Context aware adaptable approach for fall detection bases on Smart textile

N. Mezghani, Y. Ouakrim, Md. R. Islam, R. Yared, and B. Abdulrazak

Abstract—**fall detection is very important to provide adequate interventions for aging people in risk situations. Existing techniques focus on detecting falls using wearable or ambient sensors. However, they do not consider fall orientations. In this paper, we present our novel fall detection system based on smart textiles and machine learning techniques. Using a non-linear support vector machine, we determine the fall orientation which will be helpful to study the impact of a fall according to its orientation. Additionally, we classify falls based on their orientations among 11 classes (moving upstairs, moving downstairs, walking, running, standing, fall forward, fall backward, fall right, fall left, lying, sitting). Results show the reliability of the proposed approach for falls detection (98% of accuracy, 97.5% of sensitivity and 98.5% specificity) and also for fall orientation (98.5% of accuracy).**

I. Introduction

Fall detection is very important in order to provide appropriate interventions to rescue people. The recent advances in sensor technology empower smart systems targeting safety particularly for aging people [1]–[3]. Fall is the major risk that aging people face while performing their indoor and outdoor Activities of Daily Living (ADL). Thus, falls must be quickly detected to prevent further injuries. The first generation of systems to manage falls require people intervention (e.g., push a button or make a call) to notify a center or a person that initiates the intervention [4]. Advances in sensor technologies enabled to build a new generation of ambient assistive technology that automatically detects falls and imitate interventions. This ambient technology also helps physical therapists and caregivers to clearly know the circumstances of falls, allowing for better caregiving [1].

The techniques targeting fall rely on detecting falls using wearable, ambient sensors, or multiple sensors that use a combination of two or more sensor types. Wearable sensors include accelerometer and smartphone sensors [5]. Non-wearable systems include: cameras and vision-based approaches (a single camera, or multiple-camera networks); and ambient sensors–based approaches (e.g., motion detectors involving infrared sensors that identify motion, acoustic sensors, pressure sensors that are placed in people's environment and use various measurements to determine if a person has fallen [6].

This study presents a novel fall detection approach based on smart textiles. Our approach enables to determine the fall orientation that is helpful to study the impact of a fall according to its orientation. We also present our study of fall detection in various situations. We consider falls among 11 classes based on their orientations (i.e., moving upstairs, moving downstairs, walking, running, standing, falling forward, falling backward, falling right, falling left, lying, sitting).

The paper is organized as follows. Section 2 presents the related work concerning fall detection based on wearable sensors with various detection techniques and algorithms. Section 3 presents our research methodology. Section 4 discusses the obtained results. Finally, Section 5 concludes the paper.

II. Related Work

The fall detection systems are based on either wearable (ad hoc and smartphones) [7]–[27] or ambient sensors to detect falls [1], [2]. Wearable systems generally rely on placing an accelerometer sensor (i.e., kinematic-based systems) device on people to monitor changes in acceleration as well as planes of motion in order to identify falls [12], [28]–[31]. The devices could be placed on the head, arms, hands or feet [32]. The smartphone sensors (e.g., accelerometers, gyroscopes, and magnetic field sensors) are used to detect falls [33]. The tri-axial accelerometer is the most used in wearable systems.

Perry et al. [34] presents a survey on real-time fall detection methods based on techniques that measure only acceleration, techniques that combine acceleration with other methods, and techniques that do not measure acceleration. They conclude that the methods measuring acceleration are good at detecting falls. They also comment that the placement of a sensor at the right position on the body can impact the accuracy of fall detection techniques.

Most of the research work in fall detection is based on threshold identification. The raw or processed sensory data is compared to a single threshold or multiple pre-defined thresholds to detect a fall situation. As representative examples of exiting solutions: Sposaro and Tyson provide a fall detection system named "iFall" based on the

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N. Mezghani and Y. Ouakrim are with the LICEF research center, TELUQ university, 5800, rue Saint-Denis, bureau 1105, Montréal (Quebec), H2S 3L5, Canada and with the laboratoire de recherche en imagerie et orthopédie (LIO), École de technologie supérieure, Centre de recherche du CHUM. (Neila.mezghani@teluq.ca , youssef.ouakrim@teluq.ca)

Md. R. Islam is with the laboratoire de recherche en imagerie et orthopédie (LIO), École de technologie supérieure, Centre de recherche du CHUM.

R. Yared and B. Abdurazzak are with DOMUS research center, Sherbrooke university, Sherbrooke (Quebec), Canada (Bessam.Abdulrazak@USherbrooke.ca , Rami.yared @USherbrooke.ca)

accelerometer sensor of a smartphone. The fall detection algorithm uses an adaptive threshold that changes with user parameters such as height, weight and level of activity. The system generates a decision by automatically analyzing the difference in position data before and after a suspected fall event [23]. Lopes et al., propose "Sensorfall" a mobile application based on a fixed threshold. Sensorfall uses the smartphone accelerometer sensor that has to be placed in trouser pockets [35]. However, smartphones are not always placed in the pocket, and a mobile phone is rarely held by people during indoor ADL. Jacob et al., [36] use both an accelerometer and two gyroscopes placed, as a single unit, on three different positions along the thoracic vertebrae. The fall detection algorithm is based on multiple thresholds that utilizes the recorded resultant gravitational acceleration, angular change, angular velocity, and angular acceleration. Their multiple thresholds algorithm enabled to improve fall detection accuracy. However, fall detection depends on (1) sensor positions, and (2) fall detection based thresholding is not sufficiently robust or reliable because there are different fall types and their nature show variations for each individual [33][37].

In this study, we propose a novel fall detection system based on smart textile and machine learning techniques. The innovative aspects of our approach include: the study of a fall orientation and the classification of falls based on their orientations among 11 classes which helps caregivers to provide the appropriate interventions according to fall class. Moreover, smart textile is among the promising emerging technologies that enables fall detection based on its advanced features. To our knowledge only one team is working on the topic [7]. The team uses simple geometric mean, posture and threshold based detection method for fall detection.

The Smart textile approach has numerous advantages, including 1) ***manage data***: the ability to communicate and collect data; 2) ***adaptability***: it is adaptable to the needs or conditions in a variety of contexts (e.g., safety, protection, health monitoring, and disease management); 3) ***flexibility and portability***: it can be used in any ambient environment without restrictions, by all age categories and with several sizes. As such, smart textile solutions are not obtrusive. They can easily be worn by people while performing ADL. Additionally, accelerometer is attached to the smart textile which minimizes the risk of losing sensor after a fall; 4) ***acquire rich physiological data***: smart textile allows to collect physiological user's data (e.g., heart-condition parameters, respiratory-condition parameters) as well as accelerometer data. Physiological data are very important for our study because it enables caregivers to study users conditions in real time after a fall).

Following we introduce our methodology to build our fall detection system based on smart textile.

III. METHODOLOGY

The innovative aspects of our approach include: the study of a fall orientation and the classification of falls based on their orientations in 11 classes which helps caregivers to provide the appropriate interventions according to fall class. Our novel textile-based approach enables to acquire physiological data after a fall, in order to help caregivers acquiring the health conditions of fallen people in real time. Additionally, to the best of our knowledge, this is the first research work that tackles the orientation aspects.

Our approach introduces extra issues. In addition to using large sets of available on the shelf features, alternative methods can be developed to derive more discriminant features for fall detection. The wavelet or Gabor transforms can be applied to raw acceleration data for analyzing the signals in more details in frequency and time domain with the objective of deriving a new set of distinctive features (e.g., wavelet energy or coefficients).

In addition to derive new features, more accurate detection methods are required. Most of the existing approaches use threshold-based detection methods while few use machine learning techniques to detect falls. Among them, Micucci et al. [8] and Albert et al. [26] use several classifiers and each classifier accuracy has been reported separately. However, combining these classifiers by the score level or decision level fusion may achieve higher accuracy and stability in detecting falls.

Our approach is based on two phases: The first phase is fall detection and the second phase is fall orientation. For fall detection, **1st** we detect a peak in real time using the accelerometric data magnitude. **2nd** we identify a region of interest based on the use of a rectangular window around the detected peak. **3rd** we perform feature extraction on the region of interest. **4th** we use a nonlinear support vector machine (SVM) to classify the feature of the identified peak whether in falls or non falls classes. For fall orientations, we perform a second feature extraction to characterize and classify the orientation using a second SVM classification system. *Figure 1* illustrates our fall detection and orientation approach. Following more details about our approach:

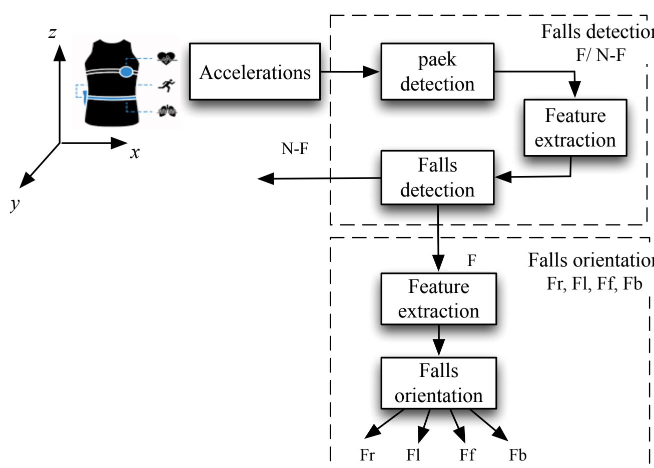

Figure 1. Bloc diagram of the proposed falls detection and orientation system.

A. Data Acquisition

This study was approved by institutional ethics committees, with all subjects providing written informed consent before it began. 13 healthy volunteers participated in the study (age 25.43 ± 7.51 years old, weight 60.7 ± 6.7 kg, heigh172.7 ± 7,2 cm). We performed the tests at the research center of the hospital center of Montreal University. Each participant wore the smart textile and repeated 5 times a sequence of 11 tasks (moving upstairs, moving downstairs, walking, running, standing, fall forward, fall backward, fall right, fall left, lying, sitting). The intelligent textile (Hexoskin, Carré technologies, Montreal, Canada) enables real-time remote monitoring of 3D acceleration data, cardiac activity and respiratory activity on smartphones and tablets using Bluetooth. The accelerations are collected using 3-axis sensors with a 13-bit resolution and a frequency of 64 Hz.

B. Fall detection:

Using the acceleration magnitude a peak detection was performed in real time. Let A_x, A_y, and A_z the accelerations along the x, y, and z axes, respectively. The acceleration magnitude A is given by:

$$A = \sqrt{A_x^2 + A_y^2 + A_z^2}$$

Peaks detection was performed by looking for downward zero crossings in the smoothed first derivative of signal A. A predetermined minimum slope threshold was fixed to eliminate the false peaks (false zero-crossing). In our study, the threshold was fixed empirically to (1.5).

Peak detection was followed by a region of interest (ROI) identification based on the use of a rectangular window of 200 points around the detected peak. The feature extraction is, then, performed on the ROI. Let S_n denotes either the A_x, A_y, A_z or A component where n is the component dimension. Extracted features consist, for each component, of the amplitude, minimum, and maximum, mean values, as well as the range and skewness of the signal component. These features are given by the following equations:

$$\text{maximum}(s) = \max_n(S_n)$$

$$minimum(s) = \min_n(S_n)$$

$$mean(s) = \mu = \frac{1}{N}\sum_{n=1}^{N} S_n$$

$$Range(s) = \max_n(S_n) - \min_n(S_n)$$

$$skewness(s) = \frac{1}{N\sigma^3}\sum_{n=1}^{N}(S_n - \mu)^3$$

where $variance(s) = \sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(S_n - \mu)^2$

These features serve the classification system for falls detection. We used a multi-class non-linear support vector machine (SVM) to classify the features of the identified peak whether in falls (F) or non falls (N-F) classes. SVM are popular machine learning methods which can efficiently perform a non-linear classification using mathematical programming and kernel functions.

C. Falls orientation

In case of a fall (F), a second feature extraction step is performed to characterize and classify the orientation using a second SVM classification system which discriminates between Fall right (Fr), Fall left (Fl), Fall forward (Ff), Fall backward (Fb).

D. Performance evaluation

The performance of the falls detection system is computed by a 10-fold cross-validation procedure: the data set is divided into 10 subsets. Each time, one of the 10 subsets is used as the test set and the other 9 subsets are used as the training set. The classification performance is computed at each time and the average error across all 10 trials is estimated to obtain the classification rate, the sensitivity and the specificity. Sensitivity (S_e) is the capacity of the system to detect falls where the specificity (S_p) is the capacity of the system to detect falls only when they occur. The performance of the falls orientation system is evaluated using the classification rate and the classification rates per class based on a10-fold cross-validation procedures too.

IV. Results & Discussion

Experimental results were performed using the data collected on 13 healthy participants. Each wore the smart textile and repeated 5 times the sequence of 11 tasks: moving upstairs, moving downstairs, walking, running, standing, falling forward, falling backward, falling right, falling left, lying, sitting. Each sequence duration is approximately 2 minutes (Figure 2).

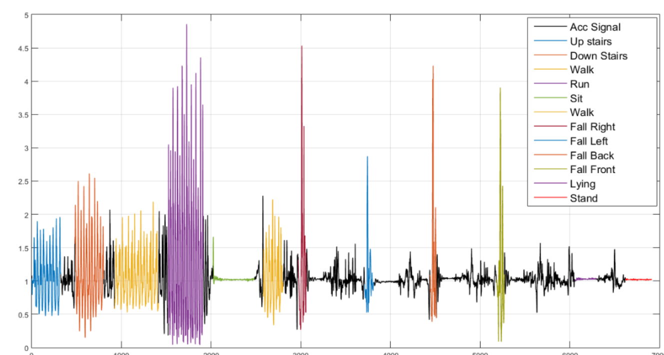

Figure 2. Acceleration magnitude of a sequence of 11 tasks

The peak detection on acceleration magnitude was performed in real time. Once a peak detected, an ROI is identified for feature extraction and classification.

The used features for falls detection were the amplitude of A_x, A_y, A_z and A and their skewness. The reliability of the falls detection system was 98% for the accuracy, 97.6% for sensitivity (S_e) and 98.5% for specificity (S_p).

For falls orientation, we used the minimum, the range and skewness of the signal component.

The performance of the falls orientation system was 98% for the accuracy. The classification rates per class were 100% for falls forward (Ff), 99% falls backward (Fb), 96% for falls right (Fr), and 96% for falls left (Fl).

The falls detection and classification system was developed using Matlab R2014b software (Mathworks, Massachusetts, United State). The system response time is approximately 0.005 second using a machine Core i7-3720 with Quad-Core CPU (2.60GHz) and 8 G of memory.

V. Conclusion

We presented in this paper, a falls detection and orientation system based on smart textile and machine learning techniques. Using a support vector machine, we determined the fall orientation which will be helpful to study the impact of a fall according to its orientation. Additionally, we classified falls based on their orientations among 11 classes (moving upstairs, moving downstairs, walking, running, standing, fall forward, fall backward, fall right, fall left, lying, sitting). Results show the reliability of the proposed approach for both falls detection and falls orientation.

Our approach enables to acquire physiological data after a fall, which helps caregivers to study the fallen person health conditions in real time.

References

[1] R. Yared and B. Abdulrazak, "Ambient Technology to Assist Elderly People in Indoor Risks," *Computers*, 2016.

[2] R. Yared, H. Mallat, and B. Abdulrazak, "Ambient Technology to Support Elderly People in Outdoor Risk Situations," *Technol. Ageing Well e- …*, 2015.

[3] H. Mallat, R. Yared, and B. Abdulrazak, "Assistive Technology for Risks Affecting Elderly People in Outdoor Environment.," *ICT4AgeingWell*, 2015.

[4] E. J. Porter, "Wearing and using personal emergency respone system buttons.," *J. Gerontol. Nurs.*, vol. 31, no. 10, pp. 26–33, 2005.

[5] Y. S. Delahoz and M. A. Labrador, "Survey on fall detection and fall prevention using wearable and external sensors," *Sensors (Switzerland)*, vol. 14, no. 10. pp. 19806–19842, 2014.

[6] F. Hijaz, N. Afzal, T. Ahmad, and O. Hasan, "Survey of fall detection and daily activity monitoring techniques," *2010 Int. Conf. Inf. Emerg. Technol.*, pp. 1–6, 2010.

[7] K. Niazmand, C. Jehle, L. T. D'Angelo, and T. C. Lueth, "A new washable low-cost garment for everyday fall detection," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010, pp. 6377–6380.

[8] D. Micucci, M. Mobilio, P. Napoletano, and F. Tisato, "Falls as anomalies? An experimental evaluation using smartphone accelerometer data," *J. Ambient Intell. Humaniz. Comput.*, 2015.

[9] C. Medrano, R. Igual, I. Plaza, and M. Castro, "Detecting falls as novelties in acceleration patterns acquired with smartphones," *PLoS One*, vol. 9, no. 4, 2014.

[10] M. Tolkiehn, L. Atallah, B. Lo, and G.-Z. Yang, "Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor," *2011 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 369–372, 2011.

[11] J. Wang, Z. Zhang, B. Li, S. Lee, and R. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, 2014.

[12] A. K. Bourke, J. V. O'Brien, and G. M. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," *Gait Posture*, vol. 26, no. 2, pp. 194–199, 2007.

[13] Q. Li, J. A. Stankovic, M. A. Hanson, A. T. Barth, J. Lach, and G. Zhou, "Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information," in *Proceedings - 2009 6th International Workshop on Wearable and Implantable Body Sensor Networks, BSN 2009*, 2009, pp. 138–143.

[14] T. Zhang, J. Wang, L. Xu, and P. Liu, "Fall detection by wearable sensor and one-class SVM algorithm," *Lect. Notes Control Inf. Sci.*, vol. 345, pp. 858–863, 2006.

[15] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy, "Wearable sensors for reliable fall detection.," in *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 2005, vol. 4, pp. 3551–3554.

[16] M. N. Nyan, F. E. H. Tay, and E. Murugasu, "A wearable system for pre-impact fall detection," *J. Biomech.*, vol. 41, no. 16, pp. 3475–3481, 2008.

[17] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and A. Vecchio, "A smartphone-based fall detection system," *Pervasive Mob. Comput.*, vol. 8, no. 6, pp. 883–899, 2012.

[18] G. Wu and S. Xue, "Portable preimpact fall detector with inertial sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 2, pp. 178–183, 2008.

[19] S. Mellone, C. Tacconi, L. Schwickert, J. Klenk, C. Becker, and L. Chiari, "Smartphone-based solutions for fall detection and prevention: the FARSEEING approach.," *Z. Gerontol. Geriatr.*, vol. 45, no. 8, pp. 722–7, 2012.

[20] H. Rabah, A. Amira, and A. Ahmad, "Design and implementaiton of a fall detection system using compressive sensing and shimmer technology," in *Proceedings of the International Conference on Microelectronics, ICM*, 2012.

[21] N. Shibuya *et al.*, "A Real-Time Fall Detection System Using a Wearable Wireless Gait Analysis Sensor and a Support Vector Machine (SVM) Classifier," in *International Conference on Mobile Computing and Ubiquitous Networking (ICMU)*, 2015, pp. 66–67.

[22] W. Zhuang, X. Sun, and D. Dai, "Fall Detection for Elder People Using Single Inertial Sensor," 2015.

[23] F. Sposaro and G. Tyson, "iFall: An android application for fall monitoring and response," in *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*, 2009, pp. 6119–6122.

[24] J. Dai, X. Bai, Z. Yang, Z. Shen, and D. Xuan, "Mobile phone-based pervasive fall detection," *Pers. Ubiquitous Comput.*, vol. 14, no. 7, pp. 633–643, 2010.

[25] R. Y. W. Lee and A. J. Carlisle, "Detection of falls using accelerometers and mobile phone technology," *Age Ageing*, vol. 40, no. 6, pp. 690–696, 2011.

[26] M. V. Albert, K. Kording, M. Herrmann, and A. Jayaraman, "Fall classification by machine learning using mobile phones," *PLoS One*, vol. 7, no. 5, 2012.

[27] S. H. Fang, Y. C. Liang, and K. M. Chiu, "Developing a mobile phone-based fall detection system on android platform," in *2012 Computing, Communications and Applications Conference, ComComAp 2012*, 2012, pp. 143–146.

[28] A. Bourke, P. Van de Ven, and A. Chaya, "Testing of a long-term fall detection system incorporated into a custom vest for the elderly," *2008 30th Annu.*, 2008.

[29] M. Kangas, I. Vikman, J. Wiklander, P. Lindgren, L. Nyberg, and T. Jämsä, "Sensitivity and specificity of fall detection in people aged 40 years and over.," *Gait Posture*, vol. 29, pp. 571–574, 2009.

[30] A. K. Bourke *et al.*, "Assessment of waist-worn tri-axial accelerometer based fall-detection algorithms using continuous unsupervised activities," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010, pp. 2782–2785.

[31] F. Bloch *et al.*, "Evaluation under real-life conditions of a stand-alone fall detector for the elderly subjects," *Ann. Phys. Rehabil. Med.*, vol. 54, no. 6, pp. 391–398, 2011.

[32] S. Chaudhuri, H. Thompson, and G. Demiris, "Fall detection devices and their use with older adults: a systematic review.," *J. Geriatr. Phys. Ther.*, vol. 37, no. 4, pp. 178–96, 2014.

[33] R. Igual, C. Medrano, and I. Plaza, "Challenges, issues and trends in fall detection systems.," *Biomed. Eng. Online*, vol. 12, no. 1, p. 66, 2013.

[34] J. T. Perry, S. Kellog, S. M. Vaidya, J.-H. Youn, H. Ali, and H. Sharif, "Survey and evaluation of real-time fall detection approaches," in *2009 6th International Symposium on High Capacity Optical Networks and Enabling Technologies (HONET)*, 2009, pp. 158–164.

[35] I. C. Lopes, B. Vaidya, and J. J. P. C. Rodrigues, "SensorFall - An accelerometer based mobile application," in *2009 2nd International Conference on Computer Science and Its Applications, CSA 2009, December 10, 2009 - December 12, 2009*, 2009.

[36] J. Jacob, T. Nguyen, D. Lie, and S. Zupancic, "A fall detection study on the sensors placement location and a rule-based multi-thresholds algorithm using both accelerometer and gyroscopes," *(FUZZ), 2011 IEEE …*, 2011.