Pilot Evaluation of an Unobtrusive System to Detect Falls at Nighttime

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

***Abstract*— Research shows that older people (aged 65 years and over) suffer many unintentional indoor falls which often lead to severe injuries. As a result of an increasingly aged population in developed countries, a sizable portion of healthcare funding is consumed in the treatment of fall-related injuries and associated long-term care. Detecting falls soon after they occur can be potentially live saving. In addition, early treatment of fall-related injuries can reduce treatment costs by minimizing health deterioration resulting from long periods spent incapacitated on the floor after a fall (a scenario known as a 'long lie') and decreasing the number of hospital bed-days required. In this study, a previously proposed unobtrusive nighttime fall detection system based on wireless passive infrared sensors and furniture load sensors is evaluated in a pilot study involving three older subjects, monitored for a combined total of 174 days. No falls occurred during the study. The system reported a false alarm rate of 0.53 falls per day, which is comparable with similar unobtrusive and wearable sensor fall detection solutions.**

I. Introduction

Population aging is a common trend among developed countries. In Australia, the proportion of people aged 65 years and over is expected to rise from 12.1% in 2010, to 16.8% by 2020, and reach 22.6% by 2050 [1]. Similar trends exist in the UK and USA [2]. Treatment of fall-related injuries and associated care expenses is one of the largest injury-related healthcare expenditures [3].

Research shows that between 20% and 35% of people aged 65 years and over, and 50% of those over 80 years, experience a fall at least once a year [4], [5]. Such high rates of incidence contribute to a significant hospitalization rate; 2.6% of all hospital admissions for persons aged 65 and over are the result of fall-related injuries, and over 60% of these incidents involve the victim suffering at least one fracture [4].

Among all unintentional falls, about 60% occur inside buildings [6]. Studies show most falls happen at home [6], where inadequate lighting is one of the most hazardous environmental risk factors. Also, the bathroom is a common location for falls due to slippery floors and lack of grab bars [7].

Globally, there are many research projects developing technologies to automatically detect falls. One possible solution uses one or more accelerometers and gyroscopes attached to the head and/or the trunk; see Schwickert *et al.* for a comprehensive review of published methods [8]. While wearable sensor solutions can indeed achieve accurate results, this approach suffers from an inherent disadvantage, namely the ambulatory device needs to be worn in order to detect the fall. People are not likely to wear these devices in situations where they wake up at night to use the toilet, or while showering.

This paper describes the pilot evaluation of an unobtrusive fall detection system, previously presented by Zhang *et al.* [9], in the homes of three older subjects. This system intends to detect falls while not interfering with normal activities of daily living. Below, a discussion of prior art is presented, before describing this work.

The majority of unobtrusive fall detection systems described in the literature rely on video processing techniques [10–14]. One important disadvantage of using video is that it is perceived as excessively invasive of the user's privacy [15]. There are also difficulties with the installation of video sensors, such as the need for calibration, to define exclusion zones (such as the bed or sofa), and to ensure the scene is not occluded by furniture. In addition, video-based systems are not easily scalable, due to their power and computing requirements.

A related solution aims to recognize the acoustic signature of a fall [16], [17]. However, these systems have shown poor false alarm rates, or accuracies.

Therefore, since wearable sensor-based systems are completely ineffective when not worn during the nighttime, and also considering the privacy and practicability of the video- and acoustic-based unobtrusive systems, this article reports the performance of an unobtrusive fall detection system, using low-cost environmental sensors. Specifically, this paper describes a pilot evaluation and refinement of a variant of the system previously described by the Zhang *et al.* [9]. This evaluation is performed in the homes of three older individuals over a period of several weeks.

II. Methods

A. System Design

A description of the core electronics and network communications-related aspects of the system can be found in Zhang *et al.* [9]. The transducers used by the system were augmented here in some important ways, which are described in the following.

1) Augmented PIR Sensor: The same passive infrared (PIR) sensor was used as Zhang *et al.* [9] (Panasonic AMN24111). However, this sensor has blind zones as significant as 1 m^2 at 5 m radial from the sensor caused by the

S. J. Redmond, Z. Zhang, M. R. Narayanan and N. H. Lovell are with the Graduate School of Biomedical Engineering, UNSW Australia. (s.redmond@unsw.edu.au)

978-1-4244-7929-0/14/$26.00 ©2014 European Union

Fresnel lens [18]. Hence, four PIR transducers are mounted onto a cylindrical surface to form a single detection unit (c.f. Fig. 1). Each PIR transducer is offset from its neighbor by $\pm 5.75°$ about the vertical. The sensor is activated if any of these four are activated by movement.

Fig. 1. Installed PIR sensor, constructed using four PIR transducer elements to cover blinds zones.

2) Load Sensors: The water resistant vinyl pressure mats (placed in the bed and on chairs to detect furniture use) used by Zhang *et al.* were replaced with smaller FlexForce load sensors (LS) (P/N: A301, Tekscan, Boston, USA). The LS are thin, flexible sensor strips with a pressure sensing area at one end, with an area of about 1 cm^2, and change their resistance with a change in applied force. Each sensor is small enough to be placed under chair legs, and sofa and bed legs/coasters.

B. Experimental Design

1) Study Participants: Three volunteers were recruited from the Thomas Holt retirement village, Sutherland, Sydney, Australia. The study participants provided written informed consent prior to any study-related activities. The study was performed between April and September, 2013. The study was approved by the University of New South Wales Human Research Ethics Advisory Panel 'H' (reference number: 08/2013/26).

Demographic information for the study participants is summarized in Table I.

TABLE I

SUMMARY OF DEMOGRAPHIC INFORMATION FOR STUDY PARTICIPANTS.

	Age (years)	Gender	Height	Weight	Falls in past year
Subject A	83	F	167 cm	55 kg	1
Subject B	84	F	152 cm	68 kg	1
Subject C	82	F	162 cm	80 kg	0

2) Sensor Installation: Sensor installation for a each residential unit took approximately 90 minutes. PIR sensors were installed in the corner of each room and attached to the walls at a height of approximately 2.5 m using 3M Command brand picture hanging strips, capable of supporting 1.8 kg per set (c.f., Fig. 1).

The bed LS were placed between the frame leg and a thin wooden baseplate to ensure the sensor was not deformed due to uneven carpet surfaces. The chair LS where fixed to the bottom of chair legs using an adhesive tape. When installing the LS, calibration is required to account for the variety of furniture weights; the device firmware is switched to a calibration mode, which averages sensor readings with and without a person sitting/lying on the furniture and sets an appropriate activation threshold.

Fig. 2 shows the floorplan of Subject C's unit. PIR sensors are shown in orange, chair LS are green, and sofa/bed LS are purple.

Due to resource limitations, sensors were not installed on every chair or in every room in the unit. Installation locations were prioritized based on what the subject suggested were their most frequently used furniture and rooms, especially at nighttime. The total number of sensors installed for Subjects A, B and C, respectively was: 4, 4 and 5 PIR sensors; 4, 4 and 2 chair LS; 3, 3 and 3 bed/sofa LS.

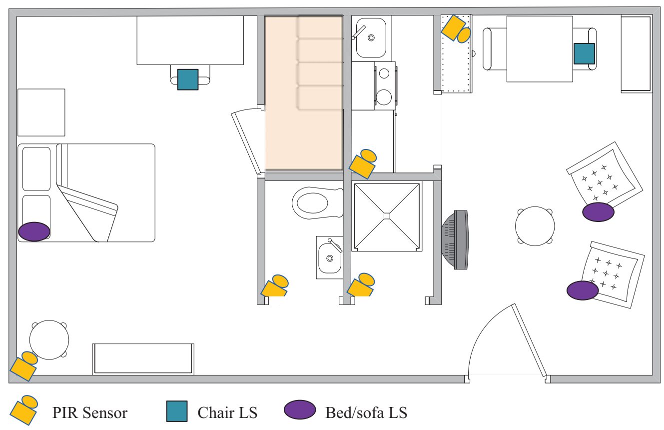

Fig. 2. Unit floorplan of Subject C, comprised of five PIR sensors (orange), two chair LS (green squares) and three sofa/bed LS (purple ovals). The storage area (shaded in orange) is not usually accessed by subject, and one of the dining chairs is also rarely used.

3) Fall Diaries and Site Visits: Weekly visits were performed to collect fall diaries to determine if the subject fell during the preceding week, and to ensure the system was working correctly. Additionally, as the fall detection algorithm is not intended to function properly if more than one person is present in the unit, by design, the fall diary requests information on whether the participant had any visitors to their unit that week. The signal database was also backed-up, and the wireless sensor batteries replaced.

C. Algorithmic Refinement and Testing

The following provides a summary of the algorithm presented by Zhang *et al.* [9]. Sensor event data is extracted from the database and uniformly re-sampled at 10 Hz, and then processed by two separate and parallel sub-algorithms: fall with unconsciousness (denoted Type-1 fall); and fall with repeated attempted recovery (denoted Type-2 fall). Type-1 falls are identified by long inactive period on all sensors, lasting longer than t_u s; Type-2 falls are characterized by a pattern of a continuous PIR activity (longer than t_{ar} s) while furniture LS are inactive, which is inferred to be a potential fall with repeated attempts to recover.

The system described by Zhang *et al.* was developed using a scripted protocol with young actors. It is also expected that the time of day for which the algorithm is active (it is designed to be used at nighttime) and the choice of fall detection thresholds will have a significant impact on its performance in a real home. Therefore, using data from Subject A, the analysis period and thresholds were optimized. These optimized values were then evaluated using data from Subjects B and C.

III. Results

A. Data Loss and Integrity Checking

Data loss occurred during the study. This was either caused by the failure of a sensor (due to firmware bugs, power regulator failure, and LS placement problems) or some part of the wireless network (problems with the wireless router). The integrity of the data was validated before analysis proceeded. The data were segmented into daily epochs, from midday of one day to midday of the next. Data for a given day was deemed corrupt if: there was no sensor activity for the entire day; or, any of the sofa/bed LS are continuously triggered for an extended period of time (more than 16 hours). Days containing corrupted data are excluded from the final analysis. The number of days of data corruption for each participant are listed in Table III.

Using this methodology, only ten days of data were considered to be corrupt, from a total of 174 monitoring days. While data loss occurred due to rectifiable issues related to firmware programming and network protocol issues, most other data loss was a consequence of the mechanical robustness of the adhesive tape used to attached the chair LS; abrasion when the chair was moved along the floor caused the adhesive tape to tear.

B. Algorithm Refinement on Subject A

None of the three participants fell inside their units during the data collection period. Table II shows the false positive counts generated by the algorithm for Subject A (using 56 days of uncorrupted data) depending on the choice of analysis period and time threshold value.

TABLE II

ALGORITHM FALSE POSITIVE (FP) RATES FOR SUBJECT A USING VARIOUS TIME THRESHOLDS (t_u) FOR TYPE-1 FALLS AND TYPE-2 FALLS (t_{ar}), DEMONSTRATING A REDUCED FALSE POSITIVE RATE WHEN THESE THRESHOLDS ARE INCREASED. ANALYSIS PERIODS OF 8PM-8AM OR 8PM-5AM ARE CONSIDERED.

		Threshold (s)			
Analysis period	**Fall type**	**280**	**600**	**900**	**1200**
8pm-8am	**Type-1 fall**	388	88	5	4
	Type-2 fall	217	76	33	19
8pm-5am	**Type-1 fall**	172	53	**3**	2
	Type-2 fall	29	**7**	7	7

To trade-off the delay incurred by selecting a longer threshold with the reduced false positive rate this provides, detection thresholds $t_u = 900$ s and $t_{ar} = 600$ s were chosen for Type-1 and Type-2 falls, respectively. In addition, the analysis period is set to 8pm-5am.

C. Testing on Subjects B and C

Table III lists the results of testing the algorithm on data from Subject B and Subject C, using $t_u = 900$ s and $t_{ar} = 600$ s, during the period from 8pm to 5am. Results for the algorithm applied to data for Subject A are also shown for completeness, remembering that the algorithm thresholds were optimized using data from Subject A.

TABLE III

FALSE POSITIVE (FP) RATES FOR SUBJECT B AND SUBJECT C, DERIVED USING THE IMPROVED ALGORITHM. RESULTS FOR SUBJECT A ARE INCLUDED FOR COMPARISON PURPOSES.

Subject	**Type-1 count**	**Type-1 rate**	**Type-2 count**	**Type-2 rate**	**Total (days)**	**Corrupt (days)**	**Combined FP rate**
A	3	0.05	7	0.13	56	4	0.18
B	9	0.12	51	0.70	73	4	0.82
C	6	0.13	16	0.36	45	2	0.49
Total	18	0.10	74	0.43	174	10	0.53

Type-1 fall: number of falls with unconsciousness detected.
Type-1 rate: number of false positive alarms per day rate for falls with unconsciousness.
Type-2 fall: number of falls with repeated attempted recovery detected.
Type-2 rate: number of false positive alarms per day rate for falls with attempted recovery.
Total (days): total validated (uncorrupted) days of data recorded for the subject.
Corrupt (days): total number of days of corrupted data.
Combined FP rate: false positive rate for all fall types (alarms/day).

IV. Discussion

A. Algorithm Refinement for Subject A

Table II shows the importance of deactivating the system at 5am, which is around the time when the subjects wake and rise. The importance of increasing the detection thresholds to 10-15 minutes is also evident.

Subject A did not fall inside their home during the study. However, after applying the new thresholds and the reduced analysis duration, there are still three erroneously detected falls with unconsciousness (Type-1) and seven falls with attempted recovery (Type-2). For the Type-1 falls, these cases happened before they went to sleep. The duration of the inactivities was greater than the detection threshold but less than 20 minutes, which suggests the subject may have moved out of the detection area (for example, left the unit), rather than due to a system failure.

For the seven Type-2 falls, five cases happened in the living room and two cases in the bedroom, all before the subject went to sleep, the events had a duration between 20 minutes and 1 hour (when subjects were not sitting/lying). It is not known what causes these misdetections, but it could have been the subject performing domestic work, or a malfunction of one of the LS.

B. Improved Algorithm Testing with Subjects B and C

Again, neither Subject B or Subject C fell inside their home during the study period. Table III indicates that the false alarm rates are higher for Subjects B and C; combined rate of 0.82 and 0.49 alarms per day, respectively. Discussions with the subjects indicate that Subject A normally sleeps from about 9pm every night. For Subjects B and C, the normal sleep time was after 11pm. In particular, the data suggested that there were two nights that Subject B did not sleep in the bed, or did not sleep at all; she confirmed this for at least one of these cases, when she was learning to use a camera she received as a gift and moved around the apartment taking photos. This resulted in prolonged periods of PIR activation pattern without furniture use, contributing to 23 Type-2 fall alarms in one night (out of 51 for the entire 73 days she was monitored). Also, Subject B normally sleeps late at night (close to midnight) and likes to cook (extended periods of activity in the kitchen) which both increase the chance of Type-2 fall false alarms.

C. Comparison to Related Systems

Until now there has only been one other unobtrusive fall detection project to have successfully conducted a real-world evaluation involving older subjects, described by Stone *et al.* [14]. This very extensive study captured nine real falls in 3,339 days of monitoring, and also used 445 simulated falls. The system uses a Microsoft Kinect camera, operates all day (not just at nighttime), and has a very low false positive alarm rate of less than 4 alarms per month, but performance deteriorates (as expected) if the view of the faller is occluded and/or the faller is far from the camera.

The only other fall detection systems which have been evaluated in a real-world setting are body-worn sensor systems. Bourke *et al.* [19] reported 0.42 false positive alarms per day, compared to the 0.53 total false alarm rate obtained in this paper. Bagalà *et al.* [20] evaluated 13 published methods on a set of 32 real falls from 15 subjects, achieving a poor sensitivity (mean±SD: 57.0%±27.3%) and moderate specificity (mean±SD: 83.0%±30.3%), and with algorithms generating between 3 and 85 false alarms per day for three representative fallers.

V. Conclusion

This paper describes the first ever real-world evaluation of a non-video-based unobtrusive fall detection system with older adults. While no actual falls occurred during 174 monitoring days, the system demonstrated a promising false positive rates of 0.53 alarms per day. This system could potentially deliver significant advantages over wearable systems in terms of user compliance, and ultimately improve the safety of older people living alone.

VI. Acknowledgments

The authors would like to express their immense appreciation to the wonderful residents of Thomas Holt retirement village for participating in this study, and to thank the staff of Thomas Holt, especially Ms. Alexandra Zammit and Ms. Kae Fowler for their assistance and unwaivering support for this project.

References

[1] "Australia to 2050: future challenges; the 2010 intergenerational report," Australian Government, The Treasury, Report, 2010.

[2] G. F. Anderson and P. S. Hussey, "Population aging: a comparison among industrialized countries," *Health Affairs*, vol. 19, no. 3, pp. 191–203, 2000.

[3] R. W. Sattin, "Falls among older persons: A public health perspective," *Annual Reviews in Public Health*, vol. 13, no. 1, pp. 489–508, 1992.

[4] C. Bradley and S. Pointer, "Hospitalisations due to falls by older people, Australia 2005-2006," *Injury Research and Statistics Series*, no. 50, 2008.

[5] M. E. Tinetti and C. S. Williams, "Falls, injuries due to falls, and the risk of admission to a nursing home," *New England Journal of Medicine*, vol. 337, no. 18, pp. 1279–1284, 1997.

[6] "Australian hospital statistics 2006-07," Australian Institute of Health and Welfare, Report, 2008.

[7] M. Cesari, F. Landi, S. Torre, G. Onder, F. Lattanzio, and R. Bernabei, "Prevalence and risk factors for falls in an older community-dwelling population," *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, vol. 57, no. 11, pp. M722–M726, 2002.

[8] L. Schwickert, C. Becker, U. Lindemann, C. Marechal, A. Bourke, L. Chiari, J. L. Helbostad, W. Zijlstra, K. Aminian, C. Todd, S. Bandinelli, and J. Klenk, "Fall detection with body-worn sensors: A systematic review," *Zeitschrift für Gerontologie und Geriatrie*, vol. 46, no. 8, pp. 706–719, 2013.

[9] Z. Zhang, U. Kapoor, M. R. Narayanan, N. H. Lovell, and S. J. Redmond, "Design of an unobtrusive wireless sensor network for nighttime falls detection," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 5275–5278.

[10] T. Lee and A. Mihailidis, "An intelligent emergency response system: preliminary development and testing of automated fall detection," *Journal of Telemedicine and Telecare*, vol. 11, no. 4, pp. 194–198, 2005.

[11] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, "Monocular 3D head tracking to detect falls of elderly people," in *Proc. of the 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, New York, 2006, Conference Proceedings, pp. 6384–6387.

[12] C. W. Lin, Z. H. Ling, Y. C. Chang, and C. J. Kuo, "Compressed-domain fall incident detection for intelligent home surveillance," in *Proc. of IEEE International Symposium on Circuits and Systems*, Kobe, 2005, Conference Proceedings, pp. 3781–3784 Vol. 4.

[13] E. Auvinet, L. Reveret, A. St-Arnaud, J. Rousseau, and J. Meunier, "Fall detection using multiple cameras," in *Proc. of 30th Annual International Conf. of the IEEE Engineering in Medicine and Biology Society*, Vancouver, 2008, Conference Proceedings, pp. 2554–2557.

[14] E. Stone and M. Skubic, "Fall detection in homes of older adults using the microsoft kinect," *IEEE Journal of Biomedical and Health Informatics*, 2014 [Epub ahead of print].

[15] S. Chaudhuri, T. H., and G. Demiris, "Fall detection devices and their use with older adults: A systematic review." *J Geriatr Phys Ther.*, 2014 [Epub ahead of print].

[16] M. Popescu, Y. Li, M. Skubic, and M. Rantz, "An acoustic fall detector system that uses sound height information to reduce the false alarm rate," in *Proc. of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vancouver, 2008, Conference Proceedings, pp. 4628–4631.

[17] X. Zhuang, J. Huang, G. Potamianos, and M. Hasegawa-Johnson, "Acoustic fall detection using gaussian mixture models and gmm supervectors," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, Taipei, 2009, Conference Proceedings, pp. 69–72.

[18] Panasonic, *Motion Sensor (Passive Infrared Type) MP Motion Sensor 'NaPiOn' (AMN 1,2,4)*, Osaka, Japan, 2010.

[19] A. K. Bourke, P. W. J. van de Ven, A. E. Chaya, G. M. O'Laighin, and J. Nelson, "Testing of a long-term fall detection system incorporated into a custom vest for the elderly," in *Proc. of the 30th Annual International Conf. of the IEEE Engineering in Medicine and Biology Society*, Vancouver, 2008, Conference Proceedings, pp. 2844–2847.

[20] F. Bagalà, C. Becker, A. Cappello, L. Chiari, K. Aminian, J. Hausdorff, W. Zijlstra, and J. Klenk, "Evaluation of accelerometer-based fall detection algorithms on real-world falls," *PLoS ONE*, vol. 7, no. 5, p. e37062, 2011. [Online]. Available: doi:10.1371/journal.pone.0037062