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# Biomechanical monitoring and machine learning for the detection of lying

* 1. **postures**
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1. Word count abstract: 243
2. Word count main text: 3957
3. Abstract
4. *Background*: Pressure mapping technology has been adapted to monitor over prolonged periods to
5. evaluate pressure ulcer risk in individuals during extended lying postures. However, temporal
6. pressure distribution signals are not currently used to identify posture or mobility. The present study
7. was designed to examine the potential of an automated approach for the detection of a range of static
8. lying postures and corresponding transitions between postures.
9. *Methods:* Healthy subjects (n=19) adopted a range of sagittal and lateral lying postures. Parameters
10. reflecting both the interactions at the support surface and body movements were continuously
11. monitored. Subsequently, the derivative of each signal was examined to identify transitions between
12. postures. Three machine learning algorithms, namely Naïve-Bayes, *k*-Nearest Neighbors and Support
13. Vector Machine classifiers, were assessed to predict a range of static postures, established with a
14. training model (n=9) and validated with new input from test data (n=10).
15. *Findings:* Results showed that the derivative signals provided a means to detect transitions between
16. postures, with actimetry providing the most distinct signal perturbations. The accuracy in predicting
17. the range of postures from new test data ranged between 82%-100%, 70%-98% and 69%-100% for
18. Naïve-Bayes, *k*-Nearest Neighbors and Support Vector Machine classifiers, respectively.
19. *Interpretation:* The present study demonstrated that detection of both static postures and their
20. corresponding transitions was achieved by combining machine learning algorithms with robust
21. parameters from two monitoring systems. This approach has the potential to provide reliable
22. indicators of posture and mobility, to support personalized pressure ulcer prevention strategies.

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1. Keywords: pressure ulcers, continuous pressure monitoring, actimetry systems, machine learning,
2. postures detection

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1. 1. Introduction
2. Systems capable of automatically classifying patterns of movement performed by a human subject
3. e.g. wearable actimetry sensors, are widely used in many clinical and research applications in
4. healthcare through advanced human-machine interfaces (Manini and Sabatini, 2010; Mathie et al.,
5. 2003; Mohammed et al., 2016). Recently, their use has been shown to improve the provision of
6. optimal turning critical for PU prevention (Ifedili et al., 2018; Pickham et al., 2018). Nonetheless,
7. there are issues with compliance to body worn sensors, and the information gleamed from actimetry
8. does not correspond to interface pressure measurements (Stinson et al., 2018), which currently
9. represents one of the primary means to assess PU risk.
10. In recent years, interface pressure measurements systems have been adapted to continuously monitor
11. subject-support surface interactions, with the resulting data being used to indirectly classify a range of
12. postures and movements (Duvall et al., 2019; Kim et al., 2018; Wai et al., 2010; Yousefi et al., 2011).
13. However, the predictive power of these algorithms for early PU risk is largely dependent on the
14. magnitude of the applied pressure in pre-determined areas of the pressure sensing mat (Wai et al.,
15. 2010) and are commonly associated with arbitrary thresholds. Only a few studies have combined
16. interface pressure measurements and actimetry signals for classifying postures, none of which were
17. directly focused on pressure ulcers (Zemp et al., 2016).
18. In a recent publication, the authors have identified a series of robust signals estimated from both
19. continuous pressure mapping and actimetry systems, which can accurately track postures and mobility
20. during different evoked postures (Caggiari et al., 2019). However, the signals in isolation
21. demonstrated limited sensitivity and specificity, therefore a combined signal analysis approach was
22. recommended. These signals resulted in large data sets (Bogie et al., 2008), which would benefit from
23. intelligent data processing. While it is well known that actimetry systems can detect posture and
24. mobility with a high degree of accuracy (Edwardson et al., 2016; Lyden et al., 2016), there is limited
25. evidence that parameters estimated from pressure distribution could act as a surrogate for detecting
26. both postures and corresponding transitions between postures during prolonged lying.
27. Accordingly, the present study was designed to develop a robust methodology for detecting static
28. postures and transitions between postures, using data acquired for pressure monitoring and actimetry
29. systems. Three conventional machine learning algorithms, namely Naïve-Bayes (NB), *k*-Nearest
30. Neighbors algorithm (KNN) and Support Vector Machine (SVM) classifiers, each of which have been
31. adopted in previous research studies to classify range of postures (Chi-Chun et al., 2008; Duvall et al.,
32. 2019; Foubert et al., 2012) were included in the evaluation.
33. The accuracy for detecting a range of static postures and their corresponding transitions, namely
34. changes in posture, were assessed using the following objectives:
35. i) Perform data reduction and feature extraction of the raw actimetry and pressure
36. monitoring signals
37. ii) Create a methodology for the automatically detection of changes in posture from the set
38. of data and
39. iii) Apply the machine learning algorithms, cross-validated with leave-one-out testing, and
40. evaluate their accuracy in classifying the range of prescribed lying postures.

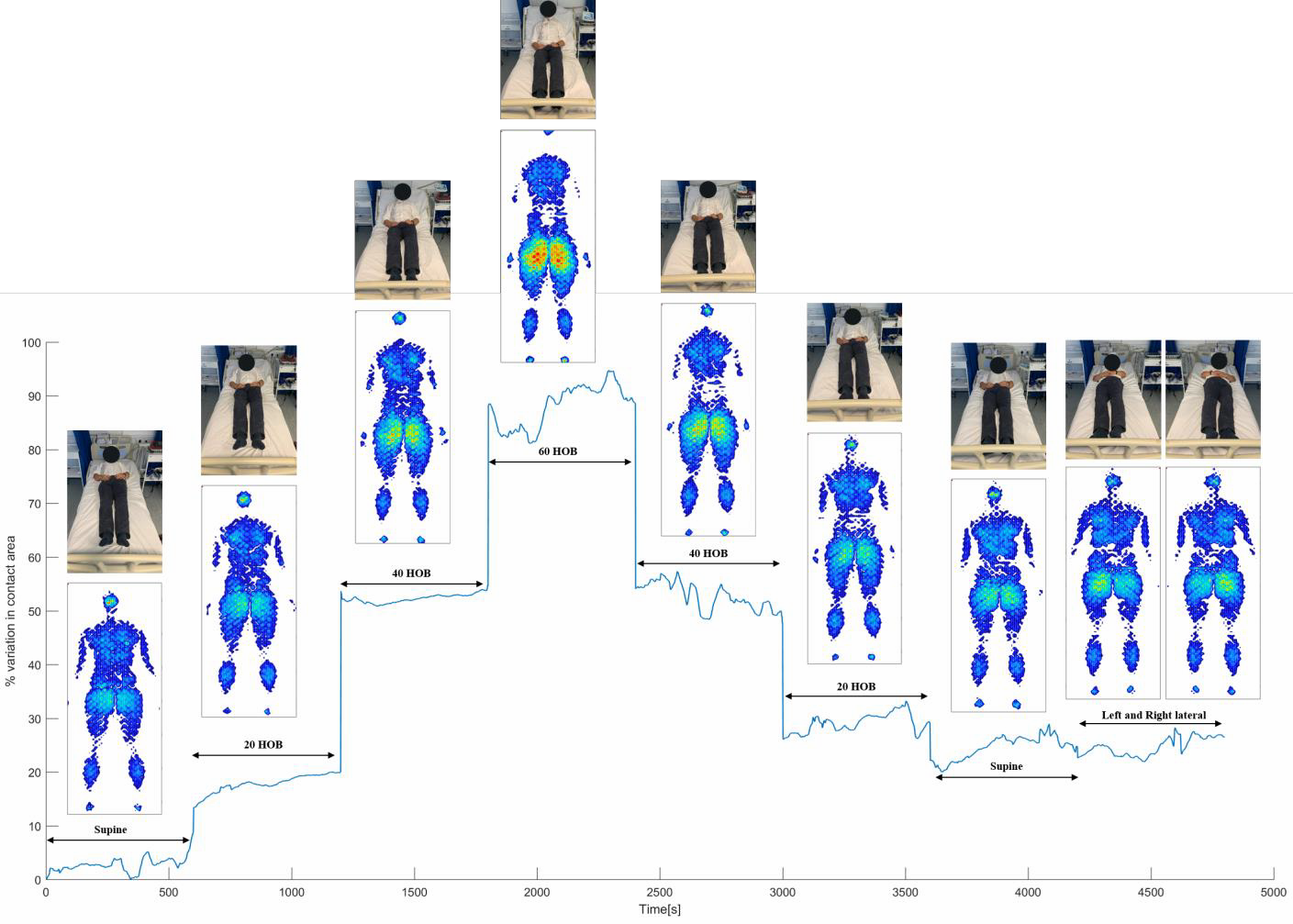
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* 1. 2. Methods
  2. 2.1 Participants
  3. The training data set was derived from the previous study evaluating the performance of pressure
  4. monitoring and actimetry signals to distinguish postures (Caggiari et al., 2019), which was conducted
  5. with institutional ethical approval (Ref: 26379). The data from nine of the healthy participants (5 male
  6. and 4 female) were allocated into the **training group**, each of whom were observed to performed a
  7. number of minimal postural adjustments during the static postures (Caggiari et al., 2019). Participants
  8. were aged between 27-36 years (mean = 32 years) with an average height and weight of 1.70 m and
  9. 72.0 kg (standard deviation = 0.1 m and 17.0 kg), respectively. The corresponding BMIs ranged
  10. between 19 to 30 kg/m2.
  11. A separate cohort of ten healthy participants (4 male and 6 female) were recruited into the **test group,**
  12. under the same institutional ethics. Participants were aged between 27-56 years (mean = 34 years)
  13. with an average height and weight of 1.73 m and 68.9 kg (standard deviation = 0.1 m and 15.7 kg),
  14. respectively. The corresponding BMIs ranged between 19 to 28 kg/m2.
  15. Exclusion criteria for both groups included participants with a history of skin conditions, neurological
  16. or vascular pathologies that could affect tissue health or those were unable to lie in a supine posture
  17. for a period of 2 hours. Informed consent was obtained from each participant of both groups prior to
  18. testing.
  19. 2.2 Test equipment
  20. The equipment and test protocol has been described in the recent paper (Caggiari et al., 2019). To
  21. review briefly, interface pressure measurements were recorded using a full body pressure monitoring
  22. system (ForeSite PT, XSENSOR Technology Corporation, Canada). The fitted mattress cover
  23. incorporates 5664 pressure measuring sensor cells, with a spatial resolution of 15.9 mm, covering a
  24. sensing area of 762mm x 1880mm. Each sensor operates within a range of 5-200 mmHg (0.7-26.6
  25. kPa) and an acquisition rate of 1 Hz. Three actimetry sensors (Shimmer Platform, Realtime
  26. Technologies Ltd, Dublin, Ireland) were attached to the sternum and the left and right anterior iliac
  27. crests with a Velcro strap. Each device represents a small wireless sensor (53mm x 32mm x 25mm),
  28. integrating a tri-axial accelerometer and gyroscope, that records real-time calibrated Euler angles data
  29. at 51 Hz (range = 2g).

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1. 2.3 Test Protocols
2. All test procedures were performed in the Biomechanics Testing Laboratory in the Clinical Academic
3. Facility in Southampton General Hospital, where room temperature was maintained at 24o.
4. Participants were requested to wear loose fitting clothing and adopt a series of sagittal and lateral
5. postures on a standard hospital bed frame (Hill-Rom, AvantGuardTM) and a castellated foam mattress
6. (Solace Foam Mattress, Invacare UK). A continuous lateral rotational system (CLRS) (Vikta
7. KomfitiltR) placed underneath the support surface enabled left and right 20-25o tilt of the overlying
8. mattress in the lateral plane with an automated 10 min cycle time.
9. Each of the subjects in the **training group** adopted a series of prescribed sagittal postures held for 10
10. minutes, achieved by adjusting the head of the bed (HOB) in 10° increments to a maximum of 60o and
11. then lowering by 10o to supine. In addition, lateral postures were evoked through a continuous lateral
12. rotational system (CLRS). An adapted version of the protocol was used for the **test group** intended to
13. evaluate the performance of the classifiers. Here, sagittal postures were held for 20 minutes starting in
14. the supine posture followed by raising the HOB angle by 20° increments to a maximum of 60°. The
15. HOB was then lowered in 20° increments to supine. Subsequently lateral postures were adopted
16. through the CLRS system, as for the training group. Interface pressure distribution and actimetry data
17. were continuously recorded throughout the two hours test period for both training and test groups.
18. Participants were instructed to remain as still as possible on the mattress.
19. 2.4 Outcome parameters
20. The results of the previous study (Caggiari et al., 2019) involving a comprehensive ROC analysis
21. revealed a number of parameters as the most accurate in detecting changes in posture, which included:
22.  Tilt angles (TA) of the trunk with respect to the sagittal and the lateral planes and
23.  Percentage variation of contact area (CA) of sensors recording a minimum threshold pressure
24. of 20 mmHg estimated at the whole body ROI.
25. These parameters were estimated for all subjects from both training and test groups. For the
26. estimation of contact area, pressure readings equal or above a 20 mmHg (2.7kPa) threshold were
27. included, as they were most indicative of evoked postural changes (Caggiari, 2020).
28. Furthermore, signals from training group were adapted to consider static postures in 20o increments of
29. HOB. As an example, Fig. 1 shows the temporal trend of the variations of contact area and the
30. corresponding pressure distribution during sagittal and lateral postures, for one subject of the training
31. group. It is evident that changes in the HOB angle are reflected in the incremental step changes in the
32. signal and changes in the pressure distribution. In particular, the relative change in signal was
33. dependent on the HOB angle, with angles <20o revealing reduced variation in contact area. This was
34. also evident for lateral postures. In addition, it is evident that there were differences in the signal
35. dependent on whether the HOB was increasing or decreasing corresponding to 20o HOB and supine
36. postures (Fig. 1).

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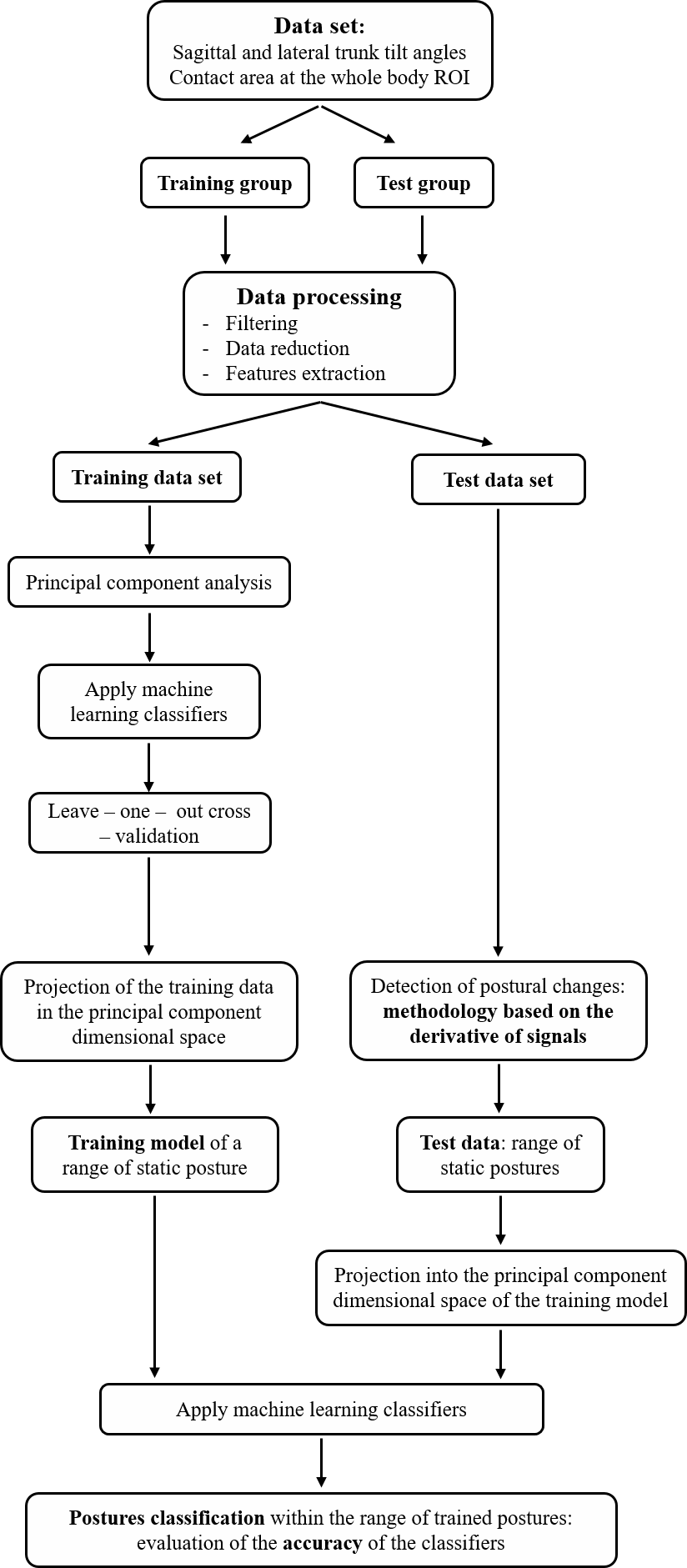
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1. **Fig. 1:** Temporal profile of the percentage variation of contact area at the whole body ROI and the
2. corresponding pressure distribution for 8 sagittal and lateral postures, involving 20o HOB increments.

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1. 2.5 Post-processing of the signals from training group
2. The flowchart in Fig. 2 illustrates the processing of the signals from both training and test groups.
3. This included a moving average filter with a time window of 30 samples for the pressure data from
4. both groups, to remove the high frequency noise. The corresponding actimetry signals, which were
5. originally acquired at 51 Hz, were re-sampled at 1 Hz and filtered using a window of 15 samples
6. (Caggiari et al., 2019).
7. The signals from training group were then manually annotated, by denoting the beginning and the end
8. of each evoked posture. The transitions between postures were not included as they contained noise
9. due to natural adjustments in posture observed in all participants. Each of the signals was then
10. interpolated in order to encompass 600 data points, for each posture, resulting in a total of 4800 data
11. points per signal. The interpolation was applied in order to include signals and hence postures of an
12. equivalent time period. All signals were then subjected to a fixed-width sliding window of 60 seconds
13. to reduce the raw data by evaluating features i.e. mean and derivative values. Mean values were
14. calculated within each sliding window for both trunk tilt angles and contact area signals, resulting in a
15. 80 point data set for each signal. The reduced signals from all the subjects were allocated to the
16. **training data set**. A principal component analysis (PCA) was performed and the training signals
17. projected onto the PCs dimensional space.

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167 **Fig. 2:** Flow chart depicting the different processes for data acquisition for use with the classifiers.

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1. 2.6 Classifiers
2. Three commonly used classifiers were employed, each of which adopts distinct approaches for event
3. classification.
4. 2.6.1 KNN classifier
5. The KNN classification rule, first described by Cover and Hart (1967), depends on the distance metric
6. between the new observation point and *k* nearest data point(s) (Short and Fukunaga, 1981). Given the
7. nature of our data, the Euclidean distance was selected as the distance metric. Moreover, the
8. parameter *k* determines how many neighbors will be chosen and its choice has a significant impact on
9. the diagnostic performance of KNN algorithm. Accordingly, a sensitivity analysis was performed and
10. *k* = 10 was identified to provide the highest accuracy and was therefore chosen for the current
11. analysis.
12. 2.6.2 Naïve-Bayes classifier
13. The Naïve-Bayes classifier represents a probabilistic strategy based on Bayes’ theorem, which
14. describes the probability of an event based on the prior knowledge that some other events have
15. already occurred i.e. conditional probability. A Gaussian distribution was considered the most
16. appropriate approach for assessing the conditional probability, which can be written as:

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1 −1

185 P(H ¦ E) =

√det(2𝜋𝜎𝐸)

exp(−

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(ℎ − 𝜇𝐸))

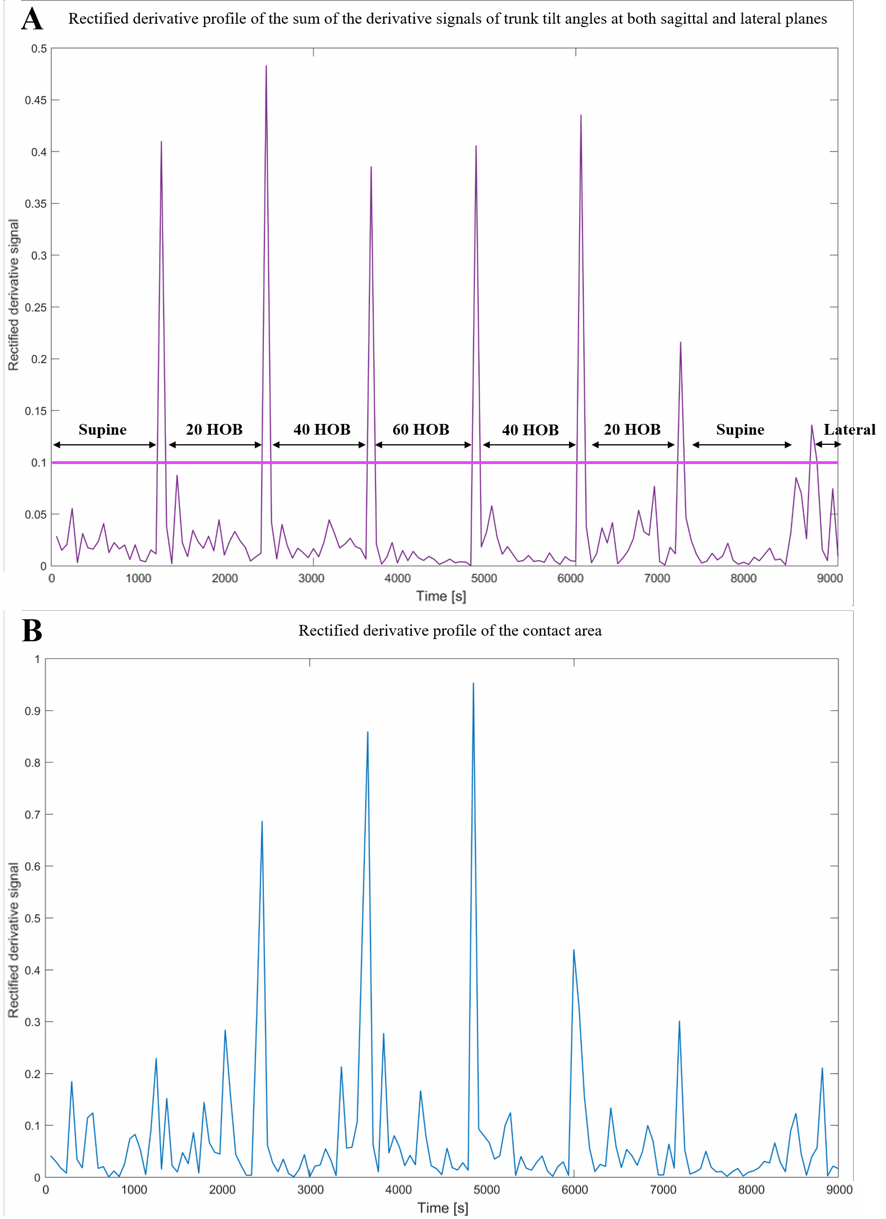
1. where H represents a new event and E is some observed event, µE is the mean and σE is the covariance
2. matrix of the observed events.
3. 2.6.3 Support Vector Machine (SVM) classifier
4. The SVM (Burges, 1998) classifier is based on defining a hyperplane that divides the clusters of data.
5. The optimal hyperplane is the one representing the largest distance to the nearest element of each
6. cluster (support vectors). SVM projects the data into a higher dimension from the original space
7. where the hyperplane can be derived from kernel functions. Gaussian kernel function was considered
8. the most appropriate for the present data.
9. 2.6.4 Cross-validation
10. A leave-one-subject-out cross-validation was performed to test the robustness of the training model in
11. detecting the range of static postures (Fig. 2). This consisted in training a model with data from 8 of
12. the 9 subjects in the training cohort, who were randomly selected. The data of the excluded subject
13. were then tested and the accuracy in postures classification was assessed. This process was repeated
14. for each individual who has been used to test the trained model and the accuracy of the classifiers was
15. determined. Subsequently, a **training model** was created with the set of data of all subjects in the
16. training cohort. The accuracy of all classifiers was then assessed by applying data from subjects in the
17. test cohort. This resulted in a percentage accuracy across all postures adopted in the test data. This
18. percentage accuracy was established for each participant within the test group and calculated as the
19. number of data points correctly classified for each posture with respect to the corresponding total
20. number of points in the signals.
21. 2.7 Test data sets
22. After filtering, signals from test group were interpolated to encompass 9000 data points (2.5 hours of
23. recording), including both static postures and the transition between postures. Signals corresponding
24. to each participant represented a distinct data set to identify changes in posture and test the training
25. model. Each of the test data sets was subjected to the 60-second sliding window for data reduction
26. and both mean and derivative values were estimated within each window prior to identify the changes
27. in posture and classify the corresponding static postures. The derivative signal of both contact area
28. and trunk tilt angles in both sagittal and lateral planes were used for the detection of any change
29. between two postures. The signals were subjected to a discriminant threshold to identify where the
30. variations in the derivative occurred. Different thresholds were examined in order to identify the
31. optimum value which accommodated all subjects. Once the changes in posture from the test data set
32. were identified, the mean signals from the subsequent sliding windows were projected onto the
33. training PCs dimensional space and subjected to posture classification.

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1. 3. Results
2. 3.1 Leave-one-out cross-validation
3. The cross-validation demonstrated an accuracy ranging between 85%-99% for classification
4. performed with Naïve-Bayes. The corresponding accuracy using KNN and SVM ranged between
5. 53%-95% and 59%-100%, respectively. Accordingly, it is demonstrated that the training data set
6. could provide a robust means for detecting static postures with the test data set.
7. 3.2 Detecting changes in posture
8. Consistent variations in the derivative magnitude of the trunk tilt angles were identified in association
9. with the sagittal changes in posture for all subjects. Smaller variations were also evident in the lateral
10. plane when lateral postures were adopted (data not shown). They were subjected to processing which
11. involved the signal rectification, in order to use a generic positive threshold. The rectified derivative
12. signal for both sagittal and lateral trunk tilt angles were then summarised to obtain a single signal
13. which included both sagittal and lateral changes in posture. An example of the rectified derivative
14. profile of trunk tilt angles for one subject is illustrated in Fig. 3A. The corresponding derivative of the
15. contact area is shown in Fig. 3B. The latter reveals that changes in posture were well distinguished in
16. magnitude at high HOB angles, but less distinctive at lower HOB angles (<20°). Indeed, perturbations
17. in magnitude were also observed during static postures, which did not enable the correct detection of
18. all changes in posture (Fig. 3B). Accordingly, only the derivative of the trunk tilt angles was used and
19. an appropriate discriminant threshold value of 0.10 for all subjects was selected for subsequent
20. detection of the transitions between postures (Fig. 3A), resulting in 100% accuracy for all subjects.

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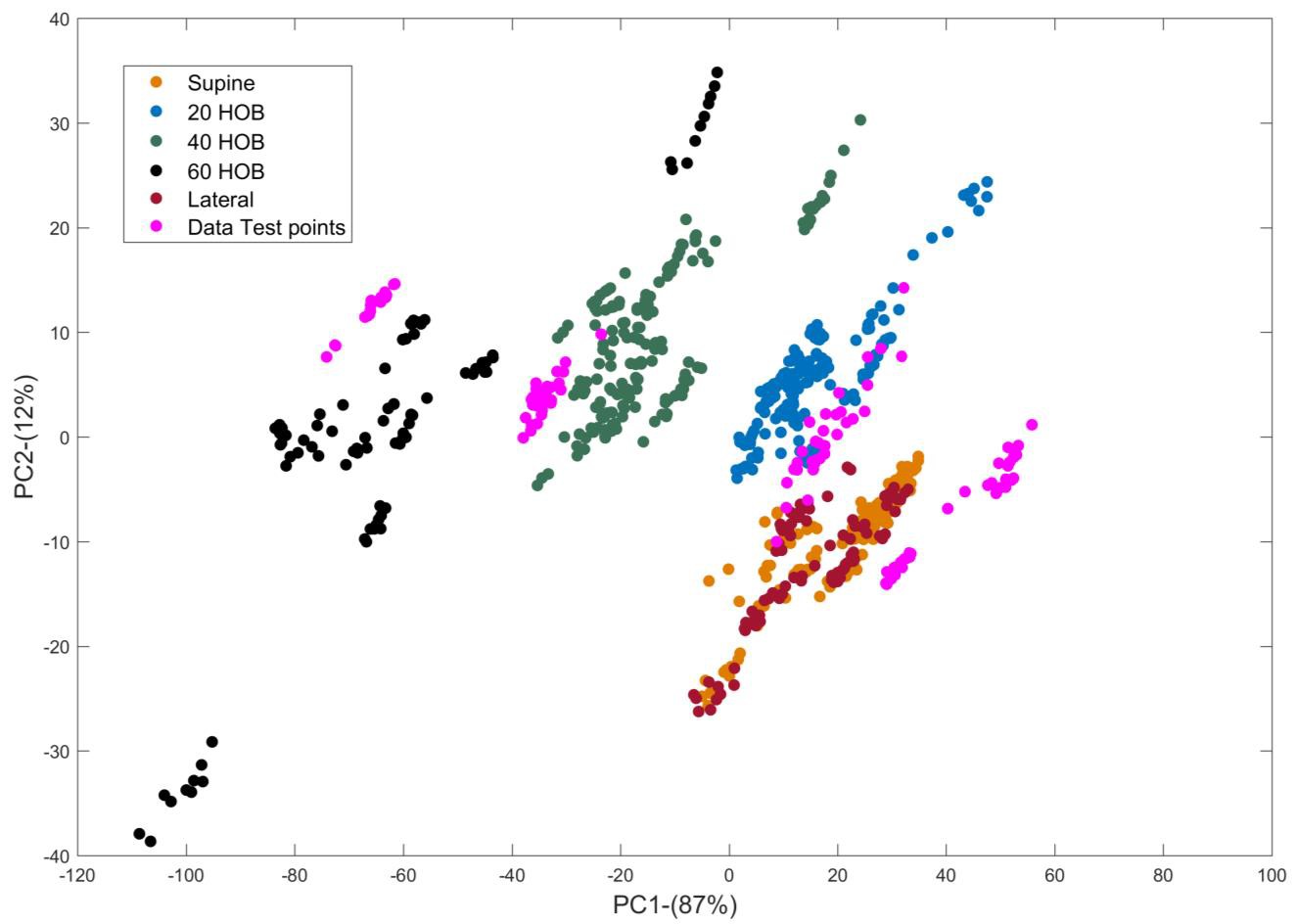


1. **Fig. 3:** Rectified derivative profile for subject #1 in the test cohort of A) the sum of the derivative
2. signals of trunk tilt angles at both sagittal and lateral planes, B) contact area. Each data point in the
3. signals corresponds to a derivative value calculated within the 60-second sliding window.

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1. 3.3 Accuracy in classifying the range of postures
2. As illustrated in Fig. 4, static postures corresponding to signals for all subjects from the training group
3. (n=9) resulted in clusters of points spatially distributed across the first and second PCA dimension,
4. which contributed to 87% and 12% of the variance in the signals, respectively. This reflects the
5. changes in signal magnitude associated with either increasing or decreasing the HOB angle (Fig 1). In
6. particular, when a reduced variation in the step changes was observed e.g. HOB <20o, there is a
7. reduced spatial distribution of adjacent clusters. This is particularly evident in the first principal
8. component (PC1) (x-axis - Fig. 4). When the signals corresponding to the static postures of one
9. subject from the test group are projected onto the training PCs space (data points in pink) separate
10. clusters are observed. These clearly overlapped with the corresponding clusters of points from the
11. training data.
12. The estimated accuracies for each of the three classifiers are summarised in Table 1. It is evident that
13. for increments of 20o in the HOB angles there was a high accuracy for each subject and all classifiers.
14. In particular, the accuracy was >80% in classifying postures using the Naïve-Bayes classifier for all
15. subjects. The corresponding accuracy using the KNN classifier resulted ≥90% in 8/10 subjects, with
16. the remaining two subjects showing an accuracy value of 70% and 74%. SVM resulted in accuracy
17. values of >80% in 8/10 subjects with the remaining two resulting in an accuracy of 71% and 69%,
18. respectively.

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1. **Fig. 4:** Signals corresponding to the training data set (9 subjects) projected onto the first two principal
2. components, PC1 and PC2, with their corresponding variance in brackets. Each posture is represented
3. by a spatially distributed coloured cluster. Signals from one subject from the testing group (data points
4. in pink) were projected onto the training PCs dimensional space.

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277 **Table 1:** Percentage accuracy in classifying the range of postures for all classifiers.

## Accuracy [%]

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | | **Subjects** | **Naïve-Bayes** | **KNN** | **SVM** |
| **1** | 90 | 94 | 97 |
| **2** | 95 | 97 | 91 |
| **3** | 98 | 90 | 86 |
| **4** | 89 | 92 | 90 |
| **5** | 97 | 93 | 97 |
| **6** | 83 | 97 | 82 |
| **7** | 93 | 90 | 97 |
| **8** | 98 | 74 | 71 |
| **9** | 100 | 98 | 100 |
| **10** | 82 | 70 | 69 |
| 278 |  |  |  |  |  |
| 279 | 4. Discussion |  |  |  |  |

1. This study has detailed the application of intelligent data processing of biomechanical signals
2. depicting changes in lying posture from angles of body segments (actimetry) and pressures measured
3. at the interface between the body and support surface i.e. contact area of pressures >20mmHg. The
4. derivative of signals was assessed to identify changes in posture in both sagittal and lateral planes. A
5. series of machine learning algorithms in the form of Naïve-Bayes, KNN and SVM classifiers were
6. applied to a set of data involving signals derived from an actimetry system and interface pressure
7. distribution estimated from a high resolution sensing array. A cross-validation technique was applied
8. using each machine learning algorithm, revealing that the training data could provide a robust means
9. of classifying the data. Subsequently, an adapted protocol was used to provide test data, which was
10. observed to correspond with the clusters derived from the training phase (Fig. 4). The resulting
11. classification accuracy of the test data ranged between 82% 100%, 70%-98% and 69%-100% for the
12. three classifiers, respectively (Table 1), with Naïve-Bayes classifier showing the highest accuracy in
13. classifying the range of static postures. A value >80% could represent a benchmark by which the
14. majority of the postures can be monitored.
15. Findings revealed that the derivative of the signal representing the trunk tilt angles correctly identified
16. the changes in posture for all subjects, as characterised by a transient increase in the magnitude of the
17. derivative at each corresponding change in posture (Fig. 3A). By contrast, the derivative of the
18. contact area signal generally revealed less distinct changes in magnitude when evaluating changes in
19. posture involving HOB angles <20o and thus it proved problematic in identifying their occurrence
20. (Fig. 3B). Accordingly, the trunk tilt angles derivative, resulting from the sum of sagittal and lateral
21. signal derivatives, was considered to represent a more robust means to automate the detection of the
22. changes in posture in the test data. Indeed this approach, based on the derivative of biomechanical
23. parameters, has been applied in several other areas of the biomedical field, for example, for the
24. detection of the different gait phases (Taborri et al., 2016).
25. Previous research have utilised intelligent data processing from machine learning algorithms to
26. classify a range of lying and sitting postures and their transitions from the distribution of pressure at
27. the subject-support interface (Foubert et al., 2012; Kim et al., 2018; Matar et al., 2019; Rus et al.,
28. 2017; Wai et al., 2010; Yousefi et al., 2011; Zemp et al., 2016). These approaches adopted and the
29. results reported are summarised in Table 2.

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315 **Table 2:** Summary of relevant studies classifying lying and sitting postures.

## Study Data used for classification Classifier(s) Accuracy Changes in posture

* 1. Raw pressure values

> 70%

Wai et al. (2010) -

* 1. Eigen vectors > 50%

*Lying posture*s

* 1. Mean, variance, standard deviation, root mean square estimated in 9 ROIs

SVM

✗

> 60%

Yousefi et al. (2011) -

*Lying posture*s

Binary pressure images projected in PCA space

KNN > 97% ✗

Kim et al. (2018) -

*Sitting postures*

Heat map of pressure distribution

Naïve - Bayes SVM

> 85%

✗

> 90%

Duvall et al. (2019) -

*Lying posture*s

Weight measured by four cells placed under the legs of the bed

KNN > 95% ✓

Zemp et al. (2016) -

*Sitting postures*

Median of the force data divided by the subject’s body weight and backrest angles

SVM > 70% ✗

Foubert et al. (2012) -

*Lying to sitting*

1. WNAS

SVM and KNN

> 90%

✓

1. COP displacements > 75%

Matar et al. (2019) -

*Lying posture*s

Oriented gradient and local binary patterns estimated from pressure distribution

Artificial neural network

> 97% ✗

Present study

Eigen vectors estimated from biomechanical parameters derived from actimetry systems and pressure distribution

Naïve-Bayes > 80%

KNN ≥ 70% ✓

SVM ≥ 69%

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1. It is evident that the present findings are comparable with previous studies, with high accuracy values
2. in postures classification reported for the detection of range of static postures. However, only two
3. studies have detected the transition phases between static postures. Foubert et al. (2012) have used
4. lateral and longitudinal displacements of the centre of pressure estimated from pressure distribution,
5. reporting an accuracy of >90%. By contrast, a separate study utilised the total weight on the bed
6. measured by using a system involving four load cells (Duvall et al., 2019). Their results reported that
7. a change of 7lb (3.2kg) in the measured weight within a temporal window of 7secs was able to detect
8. the changes in posture with an accuracy of 98%. Furthermore, limitations of many previous studies
9. included the short-term estimation of the pressure distribution (up to tens of seconds) and the limited
10. range of supine postures (i.e. supine, prone, left and right turn). There are, however, some studies
11. which have evaluated a range of postures involving the elevation of the HOB angle (Yousefi et al.,
12. 2011) and data derived from a longer period i.e. 5 minutes of pressure monitoring (Kim et al., 2018).
13. In addition, Zemp et al. (2016) utilised a composite data set involving force values acquired at the
14. support surface normalised to individual body weight and the corresponding backrest tilt angle
15. estimated with actimetry positioned on the backrest, for the detection of sitting postures. However,
16. both parameters were acquired at a single time point.
17. The present study has applied an automated method to identify the occurrence and magnitude of
18. movements based on signal derivative and machine learning algorithms. This could be achieved using
19. either actimetry or pressure parameters. To date, these temporal data are unknown in many care
20. settings.
21. It is inevitable that the use of able- bodied cohorts in a lab-based study precludes generalising the
22. present findings to individuals, from specific sub-populations, deemed to be at risk of developing
23. pressure ulcers i.e. the elderly, spinal cord injured and those managed in intensive care units. The
24. study protocol was also limited in selecting a pre-determined order of relatively small postural
25. changes (20o HOB increments) maintained for a relative short period of 10-20 minutes. Thus, future
26. studies should examine random postures involving different HOB increments and the side-lying
27. lateral posture typically adopted in clinical settings. The current method would require an
28. improvement in accuracy and validation to account for random postures on specialised mattresses
29. used by patients in both acute and community clinical settings where the recommended frequency and
30. magnitude of movements are not strictly followed (Defloor et al., 2005; Woodhouse et al., 2019). This
31. would support clinicians when informing clinical decision-making.
32. Technology to monitor individuals could provide critical means to detect posture and mobility.
33. However, it is clear that the emergence of digital health strategies will necessitate the use of robust
34. monitoring tools. Accordingly, continuous pressure monitoring represents an important tool which
35. when integrated with support and feedback technologies could promote PU prevention through self-
36. management and targeted care interventions (Tung et al., 2015). This would result in more efficient
37. practice and a personalised approach. It could also be integrated with risk assessment to create a more
38. objective means of PU risk. In addition, machine learning applied to large data sets derived from these
39. technologies could provide a robust means for translation into indicators of posture and mobility
40. associated with both frequency and magnitude of postures.
41. 5. Conclusion
42. The present study has defined a methodology for classifying static lying postures and identifying
43. transitions in between different postures. The combination of biomechanical parameters acquired
44. using pressure monitoring and actimetry technologies were combined using data reduction and
45. machine learning approaches. The combination of monitoring technologies and advanced algorithms
46. offers the potential to track posture and mobility in individuals at risk of pressure ulcers, informing
47. personalised care strategies. Further research is needed to establish the accuracy of the posture
48. prediction involving clinical data sets in sub-groups of patients at risk of pressure ulcers e.g. spinal
49. cord injured.
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56. Ethical approval
57. University of Southampton Ethics was granted for the study (Ref: 26379)

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