**Coventry**
**University**

## Coventry University Repository for the Virtual Environment (CURVE)

http://curve.coventry.ac.uk/open

# Fall Detection with Wearable Sensors—SAFE (SmArt Fall dEtection)

Olukunle Ojetola, Elena I. Gaura, James Brusey
Coventry University, Coventry, Priory Lane, CV1 5FB, UK
{o.ojetola, e.gaura, j.brusey}@coventry.ac.uk

*Abstract*—The high rate of falls incidence among the elderly calls for the development of reliable and robust fall detection systems. A number of such systems have been proposed, with claims of fall detection accuracy of over 90% based on accelerometers and gyroscopes. However, most such fall detection algorithms have been developed based on observational analysis of the data gathered, leading to thresholds setting for fall/non-fall situations. Whilst the fall detection accuracies reported appear to be high, there is little evidence that the threshold based methods proposed generalise well with different subjects and different data gathering strategies or experimental scenarios. Moreover, few attempts appear to have been made to validate the proposed methods in real-life scenarios or to deliver robust fall decisions in real-time. The research here uses machine learning and particularly decision trees to detect 4 types of falls (forward, backward, right and left). When applied to experimental data from 8 male subjects, the accelerometers and gyroscopes based system discriminates between activities of daily living (ADLs) and falls with a precision of 81% and recall of 92%. The performance and robustness of the method proposed has been further analysed in terms its sensitivity to subject physical profile and training set size.

*Index Terms*—Body Sensor Networks, Machine Learning, MEMS Accelerometers

## I. INTRODUCTION

The elderly, many of whom are prone to falls, are the fastest growing age group of most western populations [4]. According to a report by the Centre for Social Justice UK [11], falls among the elderly cost the NHS (National Health Service) more than £4.6 million per day, including the cost of keeping people in hospital. One in three people over 65 (3.4 million people) fall each year in the UK. Also, patients with motor neurone diseases, such as primary lateral sclerosis (PLS) or stroke, often have multiple falls in a year. In addition, as pointed out by Li et al. [8], there is a higher risk of falls associated with specific careers, such as fire fighting. Consequences of falls include major soft tissue injuries, fractures or even death [7], [10]. Although fall detection systems cannot directly prevent falls, detection can help avoid minor falls being unreported (thus precluding early diagnosis of developing medical conditions) and reduce the risk of fallen patients, who have been left immobilised or unconscious by a fall, from being left untreated for an extended period. The high incidence of falls, combined with their associated cost, make it imperative for a robust and effective fall detection solution be developed.

Indeed, much research has gone into finding a solution to this problem. Only a few sets of tools are available in hospitals for fall detection and many of which are not effective in predicting or detecting falls. For instance, according to Oliver et al. [13], STRATIFY, a fall prediction tool, may not be optimal for identifying high risk individuals and as Smith et al. [14] conclude from results from an experiment with 387 acute stroke patients, STRATIFY performs poorly in predicting falls in stroke patients.

The research here: i) uses decision trees to detect 4 types of falls; ii) uses a moving window filter to reduce the data rate while maintaining informational content; and iii) uses the acceleration and angular velocity vector magnitudes as a feature to improve classification accuracy. The implemented system is based on the SHIMMER (Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability) wireless sensor platform and uses annotated experimental data from 8 male subjects with heights 162–189 cm, weights 60–100 kg, and ages 21–33 years.

The rest of this paper is organised as follows: In Section II, an overview of existing acceleration and angular velocity based fall detection systems is given. Section III describes the proposed system for fall detection, including the experimental setup and data gathering process. The experimental results and system evaluation are discussed in Section IV. Section V gives the concluding remarks and identifies areas for future work.

## II. RELATED WORK

To detect falls, a number of algorithms based on wearable accelerometers and gyroscopes have been proposed. One approach in common use is to discriminate between ADLs and falls by threshold values (for acceleration and angular velocity), set mostly by observational methods for both falls and ADLs [6], [8], [9], [16]. Nyan et al. [12] investigated syncope using 3-axis accelerometer and 2-axis gyroscope strapped to the thigh and waist. They applied unique features of body kinematics to detect falls during the body's descending phase. Bourke and Lyons [1] used a gyroscope mounted on the torso to measure the pitch and roll angular velocity data. Thresholds were again used to distinguish between falls and ADLs. Dai et al. [3] proposed the use of mobile phones as a platform for fall detection. They developed a fall detection algorithm based on the phone's 3D accelerometer. The resultant acceleration vector and vertical acceleration magnitudes were computed and set thresholds were used to detect falls. The issue with setting thresholds based on observational method is that such

threshold methods do not generalise well enough with different subject and data gathering strategies.

Aside from acceleration and angular velocity-based methods, Thome and Miguet [15] proposed a Hierarchical Hidden Markov Model (HHMM) for automatic detection of falls in video sequences. By fusing sensory information from a camera and laser range finder, Huang et al. [5] used Dubois possibility theory to estimate the possibility distribution of the distance between the head and average leg position measured by a cane robot during a fall. A rule based on possibility distribution was then used in the fall detection.

Many of these methods above have not been proven to be applicable in real-time and outside the laboratory due to a variety of reasons, amongst which wearability, performance repeatability in real-life situations and infrastructure costs and lack of in-field evaluation procedures are key.

The algorithm proposed in this paper attempts to ensure accurate and repeatable falls detection by using machine learning decision tree C4.5 to detect four different types of falls (forward falls, backward falls, and falls towards the right and left directions). The next section discusses the methodology used in this experiment.

## III. METHODOLOGY

*Hardware Platform*

To acquire acceleration and angular velocity, two SHIMMER sensor nodes were used for data acquisition and transmission from subjects to a remote PC. Each sensor node consists of a 3D accelerometer and 3D gyroscope, a Bluetooth device and an MSP430F1611 microcontroller device. The SHIMMER sensor node is shown in Fig. 1.

The tri-axial gyroscope consists of an InvenSense IDG-500 dual-axis (X, and Y) and ISZ-500 single axis (Z) angular rate sensor MEMS from Freescale Semiconductor, with a full scale range $\pm 8.7$ rad.s$^{-1}$, and a sensitivity of 110 mV.rad$^{-1}$.s. The tri-axial accelerometer (MMA7260Q) from Freescale Semiconductor has a range up to $\pm 6g$. The Bluetooth device (Rovering Network RN-42) has a range exceeding 10 m, a default transmission rate of 115 kbaud, and is a class 2 Bluetooth module.
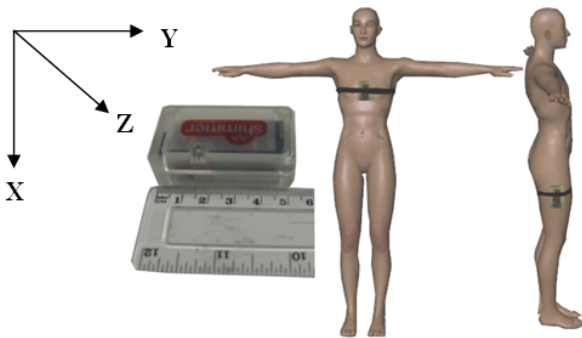


Figure 1.   Placement of SHIMMER sensor nodes.

*Experimental setup*

Eight healthy subjects took part in an experiment in which four types of falls (fall forward, fall backward, and falls toward the left and right directions) were investigated. The physical profiles of subjects are shown in Table. III. Subject's profiles were investigated to determine whether use of a variety of profiles in training of the decision trees increases performance and whether accuracy is maintained when training and testing on extreme body weights and heights respectively. Each subject wore two SHIMMER sensor nodes, one on their chest and the other on their right thigh (see Fig. 1). The 3D accelerometers and 3D gyroscopes in each sensor node acquired acceleration and angular velocity of each subject during the experiments. Data are sampled at 100 Hz and transmitted via Bluetooth to a remote PC for further processing. In addition, each sensor node reading is time stamped and each node timestamp is transmitted along side their data. Falls and ADLs were annotated by a custom written application in Labview on the remote PC. The program timed each activity for 2 mins, recorded the time for the start and end of each activity, and signaled the end of each activity. This approach somewhat automates annotation and reduces the risk of operator error. Before the start of experiments, the nodes were synchronised by banging two nodes together. This produces a brief high acceleration signal that is easily identifiable in the data and allows for accurate alignment in the annotation and processing phases.

*ADL events*

The overall aim of this system is to discriminate between falls and normal daily activities. During the experiment, postures and activities such as standing, sitting, lying and walking were maintained for about 2 mins each. To acquire realistic ADL data, it is assumed that people will normally engage in various activities such as making phone calls, reading books, or talking to other people while maintaining various postures. Therefore, the data gathering process incorporates these activities. The experiment starts with standing for 2 mins, during which a subject uses a phone while standing. At the end of the 2 mins, the subject goes from standing to sitting on a chair and remains sitting for another 2 mins. At this stage, the subject takes a book and reads. From sitting, the subject goes into a lying posture and while in the lying posture, he continues to read a book. From the lying posture, the subject returns to a sitting posture but this time, making a phone call while sitting. At the end of sitting, the subject starts to walk and while walking he also makes phone calls.

*Fall events*

Subjects were told to deliberately fall onto a 25 cm thick cushion and then change from lying to a sitting posture after few seconds while on the cushion. The time from first impact on the cushion until the subject finally stands up from after a fall is about 2 mins. This process was performed for fall forward, fall backward, and falls in the right and left directions. Some patients may fall down and remain in the lying position
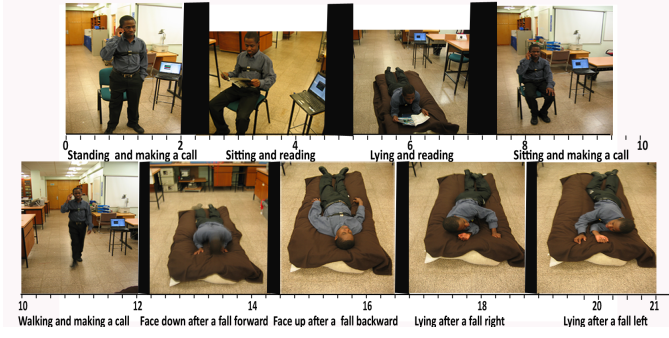
Figure 2. Protocol showing ADLs and Falls during experimentation (time scale in mins).



Figure 4. Vector magnitude for chest and thigh sensors

and some subjects may be able to sit-up whilst still on the ground after a fall. The data gathering for both the ADLs and falls was performed twice per subject. A summary of the protocol used for the experimentation is shown in Fig. 2.

*Falls annotation*

The annotation for a single fall event is shown in Fig 3. The time for a complete protocol takes an average of 21 mins per subject, and the time annotation per fall is about 5s. From the figure, the area annotated as a fall is from 850s to 855s. This shows that from point A to point B, the subject has been instructed to fall and in the process of falling. Between points B and C the subject's body makes an impact with the cushion on the floor and a high acceleration data is recorded. After a fall has occurred, the subject remains in a lying posture at point C to D. Though, point A to D was annotated as a fall, only point B to C shows a high acceleration signal. The following section discusses the data processing, machine learning and the results obtained.
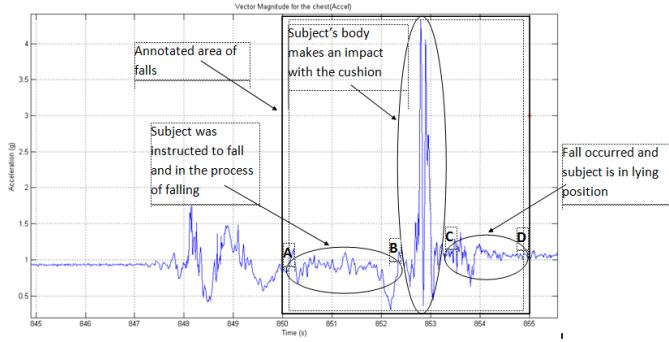


Figure 3. Fall annotation for a single fall event

## IV. RESULTS

In this work C4.5 decision trees were used to learn to distinguish between Falls and ADLs. Data gathered as described in Section III was mean filtered and re-sampled at 10Hz, thus reducing the time required for training. The acceleration and angular velocity vector magnitudes (VM) for the chest and thigh region sensor nodes were computed as proposed by Li
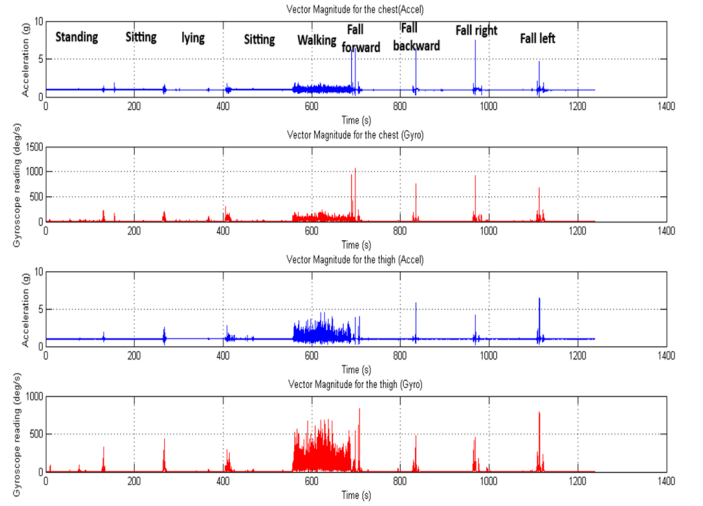
et al. [8] and used as features for the trees, together with the raw data. Example vector magnitudes are shown in Fig. 4. The use of machine learning in this paper was inspired by prior work [2] in which a decision tree was trained to classify various postures with high accuracy in real time.

The output of the decision tree was filtered using a majority filter over a non-overlapping window of 8 samples (0.8s). The size of the window was empirically determined. If the majority of samples within a window identify a fall, the whole of that window is considered a fall, otherwise that window is considered as a no-fall. This approach is essential because the decision made by the tree for a fall or no-fall condition was based on individual instances of the data thus no history; some concept of state evolution is brought by the median filter.

Table I
SUMMARY OF FALL CLASSIFICATION AT MACRO EVENTS LEVEL

TP = True positive, FP = False positive, FN = False negative

| Leave N subjects out | Ave. TP out of 4 falls | FP in an ave. of 21 mins | Ave. FN out of 4 falls |
|---|---|---|---|
| Leave1out | 3.69 | 6.06 | 0.31 |
| Leave2out | 3.59 | 16.5 | 0.41 |
| Leave3out | 3.53 | 8.08 | 0.47 |
| Leave4out | 3.60 | 11 | 0.29 |
| Leave5out | 3.52 | 13 | 0.48 |

Table II
SUMMARY OF DECISION TREE-BASED FALL CLASSIFICATION.

| | Mean precision % | 95% Confidence interval for mean precision % | | Median precision % | Std. Deviation precision % | Recall % | Accuracy % |
|---|---|---|---|---|---|---|---|
| | | Lower bound | Upper bound | | | | |
| Leave1out | 81.82 | 73.66 | 89.97 | 87.59 | 15.31 | 92.19 | 99.45 |
| Leave2out | 72.81 | 65.49 | 80.14 | 74.68 | 20.32 | 89.84 | 98.78 |
| Leave3out | 80.95 | 75.32 | 86.59 | 84.85 | 16.66 | 88.19 | 99.25 |
| Leave4out | 75.04 | 70.27 | 79.81 | 77.78 | 16.42 | 90.10 | 99.07 |
| Leave5out | 72.91 | 66.60 | 79.21 | 81.31 | 22.19 | 88.00 | 98.91 |

The performance of the algorithm was evaluated both at macro events level, i.e. "real falls" which occurred during

experimentation (a) and also with regard to the match between the annotation and the decision system (tree followed by filter) output (b). Note that: the falls annotation identified a fall as a fixed 5s window; the decision system output has a frequency of 1.25Hz; the output of the system was said to be a True Positive (TP) for all its 7 occurrences within a Fall window if at least one of the decisions was a fall. Multiple occurrences of fall decisions within a fall annotation window were accepted as belonging to the single Fall event in that window. Any occurrence of a fall decision outside the annotated windows was considered a False Positive (FP). Reversely, any window annotated as a fall without any occurrence of a fall decision, was considered a False Negative (FN) for all 7 decision occurrences.

(a) A total of 64 falls have been performed by the 8 subjects, over an average time per subject of 42 mins. The number of correctly classified falls varied from subject to subject, with the leave one subject out cross-validation procedure showing that 5 subjects have had (8/8) their falls identified whilst the rest 3 had between 5/8 and 7/8 identified falls. The number of False Positives (FPs) also varied from subject to subject, with a minimum of 3 in 42 mins to a maximum of 26. The findings from the "Leave N out" cross-validation exercise are shown in Table I. Whilst a small reduction in TPs is observed as the size of the training set is reduced, note that the FPs increase more dramatically. Given the nature of the experimental protocol (with a fall occurring on average every 5.25 mins of experimental time) and the expectation that falls in elderly may occur with a frequency of say 1 in 24 hours at most, one interpretation of the results is to calculate the frequency of FPs and FNs for a 24 hours period. The system will produce, over a 3 days period, approximately 5 FPs and will generate a FN every 12 days approximately.

(b) When considering the decision system output and the rule above, testing showed that falls were correctly classified with a precision between 72% and 81% depending on the number of subjects used for training. The *Leave one subject out cross validation* procedure on 7 subjects training set gives a mean precision of 81.82% correctly classified samples, with a upper band mean of 89.87% and lower band mean of 73.66%. A summary of the results obtained during testing for *Leave N subjects out cross validations* are shown in Table II and the box-plot in Fig. 5. From these results, more than 3 subjects are recommended to be used in training to endure a low standard deviation.

Though the accuracy for the algorithm ranges from 99.45% for training with 7 subjects and 98.91% for training with 3 subjects, it does not give clear picture of the performance of the algorithm because of the difference in data size between ADLs and falls. For a typical subject, data was gathered for about 42 mins, but only 40s of data represent falls, while the remaining are for ADLs. The imbalance in data size between falls and ADLs allow the algorithm to detect ADLs with such high accuracy and hence reporting overall high accuracy.
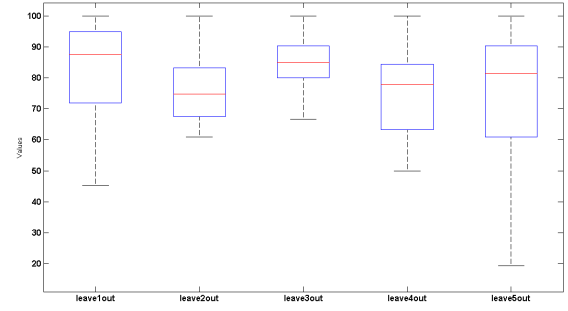


Figure 5. Box plot showing the results for leave $N$ subjects out cross validation.

*Algorithm sensitivity to body profile*

The performance of the decision system was further investigated per subject, using the leave one subject out procedure (Table III) to determine its sensitivity to body profile. A subject's weight and height does not appear to have an impact onto the performance of the decision system presented here. Further investigation of weight influence for example, on a tree trained from Subjects 1-5 (which eliminates both heavy subjects and a lighter subject) showed that the performance of subjects 6 and 8 on testing was very similar (99.49% vs 99.60% accuracy). Similar conclusions were drawn for the influence of height on the system's performance. Pearson correlation indexes for "Weight and Accuracy" and "Height and Accuracy" were 0.022 and 0.045 respectively.

Table III
EFFECT OF BODY PROFILE ON THE PERFORMANCE OF DECISION TREE.

| Volunteers | Precision % | Recall % | Accuracy% | Age (yrs) | Weight (Kg) | Height (cm) |
|---|---|---|---|---|---|---|
| Subject1 | 93.44 | 100 | 99.80 | 33 | 70 | 176 |
| Subject2 | 93.44 | 100 | 99.84 | 25 | 80 | 162 |
| Subject3 | 95.16 | 100 | 99.87 | 25 | 65 | 165 |
| Subject4 | 57.58 | 62.5 | 98.53 | 21 | 75 | 166 |
| Subject5 | 65.37 | 87.5 | 98.99 | 26 | 61 | 167 |
| Subject6 | 83.51 | 100 | 99.64 | 21 | 60 | 170 |
| Subject7 | 85.78 | 87.5 | 99.39 | 25 | 100 | 189 |
| Subject8 | 80.26 | 100 | 99.57 | 23 | 100 | 175 |

## V. CONCLUSIONS AND FURTHER WORK

This paper described a decision trees-based method for fall detection from 3D accelerometer and gyroscope data. Vector magnitude of acceleration and angular velocity were used as features for the decision trees. Mean filtering of the data was performed to reduce data set size ten fold for ease of training. A majority filter was applied at the output of the decision tree. Training was performed with subject sets of 3 to 7 subjects with heights in the range of 162 to 189 cm, weights between 60 and 100 kg and ages between 21 and 33. Four types of falls were identified with a precision of 72% for a 3-subjects training set and up to 81% for a 7 subjects

training set. The classifier's performance does not appear to be sensitive to training subjects' physical characteristics. The decision tree classifier implemented is non-real time, but has low computational complexity and is thus well suited for real-time implementation.

Based on the encouraging results obtained, further work will focus on:

- the detection of pre-fall conditions; experimental data is aimed to be gathered by using an instrumented balance board
- more realistic simulation of falls within ethical bounds
- thorough evaluation of the method against commercial fall detectors with regard to the incidence of false positives, in particular and
- the investigation of "closer to life" simulation of falls and also of observing how movement and fall patterns in general translate from young healthy volunteers to the elderly.

REFERENCES

[1] A. K. Bourke and G. M. Lyons. A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. *Medical Engineering & Physics*, 30(1):84–90, 2008.
[2] James Brusey, Ramona Rednic, Elena I. Gaura, and John Kemp. Postural activity monitoring for increasing safety in bomb disposal missions. *Meas. Sci. Technol.*, 20(075204):11pp, 2009. Online: http://dx.doi.org/10.1088/0957-0233/20/7/075204.
[3] Jiangpeng Dai, Xiaole Bai, Zhimin Yang, Zhaohui Shen, and Dong Xuan. PerFallD: A pervasive fall detection system using mobile phones. In *Proc. 8th Intl. Conf. Pervasive Computing and Communications Workshops (PERCOM Workshops)*, pages 292–297, 2010.
[4] Jane Fleming, Fiona E Matthews, and Carol Brayne. Falls in advanced old age: recalled falls and prospective follow-up of over-90-year-olds in the Cambridge city over-75s cohort study. *BMC Geriatrics*, 8, 2008.
[5] Jian Huang, Pei Di, K. Wakita, T. Fukuda, and K. Sekiyama. Study of fall detection using intelligent cane based on sensor fusion. In *Intl. Symp. Micro-NanoMechatronics and Human Science (MHS 2008)*, pages 495–500, November 2008.
[6] P. Jantaraprim, P. Phukpattaranont, C. Limsakul, and B. Wongkittisuksa. Improving the accuracy of a fall detection algorithm using free fall characteristics. In *Intl. Conf. Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON)*, pages 501–504, May 2010.
[7] Maarit Kangas, Irene Vikman, Jimmie Wiklander, Per Lindgren, Lars Nyberg, and Timo Jämsä. Sensitivity and specificity of fall detection in people aged 40 years and over. *Gait & Posture*, 29(4):571–574, 2009.
[8] Qiang Li, John A. Stankovic, Mark A. Hanson, Adam T. Barth, John Lach, and Gang Zhou. Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In *BSN '09: Proceedings of the 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks*, pages 138–143, Washington, DC, USA, 2009. IEEE Computer Society.
[9] Chien-Liang Liu, Chia-Hoang Lee, and Ping-Min Lin. A fall detection system using k-nearest neighbor classifier. *Expert Syst. Appl.*, 37:7174–7181, October 2010.
[10] C.J. Lord and D.P. Colvin. Falls in the elderly: Detection and assessment. In *Proc. Ann. Intl. Conf. Engineering in Medicine and Biology Society (EMBS '91)*, pages 1938–1939, Oct 1991.
[11] Sara McKee. The forgotten age: Understanding poverty and social exclusion later in life, 2010. Online: http://www.centreforsocialjustice.org.uk/client/downloads/20101122_Publications_Older%20Age.pdf.
[12] M. N. Nyan, Francis E. H. Tay, and E. Murugasu. A wearable system for pre-impact fall detection. *Journal of Biomechanics*, 41(16):3475–3481, 2008.
[13] David Oliver, Alexandra Papaioannou, Lora Giangregorio, Lehana Thabane, Katerina Reizgys, and Gary Foster. A systematic review and meta-analysis of studies using the STRATIFY tool for prediction of falls in hospital patients: how well does it work? *Age and Ageing*, 37(6):621–627, 2008.
[14] Jane Smith, Anne Forster, and John Young. Use of the 'STRATIFY' falls risk assessment in patients recovering from acute stroke. *Age and Ageing*, 35(2):138–143, March 2006.
[15] N. Thome and S. Miguet. A HHMM-based approach for robust fall detection. In *Proc. 9th Intl. Control, Automation, Robotics and Vision (ICARCV '06)*, pages 1–8, 2006.
[16] Aner Weiss, Ilan Shimkin, Nir Giladi, and M. Hausdorff Jeffrey. Automatic detection of near falls: algorithm development and preliminary results. *Biomedical Central*, 3(62), 2010.