Enhanced Method for Extracting Features of Respiratory Signals and Detection of Obstructive Sleep Apnea Using Threshold Based Automatic Classification Algorithm

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Abstract— Obstructive Sleep Apnea is a frequent disorder with detrimental health, performance and safety effects. The diagnosis of the disorder is cumbersome and expensive. New methods for screening and diagnosis are needed. The method we describe in this work is based on detection of four main features of respiratory signal. The automatic signal classification starts by extracting signal features from a 1 minute data segment through autoregressive modeling (AR) and other techniques. Four features are: signal energy, zero crossing frequency, dominant frequency estimated by AR and strength of dominant frequency based on AR. These features are then compared to threshold values and introduced to a series of conditions to determine the signal category for each specific epoch. The threshold values for the parameters were determined through experiment.

Keywords- Sleep Apnea, Motion Artifact, Energy Index, Respiration rate, Dominant frequency, Strength of Dominant frequency, Zero Crossing.

1. INTRODUCTION

Respiration monitors are of crucial importance in providing timely information regarding pulmonary function in adults and the incidence of Sudden Infant Death Syndrome (SIDS) in neonates. However, to accurately monitor respiration, the noise inherent in measuring devices, as well as artifacts introduced by body movements must be removed or discounted. With the recent success of media in creating awareness about the importance of sleep and effects of sleep apnea the classifying algorithm should be easy to use and provide a fair prediction that must contribute to public health. One can imagine a multitude of intelligent classification algorithms that could help to reach better identification mechanism. For example an algorithm should be capable of classifying different types of signal with different characteristics feature. Such an algorithm has the potential to become major classification tool. There have been enormous growth in developing efficient algorithm for classification of the respiratory signals, the reduced computational steps, reduced number of parameters used, increasing the capability to differentiate the signals and easy to implement in hardware setup to provide clinical support. An efficient algorithm should adopt itself to any kind of signals; it should not have any static rules for classifying the given input signal.

This work shows a simple method for respiratory signal classification using a MATLAB coding. It describes an automatic classification algorithm using features derived from the autoregressive modeling and threshold crossing schemes that was used to classify respiratory signals into the following categories: (1) normal respiration, (2) respiration with artifacts and (3) sleep apnea. This classification is capable of detecting fatigue of the human by identifying sleep apnea, early detection of sleep troubles and disorders in groups at risk, reduces the risks of being affected by serious heart diseases in future. The main contribution of this paper is the analysis of signals those are necessary for classification of the respiratory signals which yields not only the classification but also the analysis of various ailments.

Results in [1] indicate that respiratory signals alone are sufficient and perform even better than the combined respiratory and ECG signals. Respiratory signals are convenient to measure because they do not require electrodes on the skin, and people may wear the sensors for periods of several days and weeks. An apnea detection method based on spectral analysis was discussed in detail in [2]. In [3] the possibility of recognizing obstructive sleep apnea based on beat-by-beat features in ECG recordings was studied. It was also explored the application of time- varying autoregressive models and KNN linear classifier. A classification scheme of respiratory signal based on fuzzy logic was proposed in [4]. The paper [5] proposes an implementation of automatic classification of respiratory signals using a Field Programmable Gate Array (FPGA). The main novelty in [6] is that the phase difference between the two respiration signals is considered in order to determine the presence and grade of obstructive apnea. The work in [7] shows that the interval between zero crossings gives a good estimation of its frequency with reduced computational effort. The utilization of a second order autoregressive (AR) model to extract the dominant frequency and quantify its strength was discussed in [8].

2. Sleep Apnea

Sleep apnea is a common sleeping disorder. When a person has sleep apnea, he or she stops breathing for short periods of time [3]. In most cases this lasts from 10 seconds to 1 minute or more while asleep. Then the person begins breathing again. A person may stop breathing only a few times or hundreds of times in the course of the night. If apnea is kept untreated it will lead to increase the risk for High blood pressure, Heart attack, Obesity and Diabetes, Increase the risk for worsen Heart failure, Make irregular heartbeats more likely, and Increase the chance of having work-related or driving accidents. Sleep apnea can be treated by focusing on reducing airway blockage and increasing the amount of oxygen in the body. The first step is often a serious attempt at losing weight. It is also crucial to avoid alcohol and sleeping pills.

If these measures do not help, the person may need a continuous positive airway pressure (CPAP). The individual wears a mask over the nostrils or mouth that pumps in pressurized air. This increases the amount of oxygen entering the lungs. It also relieves the symptoms of obstruction. The technique can be used with or without supplemental oxygen. Dental appliances may be used to reposition the tongue and lower jaw. Uvulopalatopharyngoplasty is a type of surgery that removes excess tissue at the back of the throat. If all other methods fail, a tracheostromy may be done. This involves cutting a small hole in the neck through which the person can breathe. Medicines may be needed to increase respiratory function while the person sleeps. Antidepressants may be prescribed. These reduce the amount of time a person spends in deep sleep.

Classification of Sleep Apnea

There are three classifications of sleep apnea, including:

- OBSTRUCTIVE SLEEP APNEA, which means something, is blocking the airway or the airway does not open all the way during sleep.
- CENTRAL APNEA, in which the brain isn't signalling the muscles to breathe or the muscles don't receive or can't respond to the signal to breathe.
- MIXED APNEA, this is a combination of obstructive and central apnea.

The most common kind of sleep apnea is called Obstructive Sleep Apnea Syndrome [2]. Sleep apnea means "cessation of breath." It is characterized by repetitive episodes of upper airway obstruction that occur during sleep, usually associated with a reduction in blood oxygen saturation. In other words, the airway becomes obstructed at several possible sites. The upper airway can be obstructed by excess tissue in

the airway, large tonsils, and a large tongue and usually includes the airway muscles relaxing and collapsing when asleep. Another site of obstruction can be the nasal passages. Sometimes the structure of the jaw and airway can be a factor in sleep apnea. A sleep test, called polysomnography is usually done to diagnose sleep apnea. There are two kinds of polysomnograms. An overnight polysomnography test involves monitoring brain waves, muscle tension, eye movement, respiration, oxygen level in the blood and audio monitoring. The second kind of polysomnography test is a home monitoring test. A Sleep Technologist hooks you up to all the electrodes and instructs you on how to record your sleep with a computerized polysomnograph that you take home and return in the morning. They are painless tests that are usually covered by insurance.

The positive effects of sleep deprivation on depressed people are used in psychiatry to treat a multitude of depression types without medication and are the most rapid antidepressant available today a lifestyle device. The developed algorithm could also be a primary sleep disorder prevention system that would be more powerful than only passive prevention methods and less expensive determination method.

3. Need of Respiratory Signal

The traditional methods for assessment of sleep related breathing disorders are sleep studies with the recordings of ECG, EEG, EMG and respiratory effort. Sleep apnea detection with ECG recordings requires more number of electrodes on the skin and people may wear it continuously for effective monitoring. EEG measurement can also be used for the detection of sleep apnea but the brain signals are always random in nature. For the complete detection, we need more number of samples for analysis. Also, the mathematical modeling of EMG signals is very complex for sleep apnea detection. From the results in [1], the respiratory signals alone are sufficient and perform even better than ECG, EEG and EMG. In our paper, we consider only the respiratory signal for the detection of sleep apnea since it is more convenient and do not require more number of electrodes on the skin.

The human respiratory signal as shown in Fig.1 is classified into three major classifications namely,

- Normal respirations.
- Motion artifacts.
- Sleep apnea.

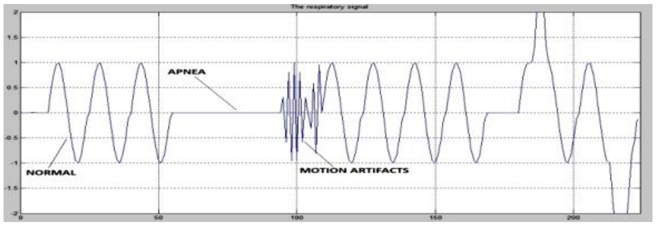

Fig.1 Human Respiratory Signal

Normal Respiration

The normal respiration is characterized by the presence of a certain rhythm and the presence of some energy level in the signal.

Sleep apnea

Apnea is easily classified as the absence of energy (ventilation activity) as well as a lack of rhythm. The respiration rate was below a critical level.

Motion artifact

Motion Artifact is generally characterized by a sudden increase in the amplitude of the signal and by a sudden variation in the rhythm of the heart usually has the higher energy when compared to the normal respiration. Motion artifacts are transient baseline changes caused by changes in the skin impedance. This type of interference represents an abrupt shift in base line due to movement of the patient while the respiratory signal is being recorded

FEATURE EXTRACTION

This classification algorithm extracts several features of respiratory signals and utilized for disease identification. The feature extraction plays a vital role since the classification is completely based on the values of the extracted features. The fundamental features of respiratory signal provide the numerical value which is compared with the threshold values and the classification results will be produced. The fundamental features of respiratory signals [8] are

- Energy Index (EI)
- Respiration frequency estimated by a modified Zero crossing scheme (FZX)
- Dominant frequency estimated by AR modeling (FAR)
- Strength of the dominant frequency estimated by AR modeling (STR)

Energy Index (EI)

Given a continuous-time signal f (t), the energy contained over a finite time interval is defined as follows.

$$E(T_1, T_2) = \int_{T_1}^{T_2} |f(t)|^2 . dt, T_2 > T_1 \qquad (1)$$

$$E_f = \int_{-\infty}^{+\infty} |f(t)|^2 . dt \qquad (2)$$

Equation (1) defines the energy contained in the signal over time interval from T_1 till T_2. On the other hand, equation (2) defines the total energy contained in the signal. If the total energy of a signal is a finite non-zero value, then that signal is classified as an energy signal. **Typically the signals which are not periodic turn out to be energy signals.** The equation for computing Energy index is,

$$EI = \frac{1}{\mathrm{N}} \sum_{\mathrm{n=0}}^{\mathrm{N-1}} |x_n|^2 \qquad (3)$$

The average power of the signal x is defined as the energy per sample

$$p_x \triangleq \frac{\varepsilon_x}{N} = \frac{1}{\mathrm{N}} \sum_{\mathrm{n=0}}^{\mathrm{N-1}} |x_n|^2 \qquad (4)$$

Respiration Frequency (FZX)

Zero-crossing is a commonly used term in electronics, mathematics, and image processing. In mathematical terms, a "zero-crossing" is a point where the sign of a function changes (e.g. from positive to negative), represented by a crossing of the axis (zero value) in the graph of the function as shown in Fig.2.

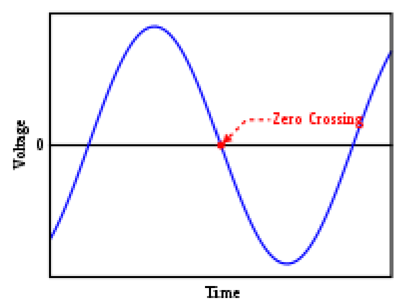

Fig.2 Representation of Zero Crossing

Counting zero-crossings is a method used in speech processing to estimate the fundamental frequency of speech. The interval between zero crossings gives a good estimation of its frequency [7]. Similarly, Respiration frequency (FZX) was determined by counting the number of times that x(n) crosses a baseline which is defined as the square root of EI.

$$FZX = \sqrt{EI} \qquad (5)$$

Dominant Frequency (FAR)

In order to obtain the features FAR and STR, coefficients of a second order AR model have to be estimated. The respiration signal can be modeled as a second order autoregressive model [4] as the following,

$$x(n)=a_1 x(n-1)+a_2 x(n-2) + e(n) \qquad (6)$$

Where e(n) is the prediction error and {a1,a2} are AR model coefficients. Autoregressive **(AR)** spectral estimation techniques are known to provide better resolution than classical periodogram methods when short segments of data are selected for analysis. In our study, we adopted the Burg's method to compute AR coefficients. The major advantage of Burg method for estimating the parameters of the AR model are high frequency resolution, stable AR model and it is computationally efficient.

Using the second order autoregressive model coefficients, one can determine the dominant frequency and signal regularity strength as the following,

$$\text{FAR} = \frac{F_s}{2\pi} \arctan \frac{a_1}{a_2} \qquad (7)$$

Where f_s is the sampling frequency. A sampling frequency of 20Hz was used for analysis.

Strength of Dominant Frequency (STR)

The AR coefficients were used to determine STR value as,

$$STR = \sqrt{a_1^2 + a_2^2} \qquad (8)$$

Basically, FAR and STR serve the same purpose as power spectrum usually does, indicating the dominant frequency and its corresponding power level. The classification of the signal is based on derived parameters shown above and thresholds would be properly initialized to allow accurate classification. The degree of reliability of the respiration rate estimate was determined by STR, which have a value between 0 and 1. For very regular rhythm, STR is very close to 1 (as in the case of normal respiration). If STR is too low, then the rate estimates FAR and FZX are deemed to be unreliable.

To make this algorithm more robust, the threshold values of classification parameters can be obtained as follows. Take the respiratory samples for one minute (two epochs) and the system performs the same analysis on these two epochs and extracts nominal values for each of the classification parameters. Then these nominal values are used to adjust the threshold values as follows [1]: low and high energy are 33% and 150% of average energy, low and high frequency are 50% and 150% of nominal frequency and low and high strength of dominant frequency are 75% and 95% of average strength. These values were determined experimentally.

The normal breathing frequency for a human being is usually between 0.2-0.3Hz and maximum frequency is unlikely to exceed 0.7- 0.8 Hz. Hence these values are used as the minimum and the maximum threshold for the respiration rate. Using the square root of the energy index as the appropriate baseline value for zero crossing, the number of times the signal crosses the baseline value was recorded and the respiration frequency was detected from it. A moving baseline was used to allow for changes in the mean respiration level. The calculated energy index, the respiration rate, the dominant frequency and the strength of the signal were compared with the set threshold values and were classified as normal respiration, apnea or respiration with artifact.

4. Simulation Results And Discussion

The input of 1200 samples of respiratory signal is as shown in the Fig.3.

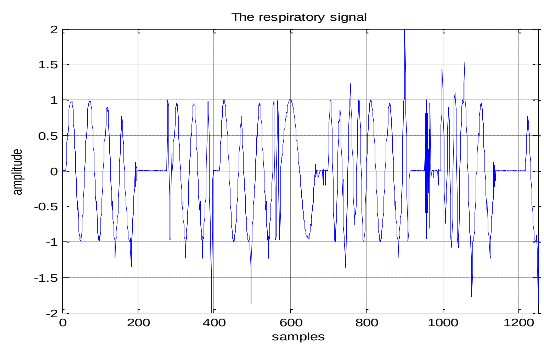

Fig.3 Respiratory Input taken for Classification

The input to our classification algorithm is human respiratory signal of 1 Hz which is given as the collection of data points which is obtained from the website www.physionet.com.The website hosted by a medical institute consist of various human bio-signals like ECG, EMG, EOG, RESPIRATORY SIGNALS., in the form of data points from which we can retrieve the required respiratory signal and can be given as the input to the classification algorithm developed.

The classification of the signal is performed by the sequential analysis of the signal in various phases of the program using MATLAB as,

- Form the mathematical model of the input respiratory signal using second order auto regressive modeling.
- Determine the various parameters of the derived mathematical model with the help of burgs algorithm.
- Extract the four fundamental features of human respiratory signals with the help of the provided mathematical equations.
- Compare the derived values with the optimum threshold values of the four fundamental features of the respiratory signal.

- Produce the classified results of the respiratory signals.

The signal was sampled at 20Hz and the total of 1200 data points is taken for analysis. The threshold values for the features to be extracted from the signal are provided as the optimum values in the program which is used for signal classification.

TABLE I. NOMINAL VALUES CALCULATED USING TWO EPOCHS

Sample	E_Low	E_High	Str Low	Str High	FAR Min	FAR Max
Normal_1	0.43	1.97	0.20	0.26	0.57	1.72
Normal_2	0.52	2.36	0.25	0.31	0.63	1.88
Apnea_1	0.27	1.22	0.14	0.18	0.45	1.36
Apnea_2	0.22	0.98	0.08	0.10	0.40	1.21
Artifacts_1	0.74	3.36	0.45	0.57	0.75	2.25
Artifacts_2	0.98	4.45	0.39	0.49	0.86	2.58

The nominal values calculated using two epochs to adjust the threshold values are given in Table I and the optimum values calculated as threshold is given in Table II.

TABLE II. CALCULATED OPTIMUM THRESHOLD VALUES

Features	Normal	Apnea	Artifacts
E_Low	0.5	0.25	0.8
E_High	2.2	1	4
Str_Low	0.2	0.05	0.4
Str_High	0.3	0.15	0.5
FAR_Min	0.6	0.4	0.8
FAR_Max	1.8	1.3	2.4

Respiration data was first divided into 20 second epochs and manually scored for comparison. The epochs were then processed with the automatic classification algorithm and compared to manual classification.

TABLE III. RESULT OF CLASSIFICATION ALGORITHM

Episode	Manual	Simulation
Normal	745	745
Artifact	148	148
Sleep apnea	292	292
Unclassified	15	15

The classified results provided in Table III shows that the proposed algorithm is capable of classifying with the accuracy of 100% in case of normal and sleep apnoic signals. Few disagreements were encountered with the detection of motion artifacts and hence 15 sections are termed as unclassified signals. The results obtained indicate that this algorithm can be an effective approach in respiration devices being developed to monitor infants at risk for SIDS and to accurately compute respiration rate on a regular base for selected patients.

5. CONCLUSION

This classifying algorithm with the help of MATLAB coding classifies the human respiratory signals into three major classifications such as normal respiration, motion artifacts and sleep apnea. The classification system is given with the human respiratory signal as the input, and the coding is developed in such way that it models the given signal as a mathematical equation using second order Auto Regressive model, then the parameters of the developed equation is determined with the help of Burgs algorithm. Then the fundamental features of the respiratory signal such as Energy index, Respiration frequency, Dominant frequency, Strength of the dominant frequency were calculated. The determined values then compared with the optimum predetermined values of the fundamental features and the results were developed with the help of the comparison. Hence the provided respiratory signal is classified successfully with the help of the formulated algorithm.

This work can be developed and implemented in real time application for detecting sleep apnea. To develop this project in real time, we have to design a processor and the algorithm should be improved by adding calibration procedures and is adjusted to run on FPGA [5]. The electrical signals which are analog in nature should be converted into digital by analog to digital converter (ADC) and is given to the FPGA kit. Then the processor will process and detect the appropriate signal. LCD or PC monitor can be used to display the name of the signal.

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