

# Toward mitigating pressure injuries: Detecting patient orientation from vertical bed reaction forces

Gordon Wong<sup>1</sup> , Sharon Gabison<sup>1</sup> , Elham Dolatabadi<sup>1</sup>,  
Gary Evans<sup>1</sup>, Tara Kajaks<sup>1</sup> , Pamela Holliday<sup>1,2</sup>,  
Hisham Alshaer<sup>1</sup>, Geoff Fernie<sup>1,2,3</sup> and Tilak Dutta<sup>1,3</sup>

<sup>1</sup>KITE, Toronto Rehabilitation Institute – University Health Network, Toronto, Ontario, Canada

<sup>2</sup>Department of Surgery, University of Toronto, Toronto, Ontario, Canada

<sup>3</sup>Institute of Biomaterials and Biomedical Engineering, University of Toronto, Toronto, Ontario, Canada

## Abstract

**Introduction:** Prolonged bed rest without repositioning can lead to pressure injuries. However, it can be challenging for caregivers and patients to adhere to repositioning schedules. A device that alerts caregivers when a patient has remained in the same orientation for too long may reduce the incidence and/or severity of pressure injuries. This paper proposes a method to detect a person's orientation in bed using data from load cells placed under the legs of a hospital grade bed.

**Methods:** Twenty able-bodied individuals were positioned into one of three orientations (supine, left side-lying, or right side-lying) either with no support, a pillow, or a wedge, and the head of the bed either raised or lowered. Breathing pattern characteristics extracted from force data were used to train two machine learning classification systems (Logistic Regression and Feed Forward Neural Network) and then evaluate for their ability to identify each participant's orientation using a leave-one-participant-out cross-validation.

**Results:** The Feed Forward Neural Network yielded the highest orientation prediction accuracy at 94.2%.

**Conclusions:** The high accuracy of this non-invasive system's ability to a participant's position in bed shows potential for this algorithm to be useful in developing a pressure injury prevention tool.

## Keywords

Pressure injuries, bed position, technology, machine learning

Date received: 10 June 2019; accepted: 6 February 2020

## Pressure injuries

Pressure injuries (PIs), also known as decubitus ulcers, pressure ulcers, bed sores, and pressure sores, are a surprisingly common problem for patients who have limited mobility,<sup>1</sup> particularly for those who are confined to a bed. These individuals are at risk of developing PIs due to a lack of blood flow to tissues that are deformed (strained) either by becoming compressed between the bed and a bony prominence or stretched from shear. One in four patients across the healthcare system in Canada will develop a pressure injury,<sup>2</sup> the vast majority of which are preventable.<sup>3,4</sup>

Pressure injuries can have a devastating impact on patients by reducing quality of life,<sup>5</sup> life expectancy,<sup>6</sup> as well as increasing morbidity and mortality.<sup>7</sup> These injuries also increase the burden on caregivers,<sup>8</sup> and are costly for the Canadian healthcare system with the average treatment cost of over \$27,000 per pressure injury.<sup>8</sup>

### Corresponding author:

Sharon Gabison, 550 University Avenue, 13th Floor, Toronto, Ontario, Canada.

Email: sharon.gabison@uhn.ca



There are two widely used best practices for preventing and managing PIs:

- a. Using specialized support surfaces (mattresses) to distribute loads more evenly.
- b. Frequent repositioning to offload strained tissues.

### Specialized support surfaces

Specialized support surfaces are meant to offload tissues by redistributing stresses more evenly over bony areas. However, the latest Cochrane review found that there is not enough evidence to conclude that specialized surfaces are more effective at preventing pressure injuries than standard mattresses.<sup>9</sup> More importantly, specialized mattresses cannot replace the need for repositioning.<sup>4</sup> A recent study that attempted to use an air-inflated viscoelastic foam mattresses to remove the need for repositioning found that 75% of the participants needed to be put back on repositioning schedules because they either got new pressure injuries, (40% of participants), or their existing pressure injuries got worse.<sup>10</sup>

### Frequent patient repositioning

Frequent repositioning, which is a commonly accepted best practice both for prevention and treatment of PIs,<sup>11–13</sup> allows tissues to return to their original shape to re-establish blood flow that delivers oxygen and nutrients to previously deformed tissue. Normally, patients are cycled between three orientations: supine, left side-lying, and right side-lying. In supine position, it is recommended that the head of the bed be elevated no more than 30° (to reduce shear forces acting on tissues near the coccyx), and that supporting pillows be placed under the calves to offload the heels.<sup>14</sup> Similarly, in side-lying positions, a pillow should be placed between the legs to offload the malleoli or reduce contact between the knees. Pillows or foam wedges are also used to keep to the patients from rolling onto their backs while in the side-lying position.

Many sources recommend repositioning patients every 2 h,<sup>11–13</sup> though there appears to be no direct evidence to support this particular frequency as the optimal rate of repositioning. In fact, a recent study was unable to find differences between repositioning schedules of 2, 3, or 4 h.<sup>15</sup> However, Fernie and Dornan did show that consistently turning patients to expose their pressure injuries to a placebo treatment for 30 min every 2 h saw dramatic reductions in wound size.<sup>16</sup> Still, the recent Cochrane review concludes that there is no clear evidence to support the effectiveness of repositioning, but recommends the practice continue because it is theoretically sound.<sup>9</sup>

Despite widespread clinical acceptance of the need, adherence to repositioning schedules remains poor with adherence rates of 38%–66%.<sup>17–23</sup> Difficulty in continuous monitoring of the patient's position, lack of reminders/alerts, and reduced staffing ratios have been suggested as possible reasons for poor adherence to repositioning protocols<sup>7</sup> and the use of automated prompting systems have been introduced to address this issue.<sup>24</sup>

### Existing repositioning prompting systems

There are a number of intelligent systems that have been developed to identify the need for patient repositioning in bed as a basis for providing prompts to caregivers.<sup>7,25–30</sup> Existing commercially available systems fall into one of two categories: pressure mats and inertial sensors.

*Pressure mats* provide a color-coded real-time visualization of the pressure distribution under a patient without disruption to the patient.<sup>21</sup> A number of companies market these pressure mats: Wellsense, Tekscan, and XSensor. The findings of studies using these devices are mixed. Studies demonstrated that pressure mats reduced hospital-acquired pressure injuries,<sup>29</sup> decreased the amount of time between patient turns<sup>21,30</sup> and promoted skin inspection of high-risk areas<sup>30</sup> while one study found no benefit.<sup>31</sup>

*Inertial sensors* are adhered to an individual's chest or embedded into their clothing to wirelessly monitor a patient's position and movement. There are two brands of inertial sensors for pressure injury management that we are aware of: Leaf (Leaf Healthcare, Pleasanton, CA) and MovinSense (Kinematix, Porto, Portugal). Leaf is a single use device while MovinSense allows reuse. In the case of the Leaf system, healthcare providers are given color-coded output that counts down to a scheduled turn and provides real-time patient position. This system was shown to increase adherence with hospital turn protocols from 44% to 98%.<sup>24</sup> The MovinSense system has been used by researchers to compare how often patients are repositioned by nursing staff and how often they move spontaneously.<sup>32</sup>

### Limitations of existing systems

Pressure mats are expensive, (~\$10,000), require storage space when not in use and have the potential to spread infection, particularly if a pressure injury is already present. Caregivers must ensure that disinfecting procedures are followed diligently.

Similarly, tissue damage can occur if the patient rolls onto a body worn inertial sensor or from adhesives used to hold the sensors on the patient's skin, which can cause skin tears for those with fragile skin. In fact,

the risk of skin tears and sensitivity to the adhesive dressings used to attach the sensors were exclusion criteria in a study that investigated the need for repositioning among those at highest risk of developing pressure injury.<sup>32</sup> Other shortcomings include the need for recurring costs associated with single-use sensors (purchase, transport, storage, and disposal), and the need for patient compliance with wearable devices.

## Monitoring patients using load cells

The present work attempts to overcome the limitations above by developing a system based on a set of four load cells placed under the legs of the patient's bed. With this design, the device does not come into direct contact with the patient, which minimizes demands on healthcare providers, and would likely cost less to purchase, install, and maintain. This project builds on the work of Beattie et al.<sup>27</sup> and Duvall et al.,<sup>26,27</sup> who have investigated similar systems.

Beattie et al.<sup>27</sup> used their system to determine the poses of healthy individuals in bed for monitoring sleep. In particular, they demonstrated that small cyclic changes in the center of mass of the bed-patient system can be seen with each inhalation/exhalation cycle. The excursion of the center of mass over each cycle traces an ellipsoid with a principal axis that changes its angle relative to the longitudinal axis of the bed as the patient changes poses. The authors demonstrated this change in angle can be used to detect the patient's orientation with 83% accuracy.<sup>27</sup> Duvall et al.<sup>26</sup> used a similar load cell-based system to detect and classify four-patient movements in bed (rolls, turns in place, extremity movements, and assisted turns). They found a machine learning K-nearest neighbor classification system was able to classify the four movements with 94.2% accuracy.<sup>26</sup>

The current study builds on this past work by combining the center of mass movement measurement from Beattie et al.<sup>27</sup> with the use of machine learning classification to categorize a simulated mobility-impaired patient's orientation in bed as either supine, left side-lying, or right side-lying. In particular, this project focused on the use of Logistic Regression and Feed Forward Neural Network predictive models, which are the most widely used models in medical domains for diagnostic and prognostic tasks.<sup>33</sup> Classifiers based

on these approaches can be improved incrementally if they incorporate new patient data into their models to customize the classifier for a particular user. Our ultimate goal is to develop a prompting system that can detect when a patient needs to be repositioned. In this context, we envision an initial calibration period could be used to tune the base classifier model to improve accuracy for each patient using incremental learning.<sup>34</sup>

## Objective

To train and evaluate machine learning classifiers using Logistic Regression and Feed Forward Neural Network (with and without incremental learning), using bed reaction forces to categorize the orientation of participants as supine, left side-lying, or right side-lying.

## Methods

### Participants

A convenience sample of 20 healthy participants (female: 12 and male: 8) were recruited from Toronto Rehabilitation Institute, University Health Network (TRI-UHN). The study protocol received approval from the UHN Research Ethics Board and all participants provided informed consent. A summary of demographic characteristics of our participants is shown in Table 1.

### Instrumentation

All data were collected from patients lying on one of two different hospital beds: Spirit Select ( $n=12$ , Carroll Hospital Group, Kalamazoo, MI) and Resident ( $n=8$ , Hill-Rom, Chicago, IL). Single axis load cells were placed under each of the four wheels of the hospital bed frame (Figure 1). Each load cell was comprised of four load sensors (model DLC902-30KG-HB, Hunan Detail Sensing Technology, Changsha, Hunan, China) arranged to create a full Wheatstone bridge circuit. Each sensor had a resolution of 1.8 g and measures remained within 0.2% of the full-scale value. The load cells were connected to a signal conditioner (GEN 5, AMTI, Watertown, MA) for amplification, filtering, and analog to digital conversion. The signal conditioner was configured for 5.0 VDC excitation and a gain of 500 for each channel. NetForce

**Table 1.** Demographics characteristics of the 20 participants recruited for this study (waist and hip measurements are of circumference).

|                    | Height (cm) | Weight (kg) | BMI (kg/m <sup>2</sup> ) | Waist (cm) | Hip (cm) | Age (years) |
|--------------------|-------------|-------------|--------------------------|------------|----------|-------------|
| Mean               | 169         | 67.8        | 23.5                     | 80.3       | 98       | 31          |
| Standard deviation | 9.2         | 15.7        | 3.8                      | 11.5       | 8.4      | 15.2        |

software (version 3.5.2, AMTI, Watertown, MA) running on a laptop PC (Thinkpad T520, Lenovo, Hong Kong, China, 2.5 GHz Intel Core i5 CPU and 4GB of RAM) was used to collect the load cell data at 50 Hz with 16-bit resolution. The sampling frequency was set to 50 Hz to allow us to capture changes in load cell signals resulting from respiration (frequency response of 0.1–0.5 Hz) and cardiac activity (frequency response of 0.5–20 Hz)<sup>35</sup> though we ultimately focused on the respiration signals only.

## Data collection

Each participant, wearing regular clothing, was instructed to lie comfortably in the bed and refrain from moving (acting as a mobility-limited patient) or speaking. Participants were encouraged to stay relaxed and were allowed to fall asleep if they wished. A member of the research team played the role of a caregiver actor and positioned the participant through a sequence of unique poses (shown in Figure 2) typically used with mobility-limited patient populations. The first four participants were positioned in seven poses (Figure 2(a) to (g)) while the remaining 16 participants adopted all 12 poses shown in Figure 2. These positions were selected after reviewing best practice guidelines<sup>14</sup> and following discussions with nursing and physiotherapy staff in a rehabilitation hospital (TRI-UHN). Each position consisted of a different combination of three variables:

- Angle of the head of the bed (flat or elevated to 30°).
- Patient position category (supine, right side-lying, left side-lying).
- Use of a positioning device in the side-lying position (no device, 30° wedge, or pillow).

Participants were asked to stay in each pose for approximately 3 min. For the side-lying pillow supported position, participants were turned onto their sides and a folded pillow was placed behind them to support the torso and pelvis. Participants were then rolled back onto the folded pillow. For the wedge (model 554026, Skil-Care, Yonkers, NY) supported side-lying positions, participants were turned onto their sides, the wedge was placed such that it supported the torso and pelvis and the participant was rolled back onto the wedge.

For the first four participants, the poses involving raising the head of the bed to 30° were omitted. The remaining 16 participants were positioned into all 12 poses.

## Data processing

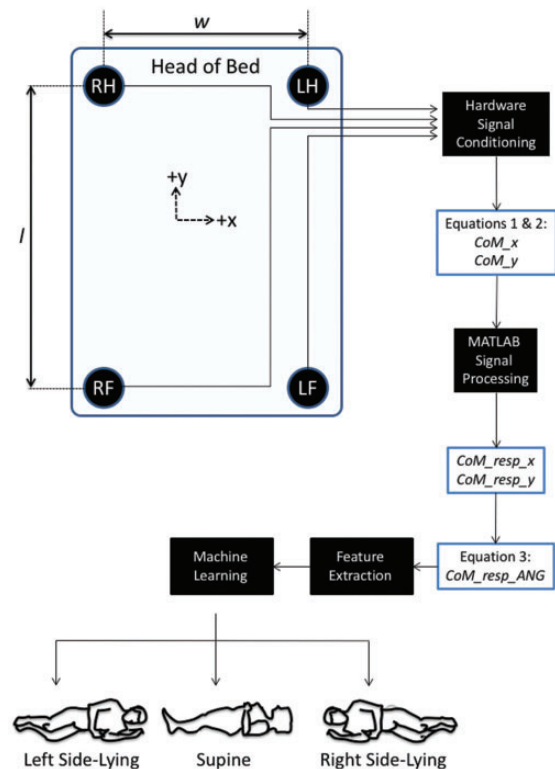
Load cell signals were exported from Netforce and processed offline using MATLAB R2016b (Mathworks Inc. Natick, MA). The data were manually segmented into trials by removing sections where the participants were changing positions.

Next, the center of mass of the bed-patient system was calculated using equations (1) and (2) below where  $CoM_x$  and  $CoM_y$  refer to the center of mass in the  $x$  (parallel to the short axis of the bed) and  $y$  (parallel to the long axis of the bed) directions, respectively (Figure 1).

$$CoM_x = \frac{w}{2} \times \frac{LH + LF - RH - RF}{LH + LF + RH + RF} \quad (1)$$

$$CoM_y = \frac{l}{2} \times \frac{LH + RH - LF - RF}{LH + LF + RH + RF} \quad (2)$$

where LH and RH correspond to the vertical forces measured by left and right sensors at the head of the bed respectively, LF and RF corresponds to the



**Figure 1.** Schematic depicting the four load cells placed under the bed: LH (left head), LF (left foot), RH (right head), RF (right foot), and how the signals from the system are collected, processed, and analyzed. The distances between the load cells are labeled as  $w$  (width) and  $l$  (length), and the coordinate axis is shown.

vertical forces measures by the left and right sensors at the foot of the bed respectively, and  $l$  and  $w$  refer to the distances between the load cells.

To isolate the changes in the CoM signals associated with respiration,  $CoM_x$  and  $CoM_y$  signals were low pass filtered using a fifth order Chebyshev Type II filter (0.5 Hz passband frequency, 0.9 Hz stopband frequency, and 30 dB stopband attenuation). This filter was applied using MATLAB's *filtfilt* function (ensuring zero-phase shift) to obtain  $CoM_{resp_x}$  and  $CoM_{resp_y}$ .

The times when maxima ( $tmax$ ) and minima ( $tmin$ ) occurred in the  $CoM_{resp_x}$  and  $CoM_{resp_y}$  signals were found by finding zero crossings for the first derivative of each signal. These times correspond with the end of each exhalation and inhalation respectively.<sup>27</sup> The angle of the principal axis of the ellipsoid traced by the resultant  $CoM_{resp}$  signal relative to the positive  $x$  axis (positive angle measured clockwise) was calculated using equation (3) for each  $tmax$  and subsequent  $tmin$ .

$$\left| \frac{CoM_{resp-y}(tmax) - CoM_{resp-y}(tmin)}{CoM_{resp-x}(tmax) - CoM_{resp-x}(tmin)} \right| \quad (3)$$

Finally, we also isolated components of the signal that captured changes resulting from the cardiac cycle ( $rmsPulse$ ). MATLAB's *filtfilt* function was used to bandpass filter the sum of the LH and RH signals using an equiripple finite impulse response filter (0.5 Hz lower stopband frequency, 0.75 Hz lower passband frequency, 1.5 Hz upper passband frequency, 1.75 Hz upper stopband frequency, passband ripple of 1, and 40 dB stopband attenuations).

Twelve features were extracted from the signals above (shown in Table 2). Each data point used for

training/testing our machine learning classifier was the average of a 45 s moving window with a new value computed by shifting the window by 15 s. Since each pose was maintained for approximately 3 min, roughly 10 data points were calculated for each pose with each participant. In order to avoid overfitting given the small number of observations, each of the 12 poses shown in Figure 2 were labeled as either right side-lying, left side-lying, or supine. The poses shown in Figure 2(a) and (h) were labeled as supine; Figure 2(b), (d), (f), (i) and (k) were labeled as right-side-lying; Figure 2(c), (e), (g), (j) and (l) were labeled as left side-lying. This data were used to train a series of machine learning classifier models.

## Data analysis

Logistic Regression and Feed Forward Neural Network classifiers were implemented using the twelve extracted features. Feature selection was informed by Beattie et al.'s work<sup>27</sup> as well as our own series of pilot investigations. A leave-one-participant-out cross validation was done to evaluate the accuracy of each classifier model where at each iteration, one subject's entire data were left out of the training set and used as the test sequence to measure the accuracy of the classifier. To evaluate the potential for improved performance of the classification model to adapt to the unseen participant, an incremental learning approach was used. Using this approach, the machine learning classifier was trained using a percentage ( $c$ , with  $c=0\%$ ,  $10\%$ ,  $20\%$ , or  $30\%$ ) of the left-out participant's data. In other words,  $c=30\%$  indicates that 30% of the left-out participant's data were used for retraining the model and the remaining 70% was used only for accuracy testing. This incremental

**Table 2.** The 12 features extracted from the load cell signals that were used to train the machine learning classifiers to predict the participant's body orientation.

| Feature                | Description   |
|------------------------|---|
| $meanCoM_x$            | The mean of $CoM_x$   |
| $meanCoM_y$            | The mean of $CoM_y$   |
| $ratio\_meanCoM$       | The quotient of $meanCoM_y$ divided by $meanCoM_x$  |
| $stdCoM_x$             | The standard deviation of $CoM_x$   |
| $stdCoM_y$             | The standard deviation of $CoM_y$   |
| $ratio\_stdCoM$        | The quotient of $stdCoM_y$ divided by $stdCoM_x$  |
| $CoM_{resp\_ANG}$      | COM angle during inhalation phase only, averaged for all occurrences  |
| $stdCoM_{resp\_ANG}$   | Standard deviation of $CoM_{resp\_ANG}$   |
| $rmsCoM_{resp_x}$      | The root mean square of the x-component of $CoM_{resp}$ during both inhale and exhale phases, normalized to the 97th percentile     |
| $rmsCoM_{resp_y}$      | The root mean square of the y-component of $CoM_{resp}$ during both inhale and exhalation phases, normalized to the 97th percentile |
| $ratio\_rmsCoM_{resp}$ | The quotient of $rmsCoM_{resp_y}$ divided by $rmsCoM_{resp_x}$  |
| $rmsPulse$             | The root mean square of the load cell signals filtered to capture changes resulting from the cardiac cycle                          |



**Figure 2.** The 12 unique poses that participants were asked to adopt in this study. (a) Supine, flat bed. (b) Right side-lying, flat bed. (c) Left side-lying, flat bed. (d) Right side-lying with wedge, flat bed. (e) Left side-lying with wedge, flat bed. (f) Right side-lying with pillow, flat bed. (g) Left side-lying with pillow, flat bed. (h) Supine, head of bed raised 30°. (i) Right side-lying with wedge, head of bed raised 30°. (j) Left side-lying with wedge, head of bed raised 30°. (k) Right side-lying with pillow, head of bed raised 30°. (l) Left side-lying with pillow, head of bed raised 30°.

learning approach simulates the potential benefits of a calibration protocol that could be undertaken with each new patient user.

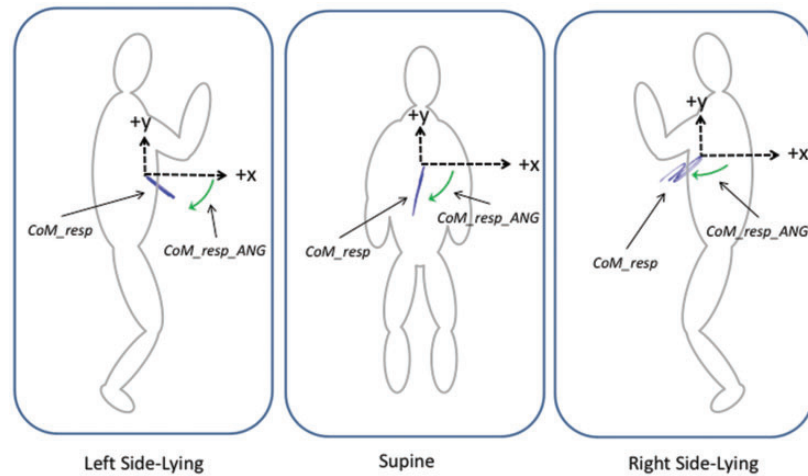
The classifiers were evaluated and compared using a nested cross validation procedure, where an inner cross validation loop was used for hyper-parameter tuning and an outer loop was used to measure the accuracy of the classifier on the test sequence. The machine learning classifier was trained using Keras with a Tensorflow backend. The hyper-parameters were found via a Gaussian-process optimization toolbox GPyOpt<sup>36</sup> version 1.2.0 on the validation set. To eliminate statistical variations arising from the randomness of parameter estimation and orientation prediction, each nested cross validation was run 10 times.

Mean relative feature weights were calculated for each trained classifier along with their respective standard errors to determine how important each feature was to each model and if any features should be removed.

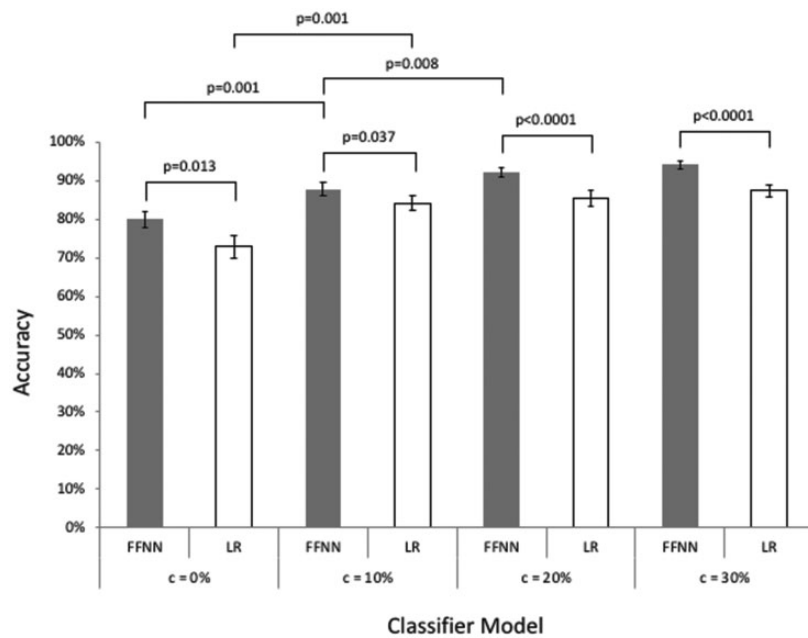
An ANOVA was run to determine if there was a significant main effect of model and a series of post hoc Bonferroni-adjusted pairwise comparisons were done to compare each model to adjacent  $c$  values within each model type. In other words,  $c=0\%$  was compared to  $c=10\%$ ,  $c=10\%$  was compared to  $c=20\%$ , and  $c=20\%$  was compared to  $c=30\%$ . Finally, post hoc comparisons were also done to compare between the Feed Forward Neural Network classifiers and Logistic Regression classifiers for each  $c$  value (0%, 10%, 20%, and 30%).

## Results

In total, 4932 observations from 20 participants were included in the dataset with a mean (SD) of 246.8 (60.1) observations per participant. Figure 3 shows the angle created by the primary axis of the ellipsoid created by the center of mass excursion with each breath ( $CoM\_resp\_ANG$ , green arrow) for the three



**Figure 3.** Representative samples of the resultant center of mass excursion ( $CoM_{resp}$ , in blue) and the corresponding angle the primary axis of the ellipsoid created by the centre of mass excursion with each breath ( $CoM_{resp\_ANG}$ , green arrow) for the three orientations categorized in this study.



**Figure 4.** Classification accuracy of Feed Forward Neural Network (FFNN) and Logistic Regression (LR) classifier models evaluated using a leave-one-participant-out cross-validation where  $c$  represents the percentage of the left-out participant's data that was used for incremental learning.

orientations categorized in this study, for one representative participant.

The overall accuracy of the eight classifier models and the performance of all eight combinations of the machine learning classification system ranged between 72.9% and 94.2% (shown in Figure 4). There was a significant main effect of the model ( $F(2.865, 54.427) = 35.148, p < 0.0005$ ) and post hoc comparisons showed that the Feed Forward Neural Network

classifier models significantly outperformed the Logistic Regression models for the same  $c$  value. Comparisons within the Logistic Regression models found significant differences between the models with  $c = 0\%$  and  $c = 10\%$ . Similarly, for the Feed Forward Neural Network models, the classifier with  $c = 0\%$  was found to be significantly different from  $c = 10\%$  and the  $c = 10\%$  model was significantly different from the  $c = 20\%$  model. The confusion matrices for the

Logistic Regression and Feed Forward Neural Network classifiers are displayed in Tables 3 and 4, respectively.

Figures 5 and 6 show the mean relative feature weights for the Logistic Regression and Feed Forward Neural Network classifier models, respectively.

**Table 3.** Confusion matrices showing classification accuracies (expressed as percentages) for Logistic Regression (LR) models evaluated using a leave-one-participant-out cross-validation where  $c$  represents the percentage of the left-out participant's data that was used for incremental learning.

|                      | Actual left | Actual supine | Actual right |
|----------------------|-------------|---------------|--------------|
| (a) LR: $c = 0\%$    |             |               |              |
| Classified as left   | 83.4        | 16.1          | 7.5          |
| Classified as supine | 12.0        | 65.5          | 19.4         |
| Classified as right  | 5.4         | 20.9          | 69.8         |
| (b) LR: $c = 10\%$   |             |               |              |
| Classified as left   | 91.4        | 11.1          | 4.2          |
| Classified as supine | 7.4         | 79.4          | 10.7         |
| Classified as right  | 1.9         | 12.0          | 81.9         |
| (c) LR: $c = 20\%$   |             |               |              |
| Classified as left   | 90.4        | 7.8           | 3.7          |
| Classified as supine | 8.6         | 83.6          | 10.5         |
| Classified as right  | 1.7         | 11.2          | 82.5         |
| (d) LR: $c = 30\%$   |             |               |              |
| Classified as left   | 91.5        | 6.7           | 3.3          |
| Classified as supine | 7.8         | 85.7          | 8.5          |
| Classified as right  | 1.4         | 10.0          | 85.1         |

(a)  $c = 0\%$ , (b)  $c = 10\%$ , (c)  $c = 20\%$ , and (d)  $c = 30\%$ .

**Table 4.** Confusion matrices showing classification accuracies (expressed as percentages) for Feed Forward Neural Network (FFNN) models evaluated using a leave-one-participant-out cross-validation where  $c$  represents the percentage of the left-out participant's data that was used for incremental learning.

|                      | Actual left | Actual supine | Actual right |
|----------------------|-------------|---------------|--------------|
| (a) FFNN: $c = 0\%$  |             |               |              |
| Classified as left   | 83.5        | 4.6           | 2.3          |
| Classified as supine | 14.1        | 87.6          | 25.7         |
| Classified as right  | 3.0         | 10.3          | 68.8         |
| (b) FFNN: $c = 10\%$ |             |               |              |
| Classified as left   | 88.3        | 2.3           | 2.8          |
| Classified as supine | 10.2        | 92.4          | 11.5         |
| Classified as right  | 2.1         | 7.8           | 82.4         |
| (c) FFNN: $c = 20\%$ |             |               |              |
| Classified as left   | 94.5        | 3.1           | 0.5          |
| Classified as supine | 5.5         | 94.9          | 8.7          |
| Classified as right  | 0.8         | 4.6           | 87.5         |
| (d) FFNN: $c = 30\%$ |             |               |              |
| Classified as left   | 95.3        | 1.4           | 1.3          |
| Classified as supine | 4.0         | 97.0          | 5.4          |
| Classified as right  | 1.3         | 4.1           | 90.2         |

(a)  $c = 0\%$ , (b)  $c = 10\%$ , (c)  $c = 20\%$ , and (d)  $c = 30\%$ .

Both figures include error bars showing standard error of the mean.

## Discussion

Figure 4 shows that the Feed Forward Neural Network models consistently outperformed the Logistic Regression models for each  $c$  value. We suspect this difference is likely because our computed features have non-linear characteristics and a Feed Forward Neural Network is better able to handle this non-linearity. Although a Feed Forward Neural Network model without a hidden layer is identical to Logistic Regression model with a sigmoid activation function,<sup>37</sup> the Feed Forward Neural Network is more flexible compared with Logistic Regression due to the non-linear input functions and the use of a non-linear decision boundaries.<sup>33</sup>

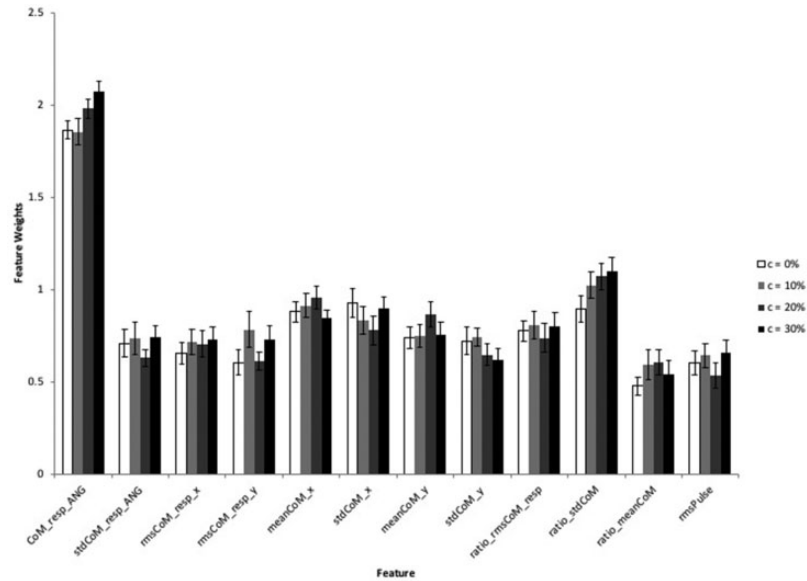
We also found that classifier models with more of the left-out-participant's data used for incremental learning tended to perform better in general although there was no statistical significance beyond  $c = 10\%$  for the Logistic Regression models and no significant difference beyond  $c = 20\%$  for the Feed Forward Neural Network classifier models. This means that it will likely be beneficial to design our repositioning prompting system to include a classifier model to be further refined for the patient by using incremental learning to improve prediction accuracy during a calibration period.

Our range of system performance (72.9%–94.2%) agrees well with the 83% average accuracy achieved by Beattie et al.<sup>27</sup> using K-means classification. A key difference in Beattie et al.'s<sup>27</sup> protocol may be that participants were able to position themselves in the two side-lying orientations while our participants were posed by a researcher. We expect that our use of pillows or wedges commonly used in a clinical environment made detection harder because these positioning aids resulted in side-lying poses that were closer to supine poses. This reasoning may explain why the Logistic Regression with  $c = 0\%$  under our protocol scored lower than Beattie's K-means classifier.

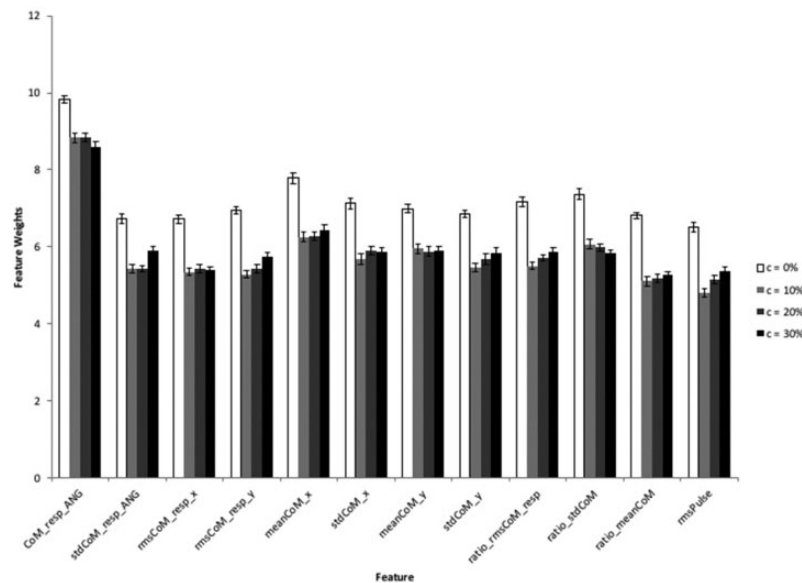
Although Duvall et al.<sup>26</sup> focused on detecting the different types of movement as opposed to different patient poses as in the present work, it is an encouraging coincidence that their system accuracy was identical to our best performing classifier model at 94.2%. This suggests that a parallel implementation of movement- and orientation-based detection could result in a system with even higher accuracy.

The confusion matrices in Tables 3 and 4 show the largest errors tended to be the result of misclassifications of right side-lying as supine, and vice versa. Looking at Figures 3, 5, and 6, we may be able to





**Figure 5.** Average feature weights for Logistic Regression classifier models (error bars show standard error of the mean).



**Figure 6.** Average feature weights for Feed Forward Neural Network classifier models (error bars show standard error of the mean).

determine the reason for difficulty in separating these two orientations. Figures 5 and 6 show that the most discriminating feature across all of our classifier models was *CoM\_resp\_ANG*. Figure 3 shows the ellipsoids created by the center of mass excursion with each breath. The ellipsoids are more similar between right side-lying and supine orientations than between other pairs of orientations. This asymmetry may be caused by differences in the relative sizes of the right and left lungs (the right lung being larger than the left). This finding highlights the need for future work to consider the effect of

patient lung capacity on accuracy of the system to determine its potential to be used with our target patient population. Figures 5 and 6 also demonstrate that there are no obvious features that should be removed from our feature set as none of them stand out as having particularly low feature weights.

### Design of a prompting system

Our ultimate goal is to develop a prompting system that can alert a caregiver when a patient needs to be

repositioned because he or she has remained in the same position or orientation (supine, left side-lying or right side-lying) for too long. We envision this system will consist of four load cells under the patient's bed legs connected to a base station placed on a bedside table that is able to process the load cell data in real-time using a Feed Forward Neural Network classifier that has been trained on data from a large number of mobility-limited patients.

We envision developing a mini PC with touchscreen user interface that will be incorporated into our existing system to prompt the caregiver via text message or audio prompt, when a mobility-limited patient in the home requires repositioning. We also envision the system sending alerts to the nursing station for patients in the institutional environment. The interface may include a recommendation for the next pose the patient should be put into at each prompt based on the patient's condition and past poses.

Based on our findings, our patient repositioning prompting tool will include the option to calibrate the predefined classifier model for each specific user (patient) using incremental learning. This calibration process will require a caregiver to manually indicate the patient's orientation after the system is installed under the patient's bed. This functionality may be implemented using a three-way selector switch to indicate whether the patient is supine, left side-lying or right side-lying each time a caregiver enters the patient's room. In this study, we found the highest accuracy with  $c = 30\%$  the equivalent of approximately 75 data points during the calibration period. If we assume a caregiver can provide a new indication of patient orientation once every two hours, the calibration procedure would take just under a week to complete. Future work will compare the costs and benefits of this calibration procedure in different settings (in the home vs in long-term care) as well as the durability of this model in real patients who are at risk of pressure injury.

## Limitations

There are two limitations in this work that should be noted. The first is that our system assumes the patient is lying parallel to the long axis of the bed. Deviations from this position will reduce the accuracy of our system's ability to detect the participant's orientation.<sup>27</sup> Further work is needed to quantify the extent to which our target population (mobility impaired older adults at risk of pressure injuries) is likely to be misaligned.

The dataset used in this study is relatively small in the context of machine learning training with an average of approximately 250 observations from each of

20 participants, none of whom were patients at risk of developing PIs from prolonged bedrest. We expect the generalizability/performance of our algorithm is limited by this small dataset and that future work will include retraining our classifiers with a larger dataset including our patient population. For instance, we expect there may be differences in the center of mass excursions seen with patients with a wider range of lung capacities and/or body mass indices that were not taken into consideration with our current healthy participant sample. The system will also evaluate performance while caregivers come into contact with the bed/patient as well as any objects such as infusion pumps, gastrostomy tubes, or tracheostomy/ventilation tubes.

## Conclusions

In this investigation, we examined the ability for Logistic Regression and Feed Forward Neural Network classifier models to categorize a person's orientation (supine, left side-lying, or right side-lying) in bed using data from four load cells placed under the bed legs. Feed forward Neural Network classifiers performed better than logistic regression classifiers. Additionally, providing a higher proportion of the left-out participant's data for incremental learning led to higher accuracy predictions. Feed Forward Neural Network classifier with 30% of the left-out participants data used for incremental learning was found to have the highest prediction accuracy of 94.2%.

## Acknowledgments

The authors would like to thank the following for their important contributions to this project: Andrew Hallisey, Cecilia Yeung, Erik Prout, James Penrose, Jessie Leith, and Jessica Babineau.




## Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The authors would like to acknowledge funding support from the Canadian Institutes of Health Research (Grant # PPP-144246), the Creaghan Family Chair in Prevention and Healthcare Technologies (Geoff Fernie), Toronto Rehab Foundation, and the Hallisey Postdoctoral Fellowship in Technology for Family Caregivers (Tara Kajaks and Sharon Gabison).

## ORCID iDs

Gordon Wong  <https://orcid.org/0000-0001-5269-2051>  
 Sharon Gabison  <https://orcid.org/0000-0002-5202-3736>  
 Tara Kajaks  <https://orcid.org/0000-0003-2848-3756>

## References

- Edsberg LE, Black JM, Goldberg M, et al. Revised National Pressure Ulcer Advisory panel pressure injury staging system. *J Wound Ostomy Continence Nurs* 2010; 43: 585–597.
- Woodbury MG, Houghton PE. Prevalence of pressure ulcers in Canadian healthcare settings. *Ostomy/Wound Manag* 2004; 50: 22–38.
- Peterson MJ, Schwab W, van Oostrom JH, et al. Effects of turning on skin-bed interface pressures in healthy adults. *J Adv Nurs*. 2010; 66: 1556–1564.
- Black JM, Edsberg LE, Baharestani MM, et al. Pressure ulcers: Avoidable or unavoidable? Results of the National Pressure Ulcer Advisory Panel Consensus Conference. *Ostomy/Wound Manag* 2011; 57: 24–37.
- Anson CA, Shepherd C. Incidence of secondary complications in spinal cord injury. *Int J Rehabil Res [Internationale Zeitschrift für Rehabilitationsforschung Revue Internationale de Recherches de Readaptation]* 1996; 19: 55–66.
- Claudia G, Diane M, Daphney SG, Daniele D. Prevention and treatment of pressure ulcers in a university hospital centre: A correlational study examining nurses' knowledge and best practice. *Int J Nurs Pract* 2010; 16: 183–187.
- Renganathan BS, Preejith SP, Sridhar N, Joseph J, Mohanasankar S. A novel system to tackle hospital acquired pressure ulcers. In: *IEEE Engineering in Medicine and Biology Society*, 2016, Conference Proceedings, pp. 4780–4783. Orlando, FL, USA.
- Yamamoto Y, Hayashino Y, Higashi T, et al. Keeping vulnerable elderly patients free from pressure ulcer is associated with high caregiver burden in informal caregivers. *J Eval Clin Pract* 2010; 16: 585–589.
- McInnes E, Jammali-Blasi A, Bell-Syer SEM, et al. Support surfaces for treating pressure ulcers. *Cochrane Database Syst Rev* 2018; 10: 1–64.
- Van Leen M and Schols J. Pressure relief, visco-elastic foam with inflated air? A pilot study in a dutch nursing home. *Healthcare (Basel)*. 2015; 3: 78–83.
- Houghton PE and Campbell KE. *Canadian best practice guidelines for the prevention and management of pressure ulcers in people with spinal cord injury. A resource handbook for clinicians*. 2013, p. 317. Toronto, ON, Canada: Ontario Neurotrauma Foundation.
- RNAO. *Risk assessment and prevention of pressure ulcers. Nursing best practice guideline*. Toronto, Canada: Registered Nurses' Association of Ontario, 2005.
- American Academy of Family Physicians. *What are pressure sores?* Leawood, KS: American Academy of Family Physicians, 2017.
- RNAO. *Self-directed learning package for health care providers. Best practice guidelines program*. Toronto, Canada: Registered Nurses' Association of Ontario, 2007.
- Bergstrom N, Horn SD, Rapp MP, et al. Turning for ulcer reduction: a multisite randomized clinical trial in nursing homes. *J Am Geriatr Soc* 2013; 61: 1705–1713.
- Fernie GR and Dornan J. The problems of clinical trials with new systems for preventing or healing decubiti. In: Kenedi RM and Cowden JM, (eds.). *Bed Sore Biomechanics*. London, UK: The MacMillan Press Ltd., 1976, pp. 315–326.
- Gunningberg L. Are patients with or at risk of pressure ulcers allocated appropriate prevention measures? *Int J Nurs Pract* 2005; 11: 58–67.
- Lyder CH, Preston J, Grady JN, et al. Quality of care for hospitalized medicare patients at risk for pressure ulcers. *Arch Internal Med* 2001; 161: 1549–1554.
- Krishnagopalan S, Johnson EW, Low LL et al. Body positioning of intensive care patients: clinical practice versus standards. *Critical Care Med* 2002; 30: 2588–2592.
- Schallom L, Metheny NA, Stewart J, et al. Effect of frequency of manual turning on pneumonia. *Am J Critical Care* 2005; 14: 476–478.
- Pompeo MQ. Pressure map technology for pressure ulcer patients: can we handle the truth? *Wounds*. 2013; 25: 34–40.
- Stockton L and Parker D. Pressure relief behaviour and the prevention of pressure ulcers in wheelchair users in the community. *J Tissue Viabil* 2002; 12: 84–99.
- International review. Pressure ulcer prevention: pressure, shear, friction and microclimate in context. A consensus document. London, 2010.
- Schutt SC, Tarver C and Pezzani M. Pilot study: Assessing the effect of continual position monitoring technology on compliance with patient turning protocols. *Nurs Open* 2018; 5: 21–28.
- Cha Y, Nam K and Kim D. Patient posture monitoring system based on flexible sensors. *Sensors (Basel)*. 2017; 17: 548.
- Duval J, Karg P, Brienza D, et al. Detection and classification methodology for movements in the bed that supports continuous pressure injury risk assessment and repositioning compliance. *Journal of Tissue Viability*. 2019; 28: 7–13.
- Beattie ZT, Hagen CC and Hayes TL. Classification of lying position using load cells under the bed. *Conf Proc IEEE Eng Med Biol Soc* 2011; 2011: 474–477.
- Marchione FG, Araujo LM and Araujo LV. Approaches that use software to support the prevention of pressure ulcer: a systematic review. *Int J Med Inform* 2015; 84: 725–736.
- Behrendt R, Ghaznavi AM, Mahan M, et al. Continuous bedside pressure mapping and rates of hospital-associated pressure ulcers in a medical intensive care unit. *Am J Crit Care*. 2014; 23: 127–133.
- Motamedi SM, de Grood J, Harman S, et al. The effect of continuous pressure monitoring on strategic shifting of medical inpatients at risk for PUs. *J Wound Care* 2012; 21: 517–527.
- Gunningberg L, Sedin IM, Andersson S, et al. Pressure mapping to prevent pressure ulcers in a hospital setting: a pragmatic randomised controlled trial. *Int J Nurs Stud* 2017; 72: 53–59.

32. Kallman U, Bergstrand S, Ek AC, et al. Nursing staff induced repositionings and immobile patients' spontaneous movements in nursing care. *Int Wound J* 2016; 13: 1168–1175.
33. Dreiseitl S and Ohno-Machado L. Logistic regression and artificial neural network classification models: a methodology review. *J Biomed Inform* 2002; 35: 352–359.
34. Faisal M, Scally A, Howes R, et al. A comparison of logistic regression models with alternative machine learning methods to predict the risk of in-hospital mortality in emergency medical admissions via external validation. *Health Inform J* 2018: 1460458218813600.
35. Albukhari A, Lima F, Mescheder U. Bed-embedded heart and respiration rates detection by longitudinal ballistocardiography and pattern recognition. *Sensors (Basel, Switzerland)*. 2019; 19: 1451.
36. The GPyOpt authors G. A Bayesian Optimization framework in Python. Sheffield Machine Learning Software. 2016.
37. Bishop CM. *Neural Networks for Pattern Recognition*. Oxford: Oxford University Press, 1995.
38. Hastie T, Tibshirani R and Friedman J. *The elements of statistical learning. Data mining, inference, and prediction*. New York: Springer, 2001.