Journal of Tissue Viability 28 (2019) 7–13

Contents lists available at ScienceDirect

Journal of Tissue Viability

journal homepage: www.elsevier.com/locate/jtv

Detection and classification methodology for movements in the bed that supports continuous pressure injury risk assessment and repositioning compliance

Jonathan Duvall*, Patricia Karg, David Brienza, Jon Pearlman

University of Pittsburgh, Department of Rehabilitation Science and Technology, 6425 Penn Ave, Suite 401, Pittsburgh, PA, 15206, USA

ABSTRACT

Pressure injuries are costly to the healthcare system and mostly preventable, yet incidence rates remain high. Recommendations for improved care and prevention of pressure injuries from the Joint Commission revolve around continuous monitoring of prevention protocols and prompts for the care team. The E-scale is a bed weight monitoring system with load cells placed under the legs of a bed. This study investigated the feasibility of the E-scale system for detecting and classifying movements in bed which are relevant for pressure injury risk assessment using a threshold-based detection algorithm and a K-nearest neighbor classification approach. The E-scale was able to detect and classify four types of movements (rolls, turns in place, extremity movements and assisted turns) with > 94% accuracy. This analysis showed that the E-scale could be used to monitor movements in bed, which could be used to prompt the care team when interventions are needed and support research investigating the effectiveness of care plans.

1. Introduction

Pressure injuries are costly, dangerous, and mostly preventable complications that occur in nursing homes, hospitals, and the home. People with pressure injuries are generally more than two and a half times as likely to die as those without pressure injuries [1,2]. The average cost for treating a pressure injury was reported to be $38,000 [2], which equates to $11 billion annually to the US healthcare system [3]. In the US, the incidence of pressure injuries has been reported as 3.3% in intensive and progressive care units [4], 5.1% (stage 2 and above) in community-based nursing homes [5], and 4% in VA Community Living Centers [6]. These numbers are similar or larger internationally. One review found the incidence of pressure ulcers to be 16% in Norway, 11% in Ireland, 1.8% in Denmark, and 20% in Sweden [7].

Pressure injuries normally occur over bony prominences that are in contact with beds and chairs with locations being indicative of the etiology. Typical sites of pressure injuries from lying on the back would be the back of the head, sacral area and back of the heel while typical sites of pressure injuries from lying on the side are the ear, outsides of the shoulder, hip, knees and ankles. Typical pressure injury sites from sitting up in a chair are the ischial tuberosities, bottom of the heel, and balls of the feet [8].

The Braden Scale is a tool to predict the risk of development of pressure injuries along with the Norton and Waterlow Scales [9] [4,10–12]. The Braden Scale has six sub-scores, and each sub-score has four levels, except for friction and shear, which only has three levels. The total score can range from 6 (highest risk) to 23 (lowest risk). To determine whether the predictive value can be improved, researchers have performed secondary analyses on Braden Scale sub-scores and other patient-related factors. These studies have revealed that while all sub-scores are significant predictors of pressure injuries, some are substantially more powerful than others [4,13]. Tescher et al. (2012) found that the strongest predictor, by far, is the friction and shear sub-score. Patients with a score of 1 (requires moderate to maximum assistance in moving …) on friction and shear were 126 times more likely to develop a pressure injury compared to those with a score of 3 (moves in bed and in chair independently …) [4]. Those with a score of 2 (moves feebly or requires minimum assistance …) were 8 times more likely to develop a pressure injury than those with a score of 3 [4]. Similar hazard scores were noted with the activity sub-score (4.25 times more likely with a 2 (chairfast) vs. 3 (walks occasionally) or 4 (walks frequently)), and mobility sub-score (~ 3 times more likely with a 1 or 2 (none or occasional slight changes in body position) vs. 3 (frequent slight changes) or 4 (frequent major changes)) [4]. These important sub-scores are all related to mobility and movement.

When risk for a pressure injury is established, typically signaled by a Braden score of ≤18, a series of strategies are put in place to try to address and reduce that risk. The most recent guidelines indicate four categories related to prevention: skin care, nutrition, repositioning and mobilization, and education [14]. The most intensive part of the

* Corresponding author.
E-mail address: jad75@pitt.edu (J. Duvall).

https://doi.org/10.1016/j.jtv.2018.12.001
Received 23 July 2018; Received in revised form 7 November 2018; Accepted 22 December 2018

prevention plan is related to repositioning and mobilization, because it often recommends a clinician to turn the patient every two hours while in bed. Adherence with these prevention protocols is low, likely because they require intense effort of the already over-extended clinical staff. Studies, for instance, have indicated adherence ranging from 4.4% [15] to 41% [16]. Adherence related specifically to turning was estimated to be 32% [2] in a study of 835 patients in 35 of the VA's Community Living Centers. These low adherence rates put people at risk for preventable pressure injuries and should be addressed. A research team investigating the barriers to successful implementation of the pressure injury prevention guidelines published by the Joint Commission [17] list four recommendations to improve pressure injury prevention protocols.

1. Observe turning practices to gain specific information about problems with maintaining turning schedules and explore with staff why adherence may be problematic.
2. Evaluate whether a two-hour turning schedule is indicated for all patients or whether there should be a plan to individualize patient-specific turning schedules.
3. Provide a prompt (for example, music, screen saver, timekeeper) to remind the nursing care team to reposition patients.
4. Consider the development of a special team to reposition and mobilize patients.

The first 3 of these recommendations can be accomplished by continuous monitoring of the person's motion in bed and then using that data to determine the best turning schedules and to prompt the nursing care team based on that schedule. Zimlichman et al. (2011) used an EverOn system (Earlysense LTD, Ramat Gan, Israel) to continuously monitor motion in bed and found that motion was significantly related to pressure injury risk based on Norton Scale (similar to Braden Scale) [18]. Other Researchers have used load cell technology under the legs of beds to monitor movements in bed for sleep quality and classifying large and small movements [19,20]. Table 1 details two such studies.

Adami et al. (2005) used a two-algorithm approach where one algorithm detects a movement in bed and the other classifies the movements as large or small [19]. The movement detection algorithm found times where the energy (short-term mean square differences) of the load cell signals was above a threshold. Movement intervals less than 3 s apart were combined to be one movement. The window size and thresholds were optimized by testing multiple values and identifying the ones with the best results. The classification algorithm used a wavelet based multiresolution analysis of the data and then a Bayesian combination rule. They achieved a 2.9% equal error rate for the event detection algorithm and 94–96% correct classification rate for the classification algorithm.

Alaziz et al. (2016) investigated 3 different feature extraction methods (Log-Peak, Energy-Peak and Zero-X Valley) from the load cell signals and then used a threshold-based approach to detect and classify movements as large or small [20]. They found that using the Log-Peak method, they were able to detect movements at a 6.3% error rate and classify them as large or small movements with a 4.2% error rate.

Fig. 1. Photo of E-scale display and 4 sensors which are placed under the bed legs. The 4 sensors each are short and wide cylinders which resemble hockey pucks. The display is a box with a small screen that resembles a digital alarm clock.

Zimlichman et al. (2011) demonstrated the clinical feasibility of continuous monitoring and Adami et al. (2005) and Alaziz (2016) have demonstrated that general motion features can be extracted from load cell data but currently there is no evidence that motion related to pressure injury risk can be extracted from load cell data. Therefore, the goal of this study was to evaluate the feasibility of using load cell technology (E-Scale) to support pressure injury prevention by determining whether load cells can provide insight into when and what type of position changes occur for an individual in bed. The E-scale is a set of load cell sensors that are placed under the legs of a bed and was designed to be able to weigh someone who is getting into or out of bed [21]. The E-scale was developed at our research laboratory by the authors and has been licensed to a company (Nexaware.com) with plans of commercialization. It has an accuracy of 1.7 lbs. and a precision of 0.4 lbs [21]. A photo of the E-scale is provided in Fig. 1. Continuous automated movement monitoring tools will improve the assessment of risk, early identification of changes in risk and monitoring of turning schedules. This work extends the previous work of classifying large vs. small motions by Adami et al. (2005) and Alaziz et al. (2016), by investigating whether E-Scale data can be used to identify position changes that are clinically known to be pressure redistributing.

2. Methods

2.1. Subjects and study protocol

Ten able-bodied subjects were recruited into this IRB-approved pilot study to complete a movement protocol while lying on a full-size bed with an E-Scale placed underneath each of four supports. The first movement protocol included a total of 62 independent movements of a combination of rolling, turning in place, and extremity movements. A fourth movement was added for five subjects where a clinician with experience in repositioning protocols [22] turned participants from their back to side (and vice versa) lying with a 30-degree positioning wedge placed behind the subject's torso and a bed pillow placed between their legs. This was added mid-way through the study to include

Table 1
Summary of movement studies. This table describes summaries of the two studies described in the text: Adami et al. (2005) and Alaziz et al. (2016).

Study	Goal	Technology	Methods	Achieved
Adami et al. (2005)	Detect movement in bed and classify them as large and small	Load cells under each bed leg	**Detection:** Identify windows where mean square differences is above threshold **Classification:** Wavelet based multi-resolution analysis with Bayesian rule	**Detection:** 2.9% equal error rate **Classification:** 94–96% correct
Alaziz et al. (2016)	Detect movement in bed and classify them as large and small	Load cells under each bed leg	Feature extraction of load cell data using Log-Peak, Energy-Peak, and Zero-X Valley. **Detection and Classification:** threshold approach to feature data	**Detection:** 6.3% error rate **Classification:** 4.2% error rate

Table 2
Pressure risk pilot study protocol. This table list the movements that were performed, descriptions of the movements, the timing and number of movements.

Movement	Description	Number and Timing
Rolling	Rolling from back to side	16 movements with 10 s between
Turn in place (rotate)	Rotate from back to side while staying at the same location on the bed	16 movements with 10 s between
Extremity movements while supine	Movement of a single extremity (leg or arm) without changing position on bed or hip contact location	15 movements with 10 s between
Random generated movements	Random set of rolling, turn in place, and extremity movements	Up to 15 movements with 10 s between[b]
Assisted turn from back to side lying with positioning wedge[a]	Clinician rolled person from back to side lying using a 30-degree positioning wedge behind torso and pillow between legs	16 movements with 10 s between

[a] Only 5 of the 10 subjects performed this movement. Since it was done at a different time, we also had each of them complete the other 3 movements again 2 times each.
[b] The random set of 15 movements included a different assisted turn without a wedge, which was removed from analysis as it is not as realistic as an assisted turn with a wedge. Also, one participant's scale broke during the trial which resulted in lower numbers of movements.

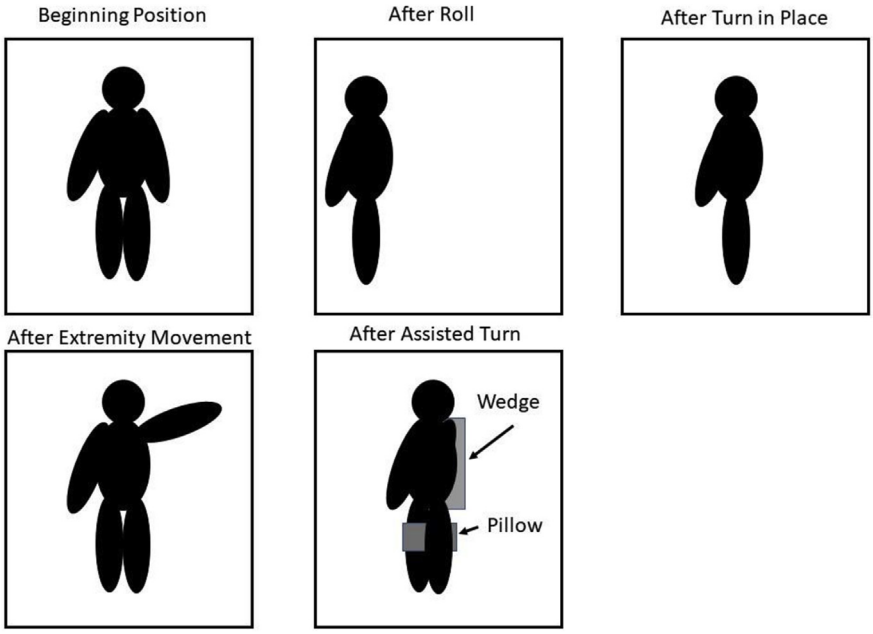

Fig. 2. Depictions of positions after each movement. The first picture is the beginning position for all movements and depicts a person lying supine with arms at the sides in the middle of a bed. The second picture is the position after a roll and depicts the person in a lateral position towards the left side of the bed. The third picture is the position after a turn in place and depicts the person in a lateral position in the middle of the bed. The fourth picture is the position after an extremity movement and depicts a person lying supine with one arm extended out to the side in the middle of the bed. The last picture is the position after an assisted turn and depicts the person lying between a lateral and supine position. It depicts a foam wedge placed under the person's back and a pillow placed between the person's knees.

non-independent position changes to the protocol. The list and order of movements performed during the protocol is described in Table 2. The participants were instructed to remain still in each position for 10 s. Example drawing depictions of the changes in positions from before and after the 4 movements are shown in Fig. 2. The data collection sessions were video recorded, so the absolute timing of the movements could be synced with the measurements.

3. Data analysis

3.1. Event detection

The E-scale recorded the weight on the four individual bed legs at approximately 33 Hz. This frequency was chosen based on processing capabilities and to be on par or higher than the previous bed movement studies which sampled at 10 Hz (Adami et al.) and 30 Hz (Alaziz et al.). The data were then combined to determine a total weight and a weight for each side of the bed as shown in Table 3 and Fig. 3.

An initial algorithm detected an “event”, which was anytime a movement occurred. This algorithm was designed to identify events where the total weight on the bed deviated by an amount greater than a specified threshold (T) during a specified window of data (W). W and T were varied to find the most accurate event detection equations. Since movements are dynamic and require a force to cause the motion, this algorithm only used the total weight data set described in Table 3. The algorithm is applied at each individual total weight data point of the E-scale, meaning the windows significantly overlap. For the entire string of data, every window of data was classified as above the threshold or below the threshold.

Table 3
E-scale sensor data streams used for algorithms. This table is used in conjunction with Fig. 3 to show how the weight data from the E-scale is used. It shows that the total weight variable is determined by summing the weights from all four E-scale sensors. Side 1 weight is determined by summing the weight from the E-scale sensors on the left side of the bed and Side 2 weight is determined by summing the weight from the E-scale sensors on the right side of the bed.

Weight Variable	Sum of weight from sensors
Total weight	1,2,3,4
Side 1	1,2
Side 2	3,4

After the data string was classified as above or below the threshold, all successive windows classified as above the threshold were combined to be a single event which started at the end of the first window above the threshold and ended at the beginning of the last window above the threshold. This was done to identify steady-state periods before and after events. Accuracy was determined by how many of the total movement timestamps were within a window of a determined event.

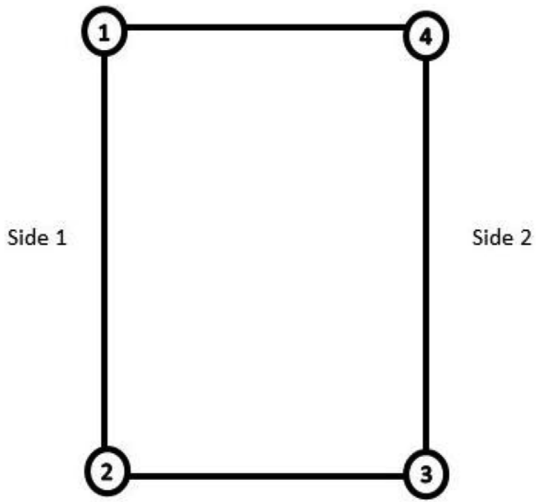

Fig. 3. Depiction of E-scale sensor placement under the 4 corners of the bed. The picture is a rectangle with side 1 labeled on the left side and side 2 labeled on the right side. The numbers 1-4 are labeled on the corners starting at the top left and going counter clockwise to the top right.

Accuracy was defined as a one-to-one match, meaning the event detected only had one movement timestamp in its window and the timestamp was only in one event window.

3.2. Event classification

A second algorithm was developed to classify the events by type of movement. The data that were used from the E-scale for the algorithm development are listed in Table 4. These data all relate to a specific movement, which is why there was the 10 s rest period between movements in the protocol. Fig. 4 shows a sample of two movements with the data identified.

A K-nearest neighbor approach [23] was used to evaluate the prediction algorithm. For the training set for the algorithm, we used two standard approaches. The first is called 'leave-one-out' which uses all other data points to classify each individual movement [24,25]. The second used a random selection of 5 movements from each of the 4 movement types performed by each subject. That created a total of 175 movements in the training set (50 for each of the roll, turn in place and extremity movements and 25 of the assisted turns, which were only completed by 5 subjects). This analysis was conducted 10 times since the training data is randomly selected and is different for each trial. The accuracy of the algorithm was then evaluated with the remaining data points. Both approaches used a standardized Euclidean distance of all three variables to find the closest K neighbors. The K neighbors were then weighted by the inverse of the distance and the movement with the largest sum of weights was chosen as the classification. A parametric study was conducted on the number of K neighbors that would result in the highest accuracy, with K varied from 1 to 25. The percentage of data points that were classified correctly was determined for each approach. The goal was for the event detection algorithm and the classification approaches to be greater than 90% accurate.

4. Results

4.1. Movement detection

686 movements were completed by the 10 subjects. The variables W and T were varied from 3 s to 8 s and from 5 lbs. to 10 lbs, respectively. The movement detection accuracies for these parameters are shown in Table 5. The combination of W = 6 or 7 s and T = 7 lbs. gave the highest accuracy at 97.7%. Of the 16 total movements missed with that configuration, 13 were from the extremity movements category in Table 2.

4.2. Movement classification

Using the 670 movements that were detected, two different classification approaches were conducted. The 'leave one out' analysis was conducted with K varying from 1 to 25. Table 6 indicates the classification accuracies for all values of K for these two analyses. The maximum accuracy of the leave one out analysis was 96.4% when K = 9 and 10 and the minimum was 95.8%. The random training set analysis resulted in the highest accuracy of 96% when K = 16 and the minimum was 94.8%. The range of accuracy only varied < 2% across all values of K for both analyses.

Table 7 shows the classifications broken down by movement for the random analysis when K = 16. All movements were classified correctly more than 91% of the time. The only misclassification that occurred more than 2% of the time was when independent turns in place and assisted turns were misclassified as each other. Two-dimensional plots comparing the four movements over the three variables (defined in Table 4) are shown in Fig. 5. These plots show the clustering of data.

5. Discussion

These results indicate that using load cells under the legs of a bed can be used to detect and classify movements in bed. The movements were classified into 4 categories: roll, turn in place, extremity movements and assisted turn. Overall, 670 out of 686 (97.7%) of movements were detected. The lowest detected movement was the extremity movements which were detected at a rate of 93.2% The movements could also be aggregated to be classified as pressure redistribution movements or non-pressure redistribution movements. Since the rolls and turns in place were full rotations (back to side) and the assisted turns were conducted in the same manner as recommended turning and positioning protocols, they would all be considered effective pressure redistribution movements [22]. The extremity movements would not effectively redistribute pressure from one part of the pelvis or body to another since the person's overall posture did not change [22]. The sensitivity and specificity of the extremity movements vs. any other classification was 95.0% and 99.2%, respectively.

The optimal movement detection algorithm detected 97.7% of the movements. Of the 16 movements that were not detected, 13 of them were extremity movements which means the algorithm was 99.6% accurate in detecting movements which redistribute pressure around the pelvis. Two of the other 3 movements were assisted turns and were detected, but as two movements (one for the roll and wedge placement and another for pillow placement). The last movement was a roll that

Table 4
Variables extracted from the E-scale for pressure risk pilot study. This table is used in conjunction with Fig. 4 describes the three variables used for classification of the data and the rationale for why the variables were chosen.

Data from each Movement	Rationale
Weight Variance (standard deviation)	Shows consistency of forces during movement (a smooth movement vs. large force change)
Duration of movement (time)	Shows how long the movement lasted
Percent change in center of mass	Shows how far the position of the person changed across the bed

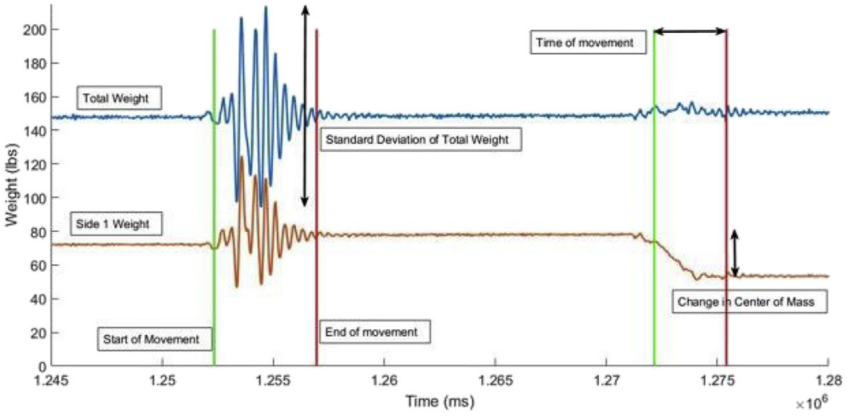

Fig. 4. Plot of total weight and side 1 weight with variable data identified. This plot has time as the x-axis variable and weight as the y-axis variable. Two streams of data are shown. Total weight is centered at approximately 150 lbs. and side 1 weight is centered at approximately 75 lbs. Two portions of the plot are identified by verticle lines (one before and one after) showing two movements. The vertical line before is labeled start of movement and the vertical line after is labeled end of movement. A horizontal double arrow line between the line before and the line after is labeled time of movement. A vertical double arrow line from the minimum to the maximum of the total weight is labeled standard deviation of total weight. Another vertical double arrow line showing the change in side 1 weight from before to after a movement is labeled change in center of mass.

Table 5
Results of movement detection parameters. This table shows the accuracy of the event detection algorithm when the threshold variable is varied from 5-10 lbs. and the window variable is varied from 3-8 seconds. The maximum accuray (97.7%) is when the threshold is 7 lbs. and the window is 6 or 7 seconds.

Accuracy of event detection		Threshold (T) in lbs.					
		5	6	7	8	9	10
Window (W) in seconds	3	73.5%	91.5%	90.4%	81.3%	72.9%	67.2%
	4	64.0%	92.4%	92.6%	82.5%	73.9%	68.1%
	5	57.6%	94.3%	96.2%	86.0%	77.3%	71.1%
	6	50.7%	93.7%	97.7%	88.2%	80.0%	73.0%
	6.3	50.1%	92.9%	97.4%	88.3%	80.3%	73.3%
	6.5	49.6%	92.6%	97.4%	88.3%	80.5%	73.5%
	6.7	48.4%	92.4%	97.5%	88.5%	80.5%	73.5%
	7	47.4%	90.8%	97.7%	88.5%	80.8%	73.3%
	8	45.0%	84.8%	96.4%	88.3%	81.2%	74.5%

Table 6
Accuracy of Classifications as a function of different K nearest-neighbors. This table shows the accuracy of the 'Leave on out' and Random approaches for K values from 1-25.

K	Accuracy	
	Leave one out	Random
1	95.8%	94.9%
2	95.8%	94.8%
3	95.8%	95.6%
4	96.3%	95.9%
5	96.3%	95.9%
6	96.0%	95.5%
7	96.1%	95.5%
8	96.3%	95.9%
9	96.4%	95.6%
10	96.4%	95.6%
11	96.3%	95.7%
12	96.3%	95.5%
13	96.0%	95.8%
14	96.0%	95.9%
15	96.1%	95.5%
16	96.0%	96.0%
17	96.1%	95.6%
18	96.0%	95.8%
19	96.0%	95.4%
20	95.8%	95.4%
21	96.0%	95.7%
22	96.0%	95.7%
23	96.0%	95.3%
24	96.0%	95.8%
25	95.8%	95.8%

Table 7
Classification accuracy by movement. This table shows a matrix of the percentages of how each of the four actual movements were classified. The important data is described in the text.

Actual Movement	Classified as			
	Roll	Turn in place	Extremity	Assisted turn
Roll	98.5%	0.0%	0.4%	1.1%
Turn in place	0.0%	95.7%	0.8%	3.5%
Extremity	1.9%	2.0%	95.0%	1.1%
Assisted turn	0.0%	6.4%	1.8%	91.8%

was so smooth, that the total weight never fluctuated by more than the 7-pound threshold.

The classification of the movements using a K-nearest neighbor approach resulted in 94.8% or higher accuracy for all permutations. The 'leave one out' approach is thought of as an optimistic approach [24], but the random training set analysis also showed high accuracy for classification. Varying the value of K had a small effect on the accuracy of the classification, which means the variables are highly clustered. Combining the optimal movement detection and movement classification parameters, 646 out of 686 movements (94.2%) were detected and classified correctly.

The highest misclassification was between turns in place and assisted turns. This is a result of the data for assisted turns being the least clustered and the overlapping of clusters seen in Fig. 5. Clinically, it is unlikely that someone who is capable of performing a turn in place, which requires lifting portions of the body off of the mattress, would be in need of assisted turns. However, secondary analyses could be developed to better distinguish these two movements. One such approach would be to identify movements that were classified with low certainty (i.e. the total weighted classification of the first and second most likely classifications were close). Then the analysis could be reconducted using only the nearest neighbors of those two classifications or the variable which most highly distinguishes those two movements could be weighted more heavily.

Other technologies have been developed to attempt to monitor pressure in the bed. Some are real-time pressure monitors which display areas of high pressure to clinicians for interventions, such as the ForeSitePT from Xsensor (xsensor.com) which is a pressure mapping mattress overlay [26]. Another sensor, the Leaf sensor (leafhealthcare.com), is adhered to a person's chest and monitors the angle of their torso over time [27]. The E-scale could be another option along with these technologies which works with most any bed, yet is non-contact and does not impact the pressure-redistributing surface characteristics. It also has the dual purpose of measuring weight.

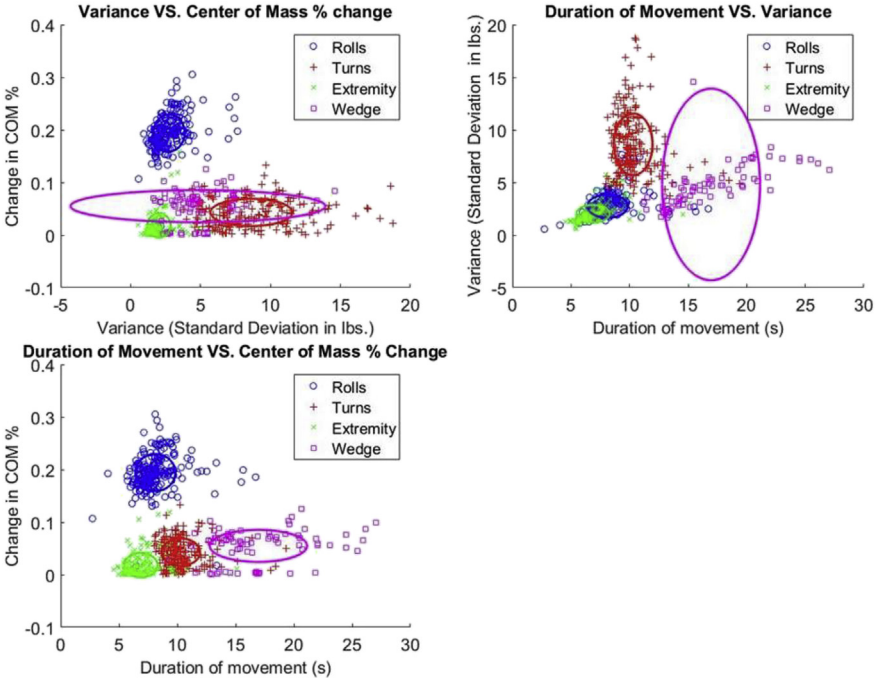

Fig. 5. Scatter plots of four movements comparing the three variables. This picture shows three plots comparing all permutations of Change in center of mass, Duration of movement, and Variance. The legends show the four movements: Rolls, Turns, Extremity, and Wedge. All four movements have different shapes for the data so that the clustering of the data can be seen visually.

6. Limitations

Generalization of the results from this study is limited because it was conducted with able-bodied people performing prescribed movements on one type of bed. People in nursing homes or assisted living facilities who are at risk for pressure injuries may not be capable of performing some of these movements, such as the turns in place. Also, this study only had one person performing the assisted turns, and techniques may vary by facility and/or by clinician assisting with repositioning. Future studies should expand this research by conducting studies in the real-world environment.

7. Conclusion

This pilot study found that the E-scale could detect and classify four movements (rolls, turns in place, extremity movements, and assisted turns) with greater than 94% accuracy. This shows that the E-scale has good feasibility for detecting and classifying movements occurring in the bed. With some further research, it could be used in facilities to continuously monitor movements in bed to evaluate pressure injury risk and compliance with pressure injury prevention protocols.

Funding

This research was supported by the University of Pittsburgh's Clinical and Translational Science Institute by the National Institutes of Health through Grant Number UL1TR001857 and in part through funding received from the SHRS Research Development Fund, School of Health and Rehabilitation Sciences, University of Pittsburgh.

Conflicts of interest

Authors Jonathan Duvall and Jon Pearlman were inventors of the E-scale technology. The technology was licensed by the University of Pittsburgh to a startup company called Nexaware. None of the authors have financial interests in the company.

References

[1] Lyder CH, Wang Y, Metersky M, Curry M, Kliman R, Verzier NR, Hunt DR. Hospital-acquired pressure ulcers: results from the national medicare patient safety monitoring system study. J Am Geriatr Soc 2012;60(9):1603–8.
[2] Russo A, Elixhauser A. Hospitalizations related to pressure sores, 2003. Healthcare Cost and utilization project statistical brief #3. Agency for Healthcare Research and Quality; 2006.
[3] Russo CA, Steiner C, Spector W. Hospitalizations related to pressure ulcers, 2006. Healthcare Cost and utilization project statistical brief #64. Agency for Healthcare Research and Quality; 2008.
[4] Tescher AN, Branda ME, Byrne TJO, Naessens JM. All at-risk patients are not created equal: analysis of Braden pressure ulcer risk scores to identify specific risks. J Wound, Ostomy Cont Nurs 2012;39(3):282–91.
[5] Centers for Medicare and Medicaid Services. Nursing home data compendium 2015 edition Available from: https://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/CertificationandComplianc/Downloads/nursinghomedatacompendium_508-2015.pdf; 2015.
[6] Hartmann CW, Shwartz M, Zhao S, Palmer JA, Berlowitz DR. Longitudinal pressure ulcer rates after adoption of culture change in veterans health administration nursing homes. J Am Geriatr Soc 2016;64(1):151–5.
[7] Moore Z, Johanssen E, van Etten M. A review of PU prevalence and incidence across Scandinavia, Iceland and Ireland (Part I). J Wound Care 2013;22(7):361–2. 364-8.
[8] Drugs.com, *Bedsores (Decubitus ulcers)*. [Updated Oct. 8, 2018; cited Nov. 7, 2018]. Available from: https://www.drugs.com/health-guide/bedsores-decubitus-ulcers.html.
[9] Pancorbo-Hidalgo PL, Garcia-Fernandez FP, Lopez-Medina IM, Alvarez-Nieto C. Risk assessment scales for pressure ulcer prevention: a systematic review. J Adv Nurs 2006;54(1):94–110.
[10] Bergstrom N, Braden BJ, Languzza A, Holman V. The Braden scale for predicting pressure sore risk. Nurs Res 1987;36(4):205–10.
[11] Horn SD, Bender SA, Ferguson ML, Smout RJ, Bergstrom N, Taler G, Cook AS, Sharkey SS, Voss AC. The National Pressure Ulcer Long-Term Care Study: pressure ulcer development in long-term care residents. J Am Geriatr Soc 2004;52(3):359–67.
[12] Lahmann NA, Kottner J. Relation between pressure, friction and pressure ulcer categories: a secondary data analysis of hospital patients using CHAID methods. Int J Nurs Stud 2011;48:1487–94.
[13] Bergquist S. Subscales, subscores, or summative score: evaluating the contribution of Braden Scale items for predicting pressure ulcer risk in older adults receiving home health care. J Wound, Ostomy Cont Nurs 2001;28(6):279–89.
[14] National Pressure Ulcer Advisory Panel. Pressure injury prevention points cited 2016; Available from: http://www.npuap.org/wp-content/uploads/2016/04/Pressure-Injury-Prevention-Points-2016.pdf; 2016.
[15] Paquay L, Wouters R, Defloor T, Buntinx F, Debaillie R, Geys L. Adherence to pressure ulcer prevention guidelines in home care: a survey of current practice. J Clin Nurs 2008;17(5):627–36.
[16] Saliba D, Rubenstein LV, Simon B, Hickey E, Ferrell B, Czarnowski E, Berlowitz D. Adherence to pressure ulcer prevention guidelines: implications for nursing home quality. J Am Geriatr Soc 2003;51(1):56–62.
[17] Jankowski IM, Nadzam DM. Identifying gaps, barriers, and solutions in

implementing pressure ulcer prevention programs. Joint Comm J Qual Patient Saf 2011;37(6):253–64.
[18] Zimlichman E, Shinar Z, Rozenblum R, Levkovich S, Skiano S, Szyper-Kravitz M, Altman A, Amital H, Shoenfeld Y. Using continuous motion monitoring technology to determine patient's risk for development of pressure ulcers. J Patient Saf 2011;7(4):181–4.
[19] Adami A, Hayes T, Pavel M, Singer C. Detection and classification of movements in bed using load cells. Conf Proc IEEE Eng Med Biol Soc 2005;1:589–92.
[20] Alaziz M, Zhenhua J, Jian L, Richard H, Yingying C, Yangyong Z. Motion scale: a body motion monitoring system using bed-mounted wireless load cells. IEEE First Int Conf Connect Health Appl Syst Eng Technol (CHASE) 2016;00(0):183–92.
[21] Mhatre A, Duvall J, Ding D, Cooper R, Pearlman J. Design and focus group evaluation of a bed-integrated weight measurement system for wheelchair users. Assist Technol; 2016. p. 1–9.
[22] National Pressure Ulcer Advisory Panel/European Pressure Ulcer Advisory Panel/Pan Pacific Pressure Injury Alliance. Prevention and Treatment of pressure ulcers: clinical practice guideline. 2014. p. 1–308. Perth, Australia.
[23] Altman NS. An introduction to Kernel and nearest-neighbor nonparametric regression. Am Statistician 1992;46(3):175–85.
[24] Vapnik V. Estimation of dependences based on empirical data. first ed. Springer-Verlag New York, Inc.; 2006. p. 505.
[25] Guyon I, Elisseeff A. An introduction to variable and feature selection. J Mach Learn Res 2003;3:1157–82.
[26] Wong H, Kaufman J, Baylis B, Conly JM, Hogan DB, Stelfox HT, Southern DA, Ghali WA, Ho CH. Efficacy of a pressure-sensing mattress cover system for reducing interface pressure: study protocol for a randomized controlled trial. Trials 2015;16:434.
[27] Pickham D, Pihulic M, Valdez A, Mayer B, Duhon P, Larson B. Pressure injury prevention practices in the intensive care unit: real-world data captured by a wearable patient sensor. Wounds 2018;30(8):229–34.