A Multi-Feature Classification Approach to Detect Sleep Apnea in an Ultrasonic Upper Airway Occlusion Detector System

Soheil Shafiee, *IEEE Student Member*, Farhad Kamangar, *IEEE Member*,
Laleh SH. Ghandehari, *IEEE Student Member* and Khosrow Behbehani, *IEEE Fellow*

Abstract— **Obstructive Sleep Apnea (OSA) is the most common form of sleep disorder breathing. It is estimated that this insidious disease affects 15% of the US adult population. Current procedure of diagnosing OSA requires polysomnography (NPSG) conducted in accredited sleep laboratories and the data getting scored by certified sleep technicians, a costly process that is not readily available in all areas. Ultrasonic techniques are increasingly used in the area of medical diagnosis and treatments due to their safety and economic costs. This paper investigates a feasibility study of a multi-channel ultrasonic OSA detection system. The approach utilizes wavelet-based as well as temporal and spectral features extracted from multiple ultrasound waves transmitted through patient's neck during sleep. Using NPSG data as gold standard, the proposed classifier makes a preliminary decision on the data sequence by labeling epochs as normal or apneic. A Finite State Machine (FSM) is employed to update the classified labels for a more robust detection. Experimental results on three sleep disordered patients suggest that it may be feasible to consider the proposed approach for an ultrasound based detection system.**

I. Introduction

Sleep disordered breathing (SDB) refers to respiration abnormalities during sleep. The most common form of SDB is obstructive sleep apnea (OSA) which is caused by occlusion of the upper airway for 10 s or more during sleep. It is believed that this syndrome is caused by excessive muscle relaxation of the posterior oropharynx during sleep. When the occlusion of the upper airway during sleep is partial (>50% but not 100%), the respiratory anomaly is referred to as hypopnea. Sleep apnea episodes vary in duration and may last as long as 60 s. The frequency of events also varies among patients. To quantify the severity of SDB, apnea hypopnea index (AHI) which is defined as the average number of apneic events per hour of sleep is used. Apnea and hypopnea episodes result in desaturation of blood oxygen and an increase in CO_2 concentration. Multiple studies have linked OSA to serious cardiovascular disorders such as hypertension, and stroke [1, 2]. In addition, daytime sleepiness is highly common in the OSA patients and increases the risk of driving or job related accidents [3].

S. Shafiee and L. Ghandehari are Ph.D. students with Computer Science and Engineering Department, University of Texas at Arlington, TX 76019 USA (e-mail: {soheil.shafiee, laleh.shikhgholamhosseing}@mavs.uta.edu).

F. Kamangar is a professor with the department of Computer Science and Engineering, University of Texas at Arlington, Arlington, TX 76019 USA (e-mail: kamangar@uta.edu).

K. Behbehani is a professor of Biomedical Engineering and dean of the College of Engineering, University of Texas at Arlington, Arlington, TX 76019 USA (e-mail: kb@uta.edu).

Young, et al. [4, 5] have reported that approximately 15% of adult population of the US suffers from untreated OSA. The standard method that is currently used to diagnose OSA is nocturnal polysomnography (NPSG) which involves an overnight study in an accredited sleep laboratory. During NPSG multiple electrodes and sensors are attached to patient to obtain electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), electromyography (EMG), abdominal wall movement, chest wall movement, and end tidal CO_2 data are recorded. Using the captured data, a sleep technician labels the sleep stages as well as apnea/hypopnea events. A sleep medicine physician recommends the treatment type based on the performed labeling. NPSG is a costly process since it uses multiple instruments and the manual scoring of data is required. The relatively high costs of NPSG and the lack of accredited sleep laboratories in all areas suggest the need for a lower cost and more practical method of SDB diagnosis.

The idea of using ultrasonic transducers to detect OSA was first introduced by Al-Abed, et al. [6]. For this purpose, ultrasonic waves were transmitted across the airway during sleep and detected laterally across the neck. It was hypothesized that airway obstruction results in changes in the transmitted ultrasound signal and these changes can be quantified to detect the airway occlusion. This approach is attractive as it is safe, non-invasive, low cost and can ultimately be made to be portable. The characterization of the ultrasonic sensors for the purpose of OSA detection has been reported in [6, 7] for in vitro and in vivo studies, respectively, where temporal features of the received signals were used for classification. As a complementary study, [8] introduced the use of spectral features of the ultrasonic signals to detect OSA.

In this paper, we propose a feasibility study of OSA detection based on a sequence of multi-channel ultrasound recordings of the system introduced in [8]. Our novelty in comparison with [6, 7, 8] is the proposed feature selection and classification methods where multiple temporal, spectral and wavelet-based features are calculated using the ultrasound signals. Multiple SVM classifiers (one classifier for each channel) are then trained and used to detect apnea in the received signals. Final labeling of the data is boosted by employing sequence labeling by a Finite State Machine (FSM) to achieve a more robust and accurate classification. The proposed method is evaluated over recordings from 3 SDB patients and the final classification rates confirm the feasibility of incorporating ultrasound in OSA detection.

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

II. Materials and Methods

Based on the clinical study proposed in [8], a novel ultrasound device is presented to detect upper airway occlusion. In this device, small piezoelectric ultrasound transducers (7 transmitters and 12 receivers) are placed on opposite sides of patient's neck for full night studies signal recording in an accredited sleep lab. Transducers generate roughly 3 MHz ultrasound burst every 100 msec on one side of the patient's neck and on the other side, the initial 200 µsec of the received signals are recorded in 12 channels for further processing. Therefore, for every second of a single channel, there exist 10 bursts of 200 µsec duration. The sampling frequency of the signal recorder is selected to be 30 MHz to be at least 10 times faster than the excitation frequency of the piezoelectric transmitters. Considering this rate and 12 channels, each receiving burst contains 12×6000 samples. Every second of the recordings are labeled by a certified sleep expert based on NPSG information recorded during the sleep time. More details on the transducers design and placement, data acquisition, patient selection and labeling process are discussed in [6, 7, 8]. In this work, experiments were performed on 3 subjects with sufficient amount of normal and apneic events. Table I shows the total sleep duration and the calculated AHI index for each patient as well as the total time in which a patient suffers from apneic breathing.

After pre-processing of the received signals, 13 dimensional feature vectors are extracted from each of the 12 channels for each burst. Features are selected such that they maximize discriminative information for OSA detection. In the next step, a small portion of the recorded data is used to train and validate different classifiers for each channel. These classifiers make an initial decision on every burst and finally, a finite state machine refines the classified labels.

A. Pre-processing

At the pre-processing stage, all the signals from all channels are filtered by a band-pass FIR filter (f_L=150 KHz and f_H=1 MHz). Considering the ultrasound wave propagation time through patient's neck which varies from person to person, the first 63 µsec (1904 samples) in each burst is discarded and the last 137 µsec (4096 samples) is preserved as the Region of Interest (ROI) for further processing. For future clinical studies and in order to save space and energy, the recorder system may start recording after a delay or after detecting appropriate changes in signal.

B. Feature Extraction

A total of 13 features were extracted from the filtered ROI of each channel c for each burst B (B_c) as follows (in all formulas, T is the length of the signal of interest):

Energy related features:

1- *ROI Energy:* The first feature is calculated by

$$f_{1,c} = \sum_{t=1}^{T} \left[B_{c,t}\right]^2. \quad (1)$$

2- *ROI Peak:* Maximum absolute value of the burst

$$f_{2,c} = \max\{|B_{c,t}|\}. \quad (2)$$

3- *High Energy Start Time:* Energy for each 64-sample sub-segment of every burst is calculated and the starting time for the sub-segment with the highest energy is selected as a feature.

Mean Crossing Rate (MCR) related features: MCR for signal S is the number of times that S crosses its mean or

$$MCR_S = \frac{1}{T}\sum_{t=2}^{T}\{\text{sgn}([S_t - M_S] \cdot [S_{t-1} - M_S])\}, \quad (3)$$

where $\text{sgn}(\cdot)$ is the sign function and $M_S = \frac{1}{T}\sum_{t=1}^{T} S$ is the average signal S.

4- *Rectified Burst MCR:* Equation (3) when $S = B_c$

5- *Envelope MCR:* Envelope of each rectified burst is calculated by finding its peaks. Then, MCR is calculated over the envelope using equation (3).

Spectrum related features

6- *Spectral Peak:* Maximum intensity of the FFT absolute value of the burst in each channel.

7- *Strongest Frequency:* The frequency where the peak intensity (feature 6) occurs.

Wavelet related features: The next 6 features are calculated by applying symmetrical discrete Meyer wavelet in 4 levels. The high frequency component of the 4th level decomposition (cH_4) is used for the following calculations.

8- cH_4 *Energy*.

9- cH_4 *Sum of Absolute Values*.

10- cH_4 *Total Variation:* For channel c this measure is defined as

$$f_{10,c} = \text{TV}(cH_{4_c}) = \sum_{t=0}^{T}\left|cH_{4_{c,t+1}} - cH_{4_{c,t}}\right| \quad (4)$$

11- cH_4 *Center of Mass:* This feature is calculated by

$$f_{11,c} = \frac{\sum_{t=1}^{T} t\cdot|cH_{4_c}|}{\sum_{t=1}^{T}|cH_{4_c}|} \quad (5)$$

12- cH_4 *MCR:* MCR (equation (3)) is calculated over cH_4.

13- cH_4 *Envelope Energy:* cH_4 envelope is calculated and the energy of this signal is calculated.

C. Training Classifiers

The next process is to design a classification framework to detect apnea in the received ultrasound signals. For this purpose, all data labeled as non-normal are considered as apnea. Since the classification problem is only concerned with two classes (apnea, or normal breathing), Support Vector Machine (SVM) [9] with Radial Basis Function (RBF) kernel

TABLE I. FULL NIGHT STATISTICS FOR THE 3 RECRUITED PATIENTS

Patient	Total Sleep Time	Apnea Duration	Number of Apneic Events	AHI
P-1	5:58'	3:25'	451	75.45
P-2	6:59'	3:48'	561	80.11
P-3	6:39'	3:12'	424	63.60

TABLE II. CALCULATED WEIGHTS FOR 12 CHANNELS' SVMS FOR PATIENT 1~3.

CH. / PAT.	CH-1	CH-2	CH-3	CH-4	CH-5	CH-6
	CH-7	CH-8	CH-9	CH-10	CH-11	CH-12
P-1	0	0	0.07	0.12	0.14	0.15
	0.14	0	0.15	0.10	0.10	0
P-2	0.04	0	0.06	0.13	0.14	0.08
	0.13	0.04	0.13	0.05	0.07	0.07
P-3	0.06	0.07	0.07	0.07	0.06	0
	0.13	0.11	0.13	0.12	0.13	0

(with scaling factor σ=1.5) is selected as the base method for classification. For each patient, classifiers are separately trained for each channel, i.e. 12 SVMs are trained using the 13 dimensional feature vectors from the bursts recorded during full night studies. Since in some periods of the captured data, the received signal intensity is not satisfactory, bursts with low energy signals in a majority of their channels are excluded from the training data. 500 normal and 500 apneic bursts are randomly selected for training (results in a total duration of 100 seconds of data from the full night study). In addition to training data, a set of bursts (500 normal and 500 apneic) are selected to validate each classifier after training. The most discriminative RBF scaling factor (σ=1.5) is determined using validation data. Validation results are also used to assign a confidence level (weight) for each channel which is calculated by representing its classification effectiveness, i.e.

$$w_c = {}^1\!/_2 \log\left(\frac{R_c}{1-R_c}\right), \quad (6)$$

where R_c is the SVM recognition rate (duration of the correctly classified data to the total duration) of channel c on the validation data. These weights are then normalized and stored in the 12 dimensional vector $\boldsymbol{w} = [w_1, w_2, \dots, w_{12}]^T$ which is later used to make the final decision on test signals. Table III shows the classifiers' weights calculated for the 3 subjects. It can be seen that some channels are associated with zero weight and this happens since during data recording, these channels didn't record signals with an acceptable energy level.

D. Classification

For classification, full night study sequences of bursts are labeled as apnea or normal, using our classification method which consists of four main steps.

Step A: SVM Classification of Bursts: At the first step, each individual channel of the recorded burst is classified into apnea (1) or normal (-1) by its corresponding SVM classifier. As a result, there would be a 12 dimensional classification vector $\boldsymbol{v} \in \{-1,1\}$ for every burst corresponding to 12 channels of data. A label is assigned to burst B using

$$\text{Label}(B) = \text{sgn}(\boldsymbol{w} \circ \boldsymbol{v}) \in \{-1,1\} \quad (7)$$

where $\circ$ denotes the inner product operator.

Step B: One Second Labeling: Every 10 bursts -which were classified in previous step- vote for one second of the recorded data to be labeled as apnea or normal. In the voting process, the majority vote is considered in one second of the data (10 votes) and in case of a tie, "apnea" is used. One second window is selected based on the available annotation which is performed for every one second during sleep.

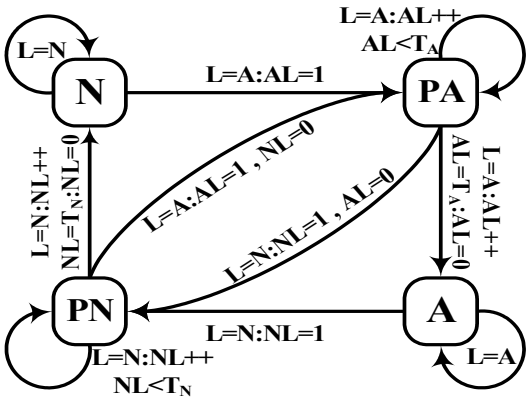

Figure 1. Finite State Machine (FSM) used for sequence labeling.

Step C: Finite State Machine: In this step, a Finite State Machine (FSM) [10] modifies the label assigned to one second of the signal coming from the previous step. In this work, a state machine with four states is used. The states include Normal (N), Apnea (A), Possible Normal (PN), and Possible Apnea (PA). The transition from one state to another is controlled by two constraints: The labeling decision on the one second period from step B and the allowed minimum duration constraints, T_N and T_A, imposed to consecutive normal and apnea events length, NL and AL, respectively. Whenever the classifier makes a decision change (from normal to apnea or vice versa), FSM prevents the detection system from immediately switching to new state by transiting to temporary states (PN or PA) and remains there until a minimum number of new states are detected. Figure 1 shows the block diagram of the proposed FSM. In this diagram, the statement on the left side of ":" checks the constraints and if it is true, the action (right side of ":") would be executed and transition to a new state takes place.

Step D: Refining FSM Temporary Labels: In the final step, an algorithm refines the labeling from step C such that all sequences of temporary labels (PN and PA) are replaced with permanent labels, N or A, depending on their last preceding burst labeled with N or A, respectively. In other words, whenever a temporary state (PN or PA) is reached, this step prevents the final labeling from changing until a permanent state is detected.

III. RESULTS

In the classification process, after multi-channel classification and applying channel weights in burst level (Step A), every 10 consecutive bursts vote to label a one second period of the recorded signal (Step B). The one second labeled signal is then fed into the proposed FSM machine (Figure 1) with the parameters T_N and T_A equal to 4 and 2 seconds, respectively. The FSM labels the data to 4 different states (Step C). Finally, a modified 2 states labeling is considered

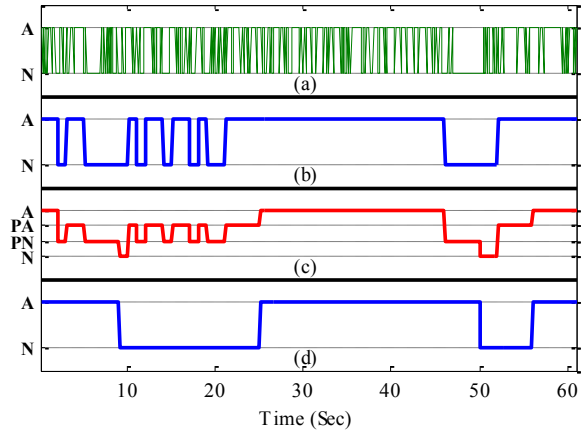

Figure 2. (a) ~ (d): Assigned labels in steps A~D in an OSA detection on one minute recording for Patient 3.

as the detection output (Step D). Figure 2 illustrates the outputs of different classification steps on a one minute period for patient 3, where labels A, N, PN and PA are associated with the diagram labels in Figure 1.

Classification results of steps A, B and D are shown in Table III for the 3 subjects. Accuracy is the ratio of correct classification duration to the total sleep duration. Sensitivity is the ratio of total duration of the correctly classified apnea to the total duration of annotated apnea and specificity is the same measure for normal breathing. It is clearly seen that the best accuracy and sensitivity rates for all 3 subjects are achieved after applying step D. In step A, SVM classifiers analyze each burst individually which results in sensitivity rates in the range of 68%~70%. By applying burst voting in step B, these values increase to 75%~77% for all subjects. Finally, using FSM in steps C and D result in the best sensitivity rates of 79%~83%. On the other hand, using FSM to modify the labels from step B degrades specificity rates while total accuracy increases similar to sensitivity. In the proposed system, parameters T_N and T_A can be used as a trade-off for Sensitivity/Specificity.

TABLE III. ACCURACY, SENSITIVITY AND SPECIFICITY OF THE 3 STEPS OF THE PROPOSED DETECTION METHOD ON 3 RECRUITED PATIENTS.

Patient	Step	Accuracy	Sensitivity	Specificity
P-1	A	66.98%	69.89%	**63.08%**
	B	69.71%	75.20%	62.36%
	D	**69.87%**	**79.09%**	57.58%
P-2	A	68.28%	68.56%	67.95%
	B	72.68%	75.94%	**68.78%**
	D	**72.89%**	**81.91%**	62.12%
P-3	A	74.24%	70.06%	78.13%
	B	78.04%	77.14%	**78.87%**
	D	**79.31%**	**83.66%**	75.26%

IV. CONCLUSION

In this paper, we propose an OSA detection method on multi-channel recorded signals of an ultrasonic device. This device may be initially used as a screening tool to determine which patients should undergo full NPSG studies and as a result, the overall diagnose and treatment costs may be reduced. The algorithm proposed in this paper employs temporal, spectral and wavelet-based features of the received ultrasound waves in multiple channels. These features along with manual annotations are used to train a multi-classifier structure of SVMs which is then used for the initial classification of the captured data sequence. Finally, a Finite State Machine updates the classified labels for a more robust OSA detection. Experimental results on clinical full night study data of three different SDB patients show the performance of the proposed algorithm in terms of accuracy, sensitivity and specificity. More specifically, the proposed method could detect apneic events within the range of 79%~83%. This work is a feasibility study on the effectiveness of ultrasound waves in detecting apneic events. Further improvements (both in hardware and algorithms) and more comparisons to other existing methods are necessary to achieve a practical OSA detection system. Specifically, both the system hardware and algorithms may be improved for better detection and to work in a patient-independent and channel-independent condition. More clinical full night studies also help to evaluate the overall system on different patients in terms of OSA severity (especially less severe cases) and body and health characteristics.

REFERENCES

[1] F. Roux, C. D'Ambrosio, and V. Mohsenin, "Sleep-related breathing disorders and cardiovascular disease", The American Journal of Medicine, vol. 108, no. 5, pp. 396-402, 2000.

[2] J. W. Shepard, Jr, "Hypertension, cardiac arrhythmias, myocardial infarction, and stroke in relation to obstructive sleep apnea", Clinics in Chest Medicine, vol. 13, no. 3, pp. 437-58, 1992.

[3] T. Young, J. Dempsey, J. Skatrud, S. Weber and S. Badr, "The Occurrence of Sleep-Disordered Breathing among Middle-Aged Adults," *N Engl J Med*, vol. 328, pp. 1230-1235, 1993.

[4] T. Young, M. Palta, J. Dempsey, P. E. Peppard, F. J. Nieto, and K. M. Hla, "Burden of sleep apnea: rationale, design, and major findings of the Wisconsin Sleep Cohort study", Wisconsin Medical Journal, vol. 108, no. 5, pp. 246-249, 2009.

[5] T. Young, P. E. Peppard and D. J. Gottlieb, "Epidemiology of Obstructive Sleep Apnea A Population Health Perspective", American Journal of Respiratory and Critical Care Medicine, vol. 165, no. 9, pp. 1217-1239, 2002.

[6] M.A. Al-Abed, P. Antich, D.E. Watenpaugh, K. Behbehani, "Detection of airway occlusion in simulated obstructive sleep apnea/hypopnea using ultrasound: An in vitro study,", Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp.284-287, 2010

[7] M.A. Al-Abed, P. Antich, D.E. Watenpaugh, K. Behbehani, "In vivo characterization of ultrasonic transducers for the detection of airway occlusion in Sleep Disordered Breathing,", Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp.7687-7690, 2011

[8] M.A. Al-Abed, P. Antich, D.E. Watenpaugh, K. Behbehani, "Upper airway occlusion detection using a novel ultrasound technique", Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp.5650-5653, 2012

[9] V. Kecman, "Learning and soft computing: support vector machines, neural networks, and fuzzy logic models", MIT press, 2001.

[10] S. Shafiee, F. Almasganj, B. Vazirnezhad, A. Jafari, "A two-stage speech activity detection system considering fractal aspects of prosody", Pattern Recognition Letters, vol. 31, np. 9, pp. 936-948, 2010.