Testing Real-Time In-Home Fall Alerts with Embedded Depth Video Hyperlink

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Abstract. A method for sending real-time fall alerts containing an embedded hyperlink to a depth video clip of the suspected fall was evaluated in senior housing. A previously reported fall detection method using the Microsoft Kinect was used to detect naturally occurring falls in the main living area of each apartment. In this paper, evaluation results are included for 12 apartments over a 101 day period in which 34 naturally occurring falls were detected. Based on computed fall confidences, real-time alerts were sent via email to facility staff. The alerts contained an embedded hyperlink to a short depth video clip of the suspected fall. Recipients were able to click on the hyperlink to view the clip on any device supporting play back of MPEG-4 video, such as smart phones, to immediately determine if the alert was for an actual fall or a false alarm. Benefits and limitations of the technology are discussed.

Keywords: fall detection; fall alerts; Kinect

1 Introduction

The Center for Disease Control and Prevention states that one out of three older adults (those age 65 and older) falls each year [1]. Of those who fall, many suffer serious injuries which reduce their mobility and independence. The direct medical cost of falls among older adults in the United States in the year 2000 was over $19 billion [2], and this cost does not account for the decreased quality of life many individuals experience after suffering a fall. Beyond the injuries and costs incurred as a result of the fall itself, studies have also found an increased risk of physical and physiological complications associated with prolonged periods of lying on the floor following a fall, due to an inability to get up [3]. Older adults living alone, or in independent settings, are at great risk of delayed assistance following a fall.

Many methods for reporting or detecting falls have been developed. This includes wearable devices, such as manual push buttons and automatic fall detection systems based on accelerometers [4, 5]. However, wearable devices must be continuously worn, may be forgotten, and require battery changes or charging. Studies have also indicated a preference for non-wearable sensors among older adults [6]. For these reasons, many researchers have investigated the use of environmentally mounted sensors, such as passive infrared (PIR) sensors [7], acoustic sensors [8], and video-based sensors [9-13], among others. Although privacy is always a concern with video-based sensors, studies have found that privacy concerns may be alleviated by use of appropriate privacy preserving techniques such as the use of silhouettes [14].

This work investigates the use of a fall detection system (described in [15]) that uses an inexpensive depth imaging sensor, the Microsoft Kinect, to send real-time email-based fall alerts to staff members of a senior housing facility. Each alert contains basic information about the suspected fall, such as time and location, as well as an embedded hyperlink to a short depth video clip viewable on smart phones carried by staff members. The video clip allows recipients to immediately determine whether the alert corresponds to an actual fall, or a false alarm, without the need to go physically investigate the alert, significantly reducing the cost of false alarms and unnecessary disturbances.

2 Related Work and Motivation

Few automatic fall detection systems have undergone significant, real-world, real-time testing in older adult housing. In [21], the authors evaluated a custom vest with an attached tri-axial accelerometer in a nursing home. The vest was worn by 10 elderly subjects for 8 hours a day, 6 days a week, for approximately 4 weeks. In total 833 hours of monitoring was recorded. Alert messages were sent to a care-taker terminal. A total of 42 fall alerts were generated; however, no actual falls were reported, yielding an overall false alarm rate of 1.2 per day for the vest. Feedback from subjects and staff indicated they did not appreciate the vests in their current form, stating they were uncomfortable and bulky.

In a recently published study [22], the authors used previously recorded acceleration data on a set of high fall risk patients to evaluate 13 published acceleration-based fall detection algorithms. The data contained 29 actual falls of older adults that were used for analysis. Results indicated that the algorithms performed worse in terms of sensitivity and specificity as compared to what was originally reported on simulated data. Mean sensitivity was 57 percent, with a maximum of 83 percent. Additionally, the number of false alarms generated during 24 hours (based on three representative fallers) ranged from 3 to 85.

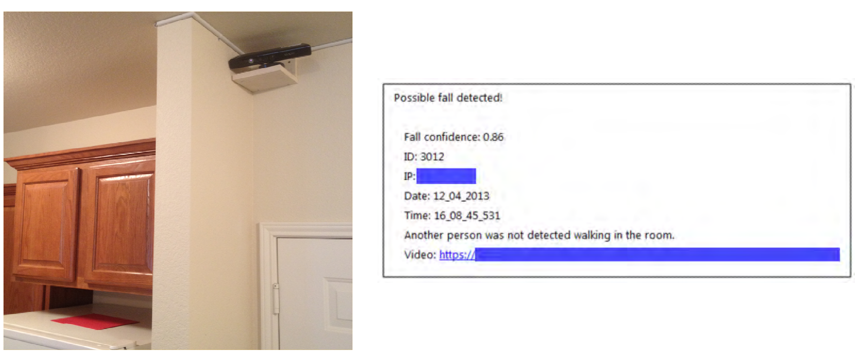
As with other sensing technologies, a number of methods for fall detection using the Microsoft Kinect sensor have been published [15-20]. Although all these studies show encouraging results, the major limitation of most is the lack of sufficient (if any) evaluation in real-world settings. In [15], the authors compared their method to five previously published methods [12, 17-20] developed and evaluated using laboratory data. All six methods were evaluated on a combined 9 years (80,939 hours) of previously recorded depth data collected in 13 actual older adult apartments. The data contained 445 falls performed by trained stunt actors and 9 real falls. All five previously published methods performed worse than originally reported, generating many false alarms at relatively low detection rates. This is not surprising given the wide range of conditions and issues that occur in complex, dynamic, real-world settings, which make it virtually impossible to create a realistic data set in the lab.

Although the fall detection method described in [15] was developed and evaluated on 9 years of previously recorded real-world data, further real-time evaluation of the system is critical for a number of reasons, including: 1) to better assess performance on real falls, 2) to get feedback from facility staff, and 3) to further assess performance in untrained settings. The previously recorded data almost exclusively contained stunt actor falls. Only 9 falls (less than 2 percent) were real falls. System performance (detection rate vs. false alarm rate) could be significantly different on only real falls. Additionally, real-time evaluation, in which alerts are actually sent to caregivers, is the only way to assess the perceived benefits and costs of the system by end users. If the perceived benefits are low and costs high, it will not be used. Finally, testing in new, untrained settings will help determine whether the previously recorded data is sufficient, or whether additional training may be necessary in new settings.

3 Methodology

Fig. 1a shows the Kinect sensor installed in one apartment included in the study. The Kinect is placed on a small shelf a few inches below the ceiling (height 2.75 meters), above the front door. A small computer (Acer Veriton N2620G) is placed in a cabinet above the refrigerator. Readers are referred to [15] for a description of the fall detection algorithm and system operation.

A fall confidence is computed for each possible fall event identified by the algorithm in [15] within 6-8 seconds of the initial event trigger. The confidence is immediately compared against an alert threshold (specified individually for each apartment), and if the confidence is greater than or equal to the alert threshold an email alert is generated and sent to a list of recipients defined in a configuration file. A sample email-based fall alert is shown in Fig. 1b. The alert contains basic information regarding the suspected fall, including: fall confidence, the research ID



(a) **(b)**

Fig. 1. (a) Kinect and computer (inside cabinet) installed in an apartment. (b) Sample email-based fall alert with embedded hyperlink to depth video clip of the suspected fall.

associated with the apartment, the IP address of the system, the date and time the fall occurred, and whether another individual was detected walking in the room during (or immediately following) the fall. In addition, a hyperlink to a 10 second depth video clip centered on the fall impact is embedded in the alert. The depth video clip can be viewed, following secure password authentication, on any device supporting playback of MPEG-4 video. This includes smart phones carried by staff members while in the facility, as well as laptop or desktop computers. Selected frames from two depth video clips of alerted falls are shown in Fig. 2.

Alert 1:

Alert 2:

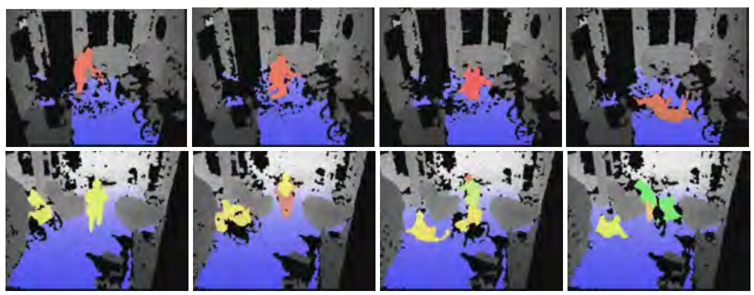


Fig. 2. Selected frames from two depth video clips. Ground is shaded blue, while foreground objects are shaded yellow, red, and/or green, based on segmentation and distance.

4 Evaluation

As part of an IRB approved study, a Kinect sensor and computer where installed in the main living area (in a similar fashion as shown in Fig. 1) of 12 apartments in a senior housing facility. Ages of the 14 residents ranged from 68 to 98 and 6 were male. Informed consent was obtained from all. Tables I and II contain alert and real fall statistics for the apartments for two time periods totaling 101 days. The first time period covers the initial 41 days when alerts were active. The second time period, beginning October 2, 2013, covers the final 60 days. At approximately midnight on the evening of October 1, 2013, an updated version of the fall detection model was installed on each system.

The original fall model was trained on 9 years of data collected in 13 apartments during 2012, which included Apartments 1-6 and 9-10 from this study. The updated fall model was obtained by adding two months (July and August, 2013) of data from Apartment 8 to the original training data, and then retraining the model. The additional data contained no falls, but a number of false alarms caused by dogs jumping off furniture. As no similar data points existed in the original data, these lead to a high number of false alarms in Apartment 8 during the initial 41 day period.

A total of 21 falls occurred in the main living area across all apartments during the initial 41 day period. In addition to the alerts, falls in the main living area were identified by cross checking incident reports filled out by staff members after responding to a fall, or having a resident report a fall, with the depth video from the apartment (if available). Despite best efforts to track falls, it is possible that additional falls exist in the data. Of the 21 total falls, 19 were declared detectable. That is, the fall occurred in view of the Kinect, and occurred when the system was operational. Of the 19 detectable falls, 15 triggered an alert email, yielding a combined alert rate of 79 percent. Meanwhile, 28 false alarms were sent during this period across all apartments, yielding a combined false alarm rate of 1.83 per month per apartment.

TABLE I

Main Living Area, Aug. 22, 2013 – Oct. 1, 2013, 41 days, Original fall model

Ap. #	Up Time (Days)	Alert Threshold	Target FA rate (FA/month)[1]	Total Falls[2]	Detectable Falls[3]	Alerted Falls	Missed Falls[4]	Alert Rate[5]	False Alarms	FA rate (FA/month)[6]
1	41	0.55	1.0	0	0	0	0	--	0	0.00
2	41	0.55	1.0	0	0	0	0	--	4	2.97
3	41	0.55	1.0	0	0	0	0	--	0	0.00
4	32	0.55	1.0	0	0	0	0	--	1	0.95
5	41	0.55	1.0	0	0	0	0	--	0	0.00
6	41	0.55	1.0	0	0	0	0	--	2	1.48
7	41	0.55	1.0	0	0	0	0	--	0	0.00
8	33	0.55	1.0	0	0	0	0	--	7	6.45
9	32	0.55	1.0	0	0	0	0	--	0	0.00
10	41	0.45	2.0	2	2	1	1	0.50	3	2.23
11	41	0.45	2.0	5	5	3	2	0.60	4	2.97
12	40	0.45	2.0	14	12	11	1	0.92	7	5.32
Total	**465**	--	--	**21**	**19**	**15**	**4**	**0.79**	**28**	**1.83**

TABLE II

Main Living Area, Oct. 2, 2013 – Nov. 30, 2013, 60 days, Updated fall model

Ap. #	Up Time (Days)	Alert Threshold	Target FA rate (FA/month)[1]	Total Falls[2]	Detectable Falls[3]	Alerted Falls	Missed Falls[4]	Alert Rate[5]	False Alarms	FA rate (FA/month)[6]
1	60	0.55	1.0	0	0	0	0	--	0	0.00
2	55	0.55	1.0	0	0	0	0	--	0	0.00
3	54	0.55	1.0	0	0	0	0	--	0	0.00
4	24	0.55	1.0	0	0	0	0	--	0	0.00
5	60	0.55	1.0	0	0	0	0	--	0	0.00
6	60	0.55	1.0	0	0	0	0	--	1	0.51
7	60	0.55	1.0	0	0	0	0	--	0	0.00
8	55	0.55	1.0	0	0	0	0	--	2	1.11
9	32	0.55	1.0	1	0	0	0	--	0	0.00
10	48	0.45	2.0	1	1	0	1	0.00	1	0.63
11	54	0.35	3.0	4	4	4	0	1.00	8	4.51
12	60	0.35	3.0	26	21	15	6	0.71	2	1.01
Total	**622**	--	--	**32**	**26**	**19**	**7**	**0.73**	**14**	**0.68**

[1] Approximate. Determined from cross validation results in [15].

[2] Includes falls identified by cross checking incident reports filled out by staff members with depth video from apartments.

[3] Excludes falls outside Kinect field of view and falls that occurred while system was not operational.

[4] Calculated as detectable falls minus alerted falls.

[5] Calculated as alerted falls divided by detectable falls.

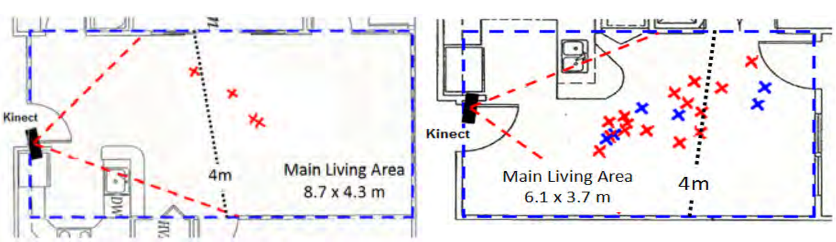
[6] Calculated as (365/12) multiplied by the number of false alarms divided by up time (in days).

During the final 60 day period, a total of 32 falls occurred in the main living area across all apartments. Of the 32 falls, 26 were declared detectable. Of the 26 detectable falls, 19 triggered an alert email, yielding a combined alert rate of 73 percent. Meanwhile, 14 false alarms were sent, yielding a combined false alarm rate of 0.68 per month per apartment.

4.1 Apartments 11 and 12

Apartment 11 had two residents, one of whom is a relatively frequent faller and used an assistive walking device on a regular basis when moving around the apartment. Over the final 60 day period (with the updated fall model in place), this resident suffered 4 detectable falls in the main living area, all of which were alerted. Of the 4 falls, 3 were standing falls that occurred after the resident bent over to pick something up off the floor, and 1 was a sitting fall that occurred when the resident attempted to get up from a wheel chair. Of the 8 false alarms sent during the final 60 days, 2 were the result of children dropping to the floor while playing, and 6 were the result of items being dropped or placed on the floor by the residents or staff. A retrospective analysis found that all falls would have been alerted at a false alarm rate of roughly 2.5 false alarms per month. Fig. 3a shows the floor plan of Apartment 11, along with the position of the Kinect and its field of view, and the location of the alerted and not alerted but detectable falls (all falls were alerted).

Apartment 12 had a single resident who is a very frequent faller and used an assistive walking device almost exclusively when moving around her apartment. Over the final 60 day period, this resident suffered 21 detectable falls in the main living area, 15 of which were alerted. Of the 21 falls, all were standing falls that occurred while the resident was using her walker. The 2 false alarms sent during the final 60 day period were both caused by staff members placing or moving large items on the floor. A retrospective analysis found that all falls would have been alerted at a false alarm rate of roughly 23 false alarms per month. Fig. 3b shows the floor plan of Apartment 12, with the position of the Kinect and the location of the alerted and not alerted but detectable falls.



(a) **(b)**

Fig. 3. Floor plan of (a) Apartment 11 and (b) 12. Position, field of view, and 4 meter distance reference for Kinect are overlaid, along with location of alerted (red +) and not alerted (blue x) detectable falls during final 60 day period. Dashed blue rectangle covers main living area.

6 Discussion

Kinect-based fall detection systems installed in 12 older adults' apartments successfully sent real-time fall alerts via email to facility staff members. Results over a 101 day period showed an overall alert rate of roughly 75 percent with a false alarm rate of 1 per month per apartment. It should be noted that no data from Apartments 7, 11, or 12 were ever used to train the fall detection system. In these apartments, a total of 21 false alarms were generated. Given the target false alarms rates, 20 false alarms would have been expected. Although the false alarms were somewhat unequally distributed among the apartments, the results indicate that the previously recorded data from [15] is likely sufficient training data for many senior housing settings. However, inclusion of additional unique false alarms (such as dogs jumping off furniture) could likely improve performance in certain cases.

Better results (a higher alert rate at a lower false alarm rate) could almost certainly have been achieved by training on a few of the real falls from Apartment 12, due to the fact they tended to differ considerably from the falls in the training data. During these falls, the resident typically used her walker as a point of support, leading to significantly reduced vertical velocity and acceleration compared to falls in the training data. Although the training data contained sitting falls, none of the falls in the training data involved individuals using a walker, or using any object as a point of support during a standing fall. The seven missed falls in Apartment 12 were largely due to this issue, in combination with partial occlusion by the walker in some cases.

Feedback from staff members was quite positive. The embedding of a hyperlink to a depth video clip of the suspected fall (that could be viewed on a smart phone) was seen as a major benefit over other approaches. Removing the need to physically investigate false alarms significantly reduces the costs, both in terms of time and frustration, associated with false alarms for staff members and residents. Staff members could potentially review 10 to 15 video clips in the time it would take to physically investigate a single alert, depending on a facility's size. Out of 76 alerts sent, there was not a single case in which it was not obvious to all recipients whether the alert was for an actual fall or a false alarm. There was some desire to operate at a higher false alarm rate, perhaps upwards of 5 per month per apartment, to achieve higher alert rates. The videos also provide a record of what happened before the fall, which creates new opportunities for fall analysis and prevention strategies in senior living facilities. Meanwhile, the use of only depth video, and not traditional color video, helps preserve the privacy of users.

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