when the activity recognition is performed by means of the expert rules.

Tripping and fainting were recognized quite reliably in both cases. What proved problematic was detecting falling from a chair. Due to the noise in the data from the localization system, which is particularly high near the ground, sitting on the ground and sitting on a chair were sometimes difficult to distinguish. Placing a tag on the chair would solve this problem.

[3] A video example is available online: `http://www.youtube.com/watch?v=r9gSUn9RPgk` or keywords *confidence prototype*.

Case	Machine learning accuracy [%]	Expert rules accuracy [%]
Tripping	100	96
Fainting standing	88	92
Sliding from the chair	56	40
Jumping in bed	100	100
Sitting down quickly	100	96
Searching under a table/bed	96	72

Table 1. Performance in critical situation detection.

The system raised very few false alarms – machine learning actually raised only one. Difficulties were observed when searching under bed/table in case when activity recognition is done by expert rules. Main cause for this is the inability of expert rules to accurately distinguish person on all fours from person lying on the ground.

5 Conclusion

We have presented work in progress of the system that aims to prolong the independence of the elderly by detecting falls and other types of behavior indicating a health problem. The focus was on reconstruction and interpretation subsystem which inferences about a user in the environment. Preliminary results in detecting complex fall scenarios are promising and indicate an important increase in detection of critical situations.

Machine learning (with random forest) performed overall significantly better than expert rules, but rules offer transparency and explanation. Further research is needed in the last year of the project to upgrade the system to the desired applicable level.

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