# Stationary Segment Method to Localize and Estimate the Duration of the ANS Sympathetic and Parasympathetic Activities

A. BOUZIANE, B. YAGOUBI, and S. BENKRAOUDA

***Abstract*—** The heart rate variability (HRV) signals, extracted from an electrocardiograph (ECG) signal, are strongly linked to the activities of the Autonomous Nervous System (ANS). In this work, we propose a method to compute the duration of the two ANS activities; Sympathetic and Parasympathetic as well as observing their instantaneous evolution in time. The HRV signal in the low frequency and high frequency bands is, naturally, non stationary due to the non steady state of the sympathetic and parasympathetic behavior. We believe that a steady state or steady behavior of the ANS is, in fact, a stationary state of the HRV signal, and it is the result of one activity dominance only and not an alternation of both of the two activities. We have, therefore, segmented the HRV signal into stationary segments, and henceforth each of them was represented by Gaussian white noise whose variance is also its Power Spectral Density (PSD). We have obtained good duration estimation and localization of the two activities using stationary segments with 16 samples each.

***Keywords*—** Heart rate variability; stationary segment; fast Fourier transform; interpolation; Welch's method.

## I. Introduction

Heart rate variability (HRV) is a marker of sympathetic and parasympathetic influences on the modulation of heart rate [1].The heart rate may be increased by slow acting sympathetic activity or decreased by fast acting parasympathetic (vagal) activity. The heart rate is given by the reciprocal of the RR-interval (inter-beat) in units of beats per minute. In the literature spectral analysis of the RR tachogram is typically used to estimate the effect of the sympathetic and parasympathetic modulation of the RR-intervals. The two main frequency bands of interest are referred to as the Low-Frequency (LF) band (0.04 to 0.15 Hz) and the High-Frequency (HF) band (0.15 to 0.4 Hz) [1]. Sympathetic tone is believed to influence the LF component whereas both sympathetic and parasympathetic activities have an effect on the HF component [2], with the priority of the parasympathetic activity. To localize these activities and estimate their duration, the power spectral density (PSD) cannot be used because it can only indicate the overall dominance of one activity over the other but it does not show when this dominance occurs and how long it lasts due to the PSD lack of information in the time. To overcome this problem, wavelets have been used due to their time frequency (scale) dependency [3,…,6]. However, despite their global consistency and their interesting results, difficulties in their implementation and the choice of an adequate wavelet may hamper their performances. To find the duration and the localization of the two ANS activities, we suggest, therefore, in this paper an alternative and simple method based on a segmentation of the HRV signal into small stationary segments modeled by a Gaussian white noise [7].

This work was supported in part by the faculty of Science and Engineering, University of Mostaganem, Algeria.

A. Bouziane is with the Laboratory of signals and systems, University of Mostaganem, Algeria ( e-mail: bouziane. Ahmed113@hotmail.fr).

B. Yagoubi is with the Department of Electrical Engineering and Laboratory of signals and systems, University of Mostaganem, Algeria (phone: 213 73689585, e-mail: yagoubibenabdellah@yahoo.com).

S. Benkraouda is with the Laboratory of Signals and Systems, University of Mostaganem, Algeria (e-mail: slimane95100@hotmail.com).

## II. Data Collection

The analyzed data in this paper were obtained from a Fantasia Database in *MIT-BIH* arrhythmia *database [8*]. This collection consists of 10 heart beat time series; 5 young (Y) subjects and 5 old (O) subjects rigorously screened healthy subjects underwent 120 min of continuous supine resting electrocardiograph (ECG) test. We analyzed the inter-beat interval time series using frequency domain. All subjects remained in a resting state in sinus rhythm while watching the movie Fantasia (Disney, 1940) to help maintain wakefulness. In this study, our analyses were based on only the R-R interval, the continuous ECG was digitized at 250 Hz. Each heartbeat was annotated using an automated arrhythmia detection algorithm. The R-R interval (inter-beat interval) time series for each subject was then computed. The characteristics of each subject are shown in Table 1.

Table 1: Characteristics of each subject

| | Y 1 | Y 2 | Y 3 | Y 4 | Y 5 | O 1 | O 2 | O 3 | O 4 | O 5 |
|---|---|---|---|---|---|---|---|---|---|---|
| Age | 23 | 28 | 34 | 31 | 23 | 77 | 73 | 73 | 81 | 76 |
| Sex | F | F | M | M | M | F | F | M | M | M |

## III. Methods

### 3.1 Gauss approximation

The principle is based on dividing the HRV signal into several segments of even length (number of RR intervals or sample). Figure .1 shows a non stationary HRV signal. We can see in this figure that the interval [8 72] is non stationary because it is very long (64 samples). However, if we focus on a small interval of the same signal, then the curvature may not vary too much and, thus, it could be considered as approximately constant [7]. This is particularly illustrated in figure .2 by the small interval [8 24] (16 samples).

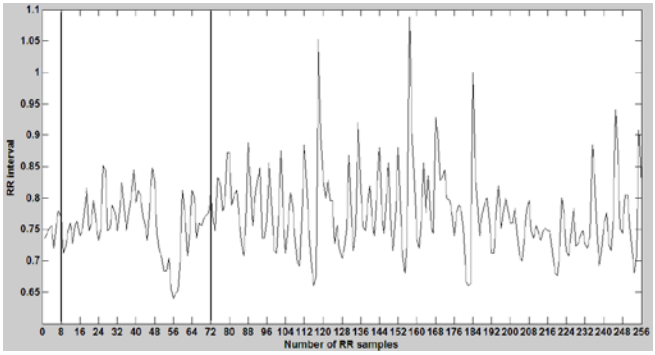



Fig.1: Non stationary signal, the interval [8, 72] is very large, hence non stationary.

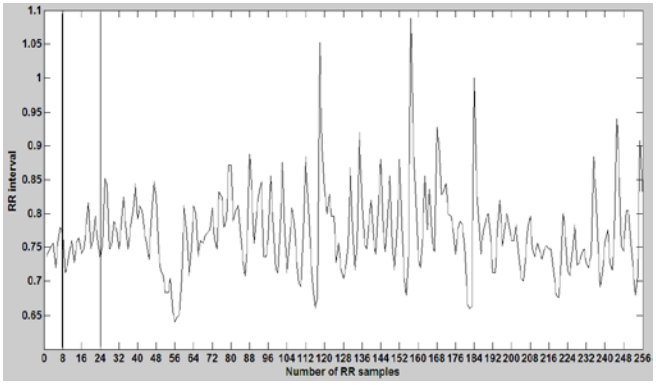



Fig.2: Non stationary signal, the interval [8, 24] is small enough to be considered as stationary.

This approximation is known as Gauss approximation. It is possible, therefore, to divide the signal into many small stationary intervals. The latter were, in addition, modeled by a Gaussian model.

### 3.2 Spectral analysis

The goal of our spectral analysis is to make a separation between the two autonomic nervous system activities for each interval; the main idea is that over a short period of time, the autonomic nervous system is under the dominance of either the sympathetic activity or the parasympathetic activity and not an alternation of both activities.

The time series constructed from all available RR intervals is clearly not equidistantly sampled, but has to be presented as a function of time, i.e. as values [t(i),RR(i)], and we know that the regular PSD estimators implicitly assume equidistant sampling and thus, the RR interval series is converted to equidistantly sampled series by interpolation methods prior to PSD estimation [9]. In the analysis of the HRV, three main alternatives have been used to get around this problem: a) by assuming that HRV signals to be evenly sampled, b) by using direct spectral estimation methods from the irregular sampled signal and c) by using interpolation methods to recover an evenly sampled signal from the irregularly spaced samples prior to the PSD estimation [6].

Various spectral methods [11] have been applied since the late 1960s. Although the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology [1] provided an extensive overview of HRV estimation methods and the associated experimental protocols in 1996. The PSD estimation is generally carried out using either Fast Fourier Transform (FFT) methods or Auto-regressive (AR) modeling methods. In the literature the use of the FFT with linear or cubic spline interpolation for beat replacement and re-sampling are considered standard methods for spectral HRV analysis [10]. Therefore in this work, the HRV spectrum is calculated with FFT based on cubic spline interpolation method, where the sampling rate of the interpolation is equal to 4Hz.

To compute the PSD, we have used Welch Periodogram method for some advantages such as reducing the number of calculations and basic storage requirements, and practical application in the non-stationary test [12].

The Welch Periodogram is a method by which a large time-sampled waveform can be frequency-transformed by partitioning the data into shorter segments, transforming each segment, then, averaging the results over all the segments to create a composite frequency-space waveform as described in [13]. In order to create a PSD profile, window sizes and overlap size need to be considered [14], in our case, we have chosen the value of the window (number of samples) equal to the width of the interval obtained by the Gaussian approximation combined with the cubic spline interpolation. The problem of using data segments is that taking FFTs of various data segments can introduce discontinuities at the segment boundaries or edges. To reduce these spurious components, a windowing function tapers the data down to zero at each end of the data segments. The window is multiplied by the data segment and has a width equal to the segment length [15].

## IV. Results and Discussion

The aim is to obtain stationary segments of even length from the HRV signal and each of them can be represented by a Gaussian white noise model [7]. The number of these intervals and the adequate model depend on how the reconstructed version is close to the original HRV signal. We have, therefore, plotted in each of the following figures, the original

HRV signal and its reconstructed version. We have, in addition, calculated the mean square error (MSE) between each original and its corresponding reconstructed signal for four different numbers of intervals. These results obtained for HRV signal of 512 samples, are presented in Table 2.

Table 2: MSE for different numbers Ni of intervals in each of the ten HRV signals

| Subjects | MSE (Ni=4) | MSE (Ni=8) | MSE (Ni=16) | MSE (Ni=32) |
|---|---|---|---|---|
| Young1 | 0.0094 | 0.0084 | 0.0096 | 0.0099 |
| Young2 | 0.0125 | 0.0127 | 0.0138 | 0.0117 |
| Young3 | 0.0075 | 0.0051 | 0.0046 | 0.0037 |
| Young4 | 0.02 | 0.0179 | 0.0183 | 0.0145 |
| Young5 | 0.0047 | 0.0048 | 0.004 | 0.0043 |
| Old1 | 0.0023 | 0.0024 | 0.0019 | 0.0012 |
| Old2 | 0.0005 | 0.0005 | 0.0004 | 0.0003 |
| Old3 | 0.0021 | 0.0023 | 0.0021 | 0.001 |
| Old4 | 0.0048 | 0.0043 | 0.0044 | 0.003 |
| Old5 | 0.001 | 0.0008 | 0.0007 | 0.0004 |

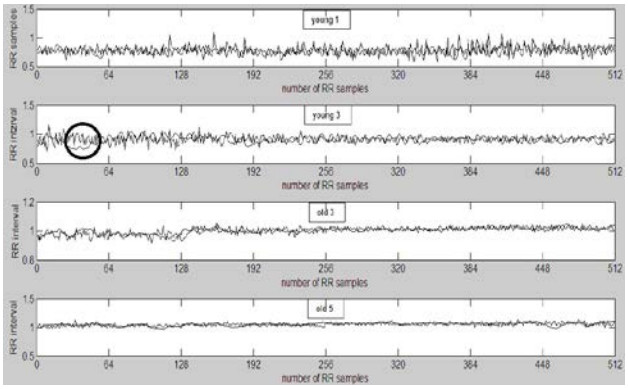



Fig.3: HRV signal with their reconstructed signal, for a number of intervals Ni=4

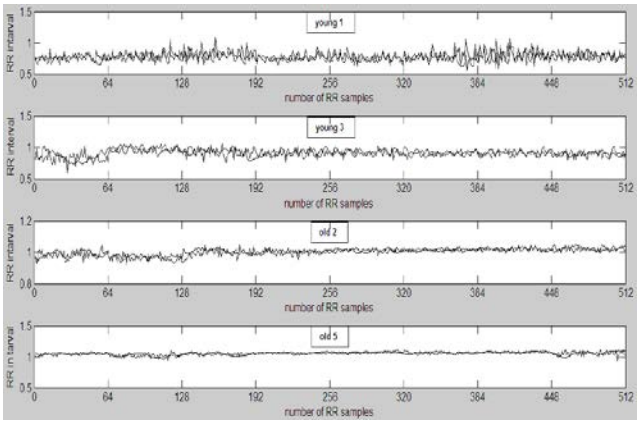



Fig. 4. HRV signal with their reconstructed signal, for a number of intervals Ni=8

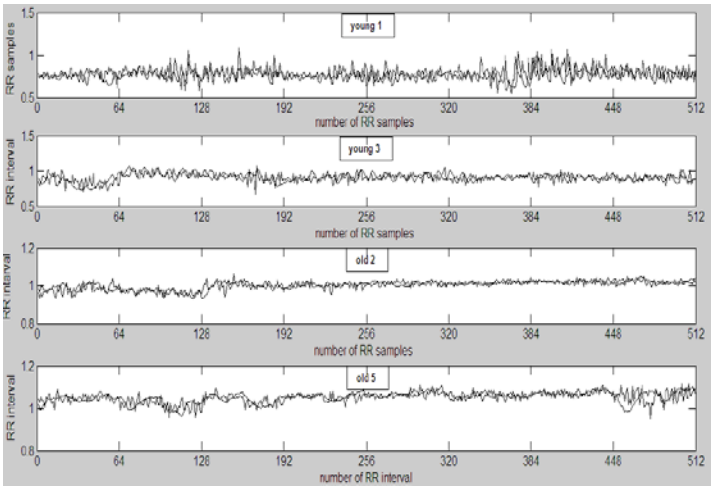



Fig.5 HRV signal with their reconstructed signal, for number of intervals Ni=16.

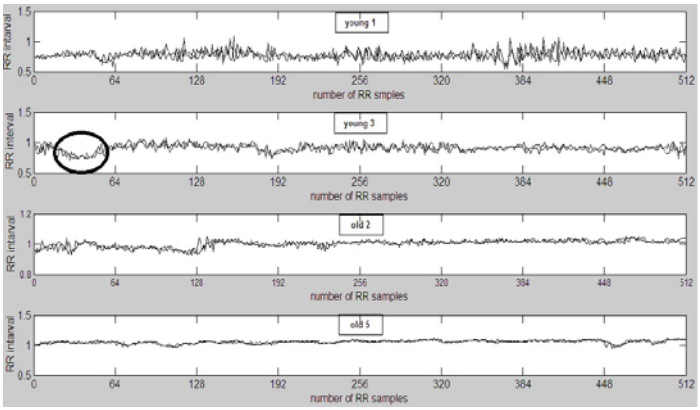


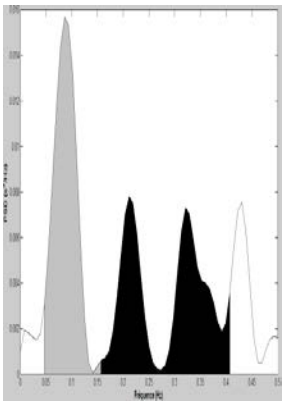

Fig. 6. HRV signal with their reconstructed signal, for number of intervals Ni=32

We have plotted in each of the previous 3 to 6 figures, four original HRV signals and their corresponding reconstructed versions using our Gaussian white noise approach. In order to see the quality of this approximation, we have presented the results corresponding to ¶two young and two old only.

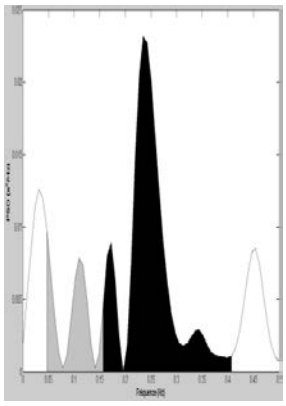
The aim is to obtain stationary intervals in the HRV signal such that the reconstructed HRV from these intervals should represent its original version as good as possible. Once this is achieved, the interval duration should be, roughly, that of any steady HRV behaviour. So, to obtain the best reconstructed HRV to the original version, we have reduced gradually the interval length by dividing the HRV into more many intervals as indicated in figures 3,4,5,6. Initially looking at figure 3 (look in the circle) we can say that there is a large difference observed between the two signals (original and reconstructed). This error is in fact due to the length of the interval (4 intervals so there are 128 samples in each interval) since it is not stationary. However we see that when the interval length is more reduced by dividing each signal into 8 intervals (fig. 4), the reconstructed signal is getting closer to the original signal but there is still a significant difference. In figure 5, we can say that there is a significant improvement; the two signals are

closer. In figure 3, corresponding to 8 intervals in the case of young 3 represented by the second curve from the top, we can say that there is a slight difference between the HRV signal and its reconstructed version whereas in figure 6, corresponding to 32 intervals, the two signals are almost concurrent ( see in the circle). This can be, further, clarified by the mean square error (MSE) given in Table 2. Notice that the size of the vector representing the Gaussian model in each case is (2xNi), while the original vector size is 512. (2xNi) is the number of the model parameters; the variances and mean values. After setting the previous parameters, described in the paragraph 3.1, we now proceed to calculate the PSD but according to The European and North American Task force on standards in HRV [1] which suggested that the shortest time period over which HRV metrics should be assessed is 5 minutes. As a result, the lowest frequency that can be resolved is 1/300≈0.003Hz (just above the lower limit of the VLF region). On the other side, we are only interested to low and high frequency which can be determined in the interval [0.04 0.4] to study the sympathetic and parasympathetic activities. So we can reduce the interval length if it is desired. With the result obtained in 3.1 we have chosen to work with only the value of Ni=16 and Ni = 32 since they present the best results in terms of the error and also the duration of the interval. For practical reasons, we can't present the simulations of the PSD for each interval in the two cases (Ni = 16, Ni = 32) and for 10 subjects, for this reason, we choose to do the calculations for every subject, but we simulate just 4 PSDs for the subject Young 3 in both cases (Ni = 16, Ni = 32).

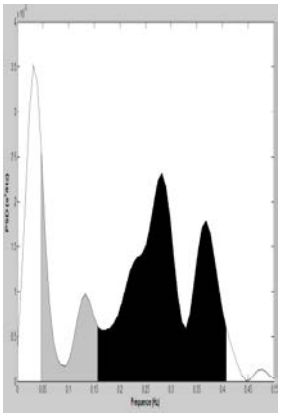
We can notice in figure 7 corresponding to Ni=16 (segments less stationary), that there are alternation of dominance of the two activities, whereas in figure 8 with Ni=32 (segments more stationary), we can observe that there is only one dominant activity and no alternation of both. This is, indeed, a fairly firm confirmation that our suggestion based on stationary segments method for estimating the duration as well as localizing the ANS activities, is more accurate and efficient than the wavelet method. The main problem, however, lays in the fact that the lowest frequency that can be resolved is best when the signal is divided into 16 intervals (long and less stationary) according to Heisenberg Principle. This is mainly due to the fact that in this interval, the shortest time for the ten subjects is equal to 23.7920s, indicating that the lowest frequency that can be resolved is 1/ 23.792≈ 0.042Hz, whereas in the case of 32 intervals, the shortest time is equal to 11.388, which means that the lowest frequency that can be resolved is 1/ 11.38≈ 0.0878Hz. As it is known the peak of the LF wave is approximately situated around 0.1Hz [16], hence we can detect this wave in the two cases. In order to choose the necessary and adequate number of intervals, we must balance the requirement of stationary versus the time required to resolve the information that is present. We have, therefore, chosen to make the temporal estimation with Ni=32 segments.



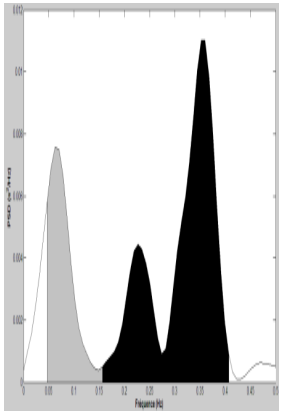
a) Interval number =4



b) Interval number =8

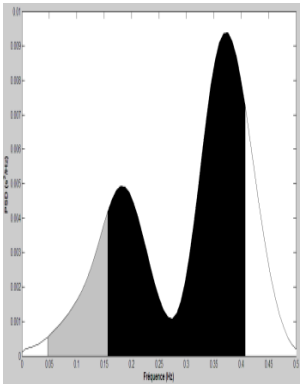


c) Interval number =12

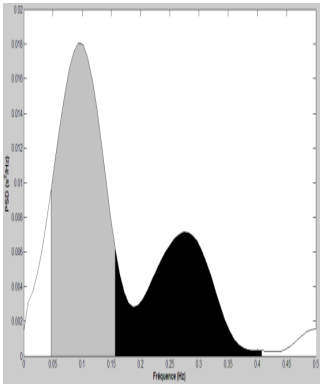


d) Interval number =16

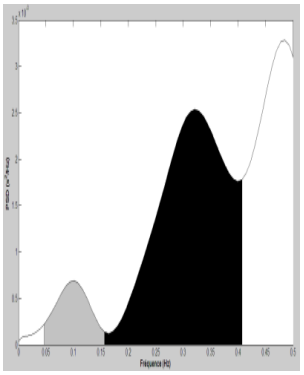
Fig. 7. The PSDs in the case Ni=16



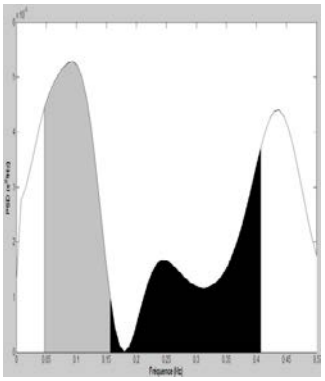
a) Interval number =8



b) Interval number =16



c) Interval number =24



d) Interval number =32

Fig. 8. The PSDs for the case Ni=32.

To determine the duration of the sympathetic nerve activity or the parasympathetic, we compute the PSD in each interval, and since the duration of each interval is short, then we consider that each interval is under the influence of the sympathetic nerve activity if the peak LF > peak HF and under the influence of the parasympathetic activity if the peak HF > peak LF. For example in the figure 8b (Interval number =16) the sympathetic nerve activity (grey curve) is dominant, whereas in figure 8a, the parasympathetic effect is clearly dominant (dark curve). Overall activity dominance duration for each subject is shown in table 3.

Table 3: Duration of time of the two activities and for the ten subjects

| | Total duration | Duration of sympathetic activity | Duration of the parasympathetic activity |
|---|---|---|---|
| Y 1 | 395.464 | 111.288 | 284.176 |
| Y 2 | 501.964 | 155.564 | 346.4 |
| Y 3 | 465.364 | 103.008 | 362.356 |
| Y 4 | 676.888 | 273.44 | 403.448 |
| Y 5 | 494.208 | 108.336 | 385.872 |
| O 1 | 498.392 | 155.272 | 343.12 |
| O 2 | 513.4 | 128.008 | 385.392 |
| O 3 | 495.688 | 141.976 | 353.712 |
| O 4 | 597.716 | 147.828 | 449.888 |
| O 5 | 537.988 | 117.896 | 420.092 |

We observe in table 3 that for the ten subjects most of the duration of the test is influenced by the parasympathetic activity. This is, probably, due the fact that the subjects watching a movie, are at rest. We have illustrated, in figure 9, the evolution of both activities (sympathetic and parasympathetic) corresponding respectively to LF and HF PSD peaks.

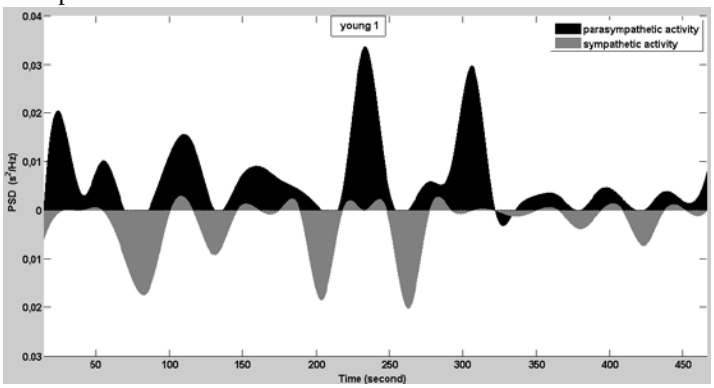



Fig.9 Temporal localization of the PSD for LF and HF peaks (y1)

The most important information, given by this example, is the temporal localization of the influence of the two autonomous nervous system activities. This localization is useful to link the activity to the external cause. We note here that we applied a cubic spline interpolation with freq = 16 Hz, and each graph is a mixture of the PSD of HF peaks (above) and LF peaks (below).

## V. Conclusion

We have proposed a method to estimate the duration of the ANS sympathetic and parasympathetic behaviours as well as localizing them in time. This method is based on dividing the HRV signal into stationary Gaussian white noise even segments. This localization in time is useful to link, accurately, a specific activity to its corresponding external cause. Furthermore, this method can be used, particularly in psychological problems, to observe the behaviour of individuals in real time.

## References

[1] *Task Force of the European Society of Cardiology, the North American Society of Pacing, and Electrophysiology, "Heart rate variability: standards of measurement, physiological interpretation, and clinical use", Circulation,* 93:1043-1065.

[2] M. Malik and A. J. Camm, Heart Rate Variability, Futura Publishing, Armonk, *NY*, 1995.

[3] R. Kher, T. Pawar, V. Thakar. Comparative Analysis of PCA and Wavelet based Motion Artifact Detection and Spectral Characterization in W-ECG. *WSEAS TRANSACTIONS on SIGNAL PROCESSING*, vol.10, pp. 116-123, 2014.

[4] P.A. Kharat, S. V. Dudul. *Daubechies* Wavelet Neural Network Classifier for the Diagnosis of Epilepsy. *WSEAS Transactions on Biology and Biomedicine*, vol. 9(4), pp. 103-113, 2012.

[5] Chin-Feng Lin, Shan-Wen Yeh, Yu-Yi Chien,T Peng, J. Wang, S. Chang. A HHT-based Time Frequency Analysis Scheme in Clinical Alcoholic EEG Signals. *WSEAS Transactions on Biology and Biomedicine*, vol. 5(10), pp. 249-260, 2008.

[6] U. Wklund, M. Akay and U. Niklasson, "Short-term analysis of heart-rate variability by adapted wavelet transforms.", *IEEE Eng. Med. Biol*, 1997, 16(5) pp. 113-138

[7] P.A. Kharat, S. V. Dudul. Daubechies Wavelet Neural Network Classifier for the Diagnosis of Epilepsy. *WSEAS Transactions on Biology and Biomedicine*, vol. 9(4), pp. 103-113, 2012.

[8] Chin-Feng Lin, Shan-Wen Yeh, Yu-Yi Chien,T Peng, J. Wang, S. Chang. A HHT-based Time Frequency Analysis Scheme in Clinical Alcoholic EEG Signals. *WSEAS Transactions on Biology and Biomedicine*, vol. 5(10), pp. 249-260, 2008.

[9] U. Wklund, M. Akay and U. Niklasson, "Short-term analysis of heart-rate variability by adapted wavelet transforms.", *IEEE Eng. Med. Biol*, 1997, 16(5) pp. 113-138.

[10] B. Yagoubi ; "A geometric approach to a non stationary process" ; *Proceedings of the 2nd international conference on Mathematical Models for Engineering Science ;* Pages 179-183.

[11] *http://www.physionet.org/physiobank/database/fantasia/*

[12] Clifford, G.D. and Tarassenko, L,"Quantifying errors in spectral estimates of HRV due to beat replacement and resampling". *IEEE Trans. Biomed. Eng.* v52 i4.630-638.

[13] Mateo J, Laguna P, "Improved heart rate variability signal analysis from the beat occurrence times according to the ipfm model". *IEEE Trans Biomed Eng* 2000; 47(8):985–996.

[14] Kay SM, Marple SL. "Spectrum analysis: a modern perspective". *Proc IEEE.* 1981;69:1380-1419.

[15] Welch, P.D. "The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms", *IEEE Trans. Audio Electroacoust.* Vol. AU-15, Pgs. 70-73, June 1967.

[16] http://www.wavemetrics.com/Products/IGORPro/dataanalysis/signalprocessing/powerspectra.htm

[17] J. Niskanen, M.P. Tarvainen, P.O. Ranta-aho P.A. Karjalainen, *"Software for advanced HRV analysis", Comput. Meth. Prog. Biomed.*,76 (2004) 73–81.

[18] http://www.engr.uky.edu/~donohue/ee422/Lab2_EE422.doc

[19] McSharry P.E., Clifford G.D., Tarassenko L., Smith L., "A dynamical model for generating synthetic electrocardiogram signals", *IEEE Transactions On Biomedical Engineering*, 50(3), 289-294, March 2003.