Stress Index Calculation and Analysis based on Heart Rate Variability of ECG Signal with Arrhythmia

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Abstract: **Electrocardiogram (ECG) is a biological signal that plays a significant role in the detection of heart diseases. Translating the QRS complex is a standout amongst the most imperative parts of ECG signals and its processing and flag preparing. R wave is the real segment in the intricate, which has a basic job in the analysis of heart Rate abnormalities and furthermore in deciding pulse fluctuation (HRV). In this paper, we are utilizing MATLAB to pin the information from the crude MAT-documents from physio bank and Kubios HRV programming to dissect the information. Three unique methodologies were taken for consideration for the investigation, Time-area analysis, Frequency space analysis, and non-linear analysis methods. The correct utilization of MATLAB capacities (both implicit and user characterized), toolbox and Simulink software can lead us to work with raw ECG signals for preparing, separating and examine by simulation with extraordinary accuracy and ease. The product acknowledges distinctive info information groups for electrocardiogram (ECG) information and beat-to-beat RR interim information. The product figures all the normally utilized time-area and recurrence space HRV parameters and more than 40 investigation parameters. The examination results are spared as an ASCII content record, MATLAB MAT-document, or as a PDF report. The product is essentially a direct result of its reduced graphical UI. The product can be utilized uninhibitedly on Windows and Linux working frameworks.**

Keywords: Heart rate variability, Kubios, Electrocardiogram, Frequency analysis, Heart rate

1. INTRODUCTION

Pulse Variability (HRV) is a physical event of the variety of time interims between every heartbeat. The variety of time length between the heart pulsates contains deep-rooted information about any flow ailment or ceaseless heart issue. Dissecting and examining the HRV gives the capacity to survey the general wellbeing of the heart and the Autonomous Nervous System (ANS) which oversees in managing the characteristic and significant rhythm of the person's heartbeat. The smooth harmonious balance between the sympathetic and parasympathetic nervous system, which are the real segment of the ANS is the key for a healthy heart rate in a person.

The sympathetic nervous system activates in presence of sympathetic stimuli, like stress exercise or any heart related disease. These stimuli increase the Heart Rate (HR) by increasing the firing rate of the Sino-atrial node of the heart and decrease the heart rate variability. The parasympathetic actions like internal organs functioning, allergic reactions and other functions like maintaining hemostasis triggers the parasympathetic nervous system. They diminish the Heart Rate (HR) and increment the Heart Rate Variability (HRV) of the individual. Each different commitment of both thoughtful and parasympathetic activities prompts tweak and the progressions of the "R-R" interim of the QRS complex of the ECG [7], [8], [10], [11], [12], [13], [14].

The sympathetic activities and work are related to low frequency range of 0.04-0.15Hz. Whereas the parasympathetic activities and exercises are related to the higher frequency range of 0.15 Hz – 0.4 Hz.[22], [23] HRV and Heart Rate conditions are affected by the stress, cardiovascular conditions and other pathological states. Dominant sympathetic activities and reduced parasympathetic activities controlling the cardiac functions are majorly found in patients with myocardial infraction. HRV is also modified by the central and other peripheral nervous systems, severe cyclic changes in HR are reduced due to strong brain damage or depression. Dependency of HRV on age and sex is also quite prominent and observable. HRV is found more in physically active young and old women[1], [2], [3], [4], [19], [20].

2. METHODOLOGY

2.1 Data Extraction and Computational Algorithm:

PhysioNet is an open source website which provides free access to large collection of recorded physiological signals which includes cardiopulmonary, neural and other biomedical signals of patients suffering from various disease related torments and of other normal patients. The collected

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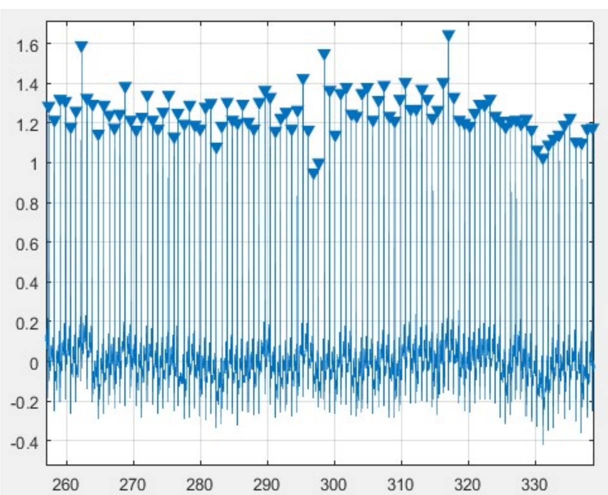
data are very precious to the research community as they support their field of research develop their work.

The signal which we are using in here is MIT_BIH arrhythmia database signals. The signals are perambulatory recordings of around 47 subjects examined in MIT-BIH arrhythmia laboratory. These recording were converted into digital format at 360 samples per second rate with 11-bit resolution in a range of 10mV range. The bandpass channel signals were digitized at 360 Hz for every signal in real time circumstance utilizing versatile equipment. The ADCs utilized for digitization intention were utilized likewise structured with 11-bit goals in a scope of + 5 mv range and test esteems running from 0 to 2047, with 1024 relating to 0 V. The data is extracted using MATLAB [1].

The crude ECG data files are downloaded from the PhysioNet website in MATLAB format, i.e., .m file format which is converted into physical signals by subtracting the base value for the data file from the value and then dividing it by the gain, by doing this we get the actual signal captured from the ECG. The sampling frequency for every sample is around 360 Hz. The total Time period for the entire ECG sample for every patient was taken out by inversing the sampling frequency and multiplying it by the sample length.

Using Peak analysis and function *'findpeaks'* we detect the R waves from the ECG data available to us MATLAB readable format, i.e., mat extension files. A minimum threshold value for amplitude of r- peak was of 0.5 mV and minimum time separation between two R waves was kept 300ms [1]. The threshold setting for detection of the R waves from the ECG heart signal make it more precise and accurate. The .info extension files contained some basic information about the heart signals in the other file and making it feasible to read and plot those data in the software. The detected R waves from the data files, which can be seen in the figure 1, were stored in a matrix along with the corresponding time in a different matrix. The values of the extracted R- waves were exported to a text file in ASCII format which is feasible for Kubios to read and interpret the file.



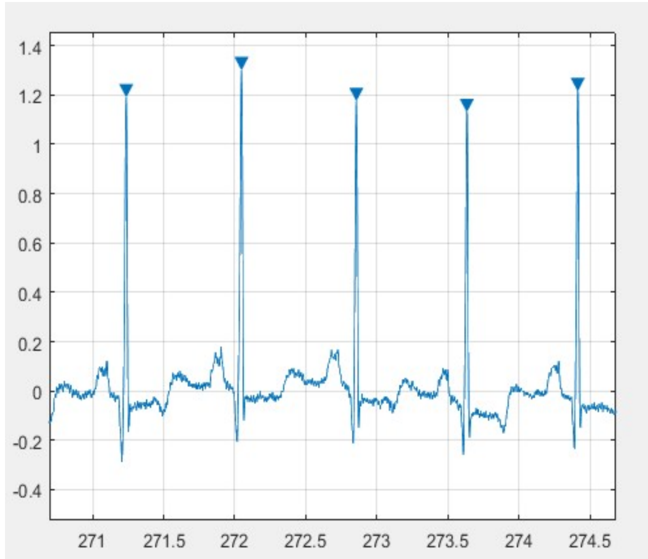


Fig.1: 1(a) R-wave plots in MATLAB, 1(b) detection of R-wave peaks in MATLAB by small Arrow heads at top of every R peak of the ECG.

The values were written into the text file using the command "*dlmwrite*" which allowed saving the values with proper delimiter separating them. The text ASCII format text files were saved with the exact name as that of the database files.

2.2 Kubios Analysis Methods:

Kubios HRV is a cutting-edge and simple to use freeware for coronary heart Rate variability (HRV) analysis. It comprises an improvised QRS detection algorithm and tools for noise correction, trend removal and analysis sample selection [5].

2.2.1 Time-domain methods

These are applied immediately to the collection of successive RR interval heart values and consequently are the best to carry out. The suggested mean-value of RR intervals or, the correspondingly, the mean HR is the maximum obtrusive such degree. There are other variables that degree the variability inside the RR series. (SDNN) i.e. the Standard old Deviation of RR intervals is given as

$$\text{SDNN}=\sqrt{\frac{1}{\text{N-1}}\sum_{j=1}^{N}\left(RR_j\text{-}\overline{\text{RR}}\right)^2} \qquad (1)$$

where N is the total complete number of progressive interims and RRj speaks to the estimation of j'th RR interim. The general variety inside the RR interim arrangement is given by SDNN which incorporates both short-and long-term variations of the heart.

Standard Deviation of Successive RR interval differences (SDSD) is given by

$$SDSD = \sqrt{E\{\Delta RR_j^2\} - E\{\Delta RR_j\}^2} \qquad (2)$$

This can be employed for short term variability of the heart. $E\{\Delta RR_j\} = E\{RR_j+1\} - E\{RR_j\} = 0$ is for stationary RR series. SDSD is expressed as the root mean square of consecutive differences (RMSSD) and is given by

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}(RR_{j+1} - RR_j)^2} \quad (3)$$

NN50 is also alternate measure calculated from successive RR interval period variations, this is the quantity of successive periods differing more than 50 ms or the corresponding relative quantity, given by using

$$pNN50 = \frac{NN50}{N-1} \times 100\% \quad (4)$$

Apart from all these statistical tools and measures, there are also various geometric parameters that are calculated and analyzed from the RR interval histogram.

2.2.2 Frequency-domain methods

In this method, a Power Spectrum Density (PSD) approximate is computed for the RR interval series. The general PSD estimators indirectly presume equidistant sampling and, accordingly, the RR interval series is transformed to equidistantly sampled collection by interpolation means before PSD estimation. In Kubios, cubic spline interpolation technique is used [18].

The PSD approximation in the course of HRV evaluation is typically completed the use of FFT based totally or invariable AR modelling techniques. The implementation of FFT based method is simpler whilst compared to other technique and also, it is able to be factorized into separate spectral components. While, AR spectrum has a few dangers, inclusive of the complexity of model order choice and the contingency of poor additives within the spectral factorization.

In Kubios, the HRV spectrum is evaluated with help of FFT based Welch's periodogram method and with AR method[26].

2.2.3 Nonlinear methods

Non-linear techniques are involved in the source of HRV because of the complex control techniques of the heart [21] .These nonlinear properties of HRV can be analyzed using means like Poincaré plot [5], approximate and sample entropy[16], [17], detrended fluctuation analysis, correlation dimension and recurrence plots. The disadvantage of these methods is still the difficulty of physiological explanation of the results.

2.2.4 Poincaré plot

This is one of the most commonly used nonlinear methods that is simple while interpretation which is denoted by a graphical representation of the correlation between consecutive RR intervals, i.e., plot of RR_j+1 [17],[24] as a function of RR_j. This relation is described by the following fig.

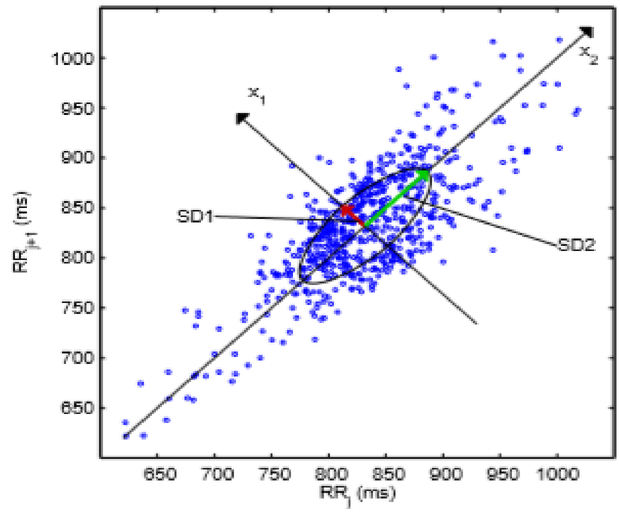


Fig.2: Poincaré plot analysis along with the ellipse fitting procedure, where SD1 and SD2 are the standard deviations in the directions x1 and x2, where x2 is known as the line-of-identity for which RRj = RRj+1

The essential and most crucial feature of this method is the shape of the plot. Fitting an ellipse in the plot as conveyed in the above figure is a general viewpoint to parameterize the shape. The ellipse as shown in the above figure, is aligned with accordance to the line-of-identity ($RR_j = RR_j+1$)[5]. SD1 is represents the standard deviation of all the points which are perpendicular to the line-of-identity, which links the short-term variability which is chiefly generated by RSA. SD1 is represented by the time-domain measure SDSD which is indicated by

$$SD1^2 = \frac{1}{2}SDSD^2 \quad (5)$$

And SD2 is represented for the standard deviation across the line-of-identity which defines the long-term variability and is related to time-domain measures SDNN and SDSD by

$$SD2^2 = 2SDNN^2 - \frac{1}{2}SDSD^2 \quad (6)$$

Standard Poincaré plot is reviewed to be of the first order. The second order plot would be a 3-dimensional plot of all the values (RR_j, RR_{j+1}, RR_{j+2}) [2].

3. RESULTS:

The origin of ECG used for study from the MIT-BIH arrhythmia database of PhysioNet was noted by the Beth Israel Hospital Arrhythmia Laboratory for 4 years from 1975. Out of 48 records, the first 21 records were selected at random and the other records with rare conditions and phenomena were noted down [[1]].

The below attached table 1 gives the necessary and important ECG details of the patients who were admitted for the case of arrhythmia.

Table I. HRV analysis and Stress index report of ECG data from various arrhythmia conditions

ECG Data	**ECG PARAMETERS**						
	Mean RR	**Mean HR**	**Min HR**	**Max HR**	**Stress Index**	**SD1**	**SD2**
100m	1068	56	46	74	**4.2**	87.8	91.4
101m	1436	42	35	65	**2.3**	129.6	130.1
102m	867	69	59	114	**4.4**	78.7	90.3
103m	1783	34	27	48	**1.7**	144.5	113.9
104m	1086	55	38	74	**2.4**	334.4	258.2
105m	1361	44	25	54	**1.9**	244.2	234.2
107m	2054	29	21	40	**1.1**	221.4	261.4
108m	1360	44	25	54	**1.9**	244.6	233.9
109m	1606	37	21	86	**2.5**	112.3	153.9
111m	811	74	46	106	**2.2**	184.1	187.8
112m	841	71	45	97	**3.3**	117.2	139.8
113m	2012	30	27	35	**1.8**	177.8	164.5
114m	746	80	53	112	**2.8**	155.2	184.0
115m	1769	34	27	49	**1.8**	130.2	154.4
116m	2176	28	18	97	**0.9**	303.6	345.3
117m	818	73	46	102	**4.0**	69.5	110.4
118m	1556	39	29	57	**1.5**	170.9	183.6
119m	2572	23	19	31	**0.8**	312.5	286.8
121m	923	65	36	90	**2.3**	137.1	213.7
122m	1702	35	32	42	**3.2**	64.2	75.9
123m	2401	29	25	36	**1.8**	145.6	147.4

The first group of 25 recordings were serving as representative sample for different waveforms and other artefacts that an arrhythmia detector might face in a patient's ECG recording.

The second group chosen for recording were patients who suffered from complex ventricular, junctional and super-ventricular arrhythmias and conductor abnormalities.

Several of these records were selected because features of the rhythm, QRS morphology variation, etc.

The subjects were about 25 men within the age group of 23 to 89 years and 25 women within age group of 23 to 89 years.

The Baevsky's stress index (SI) [6][8][25] is computed according to the formula

$$SI = \frac{Amo \times 100\%}{2Mo \times MxDMn} \qquad (7)$$

Where in the above, Amo is referred as mode amplitude denoted in terms of %, Mo here is the mode (the most

ECG Data	ECG PARAMETERS						
	Mean RR	**Mean HR**	**Min HR**	**Max HR**	**Stress Index**	**SD1**	**SD2**
124m	2250	27	21	52	**1.1**	241.4	271.5
200m	1165	51	37	70	**2.0**	244.1	199.7
201m	1051	57	45	70	**2.7**	152.5	118.0
202m	1576	38	29	53	**1.8**	125.3	138.2
203m	1615	37	27	69	**0.9**	411.3	348.7
205m	1180	51	41	70	**3.7**	83.4	97.1
208m	1916	31	25	54	**0.8**	321.4	299.4
209m	1347	45	36	59	**2.6**	146.4	144.8
210m	1204	50	42	94	**2.0**	147.2	161.5
212m	1568	38	27	55	**2.1**	120.4	150.1
213m	2587	23	19	36	**0.8**	354.3	322.8
214m	2192	27	23	43	**1.3**	238.6	225.9
215m	1225	49	30	73	**1.5**	463.7	390.9
217m	1627	37	25	57	**1.1**	294.2	293.4
219m	2323	26	21	33	**1.2**	231.9	237.9
220m	2108	28	25	35	**4.1**	51.3	57.5
221m	1588	38	31	51	**2.4**	114.5	119.2
222m	972	62	42	107	**2.5**	145.7	185.5
228m	1339	45	23	100	**1.1**	495.9	546.4
230m	1723	35	24	50	**1.4**	186.1	234.8
231m	1685	36	29	50	**2.4**	127.0	128.5
232m	818	73	53	108	**3.9**	101.4	129.3
233m	1831	33	27	62	**1.4**	223.6	247.6
234m	1716	35	29	44	**1.5**	170.5	182.6

Table 1: contains essential details of patients from ECG data number 100 to 205, containing all the necessary data like RR HR and stress index of each patient. (part-2): contains essential details of patients from ECG data number 208 to 234, containing all the necessary data like RR HR and stress index of each patient

recurring RR interval) and MxDMn represents the variation scope reflecting degree of RR interval variability of the heart

4. CONCLUSION

The PNS index and SNS index tells about the Parasympathetic and Sympathetic Nervous system of the Autonomous Nervous system. The PNS and SNS index were computed using various parameters like mean RR, mean HR and Baevsky's stress index [6]. PNS and SNS indexes provide reliable estimates of autonomic nervous system activities as compared to normal resting values. PNS are related to vagal stimulation and are responsible for decreasing Rate of Heart and increase the heart rate variability. The SNS has the opposite effect on the Rate of Heart and Variability of Heart Rate.

Several other factors are also considered to evaluate the index, like HF power and RMSSD (Root Mean Square of Successive R-interval Difference) [15].

In the stress index calculation, the mode Mo is normally taken as the median of the RR intervals. The length of the normalized RR interval histogram is the AMo and the distance between shortest and longest RR interval values is the MxDMn. So as to make SI less sensitive to slow changes in mean heart rate (which would increase the MxDMn and lower AMo), in the RR interval time series, by using the smoothness prior method, the very small frequency trend is removed. Also, in order to transform the tailed distribution of SI towards normal distribution, the square root of SI is taken. The SNS index described below is made less sensitive to extreme SI values by transformation using square root.

Heart Rate variability or abbreviated as HRV is a vital and broadly utilized proportion of autonomic working, particularly in the appraisal of autonomic heart action. HRV is the variety in beat-to-pulsate interims of the human heart that enables the organ to respond to boosts. The SI is a changed proportion of HRV. The Stress Index (SI) is a changed proportion of pulse fluctuation that is resolved through a smaller than expected advanced multi-channel electrocardiogram framework. The standard deviations here in x1 and x2 of the plot are SD1 and SD2, where in the line-of-identity in which RRj is equal to RRj+1 is x2 [5].

Figure 3(a): R-R intervals in Kubios where blue shade region is the sample range for the analysis (b): R-R analysis for Kubios selected in the blue shade region in a different window. (c): Result overview of the Kubios analysis, giving overview of the Autonomous Nervous System.

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