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ESTIMATION OF CENTRAL NERVOUS SYSTEM ACTIVITY BY DATA MINING NORMAL SINUS-ECG RHYTHMS

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ABSTRACT

In this study, we propose a method to assess central nervous system activity in terms of activity-degree in sympathetic and parasympathetic state by estimating the cardiac oscillator-parameters of Integral Pulse Frequency Modulation (IPFM) model in which the artificial heart rhythms are generated by modulating sinusoid signal with applying the threshold level for resolving R-peaks. With this aim, we proposed a modified IPFM model by the empirical method with applying preset-threshold of unity. The artificial R-R interval data are analyzed by the time and frequency-domain features to describe Heart Rate Variability (HRV) under the effects of cardiac oscillator constants. The benchmarking MIT/BIH database consisted of Normal Sinus Electrocardiogram rhythms (NSR-ECG) are utilized to estimate the sympathetic and parasympathetic constants by comparing HRV measures on MIT/BIH NSR with those on the data generated by our modified IPFM model. Based on our experimental results on estimating the modulatory parameters of central nervous system activity, we can conclude that IPFM parameters on the real ECG data can be effectively estimated to assess cardiac-sympathetic and parasympathetic activity.

Keywords: *Electrocardiogram (ECG), Heart Rate Variability (HRV), Integral Pulse Frequency Modulation (IPFM), Autonomic Nervous System (ANS), sinus rhythm, Poincare plot.*

1. INTRODUCTION

Many biomedical measurements are influenced by the balance of autonomic nervous system (ANS) in terms of sympathetic and parasympathetic nerve activity [1]. The Electrocardiogram (ECG) also reflects the activities of two subsystems by revealing the variability in the time between successive heart beats. The prominent fiducial feature in ECG for estimating heart rate is R-peak wave and Heart Rate Variability (HRV) analyses the variability in R-R intervals [2],[3],[4]. Mathematical models for generating the artificial R-R intervals have been suggested to estimate the effects of autonomic nerve activity. Integrate Pulse Frequency Modulation (IPFM) model [5],[6],[7] aimed to produce heart beat-to-beat fluctuations by integrating the modulated sinusoid signals with the coupled-oscillating coupling constants: sympathetic oscillator, C_s and parasympathetic oscillator, C_p. The effects of coupling parameters were investigated by interpreting time-domain or power spectrum features of HRV applied on the artificially generated heart-beats [8]. However, none of the proposed IPFM models offered a method to estimate the values of C_s and C_p based on the ECG data obtained from the real cardiac patients. With this aim, a new IPFM model is proposed with applying preset-threshold of unity to generate R-R intervals and then the time and frequency-domain features of HRV on the simulated time series are computed with varying cardiac oscillator parameters, C_s and C_p. In order to validate the proposed IPFM model, PhysioBank MIT-BIH benchmarking-ECG database [9],[10] that consists of Arrhythmia and Normal Sinus-ECG rhythms (NSR) obtained from the real cardiac patients was considered to assess the effects of sympathetic and parasympathetic constants by comparing HRV measures on NSR with the features on the simulated data generated by the modified IPFM model.

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2. MATHEMATICAL MODEL FOR GENERATING ARTIFICIAL HEART BEATS

The IPFM model simulates heart-beat fluctuations, *m(t)* by modulating sinusoidal signal coupled with sympathetic and parasympathetic oscillator constants, C_s and C_p as illustrated in Figure 1 and equation (1) [11]:

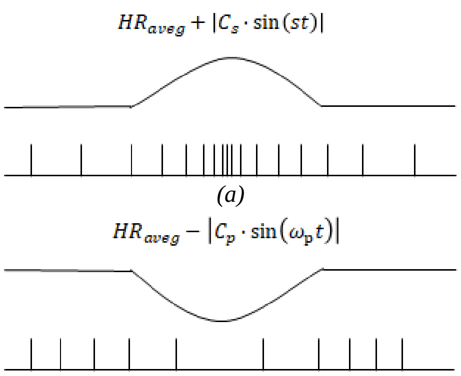

Figure 1: The role of C_s and C_p for modulating sinusoidal signal.

$$m(\mathrm{t}) = C_s \cdot \sin(\omega_s t) + C_p \times \sin(\omega_p t) \quad (1)$$

$$HR_{aveg} \gg \frac{\omega_p}{2\pi} > \frac{\omega_s}{2\pi} \quad (2)$$

, where ω_p, ω_s are oscillating frequencies for modulating virtual cardiac control system and HR_{aveg} denotes the average time-duration between heart beats. The output of IPFM model is a series of pulses, t_k's where each of amplitude exceeds the predefined threshold value of unity as shown in Figure 2 [11].

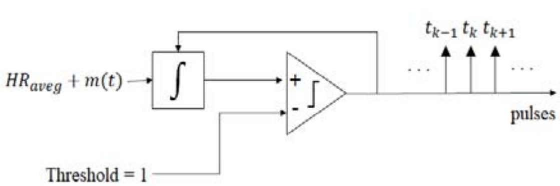

Figure 2: Block diagram of IPFM model.

A typical power spectrum of HRV has three frequency ranges: very low frequency (VLF) (0 ~ 0.04 Hz), low frequency (LF) (Mayer waves, 0.04 ~ 0.15 Hz) and high frequency (HF) range (RSA waves, 0.15 ~ 0.04 Hz) (Figure 3) [12].

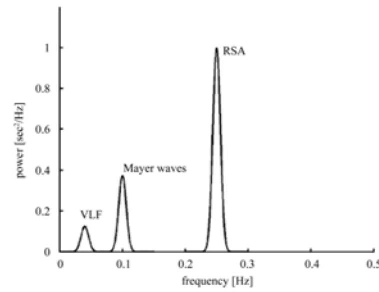

Figure 3: Three-main waves in the power spectrum of HRV.

Attarodi et al. [6] proposed IPFM integral-model using four inputs of sinusoidal signals to simulate three-prominent peaks in the power spectrum of HRV. However, this IPFM model yielded the power spectrum of HRV with some spectral leakages between main waves. Thus, we propose an empirical IPFM model by employing data mining approach on MIT-BIH database.

$$HR_{aveg} + m(\mathrm{t}) = HR_{aveg} + |C_s \cdot \sin(\omega_1 t)| + \frac{C_s + C_p}{8} \cdot \sin(\omega_2 t) + |C_p \cdot \sin(\omega_3 t)| \quad (3)$$

Here, HR_{aveg} was estimated by the average value of R-R intervals with considering NSR database: MIT-BIH record: 16265, 16272, 16273, 16240, 16483, 16539, 16773, 16786, 16795, 17052, 17453, 18177, 18184, 19088, 19090, 19093, 19140 and 19830. Each record contained 20 ~ 22 hours ECG measurements sampled with 360 Hz. The proposed IPFM model generates the simulated R-wave of the ECG signal when the output of integrator reaches the threshold value of unity. Figure 4 shows the power spectrum of HRV signals based on the proposed IPFM model by exemplifying the oscillator constants:

(a) $C_s = 0.06$, $C_p = 0.34$

(b) $C_s = 0.1$, $C_p = 0.1$

(c) $C_s = 0.5$, $C_p = 0.1$

, with $\omega_1 = 2\pi \cdot 0.01$, $\omega_2 = 2\pi \cdot 0.1$, $\omega_3 = 2\pi \cdot 0.15$ and $HR_{aveg} = 1.27$sec, respectively.

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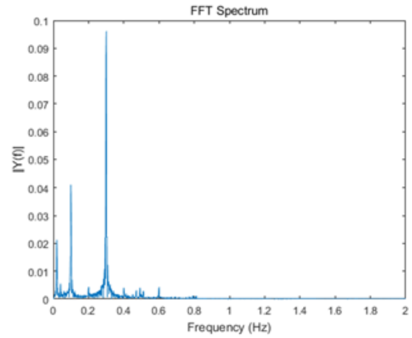
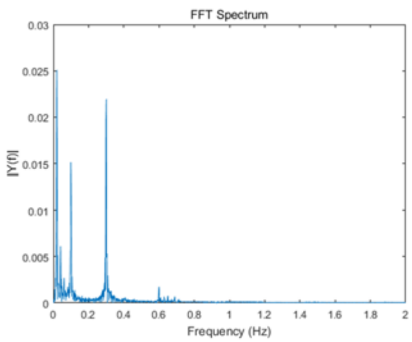


(a)



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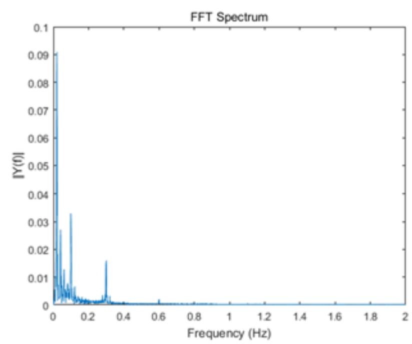

(c)

Figure 4: Power spectrum of HRV signal based on our proposed IPFM model, (a) $C_s = 0.06$, $C_p = 0.34$, (b) $C_s = 0.1$, $C_p = 0.1$, (c) $C_s = 0.5$, $C_p = 0.1$.

3. HRV MEASURES FOR ESTIMATING THE OSCILLATOR PARAMETERS OF ROPOSED IPFM MODEL

In order to evaluate the roles of C_s and C_p in the proposed IPFM model as expressed in equation (3), we selected time-domain and power spectrum measures as summarized in Table 1. Here, Poincare plot represents the geometrical pattern of R-R time series on Cartesian plane by visualizing the correlation between consecutive R-R intervals [13]. Also, Welch-LF/HF, Burg-LF/HF and Lomb-LF/HF imply the ratio of LF and HF power spectrum computed by Welch, Burg and Lomb's periodogram processing method, respectively [14]. For our computations of HRV measures, we applied HRVAS (HRV Analysis Software) open source Matlab library which was developed to analyze HRV features [15].

Table 1: HRV measures selected for estimating the parameters of autonomic nervous activity [16].

Variable	Units	Descriptions
SDNN	ms	The standard deviation of all normal beat to normal beat (NN) intervals.
SDNN index	ms	Mean of the standard deviations of all NN intervals for all 5 min segments of the entire recording
SDANN	ms	The standard deviation of the average of NN intervals in all 5 min segments of the considered ECG recordings.
RMSSD	ms	The square root of the mean of the sum of the squares of differences between the adjacent NN intervals.
NN50	-	Number of pairs of adjacent NN intervals differing by more than 50 ms in the ECG recordings.
pNN50	%	NN50 counts divided by the total number of all NN intervals.
SD_1	ms	The standard deviation of the perpendicular distance to the line of identity in Poincare plot.
SD_2	ms	The standard deviation of the distance along to the line of identity in Poincare plot.
Welch-LF/HF	-	The ratio of LF and HF spectrum in HRV by Welch Power Spectrum estimation.
Burg-LF/HF	-	The ratio of LF and HF spectrum in HRV by Burg Power Spectrum estimation.
Lomb-LF/HF	-	The ratio of LF and HF spectrum in HRV by Lomb Power Spectrum estimation.

4. EXPERIMENTAL RESULTS AND ANALYSIS

For the experimental simulations, we adopted the eighteen sets of NSR and each HRV signal is computed based on non-overlapping ECG data segment of five minutes duration. HRV measures as specified in Table 1 were calculated and compared with the corresponding HRV feature on the artificial R-peaks by increasing or decreasing C_s and C_p value with using a scale of 0.01. The computing range of C_s is from 0 to 1 and the scope of C_p is from 0 to 0.5. Figure 5 shows the computed HRV features based on our proposed mathematical model for generating artificial heart beats.

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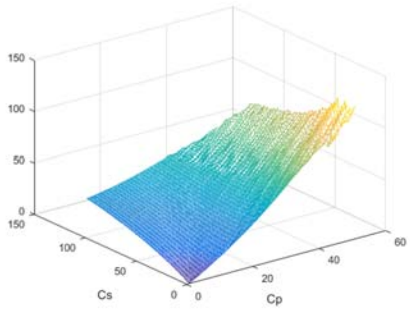
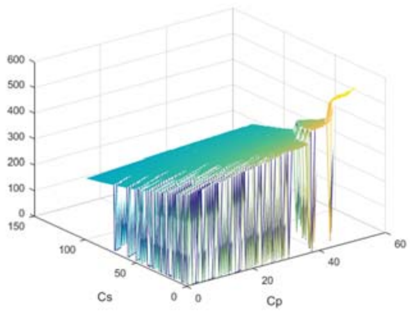
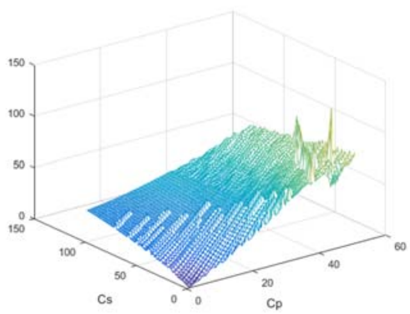


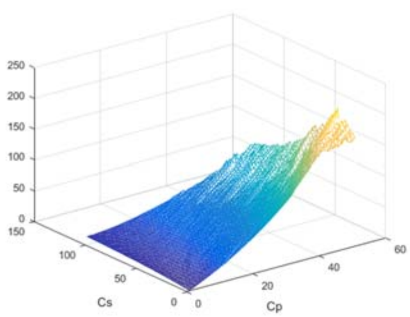
(a) SDNN



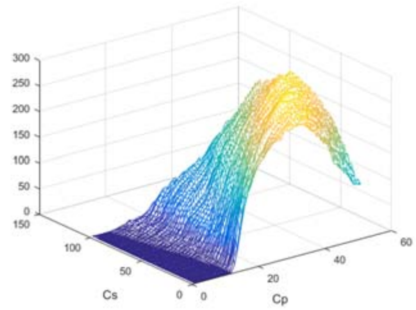
(b) SDNN index



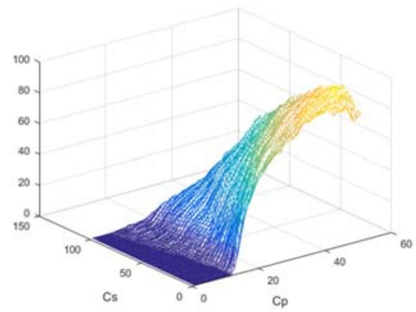
(c) SDANN



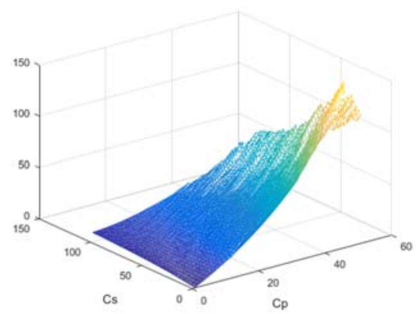
(d) RMSSD



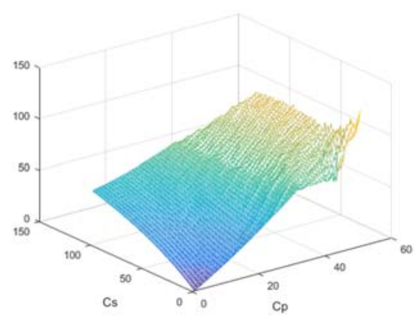
(e) NN50



(f) pNN50



(g) SD_1



(h) SD_2

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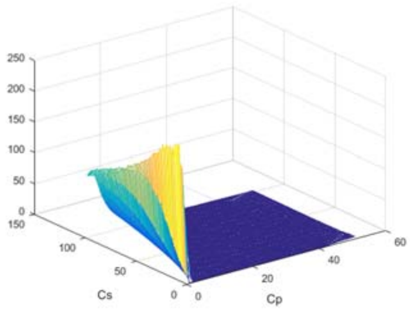
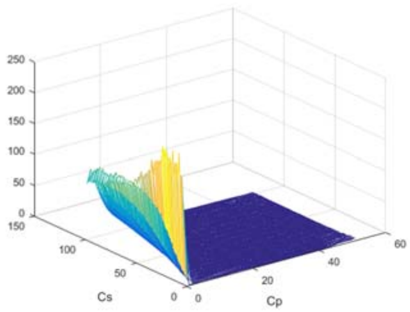
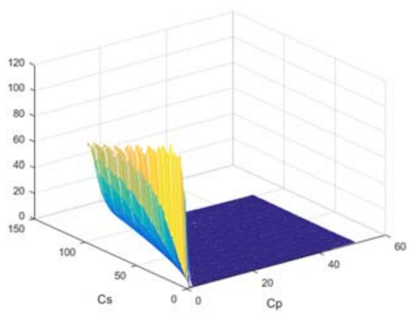


(i) Welch-LF/HF ratio



(j) Burg-LF/HF ratio



(k) Lomb-LF/HF ratio

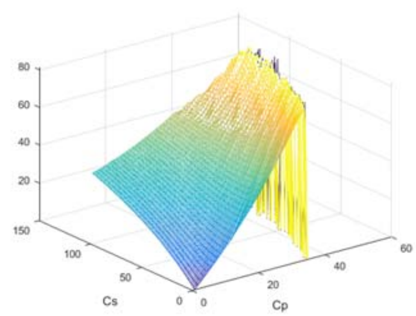
Figure 5: The computed HRV measures on the artificial heart beats. The index represents the scaled version (100 times) of actual values of C_s and C_p. In other words, C_s (C_p) ranges from 0 to 1.0(0.5) with increasing by 0.01.

Similarly, we calculated HRV features using the MIT-BIH NSR database and tried to eliminate the outliers by applying Interquartile-range (IQR) statistical analysis [17]. Table 2 shows the HRV features which exists in the range of Q_1-1.5·IQR ~ Q_3+1.5·IQR, where Q_1 and Q_3 denote the first quartile and third quartile of the total range, respectively.

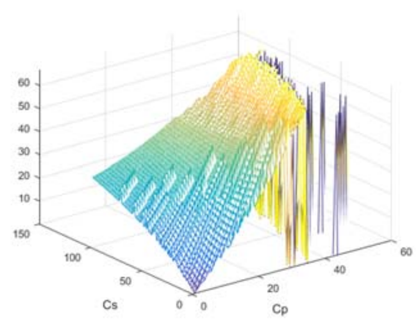
Table 2: HRV features resulted from applying IQR analysis on MIT-BIH NSR dataset.

HRV Features	Maximum value	Minimum value
SDNN	81.5	-3.3
SDANN	66.9	-1.9
RMSSD	76.85	-8.35
NN50	179	-85
pNN50	53.1	-26.1
SD_1	54.45	-5.95
SD_2	101.5	-4.1
Welch-LF/HF	8.552	-3
Burg-LF/HF	8.9745	-3.4375
Lomb-LF/HF	8.6235	-3.1085

The outliers that exist in the computed HRV measures as shown in Figure 3 were eliminated by applying Interquartile-range analysis as stated in Table 2. Figure 6 displays HRV feature resulted from removing outliers. Note that SDNN index feature was not considered due to its nonlinearity and the negative values displayed in Table 2 were not used.



(a) SDNN



(b) SDANN

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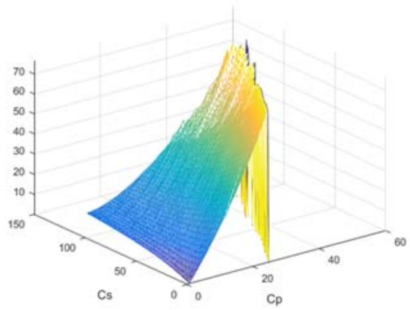
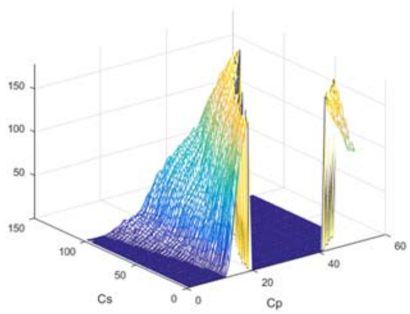
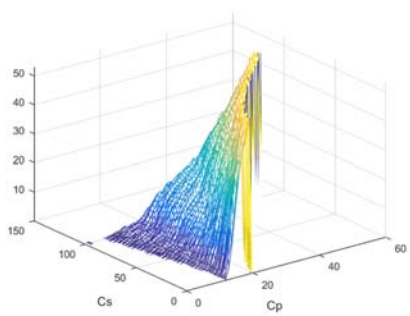


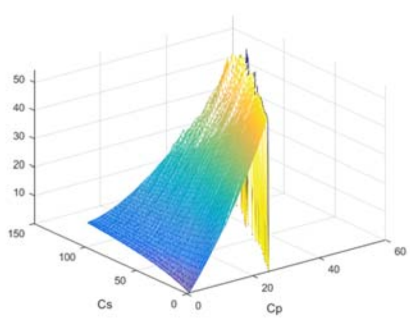
(c) RMSSD



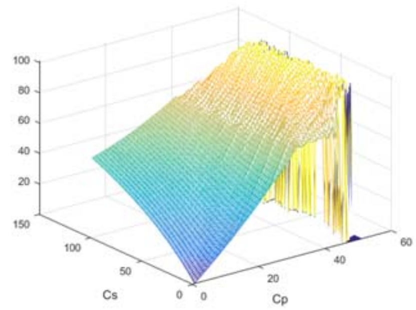
(d) NN50



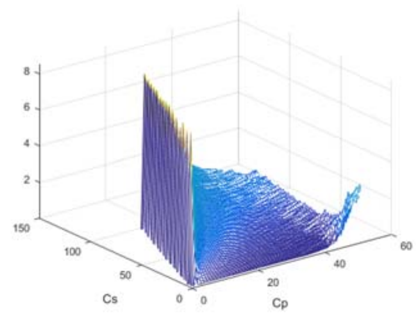
(e) pNN50



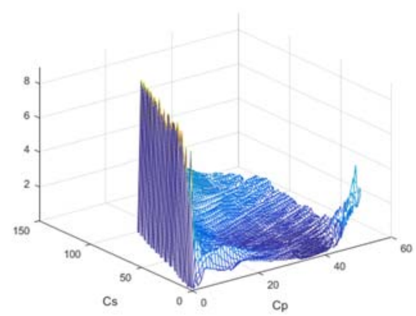
(f) SD_1



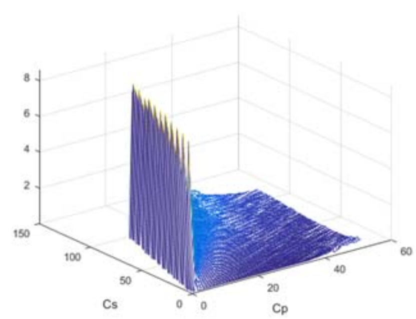
(g) SD_2



(h) Welch-LF/HF ratio



(i) Burg-LF/HF ratio



(j) Lomb-LF/HF ratio

Figure 6: HRV measures based on MIT-BIH NSR database with removing outliers.

The valid range of C_s and C_p was determined by overlapping ten HRV features as shown in Figure 7.

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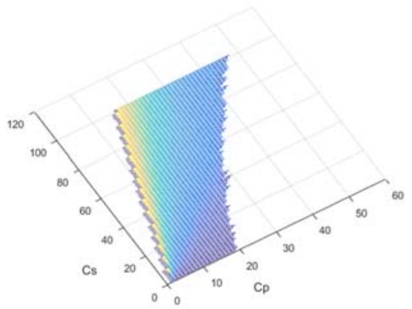
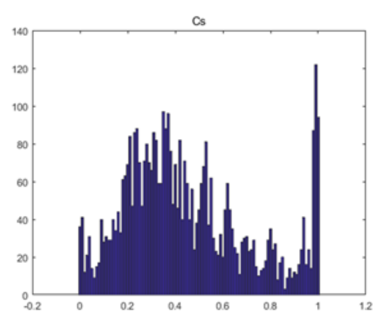


Figure 7: The decision logic map for determining the valid range of C_s and C_p. The real C_s and C_p values can be obtained by dividing 100.

The final C_s and C_p value on the real ECG segments are estimated by finding the minimum mean-square-error (MSE) as the differences of HRV measures on between the annotated ECG segment and the IPFM output. We tested 18 MIT-BIH NSR dataset (16265, 16272, 16273, 16240, 16483, 16539, 16773, 16786, 16795, 17052, 17453, 18177, 18184, 19088, 19090, 19093, 19140 and 19830) by encoding the data into 5 minutes-segments. Figure 8 represents histogram distribution of C_s and C_p evaluating on MIT-BIH NSR dataset. It also shows that C_s (C_p) have a Gaussian distribution ranging from 0 to 1.0 (0.5) for Normal sinus rhythms.



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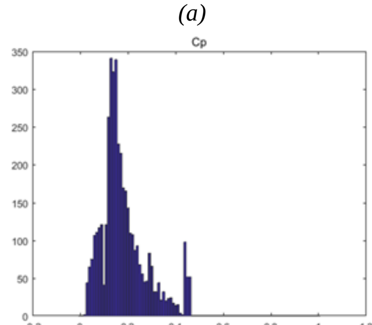

(b)

Figure 8: Histogram distribution of (a) C_s and (b) C_p by evaluating MIT-BIH NSR dataset.

To illustrate effects of C_s and C_p by Poincare plot, we sought particularly three cases: (a) high C_s and low C_p, (b) low Cs and high C_p and (c) similar range of C_s and C_p, respectively. With this aim, we considered MIT-BIH (a) five-minutes duration of 16272 elapsed by 22 hours, (b) five-minutes duration of 16773 between 20 and 22 hours elapsed and (c) five-minutes duration of 16272 between 8 and 10 hours elapsed. Table 3 displays HRV measure on the selected MIT-BIH NSR dataset and Table 4 shows the estimated C_s, and C_p values.

Table 3: HRV measures on five-minutes duration of 16272, 16773 and 16272 record, Respectively.

	(a)	(b)	(c)
SDNN	39.7	130	24.7
SDANN	29	98.8	19.3
RMSSD	23.1	143.2	28.5
NN50	10	141	21
pNN50	4.1	65.6	6.9
SD_1	16.3	101.5	20.2
SD_2	53.7	153.3	28.5
Welch-LF/HF	26.304	2.74	1.09
Burg-LF/HF	28.614	3.251	0.796
Lomb-LF/HF	9.468	2.237	1.378

Table 4: The estimated C_s and C_p based on the records as specified in Table 3.

	Cs	Cp
(a)	0.98	0.08
(b)	0	0.46
(c)	0.13	0.13

Figure 9 shows the ECG segment (five-minutes duration) with illustrating heart beats by Poincare plot.

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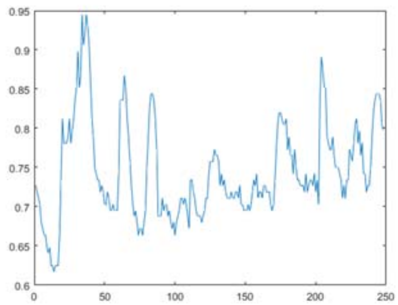

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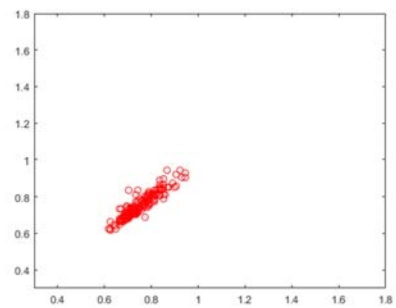

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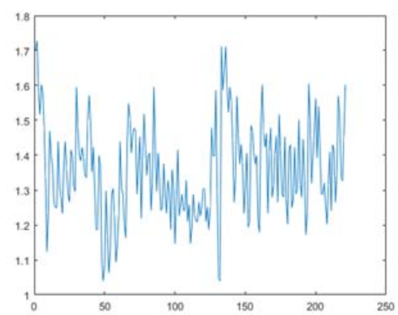

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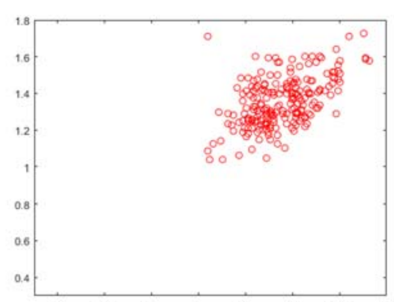

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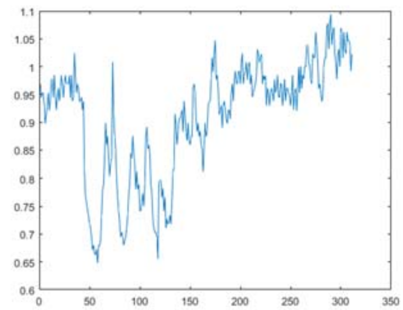

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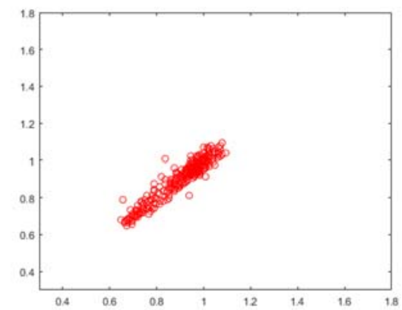

(c')

Figure 9: The estimated activity of autonomic nervous system (a): the five-minutes duration of MIT-BIH: 16272 (C_s = 0.98, C_p= 0.08) (a)' : Poincare plot of (a) (b): the five-minutes duration of MIT-BIH: 16773 (C_s = 0.0, C_p= 0.46) (b)': Poincare plot of (b) (c): the five-minutes duration of MIT-BIH: 16272 (C_s = 0.13, C_p= 0.13) (c)': Poincare plot of (c).

5. CONCLUSIONS

In this study, we have proposed a new IPFM model to generate the artificial R-R time-series using the threshold of unity and it can effectively resolve three main-peaks in power spectrum of HRV. In order to estimate the values of C_s and C_p parameters, the difference of HRV measures on between MIT-BIH NSR dataset and IPFM output was evaluated by MSR performance index. Our experimental simulations based on real-patient data demonstrated that the cardiac activity of autonomic nervous system can be interpreted in terms of C_s and C_p using the proposed IPFM model as follows;

i) The real values of C_s & C_p parameter can be estimated by using data mining approach on MIT-BIH NSR dataset.

ii) C_s (C_p) have a Gaussian distribution ranging from 0 to 1.0 (0.5) for MIT-BIH NSR dataset.

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