

## Original Research

# User-Based Motion Sensing and Fuzzy Logic for Automated Fall Detection in Older Adults

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### ABSTRACT

More than one third of community-dwelling older adults and up to 60% of nursing home residents fall each year, with 10–15% of fallers sustaining a serious injury. Reliable automated fall detection can increase confidence in people with fear of falling, promote active safe living for older adults, and reduce complications from falls. The performance of a 2-stage fall detection algorithm using impact magnitudes and changes in trunk angles derived from user-based motion sensors was evaluated under laboratory conditions. Ten healthy participants were instrumented on the front and side of the trunk with 3D accelerometers. Participants simulated 9 fall conditions and 6 common activities of daily living. Fall conditions were simulated on a protective mattress. The experimental data set comprised 750 events (45 fall events and 30 nonfall events per participant) that were classified by the fall detection algorithm as either a fall or a nonfall using inputs from 3D accelerometers. Significant differences for impacts recorded, trunk angle changes ( $p < 0.01$ ), and detection performances ( $p < 0.05$ ) were found between fall and nonfall conditions. The proposed algorithm detected fall events during simulated fall conditions with a success rate of 93% and a false-positive rate of 29% during nonfall conditions. Despite a slightly superior identification performance for the accelerometer located on the front of the trunk, no significant differences were found between the two motion sensor locations. Automated detection of fall events based on user-based motion sensing and fuzzy logic shows promising results. Additional rules and optimization of the algorithm will be needed to decrease the false-positive rate.

### INTRODUCTION

FALLS ARE A MAJOR PUBLIC HEALTH CONCERN and one of the greatest obstacles to independent living for older adults. More than one

third of community-dwelling older adults and up to 60% of nursing home residents fall each year.<sup>1</sup> The incidence of falls rises steadily with advancing age and gets even worse among nursing home residents, where multiple falls

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(more than 3 per year) are more frequent and injurious.<sup>2</sup> For older adults who live alone, becoming incapacitated and unable to get help immediately after a fall is also a common experience. In a population-based study, Gurley and colleagues<sup>3</sup> showed that in people 65 or older who lived alone, the annual risk of being found helpless or dead at home by paramedics is 3.2%. Weakness or the inability to get up and falls were the most frequently cited precipitating causes of incapacitation among the survivors found. Nevitt and colleagues<sup>4</sup> reported 539 falls after a 1-year prospective cohort study on 189 ambulatory adults over 60 years of age who had fallen once in the previous year. Fifty percent of the fallers reported being unable to get up without assistance in 41% of the falls.

Even though most falls have limited physical consequences and are not functionally limiting,<sup>4</sup> they can lead to a loss of confidence and the development of a fear of falling.<sup>5</sup> Community-based studies of independently living older adults have estimated that 25–50% of this population have a fear of falling.<sup>6–9</sup> Fear of falling is a complex problem that can affect not just people who have fallen but also those who have not. It increases with age, especially for those who have had a fall in the past, and can also lead to other negative outcomes, such as functional decline,<sup>10</sup> balance deterioration,<sup>11</sup> and decreased social contact.<sup>12</sup>

Fear of falling has generated an industry marketing automatic alarm-and-notification systems, commonly called personal emergency response systems (PERS). PERS take many forms, but the common thread is that the person at risk is equipped with an electronic device carried or worn that, after being activated by the user, can inform a central system when a potentially adverse event occurs. Studies on the use of PERS as a substitute for in-home supervision have found them to be cost-effective in the context of hospital utilization rates and institutionalization among community-dwelling elders.<sup>13,14</sup> Moreover, they offer a sense of security to family members caring for older adults living alone and can alleviate their perceived burden.<sup>15,16</sup> Although PERS constitute important technological adjuncts to home care, they require the direct intervention of the person to activate the signal indicating an emer-

gency. In the case of a fall-related emergency, this can be impractical when the person is lying unconscious on the floor,<sup>1</sup> is unable to activate the button, or suffers from cognitive impairments. Reliable automated fall detection, coupled with an appropriate help response from a community alarm center, can increase confidence in people with fear of falling, promote active safe living for elders, and reduce complications from falls.<sup>17,18</sup> Over the years, many technological approaches have been developed to address this issue. They can be divided into two groups: environmental motion sensing based on “exosensors” positioned in the individual’s home<sup>19–21</sup> and user-based motion sensing with “endosensors” worn by the individual. Environmental sensing uses algorithms to determine whether, according to inputs from image sensors (cameras, single-element passive infrared sensors, pyroelectric infrared sensor arrays) positioned in the environment, a fall has occurred in a known volume.

Numerous groups have studied fall detection employing user-based motion sensing with wearable devices.<sup>17,22–27</sup> Typically, motion sensors embedded with a microcontroller record the kinematics of body segments and detect fall events from the recorded signals using expert systems. Once a fall event is detected, an alarm is sent through a radiofrequency link with a communication device connected to a PERS. Variations on this design have appeared in various commercial forms and/or are still under development. All of these designs use similar motion sensors (mostly 2D or 3D accelerometers) but detect fall events differently, using (1) kinematic signals recorded at different locations on the body (waist, neck, midtrunk, arm); or (2) different inputs and processing approaches from the recorded signals (impact, energy of the impact, change in position, etc.); or (3) different expert systems (Boolean logic, fuzzy logic, neural nets) to infer from these inputs that a fall has occurred. Although numerous designs and systems for automated fall detection based on motion sensing with wearable devices have been proposed and in some case commercialized, published experimental data on their performance in real life or under laboratory condi-

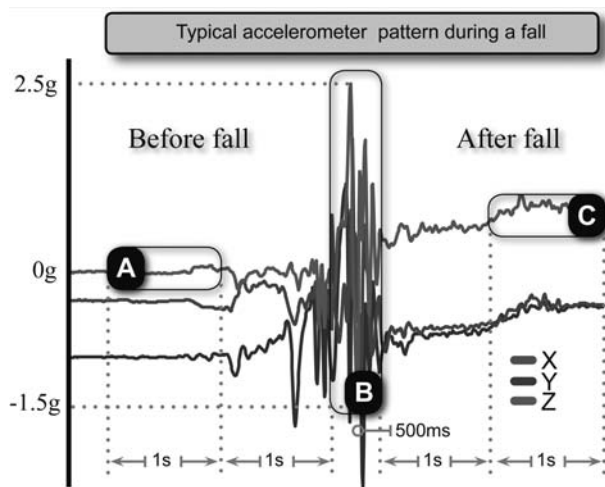


FIG. 1. Typical accelerations pattern during a fall. The algorithm detects the highest peak of acceleration (absolute value) in (B) and considers this event as the impact on the ground. The mean value of acceleration over a 1-second period before (A) and after (C) an impact is detected and used to calculate changes in static trunk angle before and after the fall.

tions are scarce and generally of poor scientific quality.

The objectives of this study were (1) to explore the validity of a two-stage fall detection algorithm based on fuzzy logic using experimental data collected from simulated falls with human participants, and (2) to determine the influence on the detection performance of the algorithm considering inputs from 3D accelerometers positioned at 2 locations on the trunk. The fall detection algorithm and its per-

formances during simulated conditions of falls and non-falls are described below.

## MATERIALS AND METHODS

### Fall detection algorithm

The proposed fall detection algorithm is based on the identification of 2 separate events common to most falls: impact amplitudes when the body decelerates as it makes contact with the ground, and relative changes in trunk position associated with those impacts (Fig. 1). We hypothesize that the combination of these two events as inputs for a fall detection algorithm will provide strong identification performance of simulated falls and eliminate most of the false-positive situations (i.e., where a fall did not occur but the fall algorithm identifies one). The schematic of how these two inputs are used for fall detection is illustrated in Figure 2. Briefly, detected impacts are classified using a fuzzy logic. Then Boolean logic combines the level of impact and the changes in trunk angles to make a final decision (fall or no fall).

*Impact classification using fuzzy logic.* Fuzzy logic is typically used to ease the modeling and processing of complex tasks by allowing uncertain states. For example, driving a car would be considered quite complex if the driver would need to calculate the exact speed of the car as well as the precise force to apply on the brake and throttle. In this particular scenario,

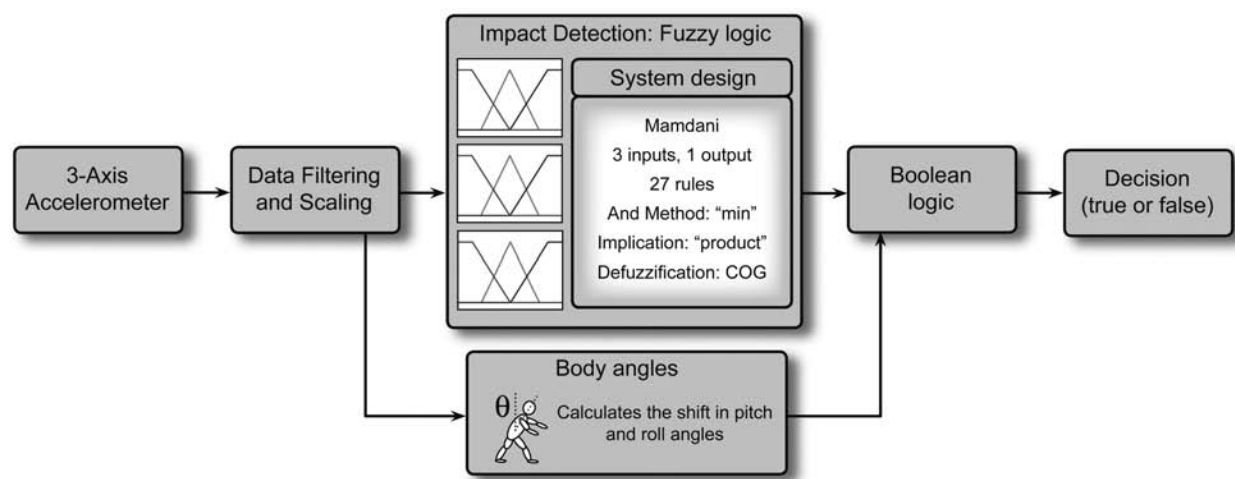


FIG. 2. Schematic of input and expert system used for fall detection algorithm.

the human brain is similar to a fuzzy logic algorithm because it does not require precise information to perform the task. In fact, knowing that the car's speed is "fast" and that a stop sign is "really near" would result in a "high" force on the brakes. The combination of imprecise concepts like car's speed (low, medium, and fast) and stop sign distance (really near, near, and far) will result in an imprecise output to control the force on the brake (low, medium, and high forces). These concepts are known as membership functions and they are usually derived from experience or knowledge from experts. A similar analogy can be used to determine whether a fall has occurred or not. To help determine the membership functions, we rely on the general conception of falls derived from many experiments conducted in our research laboratory. Two features seem to be present in every fall: (1) high amplitude from the accelerometer signals on at least one axis and (2) distinctive set of frequencies. Because impacts associated with activities of daily living (e.g., impacts due to walking or climbing stairs or sitting in a chair) would be difficult to discriminate from impacts due to falls, the fuzzy approach seemed to be promising. The fuzzy algorithm suggested in this paper uses 3 orthogonal axis of acceleration as input variables to 3 membership functions (weak, medium, and high impact) and 1 membership for the output stage for defuzzification (no, maybe, and yes). Mamdani's fuzzy inference method was used. Operators were chosen to optimize results: the "And" method was applied with a "Min," the implication was computed with the "product" operator, and the defuzzification was done with the center-of-gravity method.

*Estimation of trunk angles using the accelerometer as a tilt sensor.* During activities of daily living, we are likely to detect impacts that are not related to falls. For those cases, we chose to look at changes in trunk position that precede an impact to confirm whether the impact detected is associated with a fall event. Changes in trunk position can be measured by estimating trunk angle changes from static positions using the accelerometer as a tilt sensor.<sup>28,29</sup> By measuring the angle of the trunk 1 second before and after impact, it is possible to identify a shift in trunk position that would imply a fall. To in-

crease the distinction between "fall" and "non-fall" event in the presence of an impact, both the impact percentage and the delta of the trunk angles ( $x$  = anteroposterior,  $y$  = medio-lateral) are used as inputs to a Boolean module, which helps to classify all the "maybe" impacts. This module act as a simple 2-state classifier (fall or nonfall) based on combination of thresholds, which helps to classify all the "maybe" impacts.

#### *Experimental validation of fall detection algorithm*

The fall detection algorithm was tested experimentally on 10 young participants (mean age 21.2 years) during simulated falls (9 conditions) and nonfall events (6 conditions). Participants consisted of 8 women and 2 men with an average height and weight of 1.72 m and 61.2 kg. The experimental setup and protocol used to obtain data to test the algorithm area are illustrated in Figure 3. All fall events were simulated on a protective mattress. For the purpose of obtaining a data set of impacts and changes in trunk position during simulated conditions, 2D accelerometers (ADXL210) were paired to obtain 3D acceleration measurements from 2 locations on the trunk (front and side). Accelerometers were embedded in rigid plastic sensors modules that were secured on the body using straps. Acceleration signals from both sensor locations were sampled at 100 Hz and converted using a 16-bit acquisition card (DAQPad-6052E, National Instruments) connected to a PC running a dedicated data collection program (Labview).

The experimental data set comprised 750 events (45 fall events and 30 nonfall events per participant) that were classified by the fall detection algorithm as either a fall or a nonfall using inputs from the accelerometers. The events simulated consisted of 15 different experimental conditions chosen to challenge the detection algorithm. The conditions included 9 fall conditions, 2 near falls, and 4 nonfall conditions. The details of the simulated conditions are listed in Table 1.

Subjects executed the simulated conditions in a fixed order at their own pace without any time constraints. Each condition was repeated 5 times. Data were collected over a 1-month pe-



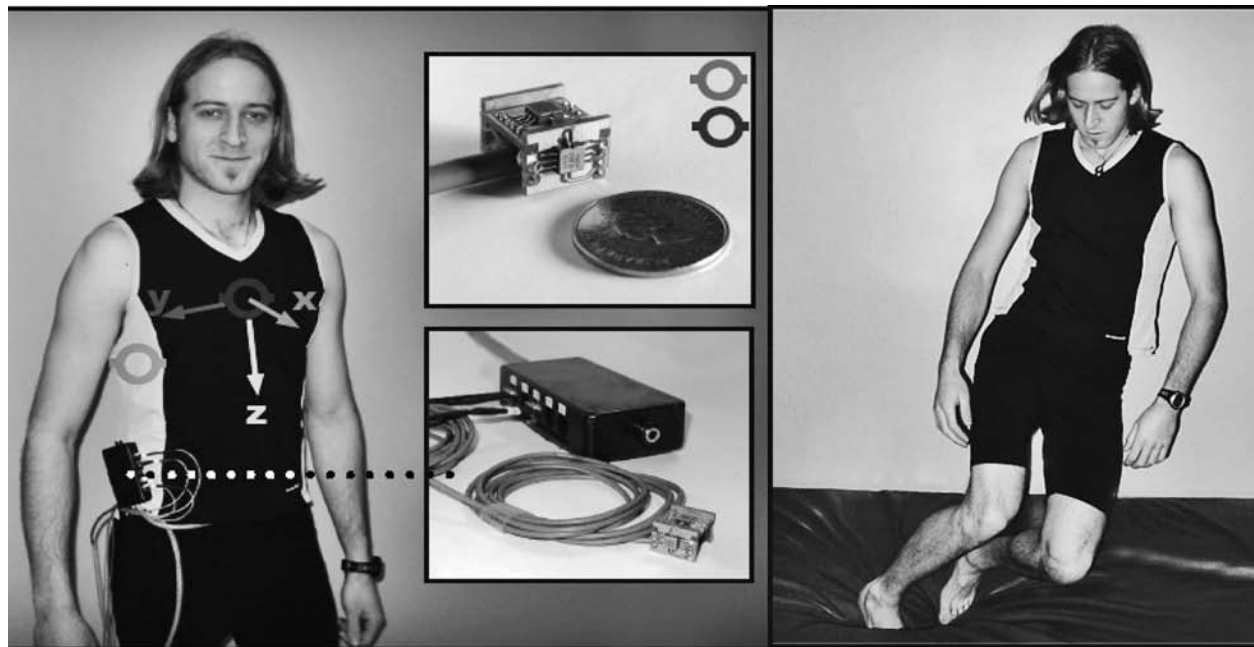


FIG. 3. Experimental setup used to obtain data to test the fall detection algorithm. Circles represent sensor location on the trunk.

riod at the Research Centre on Aging, Sherbrooke, Quebec, Canada. The Sherbrooke Geriatric University Institute Institutional Review Board approved this investigation and all participants gave their informed consent.

TABLE 1. LISTING OF SIMULATED CONDITIONS FOR FALL AND NONFALL EVENTS

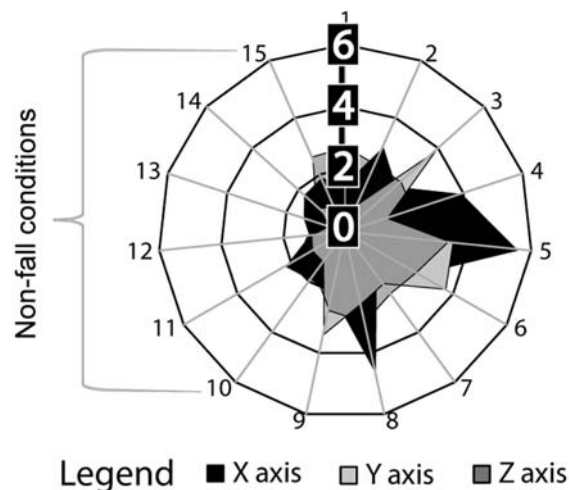
	Task no.	Description
Fall	1	Backward falling, seated landing
	2	Backward falling, flat landing
	3	Backward falling, rotation, landing on side
	4	Frontward falling, landing on knees with arms extended for protection
	5	Frontward falling, flat landing without protection
	6	Frontward falling, with rotation, landing on side
	7	Vertical fall against a wall, seated landing
	8	Vertical fall on the knees, flat landing
	9	Vertical fall with rotation, landing on side
Nonfall	10	Backward slip with balance recovery
	11	Forward trip with balance recovery
	12	Lying down on a bed
	13	Walking, stopping, kneeling, and tying shoe laces
	14	Walking forward and colliding against an obstacle
	15	Sitting down on a chair

## RESULTS

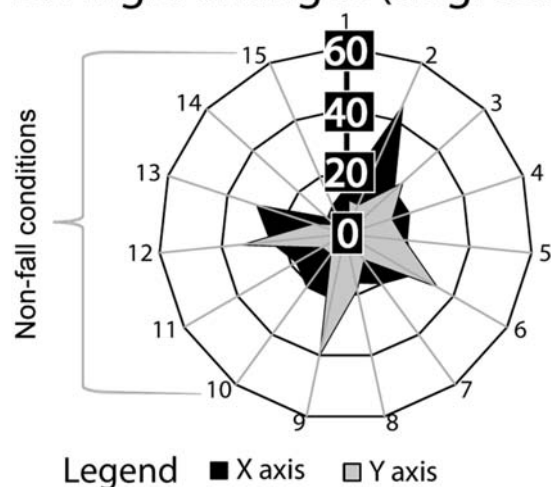
### *Detection of impact magnitudes and trunk angle changes*

Impact magnitudes and trunk angle changes recorded during simulated fall and nonfall events for the 10 participants are illustrated in Figure 4. Group data obtained from the average impact and trunk angle changes from both sensor locations are presented. Results show that impacts recorded across participants, especially for the vertical axis (z axis), demonstrate large variations and that these variations are more pronounced for fall events (conditions 1–9). However, variations in impact magnitudes and trunk angle changes across multiple trials of the same simulated condition were not statistically different ( $p < 0.05$ , analysis of variance for repeated measures), suggesting that fall and nonfall events were simulated consistently by the participants. With the exception of a few instances, impact magnitudes and trunk angle changes recorded at both sensor locations were not statistically different ( $p < 0.05$ , paired  $t$ -test), indicating that sensor location did not affect the sensitivity of the inputs used in the fall detection algorithm.

## A. Trunk accelerations (g)



## B. Angle changes (degrees)



**FIG. 4.** Impact magnitudes and trunk angle changes recorded during simulated fall and nonfall events. (A) Mean accelerations recorded in the 3 axis from 10 subjects across fall conditions and nonfall conditions. (B) Trunk angle changes recorded in 2 axis from 10 subjects across fall conditions and nonfall conditions. Means in both A and B are computed from signals recorded from both sensor locations (accelerometers in the front and side of the trunk).

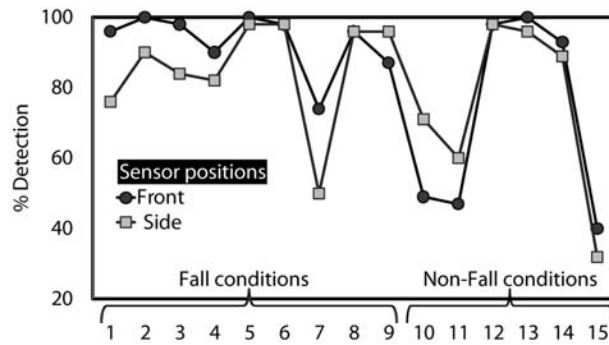
For the sake of brevity, results from only 1 sensor location will be described (sensor location 1 = front of the trunk at neck level). Overall, average impact magnitudes and trunk angle changes recorded across fall events (conditions 1–9) from sensors located on the front of trunk were statistically higher ( $p <$

0.01, paired  $t$ -test) than those recorded during nonfall events (conditions 10–15). Impact magnitudes for fall events varied from  $0.96 \pm 0.16$  g to  $5.23 \pm 0.36$  g and the highest impacts detected were for conditions 1, 5, and 7 in the anterior–posterior axis of motion ( $x$ -axis). Most of the impact magnitudes recorded during nonfall events were low (i.e.,  $< 2$  g), with the exception of impacts recorded during condition 15 (sitting down on a chair) in the anterior–posterior axis of motion ( $x$ -axis) and the mediolateral axis of motion ( $z$ -axis). Impact magnitudes for all other nonfall conditions varied from 1.02 to 2.33 g in the anterior–posterior axis of motion ( $x$ -axis), 0.53–1.18 g in the vertical axis of motion ( $y$ -axis), and 0.85–2.79 g for the mediolateral axis of motion ( $z$ -axis). Trunk angle changes varied from 10.01 to 50.9° during fall events, with the highest angle changes recorded during conditions 2 and 3.

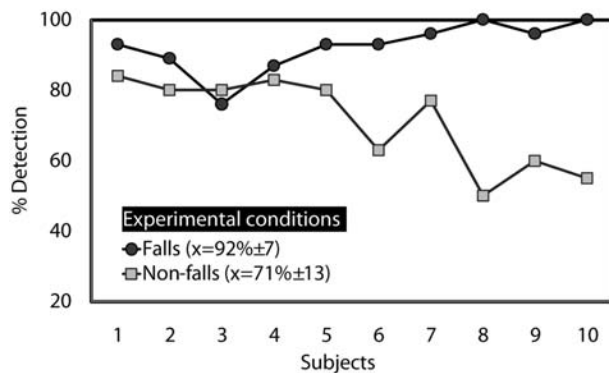
### Identification performances of fall detection algorithm

Identification performances of the fall detection algorithm for simulated fall events and nonfall events are presented in Figure 5. Results are presented as percentages of correct detection (i.e., accuracy) across experimental conditions (50 trials per experimental condition) using inputs from the 2 sensor locations (sensor location 1 = front of the trunk at neck level, sensor location 2 = side of the trunk). The percentages were computed from the number of times a given event was correctly identified across participants as a fall event or nonfall event. Overall, fall event detection was more accurate when using inputs from the sensor located on the trunk at neck level (sensor location 1). With the exception of 1 condition (collapsing/falling against a wall after a loss of consciousness), accuracy using sensor inputs from this location was higher than 96%. Sensor location did not significantly affect the false-positive rate. The proposed algorithm recognized fall events (conditions 1–9) with an accuracy rate varying between 74% and 100%, with an average of 93% using inputs from the sensor located on the trunk at neck level. The accuracy rate for detecting fall events using inputs from the sensor located on the side of the

## A. % accuracy of algorithm (group data)



## B. % accuracy of algorithm (subject data)



**FIG. 5.** Identification performances of the fall detection algorithm for fall events and nonfall events. **(A)** Accuracy (% of correct detection rendered by the algorithm) according to the position of the sensor module for 10 subjects in each experimental condition. Experimental conditions are listed in Table 1 ( $n = 10$ ). **(B)** Overall accuracy (% of correct detection rendered by the algorithm) calculated for acceleration signals recorded with the sensor module positioned on the front at the neck level. Accuracy for fall events and nonfall events is illustrated.

trunk varied from 50% to 98%, with an average of 86%. False-positive rates, defined as inaccurate detection of a fall event during nonfall events (conditions 10–15), varied from 40% to 100%, with an average of 71% using inputs from the sensor located on the trunk at neck level, and from 32% to 98%, with an average of 74% using the sensor located on the side of the trunk.

The proposed algorithm detects fall events more accurately than nonfall events ( $p < 0.05$ ). The worst detection performances observed for fall events were obtained for conditions when the participants simulated a loss of consciousness that ended with a fall against a wall (74% for sensor 1 and 50% for sensor 2). The worst

detection performances observed for nonfall events were obtained for conditions when the participants simulated the following 3 experimental conditions: recovering from an almost backward fall after a trip (49% for sensor 1 and 71% for sensor 2); recovering from an almost forward fall from an upright position (47% for sensor 1 and 60% for sensor 2); and going from a standing upright position to a sitting position on a chair (40% for sensor 1 and 32% for sensor 2). Average detection performance when combining fall and nonfall events was 84.3% using inputs from the sensor located on the trunk at neck level and 80.5% using the sensor located on the side of the trunk.

## DISCUSSION

We tested the performance of a 2-stage algorithm to identify fall events using inputs recorded during simulated falls and nonfall events from 3D accelerometers positioned on 2 locations on the trunk. Even though our experimental conditions were certainly not ideal (fall events were simulated on a mattress) and represented only an approximation of real-life conditions, the data collected (>750 events) offer interesting insights into the acceleration profiles associated with impacts recorded during falls and activities of daily living.

Results show that distributions of impact magnitudes for fall events reached 6 g, suggesting that the measurement range of accelerometers used for impact sensing in the context of automated fall detection should be adapted accordingly, especially given the fact that the fall conditions were simulated on a mattress. Although in many types of falls the acceleration seems to follow some type of pattern, interindividual and intraindividual differences in acceleration magnitude due to the physical characteristics of the person falling or the similarity of impacts detected during fall events and nonfall events warrant the consideration of a redundancy check to ensure optimal results. Indeed, the overlapping distribution of impact amplitudes measured during simulated fall and nonfall events supports the use of fuzzy logic to enhance fall detection when using impacts from accelerometers as in-

puts. Our results clearly show that certain non-fall conditions (e.g., sitting down on a chair from the upright position) share similar impact amplitudes with fall conditions. The proposed algorithm, using acceleration magnitudes with fuzzy logic and changes in trunk orientation as confirmation, detected fall events (93% correct detection) more accurately than nonfall events (71% correct detection). The location of the sensors on the trunk did not statistically affect the identification performance of the algorithm. However, considering the context of use of an automated fall detection system, the small difference (4% better performance for the sensor on the front of the trunk) could be relevant in real world applications.

Despite the fact that fixed rule-based expert systems such as those proposed by others<sup>17,22–24,26,27</sup> offer relatively good performance under the experimental conditions they were tested in, one can question the robustness of their approach under the experimental conditions used in this study. In this study, we deliberately chose to test the limits of the proposed algorithm under complex test scenarios using experimental conditions that mimicked or closely resembled falls (e.g., falling motion induced by slipping or tripping with balance recovery) and generated impact profiles similar to those observed during falls or that were atypical (e.g., vertical fall against a wall in a closed environment). The data set used to evaluate the performance of the algorithm was collected on 10 participants, 8 of whom were blinded to the objective and details of the study. This constitutes the most exhaustive data set produced to date to test a fall detection algorithm. The proposed algorithm performed relatively well for most fall conditions, with the exception of the condition where the participants fell in such a way that they were not parallel with the ground and the impact was low. This problem was also reported by others.<sup>24</sup> However, the algorithm returned a high rate of false positives for nonfall conditions. Although reliable identification of fall events is the main factor driving the development of an automated fall detection system, under real-world conditions, this high false-positive rate can become a burden to the user and would be an obstacle to its use.

The high false-positive rate can be partially explained by the nature of the nonfall conditions simulated. The use of conditions where participants are recovering from a fall induced by tripping or slipping (conditions 10 and 11) and the instructions given to subject (“let yourself fall back on the chair as if you couldn’t stop yourself”) as they sat on the chair (condition 15), probably introduced uncertainty that the algorithm did not take into account. As already mentioned, the testing scenario was designed specifically to establish the limits of the algorithm. One way to correct this would be to optimize the algorithm by adding more rules to the system, specifically by considering, as proposed by Brown,<sup>24</sup> a period of inactivity after impact detection and a change in trunk orientation preceding the impact. This could be easily implemented and would correct most of the false positives found in the experiment. Unfortunately, we did not design our experiment to consider what happens after a fall (i.e., the data epoch recorded consisted of short 10–15-second events that concluded after the participants executed the tasks).

Research focused on automated fall detection methods has been fertile over the years and several patents have been awarded. Commercially, however, mature products are few and far between, and demonstrating their effectiveness and impact under real-life conditions remains a challenge. The principal obstacles to the deployment of such systems are balancing the right context of use, accurate detection, and usability. With respect to the context of use, while community alarm users are in general satisfied with the service provided, consultations of elderly inner-city users of community alarms systems has shown that users are open to expanding the functionality of the existing systems.<sup>18</sup> Automatic fall detection received the most interest (77% of 176 users) among potential telecare options such as lifestyle monitoring, telemedicine, and videoconferencing. However, a subsequent study by the same group looked at the effect of automatic fall detection units on the fear of falling of community alarm users who were living in the community and who had experienced a fall in the previous 6 months.<sup>30</sup> Of those approached, 31% consented to take part; the main reason given



for potential participants declining involvement was that they were happy with the technology they already had. Benefits over the 17-week monitoring period were mitigated by how often subjects wore the automated fall detector unit, and no significant differences were observed between the intervention (automated fall detection) and control (community alarm) groups in their mean ratings of fear of falls (40.3 versus 37.5, difference 2.8, 95% CI 6.2–11.8), health-related quality of life, or morale. Institutional settings (i.e., nursing home, assisted-living facilities) and older adults with a certain profile (cognitive problems and recurrent falls) might be a better context of use to start the deployment of such systems. Engstrom and colleagues<sup>31</sup> measured staff members' satisfaction with their work before and after increased information technology (IT) support in dementia care. The IT technology included general and individualized passage alarms, sensor-activated nighttime illumination, *fall detectors*, and Internet communication. Results showed that IT support in dementia care increased staff members' satisfaction with their work in several ways.

Notwithstanding the difficulty of selling this approach to potential users, accurate automated fall detection through user-based motion sensing appears to be an attainable goal from a technical standpoint. Using fuzzy logic to consider impact signals detected from 3D acceleration sensors as fall events and confirming the decision of the expert system by looking at changes in trunk orientation preceding those impact signals, we were able to obtain reliable fall detection under simulated fall conditions. The identification performance of the proposed algorithm compares favorably with experimental results presented in the literature on expert systems using inputs from user-based motion sensing for fall detection.<sup>17,22–24,26,27</sup> Evidence from this and other studies thus suggests that robust algorithms can be developed to accurately detect falls under controlled conditions. Several approaches in terms of inputs and expert systems used with these algorithms can be used with relatively good results. In terms of accuracy, false positives can become a nuisance and limits the acceptability of an automated approach to fall detection. The impact

of false positive in real-life applications of an automated fall detection system, however, can be significantly reduced by providing the user with a reset button (ex: 1 = minute window to cancel the alarm function after a fall was detected). Further extensive experimental studies will be needed to develop and continue to refine such algorithms and their eventual embedding in wearable sensor products.

Usability testing under real-life conditions with older adults will be another key factor to consider for the successful design and implementation of such products. Size, wearability, and overall look of such device will need to be optimized to make it as unobtrusive as possible and ensure the reliability of the product (i.e., people have to wear it). Recent technology advances in wireless networking, microfabrication, and integration of physical sensors, embedded microcontrollers and radio interfaces on a single chip, promise a new generation of miniature wearable wireless sensors, suitable for the creation of wireless body area networks (WBAN).<sup>32,33</sup> WBAN combine small sensor footprint with commercial wireless communication platforms based on different protocols and technologies (*Wi-Fi*, *WiMax*, *Bluetooth*, *Zigbee*, *UMTS*, *UWB*). WBANs are generally built around several sensing devices wirelessly linked together using narrow band radio communication.<sup>34</sup> These technologies offer a wide range of characteristics in terms of speed, transmission range, power requirements, connectivity, and cost. We are currently investigating, after positive results from a proof-of-concept study, the use of a Zigbee-based WBAN.<sup>35</sup> The system is composed of multiple sensor modules (embedded 3D accelerometers, gyroscopes, microcontroller with a radio transmitter) connected wirelessly to a computer. At this moment the unit is the size of a pager. We will be migrating the system to a different communication platform to reduce its size to the equivalent of a wrist watch, similar to what was developed by Degen and colleagues,<sup>25</sup> that can be worn as a necklace. In consideration that falls are generally underreported,<sup>36,37</sup> particularly in nursing homes,<sup>38,39</sup> the next step in our development efforts will be to assess the accuracy of an automated fall detection system based on our algorithm with staff-reported incidents us-

ing this WBAN, under a controlled environment (i.e., long-term care unit). The system first will be used passively to record fall events and compared it with administrative logs.

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