A Smartphone-based Fall Detection System for the Elderly

Panagiotis Tsinganos[1] and Athanassios Skodras[2]

Department of Electrical and Computer Engineering, University of Patras, Greece

[1]panagiotis.tsinganos@yahoo.gr, [2]skodras@upatras.gr

I. Introduction

Fall: "when a person comes to rest inadvertently on a lower level" [1].

- Chronic problems
- Diseases
- Environment hazards

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- Physical injuries
- Depression
- Avoidance of activity
- Healthcare costs

Prompt health care provision to prevent and restore any harm.

Proposed fall detection system

Sensing
- smartphone accelerometer (pants pocket)

Analysis
- thresholds (FSM)
- machine learning (kNN)

- battery drain
- user patterns

The typical fall pattern (Fig. 1) can be decomposed into a series of stages which can be identified during the detection process using a Finite State Machine (FSM):

- The pre-fall period, characterized by conventional ADLs containing some signs of instability
- The free-fall phase, during which the human body moves toward the ground.
- The impact phase, characterized by a sudden peak of the acceleration magnitude.
- A post-fall phase, in which the body lies on the ground.
- A recovery phase during which the fallen remains motionless if he is unconscious or injured.

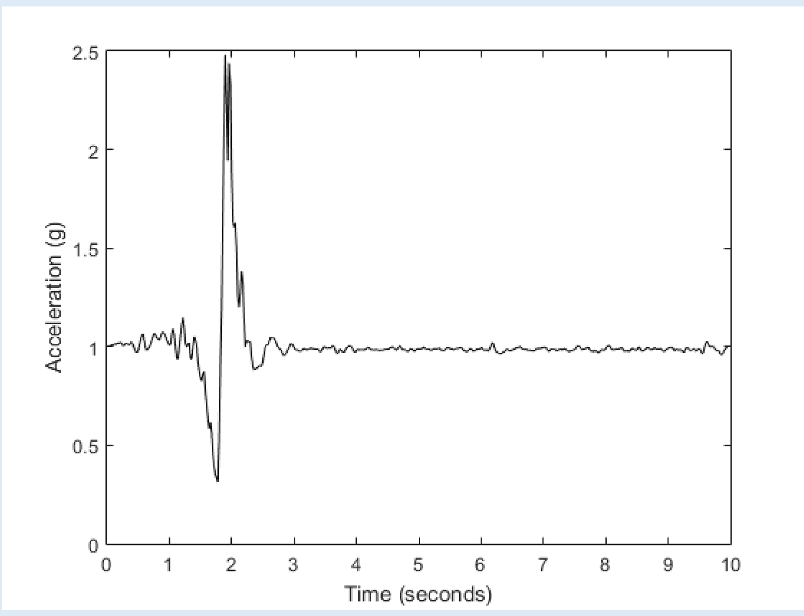

Fig. 1. Wearable sensor acceleration signal of falling event

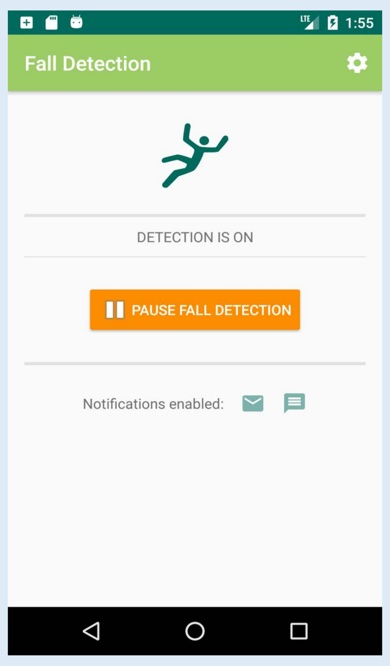

Fig. 2. Home screen of the Fall Detection app

II. Implementation

A. Overview

Detection
- Sensing (acceleration, 50Hz)
- Analysis (FSM, kNN)

fall detection →

Notification
- SMS/Email
- Position

These elements were implemented using the Java programming language and the WEKA library (Fig. 2).

B. Data-Preprocesssing

- Sampling rate 50Hz
- Accelerometer bias
- Median filter (60ms window)

C. FSM [3]

- 5 stages
- thresholds and timers

D. Features

- 14 features
- Time (AAMV, IDI, MPI, PDI, ARI, FFI, SCI)
- Statistical (SKEW, KURT, IQR, POWER_IMP, STD_IMP)
- Wavelet (CWENERGY, CWPEAKS)

E. Wavelet Features

- Custom wavelet from 2s fall segments
- Adapted with MATLAB Wavelet Toolbox (Fig. 3)
- Continuous Wavelet Transform (CWT)

F. kNN Classifier

- 7 neighbors
- Manhattan distance
- Distance based voting

G. Personalization

- Reduce false positives
- User can signal a fall as false positive
- Feature values appended to dataset as ADL

H. Power Consumption

- Adjustable sampling rate
- Level of sensor activation $f(x) \sim N(\mu, \sigma^2)$
- In low activity $x \in [\mu - 2\sigma, \mu + 2\sigma]$ set sampling to 10Hz

III. Results

The MobiAct [4] dataset, which was used for the evaluation of the model, contains 647 fall patterns and 1879 patterns of daily activities. This set of activities was separated into train and test datasets using a 10-fold cross validation in order to evaluate the entire classifier model (Table 1). The performance results for the final model are:

- sensitivity=0.98
- specificity=0.95

Table 1. 10-fold cross validation results

	Predicted	
Actual	Fall	ADL
Fall	618	29
ADL	55	1824

To further assess the proposed algorithm, a comparison with other similar studies is carried out (Table 2).

Table 2. Comparison of algorithms based on sensitivity and specificity

	S. Abbate [3]	J. Dai [5]	R. Lee [6]	B.S. Yang [7]	P. Tsinganos [2]
Sensitivity	1.00	0.97	0.77	0.95	0.98
Specificity	1.00	0.91	0.81	0.94	0.95

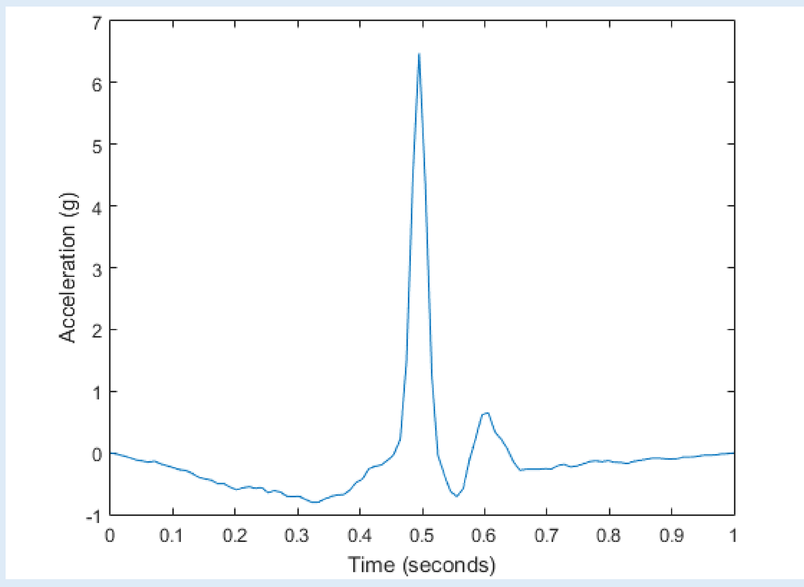

Fig.3. Adapted mother wavelet

Table 3 Battery consumption of Fall Detection app

	Enabled	Disabled
ASUS	0.01%	0.66%
LG	0.36%	0.92%

To quantify the reduction in the required power of the proposed battery-drain reduction algorithm two tests were performed with two different smartphones: a LG D160 and an ASUS Zenfone 2 (Table 3). There is a difference between the two smartphones that affects how our application drains the battery. What is clear, however, is that when the power management system is enabled the battery consumption is drastically reduced regardless of the smartphone.

IV. Conclusions

This study developed a fall detection system based on an Android smartphone device. Identifying signal patterns and extracting parameters that can be used by a classifier can be applied to distinguish falls from daily activities.

In a future work we would like to collect accelerometer data from a wider range of population and test the algorithm in a real world environment. Another aspect of the fall detection system that we would like to study further, is how the algorithm is affected from user context. Finally, improving the personalization component is of primary importance.

V. References

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