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Spectral Analysis of Heart Rate Variability Signals using Stockwell-Transform

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Abstract

This paper introduces the use of Stockwell transform (ST) for spectral analysis of heart rate variability (HRV) signals in time-frequency domain. The ST is depicted numerically and compared with well-liked method of wavelet transform known as continuous Morlet wavelet transform (CMWT). The results of this study show that the normalized mean power and total normalized power in VLF (0.004–0.04 Hz), LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) were improved compared to CMWT for statistical significance value of p=0.00016 and P<0.00001. For this analysis, electrocardiogram (ECG) was recorded in fifteen normal subjects (mean age approximate 28, range 23–34 years and mean height approximate 162 cm) in supine position for twenty minutes.

Keywords: Stockwell transform, scalogram, normalized mean power, ectopic beat, trend

Abbreviations: ANS, autonomic nervous system; **CMWT,** Morlet wavelet transform; **ECG,** electrocardiogram; **HRV,** heart rate variability; **HF,** high frequency; **LF,** low frequency; **ST,** Stockwell transform; **VLF,** very low frequency

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INTRODUCTION

The time-frequency analysis of the heart rate variability (HRV) has been used as a non-invasive tool to explain the several mechanisms of the autonomic nervous system (ANS) modulation on heart rate. From electrocardiogram (ECG) records, in which R-R intervals are measured, beat to beat variation of R-R interval is known as heart rate variability. It is feasible to obtain information about how power of the HRV is distributed across frequency and time. HRV spectrum can be divided into three main frequency bands: a high frequency (HF) band (0.15 to 0.4 Hz), low frequency (LF) band (0.04 to 0.15 Hz) and very low frequency (VLF) band (0.004 to 0.04 Hz). High frequency heart rate oscillations are associated with respiratory sinus arrhythmia and reflect parasympathetic activity. Low frequency heart rate oscillations are considered to be modulated by combined sympathetic and parasympathetic activity. VLF band which may reflect the influence of several physiological mechanisms, including the rennin-angiotensin system, vasomotor tone and thermoregulation on heart beats.[1–4] The time-frequency power spectral indexes extracted from the R–R interval time series provides information related to the autonomic neural cardiovascular control. In many clinical situations such as diabetes[5–8] hypertension[9] heart failure[10,11] and heart disease[12,13] spectral indexes can be changed. Thus, reduced HRV is a notable to predict of cardiac event including sudden death in coronary artery disease,[14] heart failure[15] and following myocardial infarction. Therefore

HRV has been increasingly used as a predictive index as well to monitor treatment results in several diseases affecting the interaction between the autonomic nervous system and heart rate control.[16]

HRV is analyzed in the frequency domain the power spectrum of HRV does not show its temporal changes.[17] There are many physiological situations of interest where heart rate changes rapidly over time and the monitoring of these temporal changes may be very important.[18] HRV signals are characterized by time-varying signal properties i.e. from the statistical perspective they are non-stationary. Therefore time-variant signal processing methods are part of the standard assortment in biomedical signal analysis. Both the frequency of occurrence as well as the shape and time-frequency characteristics of transient signal components have a high diagnostic value[19,20] leading to more frequently applications of time-variant analysis methods. Signal components with time-variant properties in HRV may occur at different frequencies. The time-frequency analysis is performed on the HRV data to show vagal tone and the sympatho-vagal balance as a function of time.[21,22]

The best-known and most frequently applied techniques for the time-frequency analysis of HRV are the short-time Fourier transform (STFT) or Gabor transform (GT), the continuous Morlet wavelet transform (CMWT),[23] and the Smoothed Pseudo Wigner-Ville (WV). The STFT cannot track the signal dynamics properly for non-stationary signal due to the limitations of fixed window width and also posse's poor frequency resolution. The WV method used analytical signal (Hilbert transform) for process of HRV,[24] which has smoothen the power spectral but with poor time-frequency power resolution due to cross terms in the spectrogram.[25]

CWT is better method compared to all the above methods for time-frequency analysis as its window width is variable by scaling. Therefore this method analysis is computationally efficient for non-stationary signal and produces reasonable result for large class of signal processing.[26] In spite of this compensation, there are several inherent performance restrictions of the CWT approach like, CWT normally employs an octave scaling for frequencies, which results in an oversampled representation at the low frequencies and an under sampled representation at the higher frequencies.[27] However, wavelet has its own drawback that their analysis results depend on the choice of the mother wavelet base function. This may lead to a one-sided and a prior hypothesis on the characteristics of the signal. As a consequence, only the signal characteristics that correlate well with the shape of the wavelet base function have a chance to produce high value coefficients.[28] Any other characteristics will be masked or completely ignored. Therefore it is not having high time-frequency power and resolution in each frequency band (VLF, LF and HF) of HRV signals.

MATERIALS AND METHODS

Subjects

For this analysis we have to use 15 healthy subjects, mean age approximate 28, ranging from 23–34 years and mean height of approximately 162 cm. The subjects were asked to avoid consumption of coffee, tea and cigarettes one hour before the recording. We have taken the clinical information allied with each record of the database in order to select a uniform group of records to be analyzed. None of them was suffering from diabetes and heart disease. An ECG was continuously recorded for 20 min of each subject in the relaxed supine position in a room free from any kind of disturbance with controlled temperature (22–25^{o}C). All ECG measurements were taken at the

National Institute of Technology Jalandhar, India.

Data Acquisition and Pre-Processing

The recording of ECG was done at the sampling rate of 500 Hz with BIOPAC (MP150) in corporation with Acknowledge software. Initially the D.C. drift of ECG signal was removed and after that the ECG signal is passed through a chebyshev type-2 low pass filter having a cut-off frequency of 15 Hz (Normalized frequency 0.03) to remove unwanted high frequency components which are present in ECG signals. Then it is passed through a chebyshev type-1 high pass filter with a cut-off frequency of 5 Hz (Normalized frequency 0.01) to remove the so called baseline wander.[29] A Notch filter with a cut-off frequency of 50 Hz is used to remove power-line interference noise. The R peaks of the ECG signal were detected using Tompkins's algorithm and get R-R interval.[30,31] HRV analysis were carried out in time-frequency domains using MATLAB version R2012a (7.14.0.739) by using m-file of signal processing and wavelet tool box of the Matlab.

Pre-processing of IBI time series data is necessarily required before analysis of HRV signal to reduce error and enhance the sensitivity of time series data. First we have done ectopic beat or interval detection and correction, de-trending and resampling type of pre-processing before HRV analysis. In this paper, the ectopic beats were detected on the basis of stander deviation filter method which marks outliers as being intervals that lie outside the overall mean IBI by a user defined value of standard deviation.[18,32] The user defined value was used as three times of standard deviation. To remove such type of beats a qubic spline interpolation method was used. After replacing R-R intervals (second), now it is known as normal to normal intervals (NN intervals). The NN intervals were de-trended using linear method to remove low frequency and the mean of NN intervals were subtracted from NN intervals measure in order to remove trend.[33] The NN intervals were resampled at 4 Hz using qubic spline method and the results are shown in Figures 1(a)–(c).

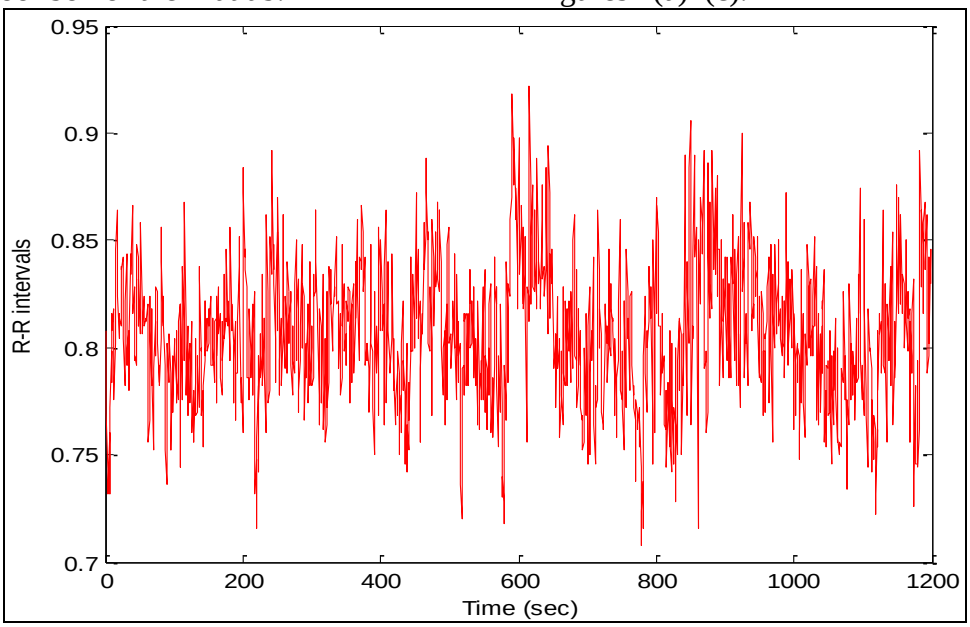

Fig. 1a. *Typical Plots of R-R Interval Overtime.*

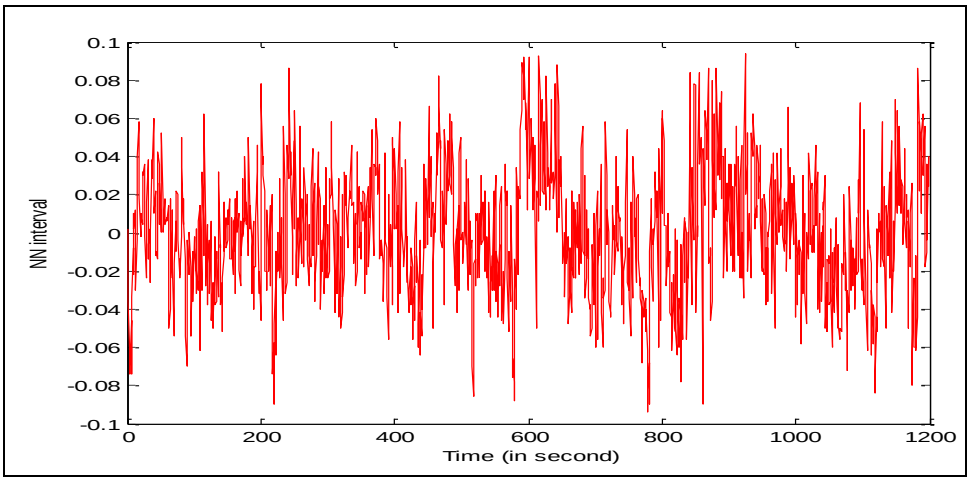

Fig. 1b. *Typical Plots of R-R Interval With Ectopic Beat Overtime.*

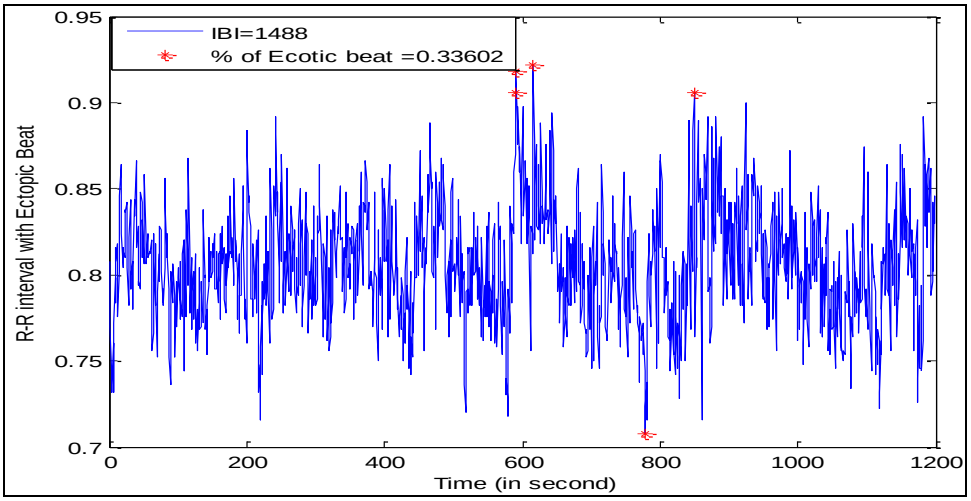

Fig. 1c. *Typical Plots of NN Interval after Replaced and De-trend Value of R-R Interval Overtime.*

Stockwell Transform

The ST was proposed by Stockwell *et al.*[34–36] The ST entirely refers to about the local information and frequency dependent resolution of time-frequency domain. The ST is capricious window of short time Fourier Transform (STFT) or addition of wavelet transform. It is based on a scalable Gaussian window and depends on frequency resolution. The STFT of signal $h(t)$ is defined as in Eq. (1) and it is basic equation for derivation of ST, in which the variable parameters τ and f denote the time of spectral localization and Fourier frequency respectively and $g(t)$ represent the window function. The ST can originate from the above equation by replacing the window function $g(t)$ with Gaussian function and define as in Eq. (2).

$$STFT(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t) e^{-j2\pi ft} dt \quad (1)$$

$$Cofficient = S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-j2\pi ft} dt \quad (2)$$

Coefficient is a la-by-lx matrix, where la is the length of scales and lx is the length of the input $h(t)$ and coefficient is a complex matrix.

Scalogram

The scalogram is the absolute value and square of the output of the ST as in Eq. (3). The meaning of scalogram is the ST energy density function which is the

contribution to the signal energy at the specific scale parameter $1/f$ and location parameter τ. It is analogous to the spectrogram the energy density surface of the STFT. The scalogram (SC) represents the percentage of energy for each coefficient and is defined as in Eq. (4).

$$SC = |S(\tau, f)|^2 = \left| \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau - t)^2 f^2}{2}} e^{-j2\pi ft} dt \right|^2 \quad (3)$$

$$\% \ of \ energy = \frac{SC(\tau_i, f_j)}{\sum_{j=1}^{la} \sum_{i=1}^{lx} SC(\tau_i, f_j)} \times 100 \quad (4)$$

Algorithm to calculate normalized power with respect to time:

- Calculate the power as S=abs (coefficient*coefficient).
- Find the location of calculated power being range of frequency (f) use Mat command 'find' example: for VLF find ((f>=0.003) and (f<0.04)).
- Find the sum of power corresponding to location of frequency with respect to time example: VLF Power=Sum(S(location:)).
- Normalized power w.r.t. time=VLF Power/Max (VLF Power).
- Total normalized power=Sum (normalized power w.r.t. time).

RESULTS

The bar chart of normalized mean power of VLF, LF and HF are shown in Figures 2(a)–(c) for fifteen normal subjects and evidently indicate that ST method is better compared to the CMWT method.

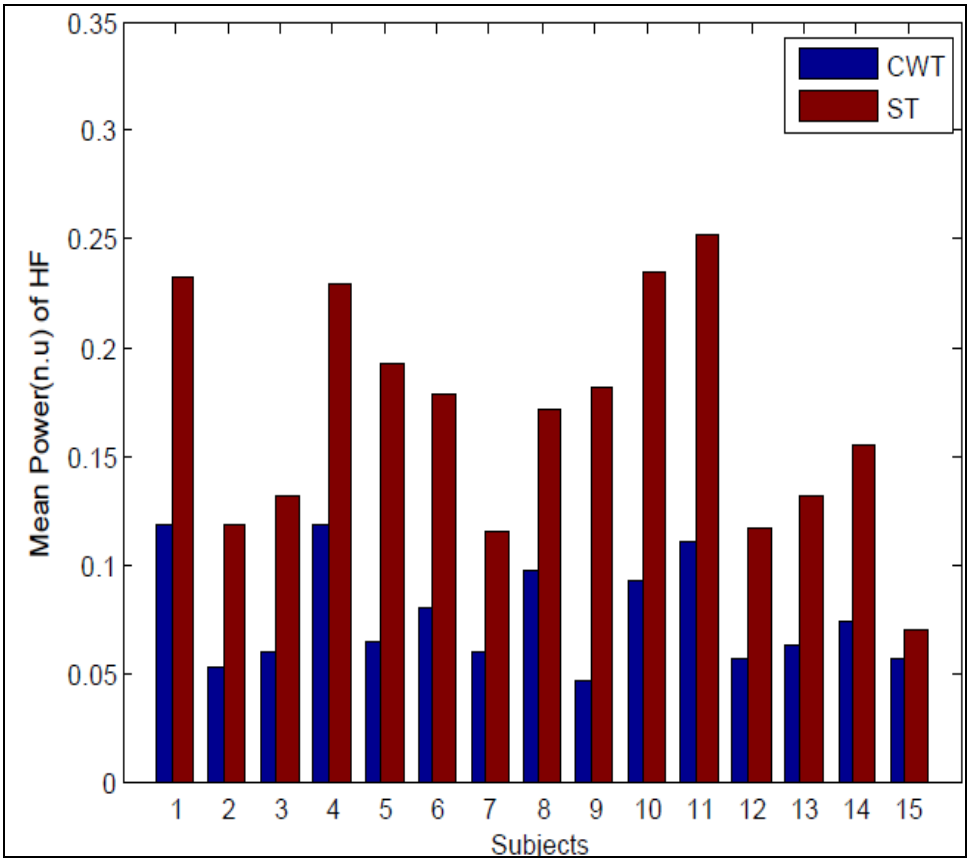

Fig. 2a. *Typical Bar Chart Comparison Plots of CMWT and ST Method for Normalized Mean Power of HF.*

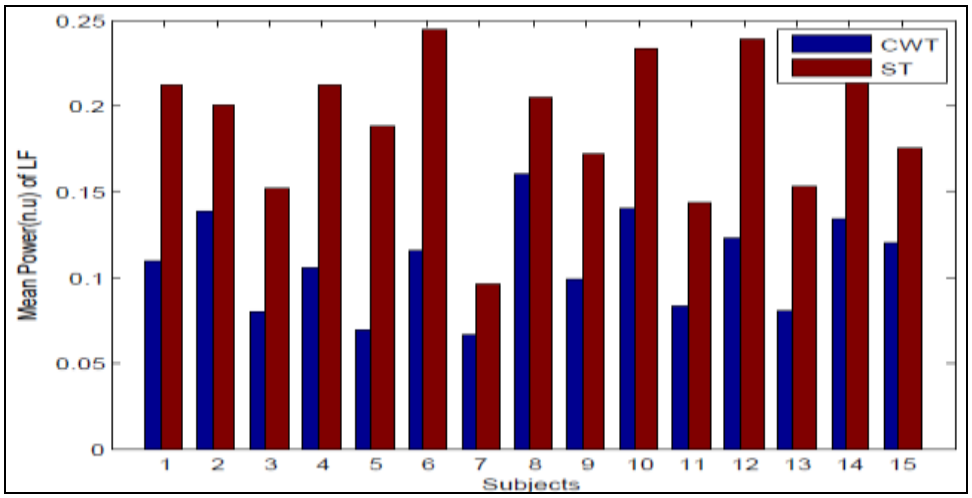

Fig. 2b. *Typical Bar Chart Comparison Plots of CMWT and ST Method for Normalized Mean Power of LF.*

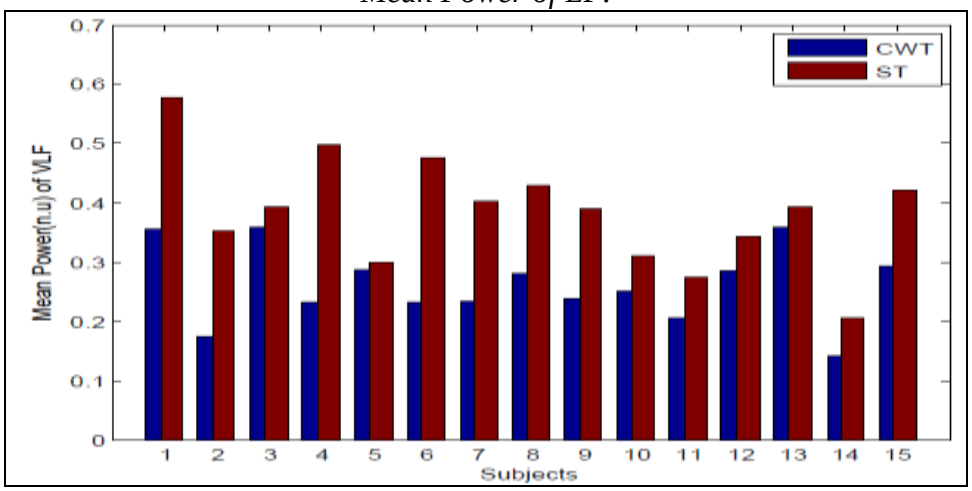

Fig. 2c. *Typical Bar Chart Comparison Plots of CMWT and ST Method for Normalized Mean Power of VLF.*

Figures 3(a)–(d) demonstrate the 3-D and contour plot of scalogram of the ST and CMWT. Where scalogram of ST has sufficient power resolution of LF and VLF components of each sample time series HRV signal but optimal frequency resolution for HF components of HRV signal compare to CMWT. The results are reported in Table 1, which show the improvement of mean normalized power in frequency range like VLF (0.004 to 0.04 Hz), LF (0.04 to 0.15 Hz) and HF (0.15 to 0.4 Hz) compare to CMWT method. The results show the mean normalized power improved compared to CMWT transform and correspond the subsequent statistical significance was measured using Student's *t*-test one tailed and unequal variance.

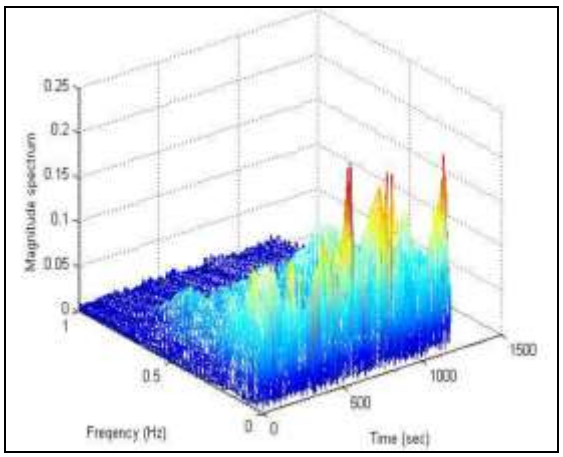

Fig. 3a. *3-D Plot of HRV Signal of CMWT.*

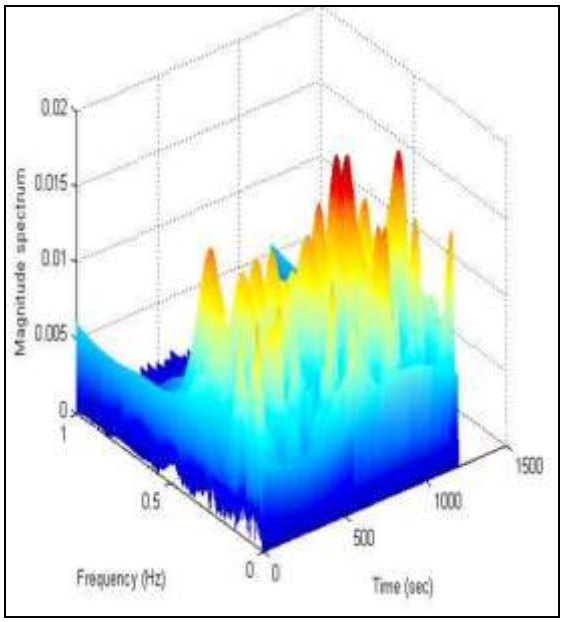

Fig. 3b. *3-D Plot of HRV Signal of ST.*

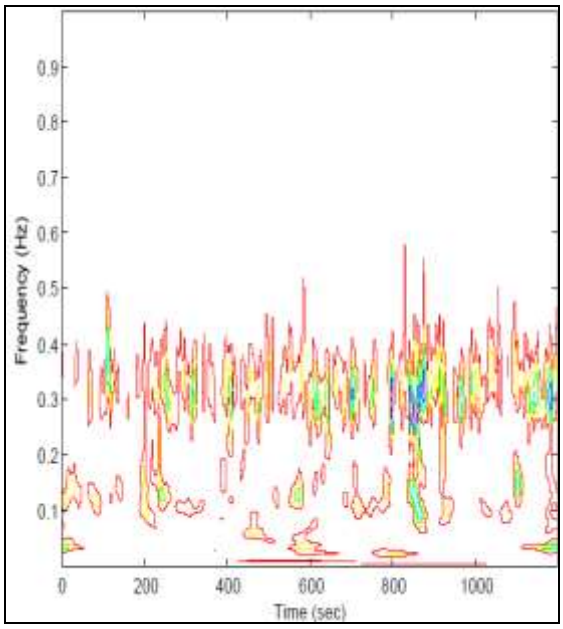

Fig. 3c. *Scalogram Contour Plot of HRV Signal of CMWT.*

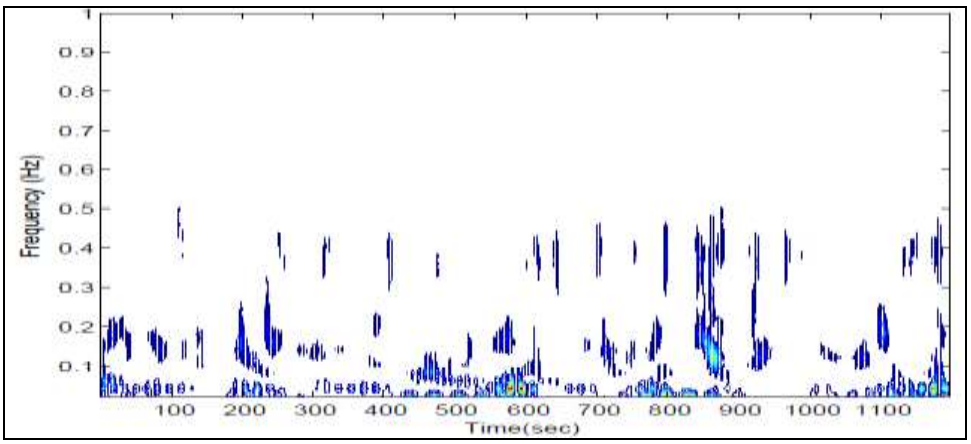

Fig. 3d. *Scalogram Contour Plot of HRV Signal of ST.*

The results are reported in Table 2, which show that improvement of total power resolution in frequency range like VLF, LF and HF compared to CMWT method. The results listed in Table 2 suggest, the average of total power improved compared to CMWT transform and correspondingly the subsequent statistical significance was measured using Student's *t*-test one tailed and unequal variance.

Table 1. *Mean ± SD of Power of being Frequency Range of HRV Signals for 15 Subjects Corresponding P-Value Using Student's t-Test (One-Tailed and Unequal Variance).*

Mean Norm. Power VLF (Mean ± SD)		**Mean Norm. Power LF (Mean ± SD)**		**Mean Norm. Power HF (Mean ± SD)**	
CMWT	**ST**	**CMWT**	**ST**	**CMWT**	**ST**
0.26209±0.06484	0.3843±0.09334	0.10869±0.02837	0.19033±0.0417	0.07698±0.02466	0.16751±0.05398
p=0.00016		P<0.00001		P<0.00001	

Table 2. *Mean ± SD of Total Power (**Sum of Each Normalized Coefficient of Power) of Being Frequency Range of HRV Signals for Fifteen Subjects Corresponding P-Value Using Student's t-test (One-Tailed and Unequal Variance).*

Total Power VLF (Mean±SD)		**Total Power LF (Mean±SD)**		**Total Power HF (Mean±SD)**	
CMWT	**ST**	**CMWT**	**ST**	**CMWT**	**ST**
606.42759±143.45336	883.26±182.795	254.32431±73.71199	444.04±107.33	177.45062±52.57516	387.64±122.726
P<0.00001		P<0.00001		P<0.00001	

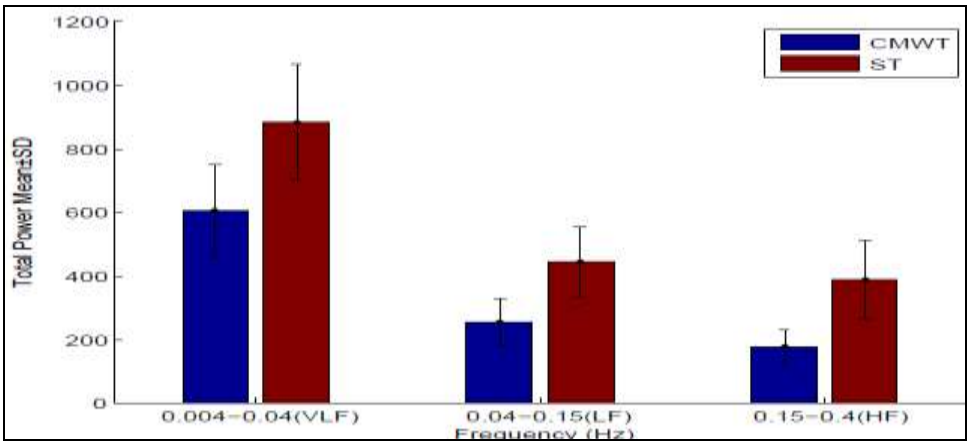

Fig. 4. *Bar Chart Represents the Comparative (Mean ± SD) Value of Total Power in Frequency Range (VLF, LF and HF) of HRV Signals.*

DISCUSSION

There are various signal processing tools to measure important information from HRV signals but for correct analysis the results should be analyzed properly.[37,38] In general, these signal processing tools can be divided in linear and nonlinear techniques. The linear group is subdivided into time domain, frequency domain analysis and time-frequency domain. The nonlinear techniques are based on chaos theory. Artifacts and outliers affect the sensitivity and specificity of the time domain methods.[39] Furthermore, it is probable that, one can have different R-R beat (HRV) signals with identical means and standard deviations.[40,41] Hence, time domain analysis is not practical to analyze the nonlinear and non-stationary as HRV signals. However HRV analysis in the frequency domain considered that the HRV signals are stationary and periodic. But, this assumption is not suitable for the HRV signals especially in case of long ECG recordings which show clear signs of nonlinearity. In analysis of HRV and multi-component signals, the time-frequency techniques are suitable signal processing tools to understand and analyze situation where the power content of HRV signals is changing with respect to time and frequency.

The normalization of the ST is a vital distinction from the wavelet approach. The unit area localizing function (the Gaussian) preserves the HRV power spectral response of the ST and ensures that the power spectral response of the ST is invariant to the frequency. The mean total power spectral is improved for all three of the components of HRV signals like VLF, LF and HF which is equal to 1.5, 1.74 and 2.18 times as compared to CMWT as shown in Table 2 and Figure 4 for statistical significance of ($p<0.00001$). The

ST returns the correct time frequency power spectral for all three components, shown in Figures 3(a)–(c) compared to CMWT time-frequency power spectral. In case of CMWT, the power spectrum is large for the lower frequencies, and diminishes as the frequency increases. This is due to the normalization of the wavelet transform but it does not happen in ST. This is because the ST combines frequency invariant amplitude, and absolutely phase properties and no side lobes in a Gaussian function of all these characteristics.[42] It is clear from our observation that all components of HRV are present and no attenuation of power in high frequency like CMWT method.

CONCLUSION

In this paper, we have applied concept of ST to enhance the power concentration of VLF, LF and HF of HRV signals in the time-frequency domain. The results have shown that the ST can significantly enhance the power of three frequency bands of HRV signals without attenuation of power of high frequency.

The improvement was observed for total mean power in VLF 1.5 times, LF 1.74 times and HF 2.18 times compared to CMWT method. The total mean power was generated from HRV signals and provides information related to the neural cardiovascular control and used full to clinical applications to predict accurate spectral power index altered of subjects suffering with ailments such as diabetes, hypertension, heart failure and heart disease.

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