35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Design of an Unobtrusive System for Fall Detection in Multiple Occupancy Residences

Arni Ariani[1], *Student Member, IEEE*, Stephen J. Redmond[1], *Member, IEEE*,
Zhaonan Zhang[2], *Student Member, IEEE*, Michael R. Narayanan[1], *Member, IEEE*
and Nigel H. Lovell[1], *Fellow, IEEE*

***Abstract*— A small trial was conducted to examine the feasibility of detecting falls using a combination of ambient passive infrared (PIR) and pressure mat (PM) sensors in a home with multiple occupants. The key tracking method made use of graph theoretical concepts to track each individual in the residence and to monitor them independently for falls. The proposed algorithm attempts to recognize falls where the subject experiences a hard fall on an indoor surface that leads to loss of consciousness or an inability to get up from the floor without assistance, due to severe injuries. The sensitivity, specificity and accuracy of the algorithm in detecting falls are 85.00%, 80.00% and 82.86%, respectively.**

I. INTRODUCTION

RESEARCH has revealed that falls and their related injuries have become a leading cause of increasing morbidity, disability and higher demands on health services [1]. Among Australians age 70 and older, unintentional falls are the leading cause of death from injury, constituting 26.52% of the 9,775 injury related death cases reported in 2004-05 [2]. According to 2005-2006 survey results, 66,784 people aged 65 years and over were admitted to hospital due to a fracture as a result of falling [3]. The Australian Institute of Health and Welfare report found the cost of short-stay hospital admissions linked to falls in 2003-2004 among older people was AUD$566 million [4].

The 'long lie' scenario, which involves being unable to get up from the floor after a fall for a period of one hour or more, is a serious issue in relation to falls among elderly living at home or in a residential care facility [5]. Older people who experience this long lie scenario could experience not only physical trauma (bronchial pneumonia, hypothermia and pressure sores) [6] but also psychological trauma (fear of falling, which may lead to decreased activity levels) [5]. Such trauma may have a negative impact on one's quality of life, irrespective of whether they had a serious fall-related injury or not.

Table I presents the occurrence rates of falls and long lie scenarios for older people aged over 90 years living in Cambridge, England [7]. The results revealed that slightly below 82% of falls occurred when people were unaccompanied by their families.

TABLE I: The percentage rates of falls in different environments [7].

	Community (n=120)	**Sheltered housing (n=62)**	**Institutional settings (n=83)**	**All (n=265)**
Alone when experiencing a fall	93 (77.5%)	58 (93.6%)	66 (79.5%)	217 (81.9%)
Unable to get up without assistance	52 (43.3%)	41 (66.1%)	83 (100%)	176 (66.4%)
Time on floor ≤1 hour	97 (80.8%)	40 (64.5%)	72 (86.8%)	209 (78.9%)
Time on floor ≥1 hour	16 (13.3%)	17 (27.4%)	7 (8.4%)	40 (15.1%)
Time on floor unknown	7 (5.8%)	5 (8.1%)	4 (4.8%)	16 (6.1%)

One of the solutions to this problem is to automatically identify the occurrence of a fall as soon as possible and subsequently generate an emergency notification signal to summon help. Most research currently focuses on the use of wearable sensors to reactively identify falls [8].

However, older people tend not to use such devices due to comfort issues, the belief that it has become a symbol of frailty, or simply due to short-term memory loss or forgetfulness (which is particularly problematic for those suffering from dementia [9]), or because they have gotten out of bed in the middle of the night to go to the bathroom and fail to affix the device [10].

The accuracies of such a system, when using a video-based solution, developed by Nait-Charif and McKenna [11] was 96.9%. However it must be noted that the choice to implement video-based systems poses significant challenges related to increased concerns over invasion of privacy [12], high computational complexity and/or data storage and large sensor power consumption [13].

Based on these and other reasons, recent research themes have evolved in the direction of developing a smart home, often using an optimized number of ambient sensors for unobtrusive detection of falls.

However, so far this stream of research has focused exclusively on unobtrusive monitoring systems that are developed to cope with one individual in the home at a time [14], [15].

Preliminary work on this topic by our group has focused on the use of a wireless sensor network (WSN) software simulator to generate sensor signals, which may be considered as mimicking the real sensor signals from a subject performing certain activities, and the development of an algorithm to distinguish between falls and other activities during the day in a house with multiple residents [16]. In our simulation, the motion sensor was assumed to have a perfect detection

[1]A. Ariani, S. J. Redmond, M. R. Narayanan, and N. H. Lovell are with the Graduate School of Biomedical Engineering, The University of New South Wales, Sydney, NSW 2052, Australia. e-mail: n.lovell@unsw.edu.a

[2]Z. Zhang is with the School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney, NSW, 2052, Australia.

978-1-4577-0216-7/13/$26.00

of the moving objects. However, in a real environment, a typical passive infrared (PIR) sensor is sensitive to rapid change in the amount of incident infrared energy, so their response is affected by various factors including: the ambient temperature, humidity, the speed of motions, the orientations of motions, the distance between the sensor and moving objects, the size of moving object [17].

The obvious limitations of the simulator have motivated us to conduct a small trial in a two bedroom apartment to understand the potential effectiveness of wireless ambient sensors to unobtrusively monitor residents' activities inside their own homes and raise an alarm if a fall is detected, without having to use wearable devices, and furthermore to do this in the presence of multiple persons present in the same environment.

II. Methodology

A. Experimental design

1) Apartment environment: The floor plan of the apartment unit includes two bedrooms (a master bedroom and a bedroom), a bathroom, corridor, living room, kitchen, balcony and entrance hall. There is one wardrobe and one bed in each bedroom. The bathroom has a shower/bathtub, a sink, toilet and a wall storage cabinet. A sofa is placed against the wall in the living room. The kitchen is equipped with a dining table with four chairs, a refrigerator, a stove, a kitchen sink, six wall cabinets and six floor cabinets. The floor plan is shown in Fig. 1.

2) Sensor selection and their placement: The system comprises PIR and pressure mat (PM) sensors. The PIR sensor (MP Motion Sensor NaPiOn, Panasonic Electric Works Co., Ltd.) is able to detect human movement within the detection range/coverage area of 100° in the azimuth, ±82° in the elevation, and up to a distance of about 5 m. The PM acted as a contact switch, producing a binary signal output when a certain range of pressures (about 2-30 psi) was applied to an area of about 0.21 m^2 [18].

One PIR motion sensor is placed on the wall close to the ceiling of every room, except one bedroom and a balcony. Rectangular PMs are placed on one of the four dining chairs, the bed in master bedroom, the sofa, in front of the shower/bathtub and behind the entrance door to the apartment unit.

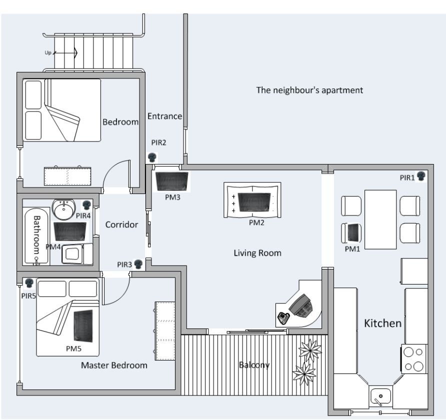

Fig. 1: Floor plan of the residential unit showing the room layout, furniture and sensor placement.

3) Participant profiles: The participants in this study were young adults (n = 5 (2 males); ages: 25-35 years, height: 155-174 cm, weight: 50-80 kg). Subjects were healthy and normal. Subjects were excluded from the study if they reported any of the following: (a) a history of one or more falls in the past twelve months; (b) a history of severe memory loss, mental confusion or dementia; (e) under long-term medication therapy. All subjects completed and returned the consent form and questionnaire to the investigators before the trial started. The study was approved by the Human Research Ethics Advisory (HREA) Panel of the University of New South Wales.

Each subject is paired with a researcher to perform two normal activities and twelve fall events. This resulted in 70 simulated events. The researcher also doubled as the second resident, and performed a series of daily activities for the entire simulated scenarios.

4) ADL and fall scenarios: A series of predefined simulated movements were performed to mimic the activities of residents in a multiple resident household. In particular, activities of daily living (ADLs), a fall from bed after waking up, a fall after getting up from a sofa, a fall while bathing or showering, and a fall when walking or standing were simulated [19].

Each normal scenario can be a series of one or more daily activities including walking, sitting on a sofa or chair, climbing into bed, preparing meals, showering and leaving the home. The aim of performing these normal scenarios is to analyze the system's false positive rate.

In the scenarios that involve falls, three types of post-fall scenario will be performed. Fall with successfully recovery: by attempting to recover from a fall, crawling to the nearest furniture (chair, sofa, bed) and sitting on the furniture for two minutes before starting to move again; fall without loss of consciousness: by remaining awake (conscious) on the floor and moving, but unable to stand up for three minutes; fall with loss of consciousness: by remaining unconscious on the floor for three minutes.

In mimicking a fall, the participant will not simulate the fall event itself, but will gently lie on the ground (on a sleeping bag) for three minutes.

Each fall event during the trial was recorded on video for further analysis. Events in the PIR and PM sensor signals are annotated using these video recordings.

B. Location tracking

To address the issue of determining if someone has fallen when multiple people are present in the residence, graph theory concepts are used to infer how many people (or groups) are present in the environment, loosely track their movement/location, and monitor them independently for falls. This graph representation is also used to identify when someone leaves the residence.

The tracking algorithm is described in more detail below:

- Active sensors at the current time are grouped into "cliques" based on whether all the sensor activations in the clique (more detailed information can be found in [16]) are attributable to a person or a group of persons.
- At successive time steps, cliques are split, paired or merged, since individuals may walk as a group and then move in different directions as individuals, or move as an individual and subsequently merge into a group.
- It is determined whether any clique from a previous time has not been identified with a clique from the current time.
  - If so, the algorithm determines whether a person has left the apartment unit, or a person has fallen unconscious, or a person may be standing, sitting or lying motionless.
    - If any clique from the previous time step contains a sensor at the entrance to the apartment, then it is assumed that the person represented by the previous clique has left the apartment.
    - If not, the algorithm places the unidentified previous clique onto a "watchlist" and continues using the fall detection decision tree described below. The watchlist contains cliques representing people that are suspected of having fallen.
  - If not, the algorithm continues with the monitoring process.

C. Fall detection

The system monitors for the event where all PIR and PM sensors in a clique are inactive. If at least one of the sensors is active, then it can be concluded that the subject has not experienced a fall event. However, if all sensors are inactive, then one of two possible situations may have occurred: (1) a person has experienced a fall with loss of consciousness, or is unable to move because of a severe injury; or (2) a person is temporarily motionless (but has not fallen) and is not sitting/lying on a PM.

If all sensors in a clique are inactive for more than two minutes (an arbitrary threshold which could be refined), it can be concluded that the subject is not performing normal activities and is not on a sofa or any other furniture. This leads to the assumption that the subject might have experienced a fall. However, if one of the sensors reactivates within two minutes, it can be assumed that the subject has not fallen, but is maintaining a largely motionless posture.

III. Fall Detection Performance

From Table II, the overall accuracy of the system and algorithm is quite improved when combined with a graph theory-based algorithm to identify different people in the residence, giving a total accuracy of 82.86%, versus 42.86%, without identifying different individuals.

IV. Discussion

A. Summary of results

An unobtrusive system for multiple occupancy residences has been designed and tested. A discussion of the results is provided below.

From Table II(a), it is clear that the system incorrectly classifies a fall either with or without loss of consciousness as a normal activity for every scenario performed. This happens primarily because the fall algorithm observes the sensors deactivation period and requires that there can be only one person inside the home, precluding its use in a multiple household (older people and their families).

The algorithm can be improved by incorporating an algorithm that can count the number of persons inside the home.

In Table II(b), the algorithm misclassified falls with successful recovery on six occasions as fall events. The majority of the situations were caused by a failure to identify a resident who might have performed activities in the sensor's blind spot or a person who was motionless long enough before recovering to cause the emergency alert to activate.

In this study, 20 out of 40 simulated falls involved a scenario where the faller is unconscious. As shown in Table II(b), the algorithm correctly detected all falls with loss of consciousness when the fall detection algorithm is augmented with a location tracking algorithm.

The results in Table II(b) also revealed that the system incorrectly classifies a fall where the subject remains conscious and moving as a normal activity on six occasions out of twenty. This happens primarily because the system uses only one sensor to monitor the entire room and does not divide the room into upper and lower sections to identify if the movement is taking place on the floor.

TABLE II: Confusion matrices and accuracy results.

		True		
		Fall	No fall	
Estimated	Fall	0	0	PPV = NaN
	No fall	40	30	NPV = 42.86%
		Sens. = 0.00%	Spec. = 100.00%	Acc. = 42.86%

(a) Confusion matrix of the falls detection system which does not use any graph theory concepts to distinguish the location of multiple persons in the environment.

		True		
		Fall	No fall	
Estimated	Fall	34	6	PPV = 85.00%
	No fall	6	24	NPV = 80.00%
		Sens. = 85.00%	Spec. = 80.00%	Acc. = 82.86%

(b) Confusion matrix of the falls detection system which incorporates graph theory to track subject's location from the patterns of sensor activation.

Sens. = Sensitivity, *Spec.* = Specificity, *PPV* = Positive predictive value, *NPV* = Negative predictive value, *Acc.* = Accuracy.

In our previous work, a similar location tracking algorithm was tested on signals generated by a software simulation of a residential environment. This algorithm was seen to be improved by incorporating two motion sensors to monitor the upper and lower parts of the room [16]. Listed results show a sensitivity of 100.00% and an accuracy of 87.33% for simulated scenarios involving an older person living with one or two family members, when using the upper and lower sensors. It can be seen clearly that the system was able to distinguish correctly all long lie scenarios. The long lie event could be recognized by the system when only sensors monitoring the lower part of room responded to movement of the fallen but conscious individual, while unconscious falls could be identified by the system when all sensors in the room were deactivated. It means that the trial results can be further improved by adapting the proposed system from [16] for the future implementation.

B. Detecting entering and leaving

The system will perform better if it is known how many people are inside the house at any given time. There is a chance that the system could missclassify a fall with loss of consciouness as a normal event if, for example, one person falls and with loss of consciouness while trying to go to the kitchen while another person (an arriving guest) knocks on the entrance door and then leaves the premises when nobody answers. In this case, the proposed algorithm would assume that the occupant has left the house instead of experiencing a fall. This issue could be addressed by placing a switch to deactivate the system near to the entrance door; however, a more robust and automated methods would be preferred.

C. Time threshold

It is important to consider the time period between an emergency alert and the arrival of medical assistance. A retrospective study based on data collected from the South Australian Ambulance Service revealed that the typical response times for acceptable medical care would be between five and fifteen minutes [20]. In the system described here, the time threshold is set to two minutes, which would facilitate this quick response, but may induce a larger number of false alarms (reduced specificity). Obviously this threshold could be optimized to balance costs associated with the number false alarms raised against the number of falls missed and response time of first aiders.

V. Conclusion

One of the main advantages when comparing ambient sensors to wearable sensors is that ambient sensor approaches makes no assumption about subject compliance and adherence, in terms of attaching and wearing a device.

The reliability of unobtrusive monitoring systems depends on many factors, including the hardware configuration, the number of sensors and the placement of these sensors.

Indeed the results revealed here are less accurate when comparing them to wearable sensor solutions, but still the achieved results demonstrates a proof-of-principle that ambient sensor devices can be used to distinguish many abnormal or dangerous events, such as falls, from normal daily activities.

In a future trial, to solve the problem of the person continuing to move after falling, the potential effectiveness of using two PIR sensors at each location (which monitor the upper and lower halves of the room) could be investigated.

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