APNEA Detection on Smart Phone

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ABSTRACT

A flexible framework that performs real-time analysis of physiological data to monitor people's health conditions is discussed in this paper. Patients suspected of suffering sleep apnea and hypopnea syndrome (SAHS) have to undergo sleep studies such as expensive polysomnography to be diagnosed. Healthcare professionals are constantly looking for ways to improve the ease of diagnosis and comfort for this kind of patients as well as reducing both the number of sleep studies they need to undergo and the waiting times. Relating to this scenario, some research proposals and commercial products are appearing, but all of them record the physiological data of patients to portable devices and, in the morning, these data are loaded into hospital computers where physicians analyze them by making use of specialized software. The aim of this paper is to show a very accurate classifier that is able of identifying the presence of sleep apneas from blood oxygen saturation signal fragments taken from pulsioximetry systems (SpO2 & HRV) implemented on smart phone in real time.

Keywords

Real time Data stream mining, signal Processing, Feature Extraction.

1. INTRODUCTION

Sleep apnea (AP-ne-ah) is a common disorder in which you have one or more pauses in breathing or shallow breaths while you sleep. Sleep apnea can be described as sleep disorder in which breathing is ceased during more than 10 seconds and occurs more than five times per sleep hour causing arousal from sleep. Although patients partially wake up, while catching up for breath, still they are not aware of their problems at the morning. Sleep apnea [6] has serious impact at health of patients; especially it causes heart problems (hypertension, coronary arterial disease, and arrhythmia). The interruption of sleep cycle has also a negative impact on quality of life. It often causes depressions, daytime fatigue and sleepiness. This results in increased accident levels due to day sleepiness and fatigue. Sleep apnea events are divided into three classes: Obstructive sleep apnea (OSA), Central sleep apnea (CSA) and mixed sleep apnea (MSA) or Complex Sleep Apnea.

This Disease is seen in all age groups and any instance of time so efficient sensing devices and wireless network are developing to improve the quality of Health care service. Sleep apnea often goes undiagnosed. Doctors usually can't detect the condition during routine office visits. Also, no blood test can help to diagnose the condition. It mainly needs to diagnose as soon as it occurs. It is not possible for doctor to observe at night time. Hence to overcome this new innovative system is proposed which would understand the changes in the physiological signals to detect apneic event.

This paper presents the analysis of HRV and SPO2 signals to monitor the apneic events.

The signals are obtained from the database and then classified accordingly. Three basic functions on the data i.e. first, to extract the required features from the data secondly to classify the tailored data and finally calculate the risk factor and evaluate its risk are performed.

2. RELATED WORK

Various methods such as pulse oximetry *[5]* which is noninvasive detection of blood oxygen levels and wireless sensor devices are used to reduce the cables attached to the body of the patients. Due to this the devices are becoming mobile. Advancement is made further in the development of such devices. When the sensor become wireless, the main aspect was to transfer it through wireless networks .This was also done soon, by developing wireless sensors containing Bluetooth technology. Due to the presence of Bluetooth the data was sent over the network to the doctor and then the doctors would analyze the data.

But the need for a continuous monitoring person was felt which was practically impossible and need for further modification was felt. Later the devices were developed which had an inbuilt alarm system. When there was rapid change in the HR or spo2 signal the alarm system used to get activated which caused ringing of the alarm *[1]*.

This was the work done till now and it was appreciable. But efficiency and accuracy were mainly to be considered. Different algorithms and methodologies were used to get the accurate data. After obtaining the accurate data, efficient detection of risk levels in apnea was also important.

In this approach, required features from HR and spo2 signals are extracted and applied to two different classifications and clustering algorithms such as K means and classification using random forests *[4]*, and checking the efficiency of both of them. As the signals are continuous in nature and processed in real time the algorithms to be used are data stream mining algorithms. Initially the class of incoming signals is not known hence first clustering algorithm is used to group the similar data and classify them with the doctor's standard rules and then this classified data will be used for further learning with the help of classification algorithm. Hence, a semi-supervised algorithm is used to perform risk analysis of apnea disease. After getting the comparison between the algorithms, data classified from the best algorithm is used for calculation of the risk components.

3. METHOD

In this, the data processing is done as shown in fig.1

Fig 1: Block diagram

3.1. Pre-processing

Basically, the aim of preprocessing is to improve the quality of physiological signals. Noise affects the original signal and makes them unreliable. The noise can be of the form of patient movement, baseline wandering, instrumentation noise etc. As the data is unreliable, a preprocessing phase has to be implemented for removing unwanted components and obtaining correct data for further processing.

3.2 Feature extraction

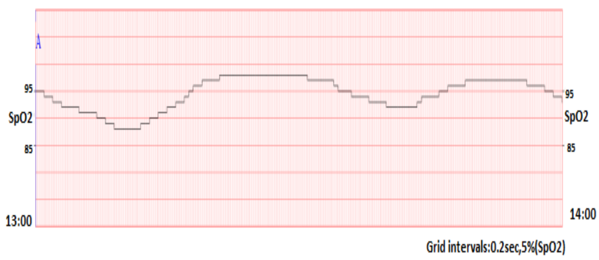


Fig 2. SpO2 record with OSA negative subject [17]

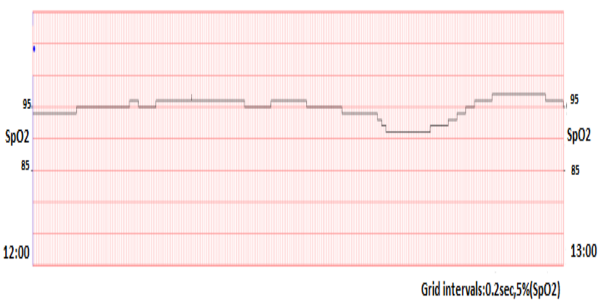


Fig 3. SpO2 record with OSA positive subject [17]

Figure 2 depicts a common OSA negative subject, and Figure 3 shows a SpO2 record with OSA positive subject. However, diagnosis of the disease is not evident by visual inspection.

From early times, feature extraction has been studied and new advancements are proposed for fast and accurate feature extraction. In this paper the concentration is on the features such as Saturation of Peripheral Oxygen (Spo2) and heart rate variation (HRV).The deviation from normal parameters will be used for diagnosis. Features of Spo2 signal to be considered for analysis are:

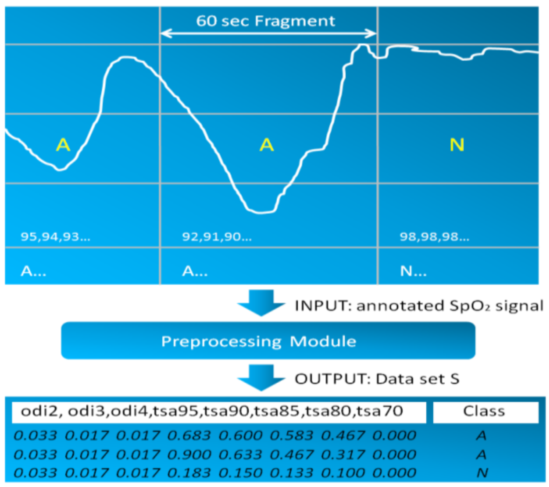
1. *Delta index (Δ index)*: This is a common measure to detect the apneic events by measuring SpO2 variability. Levy et al. [18] calculates Δ index as the sum of the absolute variations between two successive points, divided by the number of intervals. It is usually computed for 12-sec. intervals.

2. *Oxygen desaturation indices:* Oxygen Desaturation index (ODI) indexes ODI2, ODI3, and ODI4 types of Desaturation levels indicate the number of 2%, 3%, and 4% desaturation dips from baseline for per recording hour. The other indexes TSA90, TSA88, TSA86, TSA84, TSA82, and TSA80 represents to the time spent in apnea below 90%, 88%, 86%, 84%, 82%, and 80% saturation level (TSA).The system divides the SpO2 signals into fragments of 60 s, and then, it performed a pre-processing on every SpO2 signal fragment to

extract relevant features from the signal. After the pre-processing of intermediate stage, the result of the

Pre-processing of the previous signal is the set S, which is written in the bottom part of Figure. 3, where the ith record of S corresponds to the ith tuple that includes the data values

extracted from the ith SpO2 signal fragment after the pre-processing step, with its reference annotation. Firstly calculate the Desaturation Di (Di =dsi . . dei]) and the restoration Ri (Ri = [rsi . . . rei]) intervals, for every signal fragment. For each restoration interval Ri , and set the next baseline bi+1 used to calculate the dip values corresponding to the next desaturation interval Di+1,i.e., the number of 2%, 3%and 4% dips with respect to the baseline bi+1, as can be seen in Fig. 4. The ODI indexes are the sum of the dip values in every desaturation interval Di divided by the size of the signal fragment. System uses a variable moving baseline to set up the baseline, because such a strategy is more realistic baseline representation, i.e., a baseline will always stays above 90% of the average peak value. System is set as a baseline value the greatest sample in every restoration interval.



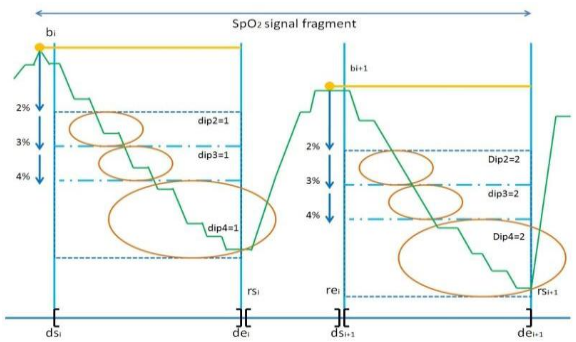


Fig 4: Pre-processing applied on a SpO2 signal fragment to get *ODI* indexes.

3.3 Risk level

In Obstructive sleep apnea (OSA), the boundaries of severity are set as follows:

1. Mild: 5 to 10 apneic events per hour
2. Moderate : 15 to 30 apneic events per hour
3. Severe :more than 30 apneic events per hour

   The extracted signal features are used to decide the severity of disease.

3.4 Data Mining Algorithms

Two data mining algorithms for clustering and classification of data are used depending upon which risk components are calculated. The algorithms used for analysis are:

3.4.1 K-means algorithm

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The main idea is to define k centroids, one for each cluster. The algorithm is composed of the following steps:

1. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

3.4.2 Classification using random forests [4]

Classification using random forests algorithm is capable of handling infinite stream of data online. It handles unsteady arrival of labeled records and adjusts parameters according to the change in class boundary in data stream. It also judges whether arrived records are capable of classification or more data is required. It is one of the best algorithms for classification of data streams in accurate and efficient manner.

Random forest is an ensemble classifier that consists of many decision trees and outputs the class that is the mode of the classes output by individual trees

Each tree is constructed using the following algorithm:

1. Let the number of training cases be *N*, and the number of variables in the classifier be *M*.
2. The number *m* of input variables to be used to determine the decision at a node of the tree is decided; *m* should be much less than *M*.
3. Choose a training set for this tree by choosing *n* times with replacement from all *N* available training cases (i.e. take a bootstrap sample). Use the rest of the cases to estimate the error of the tree, by predicting their classes.
4. For each node of the tree, randomly choose *m* variables on which to base the decision at that node. Calculate the best split based on these *m* variables in the training set.
5. Each tree is fully grown and not pruned (as may be done in constructing a normal tree classifier).

4. ADVANTAGES

The data analysis algorithms used here are characterized by a good accuracy and small number of false positives. In this paper the incoming vital signals are analyzed in Real time (online) which focuses on current input data stream. So, discrete risk levels are identified (Mild, Moderate, Severe) on continuous data stream. This helps doctor as well as patient to get accurate diagnosis.

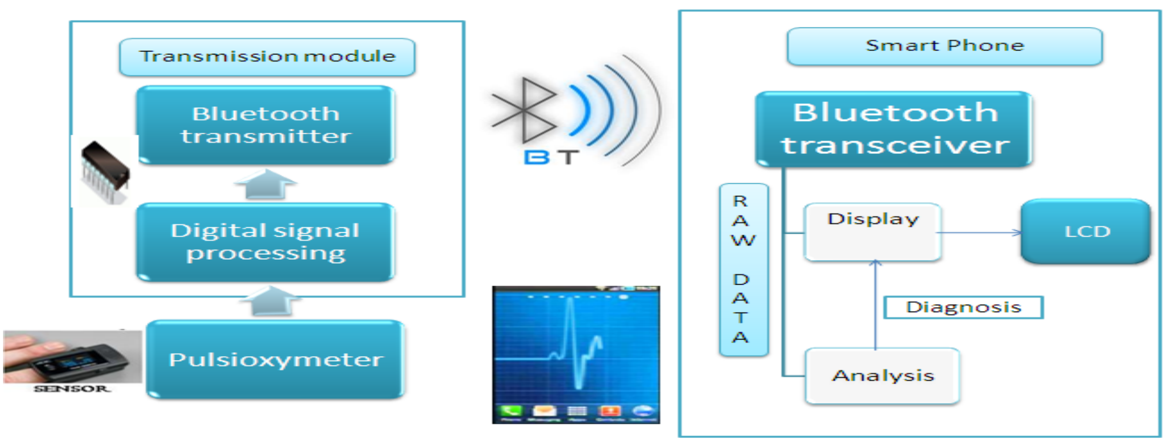


Fig.5 Architecture of system

But there are some limitations to the diagnosis because results are algorithm based. As there are limited resources as input to algorithm, it affects accuracy of algorithm.

5. RESULTS

Table 1. Comparison of Sleep Apnea Detection Approaches Se- sensitivity, Sp-specificity, Acc.-accuracy.

Method	Ref.	Approach	Performance[%]		
			Se	Sp	Acc.
Quiceno-Manrique et al.	[9]	ECG signal			92.67
Alvarez et al.	[10]	SaO2 and EEG signal	91	83.3	88.5
Ng et al.	[11]	Thoracic and abdominal signals	NA	NA	80
Lin et al.	[12]	EEG signal	69.64	44.44	NA
Schrader et al.	[13]	HRV Fourier and wavelet transformation	90.8	NA	NA
Mendez et al.	[14]	Bivariate autoregressive model of HRV	NA	NA	85
Xie et al.	[15]	Spo2 and ECG	79.75	85.89	84.40
Laiali Almazaydeh et al.	[16]	Features extraction of Spo2 signal	87.5	100	93.3

Comparative study is carried out on different sleep apnea detection techniques. Table 1 represents comparative results. As can be seen, feature extraction of Spo2 signal has achieved a comparable or better performance. This applies to the other works that rely on the SpO2 signal as well as other biometric signals.

6. FUTURE SCOPE

In this paper, as discussed the real-time acquisition, visualization and analysis of the physiological data on a cell phone. As health monitoring devices become more pervasive, it is believed that there will be a need for developing automatic pattern recognition algorithms to model, detect anomalies and ultimately get an understanding of this potentially massive amount of physiological data.

7. CONCLUSION

This paper provides improvements to the existing methods of real-time detection of apnea by adding intelligence online. The system will detect the apneic attack by analyzing the signals (SpO2 & HRV) and calculating the risk factor for alarm activation at apneic period. Also the system uses wireless sensors which are low cost, light weighted SpO2 sensors and makes it easy to wear for prolonged time and be mobile anywhere.

8. ACKNOWLEDGMENT

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