AR MODELING OF HEART RATE SIGNALS

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ABSTRACT

The electrocardiogram (ECG) is a representative signal containing information about the condition of the heart. The shape and size of the P-QRS-T wave, the time intervals between its various peaks etc may contain useful information about the nature of disease afflicting the heart. However, the human observer can not directly monitor these subtle details. Besides, since bio-signals are highly subjective, the symptoms may appear at random in the time scale. Therefore, the heart rate variability signal is used as the base signal for the highly useful in diagnostics. This paper deals with the analysis of eight cardiac abnormalities using Auto Regressive (AR), modeling technique. The results are tabulated below for specific example.

KEYWORDS: *electrocardiogram, heart rate, AR Model, FFT, arrhythmia, R-R interval*.

1. INTRODUCTION

Computer technology has an important role in structuring biological systems. The explosive growth of high performance computing techniques in recent years with regard to the development of good and accurate models of biological systems has contributed significantly to new approaches to fundamental problems of modeling transient behavior of biological system. HRV is usually extracted from ECG after detecting the regular peaks that appears in the ECG waveform due to heart beating, called R wave, and computing the time difference between two consecutive R waves. HRV is extraction from ECG signal which requires accurate detection of R peak is conventionally sampled at high sampling rates (>200 Hz). The interest in the analysis of heart rate variability (HRV), i.e., the fluctuations of the heart beating in time, is not new. And much progress was reached in this field with the advent of cheap and massive computational power, which provoked many recent advances in the application of signal processing techniques of heart rate analysis.

Past 20 years have witnessed the recognition of the significant relationship between autonomic nervous system and cardiovascular mortality including sudden death due to cardiac arrest [1, 2, 3, 4]. Numerous numbers of papers appeared in connection with HRV-related Cardiological issues [5, 6, 7, 8] which reiterate the significance of HRV in assessing the cardiac health.

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HRV is a non-invasive measurement of cardiovascular autonomic regulation. Specifically, it is a measurement of the interaction between sympathetic and parasympathetic activity in autonomic functioning. There are two main approaches for analysis: time domain analysis of HRV for standard deviation of normal to normal intervals (SDNN); and frequency domain analysis for power spectrum density (PSD). The latter provides high frequency (parasympathetic activity) and low frequency (sympathetic activity) and total power (sympathetic/parasympathetic balance) values. Spectral analysis is the most popular linear technique used in the analysis of HRV signals [9, 10, 11]. Spectral power in the high–frequency (HF: 0.15-0.5Hz) band reflects respiratory sinus arrhythmia (RSA) and, thus, cardiac vagal activity. Low frequency (LF: 0.04-0.15 Hz) power is related Baroreceptor control and is mediated by both vagal and sympathetic systems. Very low frequency (VLF: 0.0033-0.04 Hz) power appears to be related thermoregulatory and vascular mechanisms, and Renin-angio tension systems.

The spectral analysis of beat-to-beat HRV is a well-established non-invasive way to investigate the autonomic control of the cardiovascular system [10, 12, 13]. Previous studies in humans [14,15] and in dogs [15,10] showed the power spectrum to be characterized by three main components. These are high frequency component (HF), centered at the respiration rate; a low or middle frequency component (LF or MF) that is related to the vasomotor activity regulating arterial blood pressure (ABP); and a very-low frequency component (VLF) most likely related to thermoregulation. Either non-parametric method, based on the Fast Fourier Transform algorithm (FFT) [14,16], parametric methods, based on Autoregressive model (AR) [15], Moving Averaging (MA) and Autoregressive Moving average models (ARMA) have been used in the previous studies. Methods based on FFT have some technical limitations such as , (a) the use of deterministic algorithms that, in principle, are applicable only to periodical phenomena, (b) the need of windowing the data, and (c) uncertainty in defining the relative power of the various spectral components [15,17]. The AR-based methods avoid some of these limitations because they do not require windowing or filtering the data, are applicable to non-periodic phenomena and allow autonomic computation of central frequency and power of the principal spectral components [15,17]. Nihal et al, have compared the FFT and AR based sonogram outputs have explained the advantages of the 20 MHz pulsed Doppler data in real time [18].

Natalucci et al, have used the parametric analysis technique to study the heart rate variability in anaesthetized rats [19]. Recently, Dingfei et al, have classified the cardiac arrhythmia using autoregressive modeling techniques [20]. Inan Guler et al, have used AR methods for the determination of Behcet disease [21]. Elif Derya et al, have studied the spectral analysis of internal carotid arterial Doppler signals using FFT, AR, MA and ARMA methods [22]. In this work, we have studied the spectral analysis of six types of cardiac abnormalities using AR method.

2. MATERIALS AND METHOD

ECG data for the analysis and classification was obtained from MIT-BIH arrhythmia database, MIT-BIH database. Various ECG segments were selected from the databases for analysis. The data set included around 1000 segments each of Normal Synus Rhythm (NSR) ECGs, Preventricular Contraction (PVC), Complete Heart Block (CHB), Sick Sinus Syndrome (SSS), Left Bundle Branch Block (LBBB), Ischemic/Dilated Cardiomyopathy, Atrial Fibrillation(AF) , Atrial Premature Contraction (APC) and Ventricular Fibrillation (VF). The sampling frequency of the data from the MIT-BIH database is 360 Hz [23]. Prior to analysis, the ECG signals were preprocessed to remove noise due to power line interference, respiration, muscle tremors, spikes etc., to detect the R peaks in the ECG signals. The R peaks of ECG were detected using Tompkins's algorithm [24,25].

For the purpose of this study, the cardiac disorders are classified into six categories namely,

Normal
PVC
Complete Heart Block (CHB)
Sick Sinus Syndrome (SSS)
Ischemic/Dilated Cardiomyopathy
Congestive Heart Failure (CHF)

3. SPECTRAL ANALYSIS

The approaches for spectrum estimation may be generally categorized into one of the two classes. The first includes the classical or non-parametric methods that begin by estimating the autocorrelation sequence $r_x(k)$ from a given set of data. The Power spectrum is then estimated by Fourier transforming the estimated autocorrelation sequence. The second class includes the non-classical or parametric approaches, which are based on using a model for the process in order to estimate the power spectrum. Three types of modeling techniques are practically available to estimate the power spectrum.

3.1 Non Parametric Method (FFT)

The Welch method is one of the most popular classical methods to estimate the power spectrum of any sequence. The sequences are allowed to overlap and a data window w(n) is applied to each sequence. This will produce set of modified periodograms that are to be averaged. The data sequences $x_i(n)$ can be represented as

$$x_i(n)=x(n+iD) \quad n=0,1,2,\ldots\ldots,M-1 \quad i=0,1,2,\ldots\ldots L-1 \qquad (1)$$

Where iD is the starting point for the ith sequence. Finally we can form K data segments each of length 2M. The resulting modified periodogram is

$$\tilde{P}_{xx}^{(i)} = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)\, w(n) e^{-j2\pi fn}\right|^2 \qquad (2)$$

Where U is the normalization factor for the power in the window function and is selected as

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \qquad (3)$$

The Welch power spectrum is average of these modified periodograms that is

$$P_{xx}^{W}(f) = \frac{1}{L}\sum_{i=0}^{L-1} \tilde{P}_{xx}^{(i)}(f) \qquad (4)$$

3.2 Parametric method

The non-parametric method so far we have seen is a simple approach, but these methods suffer from spectral leakage effects due to windowing. The Spectral leakage leads to masking of weak signal that is present in the data. The parametric (model based) power spectrum estimation methods avoid the problem of leakage and provide better frequency resolution than non-parametric or classical method.

3.2.1 AR Method

The HRV power spectral density was estimated, epoch by epoch, with an AR-based method. Following this approach, the n^{th} HR value was considered as the output, y(n), of an AR model of order p, driven by a white noise, w(n), with zero mean and variance σ^2 :

$$y(n) = \sum_{k=1}^{p} a(k).y(n-k) + w(n) \qquad (5)$$

This linear prediction equation is characterized by p unknown parameters, $a(k)$. Within each epoch, the series was assumed to be stationary. The $a(k)$ parameters and σ^2 were, then, estimated with the Yule-Walker method[17]. The order of the model was chosen as the one that minimizes the Akaike information criterion (AIC) figure of merit [15]:

$$AIC(p) = N.In\left(\hat{\lambda}^2\right) + 2p$$

Where N is the number of data samples and $\hat{\lambda}^2$ is the estimated white noise variance. To reduce computational costs, we assumed as optimal the value of p that fulfilled the AIC criterion in the first two epochs.

An autoregressive process, *x(n),* may be represented as the output of an all-pole filter that is driven by unit variance white noise. The Burg method is one of the algorithms to get the AR model parameter. The power spectrum of a *p* th order autoregressive process is

$$P_{xx}^{BU}(f) = \frac{\hat{\bar{E}}_p}{\left|1 + \sum_{k=1}^{p} \hat{a}_p(k)\, e^{-j2\pi fk}\right|^2} \qquad (6)$$

Where $\hat{\bar{E}}_p$ is total least square error. The Burg method results in high resolution and yields a stable AR model.

One of the most important aspects of the use of AR method is the selection of the order p. Much work has been done by various researchers on this problem and many experimental results have been given in literature such as the papers presented by Akaike [27, 28, 29]. In this work the order of the AR model is taken as p= 12.

4. RESULTS

The results show that, for SSS, PVC and Normal heart rate data, the amplitude of the five-peak power spectral density is more, and for cardiac data which has less R-R variation like CHB, Ischemic/dilated cardiomyopathy and CHF these peak amplitudes will be less. Table 1 shows the distinct range of values for each class of cardiac abnormality with a confidence level of more than 98% for the AR modeling technique,

Table 2 shows the power spectral density using Welch method. In this method, we get only one peak for each type of heart rate data. Hence, the FFT by Welch method does not give more details in the spectral domain. Hence, the AR approach gives better spectral resolution as compared to the FFT method. Figure 2 and 3 shows the plot of log magnitude of power spectral density (PSD) for normal and abnormal Heart rate variability signals using Welch (FFT) method and Burg (AR) method. We can observe the spurious peaks in FFT method, which lacks in resolving proper value of PSD. The AR method (Welch) can properly resolve the existence of the power spectrum

The advantages of the AR approach compared to the FFT technique for estimation of the spectrum are: The AR spectrum has better statistical stability for short segments of signal. AR has better spectral resolution and the resolution is less dependent on the length of the record [17]. When deciding which method of modeling is good, the further the curve is from diagonal line, the better the method is. In both ROC curves diagram (Figure1), AR method is found to be nearer to the diagonal line. Hence, in our studies we can conclude that for the heart rate data the best modeling method is the AR method using Burg's method. Parametric methods do not require making such assumptions. The modeling approach eliminates the need for window functions. Parametric methods have better statistical stability.

5. CONCLUSION

Heart rate variability (HRV) signal can be used as a reliable indicator of heart diseases. It becomes less random with the cardiac diseases. This is evaluated by using the AR approach. Different ranges of P/F are proposed for various cardiac abnormalities with a confidence level of more than 98%.

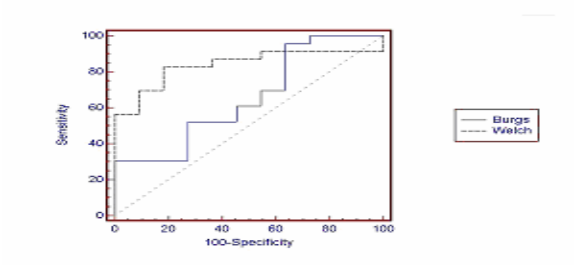

Figure 1 Comparison of AR Method and FFT (Welch) using ROC

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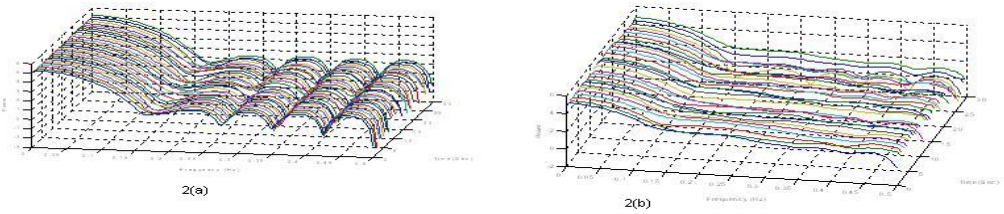

Figure 2 Power Spectral density using FFT (Welch) a) Normal heart rate and b) Abnormal heart rate

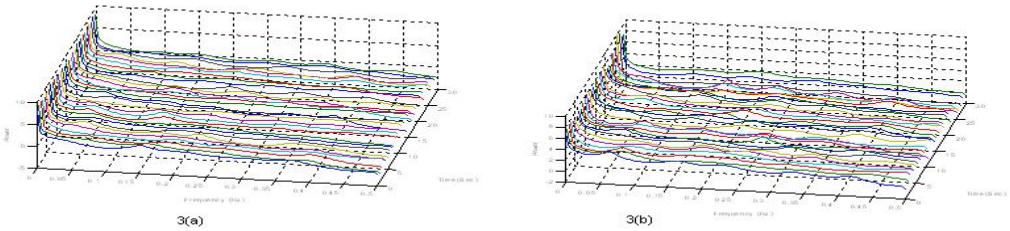

Figure 3. Power Spectral Density using AR (Burg) method a) Normal heart rate b)Abnormal heart rate

P/F	CHB	CHF	ISC/DIL	NORMAL	PVC	SSS	PVALUE
	1.87±0.69	1.16±0.90	1.74±0.73	6.52±4.58	11.04±6.89	245.17±100.86	
P1/F1	0.06±0.006	0.09±0.02	0.10±0.02	0.09±0.04	0.10±0.03	0.05±0.005	< 0.0001
	1.60±1.86	0.94±0.90	1.25±0.74	2.46±2.58	8.96±5.83	156.81±63.54	
P2/F2	0.13±0.01	0.19±0.04	0.22±0.03	0.18±0.04	0.19±0.02	0.16±0.02	< 0.0001
	0.56±0.38	0.45±0.28	0.85±0.53	1.36±1.29	10.61±6.81	209.26±135.99	
P3/F3	0.17±0.02	0.26±0.04	0.29±0.04	0.28±0.06	0.27±0.03	0.26±0.07	< 0.0001
	0.60±0.32	0.16±0.19	0.51±0.47	0.99±1.00	8.85±6.12	509.14±290.94	
P4/F4	0.27±0.02	0.36±0.068	0.37±0.05	0.37±0.06	0.33±0.02	0.35±0.06	< 0.0001
	0.92±0.93	0.01±0.009	1.24±0.57	1.03±1.01	10.36±6.78	296.45±2.53	
P5/F5	0.35±0.04	0.38±0.047	0.41±0.02	0.41±0.03	0.40±0.02	0.37±0	0.0016

PSD values are in bpm^2 and frequency in Hz.

Table 1. Result of AR modeling for various cardiac abnormalities

P/F	CHB	CHF	ISC/DIL	NORMAL	PVC	SSS	P VALUE
P1/F1	124585± 7685.3822	480668± 299964	530280± 370538	451000± 86764	627032± 28150.83	632546± 176962.6	<0.0001
	0.0039±0	0.0039±0	0.0039±0	0.0039±0	0.0039±0	0.0039±0	<0.0001
P2/F2	13.75±11.08	26±18.16	50±40	78±36.33	422±287.61	2480±1116	<0.0001
	0.03±0.003	0.04±0.01	0.05±0.01	0.047±0.02	0.05±0.03	0.08±0.05	<0.0001
P3/F3	15±5.77	28±16.43	40±30	66±25.09	168±224.87	1073±469.71	<0.0001
	0.06±0.008	0.06±0.01	0.07±0.01	0.07±0.01	0.08±0.02	0.14±0.05	<0.0001
P4/F4	12.5±5	36±24.08	36.66±25.16	68±28.64	126±120.95	1000±455.74	<0.0001
	0.07±0.01	0.08±0.01	0.08±0.01	0.08±0.01	0.10±0	0.14±0.09	<0.0001
P5/F5	12.5±5	28±16.43	28.33±22.55	68±37.01	132±123.17	943.33±327.15	<0.0001
	0.09±0.01	0.09±0.01	0.10±0.01	0.10±0.003	0.12±0.01	0.17±0.10	<0.0001

PSD values are in bpm^2 and frequency in Hz.

Table 2. Result of FFT(Welch) modeling for various cardiac abnormalities

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