Optimal ECG Sampling Rate for Non-Linear Heart Rate Variability

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ABSTRACT
The principle difficulty with the analysis of the heart rate variability (HRV) is that heart rate dynamics are non-linear and non-stationary. Detrended fluctuation analysis (DFA) and correlation dimension (CD) are non-linear HRV measures to quantify fractal-like autocorrelation properties and to characterize the complex behaviour of nonlinear time series. Optimal ECG sampling rate is an important issue for accurate quantification of HRV. High ECG sampling rate results in very high processing time and low sampling rate produces signal quality degradation results in clinically misinterpreted HRV. In this work the impact of ECG sampling frequency on non-linear HRV have been quantified in terms of short-range & long-range DFA and CD on short-term (N=200), medium-term (N=500) and long-term (N=1000) data. Non-linear HRV parameters are found to be sensitive to ECG sampling frequency and effect of sampling frequency will be a function of data length.

Keywords
ECG, HRV, Sampling frequency, DFA, CD, Signal processing.

1. INTRODUCTION
The electrocardiogram (ECG) is one of the most important physiological parameters, which reflects to ionic activity in the cardiac muscles [1]. Heart rate variability (HRV) is the time variation between RR peaks of ECG in cardiac cycle. HRV represents sympathetic and parasympathetic activities of autonomic nervous system (ANS) and is non-invasive tool for analysis of cardiovascular control of the heart [2]. Time domain, frequency domain, and non-linear method are the three ways which can be used for the evaluations and analysis of HRV [3-4].Time domain is the simplest measure of HRV but incapable to differentiate sympathetic and parasympathetic contribution of HRV hence increase the use of spectral methods for the analysis of the tachogram [5-7]. The cardiovascular system is consisting of multiple sub-systems and has both highly nonlinear deterministic and stochastic properties, and subject to hierarchical regulations [8-10]. As a result, time series generated by cardiovascular system are often highly nonlinear, non-stationary, random and complex. Due to which standard linear measures of HRV may not be able to detect subtle, but important changes in the HR time series [11]. Therefore, nonlinear methods have been developed to quantify the dynamics of HR fluctuations. Approximate entropy (ApEn) [12-13], Sample entropy (SampEn) [14], multiscale entropy (MSE) [15], Detrended fluctuation analysis (DFA) [16] and Correlation Dimension (CD) [8] are well-developed nonlinear measures to quantify the chaotic properties, complexity or irregularity of RR intervals time series.

The fast ECG sampling rate increases the processing time, requirement of large memory for data storage & access whereas signal quality degrades with low ECG sampling rate that may cause clinically misinterpreted HRV measures thus the selection of Optimal sampling rate is an important issue for researchers [17-18]. Singh B. *et al.,* investigated the errors in the estimation of the ApEn and SampEn based non-linear HRV measures by various ECG sampling frequencies [23-24]. The errors in entropy based HRV was clinically significant when ECG sampled at low sampling frequency of 125 or 250 Hz. The other researchers have also recommended the value of sampling frequency under different conditions as listed in table 1.

Table 1. Recommendation of Sampling Frequency of ECG

Recommended sampling frequency	Recommended By
250-500 Hz or higher	Task force of the European Society of Cardiology and North American society of Pacing and Electrophysiology [4]
1000 Hz	Hejjel *et al* [17]
500 Hz	Ziemssen *et al* [18]
128 Hz	Abboud and Barnea[19]

Although Task Force recommended the range of ECG sampling frequencies for accurate time and frequency domain HRV measures, a systematic study is the need of day to quantify the influence of sampling rate on nonlinearities based HRV. ECG sampling rate analysis on nonlinearities measures of HRV is required for extensive use of HRV by medical practitioners. This study aims to access the impact of ECG sampling rate on DFA and CD based HRV and to find out optimal ECG sampling rate for non-linear measures of HRV based on computer simulation.

2. DATA AQUISITION
For this study the ECG data has been acquired from the 10 healthy subjects, with no past of any cardiac disorder, in supine posture with normal breathing in a lab environment at comfortable light and temperature conditions. All subjects were refrained from alcohol, coffee and smoking for 12 hour prior to data acquisition. The ectopic-free normal RR intervals time series were derived for each subject by Lead-II ECG recordings on Biopac® MP150 system with short-term (N = 200), medium-term (N = 500) and long-term (N = 1000) data lengths having sampling frequencies of 125, 250, 500, 1000, 1500 and 2000 Hz resulting in a total of 180 time series.

3. NON-LINEAR HRV

Recent developments in the theory of nonlinear dynamics have paved the way for analyzing signals generated from nonlinear living systems. It is now generally recognized that these nonlinear techniques are able to describe the processes generated by biological systems in a more effective way.

3.1 Detrended Fluctuation Analysis (DFA)

In 1994 Peng *et al* has developed DFA which is a simple and efficient scaling method commonly used for detecting long-range correlations. It is an efficient technique used to determine the correlations within the signal and to evaluate the fractal characteristics of RR interval time series. Fractal are composed of subunits (and sub-sub-units, etc.) that resembles or show correlation with the structure of the overall time series. This technique is an enhancement of root mean square approach of random walks applied to non-stationary time series [16, 20]. The technique consists i) calculation of root-mean-square fluctuation of an integrated and detrended time series at different windows sizes ii) plotting the fluctuation against the size of the window on a log–log scale.

1. Obtain integrated series $y(k) = \sum_{i=1}^{k} RR(i) - RR_{avg}$

Here *k* is the total length of integrated series *y(k)* is k_{th} value of integrated series *RR(i)* is i_{th} inter-beat interval. RR_{avg} is the average of RR intervals over the entire series.

2. Then, the integrated time series $y(k)$ is divided into windows of equal length, *n*.

3. Least-squares line is fitted to the RR interval data in each window of length *n* which is local trend in that window. The *y* coordinate of the straight line segments are denoted by $y_n(k)$.

4. Trend $y_n(k)$ is subtracted from the integrated signal *y(k)* in order to obtain the detrended profile

$$y(k) - y_n(k)$$

5. Then root-mean-square fluctuation of integrated and detrended time series is computed by

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[y(k) - y_n(k)\right]}$$

6. The procedure is repeated for different boxes size or time scales. Finally, the relationship on a double-log graph between fluctuations *F(n)* and time scales *n* can be approximately evaluated by a linear model that provides the scaling exponent α given in

$$F(n) \approx n^{\alpha}$$

The scaling exponent α is viewed as an indicator of the roughness of the original time series: the larger the value of the scaling exponent α smoother the time series. The fractal scaling (α) for the normal subjects (healthy young) is closer to 1, and this value falls in different ranges for various types of cardiac abnormalities

DFA quantifies the correlations within the time series for different time scales [16]. For HRV analysis, correlations may be short-term or long-term fluctuations which are represented by parameters α_1 and α_2 respectively. These measures are correlation measure as a function of segment length and approximated by slopes of a log-log plot. In this work, calculations for α_1 and α_2 were obtained from ranges of 4–16 beats for α_1 and range of 16–64 beats for α_2 .

3.2 Correlation Dimension (CD)

CD, a novel method based on phase space technique to distinguish normal and abnormal cases, has been used extensively for cardiovascular signals.

A phase space plot can be obtained by representing the heart rate *RR[n]* in X-axis and the delayed heart rate *RR [n+m]* in Y-axis. The minimal mutual information technique is used to calculate an appropriate delay. The method of estimating the embedding dimension from the phase space patterns was proposed by Grassberger and Procaccia [22]. For a steady and unchanging heart rate, the phase plot will be a point; else, the trajectory spreads out to give some patterns. The emerged pattern interpreted periodic, chaotic, or random behaviour of heart rate. A CD factor is a quantitative measure of the pattern of trajectory, and the ranges of CD for various cardiac disorders are identified.

The CD of the attractor is calculated for HRV data using the following definition [22]:

$$CD = \lim_{r \to o}\left(\frac{\log C(r)}{\log(r)}\right)$$

Where the correlation integral C(r) is given by:

$$C(r) = \frac{1}{N^2}\sum_{x=1}^{N}\sum_{y=1, x\neq y}^{N}\Theta\left(r - \left|RR_x - RR_y\right|\right)$$

Where *N* is the number of data points, RR_x and RR_y are the trajectory points in the phase space; *r* is the radial distance around each reference point and Θ is the Heaviside function.

Table 2. Effect of ECG sampling frequency on short-range DFA, long-range DFA and CD based non-linear HRV for ten healthy subjects

Sampling Frequency (Hz)	Short-Range Scaling Exponent			Long-Range Scaling Exponent			Correlation Dimension		
	Data Length								
	200	500	1000	200	500	1000	200	500	1000
125	1.0734	1.1085	1.1812	0.746 44	0.7674	0.8703	1.1880	1.3392	1.6205
250	1.0818	1.1219	1.1219	0.7556	0.7742	0.8689	1.2029	1.3357	1.6090
500	1.0807	1.1295	1.1295	0.7525	0.7763	0.8695	1.0070	1.3363	1.5970
1000	1.0511	1.0847	1.0847	0.6881	0.7286	0.8304	1.0044	1.0994	1.2520
1500	1.0510	1.0772	1.0772	0.6855	0.7311	0.8310	1.0044	1.0998	1.2528
2000	1.0433	1.0837	1.0837	0.6804	0.7128	0.8314	0.9753	1.0975	1.2480

Table 3. Relative error in short-range DFA, long-range DFA and CD based non-linear HRV of ten healthy subjects by ECG sampling frequencies

Sampling Frequency (Hz)	Short-Range Scaling Exponent			Long-Range Scaling Exponent			Correlation Dimension		
	Data Length								
	200	500	1000	200	500	1000	200	500	1000
125	7.3397	2.2852	1.3218	9.7084	7.6540	4.6857	21.8027	22.0187	29.8467
250	3.6857	3.5213	1.5193	11.0610	8.6080	4.5179	23.3386	21.6968	28.9266
500	3.5803	4.2180	2.3784	10.5921	8.9108	4.5911	3.2488	21.7537	27.9618
1000	0.7434	0.0849	0.3840	1.1380	2.2172	0.1196	2.9857	0.1740	0.3173
1500	0.7428	0.6021	0.2992	0.7473	2.5690	0.0387	2.9791	0.2028	0.3880
2000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4. Correlation coefficient between increase in sampling frequency and decrease in REs of α_1, α_2 and CD of short-term, medium term and long-term data length

Short-Range Scaling Exponent			Long-Range Scaling Exponent			Correlation Dimension		
Data Length								
200	500	1000	200	500	1000	200	500	1000
0.8689	0.7860	0.8042	0.9073	0.9233	0.8978	0.7923	0.8932	0.8984

4. STATISTICAL ANALYSIS

In order to study the effect of sampling frequency on DFA and CD based HRV, the parameters α_1, α_2 and CD are evaluated. The relative errors (REs) were calculated with the non-linear measures calculated from the RR interval time series derived with reference 2000 Hz ECG sampling frequency. The parameters $\{X_1, X_2, \ldots X_n\}$ are obtained for DFA and CD based HRV measures of the short-, medium- and long-term data set with sampling frequencies of 125, 250, 500 1000 and 1500 Hz. X_{origin} is the corresponding non-linear HRV measure at reference ECG sampling frequency of 2000 Hz, the relative errors RE_k are computed as $|X_{origin} - X_k|/X_{origin} \times 100$ (%). For the statistical calculations 150 error values were derived for each HRV parameter and data length of ECG signal.

5. RESULT

The non-linear HRV measures α_1, α_2 and CD are computed for RR interval series of long-term *(N*=1000), medium *(N*=500) and short-term *(N*=200) data lengths respectively and compared with reference values at sampling frequency of 2000 Hz. Table 2 shows the effect of ECG sampling frequency on average non-linear HRV parameters α_1, α_2 and CD respectively, of RR interval time series derived from lead-II ECG of ten healthy subjects. The REs in short-term α_1 and long-term fluctuations α_2 and CD of RR intervals series derived from ECG at sampling frequency 125, 250, 500, 1000 and 1500 Hz were calculated. Then these REs were compared with reference parameters to evaluate the impact of ECG sampling frequency (Table 3).

For very low ECG sampling frequency of 125 Hz, the REs in α_1, α_2 and CD of time series data of RR intervals with respect to reference values of sampling frequency 2000 Hz were approximately 7.33, 9.7 and 21.8% for short-term data; 2.28, 7.65 and 22 % for medium data and 1.32, 4.6 and 29.8% for long term-data respectively. The REs in α_1, α_2 and CD respectively was decrease up to 0.7, 1.13 and 2.98 % for short term data; 0.08, 2.21 and 0.17% for medium term data and 0.38, 0.11 and 0.31% for longt term data respectively at medium ECG sampling frequency of 1000 Hz. The decrease in REs will be a function of level of sampling frequency and RR interval data length. The REs CD due to the ECG sampling frequency were found to be very high at low sampling frequency 125 Hz. The correlation coefficients values for the increase in sampling frequency with decrease in REs of α_1, α_2 and CD at short-term, medium-term and long-term data length are shown in Table 4.

6. CONCLUSION

The influence of ECG sampling frequency on DFA and CD based non-linear HRV parameters at short, medium and long-term data lengths have been quantified. At low sampling frequency the REs in DFA and CD based HRV are found to be clinically significant. Further, the REs in HRV measures depend upon sampling level and RR interval data length. Thus the non-linear HRV parameters estimated by the DFA and CD algorithms are sensitive to ECG sampling frequency and data length and erroneous quantification results a bias in DFA and CD measures and clinically misinterpreted HRV.

DFA and CD are the suitable tools to determine the regularity of biomedical signals. Finally it is concluded that non-linear dynamics methods DFA and CD could only be used for quantitative and qualitative physiological signals analysis at appropriate sampling frequency and data length for accurate interpretation.

7. REFERENCES

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