Characterization of Non-linear HRV Parameters among Women by Poincare Analysis

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Abstract- Heart rate variability (HRV) is the natural rise and fall of beat-to-beat heart rate as controlled by the autonomic nervous system (ANS) which, in turn, is affected by various physiological factors e.g. breathing, blood pressure, hormones, emotions, and many others. The research work reported in this paper concentrates on characterization of non-linear measures of HRV in females of different hormonal status and from different demographic regions. A total of 141 women subjects (39.97±14.18) belonging to 4 groups i.e. Reproductive and Post-Menopausal age groups from both the Plane and Hill region of West Bengal were studied for short term HRV. Based on the observations, it may be concluded that the hormonal status is properly reflected in non-linear parameters of HRV irrespective of life style and/or demographic variations.

Key Words- Heart Rate variability (HRV); Autonomic Nervous System (ANS); Non-Linear measures; Reproductive phases; Post-Menopausal phases.

I. INTRODUCTION

HRV is the natural rise and fall of beat-to-beat heart rate as controlled by the ANS which, in turn, is affected by various physiological factors e.g. breathing, blood pressure, hormones, emotions, and many others [1][2]. HRV study represents the study of the time series comprising time intervals between consecutive R-waves of electrocardiographic signals from the subject concerned. Parameters characterizing this time series are generally categorized as time domain parameters, frequency domain parameters and non-linear measures. Physiological data very often show complex structures which cannot be quantified or interpreted with linear methods. The disadvantage of the linear parameters is the limited information about the system [3], whereas non-linear measures overcome this [2]. As a result the research work reported in this paper concentrates on characterization of non-linear measures of HRV in females of different hormonal status and from different demographic regions.

Description of some of the non-linear measures are-

A. *Poincare Plot:*

One commonly used nonlinear method that is simple to interpret is the so-called Poincare plot. It is a graphical representation of the correlation between successive RR intervals, i.e. plot of RRj+1 as a function of RRj as described in Fig. 1. The shape of the plot is the essential feature. A common approach to parameterize the shape is to fit an ellipse to the plot as shown in Fig.1. The ellipse is oriented according to the line-of-identity (RRj = RRj+1) [4]. The standard deviation of the points perpendicular to the line-of identity denoted by SD1 describes short-term variability which is mainly caused by RSA. It can be shown that SD1 is related to the time-domain measure SDSD according to [4]

$$SD12 = \frac{1}{2}SDSD2.$$

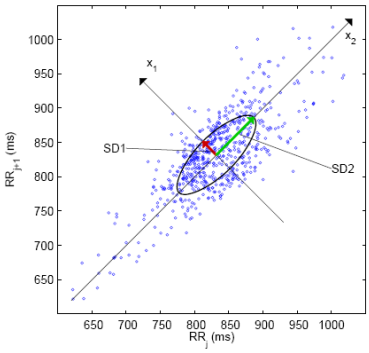

Fig1: Poincare Plot analysis

B. *Approximate Entropy:*

Approximate entropy (ApEn) measures the complexity or irregularity of the signal [5][6]. Large values of ApEn indicate high irregularity and smaller values of ApEn more regular signal. The ApEn is computed as follows. First, a set of length m vectors uj is formed

uj = (RRj ,RRj+1, . . . ,RRj+m−1), j = 1, 2, . . .N − m+ 1

where m is called the embedding dimension and N is the number of measured RR intervals. The distance between these vectors is defined as the maximum absolute difference between the corresponding elements, i.e.,

d(uj,uk) = max{|RRj+n − RRk+n|| n = 0, . . . ,m− 1}

Next, for each uj the relative number of vectors uk for which d(uj,uk)≤ r is calculated. This index is denoted with C_j^m(r) and can be written in the form

$$C_j^m(\mathrm{r}) = \frac{nbrof\{uk|d(uj,uk)\leq r\}}{N-m+1} \forall \text{ k.}$$

C. *Sample Entropy:*

Sample entropy (SampEn) is similar to ApEn, but there are two important differences in its calculation [6][7]. For ApEn, in the calculation of the number of vectors uk for which d(uj,uk)≤ r also the vector uj itself is included. This ensures that C_j^m(r) is always larger than 0 and the logarithm can be applied, but at the same time it makes ApEn to be biased. In sample entropy the self-comparison of uj is eliminated by calculating C_j^m(r) as

$$C_j^m(\mathrm{r}) = \frac{nbrof\{uk|d(uj,uk)\leq r\}}{N-m} \forall \text{ k}\neq j.$$

D. *Detrended Fluctuation Analysis:*

Detrended fluctuation analysis (DFA) measures the correlation within the signal. The correlation is extracted for different time scales as follows [8]. First, the RR interval time series is integrated

$y(k) = \sum_{j=1}^{k}(RRj - \acute{R}R), k = 1, \ldots, N$

A. *Correlation Dimension:*

Another method for measuring the complexity or strangeness of the time series is the correlation dimension [9]. The correlation dimension is expected to give information on the minimum number of dynamic variables needed to model the underlying system and it can be obtained as in the calculation of approximate and sample entropies.

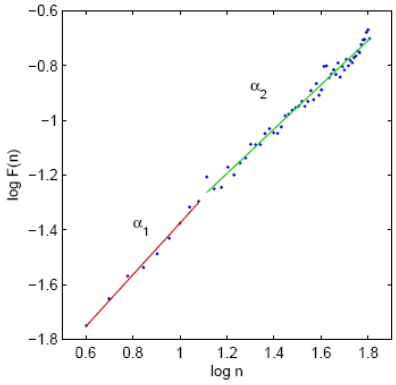

Fig2: Detrended fluctuation analysis

II. MATERIALS & METHODOLOGY

A. *Participants:*

A total of 141 women were selected for the present study. Reproductive and post-menopausal phases of female life cycle represent two distinct hormonal statuses, and therefore, women of corresponding age groups formed the study material. Again subjects of both the age groups were drawn from the plains and hilly areas of West Bengal. Data set of the subjects is listed in Table 1.

TABLE 1: CLASSIFICATION OF PARTICIPANTS

Name of the Group	No. of participants	Range of Age (yrs)	Mean Age (yrs)
Plain area Reproductive Age Group (PRAG)	33	16-48	29.94±8.98

Plain area Post-Menopausal Age Group (PPMAG)	36	43-76	56.19±6.71
Hill area Reproductive Age Group (HRAG)	55	18-43	31.29±6.8
Hill area Post-Menopausal Age Group (HPMAG)	17	45-86	53.17±9.93

The participants of PRAG were university students and working ladies. PPMAG participants were retired women and housewives. Both the HRAG and HPMAG subjects were tea garden workers.

B. *Data Analysis:*

i) ECG signal was acquired from every participant. The detailed methodology was discussed elsewhere [10][11].

ii) The RR series was obtained from ECG signal through MATLAB® programming.

iii) RR intervals were fed into the Kubios Software® for HRV parameters analysis.

iv) The classical non-linear dynamical methods such as- SD1, SD2, their ratio (SD1/SD2); Mean Line Length (Lmean), Maximum Line length (Lmax), Recurrence rate (REC), Determinism (DET), Shannon Entropy (ShanEn), Approximate Entropy (ApEn), Sample entropy (SampEn), Detrended fluctuation (DFA: α1, α2) and Correlation dimension (D2) were chosen for further analysis.

v) The Statistical analyses were done on those non-linear measures for 4 groups with different combination.

III. RESULTS & DISCUSSION

The nonlinear methods differ from the linear measures in that they do not attempt to assess the magnitude of HRV but instead describe the complexity or fractal dynamics of R-R intervals. Undoubtedly, nonlinear analysis methods may provide a different picture of HR behavior and more valuable information regarding cardiovascular regulation that is not obtainable with conventional linear methods [12].

TABLE 2: F-TEST AMONG PRAG & PPMAG

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	0.48	0.021	0.041	1.77	1.98
SD2	0.63	0.095	0.19	1.77	1.98
SD1/SD2	0.42	0.008	0.015	1.77	1.98
Lmean	0.27	0.0	0.0	1.77	1.98
Lmax	0.65	0.115	0.229	1.77	1.98
REC	0.45	0.013	0.025	1.77	1.98
DET	0.43	0.009	0.017	1.77	1.98
ShanEn	0.3	0.0	0.001	1.77	1.98
ApEn	0.08	0.0	0.0	1.77	1.98
SampEn	0.24	0.0	0.0	1.77	1.98
α1	0.47	0.016	0.032	1.77	1.98
α2	0.27	0.0	0.0	1.77	1.98
D2	1.59	0.091	0.182	1.77	1.98

TABLE 3: F-TEST AMONG HRAG & HPMAG

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	8.36	0.0	0.0	2.12	2.46
SD2	4.58	0.001	0.002	2.12	2.46
SD1/SD2	3.15	0.007	0.014	2.12	2.46
Lmean	1.53	0.176	0.352	2.12	2.46
Lmax	0.96	0.43	0.86	2.12	2.46
REC	227374.96	0.0	0.0	2.12	2.46
DET	0.55	0.051	0.102	2.12	2.46
ShanEn	0.81	2.12	2.46	2.12	2.46
ApEn	0.53	0.044	0.087	2.12	2.46
SampEn	0.56	0.061	0.121	2.12	2.46
α1	0.54	0.049	0.098	2.12	2.46
α2	0.78	0.247	0.495	2.12	2.46
D2	1.02	0.509	1.019	2.12	2.46

TABLE 4: F-TEST AMONG RAG & PMAG

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	8.72	0.0	0.0	1.53	1.66
SD2	3.72	0.0	0.0	1.53	1.66
SD1/SD2	4.86	0.0	0.0	1.53	1.66
Lmean	1.14	0.308	0.616	1.53	1.66
Lmax	0.74	0.108	0.216	1.53	1.66
REC	118688.89	0.0	0.0	1.53	1.66
DET	0.45	0.0	0.001	1.53	1.66
ShanEn	0.52	0.003	0.007	1.53	1.66
ApEn	0.36	0.0	0.0	1.53	1.66
SampEn	0.45	0.0	0.001	1.53	1.66
α1	0.6	0.018	0.037	1.53	1.66
α2	0.5	0.002	0.004	1.53	1.66
D2	1.43	0.081	0.161	1.53	1.66

Statistical F-tests were carried between reproductive and post-menopausal women of plain area (Table 2), Hilly region (Table 3) and for both the demographic regions (Table 4). From the above tables it is clear that most of the non-linear measures result significant differences at p value< 0.05 for both one and two- tail analysis.

TABLE 5: F-TEST AMONG PRAG & HRAG

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	0.03	0.0	0.0	1.66	1.83
SD2	0.1	0.0	0.0	1.66	1.83
SD1/SD2	0.02	0.0	0.0	1.66	1.83
Lmean	0.18	0.0	0.0	1.66	1.83
Lmax	0.95	0.445	0.89	1.66	1.83
REC	0.0	0.0	0.0	1.66	1.83
DET	1.2	0.271	0.542	1.66	1.83
ShanEn	0.6	0.062	0.124	1.66	1.83
ApEn	0.19	0.0	0.0	1.66	1.83
SampEn	0.43	0.006	0.011	1.66	1.83
α1	0.53	0.027	0.055	1.66	1.83
α2	0.47	0.012	0.023	1.66	1.83
D2	1.46	0.107	0.215	1.66	1.83

TABLE 6: F-TEST AMONG PPMAG & HPMAG

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	0.44	0.022	0.043	2.17	2.53
SD2	0.76	0.24	0.48	2.17	2.53
SD1/SD2	0.14	0.0	0.0	2.17	2.53
Lmean	1.03	0.497	0.993	2.17	2.53
Lmax	1.39	0.244	0.488	2.17	2.53
REC	1.32	0.283	0.565	2.17	2.53
DET	1.53	0.181	0.363	2.17	2.53
ShanEn	1.63	0.15	0.3	2.17	2.53
ApEn	1.31	0.284	0.569	2.17	2.53
SampEn	1.02	0.505	1.01	2.17	2.53
α1	0.62	0.113	0.227	2.17	2.53
α2	1.38	0.25	0.5	2.17	2.53
D2	0.94	0.42	0.84	2.17	2.53

TABLE 7: F-TEST AMONG PLAIN AND HILLY REGION

Parameters	F	p-one tail	p-two tail	F-crit one tail	F-crit two tail
SD1	0.05	0.0	0.0	1.49	1.6
SD2	0.17	0.0	0.0	1.49	1.6
SD1/SD2	0.04	0.0	0.0	1.49	1.6
Lmean	0.5	0.002	0.004	1.49	1.6
Lmax	1.23	0.198	0.397	1.49	1.6

REC	0.0	0.0	0.0	1.49	1.6
DET	1.71	0.013	0.026	1.49	1.6
ShanEn	1.26	0.164	0.329	1.49	1.6
ApEn	1.45	0.063	0.126	1.49	1.6
SampEn	0.96	0.427	0.855	1.49	1.6
α1	0.7	0.07	0.14	1.49	1.6
α2	1.06	0.4	0.8	1.49	1.6
D2	1.4	0.079	0.159	1.49	1.6

Again Statistical F-tests were carried out between the females from plain and hilly region for reproductive phases (Table 5), post-menopausal phases (Table 6) and for both the female cycles (Table 7). Non-linear measures can significantly ($p<0.05$) distinguish between plain and hill area of reproductive phases. But for post-menopausal phase only two parameters (SD1 & SD1/SD2) have the distinguishable ability.

TABLE 8: ONE WAY ANOVA AMONG 4 GROUPS

Parameters	Fisher F-Value	p-value	F-Crit
SD1	0.987	0.04	2.67
SD2	1.412	0.24	2.67
SD1/SD2	0.423	0.74	2.67
Lmean	3.597	0.02	2.67
Lmax	1.635	0.18	2.67
REC	0.52	0.67	2.67
DET	1.623	0.19	2.67
ShanEn	4.267	0.01	2.67
ApEn	9.538	0.0	2.67
SampEn	4.479	0.005	2.67
α1	0.587	0.624	2.67
α2	4.312	0.006	2.67
D2	7.869	0.0	2.67

One way Analysis of Variance (ANOVA) was done among 4 groups (Table 8) of women. The result shows most of the non-linear measures of HRV are significant at 5% level of significance.

Entropy refers to the information content. With reference to a dynamical system it is rate at which information is produced. Entropy is suitable for the physiological signal analysis which usually involves short and noisy data sets specifically the Heart rate time series data sets [2].

ApEn a complexity measure is introduced by Pincus. et. al(1991) gave inconsistent results. The limitation of ApEn is the inconsistent results and dependency on data length is overcome by SampEn introduced by Richman. Joshua's and Moorman (2000) the SampEn will not do the self matches and it is independent of data length. For larger values of data length N and threshold r both the values of ApEn and SampEn will be the same. ApEn and SampEn were used to assess HRV and complexity of time series was calculated. Entropy measures reflect both variance and correlation properties.

Shannon Entropy is a suitable measure for the time series complexity. Higher value of this entropy refers to higher complexities within the investigated time series [3].

CD is the quantification of dimensional complexity based on phase-space techniques and is one of the most widely used measures of fractal dimension. It defines the phase-filling propensity of the R-R interval time series [12].

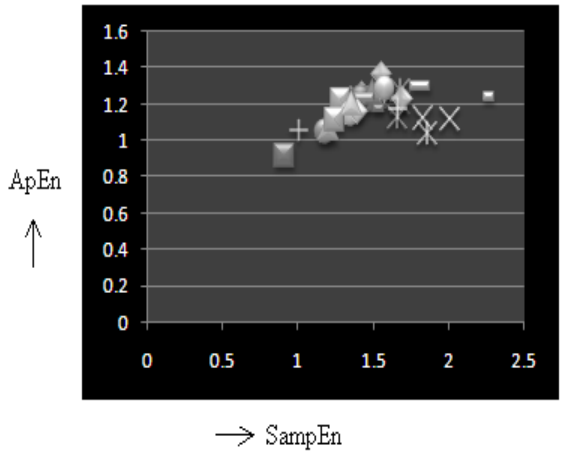

Fig 3: ApEn vs. SampEn for PRAG

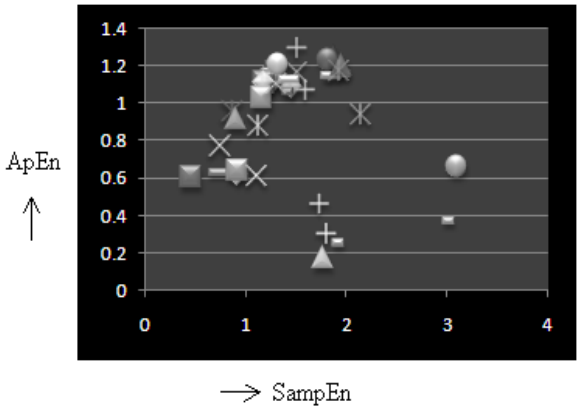

Fig 4: ApEn vs. SampEn for PPMAG

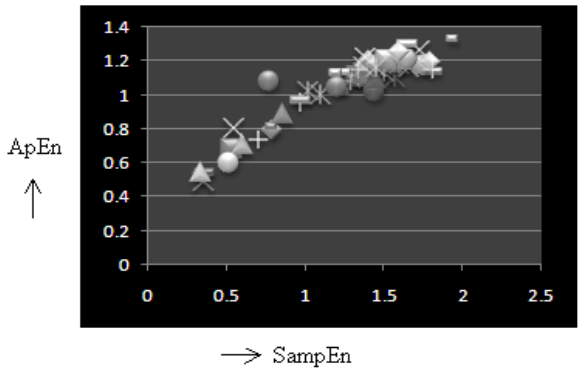

Fig 5: ApEn vs. SampEn for HRAG

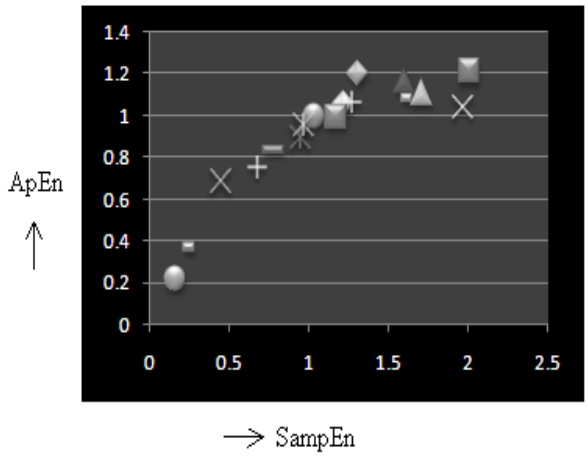

Fig 6: ApEn vs. SampEn for HPMAG

Two non-linear HRV measures ApEn and SampEn were used to plot ApEn vs. SampEn for all the four groups to obtain group wise characteristics pattern.

SampEn is a "regularity statistic." It "looks for patterns" in a time series and quantifies their degree of predictability or regularity. Larger SampEn values indicate greater independence, less predictability, and hence greater complexity in the data, whereas lower values imply greater regularity in the time series. SampEn is virtually a variant of ApEn [12].

From the figures (Fig. 3-6) it is clearly obtain that reproductive phase of both the demographic regions show a particular pattern. On the basis of pattern among PRAG and HRAG groups can also be distinguished manually. The data set of post-menopausal group of plain area (PPMAG) does not show any strong pattern to classify, whereas HPMAG group show a weak pattern. SampEn values are quiet high for both the reproductive and post-menopausal women from plain area than hilly region. So, the data set from hilly region is slightly regular than plain area.

IV. CONCLUSION

HRV non-linear measures can be used as predictive markers to distinguish among the subject groups. The results of the statistical analysis indicated that these non-linear parameters could significantly distinguish among subject groups. The group wise characterization patterns using the above parameters have also been studied. From the pattern analysis it can be concluded that Reproductive phases of women of both the demographic regions show strong pattern to classify and data set of hilly region is slightly more regular than plain area on the basis of SampEn value. Based on the observations, it may be concluded that the hormonal status is properly reflected in non-linear parameters of HRV irrespective of life style and/or demographic variations.

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