Automatic Emergency Detection Using Commercial Accelerometers and Knowledge-Based Methods

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Abstract

This paper focuses on the challenge of automatical detecting an emergency, e.g., a fall by an elderly person, and to generate an alert such as a phone call or sending a SMS to a relative as fast as possible. The presented system only needs one single triaxial accelerometer. The algorithmic part uses the paradigm of knowledge-based methods. Unlike pattern recognition algorithm [1], knowledge-based methods strictly separate between the so-called knowledge base declaratively describing the knowledge about the specific domain and the so-called inference component or inference engine that tries to derive answers from the underlying knowledge base. That is to say the knowledge base can be replaced without changing the concrete inference machine. The main part of the developed algorithm to detect falls is based on a fuzzy logic inference system and a neural network [2]. In addition, the current velocity and relative position of the person wearing the sensor are determined from acceleration data. These information can be used as further features to improve both sensitivity and specificity. The described methods were integrated into the telemedical system described in [3, 4].

1. Introduction

Due to demographic changes, life expectancy among the population, especially in industrialized countries, has increased over the past decades, and this trend will continue this way in the future. As a consequence the number of elderly people is also increasing.

The preparation of elderly people to live longer at the place they like most, while ensuring a high quality of life, autonomy and security as well as simultaneously reducing the expenditures on in-patient care will be tremendous important tasks in the very near future. This also includes assistance to carry out daily activities enhancing safety and security as well as getting access to social, medical and emergency systems. Receiving social and medical support in various innovative ways contribute to independent living and quality of life for many elderly and disabled people. All this is summarized in the field of Ambient Assisted Living (AAL). Being able to monitor a patient, vital signs can be gathered which consequently can help to supervise clinical data, such as health status, falling risk and, of course, the efficiency of rehabilitation.

There exist a variety of monitoring techniques to assess the movement of a subject. Some of these include observation, physical science techniques, diaries and questionnaires. On the contrary, there are accelerometers, which have been established in industrial applications for decades and which are establishing in medical applications now. Those sensors have significant advantages, e.g., micro-electro-mechanical system (MEMS) accelerometers can monitor the movement of the subject while simultaneously not interrupting his or her daily routines. Furthermore, they are more functional, lighter, more reliable than, e.g., optical tracking systems, and they are produced for a fraction of the costs of the conventional macroscale accelerometer elements.

In this study, the triaxial accelerometer MMA7260Q by Freescale Semiconductor extended by a bluetooth module and attached near the waist is used to capture movements and to detect falls (Fig. 1). The sensitivity of the sensor is $\pm 1.5\,g$, with a noise level of $4.7\,\mathrm{mV_{rms}}$ and a sampling rate of $512\,\mathrm{Hz}$ with 12-bit resolution.

2. Methods

2.1. Calibration using rotation

Calibration of the sensor axes with respect to the world coordinate system was conducted to be independent of the orientation of the sensor fixed at the body of the subject. This independency is mandatory for user acceptance as well as for the computation of velocity and position. The calibration respectively the rotation was realized while the sensor was static and only the gravitation component acted

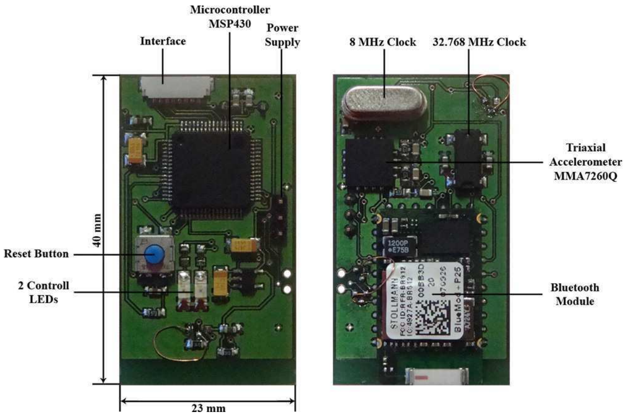

Figure 1. Acceleration sensor unit with bluetooth module

on the accelerometer. In order to compute the rotation standard image processing methods, e.g., a simple basis transformation, quaternions to represent rotations with linear equations combined with a least squares method or Rodrigues' rotation formula, can be applied [5, 6]. After determining the rotation matrix R, all the acceleration data are rotated by R before the actual algorithm is executed.

2.2. Removing peaks

Working with data of physically measured signals, we always have to deal with unwanted artifacts, like noise and peaks. Peaks occur, e.g., when the sensor is bouncing against other objects or when there is an occasional bad bluetooth connection. It is quite obvious that peaks will have a distorting effect on, e.g., the computation of velocity and displacement. Positive peaks can be easily removed by applying the morphological filtering operation called opening (combination of erosion and dilatation) and, on the other hand, negative peaks are disabled by applying the operation closing (dilatation followed by erosion) [1]. In this study, an emperically determined window size of $n = 3$ samples leads to the best results.

2.3. Reducing noise

Mathie [7] states that noise should be reduced by careful design and choice of the sensor module. But usually the system is limited to a specific sensor and hardware parameters cannot be changed. As a consequence, the acceleration data have to be smoothed in order to minimize the impact of noise to the algorithm. Using a simple one-sided moving average filter with an empirically determined window size of $n = 5$ samples lead to adequate results with the sensor module used in this work. Figure 2 shows an illustrative example.

As a consequence, the peak-to-peak noise level of the accelerometer could be reduced from $16\,\mathrm{mg}$ to $4\,\mathrm{mg}$.

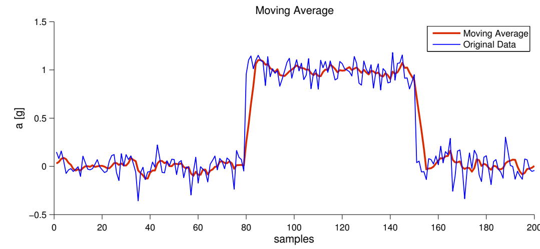

Figure 2. Moving average filter with 5 samples window size applied to acceleration signal

2.4. Signal separation

Due to the natural movement of the subject, e.g., bending forward or running, the sensor axes also change their orientation. This leads to incorrect results for the computation of velocity and displacement. In order to compensate this change in orientation the total acceleration was divided into gravitational and body acceleration components. Therefor a sixth-order elliptic IIR filter with a cut-off frequency f_{cut} of $0.25\,\mathrm{Hz}$, pass band ripples A_p with $0.01\,dB$ and a stopband magnitude A_{st} of $-80\,dB$ was chosen [7]. Using the result of the low-pass filter, the gravitational offset, a rotation update (Ch. 2.1) could be performed, e.g., every $20\,\mathrm{ms}$.

2.5. Signal transformation

After pre-processing the acceleration data as described in the previous sections, the acceleration data is transformed from Cartesian coordinates $(x, y, z)^T$ to spherical coordinates $(r, \phi, \theta)^T$ (Eq. 1-3).

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

$$\phi = \mathrm{atan2}(y, x) \tag{2}$$

$$\theta = \frac{\pi}{2} - \arctan \frac{z}{\sqrt{x^2 + y^2}} \tag{3}$$

The first coordinate r (magnitude) represents the intensity of the acceleration. The angles ϕ and θ both describe the orientation of the current acceleration. After transforming the signal, an approximation respectively an estimation of the signal magnitude area (SMA) (Eq. 4)) is calculated by filtering the magnitude r with a moving average filter ($w = 0.8s$).

$$SMA = \frac{1}{N}\left(\sum_{n=0}^{N-1}(|x_n| + |y_n| + |z_n|)\right) \tag{4}$$

The angles ϕ and θ are transformed again by computing the forward differences (Eq. 5).

Table 1. Fuzzy rules of the fuzzy inference system (FIS)

IF	THEN
SMA = ok & $\Delta\phi$ = rest & $\Delta\theta$ = rest	Mov. = rest
SMA = high & $\Delta\phi$ = high	Mov. = heavy
SMA = high & $\theta\phi$ = high	Mov. = heavy

$$\Delta\phi_n = \phi_{n+1} - \phi_n \quad \Delta\theta_n = \theta_{n+1} - \theta_n \tag{5}$$

The resulting difference vectors are smoothed by a moving average filter ($w = 1s$). In order to optimize the performance of the complete algorithm, the last step of the signal transformation chain down-samples the data from $512\,\text{Hz}$ to $128\,\text{Hz}$.
The extracted features described above contain sufficient information to build a reliable fall detection system.

2.6. Fuzzy inference system

The fuzzy logic is widely used in the field of artificial intelligence and belongs to the knowledge-based methods. It represents a generalization of the classic boolean logic. In contrast to boolean logic, logical variables can take on continuous values between 0 and 1. A fuzzy inference system (FIS) describes the mapping from a given input to an output using fuzzy logic. They have the benefit that the solution to a specific problem can be cast in terms that human operators can easily understand. The opposite way around, expert knowledge can be described quickly through the fuzzy sets, especially for tasks that are already successfully performed by humans. Table 1 shows the fuzzy rules of the FIS developed in this study. Mamdani implication is used as fuzzy inference method (Eq. 6). The intervalls of the fuzzy rules were emperically choosen and are encoded as input member ship functions [8].

$$\mu_{A\to B}(x, y) := \min\{\mu_A(x), \mu_B(x)\} \tag{6}$$

2.7. Neuro-fuzzy hybridization

The combination of the human-like reasoning style of a FIS with the learning and connectionist structure of artificial neural networks (ANN) is called neuro-fuzzy. The synergistic effect using the characteristic properties of both techniques is quite powerful. On the one hand, we can formulate human knowledge with simple IF-THEN rules and, on the other hand, ANN are universal approximators with generalization ability.
In this work a multilayer perceptron (MLP) with an input layer consisting of $640 = 5 \cdot 128\,\text{Hz}$ neurons (the width of $5sec$ for each time window was empirically determined), 2 hidden layers with 30 respectively 20 neurons, and an output layer with 1 neuron. The training of the MLP was performed using the error-back-propagation algorithm [1].

Table 2. Results of sensitivity and specificity performing different fall scenarios

Fall scenario	Sensitivity	Specificity
Collapse	88%	99.76%
Forward	96%	99.64%
Backward	96%	99.40%
Sideward	96%	99.80%

2.8. Thresholding

In order to classify the output of the ANN as a fall, it was defined that the emperically determined threshold of 0.45 has to be exceeded directly two times one after the other.

2.9. Velocity and displacement

Although both velocity and displacement information can mathematically derived from acceleration data by simple integration (Eq. 7), this task is not trivial dealing with real data.

$$s(t) = \int v(t)\,dt = \iint a(t)\,d^2t \tag{7}$$

Mathie [7] states that only the body component should be included for double-integration to give a true displacement signal. Due to poor results extracting the body component in this study, the test conditions were modified. The acceleration sensor unit was moved in a way that there was no alteration in orientation possible during movement, e.g., on a carriage of a demonstration track (movement in xy-plane) or lying on the floor of an elevator (movement in z-axis). This limitation provides satisfying results for the derivation of velocity and displacement, at least over a short time period (Ch. 3).

3. Results

In order to benchmark the developed procedures, five test persons simulated the fall scenarios listed in table 2 five times. Heavy falls result in a reliable detection rate. Nevertheless, the subjects tried not to fall too heavy. The achieved results without considering the features velocity and displacement are shown in table 2.

Several different test scenarios were generated and processed in order to evaluate the results of the computation of velocity and displacement from acceleration data as described in section 2.9. The first experimental set-up was restricted to acceleration affecting only the $z-$axis. A test scenario using an elevator was performed seven times with a distance of $3.5\,\mathrm{m}$ each time. Table 3 shows the results.

Table 3. Results of movement in vertical direction: v_z is the absolute error of velocity in vertical direction compared to $0\,\mathrm{m/s}$, the traveled distance d_z and the relative difference δd_z to the real value of $3.5\,\mathrm{m}$.

	$v_z[\mathrm{m/s}]$	$d_z[\mathrm{m}]$	$\delta d_z[\%]$
μ	0.003	3.22	8.0
σ	0.067	0.35	10.0

The second test defined no restrictions. The subject performed squats with the sensor unit fixed on the episternum. The results are illustrated in table 4.

Table 4. Results of conducting 10 squats each in an observed time interval of $t = 1.5\,\mathrm{s}$: v_z is the absolute error of velocity in vertical direction compared to $0\,\mathrm{m/s}$; the accumulated displacement d_{acc} compared to $80\,\mathrm{cm}$; the maximal magnitude of the performed squats A_{squat}; total distance moved during the window of $d_{1.5\,\mathrm{s}}$.

	$v_z[\mathrm{m/s}]$	$d_{acc}[\mathrm{m}]$	$A_{squat}[\mathrm{m}]$	$d_{1.5\,\mathrm{s}}[\mathrm{m}]$
μ	0.197	0.22	0.41	1.04
σ	0.132	0.13	0.03	0.14

4. Discussion and conclusions

The achieved detection rates show that one triaxial accelerometer is effectual to develope a dependable fall detection system. Using neuro-fuzzy allows an explicit description of a fundamental knowledge base without losing generalization ability. The defined fuzzy inference rules and the classification with a neural network give satisfying results for three fall scenarios. By defining additional adequate rules for the collapse fall scenario sensitivity should be optimized. Of course, more fuzzy rules will lead to higher computing time.

In order to obtain meaningful results in detecting one's velocity and displacement it is indispensable to minimize noise and peaks by simultaneously preserving the signal information. As the two acceleration components, gravity and body acceleration, overlap both in time and in frequency, they cannot be easily separated.

Without a continuously alignment of the sensor axes with respect to the world coordinate system accurate results were nearly impossible to achieve. Only exercises or activities with a fix orientation of the sensor axes lead to satisfying results. Consequently, the method applied on the sensor used in this study has to be improved in further works. In this case it is inevitable to expand the system by one or more further sensors, e.g., a gyroscope. By using additional sensors a correction of the sensor axes can be performed in real time. The accelerometer provides information about the movement in a specific direction whereas the gyroscope measures the change in orientation. This combination will provide a robust system determining velocity and displacement from real acceleration data. Nevertheless, for restricted tasks, e.g., rehabilitaion exercises, the presented methods are sufficient. Beyond controversy, both velocity and displacement provide important information that can be used for different applications.

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