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Respiration Rate Diagnosis Using Single Lead ECG in Real Time

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RESPIRATION RATE DIAGNOSIS USING SINGLE LEAD ECG IN REAL TIME

Strictly as per the compliance and regulations of:

Respiration Rate Diagnosis Using Single Lead ECG in Real Time

K.Ramya [α] & K.Rajkumar [σ]

Abstract - Respiration rate is the respiratory signal or the respiratory knowledge. Numeral methods can be applied to derive a respiratory signal from the ECG. The efficacy of this monitoring can be improved by deriving respiration, which previously has been based on overnight polysomnography studies where patients are stationary or the use of multi lead ECG systems. In this paper, ECG features of Heart rate variability (HRV) and ECG-derived respiration (EDR) including ECG filtering methods are examined. This ECG features are compared with the simultaneously recorded respiratory signal, it is estimate from RR-interval, R-wave time duration and R-wave amplitude. These values are evaluated using discrete wavelet transform. Based on the respiratory signal, time domain measures are MeanRR, SDRR, Maxrate, Minrate, RMSDD, SDEDR, MeanEDR, pNN50, NN50 are calculated, that reflect the Respiration rate variability (RV). Those Respiration variability measures have been established their use, by the ability to distinguish between periods of rest and during respiratory rate testing time. Moreover, these RV measures are able to differentiate between the first resting period and the periods following the respiration rate.

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I. Introduction

Respiration rate is an interesting physiological process. Numeral scheme to obtain a respiratory signal include impedance sensors, pressure sensors and a thermistor in the nose. However, there are 2 common disadvantages of using these devices: 1) these complex devices involved might interfere with natural physiological breathing. 2) Such devices cannot be used for certain clinical purposes, for example, ambulatory or long-term monitoring in naturalistic settings. Therefore, the development of a convenient method to record or estimate respiratory signals is important from a clinical perspective. ECG is the most well-known, feasible, and an accessible tool in diagnostic respiration rate, during ECG recording no extra equipment is needed. The respiration rate calculation based on these ECG two facts 1) the positions of ECG electrodes on the chest surface move relative to the heart. 2) transthoracic impedance varies at the lungs fill and empty, during the recording of the ECG. The modified V2 lead based ECG signal gives the acceptable result for the respiration rate. The respiration rate calculation mainly based on the two ECG features that are Heart rate variability (HRV) and ECG-derived respiration (EDR). These ECG features are two prominent physiological functions which are both modulated by fluctuations of the autonomic nervous system (ANS). These information's are may be used to gain insight into the autonomic control of the heart or the lung. Amendment of these modulations may appear during ageing or during the progress of a disease (e.g. congestive heart failure or sleep-disordered breathing). Based on an electrocardiogram (ECG) recording the heart rate time series may be derived with high accuracy and provides a basis to analyze the heart rate variability (HRV). Accordingly, HRV has been used extensively as a non-invasive tool to investigate the autonomic control of the cardiovascular system and many characteristic features of heart rate variations in health and disease have been explored in the past and will further be explored. The 'Breathing rate variability' or 'respiration rate variability' (in analogy to HRV) has not been established yet because it is more difficult to determine the instantaneous respiratory rate unambiguously. Throughout, everyday conditions the influence of voluntary activities like speaking or eating on respiration is more pronounced compared to that on the heart and agitate the determination of respiratory oscillations. Consequently, even if a respiratory trace is available, the determination of inspiration and expiration is less precise compared to the determination of the instantaneous heart rate. The RR-interval based HRV analysis is best compared to others. The ECG-derived Respiration may utilize the R-peak amplitude and time duration.

II. Previous Work

A constructive appraisal of ECG-derived respiration techniques is provides the groups algorithms [9] into categories based on beat morphology, heart rate, or a combination of both. This sector is included on algorithm evaluation, which stresses the importance of comparing the derived respiratory information with a simultaneous recording of the respiration signal. The Fourier transforms and spectral features based EDR values [12] analyzed. Kernel principal component analysis based algorithm is developed [11] which derive the EDR value and this value analyzed using Eigen and entropy value. Principal Component Analysis technique based three different algorithms derived [10]. These algorithms are mainly used to analysis the ECG-derived respiration. The automatic respiration rate analysis using ambulatory based single lead ECG signal [7], this ECG signal recording mainly based on the holter monitor, it describes the HRV based analysis of respiration rate. The HRV and ECG amplitude values based respiration rate is calculated [6]. The HRV features based the respiration rate is calculated [8].

III. ECG Data Processing

a) ECG Data Collection

The database collection is the one of the most important part in signal processing. In this paper, we have tested using Physionet Apnea-ECG Database [4]. This database contains totally 35 subjects sleep studies. The ECG signal recordings were visually scored by an expert for sleep apnea/hypopnea events on the basis of respiration on a per minute basis. This 35 subjects recordings (30 men, 5 women) were arranged in three groups: Group A recordings the 20 subjects with clear occurrence of sleep apnea (100 min or more), Group B (borderline) recordings (five subjects) with some degree of sleep apnea (between 5 and 99 min) and Group C (control) recordings 10 recordings of healthy subjects with no sleep apnea (fewer than 5 min).

Each apnea scoring record was divided into 1-min nonoverlapping segments. The each minute was classified as either a “nonapnea minute” or an “apnea minute” [5]. This minutes containing either apnea or hypopnea were classified as apnea minutes and also called as Apnea Index (AI) or Hypopnea Index (HI). AI is the number of apneas observed per hour and the HI is the number of hypopneas observed per hour. Apnea-hypopnea index (AHI) is defined as the sum of AI and HI. The single channel of ECG was extracted from all polysomnographic recordings, sampled at 100HZ with 16-bit resolution and 5-μV A-D converter (ADC) gain per step. The standard sleep laboratory, modified lead V2 position ECG is used.

b) Preprocessing of ECG Signals

The ECG signal mainly contains different types of noise, like frequency interference, Baseline drift, electrode contact noise, polarization noise, muscle noise, the internal amplifier noise and motor artifacts. ECG artifacts are the noise induced to ECG signals that result from movements of the real time electrodes. The most common problems in ECG signal processing is baseline wander removal. The removal of baseline wander is required in the analysis of the real time ECG signal to minimize the changes in beat morphology. The respiration and electrode impedance changes due to respiration are important sources of baseline wander in most types of ECG recordings. The baseline wander of frequency content is usually in a range well below 0.5Hz. The baseline drift can be eliminated without changing or disturbing the characteristics of the waveform. Use the median filters (200-ms and 600-ms) to eliminate baseline drift of ECG signal [2]. The process is as follows:

a) The real time ECG signal is processed with a median filter of 200-ms width to remove QRS complexes and P waves
b) Resulting signal is then processed with a median filter of 600-ms width to remove T waves. ECG signal resulting from the second filter operation contains the baseline of the ECG signal.
c) Subtracting the filtered signal from the original signal and a signal with baseline drift can be obtained.

The before and after removal of baseline wander signal sample beats from record No. a01 of Apnea-ECG Database are shown in Fig.1 where X-axis represents number of samples and Y-axis indicates the amplitude of signal in mV.

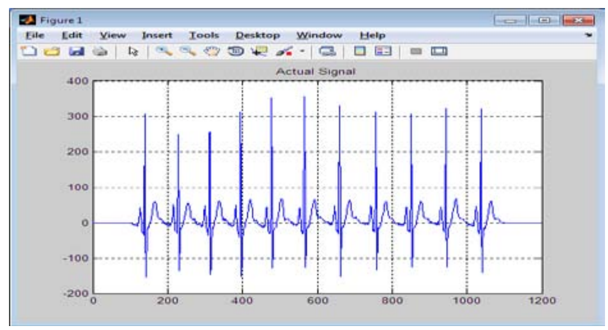

Figure 1(a) : Samples beats from record No.a01

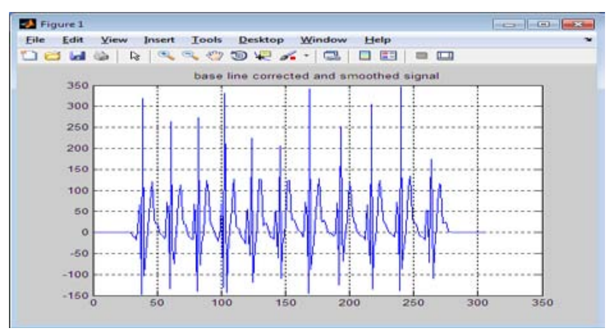

Figure 1(b) : Beats after removal of baseline wander

IV. Wavelet Technique

The wavelet transform (WT) provides a new dimension to signal processing and event detection. The time-frequency localization properties, the wavelet transform is an efficient technique tool for analyzing non-stationary ECG signals. It provides a description of a signal in a timescale domain, analogous to a time-frequency domain, allowing the representation of temporal features at multiple resolutions. The WT is achieved by the decomposition of the signal over dilated (scale) and translated (time) versions of a prototype wavelet. The prototype wavelet function is Mother Wavelet function and it is used for the analytical requirements. The Discrete Wavelet Transform (DWT) Mother wavelet function defined as:

$$\varphi_{a,b}(x) = \frac{1}{\sqrt{a}}\varphi\left(\frac{x-b}{a}\right) a, b \in R, a > 0, \tag{1}$$

Where

a=coefficient of time translation,

b=coefficient of scale (compression),

X= It is the baseline wander noise removal ECG signal,

R= It is the wavelet space,

The DWT contains number of families like Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, and Mexican Hat. The Daubechies (DB4) filter has been found to give details more accurately signal features [3]. This wavelet shows similarity with QRS complexes and energy spectrum is concentrated around low frequency noises. The DB4 filter contains number of levels based coefficient values, each level contain the wavelet function. The mother wavelet applied into the four levels of DB4 filter, it is used to calculate the features of the ECG signal. The Fig 2 has shown the coefficient levels of the DB4 filter. This coefficient level split into two type's approximation coefficient and detail coefficient. The detail level coefficient values are used to calculate the ECG feature value.

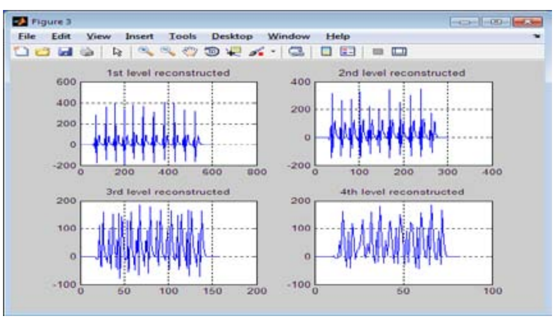

Figure 2 : The DB4 filter coefficient levels

a) ECG-Derived Respiration (EDR)

We evaluated EDR by two methods:

1. Based on the extraction of the R wave amplitude (RWA) after the subtraction of the ECG baseline.
2. Based on the calculation of the R wave duration (RWD)

b) R-Wave Amplitude (RWA)

The R-wave amplitude is calculated by using the five point derivative function. It gives the QRS-complex slope information [1]. The five point derivative with the transfer function

$$H(x) = (1/8T)(-x^{-2} - 2x^{-1} + 2x^{1} + x^{2}) \tag{2}$$

The amplitude response is

$$|H(wT)| = (1/4T)[\sin(2\omega T) + 2\sin(\omega T)] \tag{3}$$

The equation (2) difference response is

$$y(nT) = (1/8T)[-z(nT-2T) - 2z(nT-T) + 2z(nT+T) + z(nT+2T)] \tag{4}$$

The frequency response of this derivative (4) gives the slope value of QRS-complex in linear format. The after differentiation process the signal is squared point by point. The equation of this operation is

$$y(nT) = [z(nT)]^2 \tag{5}$$

This function makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies.

c) R-wave time duration (RWD)

The R-peak time duration calculation based on the Moving window integration. It is to obtain wave from feature information in addition to the slope of the R wave, it is calculated from

$$y(nT) = (1/N)[z(nT-(N-1)T) + z(nT-(N-2)T) + \cdots + z(nT)] \tag{6}$$

Where, N is the number of samples in the width of the integration window. The number of samples N is the important in the moving window. The width of the window should be approximately the same as the widest possible QRS complex. The window is too wide, the integration waveform will merge the QRS and T complexes several peaks in the integration waveform. This can cause difficulty in subsequent QRS detection processes. The width of the window is determined empirically. The QRS complex corresponds to the rising edge of the integration waveform. The duration of the rising edge is equal to the width of the QRS complex. The temporal location of the QRS complex can be determined from this rising edge according to the desired waveform feature to be marked such as the maximal slope or the peak of the R wave. Fig 3 shown the result of the RWD and RWA

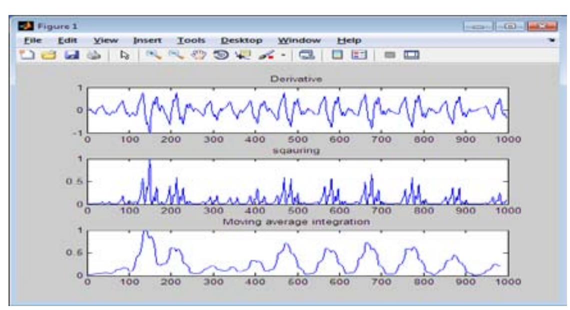

Figure 3(a) : Result of the derivative function, squaring function and moving window integration

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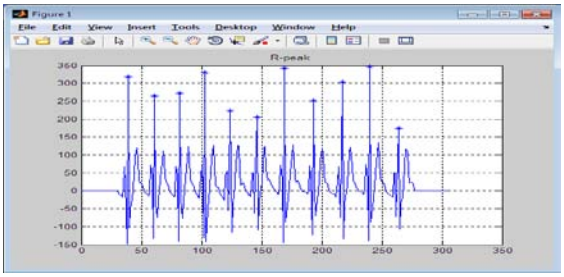

Figuar 3(b) : Thre R-peak marked value

d) Heart rate variability (HRV)

The Heart rate variability is calculated based on the RR-intervals. The RR-intervals *RRi* were calculated as the difference between the times of successive R-peaks *Ri*. Next, the time series *RRi* at the times *Ri* was transformed into an equidistant time series at a sampling rate of 10 Hz using discrete wavelet transform.

$$RR_i = RR_i + RR_{i+1} \tag{7}$$

Where i=1…N, N is number of R-peak value.

e) Features derived from HRV and EDR

RR-interval is a distance of two successive top R-waves. The EDR is the combination of both Ramp and R-peak values. These values based number of feature parameters are calculated:

- Maximum respiration rate per minute of RR-interval and EDR
- Minimum respiration rate per minute of RR-interval and EDR
- Standard deviation for respiration rate per minute of RR-interval and EDR
- Mean for respiration rate per minute of RR-interval and EDR
- Root of mean of sum of squared difference of consecutive RR-intervals (RMSSD),
- Two pNN50 measures is defined as each NN50 measure divided by the total number of NN value
- The NN50 measure is defined as the number of pairs of adjacent NN where the second respiration rate exceeds the first respiration rate by more than 50 ms

V. Result

Figure 1(a) shows the 10-sec time duration of the ECG signal recording, it is acquire from the polysomnogram studies. The ECG signal common noise is removed from the median filter. The ECG signal features are HRV and EDR values are derived from the DWT function. The DB4 filter based decomposition levels remove other low frequency noise in the ECG signal (Figure 2). The ECG signal RWA calculate from the derivative and squaring function and the RWD values are analyzed using Moving widow integration. This R-peak value based RR-interval (HRV) value analyzed. This HRV and EDR values based obtain the respiration variability features are RMSSD, MeanRR, MeanEDR, SDEDR, SDRR, MaxrateRR, MinrateRR, MaxrateEDR, MinrateEDR, pNN50 and NN50. Table 1 gives the Heart rate variability based Respiration Variability analysis features and Table 2 gives the EDR based Respiration variability examines features. This respiratory variability features gives input to the classification process, it provides the acceptable result. This RV values based sleep apnea disease is diagnosed.

VI. Conclusion

The information about HRV and EDR obtained is very useful for ECG classification, analysis, diagnosis, authentication and identification performance. The HRV can also serve as an input to a system that allows automatic cardiac diagnosis. The main advantage of this kind of detection is less time consumption compared to Holter monitor based ECG signal. Several techniques are used for respiration calculation. The discrete wavelet transform based respiration rate computation gives the precise values. This respiration variability is mainly used to diagnosis the sleep apnea disease. The future enhancement process we have apply this respiration variability features analysis the stress testing and Atrial fibrillation disease diagnosis process.

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