Poster Abstract: Breathing Disorder Detection Using Wearable Electrocardiogram And Oxygen Saturation

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ABSTRACT

Conventional diagnosis using polysomnography (PSG) on breathing disorder is expensive and uncomfortable to patients. In this paper, we present a low-cost portable and wearable multi-sensor system to non-invasively acquire a subject's vital signs, and leverage various machine learning methods on features extracted from Electrocardiogram (ECG) and Blood oxygen saturation (SpO_2) signals to detect breathing disorder events. Our preliminary predication accuracies on 110 clinical patients is 90.0%.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**;

KEYWORDS

Breathing disorder, Wearable sensors, Healthcare, Machine learning

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1 INTRODUCTION

Breathing disorder is a common medical issue during sleep. It consists of obstructive apnea, central apnea, hypopnea, etc., which independently or synergistically impact the subject's breathing behaviors. To diagnose these symptoms of a patient, the regular clinical method relies on the usage of expensive PSG equipment with multiple electrode patches attached to the body. A clinical specialist then manually identify these disordered breathing events across the entire sleep recording using his/her expertise on vital sign analysis [2].

To investigate the relationship of vital signs and breathing disorder, previous researches exploit the information of ECG and/or SpO_2 signals but on limited datasets [1, 6]. Meanwhile, even though some prior works also state good performances of apnea detection using breathing signals, those experiments are well controlled [4, 7]. In the clinical environment, the breathing signal quality is sensitively impacted by a subject's unpredictable posture changes (sitting, lying, standing, etc.), body motions, or speaking. As a result, motion artifacts frequently occur on the breathing signals. Fig. 1b shows an example of the ECG, SpO_2, and breathing signals of a subject. The breathing disorders happen where the ECG and SpO_2 signals have a large variation (green rectangles). However, some motion artifacts at the end margin of the first disorder event (dotted ellipse) might mislead the breathing disorder determination. In this paper, we present a low-cost wearable multi-sensor system for numerous actual patients, and apply various machine learning methods on the ECG and SpO_2 signals, in order to not only reliably obtain the necessary vital signs in hospital wards [3], but to have a proficient-like capacity of detecting the breathing disorder events.

2 HARDWARE

We present our wearable multi-sensor vest, *SensEcho*, which has three electrode patches for single-lead ECG signal monitoring at a 200 Hz sampling rate, and has two sensing wires for the chest and abdomen breathing monitoring at a sampling rate of 25 Hz. A wrist oximeter communicates with SensEcho using Bluetooth, whose sampling rate is 1 Hz. In addition, an ultra-low power, 3-axis digital accelerometer component ADXL345 with a 25 Hz sampling rate is embedded in the vest. SensEcho provides the capacities of local data storage and low-power WiFi-based uploading to the database cloud. Fig. 1a depicts the main board of SensEcho.

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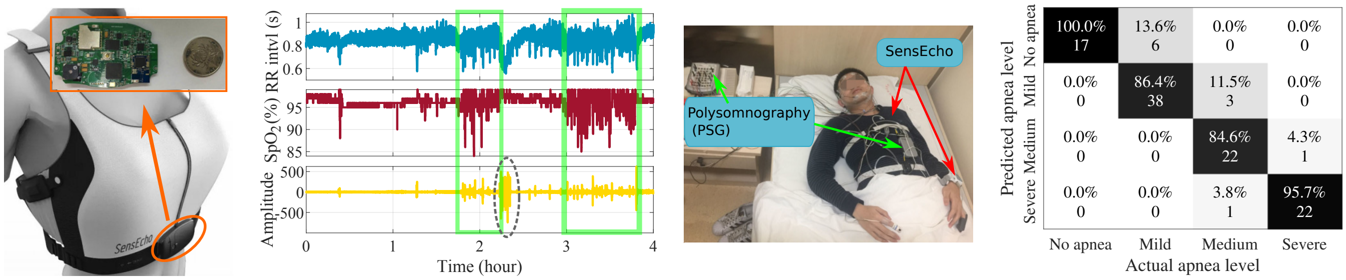

(a) Hardware design of SensEcho

(b) Example RR interval, SpO_2, and breathing signals of a patient

(c) Actual experiment set-up in the clinical hospital

(d) Confusion matrix of the sleep apnea levels

Figure 1: SensEcho's hardware, example signals, experiment set-up, and clinical results

3 PRELIMINARY EVALUATIONS

A public sleep database [5] is used at first. This database consists of the PSG monitoring of 6,600 patients in the U.S., including the records of breathing disorder event durations manually determined by clinical specialists. We construct 53 features from ECG signals, and 33 features from SpO_2 signals according to [6]. To align those disorder events with our feature space, we map all of disordered breath events into one-minute time chunks to construct a time sequence with a binary label of "normal breathing" and "breathing disorder" [1]. If a breathing disorder event happens, the corresponding time chunks of this event span are labeled with "breathing disorder". All features are then calculated inside every one-minute chunk. For example, a one-hour-long recording is transferred to a matrix of 60 $\times$ 87 (53 + 33 + 1 label). 80% of patients are randomly split out for the training set, on which five-fold cross-validation is performed for hyper-parameter search, and the data of the remaining 20% patients tests the trained model. Table 1 lists the minute-level prediction accuracies on this database using three machine learning methods. As we can see, SpO_2 signals act as a more significant role than ECG signals to independently estimate the disordered breaths, and the combination of Random Forest and the features of ECG & SpO_2 outperforms all others.

The Apnea Hypopnea Index (AHI) is used to indicate patients' apnea levels. In every hour, the amount of manually identified breathing disorder events are summed as an AHI score. AHI score could be commonly divided to four levels [4]. *No apnea*: AHI < 5; *Mild*: $5 \leq$ AHI < 15; *Medium*: $15 <$ AHI ≤ 30; and *Severe*: AHI > 30. We train and validate the prediction model of AHI using the database and the methods discussed above. The accuracy is 87.42%. This model is then tested on the 110 actual patients at Department of Respiration in Chinese PLA General Hospital, with wearing SensEcho for their breathing monitoring (Fig. 1c). Fig. 1d presents the confusion matrix of preliminary prediction accuracies of them. The overall accuracy is 90.0%, and the average AHI error is 2.0930. The previous results of 37 patients presented in [4] have the overall accuracy of 86.5%, and the average AHI error of 1.9. Considering the larger amount of patient database we have, our competitive results demonstrate that SensEcho is a promising wearable solution for breathing disorder detections.

We are currently enrolling more patients to build up our patient sleep database, and are designing advanced algorithms to involve breathing and accelerometer signal information to further improve the prediction accuracy.

Table 1: Prediction results of the public sleep database [5]

Methods	Adaboost	Logistic	Random Forest
	ECG features only		
	0.7468	0.7872	0.8490
Accuracy	**SpO_2 features only**		
	0.8154	0.8334	0.8655
	ECG & SpO_2 features		
	0.8337	0.8729	**0.8998**

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