Understanding the Physiological effect of Audio stimulus on Females using HRV and Cardiac Electrophysiology Analysis

Karan Yogesh Pande

Department of Biotechnology & Medical Engineering
National Institute of Technology Rourkela

Understanding the Physiological effect of Audio stimulus on Females using HRV and Cardiac Electrophysiology Analysis

Dissertation submitted in partial fulfillment

of the requirements of the degree of

Master of Technology

in

Biomedical Engineering

by

Karan Yogesh Pande

(Roll Number: 215bm1254)

based on research carried out

under the supervision of

Prof. Kunal Pal

May 2017

Department of Biotechnology & Medical Engineering

National Institute of Technology Rourkela

Department of Biotechnology & Medical Engineering
National Institute of Technology Rourkela

Prof. Kunal Pal
Professor

April 27, 2017

Supervisors' Certificate

This is to certify that the work presented in the dissertation entitled *Understanding the Physiological effect of Audio stimulus on Females using HRV and Cardiac Electrophysiology Analysis* submitted by *Karan Yogesh Pande*, Roll Number 215bm1254, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements for the degree of *Master of Technology* in *Biomedical Engineering*. Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

Kunal Pal
Assistant Professor

Declaration of Originality

I, *Karan Yogesh Pande*, Roll Number *215bm1254* hereby declare that this dissertation entitled *Understanding the Physiological effect of Audio stimulus on Females using HRV and Cardiac Electrophysiology Analysis* presents my original work carried out as a master student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections “Reference” or “Bibliography”. I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

I am fully aware that in case of any non-compliance detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present dissertation.

May 27, 2017
NIT Rourkela

Karan Yogesh Pande

Acknowledgement

This project will remain incomplete if I fail to acknowledge some very important people who have been a great source of inspiration, support and guidance to me through the course of this journey. Firstly, I would like to express my heartfelt gratitude towards my highly motivating and extremely supportive supervisor **Dr. Kunal Pal** from Department of Biotechnology and Medical Engineering for giving me an opportunity to carry out this research work.

I would like to acknowledge co-operation and support received from my Ph.D. Scholar in my Lab **Mr. Suraj Kumar Nayak**, my lab-mate **Mr. Pratyush Kumar Patnaik**, **Mr. Haldar Behera** and **Mr. Vivek Sharma**.

This work would not have been possible without the coordination and support provided by **Ms. Deepanjali Gaur** my batch-mate and all my **Volunteers**.

I am thankful to my **faculty members, technical staffs, friends** and **family** for their support and encouragement.

Abstract

The current study deciphers the effect of an audio stimulus (Indian classical music) on the autonomic nervous system (ANS) and the cardiac electrophysiology of female volunteers. Electrocardiogram (ECG) readings were obtained from ten volunteers for audio stimulus before and after exposing them to the respective stimuli. Various R-R interval (RRI) based analyses (like Recurrence and HRV analysis) were performed to understand the changes in the ANS and the cardiac electrophysiology. HRV analysis indicated an overall parasympathetic dominance after exposure to the audio stimulus.

Keywords—ECG; HRV; Recurrence; females; heart

Contents

List of figures

List of tables

Chapter 1

Introduction

Systematic production of sound in a definite pattern on a time frame is called music [1]. It can be produced by voice, by a musical instrument or by both. Since the dawn of human, civilization music has played a very vital role in the cultural activities of man throughout the globe. People in the Ancient Greek civilization were one of the first ones to realize the importance of music in human experience. They were among the first civilizations to attribute therapeutic value to listening to music. The Greeks believed that music could restore both the soul and the body to its state of equilibrium [1]. Coming to the present day, Modern civilization also acknowledges the importance music and humor in the day-to-day life. A lot of research effort has been put to understand how the human brain processes music and humor apart from how they affect the functioning of the human brain and elicits a specific type of emotion [2]. Music and humor have been reported to have an effect on a range of neurotransmitters affecting the brain function and perception of various kinds of emotions. Apart from neurotransmitters, they are also reported to have an effect on hormonal secretions, cytokines, lymphocytes and other metabolic functions [3].

In this study, we report the effect of an audio stimulus (Indian classical music) and an audio-visual stimulus (humorous) on the autonomic nervous system (ANS) and the cardiac electrophysiology of female volunteers. In normal healthy females, the gonadotropic hormone levels undergo continuous change during the menstrual cycle. Changes in the levels of these hormones not only affects the reproductive organs but also influences the ANS [4]. To keep the effect of hormonal changes constant, all the females involved in the study were exposed to the audio stimulus when they were on the 1st day of phase-1 (i.e. follicular phase) of their menstrual cycle. Electrocardiogram (ECG) readings were obtained from ten volunteers for audio stimulus and eleven volunteers for audio-visual stimulus before and after exposing them to the respective stimuli. The RRI-based and ECG-based analyses were used to understand the changes in the ANS and the cardiac electrophysiology, respectively.

Chapter 2

Literature Review

2.1 Processing of ECG

Before any Signal analysis can be done on acquired ECG it has to be pre-processed for analysis. The primary step of ECG processing is artifact removal. The ECG signal acquired from an individual may have various other types of signals superimposed over it like electrical noises generated by surrounding electrical equipment, muscular activity noise, noise generated at skin electrode junction and power line interference. Various types of filtering techniques have to be employed to remove these unwanted noise signals. The frequency range of ECG signals is 0 to 300 Hz [5]. ECG used for clinical applications is filtered in a bandwidth of 0.05 to 100 Hz. ECG used for heart rate monitoring uses a further reduced bandwidth of 0.5 to 50 Hz [6]. Once artifacts have been removed and the ECG signal has been bandlimited in the required frequency range now various Signal analysis techniques can be applied to this signal.

2.2 Statistical Methods of ECG Analysis

Various statistical methods have been used for segmentation, quantification, and extraction of various features from ECG signals. Autoregressive (AR) time series modeling is one such statistical technique in which a future value is predicted based on past values. Ge et al., (2002) proposed a system of classifying different types of cardiac arrhythmias using AR modeling technique which could achieve a minimum classification accuracy of 93.2% [7]. Padmavathi et al., (2015) used AR coefficients to classify a specific type of cardiac arrhythmia known as Atrial fibrillation (AF) [8]. Baselli et al., (1985) also did classification of arrhythmia classification based on AR modeling of RR interval time series [9].

2.3 Heart Rate Variability

The physiological phenomenon in which the time interval between two consecutive heartbeats keeps on varying is known as HRV. The time interval between two consecutive heartbeats is also known as RR interval. The Task Force of the European Society of Cardiology and The North American Society of Pacing Electrophysiology in their seminal work published in 1996 give standard measurement procedures, physiological interpretations and clinical applications of HRV [10]. HRV time series is analyzed in time and frequency domains.

2.4 HRV Analysis in Time Domain

Various Time Domain features are extracted from HRV time series. Few important ones are RR interval mean, RR interval standard deviation, Heart rate mean, Heart rate std deviation, RMSSD, NN50, p-NN50, RR triangular index, TINN. In 2013, Champaty et al., used time domain HRV feature along with other features to classify different menstrual phases of females with an accuracy of greater than 90% [4].

2.5 HRV Analysis in Frequency Domain

HRV has been found to consist of various frequency components which have been divided into four major bands. Ultra low frequency (ULF) ranges between 0.0001Hz to 0.003Hz, very low frequency (VLF) ranges from 0.04Hz to 0.15Hz and High frequency (HF) ranging from 0.15Hz to 0.4Hz. Various Frequency Domain features obtained by Fast Fourier Transform are VLF, LF and HF powers, percentage VLF, LF and HF, normalized LF and HF & LF by HF ratio. In a 2016 study understanding the effect cannabis consumption has on autonomic nervous system and the heart conduction system of workers employed in paddy fields of India Nayak et al., were able to achieve a maximum classification efficiency of 100% to distinguish cannabis users from non-cannabis using frequency domain HRV features along with time domain features [11].

2.6 HRV Analysis by non-linear Methods

Due to the extremely complex neurochemical control mechanisms involved in controlling functioning to heart HRV analysis using non-linear methods yields valuable information. Urbanowicz et at., (2007) found that in normal healthy volunteers heart rate variability was found to be mainly due to linear control mechanisms while in volunteers having disease condition or having a higher risk of cardiac abnormalities heart rate variability was observed to be dependent on various non-linear control mechanisms [12]. Main non-linear analysis methods used by researchers for HRV analysis are Empirical Mode Decomposition (EMD), Entropy measures, Detrended Fluctuation Analysis (DFA), Poincare and recurrence plots. A few of these methods are described below briefly.

2.7 Poincare Plot

Poincare map is a way to visualize the evolution of a dynamical system in phase space. It relates two consecutive intersection points on the same side of a plane. The difference between a Poincare plot and a recurrence plot is that a Poincare plot is defined in phase space while the recurrence plot is defined in a time space [13]. Goshvarpour et al., (2011) found that during meditation the width of Poincare plot increased as the lag in the heart rate signal increased. The authors concluded that simplicity of calculation of Poincare plot width along with its ability to adapt to the chaotic nature of ECG would make Poincare plots important tool to analyze ECG signals during meditation [14].

2.8 Recurrence Plot

A recurrence plot enables us to analyze an m-dimensional phase space using a two–dimensional pictorial representation of recurrences. Recurrence plot gives information about all the instants when the phase space trajectory passes through the same location in phase space. Hence specific recurring events and cyclic irregularities can be distinctly identified. Recurrence of states is a basic property of deterministic dynamic systems and is unique for chaotic or non–linear systems [15]. Though recurrence can be defined and measured in many different ways Sabelli et al., (2005) use two type of recurrence measurements namely isometry and similarity [16]. Isometry is defined by the recurrence of vectors having the same length. While similarity recurrence implies that two vectors should have same length and direction. In a 2010 study of RR interval patterns of Adults, Newborns and Elderly patients Sabelli et al., found recurrence plot studies to be of significance in clinical studies [17].

2.9 Objectives

Taking a note of the facts mentioned above, the following objective was formulated

To perform RRI based Recurrence and HRV analysis to understand the effect of an audio stimulus on the ANS and cardiac electrophysiology of females.

Chapter 3

Materials

EKG sensor (Vernier Software and Technology, USA), DAQ USB-4704 multifunction USB module (Advantech Corporation, Taiwan), disposable ECG electrodes (BPL Medical Technologies Pvt. Ltd, India), and LabVIEW (V13, National Instruments, USA) were used for acquiring ECG signals. The ECG signals were further processed using LabVIEW and Statistica (trial version, V13.2, Dell Inc., USA).

Chapter 4

Methods

4.1 Volunteers

Ten female volunteer students of NIT Rourkela, in the age group of 20 to 24 years participated in the study. All the volunteers were verbally informed about the nature of the study in detail, and a written consent was obtained from them as per the WHO guidelines. The ethical approval for acquiring the ECG signals was received from the Institute ethical clearance (IEC) Committee of NIT Rourkela (Ref. No.: NITRKL/IEC/ FORM/2/25/4/11/001, Dated: 13/12/2013). The volunteers were asked to make a visit to the ECG recording station at the Medical Electronics and Instrumentation Lab., Department of Biotechnology and Medical Engineering, NIT Rourkela on the 1st day of phase-1 of their menstrual cycle. ECG signals were acquired in the lead-1 configuration of Einthoven's triangle for 6 min after they sat comfortably on a chair. These ECG signals were categorized under the pre-stimulus category. Then, they were made to listen to an Indian classical music (flute composition). ECG signals were again acquired in the post-stimulus condition for 6 min and were labeled under the post-stimulus category.

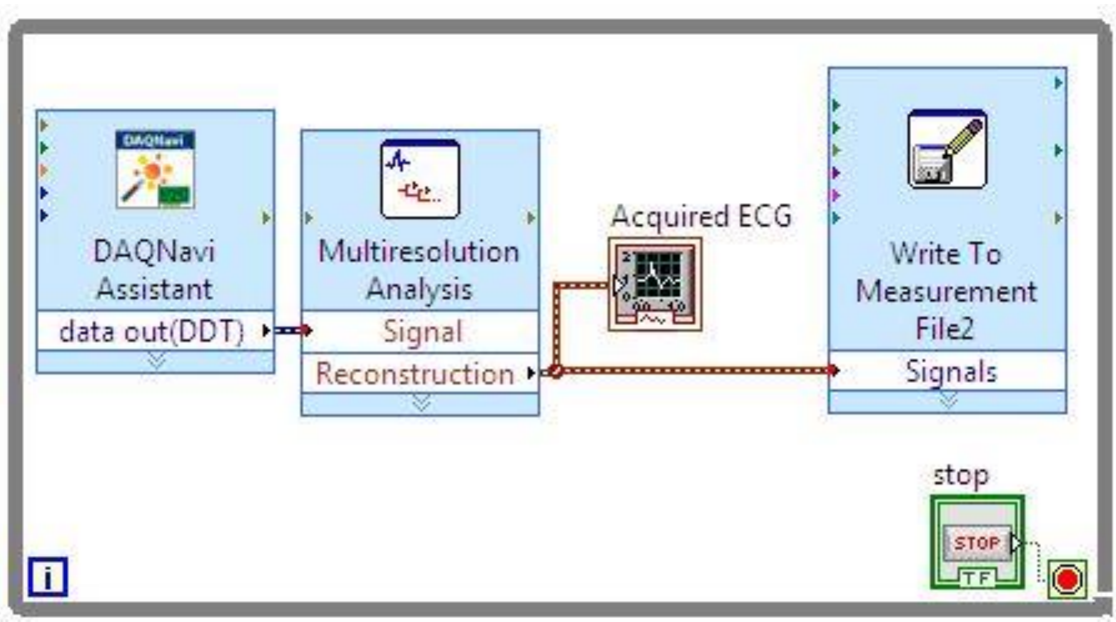

Fig. 1. Pictograph of LabVIEW program for acquiring ECG signal

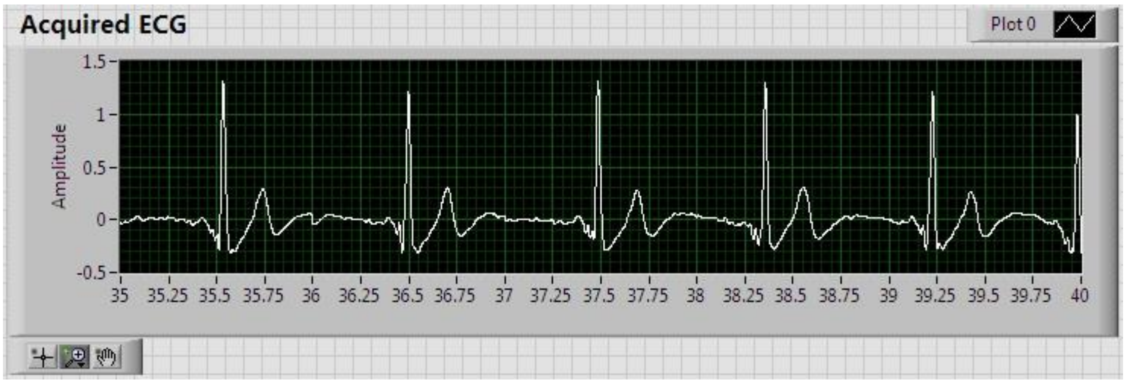

Fig. 2. Pictograph of acquired ECG signal

4.2 Recurrence Analysis of RRI Time series

Recurrence analysis has gained popularity for analyzing the dynamic processes in the phase space [18]. The 5 min RRIs were given as input to the Bios analyzer software to obtain various parameters related to the recurrence analysis of the RRI time series obtained during pre- and post-stimulus conditions [16]. Obtained parameters, namely, percentage isometry, percentage consecutive isometry, and novelty were plotted against a number of embedding. Percentage radial isometry and percentage consecutive radial isometry were plotted against cut-off radius (%). 10% cut-off radius and ten embedding were used to generate the recurrence plot.

4.3 HRV Analysis

HRV analysis was performed on 5 min recordings of the acquired ECG signals using the biomedical Workbench toolkit of LabVIEW 2013. At first, the QRS complexes were detected using a band-pass filter (BPF) with lower and upper cut-off frequencies of 10 and 25 Hz, respectively. The R-R intervals were extracted from the QRS complexes. The R-R intervals (RRI) were given as input to HRV Analyzer Toolkit of LabVIEW, and 29 HRV parameters were obtained. These 29 parameters consist of time-domain, frequency-domain and Poincare plot parameters. Variation in these parameters in pre- and post-stimulus condition were studied to ascertain the changes taking place in cardiac electrophysiology.

Chapter 5

Results and Discussion

5.1 Recurrence Analysis of RRI Time series

Recurrence analysis techniques discover patterns with respect to time in a time series by comparing sequences of adjacent elements of the time series. The recurrent patterns are discovered, plotted and quantified using these techniques. All programs performing recurrence analysis perform the analysis by sampling the time series. Bios data analyzer software allows the user to select the number of sequences of adjacent elements to be compared to find recurring patterns in them.

Bios data analyzer software was used to perform isometric recurrence analysis on RRI time series data. Isometric recurrence is defined by the recurrence of vectors in phase space having the same length [16]. Isometric recurrence is measured in percentage as a function of embedding. Embedding is the dimension of the vectors used for the calculation of isometric recurrence. A graphical plot of percentage isometry (or any of its derived parameters such as consecutive isometry, radial isometry, consecutive radial isometry and novelty) vs. embedding is known as embedding plot. A more patterned behavior in a time series has been reported to be associated with an increase in the percentage isometry [16]. Embedding plots of pre- and post-stimulus conditions are plotted in Fig. 1. Percentage isometry was found to be more in the pre-stimulus condition as compared to the post-stimulus condition (Fig. 3), which suggested more patterned behavior in the pre-stimulus condition. Percentage consecutive isometry is an important parameter derived from the percentage isometry. Two vectors are said to be in consecutive isometry if they are recurrent, and their adjacent vectors are also recurrent. Literature suggests consecutive isometry to be an indicator of causality [19]. Fig. 4 shows the consecutive isometry embedding plot for the pre- and the post-stimulus condition RRI time series data. It is observed that percentage consecutive isometry increased in both pre- and post-stimulus conditions as embedding were increased from 0 to 100. Over the entire range of embedding, consecutive isometry in pre-stimulus condition was greater than post-stimulus condition indicating a more causal behavior of pre-stimulus RRI time series in comparison to post-stimulus RRI time series. A predefined percentage of the range (difference between maximum and minimum) of the time series data values gives the cutoff radius (%). The variations observed in isometry and consecutive isometry as the cut-off radius is varied are known as radial isometry and consecutive radial isometry, respectively. It is observed from Fig. 5 and Fig. 6 that both radial and consecutive radial isometry increased with an increase in cut-off radius and both radial and consecutive radial isometry were greater in pre-stimulus condition than the post-stimulus condition. Increase in percentage isometry due to the shuffling of a time series is termed as Novelty. If the percentage isometry ratio of the shuffled and the original time series is greater than one, then the time series is said to be Novel. Novelty is one of the basic characteristics of the time series data generated by biological systems like RRI, time series data generated in capital markets and time series generated by process equations and their recursions [20]. Novelty quantifies the creative features in a time series. Fig 7 shows that Novelty increases in post-stimulus condition as compared to the pre-stimulus condition. A recurrence plot enables us to analyze an m-dimensional phase space using a two-dimensional pictorial representation of recurrences. Recurrence plot gives information about all the instants when the phase space trajectory passes through the same location in phase space [21]. Hence, specific recurring events and cyclic irregularities can be distinctly identified. Recurrence of states is a basic property of deterministic dynamic systems and is unique for chaotic or non-linear systems [21]. A typical recurrence plot for each stimulus condition is shown in Fig 8 and 9. It has been reported that the regions devoid of specific patterns (recurrence) in a recurrence plot indicate an increase or decrease in heart rate while specific pattern rich (recurrence rich) regions indicate a stable sustained heart rate [17]. From Fig. 8 and 9 we can observe that recurrence plot of the pre-stimulus condition has more recurrence rich regions as compared to post-stimulus recurrence plot suggesting a more creative tendency in the post-stimulus RRI time series.

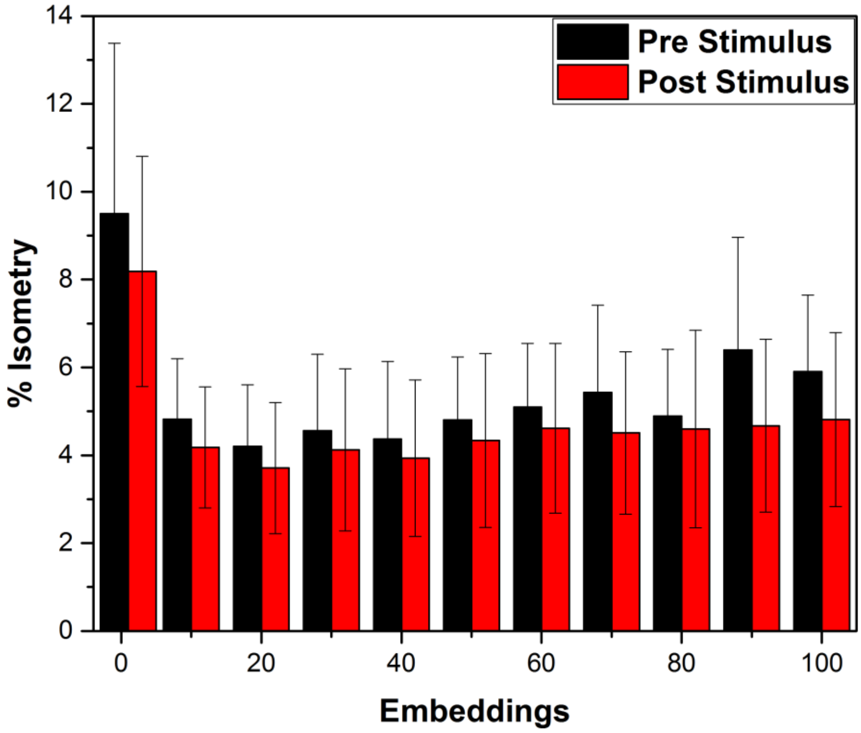

Fig. 3. Bar graph of % isometry vs. embedding

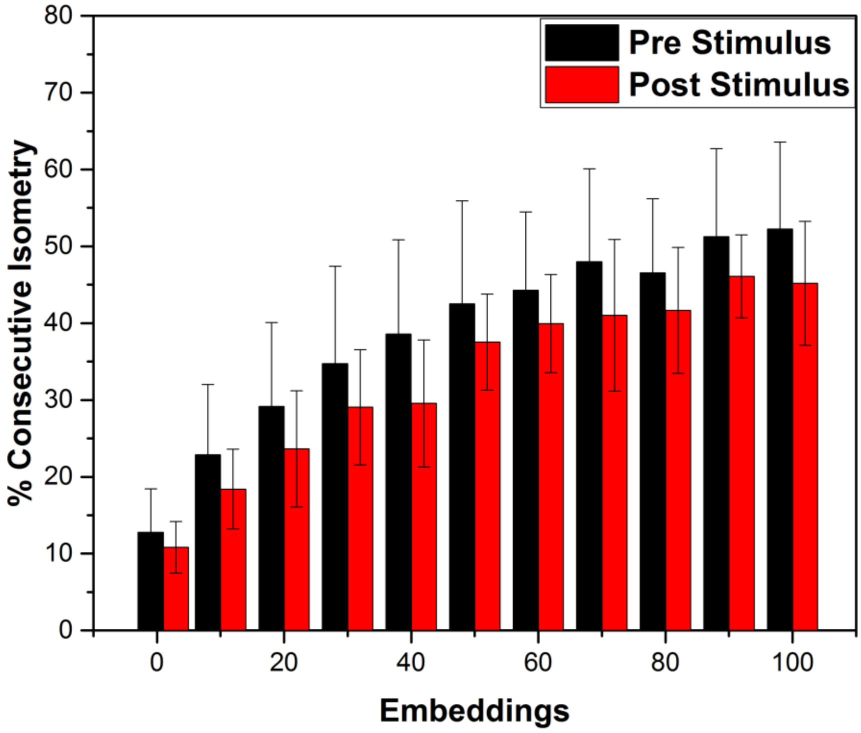

Fig. 4. Bar graph of % consecutive isometry vs. embedding

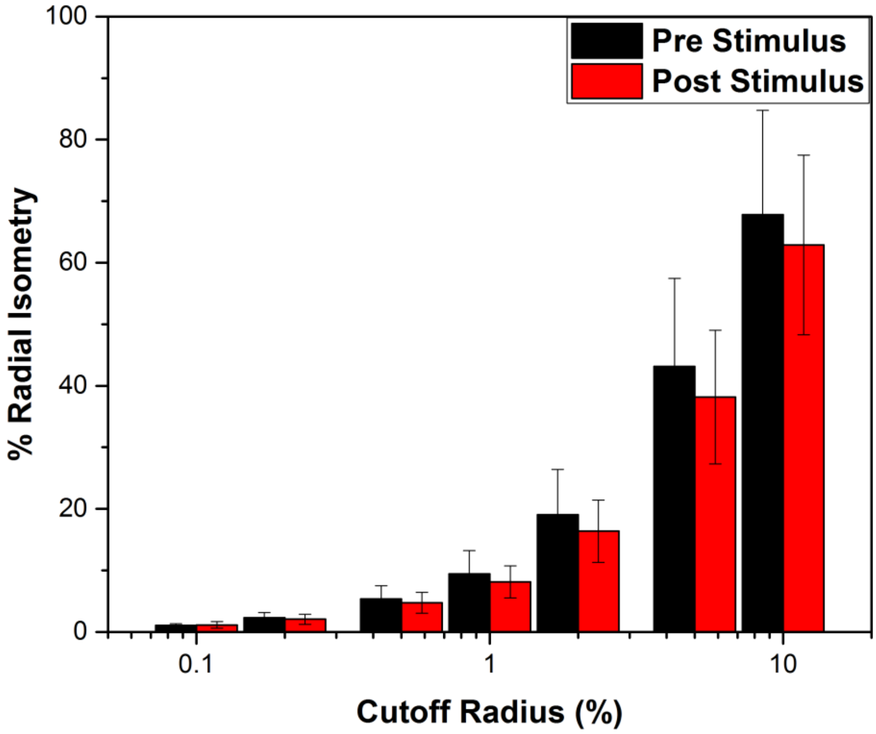

Fig. 5. Bar graph of % radial isometry vs. cutoff radius

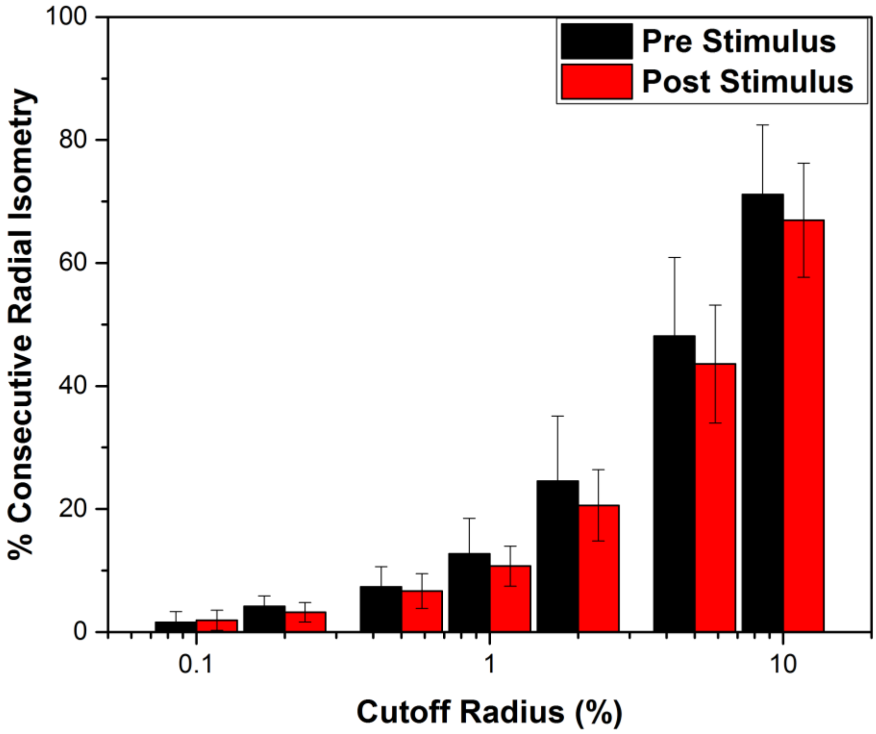

Fig. 6. Bar graph of % consecutive radial isometry vs. cutoff radius

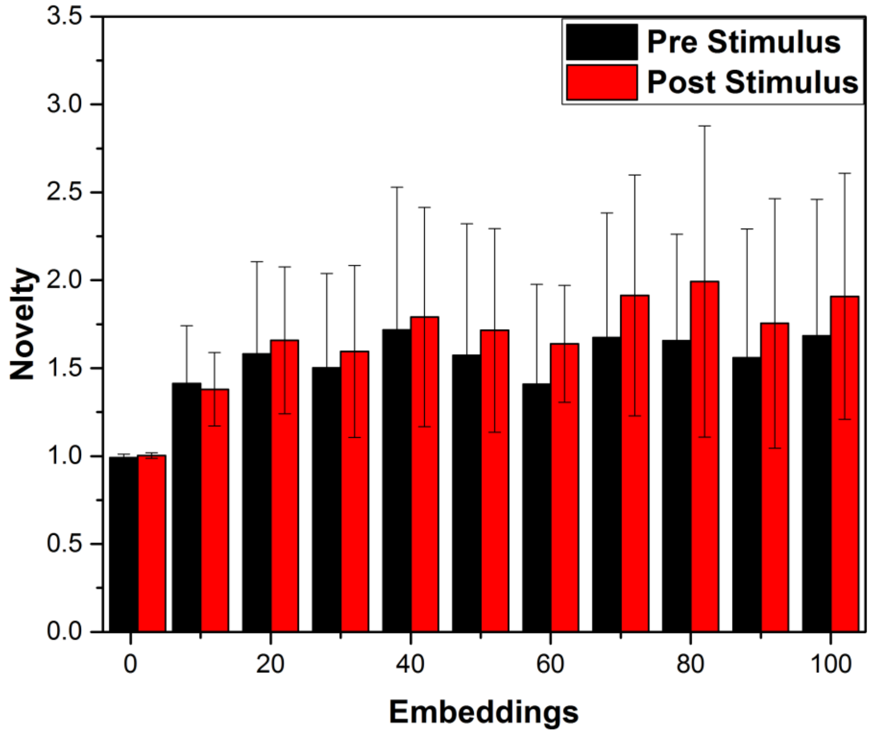

Fig. 7. Bar graph of Novelty vs. embedding

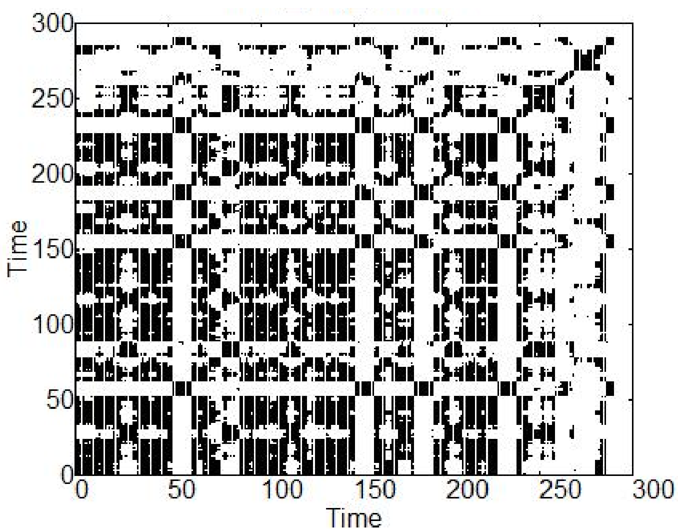

Fig. 8. Recurrence plot of pre-stimulus RRI

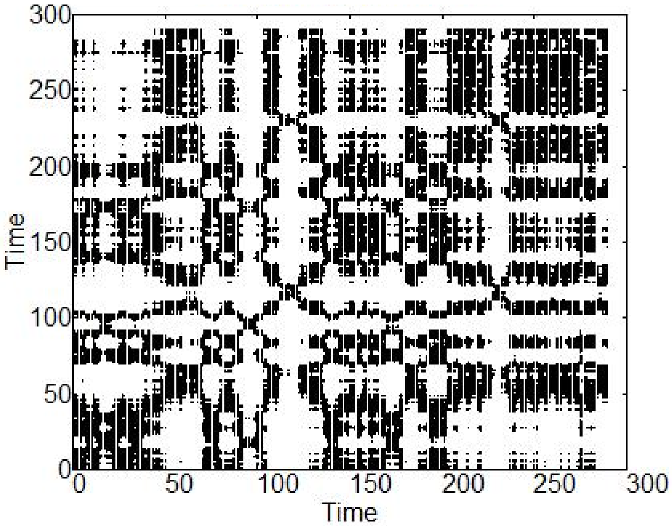

Fig. 9. Recurrence plot of post-stimulus RRI

5.2 HRV Analysis

The physiological phenomenon in which the time interval between two consecutive heartbeats keeps on varying is known as HRV [10]. Many studies indicate that HRV is a non-invasively obtained indicator of ANS activity [10]. A total of 29 HRV parameters were obtained by the time-domain analysis, frequency domain power spectral analysis by Fast Fourier Transform (FFT) and Auto Regression (AR) methods followed by the non-linear Poincare analysis of the RRIs of both pre-stimulus category and post-stimulus category RRI data (Fig. 10 and 11). The time-domain parameters included R-R mean, R-R standard deviation (R-R SD), heart rate mean (HR mean), heart rate standard deviation (HR-SD), RMSSD, NN50, pNN50, RR triangular index, and TINN. Table 1 and 2 represent the time domain parameters obtained during pre- (Fig. 12) and post-stimulus (Fig. 13) conditions of a volunteer. The Poincare analysis provided two parameters, namely, SD1 and SD2. These parameters obtained during pre- (Fig. 14) and post-stimulus (Fig. 15) conditions of a volunteer have been shown in Table 3 and 4 respectively. The frequency-domain power spectral analysis parameters were very-low-frequency (VLF) power, low-frequency (LF) power, high-frequency (HF) power, VLF%, LF%, HF%, LF norm, HF norm and LF/HF ratio. The frequency-domain power spectral analysis parameters obtained during pre- and post-stimulus conditions of a volunteer using FFT (Fig. 16 and 17) and AR methods (Fig. 18 and 19) have been tabulated in Table 5 and 6, respectively. The short-time Fourier transform (STFT) of the HRV data (RRI data) obtained during pre- and post-stimulus conditions of a volunteer are shown in Fig. 20 and 21. Similarly, the Gabor spectrogram of the

RRI data obtained during pre- and post-stimulus conditions of a volunteer is shown in Fig. 22 and 23. Finally, the wavelet coefficients of the RRI data obtained during pre- and post-stimulus conditions of a volunteer is shown in Fig. 24 and 25. Overall, a parasympathetic dominance (associated with a reduction in the sympathetic activity) during the post-stimulus condition was suggested by the HRV parameters.

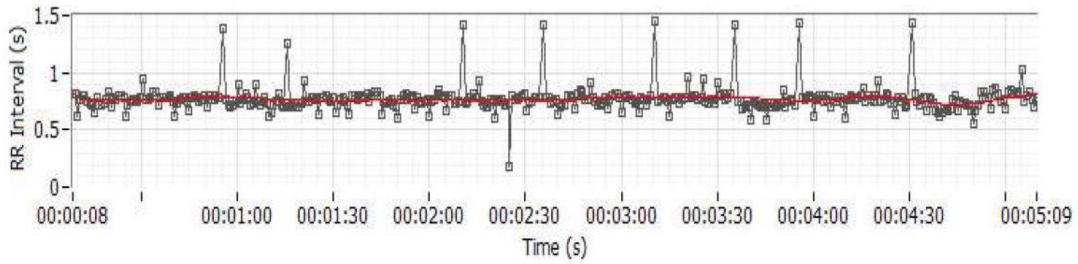

Fig. 10. RRI Waveform in Pre-Stimulus Condition

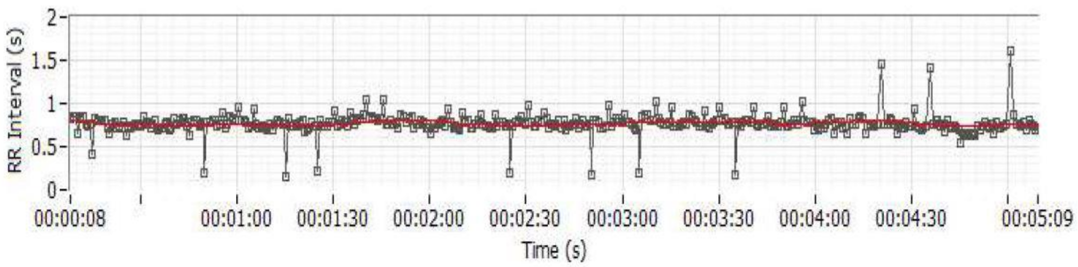

Fig. 11. RRI Waveform in Post-Stimulus Condition

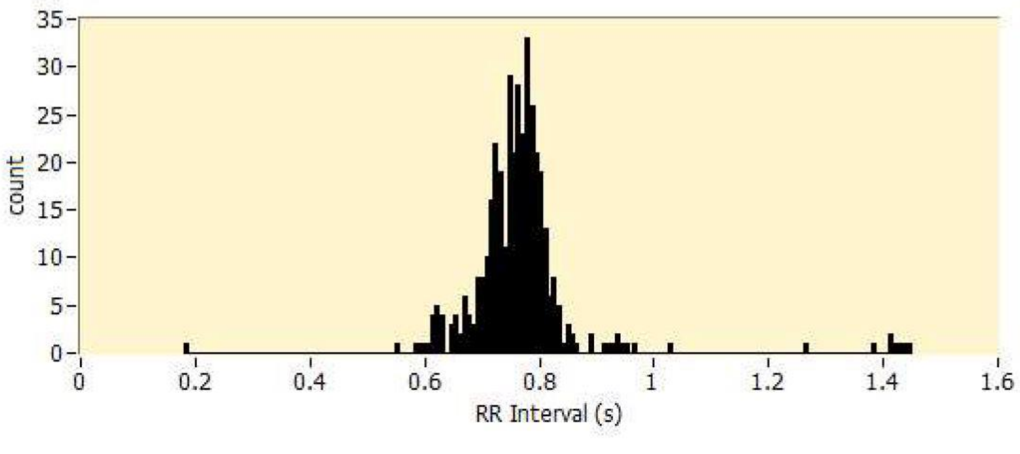

Fig. 12. RRI Histogram in Pre-Stimulus Condition

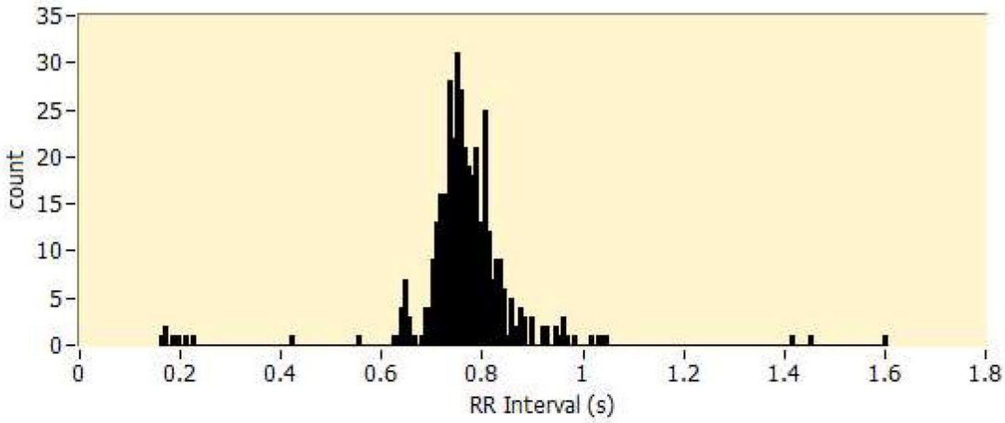

Fig. 13. RRI Histogram in Post-Stimulus Condition

Table 1. Statistical HRV Features in Pre-Stimulus Condition

RR mean	**768 ms**
RR std.	**110 ms**
Heart rate mean	**80 bpm**
Heart rate std.	**15 bpm**
RMSSD	**160 ms**
NN50	**148**
pNN50	**38**
RR triangular index	**11.9**
TINN	**168.4 ms**

Table 2. Statistical HRV Features in Post-Stimulus Condition

RR mean	**766 ms**
RR std.	**120 ms**
Heart rate mean	**83 bpm**
Heart rate std.	**34 bpm**
RMSSD	**160 ms**
NN50	**161**
pNN50	**41**
RR triangular index	**14.1**
TINN	**202.9 ms**

Table 3 SD1 and SD2 in Pre-Stimulus Condition

SD1	**110 ms**
SD2	**120 ms**

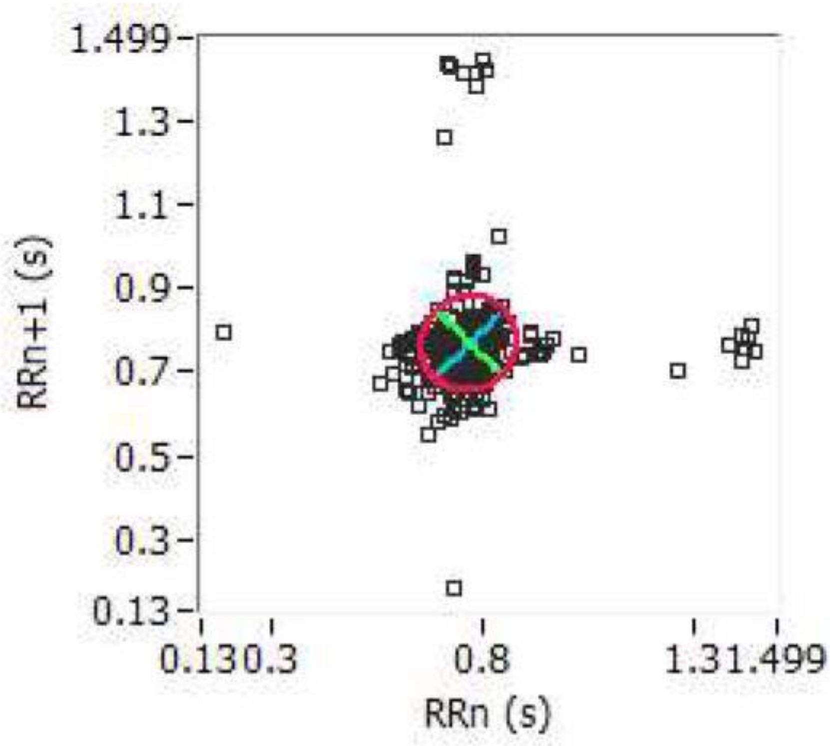

Fig. 14. Poincare Plot in Pre-Stimulus Condition

Table 4. SD1 and SD2 Values in Post-Stimulus Condition

SD1	**110 ms**
SD2	**120 ms**

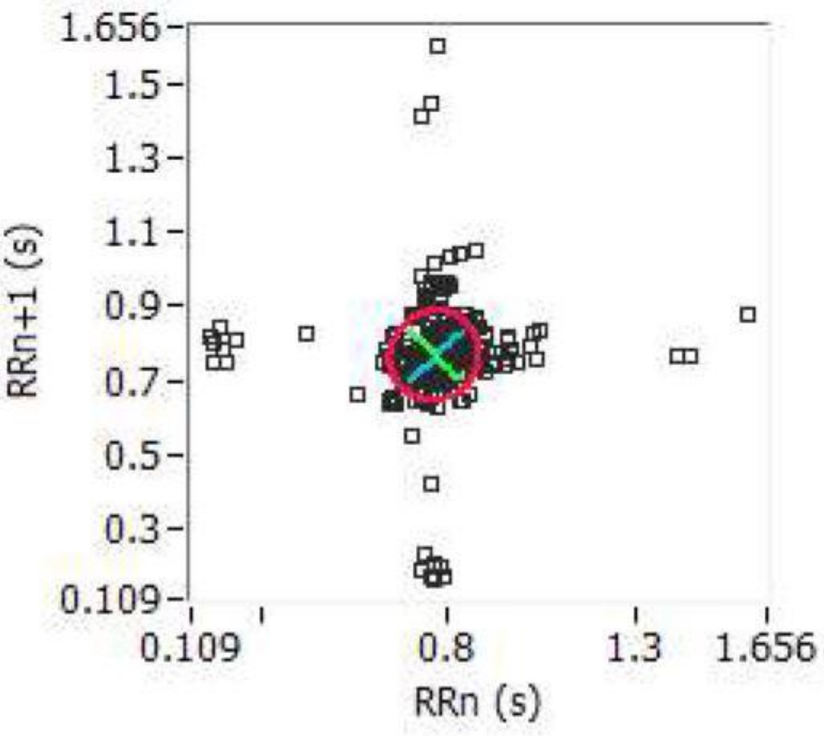

Fig. 15. Poincare Plot in Post-Stimulus Condition

Table 5. FFT Spectrum features in Pre-Stimulus Condition

VLF power	**750 ms2**
LF power	**2600 ms2**
HF power	**3820 ms2**
VLF	**10 %**
LF	**37 %**
HF	**53 %**
LF norm	**33.3 n.u.**
HF norm	**48.1 n.u.**
LF/HF	**0.69**

Table 6. FFT Spectrum features in Post-Stimulus Condition

VLF power	**420 ms2**
LF power	**1300 ms2**
HF power	**1930 ms2**
VLF	**12 %**
LF	**35 %**
HF	**53 %**
LF norm	**25 n.u.**
HF norm	**38.3 n.u.**
LF/HF	**0.65**

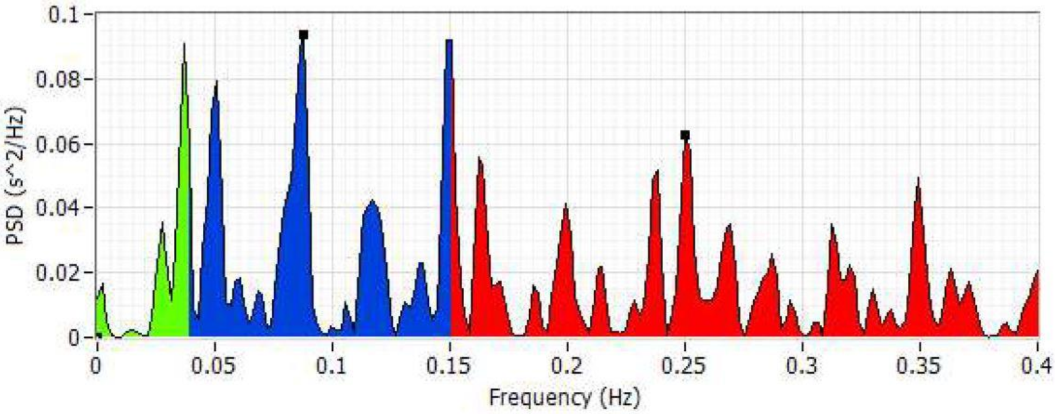

Fig. 16. FFT Spectrum Density in Pre-Stimulus Condition

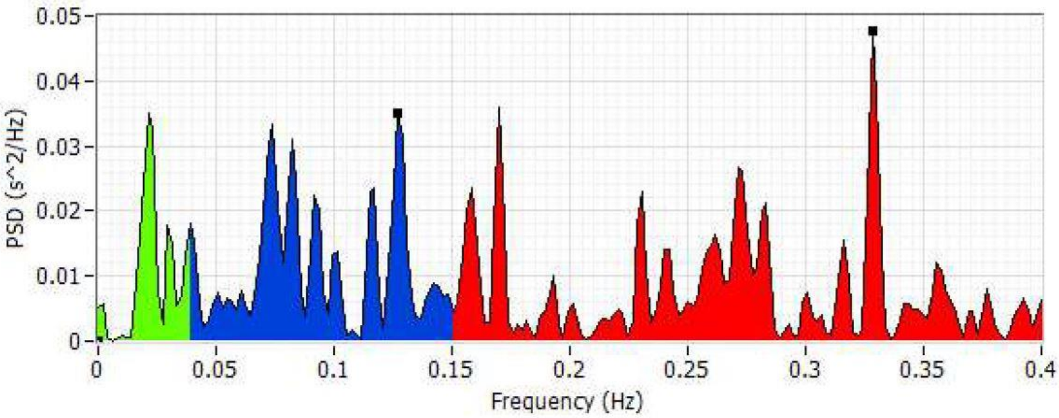

Fig. 17. FFT Spectrum Density in Post-Stimulus Condition

Table 7. AR Spectrum Features in Pre-Stimulus Condition

VLF power	**530 ms2**
LF power	**2200 ms2**
HF power	**3110 ms2**
VLF	**9.1 %**
LF	**37 %**
HF	**49 %**
LF norm	**33.8 n.u.**
HF norm	**53.6 n.u.**
LF/HF	**0.7**

Table 8. AR Spectrum Features in Post-Stimulus Condition

VLF power	**600 ms2**
LF power	**1900 ms2**
HF power	**2500 ms2**
VLF	**12 %**
LF	**38 %**
HF	**43 %**
LF norm	**32.1 n.u.**
HF norm	**50.2 n.u.**
LF/HF	**0.75**

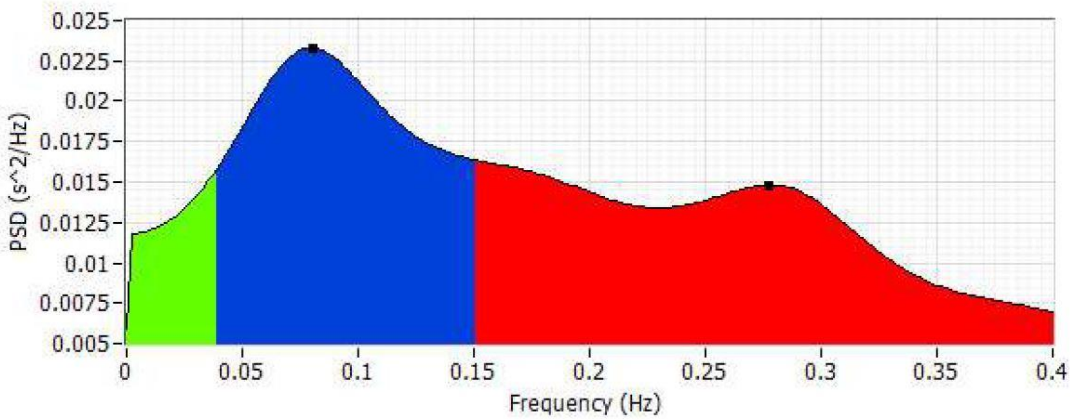

Fig. 18. AR Spectrum Density in Pre-Stimulus Condition

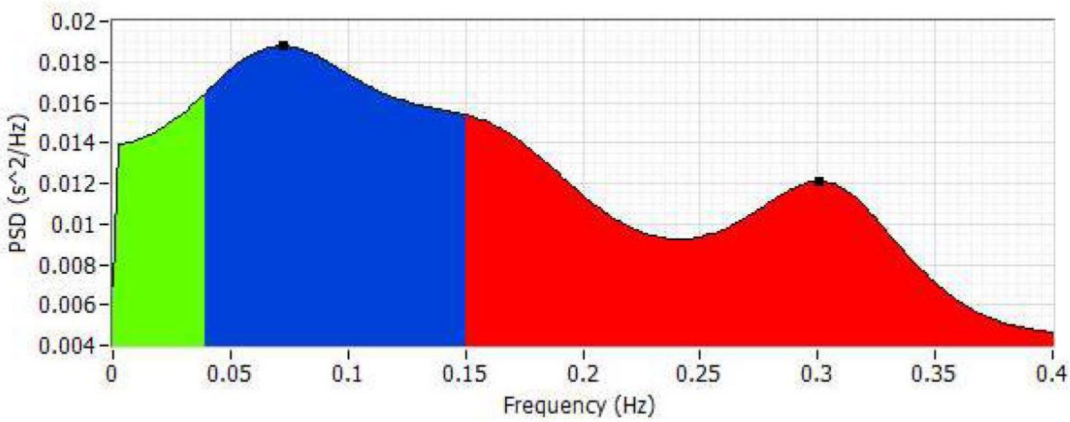

Fig. 19. AR Spectrum Density in Post-Stimulus Condition

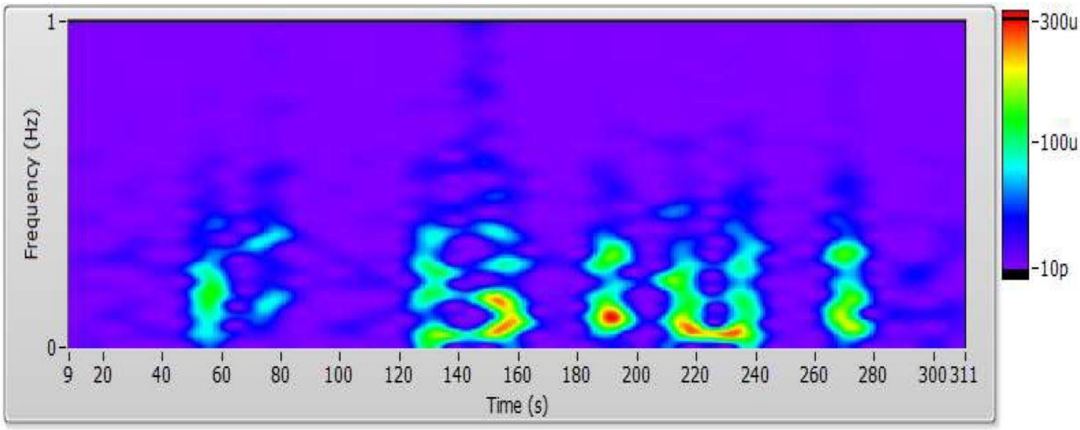

Fig. 20. STFT Spectrogram in Pre-Stimulus Condition

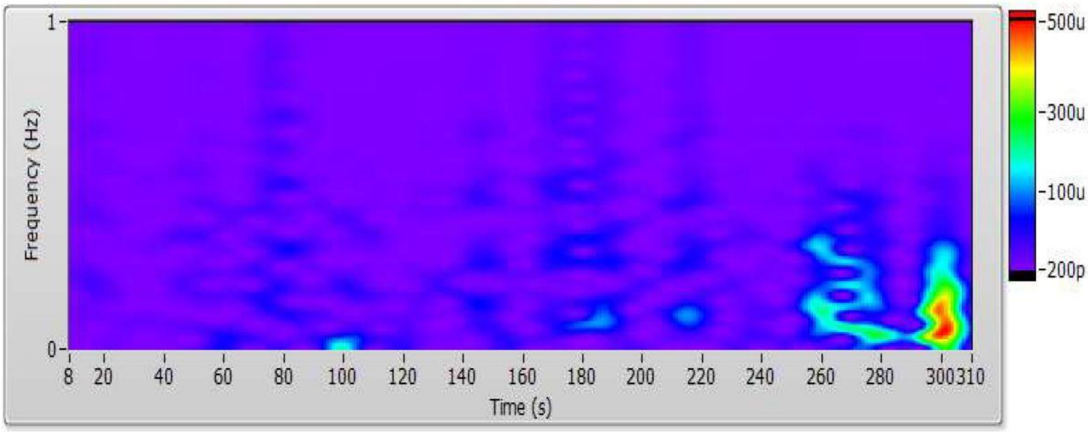

Fig. 21. STFT Spectrogram in Post-Stimulus Condition

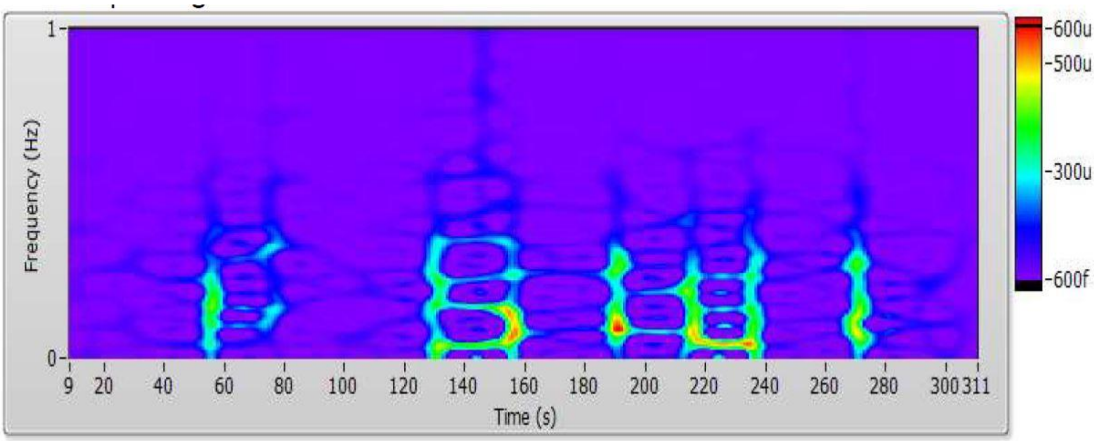

Fig. 22. Gabor Spectrogram in Pre-Stimulus Condition

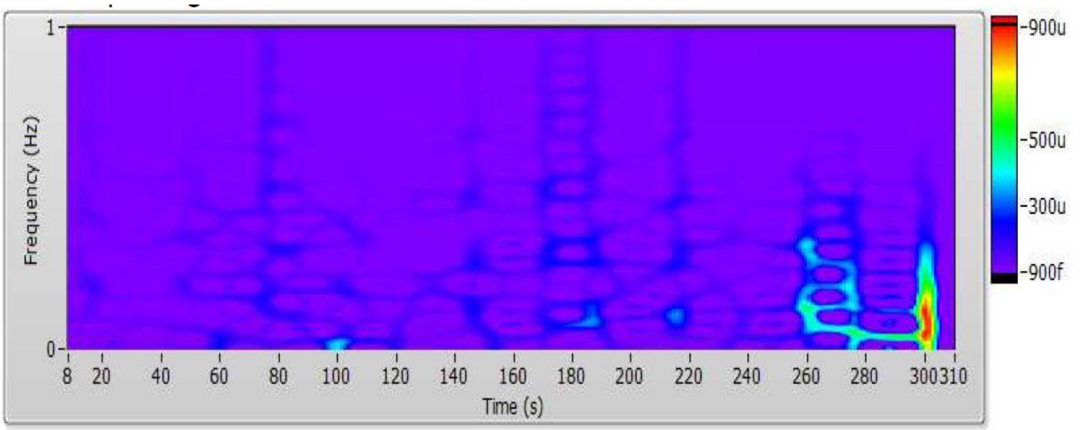

Fig. 23. Gabor Spectrogram in Post-Stimulus Condition

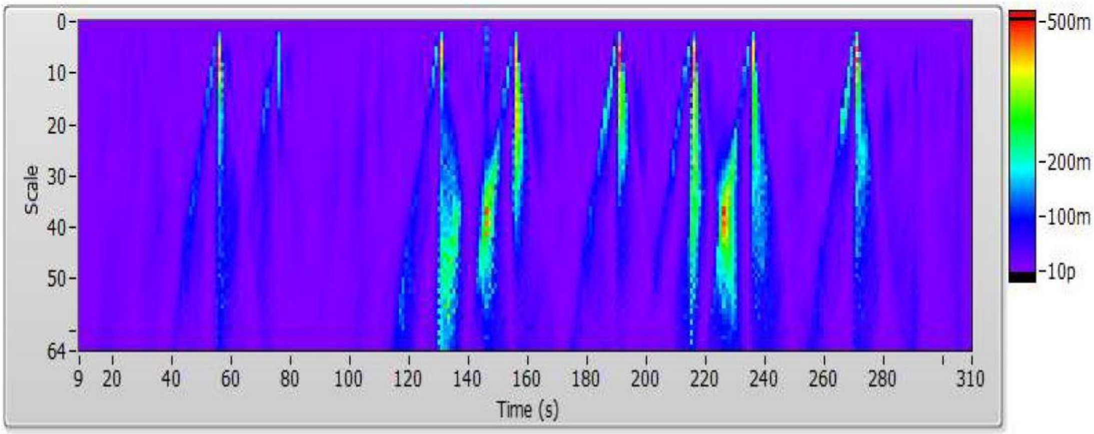

Fig. 24. Wavelet Coefficients in Pre-Stimulus Condition

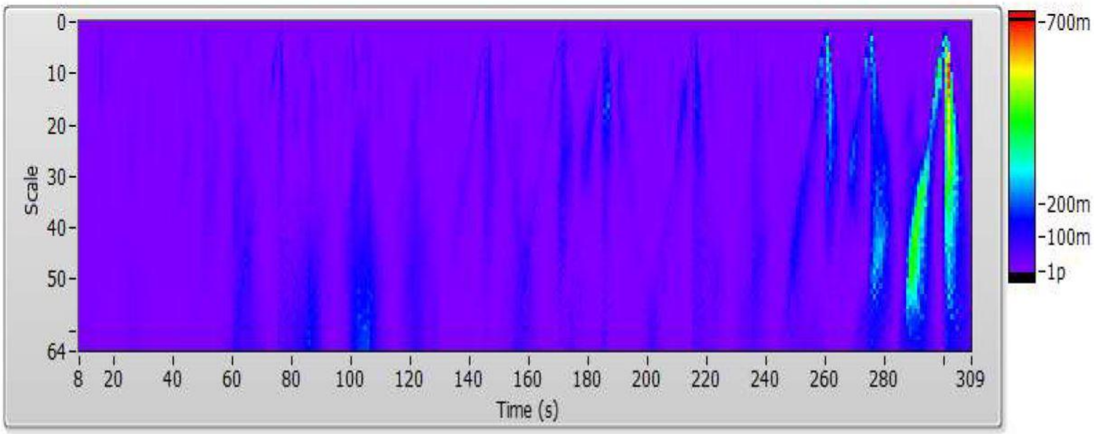

Fig. 25. Wavelet Coefficients in Post-Stimulus Condition

Chapter 6

Conclusion

In the current study, we have attempted to confirm the change in ANS and cardiac electrophysiology of females after they were exposed to Indian classical music (flute composition) as audio stimulus. ECG readings were obtained from ten female volunteers before and after being exposed to the audio stimulus. An attempt was made to understand the functioning of ANS during the pre-and the post-stimulus conditions by performing Recurrence and HRV analysis. The distinct change in patterns in Recurrence plots of pre and stimulus condition RRIs indicates a strong possibility of changes in ANS and Cardiac Electrophysiology. Variations in various HRV parameters in pre- and post-stimulus condition suggested an increase in parasympathetic activity in post-stimulus condition. However, a thorough analysis is required to ascertain actual changes taking place in cardiac electrophysiology.

References

[1] L. Rowell, *Thinking about music: An introduction to the philosophy of music*. 1984.

[2] N. Yehuda, “Music and Stress,” *J. Adult Dev.*, vol. 18, no. 2, pp. 85–94, Jun. 2011.

[3] D. Fancourt, A. Ockelford, and A. Belai, “The psychoneuroimmunological effects of music: A systematic review and a new model,” *Brain. Behav. Immun.*, vol. 36, pp. 15–26, 2014.

[4] B. Champaty, S. Bhandari, K. Pal, and D. N. Tibarewala, “Artificial intelligence based classification of menstrual phases in amenorrheic young females from ECG signals,” in *2013 Annual IEEE India Conference, INDICON 2013*, 2013.

[5] “Biomedical Engineering Education Portal - National Instruments.” [Online]. Available: http://www.ni.com/white-paper/5593/en/. [Accessed: 30-Apr-2017].

[6] R. Rangayyan, “Biomedical signal analysis,” *Library.Wisc.Edu*. 2002.

[7] D. Ge, N. Srinivasan, and S. M. Krishnan, “Cardiac arrhythmia classification using autoregressive modeling,” *Biomed Eng Online*, 2002.

[8] K. Padmavathi and K. Sri Ramakrishna, “Classification of ECG signal during Atrial Fibrillation using Autoregressive modeling,” in *Procedia Computer Science*, 2015.

[9] G. Baselli, D. Bolis, S. Cerutti, and C. Freschi, “Autoregressive modeling and power spectral estimate of R-R interval time series in arrhythmic patients,” *Comput. Biomed. Res.*, vol. 18, no. 6, pp. 510–530, 1985.

[10] T. Force, E. Society, T. North, and A. Society, “Guidelines Heart rate variability,” *Eur. Heart J.*, vol. 17, pp. 354–381, 1996.

[11] S. K. Nayak *et al.*, “Effect of Cannabis consumption on ANS and conduction pathway of heart of Indian paddy field workers,” in *2016 IEEE Annual India Conference (INDICON)*, 2016, pp. 1–5.

[12] K. Urbanowicz, J. J. Żebrowski, R. Baranowski, and J. A. Hołyst, “How random is your heart beat?,” *Phys. A Stat. Mech. its Appl.*, vol. 384, no. 2, pp. 439–447, 2007.

[13] H. Kantz and T. Schreiber, *Nonlinear Time Series Analysis*. Cambridge: Cambridge University Press, 2003.

[14] A. Goshvarpour, A. Goshvarpour, and S. Rahati, “Analysis of lagged Poincaré plots in heart rate signals during meditation,” *Digit. Signal Process.*, vol. 21, no. 2, pp. 208–214, Mar. 2011.

[15] M. Lee Abbott *et al.*, “Practical Biomedical Signal Analysis Using MATLAB,” *Muscles alive their Funct. Reveal. by Electromyogr.*, 2016.

[16] H. Sabelli *et al.*, “Bios Data Analyzer,” *Nonlinear Dynamics. Psychol. Life Sci.*, vol. 9, no. June 2014, pp. 505–538, 2005.

[17] H. Sabelli and A. Lawandow, “Homeobios: the pattern of heartbeats in newborns, adults, and elderly patients.,” *Nonlinear Dynamics. Psychol. Life Sci.*, vol. 14, no. 4, pp. 381–410, 2010.

[18] N. Marwan, M. Carmen Romano, M. Thiel, and J. Kurths, “Recurrence plots for the analysis of complex systems,” *Phys. Rep.*, vol. 438, no. 5, pp. 237–329, 2007.

[19] C. L. Webber and J. P. Zbilut, “Dynamical assessment of physiological systems and states using recurrence plot strategies,” *J. Appl. Physiol.*, vol. 76, no. 2, 1994.

[20] H. Sabelli, “Novelty, A Measure of Creative Organization in Natural and Mathematical Time Series,” *Nonlinear Dynamics. Psychol. Life Sci.*, vol. 5, no. 2, pp. 89–113, 2001.

[21] J.-P. Eckmann, S. O. Kamphorst, and D. Ruelle, “Recurrence Plots of Dynamical Systems,” *Europhys. Lett.*, vol. 4, no. 9, pp. 973–977, Nov. 1987.