Real Time Data Processing for Detection of Apnea using Android Phone

S. R. Patil, Prachi Shewale, Aditi Agrawal, Vandana Choudhari, Balika Doke

Abstract: ***Sleep apnea (or sleep apnoea in British English) is a type of sleep disorder characterized by pauses in breathing or instances of shallow or infrequent breathing during sleep. Each pause in breathing, called an apnea, can last from at least ten seconds to several minutes, and may occur 5 to 30 times or more an hour. Similarly, each abnormally shallow breathing event is called a hypopnea. Sleep apnea is often diagnosed with an overnight sleep test called a polysomnogram, or "sleep study".***

The final diagnosis of sleep apnea is established by an overnight polysomnography (PSG) that involves the recording and the studying of several neurologic and cardio-respiratory signals. Those PSGs are carried out in sleep laboratories with attending systems and specialized staff. Because these studies are expensive, it is very relevant to find reliable diagnostic alternatives using fewer biological signals and providing a high level of usability. Identifying the presence of sleep apneas from blood oxygen saturation signal fragments taken from pulsioximetry systems (SPO2). In order to build the classifier, all the methods with which we worked were trained and tested with annotated SpO2 signals available in the Apnea-ECG Database. Another additional requirement we considered was that the classifier should run in real time using, at each particular moment, past information in the SpO2 signal and not information contained in the whole signal. Moreover, we implemented a monitoring system that detects apneic events in real time while the patient is sleeping, which can be sometimes used as a valid alternative to PSGs. This monitoring system constitutes of a desktop application consisting historical database and a mobile device in which our apnea classifier runs performing a local real-time analysis that allows the system to take an active role in the monitoring process. This system can also record patients' nocturnal pulsioximetry and send data to a specific health center to be evaluated by qualified medical staff.

Keywords: Data mining, real-time monitoring, sleep apnea and hypopnea syndrome (SAHS) detection, SpO2 signal analysis.

I. INTRODUCTION

The system works for the real time data i.e. the data continuously coming. Also using the system patient can check his apnea anywhere using his android phone. System works according to the memory availability in android. In the project we will use SPO2 signals as a input, to detect apnea.

Apnea detecting software is a android based application which takes the real time spo2 signals from user and calculate the ODI2, ODI3, ODI4, TSA95, TSA90, TSA85, TSA80 and from these it identify the situation whether patient is apnic or non-apnic, based on clusters.

As reported in recent studies [1], the utilization of hand held devices such as smart phones in health-related applications will continue to increase. The rich features that today's smart phones are equipped with provide industry and researchers with a valuable opportunity to continue improving human life by developing applications that address a wide spectrum of issues. Applications that address sleeping disorders have been reported [2] and such applications focus on a wide range of disorders, including sleep apnea, mostly by utilizing the built-in features and sensors of the phone. However, although helpful, many of these systems do not provide users with a comprehensive overview of the disorder, as they tackle a single symptom rather than incorporating multiple indicators for a more conclusive diagnosis.

Sleep apnea is a sleep disorder characterized by the repetitive reduction of airflow during sleep, which in turn causes pauses and reduced breathing. These recurring arousals from sleep due to a blockage of airway cause fragmented sleeping patterns and lead to the activation of the body's sympathetic nervous system. An apnea is defined as the duration of time when there is complete blockage of airflow for 10 seconds or more, and is measured in apnea-hypopnoea index (AHI) [3].

Some of the symptoms that sleep apnea patients commonly display include snoring, pauses in breathing during sleep, choking or gasping for air following breathing disturbances, daytime sleepiness while carrying out routine tasks, headaches, dryness of throat in the morning, lack of concentration ability, urination at night, depression and irritability, and obesity [4].

According to the World Health Organization approximately 100 million people worldwide have obstructive sleep apnea (OSA). In the United States, OSA is estimated to affect 1 in 4 men and 1 in 9 women; it also affects 23 million working adults [5]. Approximately 4% of men and 2% of women over the age of 35 years have symptomatic moderate or severe OSA, affecting approximately 12

million people in the United States. It is estimated that less than 25% of OSA sufferers have been diagnosed [5].

The diagnosis of OSA can be done through a number of different tests and techniques. However, the symptoms of the OSA disorder are not very specific and may sometimes be caused by factors other than sleep apnea such as alcohol intake, lack of sleep and stress. Therefore, sleep specialists need to perform appropriate tests to rule out and distinguish these symptoms. If these results suggest sleep apnea, then further diagnostic tests need to be performed, which include medical, physical and sleep history exams [6].Once the probability of OSA is determined to be high from the conducted tests, then a polysomnography is usually conducted.

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Polysomnography is the most common sleep study that is performed overnight and measures the patient's brain activity along with a number of other measurements. It monitors electronically the sleep stages, measures eye movements, brain waves, respiratory airflow and effort, changes in breathing, blood oxygen levels and heart rate. The doctor will then measure the number of apneas that occurred and that lasted over 10 seconds. Significant apnea is diagnosed if over 5 apnea episodes occur during an hour [7].

Although polysomnography is the most effective method of diagnosis, it is highly expensive and requires a great deal of dedicated resources. As a result, a number of less expensive and simpler techniques are being developed to diagnose OSA including split night polysomnography and home sleep studies. These suggested methods may not be as accurate but can be used as a starting point or alternative to overnight polysomnography [8].

Unlike existing applications which consider only partial signs of sleep apnea, the proposed application's approach is to use the built-in sensors to collect data representing critical parameters for a proper initial diagnosis. By using the built-in sensors, this application seeks to collect a representative set of data that, upon analysis, will assist in identifying, with a high degree of certainty, whether or not sleep apnea symptoms exist.

The rest of the paper is organized as follows. Section II specifies the literature review and related work conducted during the project. Section III describes the system hardware and the software architecture. The system requirements are discussed in Section IV. The testing and implementation results are reported in Section V. Finally, the conclusion is presented in Section VI

II. RELATED WORK

Blood oxygen saturation is one of the conditions listed by American Academy of Sleep Medicine Task Force to characterize the events related with sleep apneas and hypopneas .Moreover, the technological advances in the pulsioximetry devices with respect to their size and communication features (most of them support Bluetooth communications) facilitate their connection to mobile devices, and therefore, simple monitoring systems can be built as cheaper alternatives to the current PSGs in the diagnosis of SAHS. The main advantages of such monitoring systems are: 1) they are readily available; 2) they are relatively inexpensive; 3) they can meet the large demand for the diagnostic testing; and 4) the monitoring can be done at home and repeated if necessary.

Several studies have proposed different SpO2 signal-based strategies by using pulsioximetry systems. Oxygen Desaturation index (ODI) indexes ODI2, ODI3, and ODI4 correspond to the number of 2%, 3%, and 4% desaturation dips from a previously set baseline per recording hour and the indexes TSA90, TSA88, TSA86, TSA84, TSA82, and TSA80 to the time spent in apnea below 90%, 88%, 86%, 84%, 82%, and 80% saturation level (TSA). Other studies propose *conventional algorithms* to identify desaturations from a moving baseline or resaturations happened as consequence of episodes of compensatory hyperventilation. From these desaturations and resaturations, the RDI is calculated, providing a strong correlation with the apnea plus hypopnea index (AHI, which is used to identify SAHS patients). There are also studies that assess *nonlinear characteristics* on oxygen saturation. It is shown in that AHI correlates strongly with approximate entropy (ApEn, which is a measure of quantification of regularity in sequences and time series data) on the SpO2 data, stating that positive SAHS patients have higher ApEn levels than negative SAHS patients. There is also more recent work that analyzes a combination of ECG and SpO2 data to provide an estimation of AHI and performs per epoch annotation.

All the solutions stated by these strategies are characterized by doing a data analysis on the whole SpO2 signal (*global* analysis) once the recording has finished (*offline* analysis) and being directed to issue an overall diagnosis on the patient (*per subject* analysis). Therefore, they are not prepared to perform a real-time detection of apneic episodes, which is an additional contribution of our proposal. We assume that, in general, it is not realistic that care personnel are employed so that they can react to the real-time detection of apneic episodes during the night. However, we believe that in that case, the system could make the mobile device to emit a sound, which suggests changing sleep position to the patient so that the obstruction in upper airways is overcome. If the sleep apnea events were severe or very consecutive through the time, the system could make the mobile device to wake up the patient in order to save him/her of that cyclical apnea-arousal episode. Other scenario where a real-time analysis is definitely interesting is the home apnea monitoring for preterm infants. Preterm infants are at greater risk of extreme apnea episodes than term infants are, for whom apnea monitoring after hospital discharge may be prescribed to allow parents or caregivers to respond more quickly to apneas, airway obstruction, or interruption of supplemental oxygen supply, decreasing the duration of accompanying hypoxemia.

III. SYSTEM ARCHITECTURE

System Architecture respectively describes structure and behavior Sleep Apnea Detection process. In order to find the best method to classify in real time the presence of apneas, we have followed a process similar to that presented in. It consists of building and assessing a set of experiments by using a machine-learning tool that applies different methods over a particular dataset.

Table I. Summary Of Records' Characteristics

Record	Length minutes	N	A	AHI	Age	Sex	hei.	wei.
a01	490	20	470	69.6	51	M	175	102
a02	529	109	420	69.5	38	M	180	120
b01	488	469	19	0.24	44	F	170	63
c02	503	502	1	0	37	M	180	83
c03	455	455	0	0	39	M	184	65
a03	520	274	246	39.1	54	M	168	80
a04	493	40	453	77.4	52	M	173	121
c01	485	485	0	0	31	M	184	74

N: minutes labeled as "*N*"; *A*: minutes labeled as "*A*."; hei.: height (in centimeters); wei.: weight (in kilograms).

algorithms [14] to do data-mining tasks as well as visualization of resulting classifiers along with their performance. This tool needs an input dataset in order to build and test the classifiers by applying its different methods.

This input data have to follow a particular format: it must be a set of tuples where each tuple has
a set of features, one of them is the class to be predicted, which in our case can be: A (apneic episode) or N (normal episode).

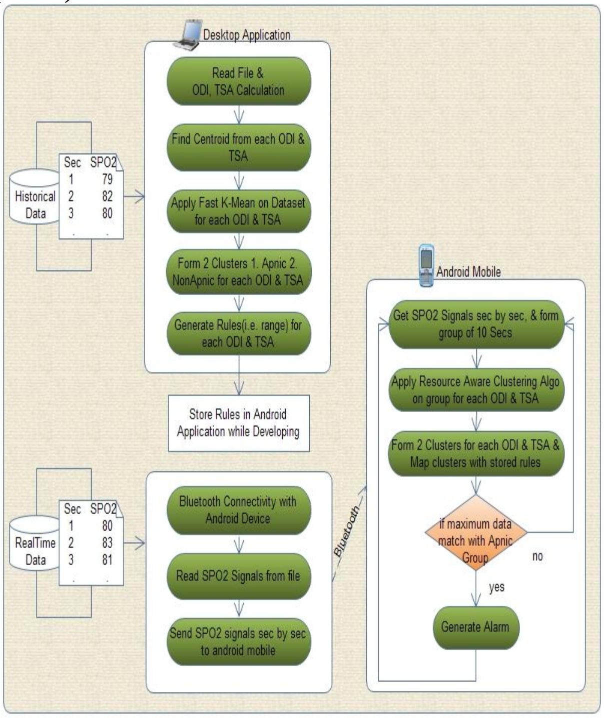

Fig: System Architecture

1) Apnea-ECG Database: In order to obtain a suitable data source with which to work in the training and testing phases, we focused on the Physionet website that provides, among other physiological signals, with the Apnea-ECG Database source. This database consists of 70 recordings, containing a single ECG signal digitized at 100 Hz with a 12-bit resolution of approximately 8 h duration, corresponding to men and women between 27 and 60 years old. Each recording comprises a set of reference annotations (A or N that means apnea or normal episode, respectively), one for each minute of recording, made by human experts on the basis of different simultaneously recorded signals. Each annotation is associated with the beginning of every minute pointing out the presence/absence of a sleep apnea at the beginning of that minute. Moreover, Apnea- ECG provides eight recordings (see Table I) containing three respiratory signals (or nasal airflow and chest and abdominal respiratory effort) and a blood oxygen saturation signal. From these eight recordings, we extracted the oxygen saturation channel and transformed it into an oxygen saturation (SPO2) signal digitized at 1 Hz (taking into account that present pulsioximetry devices deliver one SpO2 data every second). An excerpt of an annotated signal can be seen in the top part of Fig. 1.
We chose these data source because: 1) it is widely used by the scientific community, and 2) it provides a benchmark to assess our strategy against others that use different signals.

2) Signal Preprocessing: These annotated signals of the Apnea-ECG cannot be used with the Weka tool as they are not a set of tuples of the form *{(feature1, . . . , featureN, class}*.In order to get input data that can be used with Weka, we divided the SpO2 signals of Apnea-ECG into fragments of 60 s (because this is the frequency with which the signals in Apnea- ECG are annotated), and then, we performed a preprocessing on every SpO2 signal fragment to extract relevant features from the signal. The result of the preprocessing of the previous signal is the set *S*, as can be seen in the bottom part of Fig. 1, where the *i*th element of *S* corresponds to the *i*th tuple that comprises the features extracted from the *i*th SpO2 signal fragment after the preprocessing step, along with its reference annotation. In order to get the *ODI* indexes, we first identified for every signal fragment, the desaturation*Di* (*Di* = [*dsi . . . dei]*) and the resaturation *Ri* (*Ri* = [*rsi . . . rei]*) intervals. For each resaturation interval *Ri*, we 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. 2. The *odi* indexes correspond to the sum of the *dip* values in every desaturation interval *Di* divided by the size of the signal fragment. To set up the baseline, we used a moving baseline [8] because such a strategy provides
a more realistic baseline, i.e., a baseline that always stays above 90% .We set as a baseline value the greatest sample in every resaturation interval. The TSA indexes (the time the SpO2 signal. stays below 95%, 90%, 85%, 80%, and 70% saturations levels) can be seen in Fig.3.

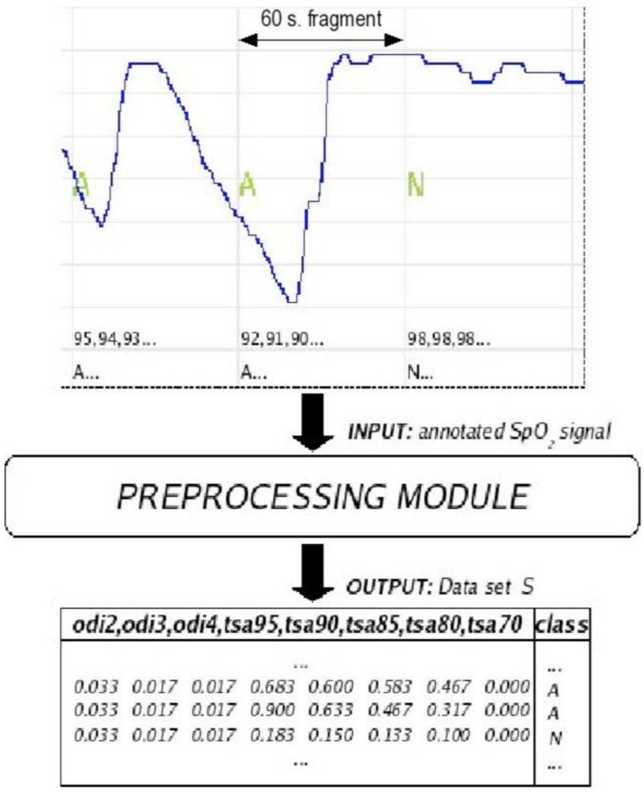

Fig.1. Example of preprocessing of three fragments of SpO2 signal

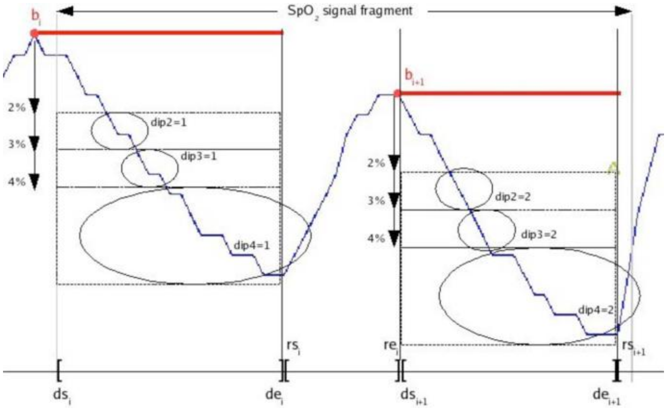

Fig.2. Preprocessing applied on a SpO2 signal fragment to get *ODI* indexes

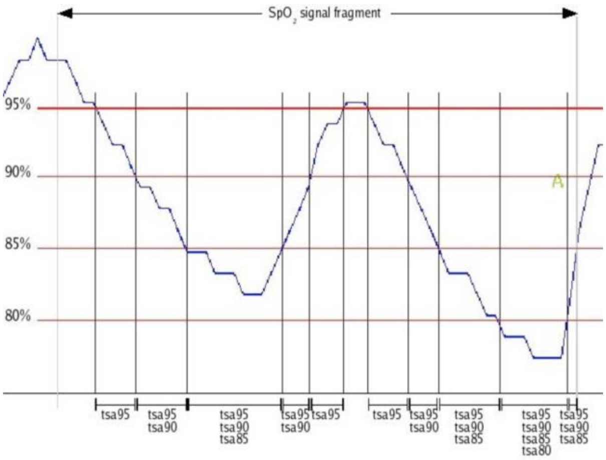

Fig.3. Preprocessing applied on SpO2 to get *TSA* indices

IV. SYSTEM REQUIREMENTS

A system can be characterized by its functional and non-functional requirements. Functional requirements describe the functionality of a system while non-functional describe attributes like reliability, maintainability and security, etc.

The systems functional requirements are as follows:

1. **Software Interface:** Bluetooth connectivity is required as an interface between the desktop application and android phone/mobile. To check the Bluetooth connectivity with Desktop application and android mobile there is a requirement of Actual Android mobile, because AVD (Android virtual Device) doesn't have Bluetooth.
2. The mobile record the SPO2 signals, send by the desktop application and stores the results on the SD card of the phone.
3. The mobile records SPO2 signals and checks with the rules generated by historical data and a specific window size is created for the data to be stored.
4. The system checks for successful logins, failed logins, and successful registrations against the stored entries in the database.

Below are some of the non-functional requirements of the system.

Performance Requirement:

1. Availability: This system will be always available to all the types of users for detection of apnea.
2. Speed: The speed of our system depends upon the processor we are using. And as the data of SPO2 signals increases the speed would not be affected as we are using resource aware high quality clustering algorithm.

Software Quality Attributes:

1. **Reliability:** It produces the same output every time we provide the same input. Here we are providing SPO2 signals for detection of apnea purpose. So, it will always show the accurate result even if it is given multiple times.
2. **Availability:** The software developed by us will be always available all time to the user. So that user can use this system anytime and anywhere.
3. **Portability:** This tool is portable because it can be processed anywhere. User requires just the android phone and Bluetooth connectivity between android and desktop application.
4. **Performance:** The performance of our system depends upon the processor we are using. And as the data of SPO2 signals increases the speed would not be affected as we are using resource aware high quality clustering algorithm.
5. **Robustness:** The tool and algorithm used in this system handles the error efficiently. For e.g. -If there are no readings of SPO2 signals, then you try for detection, then it will print the message as "No SPO2 data!!!!!"

V. SYSTEM TESTING AND IMPLEMENTATION PLAN

To check the Bluetooth connectivity with Desktop application and android mobile there is a requirement of Actual Android mobile, because AVD (Android virtual Device) doesn't have Bluetooth.

As we will not using the sensor to take the SPO2 signals, we use the text file which contains the SPO2 signals per second.

1. Requirement Specification: Complete specification of the system (with appropriate assumptions). A document detailing the same should be written and a presentation on that be made. Attempt should be made to survey more on the system and to check latest updates regarding system currently used for detection.
2. Technology familiarization: Understanding of the algorithm and technology needed to implement the project. The technology defined should be able to apply it to the project rather than from a theoretical perspective.
3. High-level and detailed Design: Listing down all the possible scenarios and then coming up with flowcharts or pseudo code to handle the scenario. The scenarios should map to the requirement specification (i.e. for each requirement is specified, a corresponding scenario should be there).
4. Implementation of the system: Implementation of the desktop application and establishing connectivity with android phone using Bluetooth. During this milestone period, it would be a good idea for the team (or one person from the team) to start working on a test plan for the entire system. This test-plan can be updated as and when new scenarios come to mind.

5. Unit Testing: The system should be thoroughly tested by running for all the scenarios. Another 1 week should be there to handle any issues found during testing of the system.
6. Inter-task Testing: The system should be thoroughly tested to check the interactions between different modules of the system are properly working or not. Another 2 weeks should be there to handle any issues found during testing of the system. After that, the final demo can be arranged.
7. Final Review: Issues found during the previous milestone are fixed and the system is ready for the final review. During the final review of the project, it should be checked that all the requirements specified during milestone 1 are fulfilled (or appropriate reasons given for not fulfilling the same.)

VI. CONCLUSION

The designed system is an android mobile application designed to remotely monitor the sleeping patterns of individuals and assess their likeliness to have symptoms of sleep apnea. Even though mobile applications that monitor sleep apnea exist, this application detects weather the person is apnic or non-apnic and is stand alone application. However, this work is different and innovative in the sense that it combines the different aspects into one system in order to provide a preliminary diagnosis of user's sleeping pattern anywhere at any time. This application is targeted at any individual who suspects a sleeping disorder, regardless of his/her age. By using this application, the user can monitor his/her sleep at a very low-cost from the convenience of his/her home, compared to the expensive Polysomnographic tests, which require the user to visit a specialized hospital and spend a night in it wearing uncomfortable monitoring equipment. This system provides an alarm system and a popup notification on the android phone if and when the person is detected of having sleep apnea. This feature can be customized and markers can be plotted according to gender, age group, employment as well as other factors for research purposes and increase awareness of this growing problem.

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