STATISTICAL ANALYSIS OF HRV SIGNALS

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Abstract: Heart rate variability is a cardiac measure derived from the ECG signal (called RR interval) which is a measure of variability in heart rate. In the method, the nonstationary signal is first modeled with a time-varying autoregressive model. Statistical analysis of HRV series display a significant departure from normality as reflected in excess kurtosis. For all series, the distribution has fatter tails and sharper peaks at the centre compared to normal distribution. Statistics of the obtained spectrum estimates are derived using the error propagation principle. The obtained spectrum estimates can further be decomposed into separate components

Index terms: Digital signal processing (DSP), HRV signals, Kurtosis.

1.INTRODUCTION

Heart rate variability is a cardiac measure derived from the ECG signal (called RR interval) which is a measure of variability in heart rate. The characteristics of heart rate variability signal are studied. It is studied based on the statistical analysis performed on those data. The results show that heart rate variability series display a significant departure from normality as reflected by the extreme excess kurtosis. Most of the series are positively skewed. All of them range from -2.44 to 2.26. The positive skew implies that the series have a higher probability of low risk. In addition the kurtosis values are much larger than three, ranging from 3.08 to 97.44. This shows that for all series the distribution has fatter tails and sharper peaks at the centre compared to normal distribution. The Jarque-Bera test was also conducted for those data.

1.2 *Heart Rate Variability Signals:*

Heart rate variability is a cardiac measure derived from the ECG signal (called RR interval) which is a measure of variability in heart rate. Mathematically modelling and generating the time series (RR intervals) for heart rate variability has been an ongoing research activity. HRV refers to the beat-to-beat alterations in heart. Under resting conditions, the ECG of the healthy individuals exhibits periodic variations in RR intervals. The analysis of HRV offers a non-invasive method of evaluating input in to cardiac rhythm. The major reason for the interest in measuring HRV stems from its ability to predict survival after heart attack. The reduced HRV predicts sudden death in patients and several other heart diseases.

Heart rate variability (HRV) provides a non-invasive method to monitor the functioning of the autonomous nervous system. The traditional methods of analysing heart rate variability based on means and variance are unable to detect subtle but potentially important changes in inter heart rate behaviour. Because cardiovascular system is not a stationary system, the traditional indexes of heart rate variability may lack the ability to detect subtle but important changes in heart rate behaviour. A number of new methods have been recently developed to quantify complex heart rate dynamics. They may reveal abnormalities in time-series data that are not apparent when conventional statistics are used.

1.3 Components of HRV:

The RR interval variations present during resting conditions represent beat-by-beat variations in cardiac autonomic inputs. However, efferent vagal activity is a major contributor to the HF component, as seen in clinical and experimental observations of autonomic maneuvers such as electrical vagal stimulation, muscarinic receptor blockade, and vagotomy. More problematic is the interpretation of the LF component, which was considered by some as a marker of sympathetic modulation but is now known to include both sympathetic and vagal influences. For example, during sympathetic activation the resulting tachycardia is usually accompanied by a marked reduction in total power, whereas the reverse occurs during vagal activation. Thus the spectral components change in the same direction and do not indicate that LF faithfully reflects sympathetic effects. It is important to note that HRV measures fluctuations in autonomic inputs to the heart rather than the mean level of autonomic inputs. Thus, both withdrawal and saturatingly high levels of autonomic input to the heart can lead to diminished HRV.

2. STATISTICAL ANALYSIS

The study of heart rate variability series is done based on the statistical analysis done on those data. The analysis shows the characteristics of heart rate variability signal. It shows excess kurtosis with each data. Also, most of the series are positively skewed. The excess kurtosis implies that for all series, the distribution is having fatter tails and sharper peaks.

2.1 Methodology Used

The various statistics used for analysing the characteristics of heart rate variability series is given:

2.1.1 Mean

Mean of a signal is defined as the average value of the signal. For a data set, the mean is the sum of the values divided by the number of values. The mean of a set of numbers $x_1, x_2, ..., x_n$ is typically denoted by $\bar{x}$.

Let X be a random variable, its mean value is:

$$\mathrm{E}[X] = \mu.$$

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2.1.2 Variance

Variance of a signal is defined as the total power in the signal. For individual power of the signal, the simple variance is taken, but for a group, normalized variance is considered. The square root of variance is known as the standard deviation of the signal.

2.1.3 Standard deviation

The **standard deviation** of *X* is the quantity

$$\sigma = \sqrt{\mathrm{E}\left[(X-\mu)^2\right]}.$$

Here the operator *E* denotes the average or expected value of *X*.

That is, the standard deviation σ is the square root of the average value of $(X-\mu)^2$.

2.1.4 Skewness

Skewness is the measure of asymmetry of the data around the sample mean. . Qualitatively, a negative skew indicates that the *tail* on the left side of the probability density function is *longer* than the right side and the bulk of the values (including the median) lie to the right of the mean. A positive skew indicates that the *tail* on the right side is *longer* than the left side and the bulk of the values lie to the left of the mean. A zero value indicates that the values are relatively evenly distributed on both sides of the mean, typically but not necessarily implying a symmetric distribution. If it is positive, then the data are spread out more to left of the mean than to the right and vice versa.The skewness of a distribution is defined as

$$Y = \frac{E[x-\mu]^3}{\sigma^3}$$

Where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t.

The skewness of the normal distribution (for any perfectly symmetric distribution) is zero.

2.1.5 Kurtosis

Kurtosis is the fourth central moment of x divided by fourth power of its standard deviation. It is a measure of how outlier-prone a distribution is. . Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3. kurtosis is a measure of the "peakedness" of the probability distribution of a real-valued random variable. Higher kurtosis means more of the variance is the result of infrequent extreme deviations, as opposed to frequent modestly sized deviations.

The kurtosis of a distribution is defined as

$$K = \frac{E[X-\mu]^4}{\sigma^4}$$

where μ is the mean of x, σ is the standard deviation of x, and $E(t)$ represents the expected value of the quantity t.

2.1.6 Jarque-Bera test

The Jarque-Bera test is a two-sided goodness-of-fit test suitable when a fully-specified null distribution is unknown and its parameters must be estimated. The test statistic is

$$JB = n/6\,(s^2 + (k-3)^2/4)$$

where n is the sample size, s is the sample skewness, and k is the sample kurtosis. For large sample sizes, the test statistic has a chi-square distribution with two degrees of freedom.

Finally the maximum and minimum values of each HRV series are also calculated.

2.2 Steps Followed

- HRV data is taken.
- Difference of HRV series is calculated
- The various statistics like mean, standard deviation, variance, skewness, kurtosis, Jbtest, maximum and minimum of the difference signal is calculated in matlab.

4. RESULTS AND DISCUSSION

The characteristics of heart rate variability series are studied. The statistical analysis of HRV series displays a significant departure from normality as reflected by excess kurtosis.

Table 4.1 Statistical analysis of HRV signals

Input data	mean	SD	var	Skewness	kur	Jb test	min	max
rr-16265	2.8592e-005	0.0286	8.1668e-004	1.5713	72.5229	1.0000 0.0010	-0.4600	0.4600
rr-16273	7.5745e-005	0.0293	8.5581e-004	-0.0450	5.9362	1.0000 0.0010	-0.1570	0.2020
rr-16420	0	0.0291	8.4685e-004	0.0533	3.1850	1.0000 0.0010	-0.1010	0.1100

rr-17052	2.7409e-005	0.0446	0.0020	-0.5891	10.5472	1.0000 0.0010	- 0.2980	0.2730
rr-17453	4.1786e-005	0.0378	0.0014	0.1512	7.1286	1.0000 0.0010	- 0.1810	0.3130
rr-17693	2.3782e-005	0.0119	1.4098e-004	0.3186	4.5020	1.0000 0.0010	- 0.0560	0.0560
rr-18184	0	0.0262	6.8442e-004	0.1631	6.6379	1.0000 0.0010	- 0.1330	0.1730
rr-f1o01	2.8650e-005	0.0137	1.8876e-004	-0.4796	4.3718	1.0000 0.0010	- 0.0680	0.0400
rr-f1o02	2.5186e-005	0.0120	1.4478e-004	-0.0349	3.9963	1.0000 0.0010	- 0.0540	0.0600
rr-f1o03	9.5290e-005	0.0213	4.5343e-004	0.8103	39.5708	1.0000 0.0010	- 0.2560	0.2280
rr-f1o04	- 4.4893e-005	0.0343	0.0012	0.8786	8.0304	1.0000 0.0010	- 0.1440	0.2320
rr-f1o05	4.0000e-005	0.0113	1.2712e-004	-0.2324	3.6652	1.0000 0.0010	- 0.0400	0.0440
rr-f1o06	- 5.2459e-005	0.0254	6.4271e-004	0.1881	5.6021	1.0000 0.0010	- 0.1680	0.1720

Table 4.1 Statistical analysis of HRV signals

Input data	mean	SD	var	Skewness	kur	Jb test	min	max
rr-f1o07	0	0.0268	7.1979e-004	1.0131	8.8777	1.0000 0.0010	- 0.1200	0.1880
rr-f1o08	3.2772e-005	0.0217	4.6893e-004	0.3421	5.7528	1.0000 0.0010	- 0.1000	0.1800
rr-f1o09	- 2.3649e-005	0.0677	0.0046	-0.1806	4.1462	0 0.0219	- 0.2840	0.2440
rr-f1o10	- 1.0768e-004	0.0218	4.7352e-004	0.1054	3.2432	1.0000 0.0010	- 0.0720	0.0840
rr-f1y01	7.5011e-005	0.0732	0.0054	1.2295	9.0854	1.0000 0.0010	- 0.2920	0.4800

rr-f1y02	-1.2576e-004	0.0679	0.0046	0.4402	5.5163	0 0.0195	-0.2040	0.4800
rr-f1y03	6.2976e-005	0.0287	8.2269e-004	0.2687	3.5490	1.0000 0.0010	-0.1040	0.1160
rr-f1y04	3.4783e-005	0.1030	0.0106	0.3408	3.4755	0 0.0108	-0.4000	0.5120
rr-f1y05	5.2288e-005	0.0472	0.0022	1.6217	15.3608	0 0.1874	-0.1720	0.4400
rr-f1y06	3.4227e-005	0.0565	0.0032	0.9752	7.4245	1.0000 0.0017	-0.1800	0.3920
rr-f1y07	9.0090e-005	0.1131	0.0128	0.7372	4.9441	1.0000 0.0010	-0.3360	0.5440
rr-f1y08	-1.4616e-004	0.0448	0.0020	0.1404	3.6653	1.0000 0.0020	-0.1400	0.1920
rr-f1y09	2.0833e-005	0.0358	0.0013	0.1738	4.8587	0 0.0087	-0.1360	0.2400
rr-f2o01	7.6628e-005	0.0311	9.6668e-004	0.6270	7.8258	1.0000 0.0031	-0.2040	0.2640
rr-f2o02	2.1831e-005	0.0353	0.0012	2.2610	63.0176	0 0.1506	-0.4200	0.5640
rr-f2o03	5.8617e-005	0.0263	6.8916e-004	0.1635	12.1297	1.0000 0.0010	-0.2440	0.1800
rr-f2o05	-7.9444e-006	0.0144	2.0736e-004	0.3211	18.8582	1.0000 0.0010	-0.1440	0.1480

Table 4.1 Statistical analysis of HRV signals

Input data	mean	SD	var	Skewness	kur	Jb test	min	max
rr-f2o06	-2.2222e-005	0.0440	0.0019	-0.2247	7.3738	1.0000 0.0010	-0.3000	0.3300
rr-f2o07	-3.3965e-005	0.0239	5.7015e-004	-0.4958	3.0875	1.0000 0.0010	-0.0960	0.0680
rr-f2o08	1.8018e-005	0.0392	0.0015	-0.2553	13.1636	1.0000 0.0019	-0.2520	0.2640
rr-f2o09	2.5094e-005	0.0200	3.9819e-004	-1.9608	97.4457	1.0000 0.0010	-0.3520	0.2440
rr-f2o10	4.2900e-005	0.0118	1.3993e-004	2.1385	62.1397	1.0000 0.0010	-0.1320	0.2200
rr-f2y04	-7.1823e-005	0.0292	8.5097e-004	-2.4432	59.8415	1.0000 0.0019	-0.5360	0.2520
rr-f2y05	1.7369e-006	0.1161	0.0135	-0.0922	42.5594	1.0000 0.0010	-0.8800	0.8920
rr-f2y07	1.6908e-004	0.0779	0.0061	0.8045	5.2995	0 0.3217	-0.2840	0.5400
rr-f2y08	-4.3812e-006	0.1162	0.0135	0.6419	8.5308	1.0000 0.0065	-0.8560	0.7200

rr-f2y09	-1.2963e-005	0.0539	0.0029	-0.1174	9.9962	0 0.2156	- 0.3360	0.3480
rr-f2y10	8.4620e-005	0.0560	0.0031	0.2486	8.4425	0 0.0102	- 0.3280	0.4400

- Figure 4.1 Original signal (rr-16265)

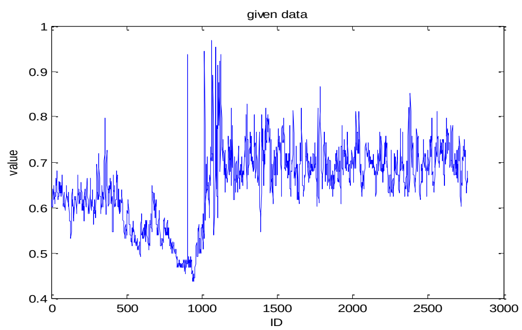


Figure 4.2 Difference signal of rr-16265

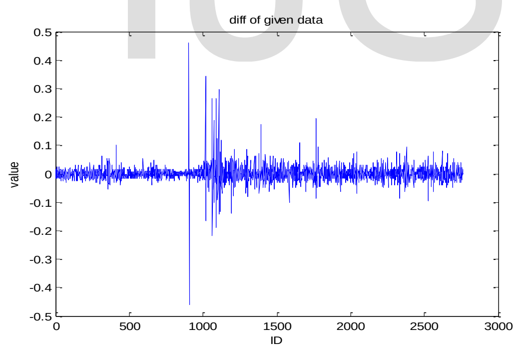


Figure 4.3 Original signal (rr-f2o02)

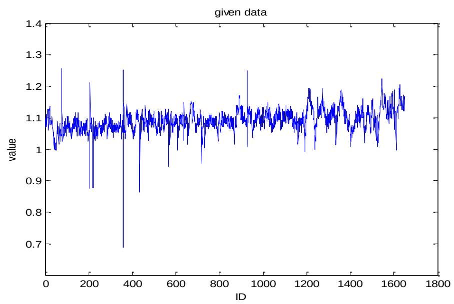
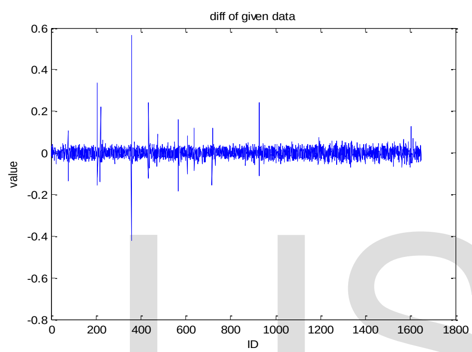


Figure 4.4 Difference signal (rr-f2o02)



5. CONCLUSION & FUTURE WORK

The characteristics of heart rate variability signal are studied by conducting statistical analysis. The statistical analysis of HRV series displays a significant departure from normality as reflected by excess kurtosis. The excess kurtosis implies that for all series, the distribution is having fatter tails and sharper peaks. In the future, the parameters for the SV model will be estimated. The estimation will be based on particle methods (particle filters and smoothers) and EM algorithm. Particle filters are Non-Linear, Non-Gaussian filters. Expectation-Maximization algorithm is used to determine the maximum likelihood estimator. To get an approximated expected likelihood particle methods are incorporated with EM algorithm.

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