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Distinguishing positions and movements in bed from load cell signals

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Supplementary material for this article is available online

Abstract

Objective: To characterize and classify six positions and movements for individuals in a bed using the output signals of four load cell sensors. *Approach*: A bed equipped with four load cell sensors and synchronized video was used to assess the load cell response of 54 healthy individuals in prescribed positions and as they moved between positions. Stationary positions were characterized by the signals from the four load cells and the coordinates of the center of mass (CoM). Movements were characterized by the changes in load cell signals, four parameters associated with the trajectory of the CoM between the initial and final position (Euclidean distance, length of the trajectory, and the x- and y- variances), and the initial position's CoM coordinates. Classification and decision tree models were used to assess the ability of these parameters to identify specific positions or movements. *Main results*: Six positions were classified with an accuracy of 74.9% and six movements were classified with an accuracy of 79.7%. *Significance*: This study demonstrates the feasibility of distinguishing certain positions and movements with load cell sensors. The identification of positions and movements for individuals in bed can be used as a tool in a variety of clinical settings.

1. Introduction

The movement of a patient in a hospital bed contains clinically relevant information about the patient's mobility (Azuh *et al* 2016, Hoyer *et al* 2016), risk of developing hospital acquired pressure injuries (Neilson *et al* 2014), sudden unexpected death in epilepsy (SUDEP) (Kloster and Engelskjon 1999), and quality of sleep (Lee *et al* 2009). In clinical settings, the assessment of activity in bed is usually performed by visual observation, which is time consuming and difficult to implement in real-time.

Various methods have been used to automate the study of bed movements, including accelerometers (Wrzus *et al* 2012), load cell sensors (Adami *et al* 2008, Austin *et al* 2012, Alaziz *et al* 2016), pressure mats (Harada *et al* 2002, Hsia *et al* 2009, Wai *et al* 2010, Pouyan *et al* 2013), and infrared cameras (Cary 2016). Systems that require additional devices or require individuals to wear equipment are less practical in clinical settings where time spent with patients is limited (Westbrook *et al* 2011).

Previous studies have shown success in using load cell sensors located in the four corners of a bed to monitor movement (Adami *et al* 2008, 2010a, Beattie *et al* 2011, Alaziz *et al* 2016). To distinguish movements from background noise it is common to combine the mean square signal from each of the four load cells into a single parameter: the feature signal (Adami *et al* 2005, 2010a, 2010b, Alaziz *et al* 2016). The start and end of a movement are identified by smoothing the feature signal and applying an arbitrary threshold. Once the start and end of a movement have been identified, the movement itself can be characterized from the shift in the center of mass (CoM) obtained from the load cells. The trajectory of the CoM during a movement can be characterized by the distance between the start and the end points, the total length of the trajectory, and the lateral and vertical variances.

Parameters associated with load cell signals have been used to differentiate between certain groups or classes of movements. In a study of prescribed and voluntary movements, major postural shifts (torso rotation of more than 45°), small and medium amplitude movements (arms and head), and leg movements were distinguished with a classification rate of 84.6% (Adami *et al* 2011). In a study of 27 prescribed movements, groups of large and small movements were distinguished with a success rate of 95.8% (Alaziz *et al* 2016). In another study of nine groups of prescribed movements, including torso rotations, individual and combined leg and arm movements, and head movements, turning directions (left or right) were successfully classified with accuracies of 91% and 90%, respectively, independent of the starting position (Alaziz *et al* 2017). These studies demonstrate the utility of using load cell sensors to classify groups of movements; however, the ability to distinguish specific positions and movements has received less attention.

Previous work using load cell sensors has focused on discriminating between lying positions, independent of movement (Beattie *et al* 2011). In a study of subjects in stationary positions, the fluctuations of the CoM in the vertical direction (along the length of the bed) were used to distinguish between prone/supine, lying on the right side, or lying on the left side, with classification rates of 92%, 75%, and 86%, respectively (Beattie *et al* 2011).

These studies suggest that bed activity can be distinguished with different levels of success. The objective of this study was to assess the ability to identify and distinguish specific movements, which implicitly includes the identification of specific positions. The overall goal of our work is to develop a technology to automate the continuous assessment of patient movements while in bed, providing clinical staff with a tool to direct clinical care more efficiently and effectively.

2. Methods

2.1. Equipment and setup

The bed system used in this study consisted of a bed frame (213.4 cm × 91.4 cm × 9.5 cm) with four legs (one in each corner), four load cell sensors each with a 250 lbs capacity (iLoad Pro Digital USB Integrated Load Cell, Loadstar™ Sensors, Fremont, CA) placed under each leg, and a mattress (214.6 cm × 81.3 cm × 15.9 cm) (figure 1(a)). The output signals from each of the four sensors (lbs) are designated as w_A, w_B, w_C, and w_D, and the sum of the load cell outputs ($w_A + w_B + w_C + w_D$) is designated as w_{tot} (figure 1(b)). The output signals were collected at 10 Hz and recorded using the load sensor software (LoadVUE, Loadstar™ Sensors, Fremont, CA).

A video camera (HERO®4 camera, GoPro, San Mateo, CA) was positioned at the foot of the bed at a height of about 3.5 feet from the ground to record the subject's movement. The video footage was used to confirm periods of time with and without movement and the quality of the movement. The quality of the movement was defined as how well the subject followed instructions when turning, i.e. did they initiate the turn in the correct direction, and whether extraneous movements occurred during the trial.

Synchronization between the load cell output and the video was achieved by dropping a ball in the center of the bed and aligning the peak in the load cell signal (w_{tot}) with the camera frame that displayed the impact of the ball.

2.2. Participants

Fifty-four healthy adults (18+ years old, 5 ft 9 in ±4 in (SD)) were recruited to participate in the study. Approval was obtained from the Johns Hopkins University Homewood Institutional Review Board and subject consent was obtained prior to participation. Exclusion criteria included anyone who was unable to give informed consent and anyone who was unable to sit and stand on their own without assistance.

2.3. Data collection

At the beginning of a trial, seven positions were described and demonstrated: (1) lying on the back (supine), (2) lying on the right side of the body (right), (3) lying on the stomach (prone), (4) lying on the left side of the body (left), (5) sitting in the center of the bed (C Sit), (6) sitting on the right side of the bed (R Sit), and (7) sitting on the left side of the bed (L Sit) (figure 1(c)). The initial position in the trial was supine: lying on the back with the sacrum in the middle of the bed, with legs and arms straight and palms facing up. The subjects were asked to return to this position after moving to each of the lying positions.

A piece of tape was placed in the center of the bed as a guide for returning to the supine position. A piece of tape was also placed in the middle of the left and right sides of the bed and subjects were asked to straddle these pieces of tape during the left and right seated positions.

A trial consisted of seven positions and 11 changes in position. Subjects were asked to move into each position in a manner that was most comfortable to them and hold that position (for approximately 5 s) until they were instructed to move into the next position. Each trial lasted between 3 and 4 minutes. Trials were excluded if the subject initiated a movement in a different direction than instructed. Three complete trials were recorded for each subject.

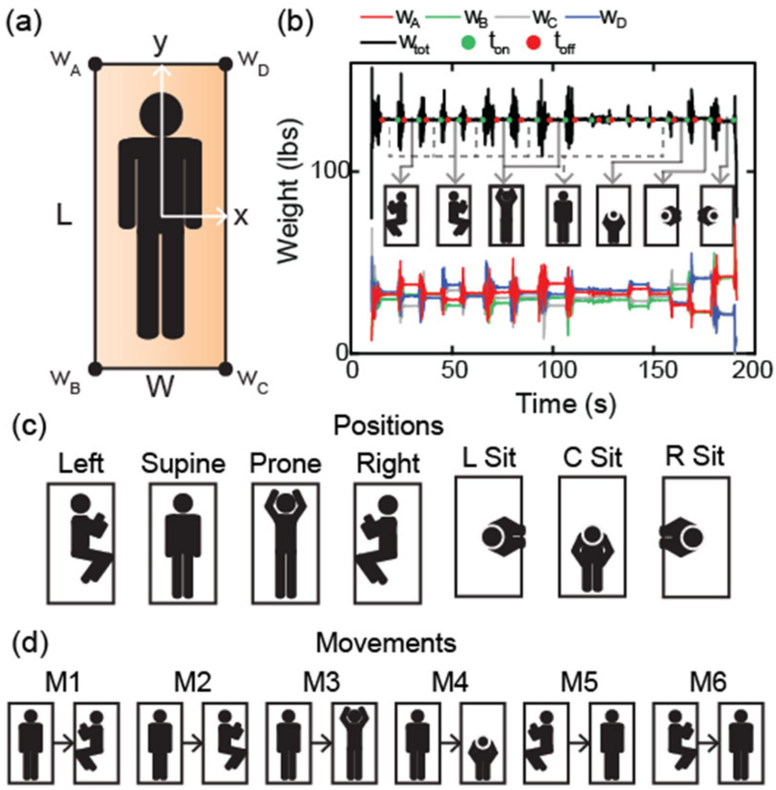

Figure 1. The bed movement trial. (a) A schematic illustration of the bed and the positions of the four load cells. The origin of the coordinate system was located at the center of the bed. (b) Representative data from one trial showing the raw signals (lbs) from the four load cells (w_A, w_B, w_C, and w_D), along with the sum of the four load cells (w_{tot}). The green and red circles on the w_{tot} trace indicate the initiation (t_{on}) and cessation (t_{off}) of a movement (see text for details). The vertical dotted lines indicate the periods the subject was in the supine position. (c) Subjects adopted seven positions during a trial. (d) Six movements were defined by the initial and final positions. M1: supine to right side; M2: supine to left side; M3: supine to prone; M4: supine to sitting in the center; M5: right side to supine; M6: left side to supine.

2.4. Movement detection

For each trial, we recorded time records (3–4 min long) for each of the four load cells with a sample interval of 0.1 s. To analyze the load cell signals associated with specific positions and the movements between positions, we first identified the beginning (t_{on}) and end (t_{off}) of each movement. The time associated with a subject maintaining a specific position is therefore defined by the end of one movement (t_{off}) and the beginning of the next movement (t_{on}).

Identifying the on- and off-times of a movement above the background signal from the load cells is non-trivial. Since changes in the signal from an individual load cell may be positive or negative, identification of movements is accomplished by defining a function $f(t)$ that is the weighted sum of the mean square load cell signals (Adami et al 2005, 2008, 2010b):

$$f(t) = \sum_{i=1}^{4} c_i(t) s_i^2(t) \quad (1)$$

where $s_i^2(t)$ describes the mean square fluctuations of the load cell signal with respect to a local mean (see below), and c_i is a weighting factor.

The parameter $s_i^2(t)$ is evaluated for each load cell at time t from the deviation of w_i from the local mean:

$$s_i^2(t) = \frac{1}{L-1} \Sigma_{k=-\left(\frac{L-1}{2}\right)}^{\frac{L-1}{2}} \left(w_i(t-k) - \overline{w}_i(t)\right)^2 \quad (2)$$

where L is an odd number representing the length of the averaging window, and $\overline{w}_i$ is the local mean value from the signal of each load cell (i) divided by length L ($\overline{w}_i(t) = 1/L \sum_{k=-(L-1)/2}^{(L-1)/2} w_i(t-k)$.

In this study we used $L = 11$, so that the window includes the preceding and following five time points. Since we use a measuring frequency of 10 Hz, this is equivalent to a 1.1 s averaging window. The purpose of the averaging window, defined by L, is to remove high frequency fluctuations and enable accurate identification of the start and end points of controlled movements (Adami et al 2010b).

To account for the fact that weight is usually distributed unevenly amongst load cells (i.e. the CoM is not at the center of the bed), the mean square fluctuations are weighted by a scaling coefficient c_i:

$$c_i\left(t\right)=\frac{1}{r_i\left(t\right)+1} \tag{3}$$

where $r_i(t)$ is the root mean square distance between the coordinates of the CoM and load cell i at time $t\,(r_i(t)=\surd((x_i-x_{CoM}(t))^2+(y_i-y_{CoM}(t))^2))$.

The location of the CoM is defined by

$$x_{\text{CoM}}\left(t\right)=\frac{w_C\left(t\right)+w_D\left(t\right)-w_A(t)-w_B(t)}{w_{\text{tot}}(t)}\frac{W}{2} \tag{4}$$

$$y_{\text{CoM}}\left(t\right)=\frac{w_A\left(t\right)+w_D\left(t\right)-w_B(t)-w_C(t)}{w_{tot}(t)}\frac{L}{2} \tag{5}$$

where $w_{\text{tot}}(t)$ is the sum of the four load cell signals and is equivalent to subject weight, W is the bed width (91.4 cm), and L is the bed length (213.4 cm).

If a subject's position is such that the CoM is at the center of the bed ($x_{\text{CoM}}=0$, $y_{\text{CoM}}=0$), then $c_i(t)$ is the same for each load cell, and the fluctuations from each load cell contribute equally to $f(t)$. However, if the CoM is shifted from the center of the bed, then the fluctuations from the load cells closer to the CoM contribute more to $f(t)$ than fluctuations from load cells further away from the center of mass.

To define regions in the time record where the subject was not moving, we used a fixed threshold of $f(t)=0.0002$. The fixed threshold value of 0.0002 was approximately one standard deviation greater than the noise of the system calculated from the average load cell signal values of an empty bed. Previous studies have used individualized thresholds based on a subject's weight to identify on- and off-times (Adami *et al* 2005, 2010b). In this study, the customized thresholds were not dependent on subject weight (figure S1 (stacks.iop.org/PM/39/125001/mmedia)) and hence we used the universal threshold described above. On average, the fixed threshold value ($f(t)=0.0002$) was more than 2-fold larger than the value while the subject was in one of the supine positions in the subset of subjects (30 out of 54) used to compare the fixed threshold value to the custom threshold value.

Regions of the time record corresponding to movements were defined by three rules: (1) the onset of a movement (t_{on}) was defined as the first point where $f(t)>0.0002$ and remained above the threshold for at least 1.5 s; (2) the end of a movement (t_{off}) was defined by the first point where $f(t)\leqslant 0.0002$ and remained below the threshold for at least 1.5 s; and (3) if time between movements ($t_{\text{off}}-t_{\text{on}}$) was $\leqslant$1 s, the movements were combined. Using these rules, we defined t_{on} and t_{off} for each of the 11 movements in each trial. The number of on- and off-times associated with each trial was verified from the video to ensure the correct number of movements were detected.

2.5. Data analysis

Load cell signals were normalized to the subject's body weight (BW). The subject's BW was obtained from the average of w_{tot} over 10 s when the subject was in a supine position. Sensor values are reported as %BW.

2.5.1. Position

Analysis of static positions was based on the average signal for (1) individual load cells (w_{A}, w_{B}, w_{C}, w_{D}), (2) four combinations ($w_{\text{A+D}}$, $w_{\text{B+C}}$, $w_{\text{A+B}}$, $w_{\text{C+D}}$), and (3) the position ($x_{\text{CoM}}(\text{t})$, $y_{\text{CoM}}(\text{t})$) of the CoM (equation (4), equation (5)) during steady state periods (i.e. between t_{off} of one movement and t_{on} of the next movement) (figures 2(a) and (b)).

2.5.2. Movement

Six movements were defined by the initial and final positions and consisted of moving from (1) supine to right (M1), (2) supine to left (M2), supine to prone (M3), supine to C Sit (M4), right to supine (M5), and left to supine (M6) (figure 1(d)). Analysis of movements between positions was based on (1) the load cell signals before and after the movement (i.e. from the time records in the preceding and following static positions), (2) the transient changes in the load cell signals during the movement, and (3) the initial position's CoM coordinates. Analysis of the load cell signals before and after a movement considered the difference in (1) the load cell signals (Δw_{A}, Δw_{B}, Δw_{C}, Δw_{D}), and (2) four combinations of load cell signals ($\Delta w_{\text{A+D}}$, $\Delta w_{\text{B+C}}$, $\Delta w_{\text{A+B}}$, $\Delta w_{\text{C+D}}$). For example, moving from the supine position to sitting in the center of the bed resulted in a decrease in the signal from w_{A} (figure 2(c)).

Analysis of the transient signals during movement also considered the trajectory of the CoM (Adami *et al* 2011, Alaziz *et al* 2017). During movements, the CoM traced out a complex trajectory dependent on the way that

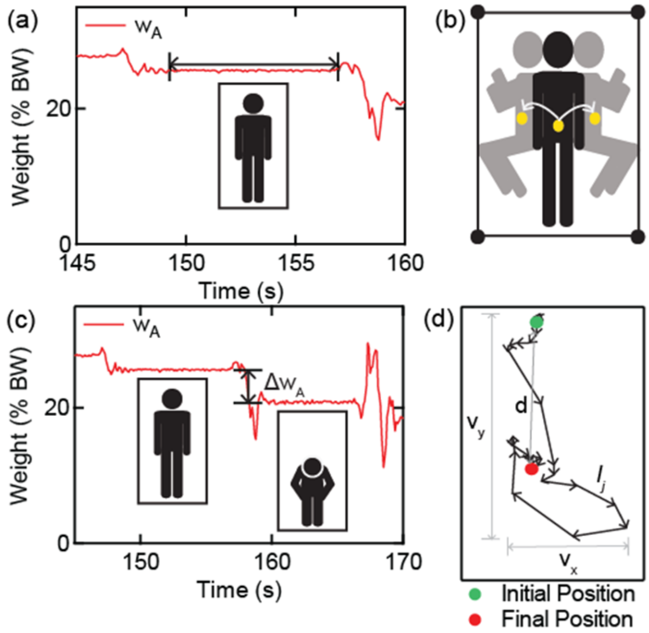

Figure 2. Parameters associated with position and movement. (a) A representative time record from a single load cell (w_A) during a steady state period, defined by the arrows, while the subject was in the supine position. (b) Three lying positions demonstrate the variation in the location of the CoM. The yellow circles indicate the location of the CoM for each position. (c) A representative change in the load cell signal associated with movement from supine (initial position) to C Sit (final position). (d) A representative trajectory of the CoM from supine (green circle) to C Sit (red circle). Parameters associated with the CoM trajectory between initial and final positions: d, the Euclidean distance of the trajectory; l_j, one segment of the length of the trajectory; v_x, the horizontal variance of the CoM trajectory; v_y, the vertical variance of the CoM trajectory.

the subject moved into the new position (figure 2(d)). The trajectory of the CoM is made up of N segments at 0.1 s intervals.

The Euclidean distance of the trajectory d is the shortest distance between the initial and final CoM and is given by

$$d = \sqrt{(x_f - x_s)^2 + (y_f - y_s)^2} \tag{6}$$

where x_s, y_s define the CoM in the start position (before the movement) and x_f, y_f define the CoM in the final position (after the movement).

The length of the trajectory l is the distance along the path traced out by the trajectory and is given by

$$l = \sum_{j=1}^{N} l_j \tag{7}$$

where l_j is the distance of a segment in the CoM trajectory ($l_j = \sqrt{((x_j - x_{(j-1)})^2 + (y_j - y_{(j-1)})^2)}$).

The horizontal (side-to-side) and vertical (top-to-bottom) variations in CoM during a movement are defined by the variance. The horizontal variance of the trajectory is given by

$$v_x = \sum_{j=1}^{N} \frac{(x_{\mathrm{CoM}}(j) - \bar{x}_{\mathrm{CoM}})^2}{N-1}. \tag{8}$$

The vertical variance of the trajectory is given by

$$v_y = \sum_{j=1}^{N} \frac{(y_{\mathrm{CoM}}(j) - \bar{y}_{\mathrm{CoM}})^2}{N-1} \tag{9}$$

where N is number of time points over the transient period, $\bar{x}_{\mathrm{CoM}}$ is the mean CoM in the horizontal x direction, and $\bar{y}_{\mathrm{CoM}}$ is the mean CoM in the vertical y direction.

2.5.3. Statistical analysis

The CoM position (x_{CoM}, y_{CoM}) and transient variables (d, l, v_x, v_y) were summarized using mean ± SE. One-way analysis of variance (ANOVA) was used to assess (1) differences in the CoM between positions, and (2) parameters related to the CoM trajectory during a movement (d, l, v_x, v_y). Multiple comparison analysis tests with Bonferroni adjusted p values identified (1) positions that were significant for CoM x- and y-coordinates and (2) movements that were significant for each parameter ($p < 0.05$). The classification and regression tree method was used to create classification models for position and movement predictions. Split-sample validation was used to test the models, with 2/3 of subjects used for training. Before training the static position model, random under-sampling was used to account for the fact that there were more instances of the supine position. Random under-sampling was used to account for the fact that when supine and prone positions were combined there were more instances of the supine/prone positions. The variables included in the static position model were: the averaged individual load cell signals (w_A, w_B, w_C, w_D), the combinations ($w_{A+D}, w_{B+C}, w_{A+B}, w_{C+D}$), and the CoM coordinates (x_{CoM}, y_{CoM}). The individual load cell signals provide information on the distribution of body weight to a corner of the bed, whereas the combinations provide insight into the distribution along the sides of the bed: w_{A+D} (top), w_{B+C} (bottom), w_{A+B} (right side), and w_{C+D} (left side). The variables included in the movement model were: the difference in averaged individual load cell signals (Δw_A, Δw_B, Δw_C, Δw_D), the combinations ($\Delta w_{A+D}, \Delta w_{B+C}, \Delta w_{A+B}, \Delta w_{C+D}$), the parameters associated with the CoM trajectory (d, l, v_x, v_y), and the initial position's CoM coordinates. All statistical analyses were performed using SPSS Statistics for Windows, version 24 (IBM Corp., Armonk, NY).

3. Results

3.1. Position

We first considered the load cell signals while the subjects remained in one of the seven static positions. The average signal from the individual load cells, as well as combinations of pairs of load cells, are summarized in a heat map (figure 3(a)). In the supine position, the signals from the upper load cells (w_A and w_D) were larger than from the lower load cells (w_B and w_C), indicating that the vertical CoM (y_{CoM}) was above the midpoint of the bed. However, $w_A \approx w_D$ and $w_B \approx w_C$ indicating that the horizontal CoM (x_{CoM}) was along the midpoint of the bed.

All four lying positions resulted in more weight being distributed on the top half of the bed, with differences that ranged from 7.7 to 11.2 %BW between the top (w_{A+D}) and bottom (w_{B+C}) load cells. Sitting in the center of the bed had more weight distributed on the bottom half compared to the top (10.7 %BW). Weight was distributed almost equally between the top and bottom halves of the bed in the right and left seated positions. In the side-seated positions, almost 75 %BW was placed on the load cells that corresponded to the side the subject was sitting on (R Sit: $w_{A+B} = 72.6$ %BW and L Sit: $w_{C+D} = 73.1$ %BW). However, in the side-lying positions, there was less than 20 %BW difference between the load cells on the right and left sides of the bed (Right: $w_{A+B} = 58.7$ %BW; Left: $w_{C+D} = 59.3$ %BW). The positions in the middle of the bed (supine, prone, sitting in the center) had similar weight values on the right and left side load cells.

The distribution of weight, inferred from the load cell signals, is clear in the distribution of the CoM for each position (figure 3(b)). The mean vertical CoM (y_{CoM}) for the lying positions were all located at the top of the bed, above the horizontal midline. The mean CoM in the supine position was closer to the center of the bed than the mean CoM in the prone position (figure 3(d)), although both were along the vertical midline (figure 3(c)). Each trial contained five supine positions, however, the differences in CoMs were statistically significant suggesting that subjects did not return to the initial supine position (figure S2).

The CoM of the side-lying positions were shifted from the vertical midline (Right: $x_{CoM} = -8.2$ cm and Left: $x_{CoM} = 8.3$ cm), and both were approximately parallel with the supine position towards the top of the bed (figure 3(c)). The overlap in the error bars reflects the fact some subjects shifted towards the vertical center of the bed when moving into the side-lying positions (figure 3(b)). This was visually observed during the data collection. The CoM of the side-seated positions was further shifted from the vertical midline compared to the side-lying positions (R Sit: $x_{CoM} = -21.2$ cm and L Sit: $x_{CoM} = 20.7$ cm) (figure 3(c)). The mean of the right seated position CoM was very close to the horizontal midline, while the mean of the left seated CoM was below the midline.

To assess the ability of the load cell data to predict the subject's position in the bed, we used the classification and regression tree method. The model was trained using the averaged individual load cell signals (w_A, w_B, w_C, w_D), the combinations ($w_{A+D}, w_{B+C}, w_{A+B}, w_{C+D}$), and the CoM coordinates (x_{CoM}, y_{CoM}) for 67% of the subjects. The model was then used to predict the position in the remaining 33% of the subjects (table 1). The supine and prone positions were combined since the prone position was indistinguishable from the other positions. Almost half of the prone positions were misclassified as supine (46.3%). If we consider only prone and supine positions, the two positions can only be distinguished with an accuracy of 52.8%.

The three seated positions had the highest classification accuracies of the six positions (R Sit: 86.8%; L Sit: 79.6%; and C Sit: 77.4%). The right and left lying positions had accuracies of 64.8% and 66.7%, respectively. More than half of the right (60.0%) and left (77.8%) position misclassifications were identified as supine/prone. Prediction of the supine/prone position had an accuracy of 75.9% and was typically misclassified as left or right; accounting for 76.9% of misclassification. The prediction accuracy of the model was almost identical if the CoM was excluded.

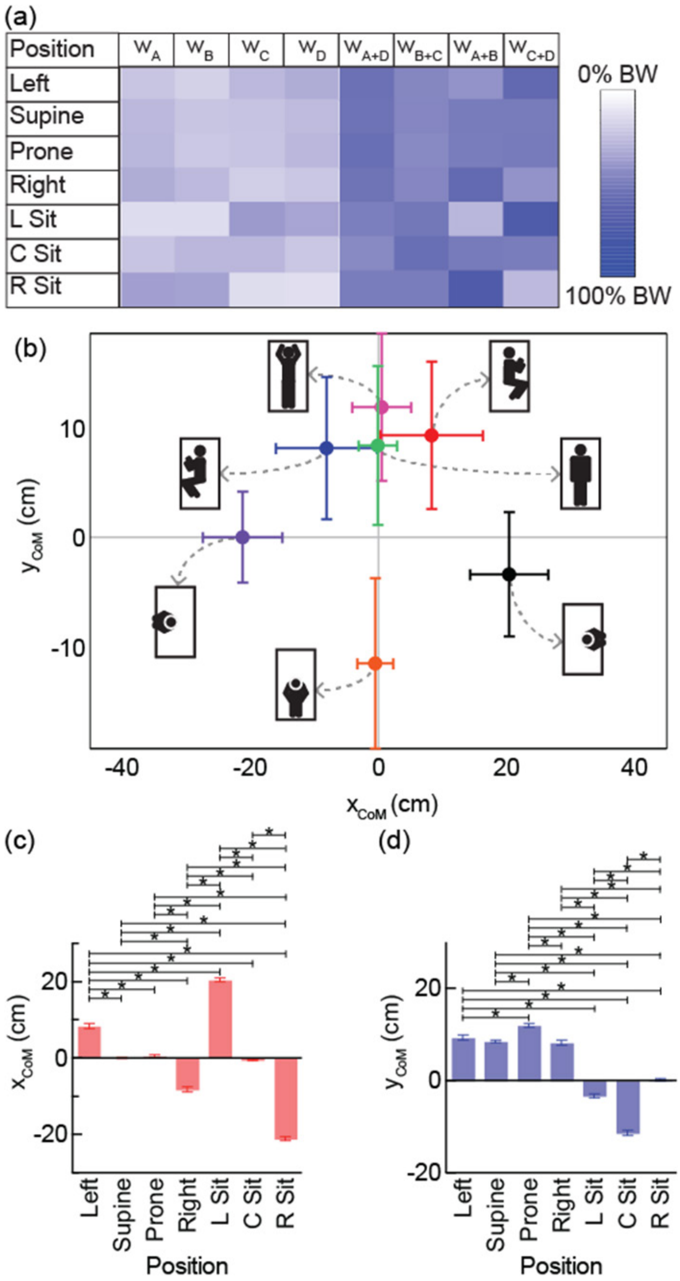

Figure 3. Load cell signatures for subjects in static positions. (a) A heat map showing the percentage of body weight (%BW) on each load cell (w_A, w_B, w_C, w_D) and different load cell combinations corresponding to sides of the bed (top: w_{A+D}, bottom: w_{B+C}, right side: w_{A+B}, left side: w_{C+D}) for each position. Darker colors are associated with a higher %BW. Left: lying on the left side of the body; Supine: lying on the back; Prone: lying on the stomach; Right: lying on the right side of the body; L Sit: sitting on the left side of the bed; C Sit: sitting in the center of the bed; R Sit: sitting on the right side of the bed. (b) The location of the CoM for each of the seven positions (mean ± SD). The origin is located at the center of the bed. (c) The x-coordinate of the CoM for the seven positions (mean ± SE). (d) The y-coordinate of the CoM for the seven positions (mean ± SE). *Significance ($p \leqslant 0.05$).

3.2. Movement

Having analyzed the load cell signatures for static positions, we next analyzed the transient changes associated with six movements from one position to another (figure 1(d)). We first considered the changes in the magnitude of the signal from the individual load cells and the pairwise combinations (figure 4(a)). The differences in the four combinations of load cell signals (Δw_{A+D}, Δw_{B+C}, Δw_{A+B}, and Δw_{C+D}) were coupled; for example, an increase in Δw_{A+D} (top of the bed) resulted in an associated decrease in Δw_{B+C} (bottom of the bed). Similarly, the changes in Δw_{A+B} (right side) and Δw_{C+D} (left side) were coupled. Most of the differences in load cell signal were observed on the right and left sides of the bed (Δw_{A+B} and Δw_{C+D}). M4 (supine to sitting in the center of the bed) produced relatively large changes in Δw_{A+D} (-10.6%BW) and Δw_{B+C} (10.6%BW) and almost no change between the right and left load cells ($\Delta w_{A+B} = -0.0$%BW, $\Delta w_{C+D} = 0.1$%BW); this was the only movement that included a seated position.

Table 1. Accuracy of the classification model in predicting static positions. Left: lying on the left side of the body; supine/prone: lying on the back and lying on the stomach; right: lying on the right side of the body; L Sit: sitting on the left side of the bed; C Sit: sitting in the center of the bed; R Sit: sitting on the right side of the bed. $N = 54$.

		Predicted						
Position		Left	Supine/prone	Right	L Sit	C Sit	R Sit	Percent correct
Observed	Left	36	14	3	0	1	0	66.7%
	Supine/prone	5	41	5	2	1	0	75.9%
	Right	1	12	35	0	0	6	64.8%
	L Sit	11	0	0	43	0	0	79.6%
	C Sit	1	8	3	0	41	0	77.4%
	R Sit	0	0	7	0	0	46	86.8%

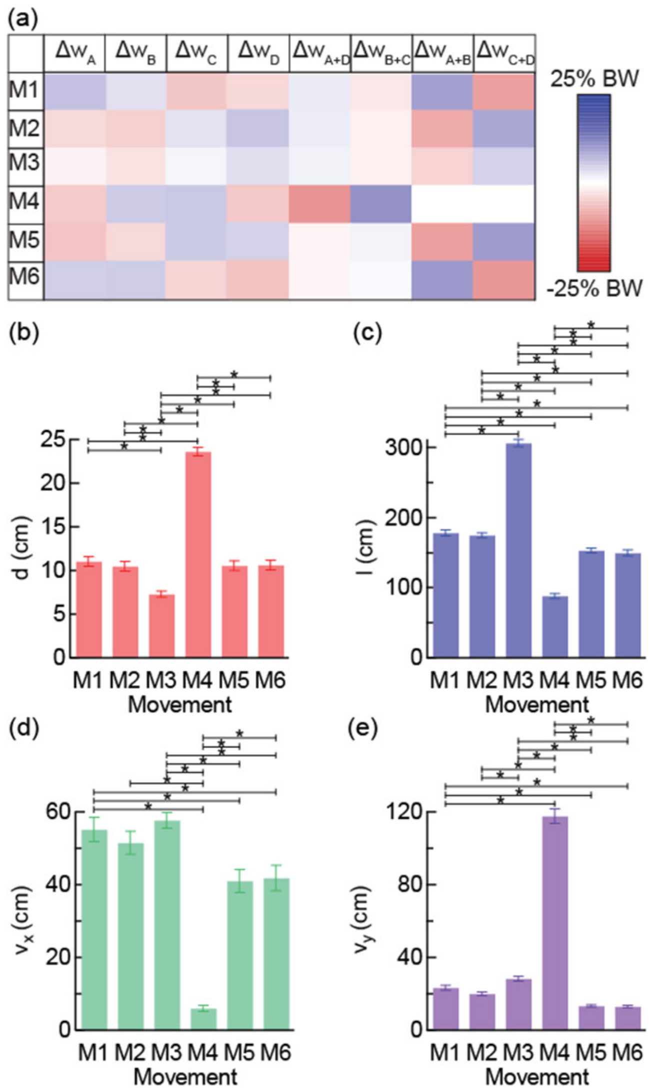

Figure 4. Load cell signatures for subjects moving between static positions. (a) A heat map showing the change in weight, from −25 to 25 %BW, on individual load cells (Δw_A, Δw_B, Δw_C, Δw_D) and pairwise combinations (top: Δw_{A+D}, bottom: Δw_{B+C}, right side: Δw_{A+B}, left side: Δw_{C+D}) for each of the six movements. Blue colors are associated with a positive change and red colors are associated with a negative change in %BW from the initial to final positions. (b) The Euclidean distance (d) of the CoM trajectory (mean ± SE). (c) The length (l) of the CoM trajectory (mean ± SE). (d) The horizontal variance (v_x) of the CoM trajectory (mean ± SE). (e) The vertical variance (v_y) of the CoM trajectory (mean ± SE). M1: supine to right side; M2: supine to left side; M3: supine to prone; M4: supine to sitting in the center; M5: right side to supine; M6: left side to supine. *Significance ($p \leqslant 0.05$).

From the CoM trajectories we obtained four derived parameters: the Euclidean distance (d) (figure 4(b)), the length (l) (figure 4(c)), the horizontal variance (v_x) (figure 4(d)), and the vertical variance (v_y) (figure 4(e)). Movement from supine to prone (M3) resulted in a shorter Euclidean distance and longer trajectory length than the other five movements. Conversely, moving from supine to sitting in the center of the bed (M4) had the longest Euclidean distance and the shortest trajectory length. There were no significant differences in Euclidean distance,

Table 2. Accuracy of the classification model for six movements using load cell signals. M1: supine to right side; M2: supine to left side; M3: supine to prone; M4: supine to sitting in the center; M5: right side to supine; M6: left side to supine. $N = 54$.

Movement			Predicted						Percent correct
			M1	M2	M3	M4	M5	M6	
Observed	M1	Supine → Right	43	2	3	0	1	5	79.6%
	M2	Supine → Left	0	34	9	0	9	3	61.8%
	M3	Supine → Prone	4	7	43	0	0	0	79.6%
	M4	Supine → C Sit	0	0	0	48	4	2	88.9%
	M5	Right → Supine	0	6	1	0	45	2	83.3%
	M6	Left → Supine	5	2	0	0	1	46	85.2%

length, and horizontal and vertical variances between M1 (supine to right side) and M2 (supine to left side), and between M5 (right side to supine) and M6 (left side to supine), which illustrates that similar movements have similar characteristics. Additionally, there were no significant differences in Euclidean distance between M1, M2, M5, and M6. However, M1 and M2 had significantly longer trajectory lengths than M5 and M6, highlighting the longer time to move from supine to a side-lying position compared to moving in the reverse direction (side-lying to supine). M4 (supine to sitting in the center) had the lowest side-to-side variance (v_x) and the highest top-to-bottom variance (v_y) on the bed.

To assess the ability of the transient response of the load cells to predict movements between two positions, we used the classification and regression tree method (table 2). The accuracy of the model was 79.7% correct. The test dataset contained 54 trials for the six movements. Classification of movement accuracy ranged from 61.8% for M2 (supine to left side) to 88.9% for M4 (supine to sitting in the center of the bed). Although the variation in the vertical component of the trajectory (v_y) was significant for some movements, the same accuracy was achieved without this parameter.

In addition to the load cell signals and parameters associated with the CoM, we also assessed four additional parameters in the classification model of subject movement: the duration of the movement (s), and three parameters derived from $f(t)$ (peak, area under the curve, and full width at half maximum). The duration of a movement was significant for some movements (figure S3(a)), and there was a strong correlation between the duration of movement and the trajectory length ($r = 0.815$) (figure S3(b)). Similarly, there was statistical significance between movements for peak, area under the curve, and full width at half maximum of $f(t)$ (figure S4). However, similar to v_y, the inclusion of these parameters did not change the accuracy of the classification model.

4. Discussion

We analyzed load cell data for subjects in seven static positions and the transitions associated with six specific movements between two positions. For a subject lying with their CoM in the center of the bed, the signal from the individual load cells corresponds to 25 %BW. In any other position, the load cell signals reflect the redistribution of weight towards or away from that load cell. The pairwise combinations of load cell signals provide insight into the top-to-bottom (w_{A+D} and w_{B+C}) or side-to-side (w_{A+B} and w_{C+D}) distribution of weight. For the positions in this study, the load cell signals varied from 21.6 %BW to 64.0 %BW. The CoM also provides information on the subject's weight distribution, with a side-to-side range of more than 20 cm, and a top-to-bottom range of more than 10 cm for the positions studied here.

Of the seven static positions, the supine and prone positions were the most difficult to differentiate from each other. Although subjects moved to the supine and prone positions from different start positions, subjects tended to re-center themselves on the bed when adopting these positions resulting in indistinguishable weight distributions. The inability to distinguish between the supine and prone positions using load cell sensors has been reported previously (Beattie *et al* 2011), and hence we combined the prone/supine positions.

Of the three lying positions (prone/supine, left side, right side) and three seated positions (left, right, and center), the seated positions had the highest classification accuracies (~77%–87%). The seated positions were easy to identify because their weight distributions were furthest from the center of the bed. However, the variation in CoM location and relatively high classification accuracy of the right and left seated positions may be influenced by the instruction to sit close to the horizontal center of the bed.

Lying positions were more difficult to distinguish than seated positions because of the locations of the lying positions on the bed. Large horizontal shifts of the CoM during the side-lying positions are difficult to distinguish from side-seated positions (if the subject's full weight is on the bed). Conversely, in some cases subjects turn onto their side but maintain their CoM in the center of the bed, a position that is difficult to distinguish from the supine/prone position. In general, cases where the horizontal CoM location was a few centimeters from the vertical midline of the bed were correctly classified as a side-lying position. The most frequent misclassification of the side-lying positions was the supine/prone position (more than half of the misclassifications), indicating that some subjects maintained a position in the center of the bed when lying on their side.

Similarly, when the CoM of the supine/prone position was not in the center of the bed, this position was difficult to distinguish from other positions; the majority were misclassified as the side-lying position. When the horizontal CoM location was shifted laterally from the center of the bed, the supine/prone position was classified as the side-lying position that corresponded to the direction of the shift. When the vertical CoM location was shifted towards the bottom of the bed, the supine/prone position was misclassified as sitting in the center of the bed. In summary, if the CoM of the supine/prone position is shifted from the center of the bed, even by a small amount, the position is likely to be misclassified.

These results suggest that it may be feasible to detect whether a subject is lying or sitting in bed, but that it would be difficult to distinguish between lying positions (supine/prone, left side, or right side), or distinguish supine/prone and sitting in the center of the bed when only considering position information.

We considered six movements between positions: supine to side (right and left), side to supine (starting on the right or left), supine to prone (counter clockwise turn), and supine to sitting in the center of the bed. The supine to prone and supine to sitting in the center of the bed movements were the only movements that were not quarter turns (supine to side and side to supine). The supine to sitting was the easiest to distinguish of the six movements. Sitting up is associated with CoM trajectories that can clearly be separated from turning.

Supine to sitting in the center of the bed is a motion that involves a large shift in the vertical CoM, changing the vertical CoM location from above to below the midline of the bed. This resulted in a large Euclidean distance between the initial and final CoM position but a short CoM trajectory length, consistent with this being a relatively simple movement even though it requires significant effort to lift the torso. This movement had the smallest side-to-side variance and largest top-to-bottom variance reflecting the directionality of the trajectory along the vertical midline of the bed; the opposite was true for turning.

The distinction between rolling over (supine to prone) and quarter turning movements was achieved from the Euclidean distance and length of the CoM trajectory parameters. As described previously, the supine and prone positions were largely indistinguishable. The Euclidean distance between the initial (supine) and final (prone) positions of the supine to prone movement was significantly shorter than the supine to side, side to supine, and supine to sitting in the center of the bed movements. In addition, rolling over requires a greater shift in the CoM than a quarter turn or sitting up in bed resulting in the longer CoM trajectory length observed during supine to prone versus the other five movements.

Compared to supine to sitting in the center of the bed and supine to prone, quarter turning movements (side to supine and supine to side) had similar CoM trajectory characteristics. All turning conditions had increased side-to-side and decreased top-to-bottom variances compared to sitting up in bed. However, the side to supine turns had smaller side-to-side and top-to-bottom variances and shorter CoM trajectory lengths than the supine to side turning conditions, indicating that it is easier to turn onto the back than on to the side.

When turning movements were misclassified they were typically classified as another movement in the same direction. For example, right to supine, supine to left, and supine to prone (counter clockwise) were counter clockwise movements. In the instances when right to supine movements were misclassified, most misclassifications were as one of the other two counter clockwise turns.

By binning movements into categories with similar CoM trajectory characteristics (independent of initial and final position) it is possible to reduce classification errors. In general, increased accuracy is achieved by broadening the definition of each movement category, and in turn, reducing the number of categories. For example, classification accuracy can be increased by binning turns as either right or left, independent of starting position, (Alaziz *et al* 2017) or by binning movements as small, medium, or large (Adami *et al* 2011). To provide a direct comparison between the accuracy of the movement model and a previous model (Alaziz *et al* 2017), the movements in this study were binned into turns to the right (M1 and M6) and turns to the left (M2 and M5). The movement model's accuracy (95.8%) to distinguish between right and left turns was slightly larger than the previous model's (90%) (Alaziz *et al* 2017). However, combining movements limits the information that can be obtained, reducing the ability to extract position information from movement. Our model is able to distinguish between specific movements, which inherently includes static positions before and after movements with an accuracy of 79.7%. This level of accuracy is slightly lower than studies that categorize movements only, achieving accuracies of 95.8% (Alaziz *et al* 2016), 84.6% (Adami *et al* 2011), and 90% (Alaziz *et al* 2017), but provides a greater level of classification specificity. The ability to classify specific movements allows the characterization of both major postural shifts and stationary positions from our model, creating a detailed picture of bed activity.

The controlled static positions and transient movements implemented in this trial have allowed us to perform quantitative assessment of bed load cell data. The results show the characteristic signatures of the selected positions and movements and indicate which ones are more distinct. The increased classification accuracy of movement compared to position illustrates the utility of analyzing static and dynamic characteristics to infer position from specific movements. Although the controlled conditions allow detailed analysis, the accuracy of the prediction models may be decreased under less controlled conditions where a subject is free to move without following directions.

5. Conclusion

The purpose of this study was to illustrate that positions and movements in bed have unique load cell characteristics. Classification models distinguished six positions and movements in bed based on parameters derived from the load cells. These results suggest that load cell monitoring may be useful in a clinical setting, providing information needed for predictive algorithms to address a wide scope of clinical issues associated with movements and positions.

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