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Letter to the Editor

Accurate Estimation of Obstructive Sleep Apnea Severity Using Non-Polysomnographic Features For Home-Based Screening

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Dear Editor in Chief

Obstructive sleep apnea-hypopnea syndrome (OSAS) is a breathing disorder during sleep and a potentially fatal condition affecting millions of individuals worldwide. The prevalence of OSAS is increasing with greater obesity and aging internationally (1). It is characterized by repeated episodes of airway occlusion (apnea) or narrowing (hypopnea) during sleep. The outcomes of OSAS range from serious cardiovascular diseases to cognitive impairment and psychiatric symptoms (2, 3). While each of these conditions significantly worsens the quality of life, many of the patients remain unrecognized at a huge medical and economic expense for themselves and the social health system (1). The standard diagnostic test for OSAS is overnight polysomnography (PSG) (4). As PSG is an expensive and time-consuming procedure, initial OSAS screening is valuable. The association of sleep apnea severity with simple non-polysomnographic features leads to a minimized strategy for its home-based detection which decreases economic burden on both the patients and public health system.

Different strategies are proposed for OSAS detection. Non-polysomnographic parameters such as body fat distribution, neck circumference, body mass index (BMI), maxillary and mandibular study of oral cavity, have been investigated (5). A large body of literature is dedicated to easily-acquired biomedical signals. The most accurate methods of this approach are based on the electrocardiogram (ECG), and pulse oximetry (6, 7).

Blood oxygen saturation (SpO2), measured by the pulse oximetry, is one of the extensively studied signals for this purpose, because it can be non-invasively recorded and is suitable for portable monitoring. Apneas and hypopneas are usually accompanied by obvious desaturation events consequently; patients with OSAS typically present unstable SpO2 signals (4). Several quantitative indices are available to measure such irregular behavior of SpO2 (7).

To enhance initial health screening facilities, we sought a novel and minimized approach to OSAS detection problem. We deliberately avoided computationally complex features with an insight to implement the algorithms on smart mobile phones. Pulse oximetery features and heart rate can be extracted through processing the red component of the finger`s pictures taken by the phone camera (8).

To reach a more accurate prediction, we applied the strong method of mutual information (MI) for checking the statistical dependency between overnight simple features (9). We then weighted the features by their degree of statistical dependency before feeding them to classification methods.

We conducted this study at the Sleep Laboratory of Ibn-e-Sina Hospital at Mashhad University of Medical Sciences, Mashhad, Iran from 158 adult individuals between July 2012 and May 2014. We determined the severity of OSAS by the value of apnea-hypopnea index (AHI) which is the number of apnea and hypopnea events occurring per hour of sleep (4).

For simplified OSAS diagnosis, we reduced the requisite features in three phases. First we selected a set of features out of the general parameters routinely reported after PSG test. In the second phase, we shrank the feature set to those parameters that do not require PSG tests. We fed the two feature sets to a self-organizing map (SOM) network for classification (10). Finally we preserved only the feature with highest MI and exploited the simpler but similar algorithm of "K-means" for classification.

The primary feature set is composed of BMI and simple polysomnographic parameters; respiratory events (i.e. apneas, hypopneas and respiratory effort related arousal (RERA)) indices, total number of blood oxygen de-saturations below 95%,90%,80% and 75% during sleep, total snore index and snoring arousals index, mean and minimum level of SpO2 (%) in wakefulness and sleep, limb movement(LM) index, periodic limb movement (PLM) index and indices of arousals associated to LM and PLM, respiratory arousals Index, minimum and maximum heart rates in wakefulness, spontaneous arousals index.

If the features are arranged in descending order according to their degree of dependency to OSAS severity, the first half of features comprises our first set: BMI, total snore index, parameters related to blood oxygen saturation (minimum level in sleep time, mean level in total recorded time, number of de-saturations below 95% in sleep), snoring and respiratory arousals indices, and minimum heart rate in wakefulness.

These features are fed to a small 2×2 SOM. SOM is an artificial neural network exploiting unsupervised learning to map the data of the feature space (training samples) to the 4-dimensional space of healthy, mild, moderate or severe OSAS (10). If the features are weighted according to their MI values, the most frequent performance of the classifier enhances (sensitivity: from 85.7% to 94.2%, specificity: from 96.3% to 97.8%, and accuracy: from 94% to 96.5%). Hence, we incorporate our findings about the dependency of features on OSAS severity to SOM classifying strategy.

In the second phase, we considered non-polysomnographic parameters (i.e. omitting the respiratory and snoring arousals). The proposed classifier remained efficient even in spite of this reduction. The mean performance values are: specificity: 85.7%, sensitivity: 96.3%, accuracy: 94%. This indicates that the remained feature set is enough for SOM classifier to perform classification with accepted performance.

In the last phase, the feature with highest MI, "total number of blood oxygen de-saturations below 95% during sleep" remained. To minimize the computational burden we exploited the simpler but similar clustering algorithm. SOMs with a small number of nodes perform similar to K-means (10). The mean performance over ten consecutive runs of the algorithm was sensitivity of 92.2%, specificity of 97.2% and accuracy of 95.5%.

These results were superior to all the reported sensitivity – specificity pairs to date. The best and most recent reported accuracy for an off-line algorithm based on complex DSP techniques for feature extraction and selection from SpO2, and SVM classifier is 96.7%, but the specificity is not reported (7).

Accurate initial OSAS screening refers only the suspected moderate or severe OSAS patients to sleep laboratories for the expensive PSG test. The achieved results hence serve as a good platform for enhancement of public health system efficiency.

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