31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Simulated Central Apnea Detection Using the Pressure Variance

Daphne I. Townsend, *Student Member, IEEE*, Megan Holtzman, *Student Member, IEEE*, Rafik Goubran, *Senior Member, IEEE*, Monique Frize, *Senior Member, IEEE*, Frank Knoefel

***Abstract*—This paper presents use of an unobtrusive pressure sensor array for simulated central apnea detection. Data was collected from seven volunteers who performed a series of regular breathing and breath holding exercises to simulate central apneas. Results of the feature extraction from the breathing signals show that breathing events may be differentiated with epoch based variance calculations. Two approaches were considered: the single sensor approach and the multisensor vote approach. The multisensor vote approach can decrease false positives and increase the value of Matthew's Correlation Coefficient. The effect of lying position on correct classification was investigated by modifying the multisensor vote approach to reduce false positives segments caused by the balistocardiogram signal and as such increase sensitivity while maintaining a low false positive rate. Intersubject classification results had low variability in both approaches.**

I. Introduction

This paper presents an overview of sleep disordered breathing and identifies older adults as a population group that could benefit from advances in the delivery of sleep assessments and apnea monitoring technology. We present an approach to the delivery of health care technology in non-traditional environments (e.g.: homes, smart apartments, palliative and continuing care) in part as a response to increasing pressures on services from the sleep lab and care needs of the increasing demographic of older adults [1]. The preliminary analysis presented here makes use of signal processing algorithms applied to non-contact pressure sensor array data to identify simulated apneas. An innovative aspect of this research is that only unobtrusive sensors are used for apnea detection. In permanent installations, the pressure sensors used in this work easily fit underneath a mattress, are not noticeable to the user.

Manuscript received April 7, 2009. This work was supported by the National Sciences and Engineering Research Council (NSERC) of Canada.

D. Townsend is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, K1S 5B6. (phone: 1-613-520-2600x1943; e-mail: dtownsen@sce.carleton.ca).

M. Holtzman is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, K1S 5B6.

R. Goubran is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, K1S 5B6 and with the Elisabeth Bruyère Research Institute at Bruyère Continuing Care, Ottawa, ON, K1N 5C8.

M. Frize is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, K1S 5B6 (with a joint appointment at the School of Information Technology and Engineering, University of Ottawa, Ottawa, ON, Canada, K1N 6N5).

F. Knoefel is with the Elisabeth Bruyère Research Institute at Bruyère Continuing Care, and with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada, K1S 5B6 FKnoefel@bruyere.org.

II. Sleep and Health in Older Adults

A. Impact on Health

Untreated sleep disorders can significantly affect the quality of life and health of sufferers. Many sleep disorders (e.g. apnea, movement disorders) are more prevalent in certain population groups. Older adults are at particular risk of sleep disorders due to comorbidities which may impair sleep or exacerbate existing sleep disorders and result in excessive daytime sleepiness and cognitive impairments [2]. Sleep disturbances also increase the risk of falling for older adults; falls are a primary cause of morbidity and mortality [2]-[3]. Studies of the relationship between sleep and aging show that 50% of older adults (65+) have difficulty falling asleep and maintaining sleep, and that 20-30% have sleep apnea [3].

B. Sleep Disordered Breathing (SDB)

Of the many types of SDB, sleep apnea is the most prevalent affecting 4% of men and 2% of women [3]. Apnea is linked to many health problems: cardiovascular (increased blood pressure, heart rate and risk of stroke), cognitive (impaired concentration, severe daytime sleepiness, headaches) and other effects such as mood changes and an "increased risk of being involved in a deadly motor vehicle accident" [4].

Apnea is identified clinically as a cessation of airflow for greater than ten seconds. The majority of sleep apnea events are obstructive and a minority are central. Obstructive sleep apnea (OSA) are characterized by a lack of airflow in spite of respiratory efforts, while central sleep apnea (CSA) is caused by lack of respiratory drive and decreased oxygen saturation and is more prevalent in older adults with congestive heart failure [3], [5].

C. Sleep Monitoring in Smart Homes

The value of unobtrusive sensors to sleep and apnea monitoring is that they require no user interaction or compliance and that they can collect long-term health information without modifying the subject's behavior. This is especially relevant for patients with cognitive difficulties or patients who do not want to wear monitoring devices.

III. Sensors for Sleep and Apnea Assessments

A complete polysomnography (PSG) is a relatively invasive procedure that includes multiple head, face and body electrodes [6].

A. Contact Sensors

By reducing the complexity and invasiveness of equipment compared to a PSG, Khandoker analysed 5-second segments of a single lead ECG and correctly classified 98.96% of CSA and OSA events using wavelet decomposition and a neural network [7].

B. Wearable Sensors

Wearable sensors used in activity and sleep-wake monitoring studies include actigraphs [8], [9] (usually embedded in wrist worn devices or in backpacks) and vests and clothing with concealed physiological sensors. Few wearable sensors are designed specifically to detect apneas.

One study [10] used a finger pulse oximeter to study children with obstructive and central apneas. Pagani et al. found that a change in pulse transit time strongly correlates to a change in respiratory effort.

In another study [11], the airway impedance measurement of the air in a continuous positive airway pressure machine was studied in ten volunteers with a diagnosis of OSA. Yen et al. correctly classified all 25 OSA and 25 CSA events by using a threshold value on the airway impedance.

C. Pervasive Sensors

Visual cameras that may detect breathing motion by tracking a projected pattern on the bed [12] or infrared cameras that analyze the apparent air temperature near the nose and mouth [13] have been presented as possible alternatives. Steele, Secombe and Brookes [14] however concluded that the use of all types of video cameras for health sensor technologies was strongly rejected by older adults in the context of long-term monitoring. Video cameras are considered non-contact but obtrusive, and suffer from additional privacy concerns (and potential for misuse) compared to other non-contact sensors [1].

Pressure sensitive mats, which form pressure distribution pictures from an array of embedded pressure sensors, can provide an enriched set of data. They allow for movement localization and posture and position recognition [15], limb movements [15], as well as the ability to extract pulse [16], and respiration [16]. This paper presents exploratory work to extend the use of pressure sensors to detect simulated central apneas.

IV. Method

A. Study Design

We examined the characteristics of breathing signals, and the feasibility of a pressure sensitive mat to recognize simulated central apnea in adult volunteers. Seven male and female participants between 20 and 30 yrs old were recruited to lie on their own beds and perform a variety of breathing patterns and body movements while pressure distribution information was collected from a pressure sensitive mat beneath their torsos.

During the experiment, they were asked to lie quietly on their back for a few minutes, and then hold their breath for up to 30 seconds to simulate central apneas as suggested in [17]. The volunteers were informed that they could stop breath holding at any point in the 30 seconds if they felt the need to breathe, though many continued for a few additional seconds. After regular breathing had begun again, they were asked to change posture and repeat the process at least twice more so that a minimum of three sets of events were recorded per individual: one for prone, supine and side lying.

B. Data Acquisition

1) Pressure Sensitive Mat Setup

A Tactex Controls Inc., Bed Occupancy Sensor (BOS) was installed on top of the bed. This pressure sensitive mat contains 24 pressure sensors in a configuration of eight rows of three sensors each at a resolution of 10cm between sensor rows and columns. The top of the mat was placed just below the bottom of the pillow area to obtain data from the shoulders and torso. For most participants, the bottom of the 80cm mat reached just below the hips.

The BOS was connected serially to a Compaq Armada 700 MHz laptop. Software provided by Tactex Controls Inc. recorded timestamps and data from each of the pressure sensors into a comma delimited text file. The data was recorded at 10Hz.

2) Annotations

Apnea and posture were noted by the investigator during data acquisition in a time-stamped log file. Actual start and end times for apnea events were realigned to account for typing delay by examining the sensor data. Posture (prone, left side, right side, and supine) and position changes were also manually annotated from the log file and realigned by examination of the sensor data.

C. Data Analysis

The recorded data was analyzed in MATLAB (Mathworks). Muscular movements, including limb movements and position changes, were automatically detected and flagged using a previously developed algorithm [18]. The aim of the classifier was to (i) correctly identify apneas because they are the rare and (ii) limit the number of false positives (breaths classified as apneas).

1) Breathing Extraction

Between movements, each sensor's output was filtered through a 30-second moving average to provide a mean load level. The mean load level is due to the weight of the participant loading the sensor and can be removed to recover the breathing signals without weight loading changes.

2) Apnea Analysis

Signal variance was identified to be a main feature for classification of apnea events because it is a measure of the spread, or distribution, of the signal over a time interval. A 1-second moving variance (σ^2) (1), was extracted from each of the sensor outputs (x) at each sample time and compared to a threshold value to classify each sample as 'apnea' (if the variance is less than the threshold) and 'breath' (if the variance is greater than the threshold).

$$\sigma(i) = \frac{N}{N-}(E[x^2(i)] - E[x(i)]^2) \qquad (1)$$

We considered two approaches: the single sensor approach and the multisensor vote approach. For the single sensor approach, each pressure sensor signal is treated as an experiment, and the results of each of 24 pressure sensor signals per patient file are combined. This is akin to placing one pressure sensor at a random location within the area covered by the mat and studying its classification ability. In the fused vote method, a vote is made every sample based on how many sensors were classified as apnea. Increasing the number of ‘apnea’ votes needed to classify a sample as apnea can reduce false positives.

To address aim ii) of this paper, Matthew’s correlation coefficient (MCC), shown in (2), is used to evaluate a classifier with unevenly distributed classes. 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.

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

First, the effect of varying the number of required votes for an apnea decision was investigated. Then, two experiments were conducted: the first used the leave one out approach to determine the interparticipant variability in choosing an optimal threshold on the variance. The second experiment divided the data according to participant position and observed the positional effect on classification.

V. Results and Discussion

The volunteers held their breath for a total of 25 simulated apneas with a mean of 28.90s, and a standard deviation of 9.36s. Simulated apneas represented 6% of all experiment data. The MCC, the true positive rate (TPR) (or sensitivity) and false positive rate (FPR) (or false alarm rate) were calculated for each threshold used, in both experiments.

A. Pressure Variance Histogram

Fig. 1 is a histogram of the 1-second moving variance signal, for 100s of prone breathing for a participant. It can be compared to Fig. 2, which is a histogram of the 1-second moving variance in a 30s apnea sample, which has a much smaller range. In the following experiments, the threshold value for the variance was tested in 0.05 increments, in a range from 0 to 10.

B. Effect of Multisensor Voting

The single sensor method was compared to the multisensor vote method. For the multisensor vote method, the number of votes was varied from 1 to 24 because the sensor array has 24 individual sensors.

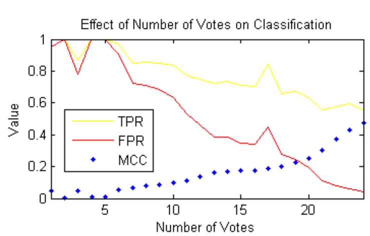

Figure 3. Effect of changing the number of votes

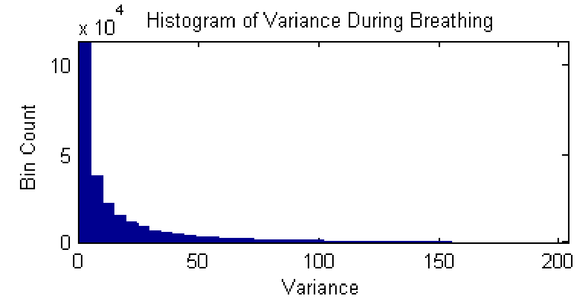

Figure 1. Histogram of prone breathing

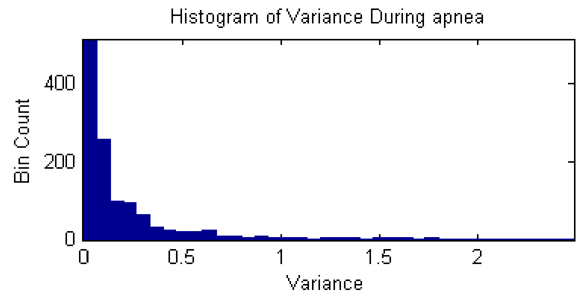

Figure 2. Histogram of prone apnea

Fig. 3 shows the effect of changing the number of votes required for an ‘apnea’ decision in the multisensor vote method. Varying the number of votes was successful at dramatically lowering the FPR.

The TPR also decreases, but not as rapidly and stabilized at 21 votes. The MCC has its quickest rise between 21 and 24 votes. Based on fig. 3, the number of votes used in the multisensor vote method in section *C* is 24. This indicates that consensus voting produces the best MCC and the lowest FPR, which are the two aims of the classifier.

C. Interparticipant Variability Results

Table I shows the results from the interparticipant classification results using the leave one out approach. The validation results were combined to produce an average (Avg) and standard deviation (Stdev) value for each column. The thresholds used for the 1-second variance that maximized the MCC are similar for each individual participant, indicating that individual participant data had a limited impact on the training. All MCC values are positives, indicating the classification is better than random, but MCC values are still quite low. Across all participants, the TPR and FPR values were consistent, as seen in the low stdev, showing the stability of the pressure variance as an indicator of simulated apneas. The low interparticipant variability suggests that the feature of pressure variance is common across all participants as an indicator of simulated apneas.

TABLE I AVERAGED INTERPARTICIPANT RESULTS

	Threshold	TPR	FPR	MCC	# Votes
Single Sensor					
Avg	1.80	0.85	0.64	0.10	N/A
Stdev	0.00	0.12	0.13	0.04	
Multisensor Vote					
Avg	8.42	0.57	0.05	0.48	24
Stdev	0.73	0.18	0.03	0.15	

D. *Effect of Position*

Table II shows results for positions (prone, supine, side) on the classification of samples of apnea for the single and multisensor methods. The threshold that gives the best MCC value is lowest for the side position in both approaches. Inspection of the raw data revealed that in side lying, more individual sensors were unloaded or saturated. These sensors had a very small variance and were very often classified as apnea regardless of participant activity. These inactive sensors may have biased the classification towards a lower threshold. The higher threshold and lower TPR in the multisensor vote method are in part due to the ballistocardiogram signal. This pulse-based signal appears in many sensors, during many simulated apneas, and contributes to a higher variance. The single sensor method has a high TPR, especially in the side position, however the FPR consistently exceeds 0.5, which is unacceptable for many clinical applications.

TABLE II RESULTS SEPARATED BY POSITION

	% apnea	Threshold	TPR	FPR	MCC	#Votes
Single Sensor						
Prone	7.34	7	0.86	0.57	0.15	N/A
Supine	5.55	1.65	0.92	0.70	0.11	N/A
Side	6.18	0.15	0.83	0.59	0.12	N/A
Multisensor Vote						
Prone	7.34	10	0.51	0.03	0.53	23
Supine	5.55	7	0.65	0.24	0.63	24
Side	6.18	4.8	0.61	0.02	0.57	24

VI. CONCLUSION

This paper presented a method to identify simulated central apnea events using an array of pressure sensors placed on top of a mattress. The multisensor vote approach shows how optimizing the number of sensor votes decrease false positives and increase the MCC. The distribution of the pressure sensor output's variance changes during breathing events and this allows the 1-second variance to be a useful classification feature. Filtering to remove the ballistocardiogram signal could further reduce false negatives as could adding other pressure signal features to the classifier.

VII. FUTURE WORK

The developed analysis will be compared to the signals of resistance plethysmography respiratory bands recorded during attended polysomnography in older adults.

REFERENCES

[1] P. Bartolomeu, J. Fonseca and F. Vasques, "Challenges in health smart homes," in *Pervasive Computing Technologies for Healthcare, 2008. PervasiveHealth 2008. Second International Conference on,* 2008, pp. 19-22.

[2] E. L. Hill, R. G. Cumming, R. Lewis, S. Carrington and D. G. L. Couteur, "Sleep Disturbances and Falls in Older People," *J. Gerontol. A Biol. Sci. Med. Sci.,* vol. 62, pp. 62-66, 2007.

[3] N. Wolkove, O. Elkholy, M. Baltzan and M. Palayew, "Sleep and aging: 1. Sleep disorders commonly found in older people," *CMAJ,* vol. 176, pp. 1299-1304, Apr. 2007.

[4] American Association of Sleep Medicine, "Obstructive Sleep Apnea," 2008.

[5] F. Giganti, G. Ficca, S. Gori and P. Salzarulo, "Body movements during night sleep and their relationship with sleep stages are further modified in very old subjects," *Brain Res. Bull.,* vol. 75, pp. 66-69, Jan. 2008.

[6] K. E. Bloch, "Polysomnography: a systematic review," *Technol. Health Care,* vol. 5, pp. 285-305, Oct. 1997.

[7] A. H. Khandoker, J. Gubbi and M. Palaniswami, "Recognizing central and obstructive sleep apnea events from normal breathing events in ECG recordings," *Computers in Cardiology, 2008,* pp. 681-684, 2008.

[8] J. Parkka et al., "Relationship of Psychological and Physiological Variables in Long-Term Self-Monitored Data During Work Ability Rehabilitation Program," *Information Technology in Biomedicine, IEEE Transactions on,* vol. 13, pp. 141-151, 2009.

[9] E. J. W. van Someren, "Actigraphic monitoring of movement and rest-activity rhythms in aging, Alzheimer's disease and Parkinson's disease," *Engineering in Medicine and Biology Society. Bridging Disciplines for Biomedicine. Proceedings of the 18th Annual International Conference of the IEEE,* vol. 1, pp. 69-70 vol.1, 1996.

[10] J. Pagani, et al, "Detection of central and obstructive sleep apnea in children using pulse transit time," *Computers in Cardiology, 2002,* pp. 529-532, 2002.

[11] Fu-Chung Yen, K. *et al.*, "A noninvasive technique for detecting obstructive and central sleep apnea," *Biomedical Engineering, IEEE Transactions on,* vol. 44, pp. 1262-1268, 1997.

[12] I. Sato and M. Nakajima, "Non-contact breath motion monitor ing system in full automation," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the,* 2005, pp. 3448-3451.

[13] R. Murthy, I. Pavlidis and P. Tsiamyrtzis, "Touchless monitoring of breathing function," in *Engineering in Medicine and Biology Society, 2004. EMBC 2004. Conference Proceedings. 26th Annual International Conference of the,* 2004, pp. 1196-1199.

[14] R. Steele, C. Secombe and W. Brookes, "Using Wireless Sensor Networks for Aged Care: The Patient's Perspective," *Pervasive Health Conference and Workshops, 2006,* pp. 1-10, 2006.

[15] T. Harada, T. Sato and T. Mori, "Estimation of bed-ridden human's gross and slight movement based on pressure sensors distribution bed," *Robotics and Automation, 2002. Proceedings. ICRA '02. IEEE International Conference on,* vol. 4, pp. 3795-3800 vol.4, 2002.

[16] M. V. D. Loos, N. Ullrich and H. Kobayashi, "Development of Sensate and Robotic Bed Technologies for Vital Signs Monitoring and Sleep Quality Improvement," *Auton.Robots,* vol. 15, pp. 67-79, 2003.

[17] K. Watanabe *et al.*, "Noninvasive measurement of heartbeat, respiration, snoring and body movements of a subject in bed via a pneumatic method," *IEEE Trans. Biomed. Eng.,* vol. 52, pp. 2100-2107, Dec. 2005.

[18] M. H. Jones, R. Goubran and F. Knoefel, "Identifying movement onset times for a bed-based pressure sensor array," in *2006 IEEE International Workshop on Medical Measurement and Applications,* 2006, pp. 111-114.