33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

# Design of an Unobtrusive Wireless Sensor Network for Nighttime Falls Detection

Zhaonan Zhang *Student Member, IEEE*, Udyant Kapoor, Michael Narayanan *Member*, *IEEE,* Nigel H. Lovell, *Fellow*, *IEEE,* Stephen J. Redmond, *Member*, *IEEE*

*Abstract*—**A significant portion of government health care funding is spent treating falls-related injuries among older adults. This cost is set to rise due to population aging in developed societies. Wearable sensors systems, often comprised of triaxial accelerometers and/or gyroscopes, have proven useful for real-time falls detection. However, a large percentage of falls occur at home and many of those happen at nighttime, when the person is unlikely to be wearing such an ambulatory monitoring device. It is envisaged that systems utilizing unobtrusive wireless sensors can be employed to survey the living space and identify unusual activity patterns which may indicate that a fall has happened at nighttime. In this study, a nighttime falls detection system designed for a single individual living at home, based on the use of passive infrared and pressure mat sensors, is explored. This paper describes both the sensor and system design, and investigates the feasibility of performing nighttime falls detection through the use of scripted scenarios using a single healthy test volunteer. In addition to normal movement activity, falls with unconsciousness, falls with repeated failed attempts to recover, and falls with successful recovery, are considered. By analyzing the location of sensor activity, periods of sensor inactivity, and unusual sensor activation patterns in uncommon locations, a sensitivity and specificity of 88.89% and 100%, respectively, are obtained (excluding falls followed by complete recovery). This demonstrates a proof-of-principle that nighttime falls detection might be achieved using a low complexity and completely unobtrusive wireless sensor network in the home.**

## I. Introduction

Population aging is a mounting challenging facing developed societies. By 2030, approximately 20% of the population of developed countries will be aged 65 or more [1]. Citi Bank predicts that, by 2050, 22.6% of the Australian population will be over 65 years of age, and the associated health costs, aggregated pensions and general aged care will soar from 29% to 47% of total government spending. Annual health care spending will increase from $2,290 per person to $7,210 per person (accounting for inflation), placing further pressure on a relatively smaller population of workers [2].

Importantly, accidental falls are a leading cause of fatality for people aged 65 years and over. In this age group, 33% suffer at least one fall per year [3]. In both the US and Australia, victims aged 65 years and over account for approximately 75% of all deaths resulting from falls, and falls- related injuries account for around 10.9% of all hospital bed days.

Timely detection of fall events can greatly reduce the cost of care and potentially save lives by signaling for immediate assistance [3]. Over 60% of falls occur in dwellings, so the implementation of falls detection systems within these dwellings might serve to improve outcomes for those who suffer falls in these environments.

The current state-of-the-art in falls detection relies primarily on the use of body worn sensors. Such devices often incorporate a triaxial accelerometer and/or gyroscope, and possibly a barometric air pressure sensor [4][5]. These wearable device systems are capable of detecting falls with good success (but still suffer from high false positive rates).

Wearable sensor systems obviously require the subject to wear the device at nighttime if they are to successfully detect a fall which might occur. Unfortunately, the subject is unlikely to wear the device while in bed, and may be equally unlikely to remount the device before nighttime toileting or visits to the kitchen. Some unobtrusive systems have been developed to address the deficits of these wearable sensor systems.

Video-based falls detection uses a network of video cameras to track subject movement. Lin and Ling used an object segmentation scheme to identify moving objects from the background, and were able to extract three features to detect and locate falls events [7]. The system assumed a fall event has a duration of 0.4-0.8 s, and was able to detect such falls with 93% accuracy. The disadvantages of such a system include an inability to detect falls where the subject attempts to break the fall, falling more slowly, and that real-time transmission of video impedes system scalability (unless extensive local video processing is performed at the capture point, which would significantly reduce device battery life).

Yu *et al.* introduced a video-based system which identifies falls by detecting shape changes and taking the duration of falls into consideration [10]. However, only a single camera system was evaluated, and no discussion is provided on how this system, or a subsequent multi-camera system, would be implemented, or what their limitations might be.

Apart from the limited accuracy of video-based falls detection systems, the most important drawback of a video-based approach is that the sensors must either process the video images locally (consuming power and increasing processor cost), or transmit the video (consuming even more power) back to a central server for further processing. Furthermore, video-based approaches also introduce privacy and ethical issues, which may hinder their ultimate acceptance.

Acoustics-based methods have also been exploited for falls detection. Popescu *et al.* propose a vertical array of

Z. Zhang is with the School of Electrical Engineering, University of New South Wales, Sydney, NSW, 2052, Australia.
U. Kapoor, M. Narayanan, N. H. Lovell and S. J. Redmond are with the Graduate School of Biomedical Engineering, University of New South Wales, Sydney, NSW 2052, Australia.

978-1-4244-4122-8/11/$26.00 ©2011 Crown

microphones to detect the height at which a noise originates, with sources above two feet deemed to not be associated with a fall [8]. The system demonstrated 100% sensitivity, but a false positive rate of five false detections per hour.

Due to the significant percentage of falls which happen at nighttime (54% for residential facilities, 76% for hospitals [6]), the expected compliance issues of wearable systems at nighttime, and privacy concerns associated with video-based methods, we propose an unobtrusive wireless sensor network, using passive infrared (PIR) motion sensors and pressure mat (PM) force sensors to detect falls which occur at night in a dwelling with a sole occupant. This system aims to complement a wearable sensor system which will be more efficacious during daytime hours.

The following describes both the sensor and system design, and investigates the feasibility of performing nighttime falls detection through the use of scripted scenarios using a single healthy test volunteer.

## II. Methodology

### A. Sensor selection

PIR and PM transducers are chosen for the task as they are reliable, cheap, easy to use, and generate very low bandwidth signals. The PIR sensor (Panasonic AMN24111) has a digital output, a detection range of 10 m, a coverage angle of $\pm 55^{o}$ in the *x*-*y* plane and $\pm 46.5^{o}$ in the *y*-*z* plane. These sensors detect the movement of warm bodies in the room but do not respond to stationary environments or ambient light. The PM is a momentary on/off switch sensor, constructed with a water resistant vinyl material, with dimensions of 790 mm x 540 mm.

### B. Sensor design

The battery powered sensor device, to which one of the above transducers are connected, comprises a microcontroller (Texas Instruments MSP430F5438) and a low power WiFi module (Roving Networks WiFly GSX, with 2.4GHz IEEE 802.11g protocol). The WiFi module has a Class 1 output level (18dBm), and the tested indoor transmission range is about 30 m.

A common sensor board design can be fitted with either a PIR or a PM sensor and loaded with the associated firmware. The sensor device operates in a sleep/active cycle which draws 60-120 mA when transmitting and 6-11 mA in sleep mode. Data are buffered to minimize the wake time and are transmitted at predefined intervals. The sensor runs for up to two weeks on two standard AA batteries, depending on the level of activity in the environment. The sensor printed circuit board is housed in a 70×54×14 mm enclosure and weighs 57.5 g, which can be mounted on a wall.

The sensor periodically sends a status packet at predefined intervals (usually 10 minutes in laboratory testing). The status packet informs the server of the sensor's continued existence within the network. The status packet also reports the sensor's operational status, such as the sent packet count, status packet interval and battery voltage. During normal operation, as the sensor is usually sleeping with its radio off, all data transmission is unidirectional and the server listens passively to the data sent by the sensor.

Rather than sending a continuous data stream, the sensors only transmit event-based data to conserve power. The time at which the event occurred and the transition value (sensor off-to-on, or on-to-off) is buffered for later transmission, which will happen immediately after the next status packet, or instantaneously if the buffer is full. As a result, the worst case delay for the event data is the full interval of the status packet. All sensors are synchronized using a network time protocol (NTP) server.

Using a hardware switch, the sensors can be manually switched into configuration mode during installation, at which point they will remain in a wake state and continuously sample and transmit the PIR or PM signals at 10 Hz. This is an important function during installation to test and debug the sensors in real-time, before they are finally switched into their low power modes. While in configuration mode, the sensors can receive configuration commands over the wireless network to set various sensor parameters, such as the status packet interval time.

### C. Network and data flow

A star topology WiFi network is used, using a standard WiFi router as a base station. A PC-based server connected to the router acts as the centre point of the network. The server hosts an SQL server (MySQL version 5.1.48) and a JAVA-based TCP data handling application, which listens for sensor traffic. On power-up, or when data are ready for transmission, the sensor will wake up and initiate a TCP connection with the JAVA TCP server. A JAVA TCP server will process the received packet and insert the data into the SQL database as it arrives. A JAVA graphical user interface (GUI) application connects to the TCP server. By displaying the operational information of the sensors contained in the status packets, it allows the user to have an understanding of the overall system health, and detects if a sensor has stopped working (via a status packet timeout) and generates a warning dialogue. Furthermore, this GUI application allows the user to configure sensor parameters during installation (once they are set in configuration mode, as specified in Section II.B) and view the PIR and PM signals in real-time.

### D. Test environment

In this study, a series of typical nighttime activities, including falls and non-fall events, were performed in the bedroom, corridor and bathroom of an apartment. Three PIR sensors and two PM sensors are used. The placement of these sensors is illustrated in Fig 1. A PIR sensor is placed in the bedroom ($PIR_{bed}$), corridor ($PIR_{cor}$) and bathroom ($PIR_{bath}$). One PM sensor is put under the fitted sheet of the mattress ($PM_{bed}$) and the second PM sensor is placed in front of the toilet seat ($PM_{bath}$). In a full scale deployment, every chair, bed and toilet seat will be fitted with a PM sensor and the entire living space will be covered by PIR sensors.

Simultaneous video, stamped with the PC system time, is captured using two USB cameras attached to the same PC

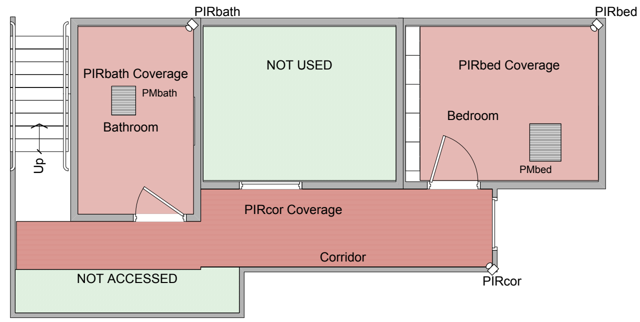


Fig. 1. Floor plan of test environment, with PM sensor in front of toilet seat and on the bed; PIR sensors are installed in the corner of bedroom, corridor and bathroom, facing 45° outward from the corner.

running the SQL server. This video is used to later annotate events in the PIR and PM signals.

## *E. Data collection protocol*

A series of predefined simulated movements, mimicking nighttime movements, are performed by a single healthy subject to provide a proof-of-concept assessment of the feasibility of using a system of this design to unobtrusively detect falls at night in the home of an elderly individual living alone. In the scenarios that involve falls, one scenario with no falls and three different types of falls will be simulated:

1) *Fall with unconsciousness:* The subject moves to a particular location, falls, and then lies stationary on the floor for a predefined duration.

2) *Fall with failure to recover:* Subject falls, remains conscious, and repeatedly tries to stand up for about two minutes, with short breaks in between attempts, but fails each time. Fig. 2 provides an illustrative example of this scenario.

3) *Fall with successful recovery:* subject falls onto the floor but is able to immediately stand up and recover.

The exact scenarios performed are listed below in more detail. Each of these scenarios is repeated three times.

*a) Enter and leave room*: Subject enters the room from the corridor, stays in the room for five minutes, performing either clothes sorting, or preparation of the bed, then leaves the room (6 scenarios incl. 0 falls.).

*b) Out of bed and dresses to leave room:* Subject lies in bed for five minutes, wakes up, gets dressed, then either leaves the room, falls but unable to recover (either unconscious or attempting to recover) for 5 minutes, or recovers and leaves the room into corridor. (12 scenarios incl. 9 falls.)

*c) In bed, wake up and have a drink and back to sleep:* Subject lies still in bed for three minutes to mimic sleeping.

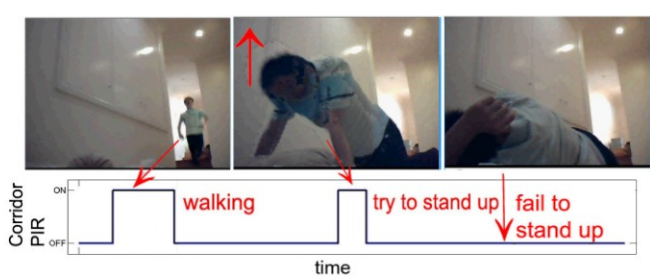


Fig. 2. Subject walks out of bathroom and falls onto the floor in the corridor. Also shown is the data captured by the corridor PIR sensor

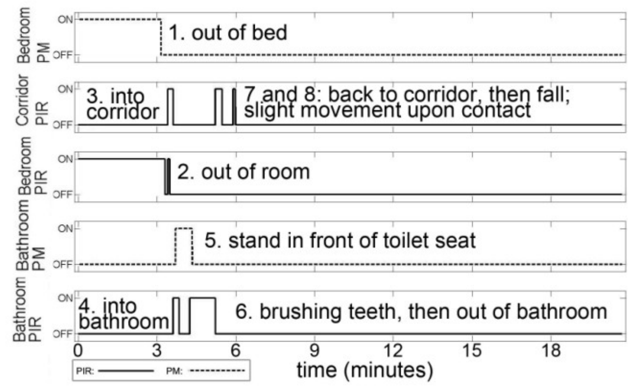


Fig. 3. Activity vs. time taken from scenario *f)*, where the subject fell and simulated unconsciousness for about 15 minutes. Each activity is annotated and numbered.

Subject wakes up, switches on the light and drinks some water. Subject then switches off the light and goes back to sleep, lying still for three minutes. (3 scenarios incl. 0 falls.)

*d) Sit on toilet, then leave bathroom:* Sits on the toilet for 5 minutes then stands up and leaves the bathroom (3 scenarios, incl. 0 falls.).

*e) Bedroom to bathroom, and back to bed (fall in corridor):* In bed for one minute, walk from the bedroom into the bathroom via corridor. In the bathroom, stand on the pressure mat in front of the toilet seat for 30 s, then brush teeth, walk out of room into the corridor. On the way back to the bedroom the subject either continues without falling or simulates each of the three fall scenarios in the corridor; falls with failure to recover are simulated for 15 minutes. An example of the signals resulting from a fall with unconsciousness is shown in Fig 3. (12 scenarios incl. 9 falls.)

*f) Bedroom to bathroom, back to bedroom (fall in bathroom):* Lie in bed for three minutes, get out of bed go to the bathroom via the corridor. Subject sits on the toilet seat for four minutes, after which the subject either returns to the bedroom or falls; again, falls with failure to recover are simulated for 15 minutes. (12 scenarios incl. 9 falls.)

## *F. Falls detection algorithm*

The event data from the SQL database is interpolated and resampled at 10 Hz for further signal processing. All sensor data is aggregated using a logical OR operation, to generate a single sensor activity signal. If this signal is inactive for more than a predefined time threshold of four minutes, a fall alarm is generated.

To indentify falls which are followed by several failed attempts to recover, PIR data from all PIR sensors are analyzed to determine there are more than four separate PIR activations in the last two minutes, while no PM sensors are activated. This would not work during the day, but such movement would be abnormal at night. No attempt is made to detect falls from which the subject successfully recovers.

# III. RESULTS

Including all three falls types, the system achieved 59.26% sensitivity. This result improves to 88.89% after excluding scenarios where the subject recovers by themselves. The sensitivity increases to 100%, when only including falls where unconsciousness occurs. The specificity is calculated at 100%. These results are summarized in Table I.

TABLE I
FALLS DETECTION PERFORMANCE

| | | | Predicted Fall | Predicted No fall | Sens. % | Spec. % | PPV % | NPV % | N |
|---|---|---|---|---|---|---|---|---|---|
| A | Actual | Fall | 16 | 11 | 59.26 | 100.00 | 100.00 | 65.63 | 48 |
| | | No fall | 0 | 21 | | | | | |
| B | Actual | Fall | 16 | 2 | 88.89 | 100.00 | 100.00 | 91.30 | 39 |
| | | No fall | 0 | 21 | | | | | |
| C | Actual | Fall | 9 | 0 | 100.00 | 100.00 | 100.00 | 100.00 | 30 |
| | | No fall | 0 | 21 | | | | | |

Sens.: sensitivity; Spec.: specificity; PPV: positive predictive value; NPV: negative predictive value; N: total scenario count.
A: All scenarios included.
B: All scenarios except fall with successful recovery.
C: Only ADL and falls with unconsciousness.

## IV. Discussion

A low cost, low complexity, unobtrusive falls detection system for detecting falls at nighttime has been designed, and proof-of-concept testing has been performed on a single healthy volunteer. The system attempts to identify falls at nighttime where the subject is rendered unconscious or is unable to recover without help; the latter recognized by analyzing the frequency of sensor activation while the subject attempts to recover.

As this study aims only to evaluate the wireless sensor system and explore the feasibility of performing unobtrusive falls detection with this suite of sensors, all the scenarios are simulated. Limiting the system to falls detection at nighttime further allows the simulated scenarios to closer approximate real nighttime activities which are more limited in their variety; this is very different to simulating a vast array of possible daytime activities.

There is an inherent delay in the detection of falls events using this system, which come from two sources. Firstly, the data are buffered at the sensor and only sent after each status packet, at ten minute intervals in this study (but is configurable). Secondly, the fall detection algorithm functions by analyzing recent data (c.f., Section II.F). The delay in detecting a fall will be given by whichever of these two delays is larger. A delay of several minutes is still preferable to having no monitoring at all.

Of course, the results presented here do not approach the accuracy of wearable sensor solutions, such as those presented by Bianchi *et al.* (97.5%) [5], however this is compensated by the unobtrusive nature of the system, which obviates the issue of compliance that plagues wearable solutions, particularly at nighttime.

Chen *et al.* achieved 90% accuracy using a video-based system [9]; however, the implementation of video-based solutions poses significant challenges related to image processing, data transmission and scalability, cost and privacy, as discussed earlier.

Zhuang *et al.* [11] proposed an acoustics-based system, which recognized the noise associated with the impact of a fall, achieving only a 70% detection rate. This is somewhat expected, given the plethora of flooring surfaces on which falls occur and the manner in which they happen.

Future improvements to this system will add context awareness, such as modifying inactivity and repeated activity thresholds to tailor them for individual sensors; for example, more than ten minutes of intermittent activity on a corridor sensor late at night would be an unusual occurrence, or spending more than an hour in the bathroom might be equally abnormal. Furthermore, it may be possible to allow the system to adapt to the behaviors of the user through learning which is reinforced through the ability to cancel a false alarm in real-time during a trial deployment.

## V. Conclusion

In this study, an unobtrusive wireless nighttime falls detection system, intended for use by older individuals living alone, is presented. The design is motivated by the large percentage of falls which occur at night, during which time compliance with the use of wearable falls detection sensors is low. By identifying periods of inactivity, or repeated intermittent activity on PIR sensors, while no PM as activated, simulated falls scenarios are accurately identified; however, real-world testing is required to truly validate this method. This system is likely to be a useful adjunct to wearable falls detection systems in the smart homes of the future.

## VI. References


[1] H. Alemdar and C. Ersoy, "Wireless Sensor Networks for Healthcare: A Survey", *Computer Networks*, vol. 54, pp. 2688-2710.

[2] E. Prior, F. Faria, A. Smith, et al, "*Australia's Aging Population, ASX-Listed Exposure in Healthcare, Accommodation & Wealth Management*", Citigroup, 2010.

[3] N. Noury, "A smart sensor for the remote follow up of activity and fall detection of the elderly*", presented at the 2nd Annual International IEEE-EMB Special Topic Conference on Microtechnologies in Medicine & Biology,* Madison, WI , USA, 2002, pp314-317.

[4] Y. Lee, J. Kim, M. Son and M. Lee, "Implementation of Accelerometer Sensor Module and Fall Detection Monitoring System based on Wireless Sensor Network", *Presented in 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* Lyon, 2007, pp. 2315-2318.

[5] F. Bianchi, S.J. Redmond, M.R. Narayanan, S. Cerutti, and N.H. Lovell, "Barometric Pressure and Triaxial Accelerometry-based Falls Event Detection", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, pp. 619-627, 2010.

[6] J. Ozanne-Smith, J. Guy, M. Kelly and A. Clapperton, "*The relationship between slips, trips and falls and the design and construction of buildings",* Monash University Accident Research Centre, Monash University, 2008.

[7] C. Lin and Z. Ling, "Automatic Fall Incident Detection in Compressed Video for Intelligent Homecare", *Proceedings of 16th International Conference on Computer Communications and Networks*, Honolulu, HI, USA, 2007, pp. 1172-1177.

[8] M. Popescu, Y. Li, Skubic, M., Rantz, "An Acoustic Fall Detector System that Uses Sound Height Information to Reduce the False Alarm Rate", *30th Inernational. IEEE EMBS Conference*, Vancouver, BC, 2008, pp. 4628-4631.

[9] Y. Chen, Y. Lin and W. Fnag, "A video-based human fall detection system for smart homes", *Journal of the Chinese Institute of Engineers,* vol. 33, pp. 681-690, 2010.

[10] X. Yu, X. Wang, P. Kittipanya-Ngam, H. Eng and L. Cheong, "Fall detection and Alert for Ageing-at-Home of Elderly", *Lecture Notes in Computer Science*, vol. 5597, pp. 209-216, 2009.

[11] X. Zhuang, J. Huang, G. Potamianos and M. Hasegawa-Johnson, "Acoustic fall detection using Gaussian mixture models and GMM supervectors", *2009 IEEE International Conference on Acoustics, Speech and Signal Processing,* Taipei, Taiwan, 2009, pp. 69-72.