Non-intrusive Bedside Event Recognition Using Infrared Array and Ultrasonic Sensor

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Abstract. Falls in hospitals, in residential care facilities and in home of elderly commonly occur near the bed. Recognizing bedside events may give caretakers the opportunity to intervene, thereby preventing a fall from happening. Most approaches today either use cameras which invade privacy, or sensor devices attached to bed. In this paper an experimental approach for recognizing bedside events using a ceiling mounted 60 × 80 longwave infrared array combined with an ultrasonic sensor device is presented. This novel approach makes it possible to monitor activity while preserving privacy in a non-intrusive manner.

Keywords: Bedside event detection · Fall detection · Longwave infrared array · Ultrasonic sensor · Decision tree

1 Introduction

Investigations into where falls happen done by the Public Health Agency of Canada shows that around 20 % of all registered falls occur in hospital or intervention settings [1, 2]. These falls happen to people that already has problems, either cognitively or physically, and amplifies to the already complicated situation. This increase the healthcare costs not only for the hospitals, but also for the patients and their family [3]. Most falls in nursing homes occur in the resident's room, especially during attempts to get in or out of bed [6, 7, 11, 19]. This is also true in a hospital setting [6, 12, 19].

Systems using sensors attached to the body [9], bed [8] and floor [7] exist in the market despite the lack of evidence that such equipment reduce the number of falls or severity of falls [13–15]. The presence of multiple bed exit alarm devices in the market is however evidence that clinicians are searching for methods to alert them to patients or residents trying to get out of bed so that they might be able to intervene with the hope of possibly preventing a fall.

Bedside event recognition systems are one approach being employed clinically, and trialed in research to provide staff with warning that patients with increased risk of falls (often older patients with cognitive impairment and multiple comorbidities) are about to get up from the bed or chair without the required supervision or assistance [9]. How effective in terms of reducing falls the bed-exit alarms are, is however not clear. In hospital wards the fall rate is relatively low compared to what is observed in nursing homes or subacute wards with the cognitively impaired [20]. An older underpowered study (n = 70) in a geriatric hospital ward found no reduction in falls or fall related

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injury with pressure sensor bed exit alarms [3]. Similarly, a more recent, larger cluster randomized control trial did not find a reduction in falls rate even though there was increased use of pressure sensor alarms [13]. Shee et al. [20] did a single cohort study evaluating the effectiveness of an electronic sensor alarm in reducing falls in patients (n = 34) with cognitive impairment. The study used a repeated measure (A-B-A) single cohort design to examine the effectiveness of the electronic sensor bed/chair alarm on fall outcomes. The electronic alarm system was found to be a feasible, effective, and acceptable fall prevention strategy for patients with cognitive impairment and they observed a significant decrease in number of falls in the intervention period compared to pre- and post-intervention periods.

It is likely that the lack of evidence of bed-exit alarms as a valuable tool for reducing falls is based on evaluations of the installations of the devices as a single intervention tool only. It seems however that the bed-exit system and protocol need to be tuned differently based on cognitive capabilities of the individual being monitored. Shee et al. [20] used the bed-exit alarms in a ward with cognitively impaired (mean Mini-Mental State examination score: 12.2) patients to signal nurses about individuals that was getting out of bed. With individuals not being cognitively impaired, different approaches may be more effective. In a larger six-month study performed in 2009, Dykes et al. [16] found a positive correlation between awareness of fall risk and the actual number of falls, both in hospital settings and intervention settings. If awareness of fall risk of the individual being hospitalized was altered according to the actual fall risk by recognizing specific actions prior to rising up from bed or sitting down in bed, we expect bed-exit systems to become most valuable. A discussion and design of a fall risk awareness protocol that may be suitable for such an approach is provided by Danielsen et al. [29]. It is however imperative to recognize fall risk awareness as not only a process involving the bed-exiting individual, but moreover a process involving everyone with formal or informal responsibilities in respect to care of the person being monitored [16–18].

This paper presents a novel approach towards bed-event recognitions using a FLIR Lepton 80×60 infrared array combined with ultrasonic radar as sensors and a BeagleBone Black as processing device.

2 Related Work

There have been several studies presenting approaches on automatic sensing systems inside hospital rooms to recognize falls out of bed, patients leaving bed, and bed occupancy. In [8] Madokoro et al. developed a sensor using piezoelectric film between two layers of polyethylene terephthalate (PET) plates of laminated polyester. These sensors where placed strategically in bed to detect movement. The signals where amplified, noise cancelling performed, and the output was fed into Counter Propagation Networks (CPNs) – a supervised learning algorithm based on self-organizing maps (SOMs), recognizing 7 distinct behaviors with a mean recognition accuracy of 75 %.

Capezuti et al. [9] investigated two types of bed-exit alarms to detect bed-exiting body movements: a pressure-sensitive, and a pressure sensitive combined with infrared beam detectors (dual sensor system). They also evaluated the occurrence of nuisance alarms, or alarms that are activated when a participant does not attempt to get out of bed. In the investigation they concluded that dual sensor (pressure sensitive plus infrared beam detectors) bed-exit alarm was more accurate than the pressure sensitive alarm in identifying bed-exiting body movements and reducing the incidence of false alarms. Poisson regression modeling was used to recognize alarm conditions.

In [10] Ranasinghe et al. investigated the accuracy of a continuously wearable, battery less, low power and low cost monitoring device (Wearable Wireless Identification and Sensing Platform - WISP) with a single kinematic sensor capable of real-time monitoring. Three-dimensional acceleration readings and the strength of the transmitted signal from the WISP were interpreted to identify bed exit events and sensitivity, specificity and Receiving Operator Curves (ROC) were determined. Two sensor locations was evaluated, over sternum or attached to mattress. The best sensor location was determined to be over sternum. It performed with sensitivity and specificity values of 92.8 % and 97.5 % recognizing bed entry events, and respectively 90.4 % and 93.80 % for detecting bed exit events.

In addition to the approaches that use sensors attached to the actual bed or body, camera-based solutions have been investigated as well. Ni et al. [22] developed a system analyzing depth images on the Microsoft Kinect Depth platform. They recognized the "patient gets up from the bed" event and was able to get an overall accuracy rate of 98 %. Rantz et al. [23] used a similar platform to detect falls from a standing position, from a bed, and rolling out of a bed. They reported a sensitivity of 92 % and 95 % specificity.

The number of approaches towards fall detection, activity or bed-side event recognition using infrared arrays is however very limited. In [24] Sixsmith et al. used a 16×16 thermal array to recognize falls. The system recognized 30 % of all falls. More recently Mashiyama et al. [26] have reported on 8×8 low-cost infrared array mounted in ceiling, which use a k-nearest neighbor (k-NN) algorithm as classifier on a dataset consisting of 20 consecutive frames to detect falls with a fairly high accuracy of approximately 95 %. We have not been able to find any reports on using infrared arrays to recognize bed-side events or bedside falls, neither alone or in combination with other sensors.

3 Experiment

The hardware setup consisted of a BeagleBone Black (BBB) processing platform, a FLIR Lepton 80×60 infrared array, and a Maxbotix ultrasonic sensor, all integrated into a single unit and mounted in the ceiling. The BeagleBone Black [25] is a credit-card sized, low-cost, community-supported development and processing platform running Debian Linux with 512 MB memory, 4 GB 8-bit eMMC on-board flash storage, and a 1 GHz ARM Cortex A8 processor.

The FLIR Lepton 80×60 Infrared Array [28] is a long-wave infrared (LWIR) camera module with 51° Horizontal Field of View and 63.5° Diagonal Field of View. It captures infrared radiation input in its nominal response wavelength band (from 8 to 14 microns) and outputs a uniform thermal image using the Serial Peripheral Interface Bus (SPI) as video interface with an 8.6 framerate. Each frame is transferred as a sequence of integer numbers that represent the temperature in each pixel of the frame. The thermal sensitivity in the infrared array is 0.05° Celsius. The sensor is controlled using a two-wire I2C-like serial-control interface. Due to the nominal response wavelength band, the FLIR Lepton do not need any external light source to function. The data put into the image are purely heat measurements.

The Maxbotix Ultrasonic Sensor MB-1202 I2CXL-MaxSonar EZ0 [21] use I2C two-wire serial control for access and control, and is able to take up to 40 readings per second. Distance readings range from 25 cm up to around 220 cm in our setting.

The FLIR-sensor was mounted in the FLIR Breakout Board [5] and interfaced to the BBBs I2C-bus along with the Maxbotix ultrasonic sensor. The size of the unit containing both sensors and processing unit was 8 × 12 × 3 cm.

3.1 Recognizing the Location of the Bed

The experiments were executed in a hospital bedroom at UiT nursing school in Narvik, Norway. The layout of the room used during experiment is shown in Fig. 1a. The bed used was an ordinary hospital bed with rails. During the experiment the bed was altered into three positions, as shown in Fig. 1b, c and d.

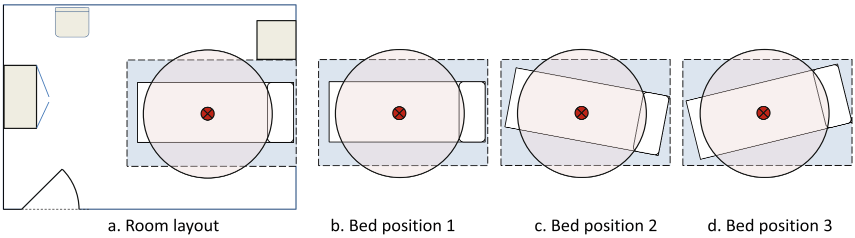

Fig. 1. Room layout and positions of bed during experiment (Color figure online)

The dark red point over the bed is the location of the ceiling mounted sensors and processing device. The square blue area is the area registered by the FLIR sensor, and the circular area is the area monitored by the ultrasonic sensor.

Temperature is usually not evenly distributed in a room. The floor tends to be slightly colder than the upper parts of the room. This feature suggests that objects in different heights in a room will have slightly different temperatures. In the experiment the bed was positioned around 50–70 cm above the floor and the outline of the bed, with or without bed linen, was clearly visible in the infrared representation due to The FLIR sensor thermal sensitivity of 0.05° Celsius. In Fig. 2a the infrared image captured by the FLIR sensor is presented with a temperature range from 11° to 20° Celsius. The graph presented in Fig. 2a show the temperature distribution in the actual frame. Based on this observation a bed-detection algorithm was developed which executed periodically when a person was not detected in 10 consecutive frames. The bed-detection algorithm uses the Sobel (Fig. 2c) and Canny (Fig. 2d) edge detection algorithms on each frame. On the 20 frames resulting from the 10 frames, a Hough line detection is executed, extracting the two longest and most parallel lines which are furthest apart. Since no heat signature from a person is present in the room obscuring the view, the result is two lines representing the two longest sides of the bed. In Fig. 2b these two lines are superimposed on an IR representation image ranging from 10° to 38° Celsius. The graph presented in Fig. 2b shows the temperature distribution in the actual frame based on this scale.

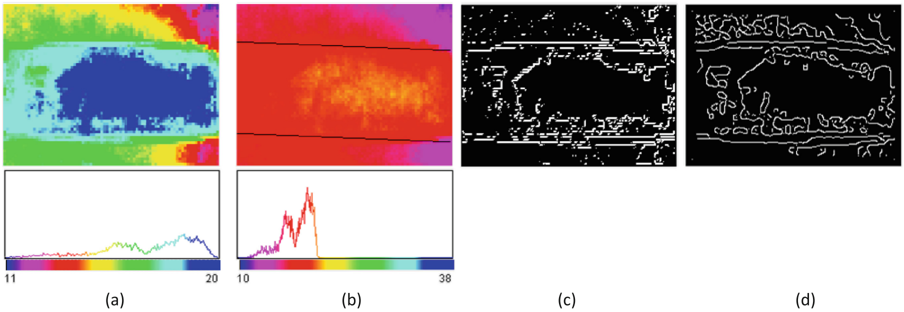

Fig. 2. Bed outline recognition

3.2 Extracting Features

The heat signature of a person is defined to be from 25° Celsius and above. Images without heat signatures are used to filter out the background of the images with individuals in. In addition, the features presented in Table 1 are used for evaluation purposes. The event detection algorithms use the features in Table 1 for analyzing *N* consecutive frames leading up to the current frame recognizing transitions as shown in Fig. 3.

Residual heat left in bed when an individual leave the bed is detected based on a heat disposal algorithm using the identical *N* consecutive frames used for event recognition in addition with detection of movement based on M_f. The heat disposal is recognized using temperature trends in areas with sudden temperature changes.

In Fig. 3, the locations where the body heat signature is detected is separated using dashed blue lines (N/A, Floor, Bed, and Bedrail). The oval shapes indicate postures (N/A, Standing, Sitting, Laying) recognized in the different locations. The solid arrows between postures show how postures change. Any change of Posture into Laying or Sitting posture on Floor is interpreted as a Fall-event. Other events recognized are Area Entry/Exit and Bed Entry/Exit.

The approach presented use the size of the heat imprint in-bed (P_{fmax_in}) and out-of-bed (P_{fmax_out}) to determine location (L_f) along with the maximum temperature observed in-bed (T_{fmax_in}) and out-of-bed (T_{fmax_out}). The maximum temperature spot, independent of location, will in most cases be an individual's head, and as such a strong suggestion of the location of the body. Secondly, the size of the heat imprint in or out of bed is a further indication. This approach towards determining location make recognition of location less sensitive towards the use of bed linen.

Table 1. Features extracted for evaluation

P_{fmax_in}	The number of heat pixel found within boundary of bed in frame f
P_{fmax_out}	The number of heat pixels outside the boundary of the bed in frame f
T_{fmax_in}	Max temperature registered within boundary of bed in frame f
T_{fmax_out}	Max temperature registered outside bed boundaries in frame f
D_f	Distance (D_f) is the number of centimeters from the ceiling mounted ultrasonic sensor to the closest reflecting object in frame f
L_f	Location (L_f) is the location of the heat signature in frame f. It is recognized as one of: Bed, Floor, Bedrail, and N/A. N/A indicates no heat signature (above 25^{o} Celsius) in the image or heat signature is not determinable as a single person
PO_f	Posture in frame (PO_f) is posture recognized in frame f. It is evaluated to one of the following: Laying, Sitting, Standing, or N/A. N/A indicates that not sufficient information is available to determine posture
M_f	Magnitude (M_f) of changes from the previous frame to the current frame f. Expressed as an integer from 0 indicating no changes other than normal disturbance, and upwards. The larger the number, the more changes have occurred
Δt	Time between frames

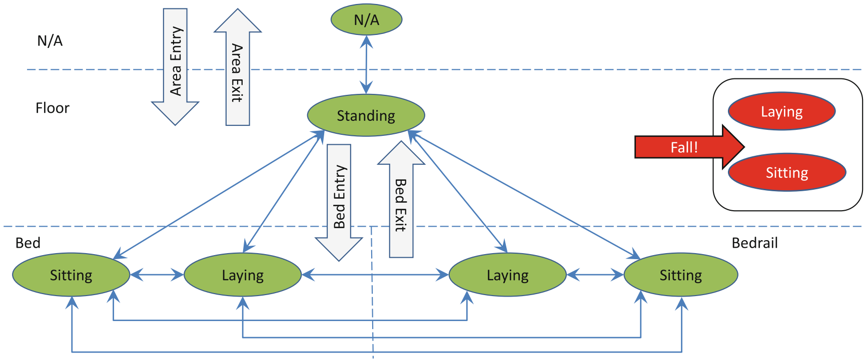

Fig. 3. Transitions and event identification (Color figure online)

3.3 Training

The training set consist of 829 frames out of a total of 8032 frames. One person was used in training set to simulate all transitions expressed in Fig. 3. The data generated from the 8032 frames are P_{fmax_in}, P_{fmax_out}, T_{fmax_in}, T_{fmax_out}, and D_f.

Decision Tree #1. In the first part P_{fmax_in}, P_{fmax_out}, T_{fmax_in}, T_{fmax_out} and D_f, have been manually labeled with the correct location L_f for teaching purposes. This was used to generate a C4.5 [4] generated decision tree using the J48 implementation of WEKA. The generation uses a 10-fold cross validation test mode; resulting in a pruned tree with a 94.5 % correctly recognized instances (783) and 5.5 % incorrectly recognized instances (46).

Decision Tree #2. The second tree use the training set result of Decision Tree #1 where location was correctly recognized (783 instances), the correct posture PO_f was manually added to the result for teaching purposes. This data, consisting of P_{fmax_in}, P_{fmax_out}, T_{fmax_in}, T_{fmax_out}, D_f, L_f, and PO_f, was used to generate a C4.5 [4] generated decision tree using the J48 implementation of WEKA. The generation uses a 10-fold cross validation test mode; resulting in a pruned tree with a 98 % correctly recognized instances (767) and 2.0 % incorrectly recognized instances (16).

3.4 Event Recognition

Event recognition is done analyzing N consecutive frames in terms of Location (L_f) and Posture (PO_f) in frame f, with corresponding distance readings (D_f). The Fall event is recognized as a change from any other posture or location resulting in a situation which the individual is recognized with L_f = Floor and posture PO_f = (Laying | Sitting), in $N-1$ consecutive frames. The recognition of the fall event uses $N = 10$ frames for this purpose. In addition, in each frame D_f (distance from ultrasonic sensor device to reflecting object) is evaluated to ensure that frames with incorrectly recognized L_f and PO_f are dismissed. M_f is analyzed due to a fall often being a violent incident which significantly alter the heat-impression between frames. Finally, in case an individual falls out of bed, the number of heat impression pixels along with the value of the heat impression in the bed should steadily decrease, while the number of heat impression pixels outside the bed should abruptly increase and then become fairly stable.

The Area Entry and Area Exit events detect situations in which a heat signature totally leave or enter the IR sensory area.

The Bed Entry and Bed Exit events use a similar approach as detection of Fall event, but evaluates on whether the heat signature enter or leave the bed using threshold values. Consequently, a fall incident from bed may trigger two events; Bed Exit and Fall.

3.5 Instructions

Four different predefined sessions were defined to be executed by all participants as shown in Table 2. The hospital bed was positioned in different positions as shown in Fig. 1. The instructions, as expressed in Table 2, were given orally, but no guidance on how to execute the instructions was given.

3.6 Execution

A total of 28 recordings were done by 7 participants, 3 women and 4 men, all young and healthy. The first recording of Scene 1, 2 and 3 by person #1 was used as learning set to create the decision trees. The rest of the dataset, 25 recordings in total, was used for testing. All participants did all four scenes independently of each other. Time between infrared frames, Δt, was 1 s. The bed had full bed linen and some of the participants used this. The participants were instructed to perform an activity, but not

Table 2. Timing scene instructions to participants

Time	Scene 1	Scene 2	Scene 3	Scene 4:
00:00	Enter room Sit down on bed	Enter room Falling down beside bed (knees on the floor)	Enter room Lay down on the bed	Enter room Lay down on the bed
01:00	Lay down on the bed	Try to stand up (do not succeed)	Changing poses randomly during 1–2 min	Laying during one-two minutes, and changing poses
02:00	Laying down changing poses	Sit down or lay down on the floor Change poses	Slip down from the bed to floor Change poses	Sit on the bed
03:00	Sit on the bed Move if you want			Fall down when trying to stand up
03:30	Stand up, walking around the bed			Sit down or lay down on the floor
04:00	Exit room			Exit room

specifically how to perform the activity. The hospital bed was also adjustable, and some of the participants played around with this during the experiment, changing the height/angle back support in the bed.

3.7 Results

During the experiment, a total of 7203 frames where analyzed. The recordings consisted of 130 events. Out of these events 113 events was correctly identified. Table 3 gives a detailed overview of the results from the approach used in this experiment.

Table 3. Event recognition results

	Fall	Bed Entry	Bed Exit	Area Entry	Area Exit
Actual Events	25	23	23	41	18
Recognized	29	14	21	34	15
False Positive	4	2	3	6	5
False Negative	0	11	5	13	8
True Positive	25	12	18	28	10
True Negative	101	105	104	83	107
Accuracy	96,9 %	90,0 %	93,9 %	85,4 %	90,0 %
Precision	86,2 %	85,7 %	85,7 %	82,4 %	66,7 %
Sensitivity	100,0 %	52,2 %	78,3 %	68,3 %	55,6 %
Specifity	96,2 %	98,1 %	97,2 %	93,3 %	95,5 %

4 Discussion

The recognition of the Fall event is very good with a Sensitivity of 100 % and Accuracy of 96,9 %. This is due to the usage of the D_f as a controlling parameter in terms of recognizing the location of an individual to be below the bed. In our setup, this is recognized as $D_f > 180$ during initial startup. The Fall event algorithm detected all falls and an additional 4 false positives. The false positives recognitions were all recognized as secondary falls as a result of an attempt to getting up from the floor, but failing to do so. No false positives were recognized independently of these situations.

The recognition of Bed Entry and Exit events along with the Area Entry and Exit events do not perform as well as the Fall event recognition. This is mainly due to a simplistic approach on detecting these events that should be further developed.

The experiment was executed in a controlled environment, both in terms of air and room temperature, and other factors like sunlight reflecting on floor or wall, air conditioning devices, etc. The approach presented here should be investigated in terms on how external factors influence the recognition rate and which adaptations to make to maintain the recognition rate.

Using an infrared array in activity or event recognition in this context have historically performed unsatisfactory, e.g. Sixsmith et al. [24]. Recently Mashiyama et al. [26] reported on an Accuracy of 95 % using an 8 × 8 infrared array to detect falls using a ceiling-mounted infrared array in an experimental setting. The approach presented in this paper offer both higher Accuracy and higher Sensitivity.

Microsoft Kinect based platforms have been used in similar contexts. A 92 % Sensitivity and 95 % Specificity was reported by [23] on a 100-week dataset recorded in a hospital setting. These are very good results. Li et al. [27] report 93.0 % and 94.5 % overall Accuracy on recognizing bed posture using the Kinect.

It is evident that the depth imaging capabilities of the Kinect platform is very potent. However, some problems exist. First of all, the Kinect platform use its own infrared light source to create a specter of dots that are used by the two infrared cameras to read distance from the dots and to the camera. If two or more Kinects are used in close proximity and this light specter overlaps between the two Kinects, neither will be able to read distance in the overlapping regions. Secondly, the Kinect platform includes an RGB camera that may be interpreted as invading privacy. The FLIR sensor used in this paper is both low resolution and detect temperature only, thus minimizing privacy issues. Finally, the approach presented may be easily adapted into a home environment, intervention settings or hospitals due to its compact size (8 × 12 × 3) compared to the Microsoft Kinect (8 × 28 × 8). In addition, the Kinect approach need a separate processing unit while the approach presented include the processing unit.

5 Conclusions and Future Work

The experiments got a very high Sensitivity and Accuracy detecting falls out of bed using a ceiling-mounted 80 × 60 infrared sensor combined with an ultrasonic sensor, and using a BeagleBone Black as the processing device. The results from the experiment showed no false negatives in respect to the fall event (all falls that happened was recognized). Further that all false positives (falls that was recognized as falls, but was not falls) was detected as a secondary fall of a previous recognized fall within the same sequence of frames.

The recognition sensitivity of Bed Entry and Bed Exit events is not satisfactory due to the present low-resolution algorithms for event recognition. This is being worked on. When a better recognition rate is achieved with lower False Positives and False Negatives, the system is planned to be tested out in hospital or intervention settings.

A novel approach for recognizing bed-side events by implementing a ceiling-mounted platform which use a FLIR Lepton infrared array sensor for capturing heat impressions and an ultrasonic sensor for registering proximity from the senor devices to the closest reflecting object, have been presented. The processing and recognition of Location and Posture is done using two C4.5 generated decision trees. This information is then used to recognize bedside events using a continuous sliding 10-frame window for event recognition.

References

1. Public Health Agency of Canada: Report on Seniors' fall in Canada (2005). http://publications.gc.ca/collections/Collection/HP25-1-2005E.pdf. Accessed 9 Mar 2016
2. Public Health Agency of Canada: Senior's fall in Canada – Second Report (2014). http://www.phac-aspc.gc.ca/seniors-aines/publications/public/injury-blessure/seniors_falls-chutes_aines/assets/pdf/seniors_falls-chutes_aines-eng.pdf. Accessed 9 Mar 2016
3. Inouye, S.K., Brown, C.J., Tinetti, M.E.: Medicare nonpayment, hospital falls, and unintended consequences. New Eng. J. Med. **360**, 2390–2393 (2009)
4. Quinlan, J.R.: C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, San Francisco (1993)
5. flir.com: FLIR Lepton Camera Breakout 1.4. http://www.flir.com/uploadedFiles/CVS_Americas/Cores_and_Components_NEW/Resources/flir-lepton-breakout-product-brief.pdf. Accessed 30 May 2016
6. Shojania K.G., Duncan B.W., McDonald K.M., Wachter R.M., Markowitz A.J.: Making Health Care Safer: A critical analysis of patient safety practices. Evidence Report/Technology Assessment, Number 43 (2001). http://archive.ahrq.gov/clinic/ptsafety/pdf/ptsafety.pdf. Accessed 30 May 2016
7. Capezuti, E., Maislin, G., Strumpf, N., Evans, L.: Siderail use and bed-related fall outcomes among nursing home residents. J. Am. Geriatr. Soc. **50**, 90–96 (2002)
8. Madokoro, H., Shimoi, N., Sato, K.: Bed-leaving detection using piezoelectric unrestrained sensors and its measurement system regarding QOL. Nurs. Health **1**(2), 36–45 (2013)
9. Capezuti, E., Brush, B.L., Lane, S., Rabinowitz, H.U., Secic, M.: Bed-exit alarm effectiveness. Arch. Gerontol. Geriat. **49**, 27–31 (2009)
10. Ranasinghe, D.C., Shinmoto Torres, R.L., Hill, K., Visvanathan, R.: Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions. Gait Posture **39**, 118–123 (2014)
11. Rapp, K., Becker, C., Cameronv, K., Büchele G.: Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of Bavarian nursing homes. J. Am. Med. Dir. Assoc. **13**, 187.e1–187.e6 (2012)

12. Hanger, H.C., Ball, M.C., Wood, L.A.: An analysis of falls in the hospital: can we do without bedrails? J. Am. Geriatr. **47**, 529–531 (1999)
13. Shorr, R.I., Chandler, A.M., Mion, L.C., Waters, T.M., Liu, M., Daniels, M.J., Kessler, L.A., Miller, S.T.: Effects of an intervention to increase bed alarm use to prevent falls in hospitalized patients: a cluster randomized trial. Ann. Intern. Med. **157**, 692–699 (2012)
14. Tideiksaar, R., Feiner, C.F., Maby, J.: Falls prevention: the efficacy of a bed alarm system in an acute-care setting. Mount Sinai J. Med. New York **60**(6), 522–527 (1993)
15. Bruyneel, M., Libert, W., Ninane, V.: Detection of bed-exit events using a new wireless bed monitoring assistance. Int. J. Med. Inform **80**, 127–132 (2011)
16. Dykes, P.C., Carroll, D.L., Hurley, A., Lipsitz, S., Benoit, A., Chang, F., Meltzerm, S., Tsurikova, R., Zuyov, L., Middleton, B.: Fall Prevention in Acute Care Hospitals: a randomized trial. JAMA, J. Am. Med. Assoc. **304**, 1912–1918 (2010)
17. Lee, D.-C.A., Pritchard, E., McDermott, F., Haines, T.P.: Falls prevention education for older adults during and after hospitalization: a systematic review and meta-analysis. Health Educ. J. **73**, 530–544 (2014)
18. Ryu, Y.M., Roche, J.P., Brunton, M.: Patient and family education for fall prevention: involving patients and families in a fall prevention program on a neuroscience unit. J. Nurs. Care Qual. **24**, 243–249 (2009)
19. Fonda, D., Cook, J., Sandler, V., Bailey, M.: Sustained reduction in serious fall-related injuries in older people in hospital. Med. J. Aust. **184**, 379–382 (2006)
20. Shee, A.M., Phillips, B., Hill, K., Dodd, K.: Feasibility, acceptability, and effectiveness of an electronic sensor bed/chair alarm in reducing falls in patients with cognitive impairment in a subacute ward. J. Nurs. Care Qual. **29**, 253–262 (2014)
21. maxbotix.com, "I2CXL-MaxSonar® - EZ™ Series Datasheet". http://www.maxbotix.com/documents/I2CXL-MaxSonar-EZ_Datasheet.pdf. Accessed 30 May 2016
22. Ni, B., Nguyen, C.D., Moulin, P.: RGBD-camera based get-up event detection for hospital fall prevention. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1405–1408. IEEE Press, New York (2012)
23. Rantz, M.J., Banerjee, T.S., Cattoor, E., Scott, S.D., Skubic, M., Popescu, M.: Automated fall detection with quality improvement "Rewind" to reduce falls in hospital rooms. J. Gerontol. Nurs. **40**, 13–17 (2014)
24. Sixsmith, A., Johnson, N.: A smart sensor to detect the falls of the elderly. IEEE Pervas. Comput. **3**, 42–47 (2004)
25. beagleboard.org: "BeagleBone Black" (2016). https://beagleboard.org/black. Accessed 30 May 2016
26. Mashiyama S., Hong J., Ohtsuki T.: A fall detection system using low resolution infrared array sensor. In: IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC), pp. 2109–2113. IEEE Press, New York (2014)
27. Li, Y., Berkowitz, L., Noskin, G., Mehrotra, S.: Detection of patient's bed statuses in 3D using a Microsoft Kinect. In: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 5900–5903. IEEE Press, New York (2014)
28. flir.com: "FLIR LEPTON® - Longwave Infrared (LWIR) Camera Module. http://www.mds-flir.com/datasheet/FLIR-Lepton-datasheet.pdf. Accessed 30 May 2016
29. Danielsen, A., Olofsen, H., Bremdal, B.A.: Increasing fall risk awareness using wearables: A fall risk awareness protocol. J. Biomed. Inform. **63**, 184–194 (2016)

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