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FALL DETECTION BY RECOGNIZING PATTERNS IN DIRECTION CHANGES OF CONSTRAINING FORCES

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Abstract

The severe consequences accidental falls may cause for elderly have pushed the development of mobility safeguarding systems. Threshold based fall detection algorithms in smartphones have shortcomings as accelerometer values from different devices are hardly comparable. In this work, a pattern-recognition procedure is presented whose main input consists of the change of direction of the constraining force that is exerted on an accelerometer attached laterally on the hip area. The algorithm makes use of fast wavelet decomposition and support vector machine theory.

***Keywords** – fall detection, accelerometer data, pattern recognition, fast wavelet decomposition, support vector machines*

1. Introduction

Each person carries the risk of falling. A fall can be defined as 'unintentionally coming to the ground or some lower level and other than as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure' [8]. With increasing age and poorer general health, it is difficult to keep the body in balance or balance the body in time. As a result, falls among people over 65 years increase [4]. People with cognitive disorders such as dementia are more affected. In some cases a fall leads to a loss of confidence in mobility and further results in a limitation of movement up to social isolation [4, 7]. The severe personal, social and economic consequences of accidental falls of elderly people have pushed the development of devices suitable for monitoring human activities and raising alerts in case of critical events. Although these devices are not able to prevent the occurrence of a fall, they help to avert the life-threatening consequences of a person lying helplessly and unnoticed on the floor. Apart from expensive systems that need to be installed in a user's living environment – typically comprising cameras or sensor networks – small, body worn gadgets have become of particular interest. Tailor-made systems from specialized companies exist for a couple of years now. With the advent of smartphones as programmable, almost fully featured sensor and communication platforms, the focus has shifted from specialized devices to general purpose Smartphones (cf. [1, 2, 5]).

The main effort in the application area of fall detection using body worn devices is put into the development of algorithms analyzing the device's sensor data, most importantly the data delivered by the accelerometer. It is tempting to assume that the plugged sensor hardware measures acceleration with sufficient precision – an assumption that cannot be affirmed by our own investigations.

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The simplest approach to fall detection is based on thresholds, i.e. the acceleration data are scanned for certain signal features that are typically present when an object falls onto the floor. Typically a fall event compromises two phases: a *free fall phase*, characterized by acceleration values that decrease below a certain threshold, followed by a *sharp acceleration peak* caused by the constraining force that the floor exerts on the body (and thus on the accelerometer attached to it) when it hits the floor. Due to the elasticity of the compound system of human body and device, there is a short phase where some kind of dither in the signal can be observed before the body comes to rest and remains motionless for a certain period of time. Additionally, in order to make use of the directional nature of acceleration, the direction of gravity relative to the device's reference frame during this last phase should be almost perpendicular to that at the onset of the initial free fall phase. A fall signal as recorded by one of our devices is shown in *Figure 1*.

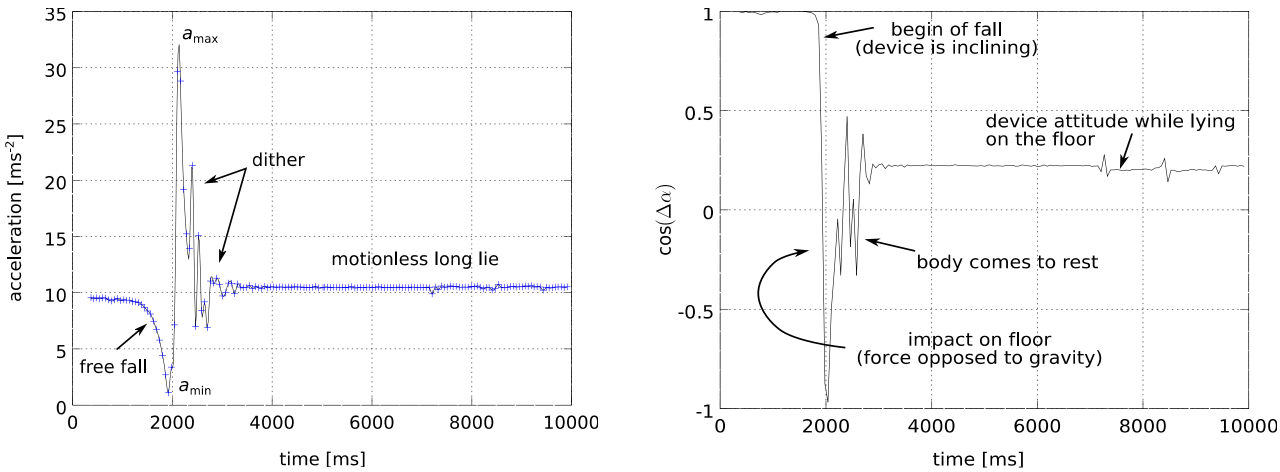

Figure 1: Absolute value of acceleration and direction change of constraining forces during a fall. A reference direction is initially defined by earth's gravity in the device's reference system. The direction of the constraining forces' sum vector relative to it is expressed via the cosine of the enclosed angle.

We found at least one application implementing this kind of feature scan and the authors report good results [5]. In order to test the applicability of the algorithms on smartphones, we developed a prototype for the Android platform with the same functionality. We tested the prototype on different devices (Samsung Galaxy S, LG Optimus, Motorola Droid). To our surprise, the sensors of different manufacturers record values in significantly different ranges for identical test scenarios, thus making it impossible to establish reliable, device-independent thresholds for minimum and maximum accelerations of a fall. The only thing that is comparable across the different devices is the morphology of the recorded signal. It seems that smartphone sensors are calibrated to measure earth gravity when held at rest, but scale differently when moved around.

In order to avoid setting individual thresholds for every single smartphone model, as required by the above algorithm, a different – and to our best knowledge novel – approach for a fall detection algorithm that depends only on relative values of the acceleration signal has been developed.

2. Data acquisition

Before describing our procedure in detail, we want to point to the challenge of obtaining fall data for testing the fall detection system: several volunteers carrying the recording devices in the rear, respectively side pockets of their trousers tried to mimic accidental falls in the forward, backward, left and right direction with a subsequent motionless phase of lying on the floor. Judging by eye, none of the falls resembled a "real" fall, which is not surprising since a fall is actually too

dangerous a movement to be carried out voluntarily in a realistic manner. In order to extend the dataset with more adequate fall data, a Judo dummy has been employed to perform falls with high impact. The smartphone was attached laterally on the dummy's hip area using a belt along with a customary, elastic smartphone protection case since no trousers would fit the puppet. In order to make it possible to distinguish between falls and non-falls, the volunteers had to carry out activities of daily living, too, some of which resemble falls (like sitting down on a chair) while others don't (walking, running, jumping).
The applicability of our algorithm in real life scenarios is based on the assumption, that deliberate falls share essential characteristics with accidental falls. The experimental setup in any case aims to accommodate the circumstances of an application in real life.

2. 1. Data sampling on Android devices

Accelerometer data has been collected at time frames of 10 seconds for each of the tested activities. The sampling rate of the recording devices is approximately 16 Hz, thus leading to a sample size of around 160 samples per record. From Nyquist's theorem it follows that the highest spectral component in the sampled activities can be 8 Hz. From our data we conclude, that a typical fall is limited in bandwidth by 5 Hz, the sampling rate of the device is thus sufficiently high. It should be noted though, that the sampling rate of smartphones is not constant. Depending on the configuration of software and hardware – especially when more sensors than just the accelerometer are switched on – standard deviations of σ = 0.5 Hz up to σ = 1 Hz have been registered. We have, therefore, resampled a cubic spline interpolation of the recorded data. Since only a portion of the sampled time frame is used for further calculations, and the fast wavelet transform requires sample sizes that are powers of 2, an up-sampling with a sample rate of at least 25.6 Hz is performed.

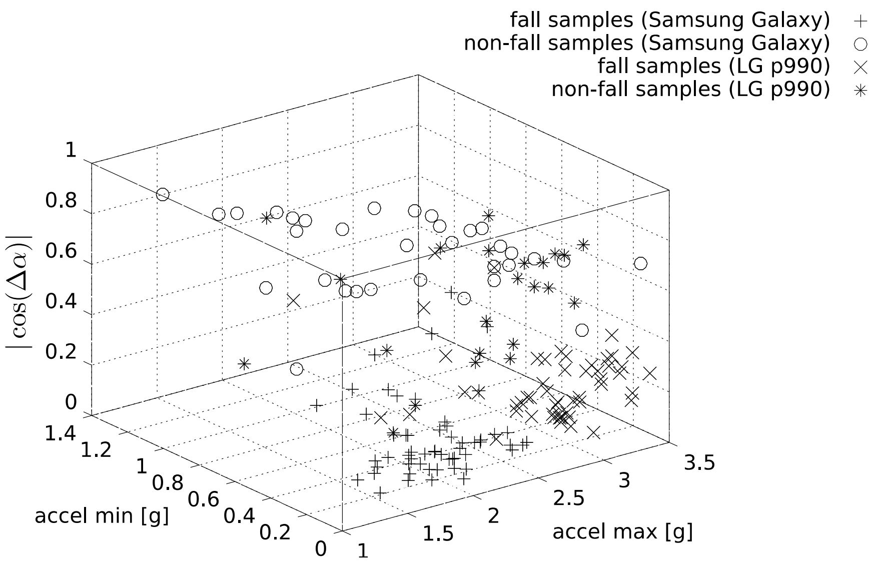

Figure 2: Distribution of falls and non-falls for 2 different devices

2. 2. Distribution of sampled data

In order to get insights in the distribution of the recorded data samples, samples from two different devices (Samsung Galaxy S, LG Optimus P990) are mapped to points in 3-dimensional space using the scalar maximum acceleration a_{max} as x-coordinate, the acceleration minimum a_{min} that occurs *before* the maximum as y-coordinate, and the change of the device attitude between start and end of the sampling $\Delta\alpha$ (respectively the cosine of this angle) as z-coordinate. The result is depicted in *Figure 2*, showing that there is a clear device-dependent clustering of fall data due to different scales of different accelerometers. Furthermore it can be assumed that the attitude change $\Delta\alpha$ in the z-direction would already present a strong measure for distinguishing falls from non-falls.

3. Description of the algorithm and comparison of performance

According to the threshold-based algorithm, fall samples are required to lie in the *lower-right front* octant of the shown cube. The exact placement of the octant depends on the chosen thresholds, of course. We have established the following *optimal* values by optimizing the accuracy of classification for a set of fall and non-fall data:

$a_{min} \leq 7.5$ m/s^2 during the free-fall phase

- $a_{max} \geq 17.5$ m/s^2 at impact on floor
- $\Delta\alpha \geq 65°$ orientation before and after the fall

According to these parameters, the elements of the datasets depicted in Figure have been classified: on the LG device, 50 out of 54 falls and 17 out of 24 non-falls have been correctly identified, which amounts to an accuracy of 85.9%. On the Samsung smartphone, which in general reports slightly lower accelerations than the LG phone, the accuracy is 83.7%: all of the 32 non-falls, but only 40 out of 54 fall samples were correctly classified with this choice of thresholds.

Other authors report to have successfully applied pattern recognition in fall detection [6]. In our studies, we have been especially attracted to the theory of support vector machines for this two-class classification problem. The SVM implementation adopted is SVM_{light} [3]. In order to be able to use this code, an appropriate input for SVM_{light} has to be created first.

Our approach to fall detection is based on the assumption that all falls share a common pattern that can be extracted using the selected pattern recognition technique. In our case the main challenge is thus to derive a scaling-independent, real-valued series from the series of 3-dimensional acceleration vector and feed it into SVM_{light}.

As a first step, the data samples are aligned according to their respective maximum (or the local minimum that precedes it; in case of a fall it is this minimum that marks the instant in time at which the body actually hits the ground and is thus more significant). These turning points serve as a gauge in order to make data samples comparable. The samples are shifted so that the minimum occurs at time t = 1s after the first data point in order not to discard too much of the information that precedes the fall. The length of the time frame is chosen to be 6 seconds, i.e. only 6 of 10 seconds of sampling time are effectively used.

As pointed out earlier, the acceleration values from different devices can/should not be used directly. Our idea is to completely disregard the magnitude of the acting forces, but to only look at the direction at which these forces act. From the series of 3-dimensional acceleration vectors $(\mathbf{a}_i)_{i=1,\ldots,n}$ we construct a real-valued series $(\Delta\alpha_i)_{i=1,\ldots,n}$, $\Delta\alpha_i \in [-1, 1]$ by simply calculating the cosine of the angle enclosed by a gauge vector[1]) with the acceleration vector relative to the device's reference frame by simply calculating a scalar product:

$$\Delta\alpha_i := (\mathbf{a}_i / |\mathbf{a}_i|) \cdot (\mathbf{a}_0 / |\mathbf{a}_0|) \qquad (1)$$

[1] The first data sample $\mathbf{a}_0$, corresponding to earth's gravity, is the canonical choice for the gauge vector.

A prototypic sequence for a fall sample is shown at the right diagram of Figure. The series obtained this way is decomposed into its wavelet components. This step corresponds to the transformation of a time series to a vector representation of the data, suitable as input to SVM_{light}. It has turned out that the choice of the wavelet basis has an influence on the final results, so obviously some wavelet types are better suited for the fall detection problem than others. A conclusion about which is the optimal wavelet basis cannot be given in this work, though. Additionally, there is some kind of noise elimination by simply setting *small* wavelet coefficients 0.

We have used the data of LG Optimus P990 for training and of Samsung Galaxy for testing. The test returns the following results (the classification result on the training set is also stated here for the sake of completeness):

- Accuracy on LG Optimus P990 data: 89.74% (53 of 54 falls and 17 of 24 non-falls classified correctly)
- Accuracy on Samsung Galaxy S data: 91.86% (49 of 54 falls and 30 of 32 non-falls classified correctly)

Our procedure outperforms the threshold based algorithm by more than 8% with respect to the overall accuracy and misses only 5 out of 54 falls on the Samsung Galaxy test set.

4. Conclusion

Using a threshold based algorithm for fall detection relies on the assumption that accelerometers are exact measuring instruments, which is not the case for accelerometers in smartphones. Considering only the direction of the constraining forces instead reveals a device independent measure surprisingly well-suited as input for a universal fall detection algorithm. Yet it is hard to decide which features in this function are characteristic for a fall and distinguish it from a non-fall. From what we have seen looking at the wavelet spectrum we are led to believe that the dither in the signal when the rather elastic human body comes to rest after hitting the floor contains especially significant information.

At time of writing we had not optimized our algorithm. The results obtained are those using “default” settings for the mathematical tools applied. Even better results can be expected with the following optimizations:

- placement and fixation of the device on the human body
- selection of the optimal wavelet family
- kernel and kernel parameter selection of the SVM

With respect to directional information, further investigations into this subject will take gyroscope data into account. The hope is that the device attitude during a fall is even as characteristic as the force direction, yet providing higher quality data as accelerometers do.

5. Acknowledgment

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