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Preliminary Results on the Effect of Sensor Position on Unobtrusive Rollover Detection for Sleep Monitoring in Smart Homes

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***Abstract*—Older adults experience increased sleep movement disorders and sleep fragmentation, and these are associated with serious health consequences such as falls. Monitoring sleep fragmentation and restlessness in older adults can reveal information about their daily and long-term health status. Long-term home monitoring is only realistic within the contact of unobtrusive, non-contact sensors.**

This paper presents exploratory work using the pressure sensor array as an instrument for rollover detection. The sensor output is used to calculate a center of gravity signal, from which five features are extracted. These features are used in a decision tree to classify detected movements in two categories; rollovers and other movements. Rollovers were detected with a sensitivity and specificity of 82% and 100% respectively, and a Mathew's correlation coefficient of 0.86 when data from all sensor positions were included. Intrapositional and interpositional effects of movements on sensors placed throughout the bed are described.

I. Introduction

Pervasive computing promises to improve healthcare "because of its ubiquitous and unobtrusive analytical, diagnostic, supportive, information and documentary functions" [1]. Smart homes are one of the many settings for older adults to benefit from pervasive computing [2]. The aim of smart homes is to support health, safety and independence of older adults by using technology to analyze acute events, everyday cognition, chronic disease management and long-term health and mobility [2], [3].

Steele et al. documented older adult's preference for ambient rather than wearable sensors since the latter are related to problems of "remembrance, rebellion and obtrusiveness," [2] in addition to perceived social stigma of requiring a sensor which can further reduce adherence [3]. Older adults' desire to age in their homes creates the need to shift healthcare technologies from in-hospital monitoring and treatment to home-based prevention and monitoring of health status [2]. Unobtrusive sensors require no action from the patient, therefore are better suited for long-term use and to mitigate compliance challenges.

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II. Sleep and Health in Older Adults

A. Sleep Disorders and Older Adults

Even in healthy older adults, sleep changes with age. The older adult has shorter continuous sleep periods, takes a longer time falling asleep, and suffers from increasingly fragmented sleep [4]. Sleep breathing disorders such as obstructive sleep apnea are more frequent among older adults, especially men, and are related to hypertension, stroke and heart disease [5].

There is also a change in the prevalence and type of body movements during the stages of sleep. In older adults, sleep movements are less defined by sleep stage and more likely to lead to an awakening. Periodic leg movements, which can cause frequent awakenings, also increase with age [5].

Rollovers are an important sleep movement because they indicate position changes. Positional sleeping has an effect on the severity of sleep breathing disorders such as apneas (both obstructive and central), snoring and Cheynes Stokes respiration [6]. Additionally rollovers do not occur during REM sleep and may be useful for sleep stage estimation [7].

B. Health Impact of Age-Related Sleep Changes

The prevalence of many sleep disorders increases with age, but the symptoms are often attributed to medical illness or medication [5]. Pain, noise, nocturia, and comorbidities can also increase sleep fragmentation. The lack of sleep and increased sleep fragmentation has health and social consequences [5]. Falls have recently been associated with sleep disturbances, because poor sleep can lead to a difficulty sustaining attention, slower response times, impairments in memory and concentration [8].

III. Sleep Assessments

The gold standard for sleep assessments is polysomnography (PSG), a multimodal over-night analysis. In PSG, limb and body movements are monitored by electromyography. The patient's body posture is also noted, usually by observation through an infrared camera. PSG is not compatible with long-term monitoring due to prohibitive costs, invasiveness and in-hospital location.

A. *Wearable Sensors*

In one study [7], rollover detection was performed in patients wearing a SenseWear Pro2 Armband. Thresholding the maximum and mean acceleration (in x and y-axis) identified posture differences "when the actigraph detected 'sleep'"; 82.4% (400 out of 475) of rollovers were detected.

B. *Non-Contact Sensors*

Unobtrusive sensors used for bed movement detection include pneumatic tubes placed under the sheet [9], load sensors under bedposts [10], [11], static charge sensitive bed [12], [13], and distributed resistive sensors [14].

In another study [15], data was collected simultaneously by a pressure sensor array and a wrist worn actigraph. Thresholds on the pressure sensor's value for standard deviation and squared difference were used to map the movements detected by the actigraph to the unobtrusive sensor with 69.6% sensitivity and 89.6% specificity (13.3% misclassification rate). Compliance problems with the use of the actigraph were reported for two of the ten study volunteers because of device positioning and device obtrusiveness [15].

C. *Sleep Diary*

A sleep diary can be used to record time in bed, approximate sleep onset and the number of awakenings, however long-term monitoring should avoid relying on self-reports, especially in a smart home scenario because of the limited information, cognitive demand placed on the older adult, and time-consuming data entry required to analyse trends. Instead, unobtrusive and non-contact sensors can be used to reliably collect and store a broader range of information that can be analysed offline.

IV. Objectives

Unobtrusive pressure sensor arrays can detect movement onset times [16] and collect respiration rate information [17]. The research presented herein extends its application to identifying rollovers.

The objectives of the research for this paper are to:

1. Compare the classification properties of intrapositional and interpositional decision trees for rollover detection.
2. Assess the effect of sensor number and position on movement classification and feature importance.

V. Methods

A. *Data Acquisition and Annotation*

A Tactex Controls Inc. Bed Occupancy Sensor was installed between a standard hospital 4-inch mattress and a 75"x34" metal bed frame. One hospital pillow was placed at

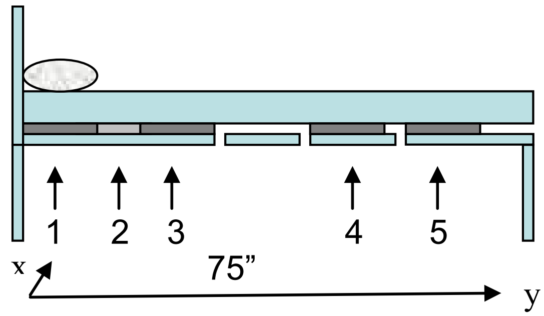

Fig. 1. Bed with pressure sensor placement

the head of the bed. The bottom plate of the bed is made of four metal sections to allow the bed to fold, though it remained in a flat position throughout these experiments. The bed sections measure 31", 9", 14" and 20". The 9" section is wide enough for the Tactex sensor, but there is an on/off switch hindering its placement.

Tests were conducted with the sensor in five positions as shown in fig. 1. A healthy volunteer performed a series of large movements (bed entry/exists, rollovers, sleep starts, posture shifts) and small movements (arm/leg twitches, gasps) with the sensor in each position.

B. *Data Annotation*

An observer noted the times of movement onset, and these values were used to manually annotate the data to identify body position, rollovers and other movements (bed entry and exit, arm, leg and other movements).

C. *Rollover Detection*

The center of gravity in the x direction (CoG*x*) was used to estimate the person's placement on the sensor array, which has 24 sensors arranged in 8 rows and 3 columns, and measures 30cm by 80 cm. Its sampling rate it 10 hertz. The CoG*x* signal was rounded to the nearest integer as shown in eq. (1) to identify a row of interest where x is the output of the pressure sensor on the i^{th} row and j^{th} column.

$$CoGx = round(\sum_{i=} \sum_{j=} x_{i\,j} * i) / \sum_{j=} x_{i\,j}) \qquad (1)$$

The features extracted from the sensor data for each recorded movement are listed in table I. MATLAB's (R2008b) decision tree classes were selected to build a classifier because their intuitive interpretation is appropriate for exploratory work and pruning can identify salient

TABLE I EXTRACTED FEATURES FROM SENSOR OUTPUT FOR EACH MOVEMENT

Feature	**Description**
Amplitude	amplitude of the CoG*x* signal
Duration	duration of CoG*x* fluctuations
#. Excurs	number of excursions in CoG*x* signal
Δ	difference between final and initial CoG*x* position
Mvar	average value of moving variance (calculated in 10 sample intervals)

features [18]. Pruning the tree to find the smallest tree with an error within one standard deviation of the best classification tree's resubstitution error was investigated to measure the computational savings. Pruning balances "predictive accuracy and model complexity for applications where model interpretation is still desired" [18].

For objective 1), a decision tree was generated for each position using stratified 10-fold cross-validation to assess intrapositional classification properties. An additional five trees were generated using the leave-one-out method; movements from four positions were used to train the tree and the movements form the left-out position was used for validation to assess interpositional classification. Finally, movements from all sensor positions were combined to build one general tree with stratified 10-fold cross-validation to produce generalized results.

For objective 2), linear discrimination analysis measured the relative importance of features from the intrapositional decision trees.

Matthew's correlation coefficient (MCC), shown in eq. (2), assessed the quality of the classifier since the classes in the dataset are unevenly distributed. MCC uses true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), to calculate a score [-1, 1], where +1 represents a perfect prediction, 0 a random prediction and -1 an inverse prediction.

$$MCC = \frac{TP*TN - FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (2)$$

VI. Results and Discussion

A. Data

In total 177 movements were recorded: 60 rollovers and 117 other movements. Table II summarizes the results of the data collection and annotation of movements.

B. Rollover Detection

Fig. 2 shows the CoGx signal for four position changes. The beginning and end of each movement was identified and the features were extracted and used in a decision tree.

The duration of rollovers in this study was 5.42 ± 4.36s, though it may be significantly longer for older adults who may require several attempts to change position. An

TABLE II Annotated Movements vs. Pressure Sensor Position

Movement	**Pos. 1**	**Pos. 2**	**Pos. 3**	**Pos. 4**	**Pos. 5**
Entry	8	11	5	7	4
Exit	7	10	5	7	3
Rollover	15	14	10	10	11
Leg(s)	0	0	0	6	1
Arm(s)	0	1	5	0	0
Whole body movement	0	8	12	5	12
Total	30	44	37	35	31

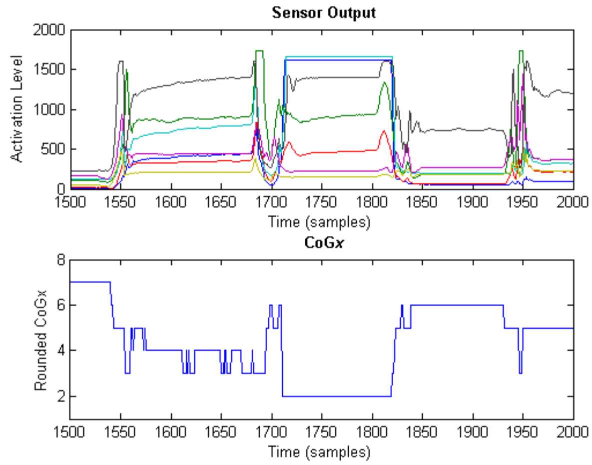

Fig. 2. Sensor output and rounded CoGx for four position changes

TABLE III Intrapositional Results (Pruned Tree)

	Pos.1	**Pos.2**	**Pos.3**	**Pos. 4**	**Pos. 5**	**Avg ±std**
Sen.	73.33	100	100	100	100	94.67±11.93
Spe.	93.33	96.67	96.23	100	75	92.26±9.93
MCC	0.68	0.95	0.94	1	0.72	0.86±0.15

increased number of attempts is expected to affect the number of fluctuations in the CoGx signal.

Table III shows the intrapositional classification results sensitivity (Sen.), specificity (Spe.) and MCC, for each pruned tree built with single position sensor data. These results indicate that the ideal sensor position for rollover detection is position 4, though position 2 & 3 maintain good classification. Data from positions 1 & 5 may be better suited for head and leg movement detection respectively.

Intrapositional decision trees built using only one sensor position differed from each other and from the generalized decision tree, suggesting that the importance of chosen features may vary with position. The results of table IV, which ranks the relative importance of features using linear discriminant analysis, suggest that feature importance also changes with sensor position. When the sensor is closer to the head or foot of the bed, other features may be required to provide the same classification rate as in centered positions.

Table V show the results from the interpositional decision trees (leave one out approach). The position listed on the first row indicates which position's movements were left out of the training and used for validation. Interpositional tree results are inferior to intrapositional results, suggesting that movements are transferred to pressure sensors differently along the length of the bed. Decreased sensitivity in the interpositional trees, compared to intrapositional and generalized trees support the finding that the effect of

TABLE IV Relative Feature Importance

Pos. 1	**Pos. 2**	**Pos. 3**	**Pos. 4**	**Pos. 5**
Δ	Δ	Δ	#. Excurs	Duration
Duration	#. Excurs	Amplitude	Δ	Δ
#. Excurs	Mvar	#. Excurs	Duration	#. Excurs
Amplitude	Amplitude	Mvar	Amplitude	Mvar
Mvar	Duration	Duration	Mvar	Amplitude

TABLE V INTERPOSITIONAL RESULTS (PRUNED TREE)

	Pos. 1	Pos. 2	Pos. 3	Pos. 4	Pos. 5	Avg±std
Sen.	59.01	31.82	27.03	28.57	26.95	37.69±13.79
Spe.	75	0	0	0	20	47.5±38.89

movements on the CoG*x* signal and its features are location specific. The zero in the specificity row of table V was caused by the absence of true negatives in three of the trees; all movements were classified at rollovers.

The generalized (random stratified 10-fold cross-validation) pruned tree correctly classified 81.67% of rollovers (49 out of 60) and 100% of movements (117 out of 117). The proportion of movements in the correct class was 93.79%, which compares with other measures reported in the literature [7], [15] and its MCC is 0.86.

An analysis of the misclassified cases revealed that the type of movement most likely to be misclassified was side-to-side rocking. The features related to the repetitive nature of this movement can be studied and added to the features list to increase specificity in rollover detection.

1) Study Limitations

Limitations of this study include the number and types of non-rollover movements recorded, and using only one volunteer in a non-sleep situation. Future work will use data acquired from the sleep lab where many more movements, including posture shifts will be observed, and will help discern which features are relevant to rollover detection.

VII. CONCLUSION

The unobtrusive pressure sensor array can be part of a long-term monitoring strategy in smart homes and used to detect specific movements in bed and gain knowledge about sleep patterns.

Decision trees applied to the pressure sensor data successfully identified most rollovers and differentiated between rollovers and other movement using features extracted from the CoG*x* signal. Interpositional effects of movements on sensors placed throughout the bed are reflected in lower values for interpositional results. The use of the pressure sensor array offers advantages compared to actigraphy and PSG in terms of cost and obtrusiveness and can be extended to identify further variables important to sleep assessments.

Studies of interpositional classification properties and feature importance can provide useful information for outfitting smart homes where it is desirable to optimize the number of sensors (minimizing cost while maintaining detection properties). Since the general tree did not perform as well as individual trees, it may not be necessary to fully cover the bed in sensor arrays for optimal rollover detection.

VIII. FUTURE WORK

The decision tree approach for rollover detection has been supported with exploratory results. Further tests will use data obtained from the sleep lab and pressure sensor array simultaneously, and from multiple subjects to create a generalizable decision tree.

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