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FEATURE EXTRACTION OF RESPIRATORY SIGNALS BY APPLYING ADAPTIVE IMPROVED BURG'S ALGORITHM FOR SLEEP APNEA DETECTION

Engineering

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ABSTRACT

This paper presents feature extraction and classification method for bio signal processing which concentrates on respiratory signal processing. Respiratory signal processing could contribute to immediate sleep apnea detection such as heart disease, Acute coronary Syndrome, Arrhythmias, and others. This paper discussed more into depth on algorithms which includes for feature extraction. The feature extraction plays an important role since the classification is completely based on the values of the extracted features.

KEYWORDS

Sleep apnea, Burg's algorithm, AR modeling, Zero crossing algorithm, Polysmnograph

INTRODUCTION

A good nocturnal rest is essential to carry out a full and healthy life. The time period necessary for a good rest ultimately depends on the particular person; however it is situated somewhere in-between seven or ten hours. Even though some people can get used to sleep fewer hours than what would be normally necessary, this ends up by affecting their judgment, reaction time and many other fundamental functions during daytime.

Many studies have proved that the lack of sleep is dangerous. Persons with lack of sleep have been exposed to driving simulators and manual and to ocular coordination test. The results showed performance as bad as –or even worse than- people in an inebriation state. Lack of sleep has also been reported to make worse alcohol effects (Powel & Chau 2010).

Based on the National Commission Sleep disorder Research, approximately 38,000 deaths occur on annual bars that relate to cardiovascular problems that in one way or other are connected to sleep apnea. It occurs in all age groups and both genders. It is more common in men although

it may be under diagnosed in women and young African-Americans. Standards of Practice Committee and American Sleep Disorders Association (SPCASDA) 1994.

OBJECTIVES

- To analyze direct respiratory signal and to identify set of features that distinguish different classification of respiratory signal, specifically the normal, sleep apnea and motion artifact.
- Proposing a new set of features, dominant frequency and strength of dominant frequency based on autoregressive model (AR) with improved adaptive Burg's algorithm.
- Implementation of improved adaptive Burg's algorithm, to update AR coefficients automatically.
- Evaluation of features extracted using AR techniques for detection of abnormalities in respiratory signal.

Features selection

- The following features are extracted from the respiratory signals using a adaptive improved Burg's algorithm with zero crossing schemes.

1. Energy Index
2. Respiration Rate
3. Dominant Frequency
4. Strength of Dominant Frequency

Dominant frequency and strength of dominant frequency are extracted accurately, which enhanced the classification of respiratory disorder with almost cent percent accuracy

Threshold Scheme

The threshold parameters for classification are obtained automatically as follows. A typical normal respiration signal of interest is divided into smaller segments and the average energy index is calculated; then, 33% and 150% of the calculated energy index are used as the low and the high energy thresholds respectively. The normal breathing frequency for a human being is usually between 0.2-0.3Hz and maximum frequency is unlikely to exceed 0.7-0.8Hz. Hence, these values are used as the minimum and the maximum thresholds for the respiration rate. The ranges of threshold limit for all features are given in Table. 1.

Table 1 Threshold values used for classification of respiratory signal

FEATURES	RANGE
EI_MIN & EI_MAX	33% & 150% of average energy
FZX_MIN & FZX_MAX	0.2 Hz &0. 7 Hz of average rate
FAR_MIN & FAR_MAX	50% & 150% of dominant frequency
STR_MIN & STR_MAX	75% & 95% of average strength

Adaptive Improved Burg's Algorithm

The proposed method, improved adaptive Burg's algorithm utilized a parametric method, which could typically assume some sort of signal model prior to the calculation of power spectral density estimate. Further, the coefficients are getting updated by using adaptive Burg's algorithm. Hence, this algorithm is referred to as improved adaptive Burg's algorithm. Burg's developed a method for spectrum estimation known as a maximum entropy method and also the same is invariably used by many researchers in the field of classification. The new weighted Burg's algorithm allows combining segments of different amplitudes.

PROPOSED FEATURE EXTRACTION ALGORITHM – IMPROVED ADAPTIVE BURG'S ALGORITHM

Algorithm – Improved Adaptive Burg's for input signal X0, X1,…..XN-1

STEP 1:
Choose Number of coefficients [m]
STEP 2: Initialization
Initialize Vector V0
Iteration i=0
The forward prediction error f0 (n) = Xn
The backward predication error b0 (n) = Xn
STEP 3:
While (i < m) do
Compute Energy Index (EI)
Compute FZX = sqrt (EI)
Compute FAR, STR
Update Vector V i+1
Update forward prediction error for next orders f i+1
Update backward prediction error for next orders bi+1
STEP 4:
Increment Iteration i = i + 1
End while
End

Classification based on features.

The complete classification procedure is

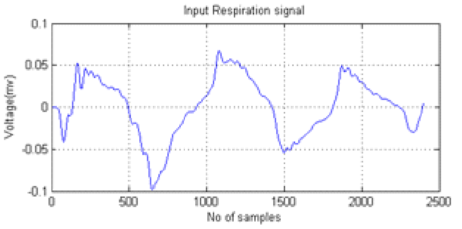

Figure.1. Respiratory signal from MIT-BIH sleep database

enunciated hereunder. The human respiratory signals are taken as samples from the Polysomnography database and clinical data are taken from the hospital. Then, the respiratory signals are classified using the program designed in MATLAB 7.9.0. The samples of respiratory signals are given as inputs to the classifier and a mathematical model is formed for the input respiratory signals using second order autoregressive modeling. Then, four features are extracted from the signals for determining the threshold values and the respiratory signal features are calculated. Threshold values are calculated using the above obtained features with reference to threshold Table 1.

Procedure Classify Disorder (EI, FZX, FAR, STR)
Begin: CHECK IF[EI < EI_low & FZX = 0] DISPLAY (1) CHECK IF[EI > EI_low] &[FZX_min < FZX < FZX_max] &[STR < STR_high & FAR > FAR_min] DISPLAY (2) CHECK IF [EI > EI_high] & [STR > STR_high] &[FZX_max < FZX < FZX_min] DISPLAY (3) End Procedure
Procedure Display (Case value)
Begin: Check Case 1: CLASSIFY as SLEEP APNEA Check Case 2: CLASSIFY as NORMAL Check Case 3: CLASSIFY as RESPIRATION WITH ARTIFACTS End procedure

Dataset used for the Study

The proposed automatic feature extraction scheme for extracting features has been developed using MATLAB (R2010a) and tested with three different datasets. The methods are used initially with simulated data and then with real patient datasets obtained from MIT-BIH sleep database. The simulated respiratory signal data comprising 600 and 2400 samples are shown in Figure.1

MIT-BIH Sleep Database

The MIT-BIH data used in this work comprised of 16 continuous polysomnography recordings of male, female and infant subjects all of whom are suffering from sleep apnea. The recordings are between 2 and 7 hours in duration and digitized at 250 Hz with 12 bit resolution. The signal used in this thesis is a direct respiratory signal. The real time respiratory signal data comprising 15000 samples are shown in Figure 4.4 and the corresponding amplitude values for each sample are given in Table 2

Table 2. MIT-BIH sleep data (15000 samples)

Samples	Amplitude (mV)
1	-0.032
2	-0.033
3	-0.046
4498	-0.014
4499	-0.017
4500	-0.018
6008	0.084
6009	0.086
6010	0.087
6011	0.083
14088	0.9
15000	0.9

The following features are calculated for 15000 samples which are given in Table 4.2. The manual calculations of feature extraction using the following mathematical expressions are given below.

Feature Extraction Calculations

Average Energy Index (EI)

$$EI = \frac{1}{N}\int_{n=0}^{N-1} |x(n)|^2 = 1/15000\ [306.424] = 0.020428$$

Respiration Rate (FZX) $= \sqrt{EI}$ =0.1429

Dominant Frequency (Freq AR) $= \frac{F_S}{2\pi} \arctan \frac{a_1}{a_2} = 41.4606$

Strength of dominant Frequency (MagAR)

$$= \sqrt{a_1^2 + a_2^2} = 1.9822$$

Implementations

For sleep apnea

EI < EI_low & FZX = 0

The Sample 1 satisfied the condition as follows:

0.001 < 0.0125 & FZX = 0.0032

For Normal:

EI > EI_low & FZX_min < FZX < FZX_max &
STR < STR_high & FAR > FAR_min

The Sample 14088 satisfied the conditions as follows:

0.019 > 0.0125 & 0.03896 < 0.0433 < 0.13636
1.0778 < 1.8831 & -41.757 > -20.7303

For Respiration with Artifacts

EI > EI_high & STR > STR_high &
FZX_max < FZX < FZX_min

The Sample 14109 satisfied the conditions as follows:

0.1> 0.0569 & 1.8914 > 1.8831
0.13636 < 0.1948

The average value of features has been calculated and the threshold values are given in Table 3.

Table.3 Calculated threshold values for a real time respiratory signal

FEATURES	RANGE
EI_MIN & EI_MAX	33% & 150% of 0.020428
FZX_MIN & FZX_MAX	0.2 Hz &0. 7 Hz of 0.1429
FAR_MIN & FAR_MAX	50% & 150% of 41.4606
STR_MIN & STR_MAX	75% & 95% of 1.9822

Based on the ranges given in the Table 3, the features are extracted for the dataset of 15000 samples using AR modelling with an improved adaptive Burg's algorithm. The available signals from the database are then given as inputs to the feature extraction coding. All these measures are calculated in MATLAB version 7.9 and based on the above features the following datasets are created and are illustrated in Table 4.

Table 4 Extracted features for data of Set 15,000 Samples

Samples	Features				Corresponding State
	EI	FZX	STR	FAR	
01 to 99	0.0015	0.00384	1.2289	-24.68	Sleep
100 to 207	0.000898	0.003	1.1434	-20.14	Sleep
200 to399	0.000271	0.0164	1.6272	-36.17	Sleep
400 to 1449	0.000272	0.0165	1.6272	-36.17	Sleep
1451 to 2304	0.0000964	0.0098	1.9414	-40.97	Sleep
2305 to 4999	0.000043	0.0066	1.8673	-40.01	Sleep
5000 to 9000	0.0000432	0.0066	1.8673	-40.01	Sleep
9001 to 12000	0.0000152	0.0039	1.7352	-38.06	Sleep
12001 to 13948	0.00000656	0.0026	1.879	-40.17	Sleep
13949 to 14021	0.000121	0.011	1.0778	-42.52	Normal
14022 to 14087	0.000000257	0.00069	1.1048	-17.47	Sleep
14089 to 14109	0.1	0.0321	1.8214	-39.38	Artifact

14110 to 14617	0.0031	0.0553	1.6398	-36.41	Artifact
14618 to14619	0.000528	0.0073	2.0538	-42.27	Normal
14620 to15000	0.0014	0.0374	1.099	-42.74	Normal

CONCLUSIONS

The fundamental features of the respiratory signal such as, Energy index, Respiration frequency, Dominant frequency and Strength of the dominant frequency are extracted using Adaptive Burg's method through second order autoregressive modeling. The extracted features are efficiently used to classify the respiratory signals. The new proposed method of feature extraction clearly reduced the misclassification of respiratory signal and achieved an accurate diagnosis of obstructive sleep apnea. Thus, respiratory signals are classified for detection of sleep apnea and motion artifacts. The classification method alone cannot provide better results in terms of detecting sleep apnea and a better feature extraction method is also required. Consequently, the extraction results of this work enhanced the classification accuracy to a greater extent.

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