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Monitoring Torso Acceleration for Estimating the Respiratory Flow and Efforts for Sleep Apnea Detection

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***Abstract*— Sleep apnea syndrome is a common sleep breathing disorder classified into two major categories: obstructive and central. In this study, we propose a method based on ensemble learning to estimate the respiratory flow, the thoracic respiratory effort and the abdominal respiratory effort from acceleration of suprasternal notch, the thorax and the abdomen respectively. The estimated flow can be used to detect the breathing cessations and the estimated efforts can be used to classify them into obstructive and central apneas. The estimated signals are compared with the signals recorded by well-established measurement methods to show overall mean errors from 11% for the abdomen effort, 17% for the thorax effort and 16% error for the flow estimation. The presented results demonstrate the feasibility of using the torso acceleration as a simple and inexpensive solution for long term measuring and monitoring of respiratory functions for sleep apnea detection.**

I. INTRODUCTION

Sleep apnea, repetitive cessations of breathing during sleep, is a common sleep breathing disorder. Clinically, sleep apnea is classified into three types: obstructive, central and mixed. Obstructive sleep apnea (OSA) is characterized by a partial or complete collapse of airways which blocks the flow of air to the lungs [1]. Central sleep apnea occurs when during sleep there is no drive to the muscles responsible for breathing. Both obstructive and central apnea syndromes require different types of treatment which makes distinguishing them essential [1]. In contrast to the obstructive sleep apnea cases, where ongoing respiratory efforts are observed, the central apnea is defined by lack of respiratory effort during the cessations of airflow. Thus, in both cases monitoring of airflow is necessary for detecting apnea periods. On the other hand, screening of the respiratory efforts is essential to distinguishing between the obstructive or central apnea periods.

In Polysomnography (PSG), the gold standard for sleep apnea diagnosis, the respiratory flow and effort indicators monitor the breathing function. Respiratory flow is measured with a nasal/oral cannula fitted near the nostrils and connected to a pressure transducer [2]. This allows detection of the breathing cessation periods indicating apnea events. Respiratory efforts are measured with two belts fastened around the chest and abdomen of patients. The belts typically use piezoelectric sensors or respiratory inductance plethysmography (RIP) techniques. Besides monitoring respiratory flow and efforts, the overnight full channel polysomnography involves comprehensive recording of biophysiological changes during sleep. The whole process is usually performed in sleep labs with long waiting list and complex and expensive procedure. Simplified testing at home is possible for selected patients [3] but uses the same basic respiratory measurement techniques as described above. Therefore, there is a considerable interest in development of reliable, simple and low cost techniques for identification of individuals with sleep breathing disorders capable of distinguishing between the central and obstructive cases.

Development of Micro-Electro-Mechanical Systems (MEMS) accelerometers induced a new wave of approaches for sleep apnea monitoring. Several studies presented different indirect methods for estimating respiratory features based on measurement of torso acceleration. In a recent study performed by Morillo et al. [4], the respiratory flow waveform has been extracted from an accelerometer mounted on the suprasternal notch of subjects resting supine. Although the proposed method achieved a reasonably low error in estimation of respiration rate, there was no result presenting the correlation between the estimated flow and the reference respiratory signal. In addition, the estimated flow was limited to the supine position, which hampers the generality of the findings. Furthermore, this method does not provide means of measuring the respiratory efforts which are essential in sleep apnea monitoring. Methods proposed by Bates et al. [5] and by Reinvuo et al. [6] used accelerometers for the same purpose but again, both are limited to the estimation of respiration rate and their ability to derive continuous flow or volume waveforms was neither investigated nor claimed. Although some of the above mentioned methods achieved a reasonable result in detecting apnea periods, none of them provided a powerful tool for classifying apnea periods into obstructive and central.

In our previous work [7], inspired by our extensive previous studies carried on seismocardiogram [8] and also by the research done by Morillo et al. [4], we demonstrated the preliminary results proving that the use of a small tri-axial MEMS accelerometer mounted on the suprasternal notch allows for indirect evaluation of respiratory flow in different body postures and different flow rates. In the current study, we have expanded our work to measure the respiratory efforts as well as the respiratory flow.

The objective of this study is to propose a complete method for monitoring respiratory functions, the upper airway flow and respiratory efforts, using signals recorded with three tri-axial MEMS accelerometers placed on the upper-

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body. The accelerometers were mounted on the suprasternal notch to indirectly monitor the airflow in the upper airway, the right seventh intercoastal space to monitor the chest wall movement, and the abdomen to monitor the abdominal movement. This method allows for indirect detection of airflow cessation events in order to detect apnea periods, and detection of respiratory efforts in order to classify the apnea events into obstructive and central. The ensemble learning approaches were adopted to estimate the respiratory activities from the recorded signals. The oral-nasal flow signal picked up by a nasal/oral cannula and the respiratory efforts obtained with two strain gauge belts fastened around the chest and the abdomen of subjects were used as reference signals.

II. MATERIALS AND METHODS

A. Participants

The participants of this study were non-smoker 17 men and 2 women aged 27 to 35, with no history of cardiopulmonary disorders and obesity.

B. Test Setup

The dataset of this study was collected at the Center for Integrative Bio-Medical Engineering Research (CiBER), Simon Fraser University, Burnaby, BC. The data acquisition involved measurement of ECG, nasal/oral airflow, thoracic respiratory effort, and abdominal respiratory effort, acceleration of the suprasternal notch, the thorax and the abdomen. The nasal/oral airflow was obtained using a nasal & oral cannula (Model 0589, Braebon Canada, Kanata, ON) connected to a pressure sensor (Model 0585, Braebon Canada, Kanata, ON). The pressure sensor was calibrated using a water manometer.

The respiratory efforts were recorded using two respiratory effort transducers (Model SS5LB, BioPac Systems Inc, Camino Goleta, CA) mounted on two elastic belts that measured the changes in thoracic and abdomen circumference.

The acceleration signals were acquired with three ADXL335z tri-axis MEMS accelerometers (Analog Devices Inc, Norwood, MA). The accelerometers were placed on the suprasternal notch, the thorax and the abdomen using a double-sided polyurethane foam tape (3M, Maplewood, MN) and further secured using an over-the-top single sided paper tape. Data acquisition was performed with a data acquisition system NI9205 (National Instruments, Austin, TX). All signals were digitized at the rate of 500 Hz. Finally, data storage was performed on a personal computer running a custom built LabVIEW Virtual Instrument (VI).

C. Procedure

Since the regression analysis was used to estimate respiratory flow and effort, for each subject we recorded two set of signals that lasted 2 and 3 minutes which were used as training and test datasets respectively in the signal processing phase. The subjects were asked to breathe tidal and deeply with about 5 breaths at each rate followed by 12 seconds of breath hold after deep breathing periods. This pattern repeated while the subjects were in supine, prone and lateral positions. On average, the experimental session for each subject lasted 35 min.

III. DATA ANALYSIS AND PROCESSING

First, the signals recorded from the three accelerometers, the oral-nasal flow and the thorax and abdomen respiratory efforts recorded from belts were band pass filtered, in the range of 0.1 and 10 Hz and down sampled to 20 Hz to remove baseline fluctuations. The Savitzky-Golay smoothing filter, frame size 100 ms, second order fitting [9] was used for removing the seismocardiogram contents from the signals. Finally, the signals were divided into tidal and deep segments using oral-nasal flow as the trigger to analyze the breathing signals at different flow rates.

For estimating the desired signals, respiratory flow and efforts, the data analysis was done in two phases: the training phase and the test phase. In the training phase, two regression models were customized for each subject using the training dataset: a non-casual FIR model (model_1) and a neural network model (model_2). The non-causal FIR model was calculated using correlation analysis and implemented by the system identification toolbox of Matlab. A structure with two hidden layers (ten neurons in the first layer and five neurons in the second layer) and one neuron in the output layer was selected for the neural network model. The neural network toolbox of Matlab was used to implement this structure.

After that, we employed an ensemble learning approach to combine the outputs of models and get a committee of experts (CE). The principle of ensemble learning is that the decision of the committee should have better overall accuracy, on average, than any individual committee member [10]. The models were combined using the very simple average linear combiner [10] as defined in Eq. 1 where *n* is the number of members or models.

$$CE = \frac{1}{n}\sum_{i=1}^{n} model(i) \tag{1}$$

The output of the committee was applied to the test dataset to estimate each desired signal and calculate the estimation error. As depicted in Figure 1, for estimating the respiratory flow, the acceleration signals recorded from suprasternal notch, thorax and abdomen of subjects were used as the input variables in training phase for customizing the FIR and the neural network models while the oral-nasal flow was considered as the observed variable.

For estimating the thoracic respiratory effort, the same approach was used; however the acceleration of the chest was used as the input variable in the training phase and the thoracic respiratory effort recorded by a belt fastened around subject's chest was used as the observed variable. The same method was used for estimating the abdominal respiratory effort. The abdominal wall acceleration and abdominal respiratory effort recorded by a belt fastened around the subject's abdomen were used as the input and the observed variables respectively.

To compare the estimated respiratory flow (F_{est}) with the reference oral-nasal flow (F_{nasal}), flow estimation error (E)

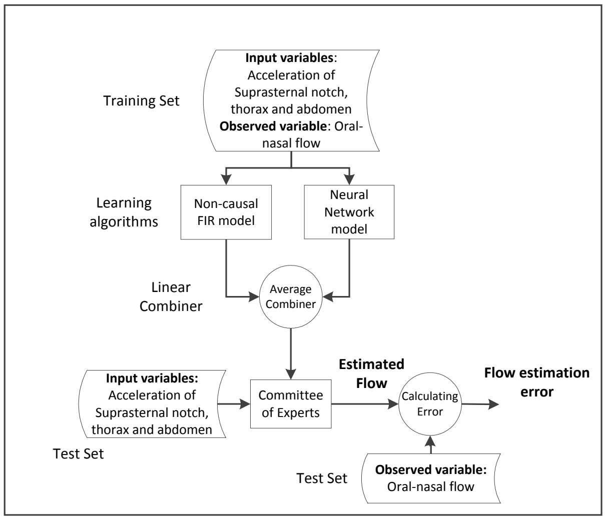

Fig. 1. Schematic representation of ensemble learning approach for estimating flow

was calculated as defined in Eq. 2 where n is the size of each segment.

$$E = \frac{\frac{1}{n}\sum_{i=1}^{n}\left[F_{nasal}(i) - F_{est}(i)\right]^2}{Var(F_{nasal})} \cdot 100 \qquad (2)$$

The error between the estimated thorax respiratory effort and the reference value measured with the belt fastened around the subject's chest was evaluated separately in the same way. A similar procedure was employed for calculating the error between the estimated abdomen respiratory effort and the reference value measured by the belt fastened around the subject's abdomen.

IV. RESULTS

A. Flow and effort estimation error

An example trace of the estimated and the oral-nasal flow is shown in Figure 2. It can be seen that the estimated flow signal follows the oral-nasal flow signal in the tidal and deep cycles and also indicates cessation periods well.

The experimental results for the flow estimation error, for all subjects in each posture and flow rate, is summarized in Figure 3. Figure 4 shows the thoracic effort estimation error and Figure 5 presents the abdominal effort estimation error for all subjects in each position and flow rate. The mean of overall errors for the estimated signals for all subjects and conditions (all positions and flow rates) is summarized in Table I.

B. Start Time of Apnea Periods

The start time of each breathing cessation in estimated flow and oral-nasal flow was compared and the absolute value of time differences between them was calculated. Table II summarizes the mean value and the standard deviation of absolute value of the time differences for all breathing cessations that happened for all subjects in three different postures.

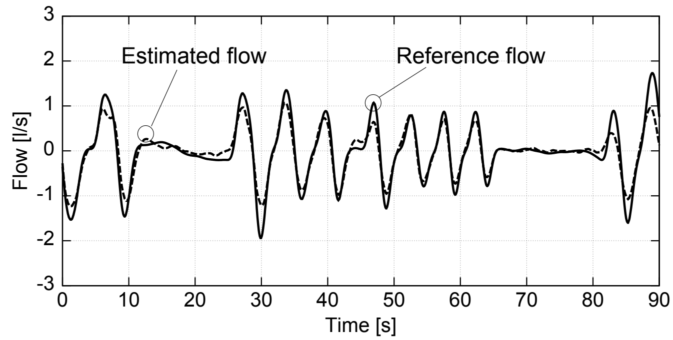

Fig. 2. An example of the actual (solid line) and estimated flow (dashed line). The estimated flow follows the reference signal in tidal and deep breathing and also in apnea periods.

TABLE I

OVERALL MEAN $\pm$ STANDARD DEVIATION OF FLOW, THORAX EFFORT AND ABDOMEN EFFORT ESTIMATION ERRORS FOR ALL SUBJECTS AND ALL CONDITIONS

Signal	Overall error
Flow	$16\% \pm 7\%$
Thorax Effort	$17\% \pm 9\%$
Abdomen Effort	$11\% \pm 6\%$

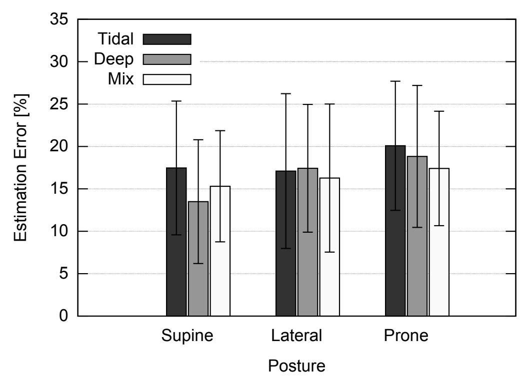

Fig. 3. Mean values of the flow estimation for all subjects in three different positions and flow rates.

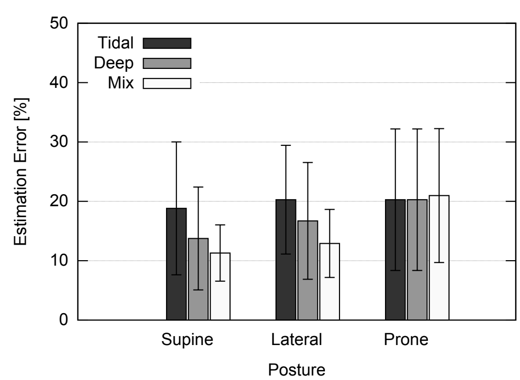

Fig. 4. Mean values of the thoracic effort estimation for all subjects in three different positions and flow rates.

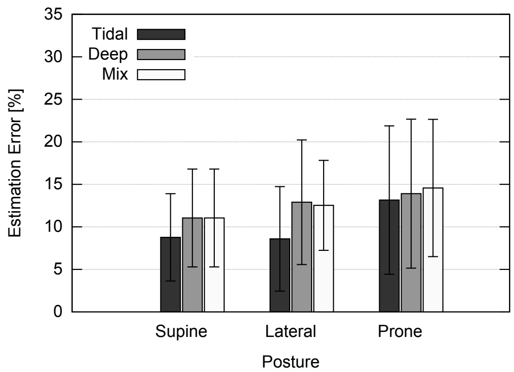

Fig. 5. Mean values of the abdominal effort estimation for all subjects in three different positions and flow rates.

TABLE II
MEAN AND STANDARD DEVIATION OF ABSOLUTE VALUES OF THE DIFFERENCES IN THE START TIME OF BREATHING CESSATION IN F_{EST} AND F_{NASAL} FOR ALL SUBJECTS IN THREE DIFFERENT POSITIONS

Posture	**Mean**	**SD**
Supine	223 ms	180 ms
Prone	232 ms	205 ms
Lateral	291 ms	230 ms

V. DISCUSSION

In this study, we presented a method for estimating the upper airway flow and the respiratory efforts using acceleration signals recorded from the upper-body by applying ensemble learning techniques.

For estimating the flow, we used the signals recorded from three accelerometers mounted on the suprasternal notch, the thorax and the abdomen, for three horizontal body positions (supine, lateral and prone) and two different flow rate regimes (tidal and high amplitude breathing). We found that using signals recorded with three accelerometers improves the results significantly in comparison with a single accelerometer mounted in suprasternal notch. For all subjects and across all conditions (all positions and flow rates) the calculated mean error is 16%. We estimated the thoracic effort using the signals recorded from an accelerometer placed on the right seventh intercoastal space. The mean of the estimated error for the thoracic effort is 17% for all subjects and all conditions. The abdominal respiration effort was estimated using an accelerometer mounted on the abdomen wall. The mean value of the abdominal effort estimation error is reasonably low at 11% and significantly lower in the tidal breathing regime compared to the deep breathing regime. We estimated the start of the apnea periods and their duration from the accelerometer signals and compared them with the actual recorded flow signals. The mean of the overall difference in the start time of apneas across all subjects and conditions is 249 millisecond (SD = 210 milliseconds).

VI. CONCLUSION

This paper presents a method for monitoring respiratory functions using three accelerometers mounted on the torso with special focus on sleep apnea monitoring. The novelty of this research is to capture all required respiratory features of flow and efforts, as are registered in PSG, using inexpensive tri-axial MEMS accelerometers and assess its accuracy in estimating the actual amplitude of the signal rather than only estimating the breath rate. Recent advances in analyzing acceleration signals, recorded from the surface of the torso [4], [11] can provide us with extra tools to also monitor the cardiovascular system in parallel to monitoring of the pulmonary system as proposed in this research.

The main objective of this paper was to introduce an inexpensive and easy method as an alternative approach to either diagnose the sleep apnea syndrome or prioritize the patients in terms of condition severity to be scheduled for PSG. There has been no intention to suggest this method as a replacement to PSG and comprehensive sleep lab studies. In the future, we plan to perform clinical study on patients suffering from both cases of sleep apnea and proceed with developing algorithms for automatic classification of the obstructive and central cases.

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