Testing Non-Wearable Fall Detection Methods in the Homes of Older Adults

Marjorie Skubic, *Senior IEEE Member*, Bradford H. Harris, Erik Stone, *IEEE Member*, K.C. Ho, *Fellow, IEEE*, Bo-Yu Su, *Student Member, IEEE,* and Marilyn Rantz, *IEEE Member*

***Abstract*— In this paper, we describe two longitudinal studies in which fall detection sensor technology was tested in the homes of older adults. The first study tested Doppler radar, a two-webcam system, and a depth camera system in ten apartments for two years. This continuous data collection allowed us to investigate the real-world setting of target users and compare the advantages and limitations of each sensor modality. Based on this study, the depth camera was chosen for a current ongoing study in which depth camera systems have been installed in 94 additional older adult apartments. We include a discussion of the different sensor systems, the pros and cons of each, and results of the fall detection and false alarms in the older adult homes.**

I. Introduction

Falls continue to be a major challenge for older adults and are often the reason they leave their home for assisted living or skilled nursing home facilities. In the U.S., about one out of every three older adults (aged 65 and above) falls each year [1]. These falls may result in serious injuries which further contribute to loss of mobility and independence, especially if the faller is not found promptly [1-2]. Older adults who live alone are especially prone to delayed help in the case of falls. An automated fall detection and alert system would provide needed assurance and timely help to the older adult.

Because of the importance of fall detection, there has been much work using a variety of approaches. For example, commercial pendants contain a call button that seniors can press when in trouble. However, many seniors refuse to wear the pendants; others will not press the button even if they fall, or they may be unable to press the button as a result of the fall. Other commercial systems are available which use accelerometers to automatically detect falls, either incorporated into the pendant or worn elsewhere. These, too, have shown problems [3]. One study testing a commercial system showed the difference between lab results and results in real world settings [4]. Although the company reported results of 94% sensitivity and 92% specificity, an independent study with 18 participants for 4 months showed much worse results. Of the 84 fall alarms reported, 83 were false alarms, and three actual falls were missed. Eight additional falls occurred when participants were not wearing the device; four of these occurred during charging of the device. Participants also had difficulties in managing the devices. Only eight participants completed the 4 months. Recent research has investigated new methods for wearable fall detection sensors [5, 6], but these, too, will have to overcome challenges of robust fall detection in the real world.

Non-wearable sensing embedded in the environment has also been studied for fall detection. These systems eliminate compliance issues because they are always on; there is no need to charge devices or remember to put something on. Various sensing modalities have been investigated, including camera [7-9], radar [10-12], depth camera [13-15], depth camera with acoustic sensing [16], and depth camera with wearable accelerometer [17]. Many of these studies report very good results; however, most have limited datasets for testing which have been compiled with young healthy volunteer participants.

The work of others, as well as our own longitudinal studies have shown that falls performed by younger adults are not the same as older adult falls, especially those which happen in natural home environments. Studies confirm this with accelerometer data; younger participants tend to compensate for the falls in a way that older adults cannot [18, 19]. Our own studies with non-wearable sensors illustrate this too. Older adults that are at risk of falling walk differently, use different standing postures, and may have slower downward movement with multiple hit points as they try to grab onto something (e.g., furniture) to break the fall. Thus, collecting data with real older adults in their homes is important to better understand the challenges of automated fall detection.

In this paper, we discuss two longitudinal studies performed with older adults in their homes. Section II reviews a two-year study in ten apartments, testing radar, webcam, and depth sensing. A discussion is included on the advantages and limitations of each. Section III describes an ongoing study in 94 homes using depth sensing for fall detection. We present results on actual older adult falls detected as well as false alarms. A discussion of the remaining challenges is included with suggestions for future work. We conclude in Section IV.

II. Comparing Radar, Webcams, and Depth Sensing

A. Study Overview

Three different fall detection systems were installed in the apartments of older adults, which included Doppler radar, a 2-webcam system, and a depth camera system (Microsoft Kinect). Participants were recruited from TigerPlace, an aging in place senior housing site in Columbia, MO. The IRB-approved protocol called for two years of continuous data collection in 10 apartments. Some participants withdrew from the study due to leaving TigerPlace, and others were recruited. The total number of participants over the two years was 19 older adults (9 men, 10 women) in 16 apartments; 3 apartments had couples. The average age at installation was 87.

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M. Skubic, B. Harris, K.C. Ho, B.-Y. Su, and M. Rantz are with the University of Missouri, Columbia, MO (skubicm@missouri.edu). E. Stone was with the U. of Missouri. He is now with Foresite Healthcare.

(a)

(b)

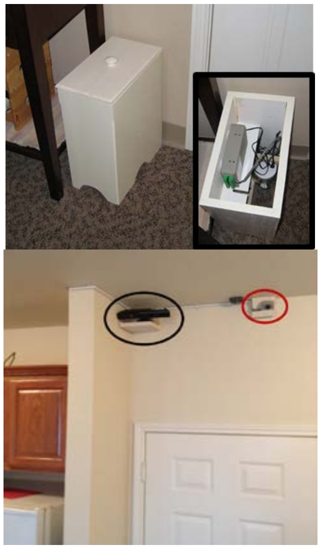

Fig. 1. In-home fall detection sensors. (a) Doppler radar installed in a wooden box; insert photo shows the contents. The attic radar system contained the same components, (b) webcam (circled in red) and Microsoft Kinect (circled in black) installed on a wall above the front door with a view of the main living area; these had wired connections to a computer located in the cabinet above the refrigerator (on the left)

The fall detection study was part of a larger study investigating automated methods of fall risk assessment using the same embedded sensing systems [20], designed to be as unobtrusive as possible (Fig. 1). Stunt actors visited the apartments each month to perform falls that were used for training and testing fall detection algorithms. To make the stunt falls as realistic as possible, stunt actors were trained in 21 different types of falls typical of seniors, including from standing, sitting, and reclining positions [21]. Stunt actors also followed a protocol designed to stress the detection system by including movements that might trigger a fall detection, such as bending over to pick up objects on the floor and stretching on the floor. One of the older adult participants fell several times during this period; these naturally occurring falls were also included. The study captured an accurate representation of the noisy home environment for older adults and thus, serves as an exceptional testbed for investigating false alarms.

B. Fall Detection Methods

Our fall detection methods have been reported elsewhere. Here, we offer a brief overview. The Doppler radar system consisted of a commercially available pulse-Doppler range control radar, modified for access to the analog signal [22]. The radar sends out pulses with a carrier frequency of 5.8 GHz, at a duty cycle of 40% and a repetition rate of 10MHz. The reflected radar return was digitized by sampling at 960 Hz, using a commercial data acquisition unit. Radar units were first deployed on the ground as in Fig. 1(a) in order to capture gait as well as falls. Later, 3 radar units were installed in the attic looking down. The Doppler radar system captures motion in the direction towards and away from the sensor. The attic sensor was found to provide better detection of the downward motion of falls. The detection methods consist of a prescreener based on wavelet coefficients at dyadic scale 4 to locate possible falls and a second phase using 6 levels of a Discrete Stationary Wavelet Transform and a nearest neighbor classifier to detect falls [22].

The webcam system used two inexpensive webcams at 640x480 resolution installed on orthogonal walls [7]. Silhouettes of moving bodies were extracted from each view using background subtraction methods, and then projected into the 3D voxel space with a 1-inch cubed voxel (2.54cm cubed) [23]. The voxels of the intersection formed a 3D model of a person in the scene. Falls were detected by tracking a person as being upright, on the ground, or in-between and then computing features to describe a transition to on-the-ground, e.g., speed and acceleration [7]. A set of fuzzy rules generated a fall confidence. Due to the computational load of extracting silhouettes, building a 3D voxel model, and performing fall detection, the method was implemented on a GPU to provide real time operation at 5 frames per second.

The Kinect depth camera was used for the third method. Due to the size of the apartments monitored, the depth images were used directly; skeletal data was not accurate or stable at the extended distance (7-10 m). Similar to the webcam system, background subtraction was used to extract and track moving bodies in depth images. The system first detects on the ground events and then uses an ensemble of decision trees and features to generate a confidence that a fall occurred. The system operates at 7.5 frames per second. See also [24] for details.

C. Results

Each of the sensing methods was evaluated separately to assess performance in naturalistic older adult homes. We present results of an attic radar above the living room in one apartment over a 10-day period, in which 13 actual falls occurred by the older adult participant, a 74-year-old women with a large cat that also lived in the apartment. The system was trained with stunt fall data collected by a radar unit located in the attic above the bathroom area. At a 90% fall detection rate, the system generates 1 false alarm per day (a rate of 30 false alarms per month). At 100% detection, the system generates 16 false alarms over the 10-day period (a rate of 49 false alarms per month). Among the false alarms, 11 were from non-human activity, e.g., the cat, 1 from random noise, 2 from adjusting the height of a chair, 1 from standing up quickly, and 1 from bending over to pick up an object. See also [22].

The webcam system was tested on a dataset of three months of data from ten apartments (300 days) with 162 falls total from the stunt actors. Of these falls, 90% were detected with a false alarm rate of 15 per month. For a 95% detection rate, the false alarm rate was 25 per month. These represent very naturalistic scenes with pets, cleaning staff, clinical staff, and other visitors entering at unpredictable times, which provides a thorough test in realistic living environments.

The Kinect depth sensing system had the most rigorous test. Results are outlined in detail in [24] for 13 apartments with 16 participants, 3,339 days of continuous data, and 454 falls (445 stunt falls and 9 naturally occurring falls from four older adults). Several apartments had pets; all had cleaning staff, clinical staff and other visitors that entered the apartments. For falls that occurred within 4 m of the sensor and were not significantly occluded, the detection rates, at 1 false alarm per month, are 98% for standing falls, 70% for sitting falls, and 71% for falls from a reclining position. For falls occurring more than 4 m from the sensor, the detection rates at 1 false alarm per month are 79% for standing falls, 58% for sitting falls, and 5% for reclining falls.

Of the 9 naturally occurring falls, 7 were standing falls and 2 were sitting falls. All but one of the standing falls (including three greater than 4m from the sensor) would have been detected at a false alarm rate of 4.6 per month. The exception was a fall that occurred at 5.5m in front of a window; sunlight blocked the depth measurements. The two sitting falls were not detected due to significant occlusion.

D. Discussion

Each of the fall detection modalities has advantages and limitations. We first discuss vision-based vs. non-vision-based (radar). Both vision-based systems suffer from potential occlusion problems, whereas the radar system can sense through structural elements. The vision-based systems have lighting issues; the webcam system is especially affected by changing lighting conditions. In contrast, the radar system is not affected by lighting level or lighting changes. However, the vision systems offer a view of what happened leading up to the fall and also provide a mechanism for confirming that a fall really did occur. The radar system does not provide this capability. The radar system had the worst performance but also had the least amount of training data (from the attic). More training data should improve performance. The Doppler radar method detects motion in the direction towards or away from the sensor. Thus, a radar device mounted on the ceiling or attic is more effective at detecting downward motion.

Between the webcam and depth sensing systems, the webcam system requires considerably more computational power and calibration of the two-camera system, whereas the Kinect depth camera is a single device that can be used with a small computer and can more easily be run at a higher frame rate. Although both systems can be affected by lighting, the webcam system provides more challenges, as it is particularly affected by sudden changes in lighting, e.g., when someone turns on a light. Additional time is required for the system to re-acquire a background model so that moving people can be segmented. The webcam system also needs adequate visible light or could be used in the dark if infrared emitters were added. The depth sensor can sense in the dark without added emitters and is not affected by sudden lighting changes. However, it can be affected by too much natural sunlight.

As a result of this study, we decided to use the depth sensor going forward with future studies. Although occlusions are still a potential problem, the ability to see what happened leading up to the fall and the ability to confirm that a fall really happened was deemed more useful. Due to the variability in the older adult falls, including slow-moving falls, we concluded that the fall detection threshold may have to be set very low for some individuals with high fall risk, even if false alarms result. We incorporated a live fall detection system with fall alerts that include a link to a depth video of the fall [25]. These can be delivered via email or text message. The link allows the receiver to easily view the depth video to determine whether this is a real fall or a false alarm. Several examples of these short depth videos of real older adult falls can be viewed at https://www.youtube.com/watch?v=TFB7YOUmHho.

III. Ongoing Longitudinal Study with Depth Sensing

A. Study Overview

As part of a longitudinal study to investigate the use of in-home sensors for early detection of health changes, depth sensors (Microsoft Kinect) were installed in additional senior apartments. These ongoing, IRB-approved studies are run with rolling enrollments; as participants drop out due to death or leaving the housing site, new participants are recruited. In total, 43 Kinect systems have been installed in TigerPlace apartments, and 67 Kinect systems in other senior housing.

B. TigerPlace Case Study Results

We first present results from one TigerPlace apartment with a separate bedroom. The Kinect fall detection system was mounted on the wall in the main living area as shown in Fig. 1(b). The resident is a single woman, aged 75 who lives with a cat. She has frequent visitors, many of whom are staff. Results are reported over 601 days. During this time, fall alerts were live with links to short depth video clips of the detected falls. During the 601 days, 217 fall alerts were generated; 142 were actual falls and 75 were false alarms. The fall videos were reviewed to examine the source of the false alarms, shown in Table I. Because of her frequent falls, the fall confidence threshold was changed after 109 days to avoid missing any falls. The higher threshold resulted in 29 detected falls with a false alarm rate of 2.4/month. The lower threshold resulted in 113 detected falls with a false alarm rate of 4/month.

The resident uses a walker and sometimes a wheelchair, and sometimes transitions herself between a wheelchair and other furniture in the home. Due to a neurological condition, she frequently falls but often grabs onto something to slow herself down and soften the fall. This is also evidenced by the fact that she has not broken any bones in spite of many falls.

TABLE I. Case Study False Alarms from Depth Sensing

Days	T**	False Alarm Source in Case Study					
		Person on floor	*Object on floor*	*Pet*	*Other*	*Total*	*FA rate**
109	38%	4	4	0	1	9	2.4
492	18%	15	18	12	21	66	4.0

* False alarm rate per month per person

** Fall confidence threshold used for fall detection

TABLE II. Other Housing False Alarms from Depth Sensing

Days	False Alarm Source in Other Senior Housing						
	Linen	*Res***	*Visitors*	*Pet*	*Other*	*Total*	*FA rate**
10707	230	83	101	70	19	503	1.4

* False alarm rate per month per person

** Resident of the apartment

C. Composite Results in Other Senior Housing

The senior apartments outside of TigerPlace are mostly assisted living studio apartments, with a single room that contains the bed and sitting area. We present composite results from 67 apartments (all residents living alone), with 52 females and 15 males. The period covered about 7 months for a total of 10,707 days (about 352 months). Over this period, 570 fall alerts were generated. Of these, 67 were actual older adult falls and 503 were false alarms for a false alarm rate of 1.4 per month per person. Table II shows the source of the false alarms, again determined by reviewing the fall depth videos. Many of the false alarms were caused by linens being thrown on the floor from the bed. Pets and visitors continue to be a significant source of false alarms.

D. Discussion

The results illustrate the challenges in detecting falls in unstructured home environments. First, older adults fall in unpredictable ways and often much differently than the younger adults used to collect training data for fall detection systems. One of the major challenges observed in our studies is the slow fall, in which older adults try to break their fall by hanging on to furniture or walkers. Thus, the speed and acceleration is less than observed in training data.

At the same time, there are also unpredictable events of visitors, pets, and items on the floor. Pets jump off furniture. Child visitors "throw" themselves onto the floor and adult visitors sit or lie down on the floor. Because these can be difficult to distinguish from older adult falls, it is helpful to have the fall alerts with links to short depth videos showing the detected fall. In this way, care providers can quickly and easily click on the link to observe whether a real fall has occurred.

In addition, linens and other items are thrown on the floor. As shown in Table II, linens contributed to almost half of the false alarms when the depth camera was placed in the same room as the bed. There is an opportunity here to distinguish inanimate objects from people, to greatly reduce the false alarm rate, e.g., by fusing depth images with other sensor modalities such as thermal imaging. In general, combining sensing modalities may be necessary to improve performance.

The bathroom area remains an open challenge. It is likely that a non-vision-based system like radar will be required due to occlusions. More work on radar fall detection (and more training data) may improve the performance for this setting.

IV. Conclusions

We described two longitudinal studies on fall detection in the homes of older adults. The first tested Doppler radar, a two-webcam system that used silhouettes, and a depth sensing system. The depth system was then selected for testing in a larger study in different types of older adult apartments. Great progress has been made on non-wearable fall detection. However, our experience shows that robust fall detection without false alarms still has significant challenges. Testing these systems in real home environments with older adults is essential for measuring realistic performance.

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References

[1] (2013). Center for Disease Control and Prevention (CDC), "Falls among older adults: An overview," [Online]. Available: http://www.cdc.gov/homeandrecreationalsafety/Falls/adultfalls.html

[2] M.E Tinetti, W.L. Liu, and E.B. Claus, "Predictors and prognosis of inability to get up after falls among elderly persons," *J. Amer. Med. Assoc.*, vol. 269, no. 1, pp. 65-70, 1993.

[3] L. Lipsitz, A. Tchalla, I. Iloputaife, M. Gagnon, K. Dole, Z. Zhong, and L. Klickstein, "Evaluation of an Automated Falls Detection Device in Nursing Home Residents," *J. Amer. Geriatrics Soc.*, vol. 64, pp. 365-368, 2016.

[4] S. Chaudhuri, D. Oudejans, H. Thompson and G. Demiris, "Real-World Accuracy and Use of a Wearable Fall Detection Device by Older Adults," *J. Amer. Geriatrics Soc.*, vol. 63, no. 11, pp. 2415-2416, 2015.

[5] G. Korats, J. Hofmanis, A. Skorodumovs, and E. Avots, "Fall detection algorithm in energy efficient multistate sensor system," *Proc., IEEE Eng. in Med. and Biology Soc. Conf.*, 2015, Milan, Italy, pp. 4974-4977.

[6] F. De Cillis, F. De Simio, F. Guido, R.A. Incalzi and R. Setola, "Fall Detection Solution for Mobile Platforms Using Accelerometer and Gyroscope Data," *Proc., IEEE Eng. in Med. and Biology Soc. Conf.*, 2015, Milan, Italy, pp. 3727-3730.

[7] D. Anderson, R.H. Luke, J. Keller, M. Skubic, M. Rantz, and M. Aud, "Linguistic summarization of activities from video for fall detection using voxel person and fuzzy logic," *Computer Vision and Image Understanding*, vol. 113, no. 1, pp.80–89, 2009.

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

[9] G. Debard, G. Baldewijns, T Goedeme, T. Tuytelaars and B. Vanrumste, "Camera-based fall detection using a particle filter," *Proc., IEEE Eng. in Med. and Biology.*, 2015, Milan, Italy, pp. 6947-6950.

[10] C. Garripoli et al. "Embedded DSP-Based telehealth radar system for remote In-door fall detection," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 1, pp. 92-101, Jan. 2015.

[11] A. Gadde, M. G. Amin Y. D. Zhang, and F. Ahmad, "Fall detection and classification based on time-scale radar signal characteristics," in *Proc. SPIE*, Baltimore, May 2014.

[12] M. G. Amin, Y. D. Zhang, and B. Boashash, "High-Resolution Time-frequency Distributions for Fall Detection," in *Proc. SPIE*, Baltimore, May 2015.

[13] G. Mastorakis and D. Makris, "Fall detection system using Kinect's infrared sensor," *J. of Real-Time Image Proc.*, 2012.

[14] R. Planinc and M. Kampel, "Introducing the use of depth data for fall detection," *Personal & Ubiq Comp*, vol. 17, pp. 1063-1072, 2012.

[15] X. Ma, H. Wang, B. Xue, M. Zhou, B. Ji and Y. Li, "Depth-based human fall detection via shape features and improved extreme learning machine," *IEEE J of Biomed. and Health Informatics*, vol. 18, no. 6, pp. 1915-1922, 2014.

[16] Y. Li, K.C. Ho and M. Popescu, "Efficient Source Separation Algorithms for Acoustic Fall Detection Using a Microsoft Kinect," *IEEE Trans. on Biomed. Eng.*, vol. 61, no. 3, pp.745-755, 2014.

[17] M. Kepski and B. Kwolek, "Detecting human falls with 3-axis accelerometer and depth sensor," *Proc., IEEE Eng. in Med. and Biology Soc. Conf.*, 2014, Chicago, IL, pp. 770-773.

[18] M. Kangas, I. Vikman, L. Nyberg, R. Korpelainen, J. Lindblom and T. Jamsa, "Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects," *Gait & Posture*, vol. 35, pp. 500-505, 2012.

[19] J. Klenk, C. Becker, F. Lieken, S. Nicolai, W. Maetzler, W. Alt, W. Zijlstra, J.M. Hausdorff, R.C. van Lummel, L. Chiari and U. Lindemann, "Comparison of acceleration signals of simulated and real-world backward falls," *Med Eng. & Physics*, vol. 33, pp. 368-373, 2011.

[20] M. Rantz, M. Skubic, C. Abbott, C. Galambos, M. Popescu, J. Keller, E. Stone, J. Back, S.J. Miller and G.F. Petroski, "Automated In-Home Fall Risk Assessment and Detection Sensor System for Elders," *The Gerontologist*, vol. 55, no. S1, pp. S78-S8.

[21] M. Rantz, M. Aud, G. Alexander, B. Wakefield, M. Skubic, R.H. Luke, D. Anderson, and J.K. Keller, "Falls, Technology, and Stunt Actors: new Approaches to Fall Detection and Fall Risk Assessment," *J Nursing Care Quality*, vol. 23, no. 3, pp.195-201, 2008.

[22] B.Y. Su, K.C. Ho, M. Rantz and M. Skubic, "Doppler Radar Fall Activity Detection Using the Wavelet Transform," *IEEE Trans on Biomedical Eng*, vol. 62, pp. 865-875, 2015.

[23] E.E. Stone and M. Skubic, "Silhouette Classification Using Pixel and Voxel Features for Improved Elder Monitoring in Dynamic Environments," *Proc, IEEE Intl Conf on Pervasive Computing and Comm. Workshops*, Seattle, WA, March 21-25, 2011, pp 655-661.

[24] E. Stone and M. Skubic, "Fall Detection in Homes of Older Adults Using the Microsoft Kinect," *IEEE J of Biomed. and Health Informatics*, vol. 19, no. 1, pp. 290-301, 2015.

[25] E. Stone and M. Skubic, "Testing Real-Time In-Home Fall Alerts with Embedded Depth Video Hyperlink," *Proc., Intl. Conf. on Smart Homes and Health Telematics*, 2014, Denver, CO.