Motion Monitoring in Palliative Care Using Unobtrusive Bed Sensors

M. Holtzman[1], R. Goubran[1,2], and F. Knoefel[1,2,3]

***Abstract*— Palliative care needs are growing with the aging population. Ambient sensors offer patients comfortable and discreet point-of-care monitoring. In this study, two palliative care participants were monitored in a sensorized bed. Motion monitoring by a two-tier gross and fine movement detector provided accurate detection and classification of movement, compared to annotations by an observer. However, ascribing the motion to the patient rather than caregivers or visitors would require supplemental sensors. Motion was indicative of pain, with 13% of time spent moving while in pain versus 3% while not noted as in pain.**

I. INTRODUCTION

As the population ages, medical services will face a surge of patients dying or facing terminal diseases. Palliative care needs are growing consequently. Up to this point, physiological monitoring in palliative care has been necessarily unsophisticated, where obtrusive sensors preclude the goals of comfort, and pain reduction. To reduce pain for patients with a heavy disease burden, caregivers should be aware of pressure ulcer development [1]. Even for shorter stretches in bed, ischemia can develop when there is pressure on the skin at a point of contact. Ischemia can lead to pain, and a patient may desire release by a posture change that they are physically unable to perform themselves. Restlessness ensues. Restlessness can also be a sign of other problems, such as restless leg syndrome, and terminal restlessness, which can cause both emotional and physical distress [2].

By introducing non-contact sensors to detect bed motion, as in Fig. 1, caregivers could make more informed decisions. For instance, if they knew that a patient had not changed position for many hours, they could shift them to prevent pressure ulcers. Conversely, if they knew if they had changed position lately, the patient would not need to be bothered by unnecessary routine shifts. Detecting a patient's restlessness due to pain, and automatically summoning nursing staff would ease suffering.

Bed based systems have been used to detect pressure ulcers [3], posture [4], and restlessness leg syndrome [5]. Detecting pain through restless motion may also be possible.

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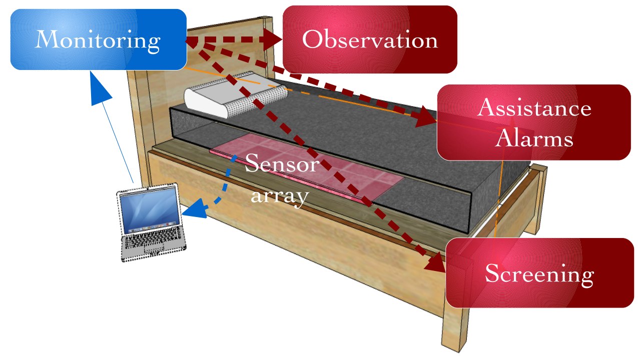

Fig. 1. A sensorized bed for ambient care

Two main types of movement detection have arisen for bed-based non-contact sensor monitoring: constant thresholds on amplitudes [6], and statistical change based detectors [7], [8]. The former is more applicable to gross movements, while the second allows smaller limb movements to be distinguished from breaths. A two-tier movement detection scheme that uses both of these types of detectors is developed here to provide redundancy and distinguish between limb movements and pressure-releasing shifts. A small study of motion-content during episodes of pain was also performed.

II. METHODS

Two patients in the palliative care ward at Elisabeth Bruyère Hospital, in Ottawa, ON, Canada, were monitored by a 50-element pressure sensor array (S4 Sensors Inc., Canada) beneath the bed. Simultaneously, a researcher at the hospital observed and annotated their movements to provide a ground truth for motion analysis. The patients were labeled "PalA" and "PalB". PalA was 81 years old and female, PalB was 55 years old and male, and both had lung cancer. PalA had the mobility impairment of a hip fracture, while PalB had no known mobility impairments. Disturbances to the patients due to the study were minimized; height and weight are unknown as they were not measured. Digitized data (12-bit, sampled at 10 Hz) from the sensors were received via serial connection on a laptop and saved to files using S4 Sensors software. 14 hours of recordings were collected for each participant. The spanned time from first to last recorded data was longer due to a couple of short non-recorded interludes for both participants and a full day of stoppage between two recordings from PalB.

A. Movement Detection

This system was implemented as depicted in Fig. 2. The

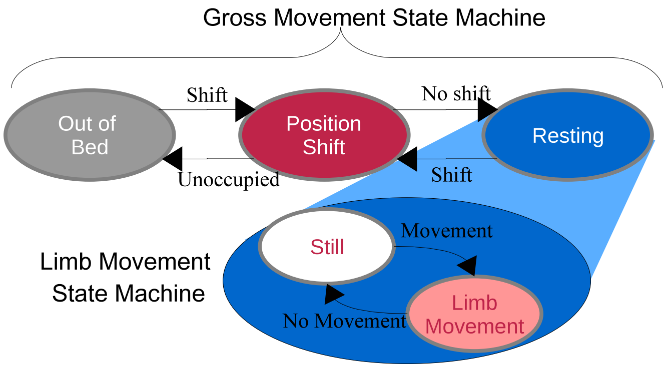

Fig. 2. A finite state machine for segmenting data by bed occupant status

gross movement state machine segmented the data into three states: $\{S$: out-of-bed, position shift, rest$\}$ with two events and their complements: $\{E$: shift detected, bed occupied$\}$. Since exiting or entering a bed requires position shifts, no transition was required between the rest and out-of-bed states. All states also have self-loops (not shown), which were the default action. Events were triggered by simple range, mean, and standard deviation operations on a sliding window of length L across the data from all sensors.

Substantial changes in pressure occur at multiple sensors during a position shift, so shifts were readily identified using the difference between the maximum and minimum value, i.e., the range, in the sliding window. To catch many combinations of shift magnitudes and weight distributions, three thresholds on the range were used and a shift was declared if any of the thresholds were exceeded. The first compared the range at any sensor to a large threshold, h_{large}. The second required a minimum number of sensors S_{shift} to surpass a medium threshold h_{med}. The last used a threshold h_{sum} across the sum of all sensor ranges. To ensure this last one is not tripped by strong breathing, the sensor range sum must also exceed six standard deviations above the mean range sum.

Occupancy was detected if S_{occup} sensors were either loaded or active. Loading was declared once the mean in the sliding window exceeded h_{zero}; activity was declared when its standard deviation exceeded h_{act}. Since the zero values of sensors were not available and this value varies considerably between sensors, a best guess for h_{zero} had to be made. h_{zero} was set to the minimum of either 110% of the minimum value in the full data record or 20% of the maximum possible value. This second possibility ensures that a data record an ever-loaded sensor is not falsely detected as unloaded.

Parameter values and thresholds were set from histograms of data from preliminary benchtop testing with known position shifts and bed occupancies. The window length L was set to 50 samples, representing five seconds of data sampled at 10 Hz. Table I lists the selected thresholds, along with their maximum range and the percentage of this maximum that the threshold represents. Each of the 50 sensors had output ranges of $[0, 3072]$, although most never surpassed half of their maximum. Unloaded outputs were observed ranging between 105 and 465, depending on the sensor.

TABLE I
THRESHOLD PARAMETER SETTINGS

Parameter	Maximum	Value	% of Maximum
h_{med}	3072	400	10%
h_{large}	3072	600	20%
h_{sum}	$3072 * 50$	2000	$< 1\%$
h_{act}	3072	2	2%
S_{shift}	50	3	6%
S_{occup}	50	20	40%

The resting segments include limb movements, which were smaller in amplitude to the position shifts and cannot be detected using preset thresholds without falsely identifying some breathing as limb movement. Movement is instead identified statistically using a previously developed movement detection algorithm [8] which sets upper and lower control limits using the mean and standard deviation of a sliding data window with length $L_c = 300$ (30 seconds).

B. Evaluation

After the data was collected, annotated movement types were classified as either position shifts or limb movement. Some notes did not clearly define which of these classes occurred. For instance, the note “Fidgeting as she tries to get her drink from the side table” does not indicate whether a lean or shift was required to perform this action or if the side table is close enough that only a limb movement is required. In such cases, the assumption was made that a shift was required. Because it was unclear which nursing procedures would occasion movements or position shifts, nursing periods were excluded from analysis. Periods without annotations were also excluded. For limb movement detection, periods with position shifts were excluded since limb movements were not detected during position shifts.

Position shift and movement detection statistics were evaluated. True positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) were incremented on an event-by-event basis according to annotated and detected events. Non-events were defined as the periods between annotated or detected events. The alternative to event-based evaluation is to evaluate sample by sample. However, annotations covered much longer periods than a given shift or movement actually lasted, and sample-based evaluation would skew results by introducing missed detections. Accuracy (Acc.), sensitivity (Sens.), Specificity (Spec.), positive predictive value (PPV), and negative predictive value (NPV) were assessed.

Although the observers were not asked specifically to note pain, it was discovered that the annotations for PalA sometimes mentioned pain. To explore the relationship between pain and muscular movements, the data for this participant was segmented into 10 minute periods and the periods were grouped according to whether pain was involved in the

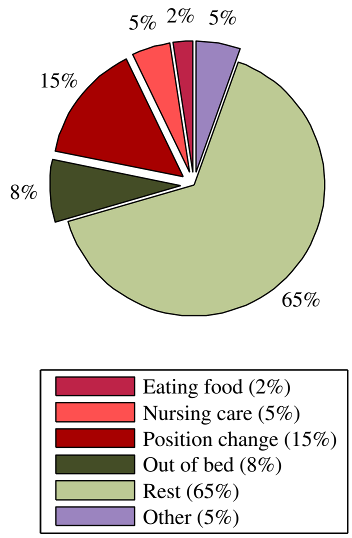

Fig. 3. Pie chart of percentage of time spent performing activities according to annotations

annotation. The percentage of time spent moving while in pain was compared to the percentage when pain was not mentioned.

III. RESULTS

Annotations overestimated the time to complete the movements, always assigning at least one minute to each position shift and sometimes combining multiple movements over several minutes into a single annotation. Although the annotations did not necessarily allow precise comparisons, they provided nonetheless a good balance between research requirements and ethical considerations. Fig 3 presents the major activities and percentage of time spent performing them, according to the annotations. PalA did not leave the bed and spent less time shifting position compared to PalB, perhaps due to her hip fracture. A good portion of movement was not performed by the patient, with 15% of movement time related to external intervention, such as nursing care, rising to 36% if joint activities, such as reaching for someone's hand, were also counted.

A. Bed Occupancy Detection

Bed occupancy was detected and compared to annotations. All of the participants' time was spent in bed, except for three intervals by PalB. All three of these were detected and no false out-of-bed detections were made. Two short false in-bed detections were made during the last out-of-bed interval. During this interval, annotations indicate that the "sheets and linens were stripped and changed by nurse".

B. Detected Position Shifts

Table II lists the resultant detection results for position shifts. There were both false detections that lowered the specificity and missed detections that lowered the sensitivity.

TABLE II
DETECTION STATISTICS FOR POSITION SHIFTS (%)

	Acc.	**Sens.**	**Spec.**	**PPV**	**NPV**
PalA	78.0	63.0	83.6	58.6	85.9
PalB	67.2	51.5	73.3	42.5	79.7
All	72.1	56.7	78.0	49.3	82.7

TABLE III
DETECTION STATISTICS FOR MOVEMENT

	Acc.	**Sens.**	**Spec.**	**PPV**	**NPV**
PalA	53.8	100.0	52.9	3.7	100.0
PalB	60.7	85.0	58.6	14.8	97.9
All	55.4	91.4	54.2	6.2	99.5

In a number of cases, an annotation seemed to be late by a minute or two compared to the shift occurring in the sensor signals. Such cases caused both a false and a missed detection, which likely should have been true positives. In other cases, the assumption that a certain movement caused a position shift did not hold. For example, reaching for the glass of water did not cause a position shift on the sensors, so this became a false negative. Some detected shifts were clearly visible in the sensor signals, but no annotation had been made.

Table II may under represent true accuracy and specificity. Since the detection statistics are event-based, long stretches of time without either detected or annotated position shifts only accounted for a single true negative event. Accuracy rises to 93.8% and specificity to 99.8% by weighting by the duration of each event and non-event.

C. Limb Movement Detection

Table III lists the resultant detection results for limb movements. The movement detector found many more movements than the observer. There were clusters of false negatives, particularly during the nights. Analysis of movement strengths showed the false positives had significantly lower strength than true positives. The sensors may be more sensitive to movements than the observer, particularly at night in low light conditions.

D. Pain and Movement

Segmentation of the 14 hours of data from PalA into 10 minutes intervals resulted in 116 intervals without annotations of pain and 4 intervals with pain annotations. The mean percentage of time moving while in pain was 13% and while not in pain was 3%. This difference was significant ($p = 0.008$) according to an unpaired t test. Fig. 4 presents a boxplot of the intervals with pain and those without.

This analysis provides some early evidence that periods with pain may be detected through motion monitoring. Given that this work only studied one participant and that pain annotations were rare, representing less than 3.3% of segments, further study is required to confirm the hypothesis and

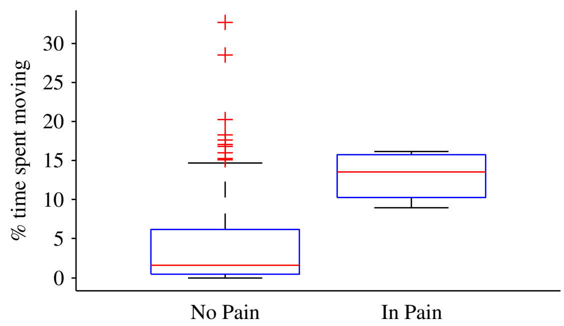

Fig. 4. Boxplot of percentage of time moving while not in pain and in pain

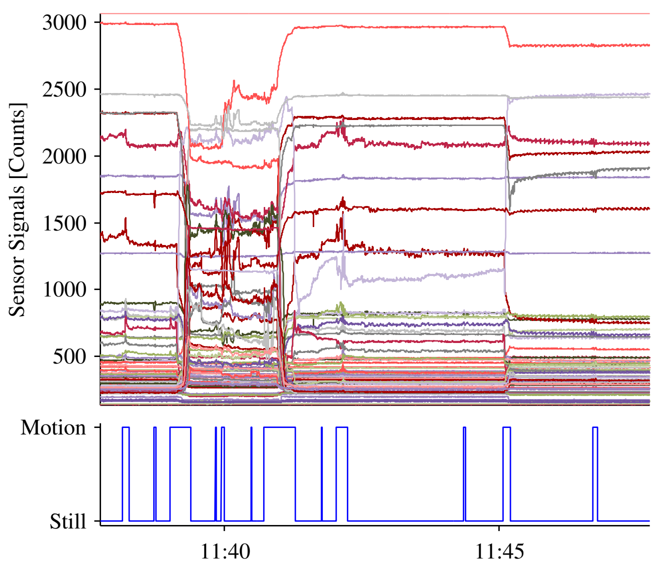

Fig. 5. Pattern displayed on sensors and of motion detection while lowering then raising the bed to a sitting posture. The following text from the annotations describes the patterns seen in this segment: "11:39: Top half of the bed is lowered. Legs are moved slightly to the left of bed by granddaughter. 11:40: Bed is moved back into sitting position."

establish movement thresholds for pain alerts. Pain was not specifically addressed in the study design, and a design that included pain scale questionnaires would provide stronger evidence.

The outliers of No Pain, marked with a "+" in Fig. 4, included all three meals, nursing procedures, and intervals that included changing the bed tilt. Some of the pain intervals also included bed tilt changes, and may be indicative of a patient looking to ease ischemia. An example ten minute interval with both lowering and raising the bed is shown in Fig. 5. Raising or lowering the bed caused a slow but steady pressure change visible on many sensors. Feature extraction and advanced classifiers such as support vector machines may be required to detect this pattern or to differentiate pain movements from movement due to regular activities.

When interpreting results pertaining to movement, external instigators must be considered. For example, washing a patient creates considerable motion, lasting more than 10 minutes. Tracking nurses in a hospital has been accomplished by ambient sensors [9]. By adding such tracking to a system, motion could be more accurately assigned to the bed occupant.

IV. CONCLUSIONS

Palliative care is particularly suited to the incorporation of non-contact monitoring due to the sensitivity of the patients to more obtrusive technologies. The unobtrusive motion monitoring system implemented here showed a clear augmentation in movement activity when the participant was in pain. Further validation of this finding is needed.

Patients are increasingly showing a preference for being cared for at home [10] and dying with dignity at home [11]–[13]. Such technology would be appropriate for both home and institutional use.

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