# HEART RATE VARIABILITY ANALYSIS FOR ABNORMALITY DETECTION USING TIME FREQUENCY DISTRIBUTION – SMOOTHED PSEUDO WINGER VILLE METHOD

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### ABSTRACT

Heart rate variability (HRV) is derived from the time duration between consecutive heart beats. The HRV is to reflect the heart's ability to adapt to changing circumstances by detecting and quickly responding to unpredictable stimuli to cardiac system. Depressed HRV is a powerful predictor of mortality and of arrhythmic complications in patients after diseases like acute Myocardial Infarction. The degree of variability in the HR provides information about the nervous system control on the HR and the heart's ability to respond .Spectral analysis of HRV is a frequency domain approach to assess the cardiac condition. In this paper one such method for analyzing HRV signals known as smoothed pseudo Wigner Ville distribution (SPWVD) is applied, The sub-band decomposition technique used in SPWVD, based on Instantaneous Autocorrelation (IACR) of the signal provides time-frequency (HF) regions identified in HRV spectrum. Results suggest that SPWVD analysis provides useful information for the assessment of dynamic changes and patterns of HRV during cardiac abnormalities.

KEYWORDS: HRV, RR Tachogram, Resampling, STFT, WVD, SPWVD

# **1. INTRODUCTION**

The Electrocardiogram (ECG) is a periodic signal containing information about the functioning of the heart. The duration and amplitudes of P, QRS and T wave in an ECG cycle contain useful information about the nature of heart disease. However, always it may not be possible to directly monitor the subtle details of the functioning of the heart just by observing EGC. The symptoms of certain diseases may appear at random in the time which will be not be seen for quite a long to give any consistent information. In, 1965, Heart Rate was identified as another significant tool in research and clinical studies of cardiology when distress was preceded by alterations in inter heart beat intervals before any appreciable change occurred in heart rate itself. Later it was found that HRV computed from 24-hour Holter records are more sensitive than simple bedside tests [1] Therefore, HRV signal parameters, extracted and analyzed using computers, are highly useful in diagnostics. Analysis of HRV also has become a popular non-invasive tool for assessing the

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activities of the autonomic nervous system [2]. These signals are essentially non-stationary; may contain indicators of disease. The indicators may be present at all times or may occur at random in the time scale [3].

The HRV which is inversely proportional to the time differences between two consecutive Rwaves in a time series of ECG is given by the equation

$$HRV = [60/t1, 60/t2, ----60/tn]$$
(1)

where  $[t_{1,t_{2}}, t_{2}, \dots, t_{n}]^{T}$  represent a time series composed of time intervals between consecutive R peaks in an ECG signal and HRV is expressed as beats per minute. Various researchers have contributed in automated analysis of HRV as an alternative to ECG characterization. Researchers have extensively discussed the investigated tools to indirectly assess the biological conditions based on HRV parameters under normal and different pathological conditions of cardiovascular system [4]. The continuous recording of HR shows regular fluctuations that reflect parasympathetic and sympathetic neural control on the sinus node [5]. The HRV has proved to be non stationary in nature. Hence the analysis of HRV expressing quantitative parameters has been carried out using time domain, frequency domain and non-linear approaches [4]. Though time domain HRV analysis is popular, when it does to the assessment of the cardiac conditions based on the HRV, it is recommended to carryout spectral analysis of the signal [5]. In frequency domain the typical spectral pattern in normal conditions of HRV show the presence of three frequency bands: a very low frequency (VLF) band from 0.00 to 0.03 Hz, a low frequency (LF) band from 0.03 to 0.15 Hz and a high frequency (HF) band in respiratory range generally more than 0.25 Hz. The value of the LF component are related to the sympathetic activation whereas the area of the high frequency component (HF) provides a quantitative index of the influence of respiration on the ECG signal and may be connected to the vagal activity. Thus the LF/HF ratio is an important marker of sympatho-vagal balance on heart rate variability control.



Figure 1. Spectrum for a normal HRV pattern showing typical VLF, LF and HF regions

The Figure 1 shows the typical spectrum of a HRV signal indicating a normal functioning of the heart. HRV spectrum obtained by RR Interval of ECG is an unusual time series as both x and y axis indicates time intervals, one being related to the other. Further, since the variability in HR

occurs on a beat-to-beat basis, the time series is inherently unevenly spaced along the horizontal axis as the number of ECG samples within each RR peaks are different [6]



Figure .2 The unevenly sampled RR Tachogram

Figure 2 shows the RR-interval data where the total numbers of samples of ECG considered for obtaining RR-intervals are shown in x-axis. The y-axis represents the distances between consecutive R-R peaks. It is seen from the plot that both x and y axes are indicating number of samples. As shown the horizontal distance between each point (time stamp) is different for each adjacent pair, with the difference recorded on the vertical axis. This plot is called RR Tachogram.



Figure.3 R Peak detection in an abnormal ECG Detection

Figure 3 shows R peak detection in an abnormal ECG which also has an unevenly sampled RR Tachogram. From the examples explained till now, fact that the RR Tachogram is unevenly sampled and this shows the necessity for re-sampling. Because, whenever spectral analysis is carried out using transformed domain approach, it is expected that the signal will have uniform sampling. Hence it is necessary to resample the Heart Rate or RR interval data before performing frequency domain analysis. Typical human heart rate is 72-82 bpm leading to heart rate of 1.5 Hz. A sampling rate of 4Hz is ideally preferred. Since the human heart rate can sometimes exceed 3Hz (180 beats per minute). However, if one knows that the RR Tachogram is unlikely to

exceed 120 beats per minute then a re-sampling rate of 4Hz is sufficient. A choice of 7 Hz for the up-sampling of the RR-Tachogram satisfies the Nyquist criterion and gives a value of 2100 points in a 5-minute window. There are different approaches to have uniformly sampled RR Tachogram. In [6] the re-sampling methods have been discussed.



Figure. 4. HRV for 4.5 Seconds with RR Low limit of 0. 421 sec and RR High limit of 1.007 Sec

Figure 4 shows typical HRV derived from re-sampling method for time duration of 4.5 seconds. The Computation of HRV is based on the Equ. (1) and Resampling rate of 4Hz is used using linear interpolation. The European and North American Task force on standards in HRV [8] suggested that the shortest time period over which HRV metrics should be assessed is 5 minutes. Though the approaches discussing the HRV derivation from RR Tachogram and HRV has been addressed by different researchers and the time frequency distribution of the HRV signals give additional information about cardiac activities. This paper aims to bring out such details using SPWVD technique. Section 2 gives the mathematical background about the method proposed. Section 3 gives the simulation results. The paper is concluded in section 4.

# 2. SPWVD METHOD FOR TIME FREQUENCY ANALYSIS

Fourier Transform (FT) provides good description of the frequencies in a waveform, but not their time of occurrence. Complex exponentials representing frequency information of the signal stretch out to infinity in time. FT analyze the signal globally, not locally. To overcome the limitation of FT the Short-Time Fourier Transform (STFT) was introduced for processing nonstationary signals [8]. A window function is applied to a segment of data, effectively isolating that segment from the overall waveform, and the FT is applied to that segment. But this necessitates a tradeoff between time localization and frequency resolution. By considering the window size as small, an increase in frequency resolution is achieved at the cost of time resolution and vice versa. As an alternative approach, the Wigner–Ville distribution (WVD) [9] alleviates this tradeoff. The WVD at any instant is the FT of the instantaneous autocorrelation (IACR) sequence of infinite lag length[10]. Though WVD gives high resolution in time-frequency domain, it is not used widely for practical application due to the interaction between different signal components, introducing cross frequency values into the spectrum called as "cross term". These terms demonstrate energies at time-frequency values where they do not exist. The Wigner function cannot be directly interpreted as a probability distribution function because, in the general case, it is necessarily negative in some regions of phase space. For an indirect probabilistic interpretation, a non-negative phase space function is necessary. The phase space distribution which is produced in simultaneous un-sharp measurements of position and momentum can be represented as a convolution sum of the WVDs of the individual signals plus additional term, the cross term. They represent the interaction of two frequencies and their relative phases. These terms may exist even for values of time at which the signal is zero and may not be negligible. The WVD may take negative values [10]. Practically, it is the Pseudo WVD (PWVD) that is computed which considers IACR only for a finite number of lags. In the PWVD the IACR is weighted by a common window function to overcome the abrupt truncation effect known as Gibbs effect. Shorttime Fourier transforms (STFTs) cannot accurately track changes in a signal's spectrum that occur over the course of a few seconds, this is a significant limitation for many biological signals. Smoothing time and frequency functions are used to enhance the readability of the Pseudo Wigner-Ville spectrum by eliminating the cross terms inherent to the bilinear nature of the distribution without affecting the resolution. This is called Smoothed pseudo WVD (SPWVD) [11]. The use of different smoothing kernels results in a class of distribution, called the Cohen's class. But the WVD obtained by using common smoothing kernel (other than rectangular) do not satisfy some of the TFR properties [12].

FT is a reversible transform. For a signal x(t), the FT is :

$$X(w) = \int_{\infty}^{\infty} x(t)e^{-jwt}dt$$
<sup>(2)</sup>

Time domain signal is:

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(w) e^{jwt} dw$$
(3)

Where x(t) is the time domain signal of interest. In equation(2), the X(w) shows the strength of the each frequency component over the entire interval ( $-\infty$ ,  $\infty$ ). It does not show when those frequencies occurred. In STFT, the Fourier Transform is applied to a segment of data that is shorter, often much shorter, than the overall waveform. A window function h(t) is chosen whose length is equal to the lengths of the segments. The window function used is a Gaussian function in the form:

$$w(t) = e^{(-a\frac{t^2}{2})}$$
(4)

The basic equation for the STFT in the continuous domain is:

$$X(t,f) = \int_{-\infty}^{\infty} x(\tau) w(t-\tau) e^{-j\pi f t} d\tau$$
(5)

where  $w(t-\tau)$  is the window function and  $\tau$  is the variable that slides the window across the waveform, x(t). However STFT suffers from the Gibb's phenomena. A time-frequency energy distribution which is particularly interesting is the WVD defined as:

$$\Psi(t,f) = \int_{-\infty}^{\infty} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j\pi f\tau}d\tau$$

$$r(t,\tau) = \int_{-\infty}^{\infty} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})$$
(8)

Where

is the instantaneous auto-correlation sequence and 
$$\tau$$
 is the time lag. In frequency domain, the WVD is given by:

$$W_{x}(t,w) = \int_{-\infty}^{\infty} X(w + \frac{w}{2}) X^{*}(t - \frac{w}{2}) e^{-jwt} dw$$
(9)

The interference terms in WVD can be reduced by smoothing in time and frequency. The result is the smoothed-pseudo Wigner-Ville distribution (SPWVD) which is defined as follows.

(8)

If one chooses a separable kernel function  $f(\xi, \tau) = G(\xi)h(\tau)$ , with a Fourier transform of the form :

$$F(t,v) = FT[f(\xi,\tau)] = g(t)H(v)$$
(10)

We obtain the smoothed pseudo Wigner-Ville distribution as:

$$SPWVD_{(t,v)} = \int h(\tau) [\int g(s-t)x(s+\frac{\tau}{2})x^*(s-\frac{\tau}{2})ds] e^{-j2\pi vt} d\tau$$
(11)

## **3. SIMULATION RESULTS**

In 1999, researchers at Boston's Beth Israel Deaconess Medical Center, Boston University, McGill University, and MIT initiated a new resource for the biomedical research community. This resource is setup to help with simulation for current research and new investigations in the study of complex biomedical signals. Physio Net is an online forum for dissemination and exchange of recorded biomedical signals, by providing facilities for analysis of data and evaluation of proposed new algorithms. The resource website http://www.physionet.org, PhysioNet is used for carrying out the SPWVD time frequency analysis for the HRV in this paper. The ECG signals of different data sets available in this resource are chosen for the simulation work in this paper. The HRV is derived from RR Tachogram and is analyzed using SPWVD technique.

The following set of data files give the details as recorded in MIT data base and their corresponding analysis. The record 101 has 342 normal beats, 3 APC beats and 2 unclassified with total of 1860 beats. The normal rhythm rate is 55 to 79. There is clean ECG for duration of 30 minutes. Figure 5.a shows the SPWVD spectrum and Figure 5.b shows its contour. The continuity of the line in the frequency axis in Figure 5.b shows the HF component of the HRV spectrum. In abnormal heart rate the HF and LF component position will be shifted indicating abnormality of the heart.



Figure 5. a normal RR interval spectrogram with ECG database 101, from MIT/BIH data base



Figure 5.b Contour plot for the record 101 which has maximum number of Normal beats. The continuity of the line at normalised frequency around 0.8, indicate the HF component of the HRV spectrum.



Figure.6. a. Plot of RR interval obtained from ECG of a patient suffering from Congestive Heart Failure. (MIT/BIH Data RR-Interval base)



Figure .6 .b SPWD spectrum for normal heart rate. Fig 10.b.Contour plot of SPWVD of RR-Interval data obtained from ECG of a subject HF component is in the middle shifted from the middle of frequency axis. The SPWD is computed with a window length of 8 sample, time smoothing window size is 16 samples

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Figure 6.c. Contour plot of the SPWD spectrum showing the discontinuity in HF component of HRV spectrum. The position of the HF is also shifted widened in the axis.



Figure 7.a.Power Spectrum using SPWVD showing the Time Frequency distribution of time series representing normal HR



Figure 7.b.Contour plot of SPWVD of RR-Interval data obtained from ECG of a subject, having normal heart rate. HF component is in the middle of the frequency axis. The SPWD is computed with a window length of 8 sample, time smoothing window size is 16 samples

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Figure.8.RR interval of a diseased subject with severe changes in the distances between the consecutive RR intervals



Figure 9.a The PSWVD spectrum showing the Time Frequency plot of Heart Rate variability for the sample shown in Figure 8



Figure 9.b. Contour plot of the HRV obtained for the RR interval time series shown in Figure 8

Figure 6.b.and Figure 6.c.shows the RR time series of abnormal heart rate shown in Figure 6.a The time-frequency plots are shown in Figure 7.a. and Figure 7.b for normal heart. Similarly for the abnormal RR time series indicated in Figure8, Figure 9.a and Figure 9.b. shows the HRV SPWED plots. The time frequency and contour plots show that the changes in the frequency of

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the components correspond to physiological changes which will be taking place. In the HRV spectrum, strength of the second component (HF) relative to that of the first decides about the normal and abnormal classification. From this point of view, the sub band processing algorithms like SPWVD have better performance However, the frequency transition from one band to the other may not have brought out well which is not of importance in this case.

## **4.** CONCLUSION

The SPWVD with any time and frequency smoothing, provides good time and frequency resolution. Paper shows how it is possible to have time frequency distribution of different HRV signal obtained for MIT database, using SPWVD. The corresponding TFDs show that whenever there are deviations from normal beating of the heart like congestive heart failure , heart beats after Myocardial Infarction ,the regular repetitive patterns of frequency distributions are changed. Though the attempt here is not made to give the statistics about time frequency analysis for the various data files used for the experimentation, it is possible to observe the extent of non-stationary behaviour of HRV in a longer duration data analysis.

## REFERENCES

- [1] Norhashimah Mohd Saad, Abdul Rahim Abdullah, and Yin Fen LowDetection of Heart Blocks in ECG Signals by Spectrum and Time-Frequency Analysis, 4th Student Conference on Research and Development (SCOReD 2006), Shah Alam, Selangor, MALAYSIA, 27-28 June, 2006
- [2] Schwartz, P.J., and Priori, S.G. (1990): 'Sympathetic nervous system and cardiac arrythmias', In: Zipes, D.P., and Jalife, J. eds. Cardiac Electrophysiology, From Cell to Bedside. Philadelphia: Saunders, W.B. pp. 330–343.
- [3] Levy, M.N., and Schwartz, P.J. (1994): 'Vagal control of the heart: Experimental basis and clinical implications', Armonk: Future.
- [4] Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology. (1996): 'Heart Rate Variability: Standards of measurement, physiological interpretation and clinical use', European HeartJournal, 17, pp. 354–381.
- [5] Berger, R.D., Akselrod, S., Gordon, D., and Cohen, R.J. (1986): 'An efficient algorithm for spectral analysis of heart rate variability', IEEE Transactions on Biomedical Engineering, 33, pp. 900–904.
- [6] Kamath, M.V., and Fallen, E.L. (1995): 'Correction of the heart rate variability signal for ectopics and missing beats', In: Malik, M., and Camm, A.J. eds. Heartrate variability, Armonk: Futura, pp. 75–85.
- [7] Kobayashi, M., and Musha, T. (1982): '1/f fluctuation of heart beat period', IEEE transactions on Biomedical Engineering, 29, pp. 456–457.
- [8] Boomsma, F.T., and Manintveld. (1999): 'Cardiovascular control and plasma catecholamines during restand mental stress: effects of posture', Clinical Science, 96, pp. 567–576.
- [9] Viktor, A., Jurij-Matija, K., Roman, T., and Borut, G. (2003): 'Breathingrates and heart rate spectrograms regarding body position in normal subjects', Computers in Biology and Medicine, 33, pp. 259–266.
- [10] Rosenstien, M., Colins, J.J., and De Luca, C.J. (1993): 'A practical method for calculating largest Lyapunov exponents from small data sets', Physica D,65, pp. 117–134.
- [11] Pincus, S.M. (1991): 'Approximate entropy as a measure of system complexity', Proceedings of National Acadamic Science, USA, 88, pp. 2297–2301.12.
- [12] Peng, C.K., Havlin, S., Hausdorf, J.M., Mietus, J.E., Stanley, H.E., andGoldberger, A.L. (1996): 'Fractal mechanisms and heart rate dynamics', Journal on Electrocardiology, 28 (suppl), pp. 59–64.
- [13] Grossman, P., Karemaker, J., and Wieling, W. (1991): 'Prediction of tonicparasympathetic cardiac control using respiratory sinus arrhythmia: the need for respiratory control', Psychophysiology, 28, pp. 201–216.