A new real-time fall detection approach using fuzzy logic and a neural network

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Abstract—**A real-time fall detection system monitors the daily activity of especially elderly people to enlist someone's help as fast as possible in case of emergency. This paper presents a new real-time fall detection algorithm using a single commercial accelerometer. After transforming the acceleration data from Cartesian coordinates to spherical coordinates, the main part of the algorithm is based on a fuzzy logic inference system and a neural network. These methods allow both the integration of specific expert knowledge about typical falls as well as generalization ability. In order to compare the achieved performance of the method to those of literature, four fall scenarios (forward, backward, sideward and collapse) were performed and evaluated in a laboratory trial with, in the first instance, 5 test subjects. The average sensitivity of those four fall scenarios reached 94% and the false positive rate was about 0.35%. These results show that one single accelerometer is completely sufficient to implement a reliable fall detection system and, furthermore, that knowledge based methods are a suitable alternative to standard pattern recognition methods.**

I. Introduction

APPROXIMATELY one third of people aged over 65 years are falling one time a year at least. The rate is increasing to one half for the group of people aged over 80 years [1]. 20 up to 30 percent of the falls are causing serious injuries. In consequence the mobility and independence is influenced in a negative way. The probability of dying an earlier death is increased significantly [2]. Elderly people stay in hospital five times more often because of falls compared to other injuries. That's why fall injuries are the leading cause for accidents with a deadly outcome for people aged over 65 [2].

Therefore it's an objective to alarm help as quick as possible in case of such an emergency.

The recent development of communication technology offers new chances in the field of home monitoring. Miniaturization of sensors and increasing performance of microcontrollers allow execution of complex algorithms directly on the sensor. This gives monitoring a new perspective of observing health parameters with complex algorithms. Comparably the knowledge and experience of human experts is supported respectively reduced by computer aided diagnosis.

In this paper a new real-time method that is able to observe daily activities and to detect falls is described. The classification differs between complex fall and non fall movement-patterns. A single triaxial-accelerometer attached near the waist is used to capture the movement data.

There exist many different algorithms to classify a fall based on data captured by a single accelerometer. Literature often describes threshold based algorithms. Most of them use combined features, like triggering of the accelerations in Cartesian Coordinates together with the angle of the orientation [3]. This doesn't work well for each fall pattern. Another approach is to trigger the magnitude r together with the orientation [4], [5], [6]. The magnitude r considers the energy of all fall directions and shows a better performance compared to triggering of all axes separately. The magnitude r is part of the spherical coordinates.

In literature there are described complex feature sets to detect a fall. The acceleration data are often classified to static and dynamic components. With these data different features are calculated to detect falls, e.g., vertical acceleration, velocity of the fall, difference between minimum and maximum amplitude in an interval of 0.1s. All those features were calculated in different combinations [7]. Another approach is to evaluate the energy expenditure to recognise activities [8]. The energy expenditure is correlated to 89% with the acceleration signal. A further development of this feature is the signal-magnitude-area (SMA) [9].

There are also knowledge based algorithms described in literature. One approach uses feature vectors with up to 48 dimensions. These vectors are classified by Gaussian Mixture Models which were adapted by an expectation maximization method [10]. This method reached an average precision of 91.3%. With a specific adaption of the algorithm to specific the patients the sensitivity is about 92.2%.

II. Methodology

A. System

The objective is to develop a fall detection system that is based on expert knowledge and, on the other hand, that keeps its generalization ability.

Expert knowledge is required to build a system which is independent of patient specific properties.

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Triggering the magnitude or the signal magnitude area allows detecting falls with a heavy impact. But slow falls like, e.g., a collapse after a heart attack are not detected by just calculating the energy of the signal. One solution is to analyse the movement pattern over time.

In this approach a fuzzy inference system (FIS) is used to apply expert knowledge. The output of the FIS is recorded over time and classified by an artificial neural network (ANN). The generalization ability of the ANN is used to recognize as much fall scenarios as possible. The components of the signal chain are shown in Fig. 1.

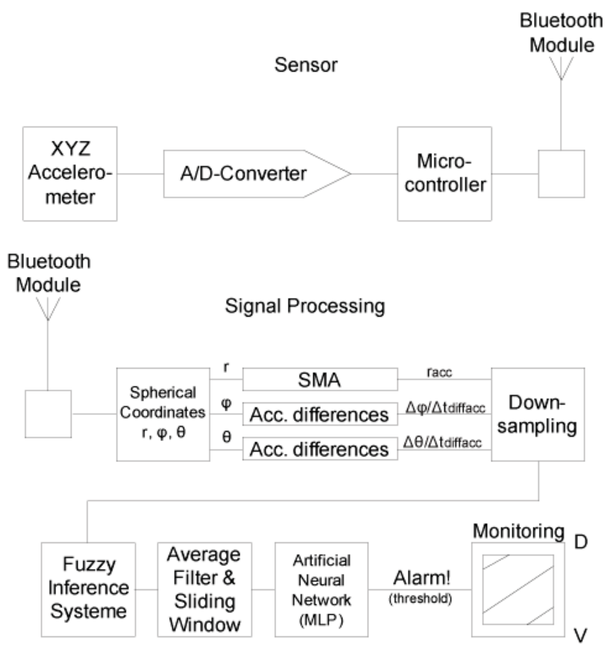

Fig. 1. Components of the signal chain

B. Sensor

The acceleration is captured in Cartesian coordinates by an accelerometer attached to the waist. The signal is sampled with 512 samples per second. Experiments have shown that the signal contains movement information up to 100Hz. This is sufficient to capture transient movements which contain high frequent harmonics. That is why a sample frequency of 256 samples per second is adequate. The acquired data are sent via Bluetooth to a computer on which the signal processing is performed. Fig. 2 shows the used acceleration sensor.

$$r = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

$$\phi = \begin{cases} \arccos(x / \sqrt{x^2 + y^2}), & y > 0 \\ 2\pi - \arccos(x / \sqrt{x^2 + y^2}), & y \leq 0 \end{cases} ; \phi = [0, 2\pi) \tag{2}$$

$$\theta = \arccos(z / r);\ \theta = [0, \pi] \tag{3}$$

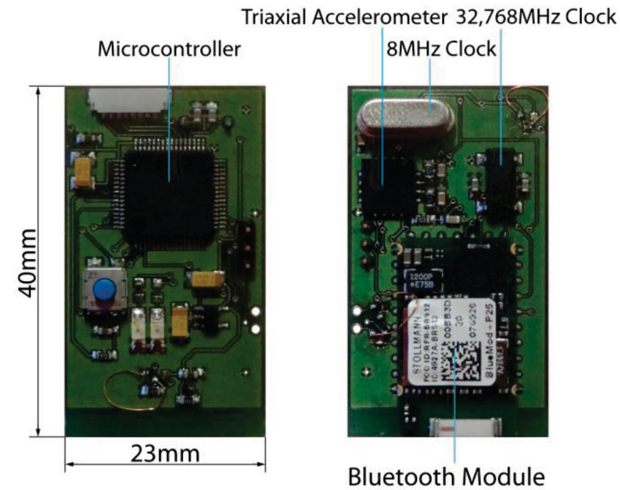

Fig. 2. The sensor unit

C. Signal transformation

The first step is the transformation of the acceleration data from Cartesian to spherical coordinates, as in (1-3). Spherical coordinates describe movements around the waist more intuitively than Cartesian coordinates. The first coordinate **r**, the so-called magnitude, represents the intensity of the acceleration. The second and the third coordinate are both angles describing the orientation of the acceleration.

In the next step, the SMA is calculated by filtering the magnitude **r** with a moving average filter (w=0.8s). The angles are transformed by estimating the differences between adjacent samples, which is followed by a moving average filtering (w=1s) of the resulting difference vector.

Fig. 3 shows acceleration data containing 3 falls before and after the transformation. In the next step the data are down- sampled from 512sps to 128sps. This step optimizes the performance of the algorithm.

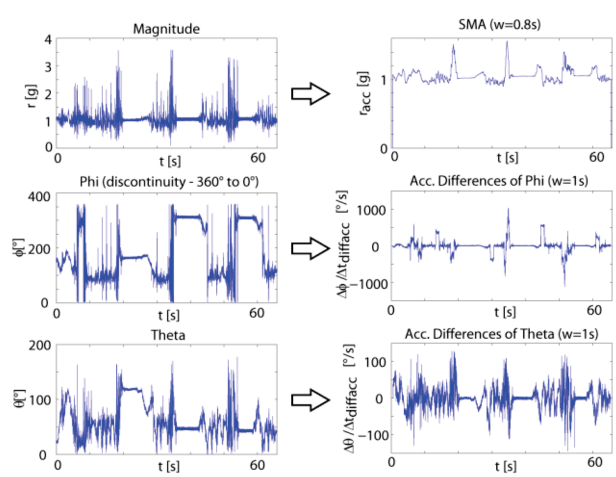

Fig. 3. left: Raw data calculated into spherical coordinates, contains 3 falls; right: transformed signal components

D. *Fuzzy Inference System*

The FIS calculates the movement activity from the transformed signal components shown in Fig. 3.

Different fuzzy sets and rules were evaluated. Expert knowledge is represented through the fuzzy sets of the membership functions. The final fuzzy system is shown Fig. 4.

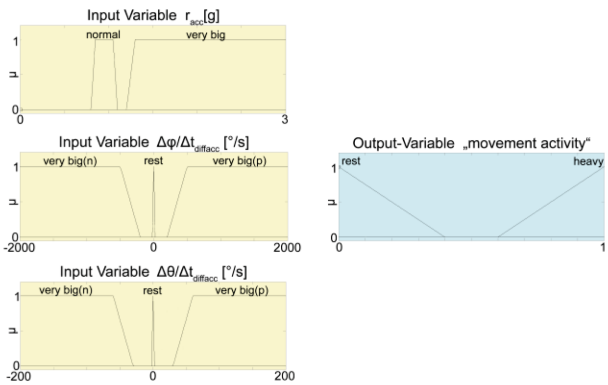

Fig. 4. left: Input membership functions; right: Output membership function

Table 1 shows the inference rules of the FIS. Mamdani's fuzzy inference method is used.

TABLE I
FUZZY RULES OF THE FIS

No.	Rules: IF	Rules: THEN
1	racc = normal AND $\Delta\Phi/\Delta t_{diffacc}$ = rest AND $\Delta\Theta/\Delta t_{diffacc}$ = rest	movement = rest
2	racc = very big AND $\Delta\Phi/\Delta t_{diffacc}$ = very big(n)	movement = heavy
3	racc = very big AND $\Delta\Phi/\Delta t_{diffacc}$ = very big(p)	movement = heavy
4 *5*	Analogue for $\Delta\Theta/\Delta t_{diffacc}$	

The fuzzy output is smoothed by a moving average filter (w=0.2s). Fig. 5 shows an example containing 3 falls, which are well-represented by the movement activity.

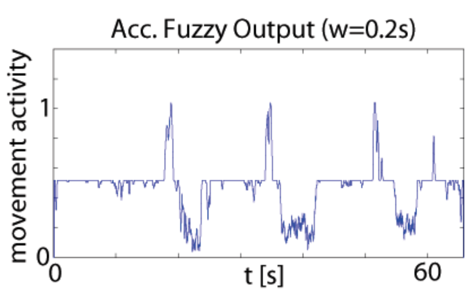

Fig. 5. FIS output smoothed with a moving average filter (w=0.2s). The 3 containing falls are easily recognizable.

E. *Artificial Neural Network*

In order to classify the movement patterns with an ANN a sliding time window is used. The width of 5 seconds for each time window was obtained empirically. The sliding window is shifted with an offset of 0.5 seconds over the fuzzy output.

The ANN is realised by a feed forward network, a multilayer perceptron (MLP). The architecture of the MLP was also chosen. The network has an input layer with 640 neurons that corresponds to 640 samples in each time window sampled with 128sps, 2 hidden layers with 30 and 20 neurons, and an output layer with 1 neuron (640-30-20-1).

For the adaption of the ANN, training patterns were recorded and annotated manually with 0 (no fall containing) and 1 (fall containing). Resilient Backpropagation (RPROP) is used as training algorithm for the MLP.

F. *Threshold*

To detect a fall the output of the neural network was triggered with 0.45. If this threshold is exceeded two times one after the other, an alarm is generated.

III. RESULTS

An evaluation of the algorithm was arranged with four different fall scenarios: forward, backward, sideward and collapse. Five test persons simulated all fall scenarios five times. During the simulation of falls, it was paid attention to falling not too heavily. The test subjects tried to break the fall by holding somewhere at a table or by falling first on their knees. Heavy falls are easily detected by the system.

The sensitivity and specificity of the trials are shown in Table 2. For the calculation; each sliding window was considered and evaluated if the result is categorized right or wrong.

The four different fall scenarios differ in their detection sensitivity. Forward, sideward and backward directions were detected with nearly equal sensitivity. The system shows a lower detection performance for the collapse.

It was reached an average precision of 90.3%.

TABLE II
RESULTS

Fall direction	Result: Sensitivity	Result: Specificity
forward	96%	99.64%
sideward	96%	99.8%
backward	96%	99.4%
collapse	88%	99.76%

IV. DISCUSSION

The essential benefit of the described algorithm is its selectivity. By calibrating fuzzy inference rules in a proper manner specific movement activity patterns can be extracted that can be easily classified. Expert knowledge could be used to include extraordinary patterns.

The five fuzzy inference rules show good performance for three fall scenarios. The sensitivity for collapse has to be improved by finding adequate additional rules. On the other hand, additional rules will cause higher calculation resources.

Because of two classifications per second the system will produce a number of false positive alarms over a longer period of time. That is why the precision can also be improved in order to full patient acceptance.

As a consequence of the missing post-analysis, certain weaknesses arise. We often got false alarms by the scenario slumping into a chair. This could be avoided by testing the height of fall. Therefore we recommend calculating an average height of fall by integrating over the vertical acceleration. Also there should be a subsequent classification of how severe the fall was.

The performance (90.3% precision) of the approach described in this paper is comparable with literature using knowledge based methods [10].

V. Conclusion

It could be shown that one triaxial accelerometer is sufficient to build a reliable fall detection system.

Knowledge based methods are suitable algorithms especially for medical applications because of improved traceability of their results. If basic conditions are changing the system can be adapted quickly, because it uses structured expert knowledge (FIS) which is explicit, easily understandable, declared by rules and fuzzy sets. On the other hand, the system keeps its generalization ability. The inference is done with an ANN based on the output of the FIS.

Spherical coordinates are a likely coordinate system to describe movement patterns with rotation. It is intuitive to describe clear inference rules with this representation.

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