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Heart Rate Variability Analysis of PC Interactive E-Learning Studies

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ABSTRACT
The objective of this particular research was the analysis of variations in the heart rate variability indicating the functionality of the autonomic nervous system as well as psychotic strain because of computer-based e-learning classroom study in the students. Comprehensive records were obtained from 25 students before and after the computer-based e-learning classroom study for 2 hours having an average age of 21 years and in accordance with two comparable 8.46-minute HRV measurements of each student. The frequency domain and nonlinear analysis of HRV were conducted using the non-parametric FFT spectrum and Poincare plot analysis receptively on RR time series data extracted from ECG recordings. The HRV factors and details disclosed considerable variations in HRV before and after computer-based e-learning classroom study in students.

Keyword: *Heart rate variability, E-learning, FFT spectrum, Poincare plot.*

I. INTRODUCTION
The past two generations have experienced the identification of an important connection in between the autonomic nervous system (ANS) and cardiovascular fatality, consisting of unexpected cardiac fatalities [1–4]. Experimental confirmation for a connection with a tendency for venomous arrhythmias to symptoms of either greater sympathetic or minimal vagal function has inspired the evolution of quantitative indicators of the autonomic function. Heart rate variability (HRV) stands among the most encouraging such indicators. The seemingly simple derivation of this particular measurement has prominent its application. Among the various presented non-invasive methods for determining the autonomic status, HRV has emerged to be an ordinary technique to assess the sympathovagal equilibrium at sinoatrial level [6]. The sinus node is controlled by both parasympathetic (vagal) and sympathetic influences. Its well-accepted that situations such as for instance presuming an upright placement, mental anxiety, and exercising are linked to an enhancement of sympathetic tone. On the other hand, vagal tone is increased during the course of relaxing situations. In average people, both the sympathetic and the parasympathetic tone varies all over the day [7]. HRV indicator like the ratio of low-frequency to high frequency power was used for describing sympathovagal harmony. In the lack of sympathetic and parasympathetic feedback to sinus node, sinus node shoots at the intrinsic rate or simply R-R interval. Whenever vagal effect dominates, the heartrate is lower than intrinsic heart rate; whenever sympathetic effect dominate, heart rate is higher than intrinsic heart rate [4]. It was discovered that the HRV reduces along with age and with an individual, HRV is optimum during the course of sleep. It's also rate centered i.e. HRV is increased at reduced heart rates [8].

Several scientific studies have confirmed variations in HRV factors in disease situations. [9–11] The explanation of this is that the particular disease condition either causes, is caused by or is linked with irregularities of cardiac autonomic regulation. The diseased situation is connected with inherent mental pressure, not due to the pathological course of action of the disorder, but merely by stress and anxiety invoked in individuals as a consequence of consciousness of the disease or disorder. Anxiety induced fatigue is found to provoke the behavioral alerting consequence in human beings, that will be pertaining to boost in sympathetic activities and a drop in parasympathetic activities in the cardiovascular system. [12] This particular alternation in cardiac autonomic function alone could influence the HRV standards in patients. The time period of academic examination is a recognized model of mental pressure in scholars, overall performance in exams can determine their precious future potential. Various scientific studies state alterations in markers of anxiety in students throughout the period of examinations [13–15]. To examine the irregularities in HRV due to computer based e-learning that is caused by student's brain functional as well as phycho-emotional state after attending class, for this 25 students in the age group of 18 to 24 years old were analyzed before and after the regular computer based e-learning classes.

II. Materials and Tools

A. Subjects

Twenty-five students of single classroom age group of 18-24 (15 males and 10 female) volunteered to the part of this research were examined. A sample of time period 8.46 minute ECG data was recorded of each student before attending the e-learning class and after the continuous computer based e-learning class of basic computer knowledge of two hours. Each ECG recording of the particular student was taken on the same day in taking account of the timing and location. All the students were non-smoker, non-alcoholic, healthy and none of the student's family member was diabetic.

B. Protocol

All the recording was taken in the simple computer lab without any external interference like sound and scene. Subjects were stationary during the recording and sitting on the stools for 10 minutes. Subjects were instructed to do not change in their breathing unnecessary and to breath spontaneously in their regular rhythm. As a part of the study all the students were instructed to have only normal breakfast before attending the regular classes. Timing of the recording of all the students was in the morning between 7 am to 11 am.

C. Tools

ECG data was recorded by the 3 lead ECG hardware having double stage amplification and interfaced with laptop by the use of Arduino Uno for real time data acquisition with the help of LabVIEW software installed in the laptop. LabVIEW recorded the real time ECG signal in laptop in dot tdms file format at the sampling frequency of 500hz. This sampled data was processed by the ECG feature extractor in Biomedical Workbench of NI for signal processing and feature extraction and RR time interval was extracted in a .txt file which can be analyzed by the HRV analysis software. Heart rate variability analyzer in Biomedical workbench is used for HRV analysis which took data directly from the ECG feature extractor after the signal processing. HRV analyzer having the Poincare plot and FFT spectrum method of HRV analysis which generates values of HRV indices with different color coding [16]. As numerous commercial products nowadays furnish automated statistic of HRV measurement, the heart specialist has been presented that has seemingly easy tool both for research as well as clinical tests [5].

III. Methods of analysis

A. Spectral Analysis

There are multiple frequencies or frequency bands in the HRV analysis. Since 1960s there are various spectral analysis techniques have been evolved for the analysis of tachogram [17]. The important and basic information about the how power is dispersing in terms of frequencies; is generated by the power spectral density analysis of the RR time interval series by applying appropriate mathematical algorithms. There are to techniques are presented to calculated the PSD of the signal; first one is parametric method and second one is non-parametric method, these both techniques uses the different mathematical algorithms for computation. In this presented paper, FFT based non-parametric method is employed with the help of software as you can see a generated FFT spectrum of one subject in the figure (1). There are main three spectral components are recognized within the spectrum computed from RR time interval series recording after applying FFT based algorithm [18,19,20,21,24]: The first spectral component is very low frequency (VLF) (0.003 to 0.04 Hz), Second spectral component is low frequency (LF) (0.04 to 0.15Hz), and the third spectral component is high frequency (HF) (0.15 to 0.4 Hz). The powers and fundamental frequency of all the frequency bands varies in accordance with the fluctuations in heart rhythms [21,22,23]. Dimension of power elements within VLF, LF and also HF bands is the absolute values of the power (ms2), although LF as well as HF can be calculated in normalized units (n.u.) [21,22].

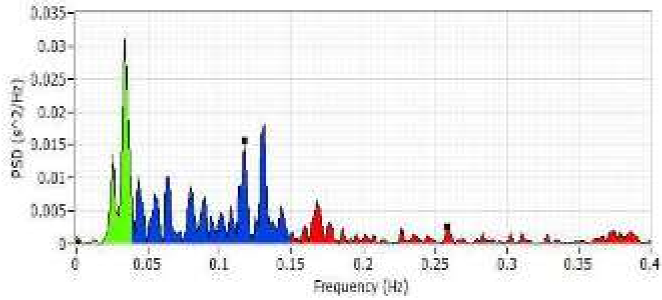

Fig. 1. HRV spectrum of sample data of one subject generated by HRV analyzer, where Green indicates the VLF spectrum, Blue indicates the LF and Red indicates the HF spectrum.

Based on the above RR-interval power spectrum Index of Centralization (IC) indicator is calculated which is associated with the brain's functional and phycho-emotional stress.

$$IC=((VLF+LF))/HF \quad (1)$$

where VLF, LF and HF are the Power spectral density in the respective frequency band. Increasing IC indicates the rise in heart rhythm [37, 38].

B. Poincare Plot Analysis

The Poincare plot as part of HRV is actually a scatter plot belonging to current R-R time interval plotted versus the prior R-R time interval. The Poincare plot can also abbreviate as Lorenz plot, scatter gram or Scatter plot and phase delay map or Return map. Poincare plot study is a simplified quantitative graphic approach in comparison to typical fast Fourier transform (FFT) exponent [27, 28]. The plot caters summary reports along with comprehensive beat-to-beat insight in regards to actions of the cardiovascular system (11). In this ellipse, points which are above the line are showing the intervals which are longer than preceding intervals and contrary points below the line showing intervals which are smaller the preceding interval.

Hence, the dispersal of point's vertical towards distinctive line of identity (width) exhibits the measure of interim HRV. The spots along with the distinctive line of identity (length) exhibit the long-term HRV [29]. Tulppo et al [30] equipped an ellipse in the form of the Poincare plot and also stated two typical descriptors of the entire plot, SD1 and then SD2, just for quantification of the entire geometry. Such standard descriptors portray the minor axis as well as the major axis on the ellipse correspondingly as displayed in Figure 2. The explanation of descriptors SD1 and SD2 with references to linear statistics, provided by Brennan et al [31] demonstrates that the typical descriptors assist the visual evaluation of the entire distribution. This exhibits an alluring pattern of the RR time interval data by portraying both the short as well as long term variations in the ECG signal [30, 31]. SD1 reveals standard deviation of short term HRV in the data. The SD2 reveals standard deviation of progressive long term RR time intervals (major axis of ellipse) is determined with horizontal axis. SD1 signifies the instantaneous beat-to-beat HRV and SD2 signifies the continual beat to beat HRV [32,33,34]. And the ratio of SD1/SD2 signifies randomness in heart rate variability (HRV) [35]. The location at which both axes contrast, represents total mean of RR time intervals. Several experts demonstrated that varying lags associated with Poincare plot. However, this will render better comprehension regarding the autonomic regulation of heart rate [27, 36]. After processing the recorded EGG data of students Poincare analysis was done by the use of HRV analyzer for each student record. A sample Poincare and its descriptors are show below for 8.46 minute ECG recording.

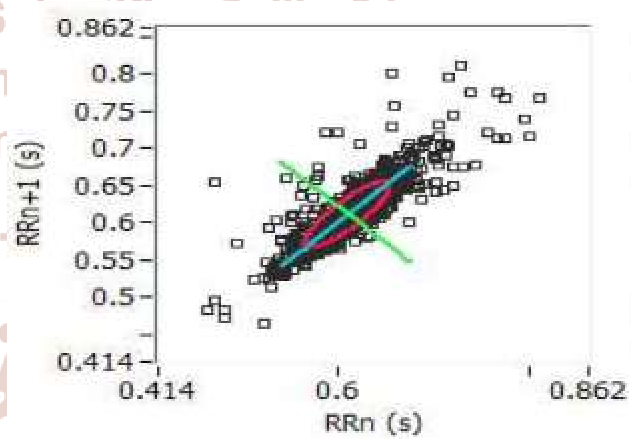

Fig. 2. Generated Poincare plot and values of SD1=16 and SD2=45 for 8.46 minute ECG data by Biomedical Workbench's HRV analyzer, where green and bluish line depicts the SD1 and SD2 respectively.

IV. Results

From the above tools and methods Non parametric FFT spectrum as frequency domain analysis is done for 25 students and power of frequency bands were calculated which are shown in the Table 1. Where we can see the variations in the values of VLF, LF, HF and IC for before and after computer based e-learning classroom study.

Table 1 Values of Power Spectrum Bands and Index of Centralization

Subject	Before e-learning study				After e-learning study			
	VLF Power	LF Power	HF Power	IC1	VLF Power	LF Power	HF Power	IC2
1	250	730	825	1.187	480	1600	395	5.265
2	110	280	284	1.373	140	440	225	2.577
3	19	250	384	0.700	81	650	141	5.184
4	72	420	93	5.290	390	900	171	7.543
5	230	510	213	3.474	150	1100	260	4.807
6	110	340	424	1.061	110	380	169	2.899
7	44	360	71.2	5.674	570	790	147	9.251
8	150	450	241	2.489	350	560	183	4.972
9	390	770	227	5.110	52	200	33.8	7.455
10	24	31	20.3	2.709	21	42	15	4.2
11	47	740	290	2.713	22	330	93.9	3.748
12	320	870	617	1.928	730	770	673	2.228
13	130	1200	1010	1.316	130	670	316	2.531
14	77	320	691	0.574	120	760	221	3.981
15	23	160	168	1.089	15	43	14.7	3.945
16	140	290	214	2.009	49	340	57.6	6.753
17	130	450	881	0.658	35	140	114	1.535
18	8.6	28	9.76	3.75	47	130	23.5	7.531
19	20	620	199	3.216	100	350	79.8	5.639
20	140	540	91.4	7.439	170	340	39.7	12.846
21	42	250	63.9	4.569	66	240	47.5	6.442
22	54	280	101	3.306	44	140	50.3	3.658
23	22	160	84.6	2.151	12	150	62.6	2.587
24	100	570	1140	0.587	150	460	709	0.860
25	260	550	299	2.709	140	650	133	5.939

A comparison graph can be plotted form above statistical data shown in Table 1 for values of IC for both before and after attending e-learning class of each student. The graph is shown in Fig. 3 which clearly showing the increment in the IC values of every student.

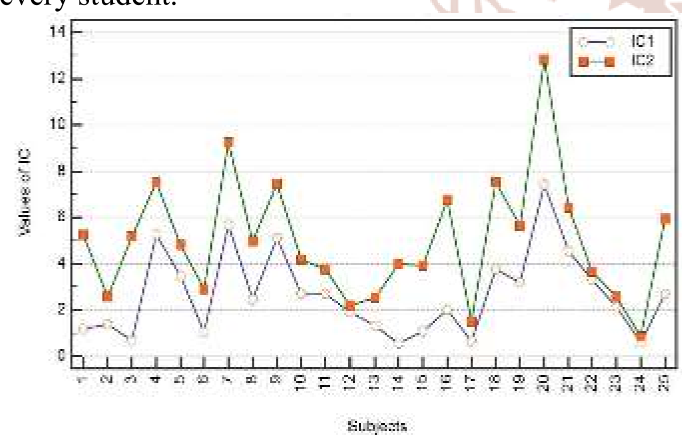

Fig. 3. Comparison graph for each student where IC1 is the value of IC before attending e-learning class and IC2, after attending e-learning class.

Using same tools Poincare plot analysis is done and values of SD1, SD2 and ratio the SD1/SD2 are calculated for both time recording before attending the e-learning class and just after the e-learning class study without any other interference or activity in between and these Poincare plot descriptors for both are shown in Table 2. Which clearly shows the variation in the ratio SD1/SD2. We can easily observe the difference, there is the decrement in the magnitude of ratio SD1/SD2 after the computer-based e-learning classes.

Table 2 Values of Descriptors Sd1 and Sd2 and their Ratio

Subject	Before e-learning study			After e-learning study		
	SD1	SD2	SD1/SD2	SD1	SD2	SD1/SD2
1	47	78	0.602	25	91	0.274
2	26	51	0.509	17	44	0.386
3	25	36	0.694	15	50	0.3
4	13	41	0.317	15	52	0.241
5	27	62	0.435	23	57	0.403
6	33	61	0.540	21	47	0.446
7	16	45	0.355	17	59	0.288
8	20	50	0.4	19	67	0.283
9	18	54	0.333	13	57	0.228
10	17	39	0.435	7	20	0.35
11	16	49	0.326	9.1	37	0.245
12	36	74	0.486	37	85	0.435
13	34	62	0.548	28	53	0.528
14	28	61	0.459	20	55	0.363
15	19	37	0.513	7.5	22	0.340
16	25	53	0.471	12	44	0.272
17	59	87	0.678	19	43	0.441
18	7.8	21	0.371	5.7	25	0.228
19	15	41	0.365	11	41	0.268
20	18	52	0.346	8.1	43	0.188
21	10	38	0.263	8.6	40	0.215
22	12	42	0.285	9.2	33	0.278
23	12	30	0.4	11	32	0.343
24	33	62	0.403	25	65	0.384
25	33	70	0.471	18	52	0.346

Based on the data generated in Table 2, A comparison graph can be plotted for each student's SD1/SD2 ratio for both times before and after the attending e-learning class, shown in figure (4) which depicts the increment in the ratio of SD1/SD2 for each student.

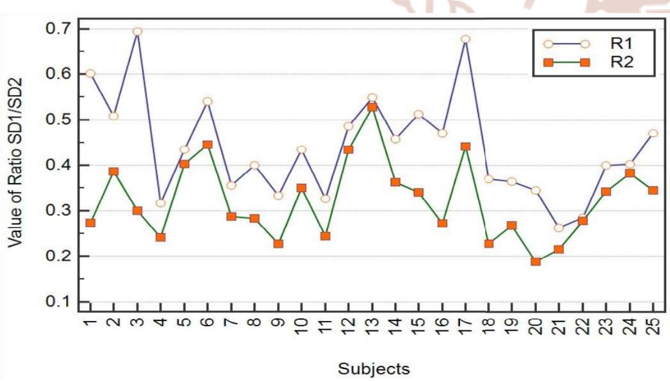

Fig. 4. Comparison graph of each student where R1 is value of ratio SD1/SD2 before attending e-learning class and R2, after attending the e-learning class.

V. Discussion

In the frequency domain analysis, the computation of index of centralization (IC) parameter by the use of VLF, LF and HF for both the times, before and the after PC interactive e-learning study of each student, demonstrates the brain's functional as well as phycho-emotional state. Which means increment in the IC indicating the increment in the central control of the student's heart rhythm. [37, 38] From the Table 1, we can see that the value of IC of each student is incremented after the computer-based e-learning classroom study as compare to prior to attend the e-learning class. Which indicates that computer-based e-learning causes the increment in the phycho-emotional stress as well as brains functionally of each student that affects the heart rate variability.

In the Poincare plot analysis, descriptor SD1/SD2 ratio is used as a key parameter for analyzing the results. As previous studies show that the ratio SD1/SD2 is lower for unhealthy persons which shows the more regular rhythm [39, 40]. And in this presented study on 25 students, we noticed decrement in the ratio SD1/SD2 after the e-learning classroom study, from which can refer that with the computer-based e-learning having the adverse effect on the cardiovascular system.

VI. Conclusion

Based on the research work done in this paper on this HRV analysis using two methods of analysis; both spectral analysis and Poincare plot analysis, this can be concluded that PC interactive e-learning studies causes the increment in the HRV which is induced by the brain's functional as well as phycho-emotional state of students. There could be numerous other factors can be involved that need further study on the same topic to identify other possible outcomes so that more precise and accurate result can be predicted based on the HRV analysis.

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