Fall detection using a head-worn barometer

Guglielmo Cola, Marco Avvenuti, Pierpaolo Piazza, and Alessio Vecchio

Dipartimento di Ingegneria dell'Informazione,
University of Pisa
Largo Lucio Lazzarino 1, 56122, Pisa, Italy
{guglielmo.cola, marco.avvenuti, alessio.vecchio}@iet.unipi.it

Abstract. Falls are a significant health and social problem for older adults and their relatives. In this paper we study the use of a barometer placed at the user's head (e.g., embedded in a pair of glasses) as a means to improve current wearable sensor-based fall detection methods. This approach proves useful to reliably detect falls even if the acceleration produced during the impact is relatively small. Prompt detection of a fall and/or an abnormal lying condition is key to minimize the negative effect on health.

Keywords: Accelerometer, Barometer, Fall detection, Head-worn device, Slow fall, Wearable sensor

1 Introduction and related work

A large fraction of older adults (about 30% at the age of 65+) are subject to a fall each year. Falls are one of the major causes of hospitalization and traumas at that age. Moreover, falls frequently represent the beginning of a sequence of physical and psychological problems for senior citizens. In fact, besides possible physical impairments, falls may bring reduced self-confidence and in some cases even depression [3]. The fear of falling again may also increase the chances of incurring in a more sedentary and less independent lifestyle. Notably, social and health problems caused by falls are going to increase because of our aging society.

Fall detection systems are aimed at automatically recognizing the occurrence of falls. Automatic detection is useful whenever the user who falls is subject to a loss of consciousness or a major trauma and he/she is thus unable to ask for help. In the context of fall detection, the term *long-lie* is typically used to refer to the condition of remaining on the floor for a prolonged time after a fall. It is also known that reducing the long-lie period has a positive impact on the outcomes of falls [12].

The majority of fall detection systems rely on wearable devices. In general, the worn device includes one or more sensors (usually accelerometers and gyroscopes) which can be used to recognize anomalous movements of the users [6, 9, 10]. In general, events characterized by values of acceleration above a given threshold are classified as falls. Some methods also include posture information to avoid raising false alarms [8].

More recently, a number of fall detection systems based on smartphones has been presented. Common smartphones include an accelerometer, a gyroscope, and a magnetic sensor, which can be used to monitor the user's movements. In addition, smartphones are easily programmable and natively include a communication subsystem, which is mandatory for sending an alarm to the caregivers. The system presented in [1] extracts a set of features from acceleration-based information; then such features are provided as input to a classification module able to recognize not only falls, but also other activities of daily living (ADLs) such as walking, sitting, and lying.

Fall detection methods based on acceleration suffer from the problem of being unable to recognize "slow falls", which occur when the subject uses the hands to soften the impact or in case of a non-instantaneous loss of consciousness. In fact, such falls may be characterized by acceleration values that are generally smaller than the threshold used to discriminate falls from ADLs (note that the threshold cannot be lowered, to avoid an unbearable number of false alarms during normal activities).

In fall detection methods based on a wearable device, the latter is generally placed at the user's waist. The rationale for this choice is twofold: a waist-mounted device is in proximity of the center of mass of the user; waist is less subject to spurious movements with respect to other parts of the body (e.g., arms). Nevertheless, we believe that studying the use of head-worn devices deserves more attention with respect to existing literature. Practically, the hardware needed for detecting falls could be embedded in headwear, glasses, or an ear-worn device[1]. This would free the user from wearing an additional device in case he/she is already using one of these accessories.

The work presented in this paper contributes to existing literature as follows: i) for the first time the use of a head-worn barometer is proposed and studied in the context of fall detection, as a means to improve detection accuracy even in the case of slow falls; ii) changes in pressure detected by the barometer are used not only for detecting falls, but also other simple postures (standing and sitting); this is achieved combining the output of the barometer with acceleration information.

2 Method

The main idea behind the proposed method is to combine accelerometric and barometric information to improve the reliability of a fall detection system, even when the fall produces relatively small accelerations (*slow fall* hereafter). In particular, the barometer is used to measure the pressure variation associated to a particular user's movement, the latter being detected with the accelerometer. The pressure variation is caused by the vertical displacement experienced by the sensor, for example when the user sits or falls down. Such pressure variation can be used to discriminate whether the movement led to a safe postural change

[1] For example, an ear-worn device embedding an accelerometer has been used for detecting anomalies in gait [4].

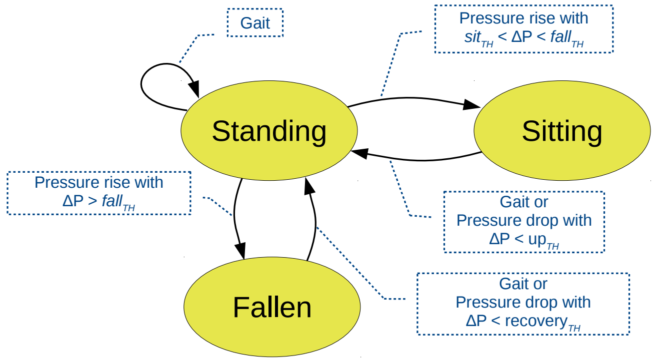
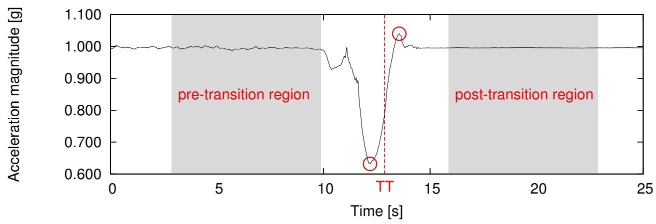
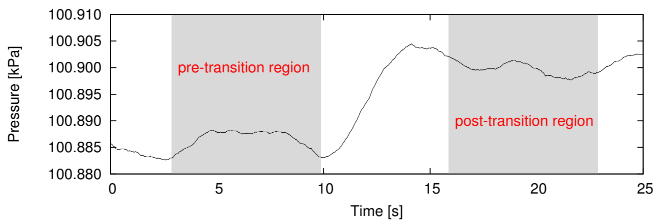


Fig. 1. State diagram representation of the proposed method.



(a) Acceleration (moving average, 2-second window)



(b) Barometric pressure (moving average, 2-second window)

Fig. 2. Slow fall example, finding pre and post-transition regions.

(such as sitting down on a chair), or to a potentially dangerous situation like being lying on the floor. The proposed technique assumes that the barometer has been placed near to the user's head. As previously mentioned, this position can be conveniently used if the sensor is embedded in headwear, glasses, or a hearing aid device. An additional motivation is represented by the fact that the user's head experiences the highest vertical displacement (and thus the highest pressure variation) during a fall.

The way we aim to combine acceleration and barometric pressure is described in Figure 1, using a finite state machine (FSM) representation. Each state in the FSM represents a particular *posture*. For the sake of simplicity, in this study we considered only three possible postures: *standing*, *sitting*, and *fallen*. Fallen actually means that the user is lying on the floor, whatever the acceleration that produced the transition to such posture. In the typical context of fall detection (an older adult living alone), the fact that the user's head is close to ground level can be reasonably used as a condition to trigger an alarm, especially if such condition persists for a significant amount of time (e.g., one minute).

When the system is started, the current posture is unknown and fall detection is based on accelerometric analysis alone. However, the FSM enters the *standing* state as soon as a short interval of walking activity (gait) is detected (e.g., six consecutive steps). To detect gait segments, the acceleration-based technique described in [8] was used. Such technique is sufficiently *lightweight* to be implemented and executed in real time on a miniaturized device with limited resources [7].

After the standing posture has been detected, the system starts to monitor acceleration for a possible *posture transition*. A possible posture transition is triggered by the presence of a "valley" in the acceleration magnitude (Euclidean norm) signal [1, 5]. The valley is detected by using a threshold ($valley_{TH}$), with an additional test to group together valleys occurring within a short interval and to discard valleys followed by walking activity.

The discrimination between different transitions exploits barometric analysis. An example is shown in Figure 2, which is relative to a slow fall happened from standing position and ending with the user lying on the floor. Figure 2a shows the acceleration signal, which is used to detect the valley. The local minimum and maximum (red circles) are used to find the transition time TT (dotted vertical line). In turn, TT is used to define two new regions: *pre-transition* $[TT - 10\ s,\ TT - 3\ s]$ and *post-transition* $[TT + 3\ s,\ TT + 10\ s]$. Finally, the barometric signal corresponding to these two regions is analyzed (Figure 2b). More precisely, it is found the pressure variation ΔP as the difference between the median value in each region:

$$\Delta P \;=\; median(post\text{-}transition) - median(pre\text{-}transition).$$

A positive ΔP like in Figure 2b, clearly indicates that the user's head has moved towards the ground. Conversely, when pressure drops the user is moving the head upward, for example because of standing up from sitting position.

Posture transitions are recognized by comparing ΔP against a set of thresholds. When the user is standing, a positive ΔP leads to the *sitting* state if the pressure variation is within sit_{TH} and $fall_{TH}$. Instead, the FSM moves to the *fallen* state state if ΔP is higher than $fall_{TH}$. The rationale is that the pressure variation is higher when the user falls to the ground, with respect to sitting on a chair. Pressure variation is also exploited to promptly detect recovery from fall, by comparing a negative ΔP (*pressure drop*) against a negative threshold (ΔP$<$ $recovery_{TH}$). Recovery is also detected if the user walks.

Besides activity recognition purposes, the recognition of the *sitting* state represents a useful information even for fall detection. In particular, while sitting down the user is closer to the ground with respect to the standing posture, and the system may produce false negatives (i.e., falls that are not detected) if a

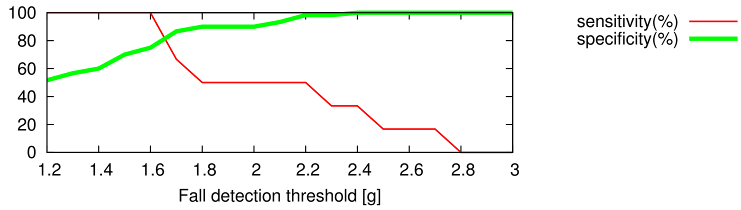


Fig. 3. Sensitivity and specificity when varying the acceleration threshold.

pressure variation above $fall_{TH}$ is required to detect a fall from a chair. As a solution, the system may temporarily disable the use of barometric pressure for fall detection while the user is sitting. Transition from sitting to *standing* is recognized either by pressure analysis (ΔP$< up_{TH}$) or by detecting gait.

3 Experimental setting

We used a Shimmer 3 device, equipped with a TI MSP430 MCU, an ST Micro LSM303DLHC accelerometer, and a Bosch BMP180 pressure sensor [11]. The accelerometer was set to operate within ± 8 g range. The barometer was operated in ultra-high resolution mode (0.03 hPa RMS noise). Acceleration and pressure were sampled with $\sim$ 50 Hz frequency and stored on the persistent storage of the device. To reduce noise, both acceleration and pressure were low-pass filtered using a moving average with a 2-second window. The Shimmer 3 was attached on a pair of common glasses, in proximity of the user's temple.

Six volunteers agreed to participate to a supervised experiment. The experiment consisted in a predefined sequence of transitions between the postures to be recognized by the proposed method. More precisely, each volunteer performed the following actions: a) walk for about 30 s; b) sit down on a chair; c) stand up; d) short walk; e) sit down on a different chair; f) stand up; g) walk for about 20 s; h) lie down on the floor (slow fall); i) stand up. Volunteers remained in each posture (standing, sitting, fallen) for at least 10 s. Experiments were recorded with a video camera in order to facilitate manual labeling of posture transitions.

4 Results and Discussion

In this section the performance achieved by the proposed method is presented and discussed. The evaluation starts by describing the results achieved by a system based on a simple accelerometric threshold, in order to highlight the contribution introduced by the combined use of acceleration and barometric pressure.

4.1 Acceleration threshold-based system

A typical approach to fall detection consists in searching for peaks in the acceleration magnitude above a predefined threshold. Indeed, a fall produces one or

Table 1. ΔP [Pa] measured for each posture transition – per-user and average results.

User ID	height [m]	stand → sit [Pa]	sit → stand [Pa]	stand → fall [Pa]	fall → stand [Pa]
1	1.63	3.1	-5.8	14.3	-16.3
2	1.75	3.4	-3.8	15.5	-12.1
3	1.90	6.7	-5.1	18.6	-18.4
4	1.73	3.5	-4.2	12.1	-15.9
5	1.90	9.0	-8.6	15.9	-16.0
6	1.75	3.9	-6.7	17.1	-18.9
Average	1.78	4.9	-5.7	15.6	-16.3

more sharp peaks in the acceleration signal, due to the impact with the ground of different parts of the body. The choice of the threshold is determined by the trade-off between *sensitivity* (the proportion of real falls that are correctly detected) and *specificity* (the proportion of normal activities that are correctly ignored by the fall detection system). If the threshold is too high, there is a risk of missing real falls (low sensitivity). On the other hand, if the threshold is too low, the system is likely to produce frequent false alarms throughout the day (low specificity) [2]. Threshold values used in the literature ranged from 2 to 3 g.

In our experiment, for each volunteer, there is one *positive* (a slow fall from standing position), and some normal activities that can lead to false positives (walking, standing, sitting). Each of these activities can be considered as a *negative* instance, which can be used to find the specificity (proportion of negatives that are correctly ignored). In total there are 11 negative instances per user (6 walking intervals, 2 sitting transitions, 3 standing transitions). We applied different threshold values to verify the performance in terms of sensitivity and specificity. The average result is shown in Figure 3. It is clearly visible that the detection of slow falls by means of a simple accelerometric threshold would lead to an unbearable number of false alarms during normal activities. For example, the highest threshold that would allow the detection of all the falls is 1.6 g – such threshold leads to a specificity as low as 75%, meaning that about 3 false alarms per user were produced during our experiment.

4.2 Proposed method results and future work

The first step of the proposed method consists in finding possible *transitions*, which are identified by the presence of a valley in the acceleration magnitude. We verified that all the effective transitions were detected by the system. In addition to real transitions, the system occasionally detected valleys produced during walking activity. However, such transitions were filtered out by means of walking detection (the possible transition is discarded if it occurs during walking activity).

After a transition is found, the system finds the ΔP value in order to determine the transition type. Table 1 shows per-user and average results in terms of the ΔP measured during a specific posture transition. More specifically, for each user it is shown his/her height, and the average ΔP measured while sitting down, standing up (from sitting), falling down, and standing up after a fall. The measured ΔP is not always consistent with the effective vertical displacement (e.g., for user 6 there is a significant difference, in terms of absolute ΔP, between sitting down and standing up from a chair). However, for the purpose of this study, the most important result is that for all the users there is a measurable difference between sitting and falling, in terms of ΔP. In the worst case (user 5), the "gap" between falling and sitting was 6.9 Pa (ΔP=15.9 Pa after falling, and ΔP=9.0 Pa after sitting).

The thresholds required to discriminate different transitions were set using a leave-one-user out cross-validation strategy and taking into account users' height. The cross-validation procedure consists in leaving one user out for validation, while other users' results are used to find the thresholds. In particular, we used the average pressure variation per meter of height displacement to estimate all of the other thresholds. For example, the minimum threshold used to detect a fall ($fall_{TH}$) threshold was set – with a conservative approach – to 70% of the expected pressure variation. The result of cross-validation was that all the transitions (posture changes) were recognized correctly. Therefore, the system was able to detect the slow falls without producing false alarms (100% sensitivity and specificity). This promising result confirms that barometric information can successfully enhance an acceleration-based fall detection system, enabling the detection of slow falls while keeping a low false positive rate.

Future work will address some scenarios that have not been considered in this preliminary study. For example, it will be evaluated whether the same approach could be used to reliably distinguish lying on a bed from lying/falling on the floor. Another interesting scenario is the possible presence of stairs. Walking down a flight of stairs produces a pressure rise that may lead to a false alarm when the user stops walking. However, acceleration and pressure information could be used to detect walking on stairs and temporarily disable the use of pressure for fall detection purposes. The use of pressure is then re-enabled as soon as the user walks on level ground. In future research, we will also investigate if pressure variation thresholds can be tuned automatically to the user, by using a semi-supervised training phase based on just normal activities. Different thresholding methods will be considered, including the use of estimated vertical displacement derived from pressure variation. Finally, it will be evaluated the use of a barometer embedded in a wrist-worn device.

5 Conclusions

A barometer, embedded in headwear, glasses, or an ear-worn device, can be successfully used to detect posture transitions and improve the reliability of a fall detection system. Whenever a possible transition is detected by acceleration analysis, the event can be safely classified as a non-fall in case the pressure variation observed by the barometer is not compatible with a fall. The barometer could be particularly helpful in recognizing slow falls, which are frequently undetected in acceleration-based methods. Future work will concern a long-term experimentation with a larger number of subjects and in uncontrolled environment.

Acknowledgements

This research was supported by the PRA 2016 project "Analysis of sensory data: from traditional sensors to social sensors", funded by the University of Pisa.

References

1. Abbate, S., Avvenuti, M., Bonatesta, F., Cola, G., Corsini, P., Vecchio, A.: A smartphone-based fall detection system. Pervasive and Mobile Computing 8(6), 883 – 899 (2012)
2. Abbate, S., Avvenuti, M., Cola, G., Corsini, P., Light, J.V., Vecchio, A.: Recognition of false alarms in fall detection systems. In: Proceedings of the IEEE Consumer Communications and Networking Conference (workshops). pp. 538–543. Las Vegas, NV, USA (Jan 2011)
3. Ageing, W.H.O., Unit, L.C.: WHO global report on falls prevention in older age. World Health Organization (2008)
4. Atallah, L., Aziz, O., Lo, B., Yang, G.Z.: Detecting walking gait impairment with an ear-worn sensor. In: Proceedings of the Sixth International Workshop on Wearable and Implantable Body Sensor Networks. pp. 175–180 (June 2009)
5. Bieber, G., Koldrack, P., Sablowski, C., Peter, C., Urban, B.: Mobile physical activity recognition of stand-up and sit-down transitions for user behavior analysis. In: Proceedings of the 3rd International Conference on Pervasive Technologies Related to Assistive Environments. ACM (2010)
6. Bourke, A., OBrien, J., Lyons, G.: Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait and Posture 26(2), 194 – 199 (2007)
7. Cola, G., Avvenuti, M., Vecchio, A., Yang, G.Z., Lo, B.: An on-node processing approach for anomaly detection in gait. IEEE Sensors Journal 15(11), 6640–6649 (2015)
8. Cola, G., Vecchio, A., Avvenuti, M.: Improving the performance of fall detection systems through walk recognition. Journal of Ambient Intelligence and Humanized Computing 5(6), 843–855 (2014)
9. Kangas, M., Konttila, A., Lindgren, P., Winblad, I., Jms, T.: Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait and Posture 28(2), 285 – 291 (2008)
10. Li, Q., Stankovic, J.A., Hanson, M.A., Barth, A.T., Lach, J., Zhou, G.: Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In: Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks. pp. 138–143 (June 2009)
11. Shimmer: http://www.shimmersensing.com (2016)
12. Tinetti, M., Liu, W., Claus, E.: Predictors and prognosis of inability to get up after falls among elderly persons. JAMA 269(1), 65–70 (1993)