International Journal of Bio-Science and Bio-Technology
Vol.6, No.4 (2014), pp.179-186
http://dx.doi.org/10.14257/ijbsbt.2014.6.4.17

Effect of ECG Sampling Frequency on Approximate Entropy based HRV

Manjit Singh[1], Butta Singh[2] and Vijay Kumar Banga[3]

[1]*Phd scholar Punjab Technical University Jalandhar and Department of Electronics and Communication Engineering, Guru Nanak Dev University Regional Campus, Jalandhar, India*
[2]*Department of Electronics and Communication Engineering, Guru Nanak Dev University, Regional Campus, Jalandhar, India.*
[3]*Amrirtsar College of Engineering and Technology, Amritsar, India*
manu_kml@yahoo.co.in, bsl.khanna@gmail.com

Abstract

Heart rate variability (HRV) analysis, instantaneous variation in RR intervals time series of electrocardiogram (ECG), is generally used for evaluating autonomic nervous system (ANS) functioning in cardiovascular research and in different human well being related applications. Approximate entropy (ApEn) is a nonlinear metric used to measure the irregularity of a RR interval time series. An increase in ApEn is often associated to increases in complexity. Linear HRV parameters are very sensitive to ECG sampling frequency and low sampling frequency may result in clinically misinterpretation of HRV. In this study consequences of errors in ApEn based HRV induced by ECG sampling frequency have been investigated. Error in ApEn measure of HRV was found to be a function of data length of RR interval time series and ECG sampling frequency. The percentage difference in ApEn was more than 3.5%.for long term data (N=1000), more than 2.5% for medium data (N=500) and less than 1% for short term data (N=200) at low ECG sampling frequency of 125 Hz with respect to reference values at 2000 Hz. Thus, the results of indices such as ApEn when applied to time series with low ECG sampling should be regarded with caution.

Keywords: *ECG, HRV, Approximate entropy, Sampling frequency, Signal processing*

1. Introduction

Electrocardiogram (ECG) contains vital characteristics that can help in the detection of abnormalities of the heart. The instantaneous variation in time intervals between RR peaks of ECG is known as heart rate variability (HRV). HRV is a reliable non-invasive tool that reflects the sympathovagal interactions in physiological and pathological conditions of autonomic nervous system (ANS) [1-2]. The methods utilized for HRV analysis involve linear methods in time domain and frequency domain, time-frequency methods and non-linear methods [3-4]. The heart rate (HR) increases with sympathetic activity and decreases with parasympathetic activity of ANS. The sympathetic mode influences the low frequency (LF), while both the sympathetic and parasympathetic modes affect the high frequency (HF). Thus, spectral analysis is typically used to estimate sympathovagal balance by looking at the LF and the HF bands of the RR intervals [5].

Cardiovascular system is composed of multiple subsystems and sub-subsystem units that exhibit nonlinear deterministic and stochastic characteristics, which are subject to hierarchical

ISSN: 2233-7849 IJBSBT

regulations. Interactions among these units may induce irregular time courses in the processes, but the underlying sub-processes include well-determined behavior. Therefore, it is presumed that these irregular time courses can be characterized more adequately by dynamic nonlinear analyses rather than by linear time series analyses [6]. Approximate entropy (ApEn) is an efficient nonlinear technique to quantify the complexity or irregularity of time series data like RR intervals [7-8]. The aptness of entropy based HRV stems from its potential to provide quantitative information about the complexity of the short length experimental data [9-10].

Besides technical and biological difficulties, data acquisition, data storage, signal pre-processing, representation and optimal sampling rate are numerous technical barrier in ECG signal processing [11-12]. Unnecessarily fast sampling rate results in high processing time, extreme memory requirement for data storage and access. Beside this Low sampling rate degrades the quality of ECG Signal results in misinterpretation of HRV measures. A low sampling rate may produce a jitter in the estimation of the R wave fiducial point, which alters the spectrum considerably and produce inaccurate results. Although patterns of HRV hold considerable promise for clarifying issues in clinical applications, the inaccurate quantification and interpretation of these patterns may obscure critical issues or relationships and may impede rather than foster the development of clinical applications. The task force of the European Society of Cardiology and North American society of Pacing and Electrophysiology recommended the use of 250-500 Hz or high sampling frequency for the measurement of HRV without any interpolation [1]. Hejjel *et al.,* investigate the consequences of errors induced by resampling on the time domain parameters of HRV [11]. They recommended an ECG sampling frequency of 1000 Hz for adequate time domain based HRV analysis without interpolation even in seriously reduced-variability samples. However, a lower sampling rate was found to be acceptable for higher variability samples [11]. Ziemssen *et al.,* evaluate the effect of different ECG sampling frequencies on parameters of spectral and baroreflex analysis of EUROBAVAR data set [12]. They found that pathologically decreased variability of RR time series was highly affected by variation in ECG sampling frequencies. ECG sampling frequency of 100 Hz in comparison to 500 Hz was recommended for spectral and baroreflex analysis by trigonometric regressive spectral [12]. Abboud and Barnea showed that a sampling frequency of 128 Hz is sufficient, in patients with normal HRV levels, to give a large enough signal to noise ratio in the RR tachogram. However, for patients with significantly lower levels (such as heart transplant patients) they found that a sampling rate of at least 1000 Hz is required [13]. The optimal range is 250–500 Hz or perhaps even higher, while a lower sampling rate (in any case $\geq$100 Hz) may behave satisfactorily only if an algorithm of interpolation is used to improve or perfect the R wave fiducial point [2].

Despite the Task Force recommendations for ECG sampling frequency for time and frequency domain HRV, to our knowledge, no systematic study has not yet been performed to quantify the influence of sampling rate on entropy based HRV. ECG sampling rate analysis on entropy measure of HRV is the need of attention for widespread use of HRV in clinical situation. In this study, an effort has been made to explore the influence of ECG sampling frequency on ApEn based HRV and to assess the optimal sampling frequency for entropy measure of HRV based on computer simulation.

2. Data

This study involves ten healthy persons having no history of any cardiac disorder. All subjects were refrained from alcohol, coffee and smoking for 12 hour prior to data recording. No participant was addicted to drugs, taking any medication or involved in endurance

training. This data acquisition was performed at rest in the supine position and the subjects were kept quiet in a natural environment at comfortable light and temperature levels. The subject were made to rest in supine position for 10 minutes prior to recording, so that the they may stabilize to the laboratory environment after that the subjects were laid on a bed in a well air-conditioned room. The ectopic-free normal RR intervals time series with data length N = 1000 (long-term data), 500 (medium-term data) and 200 (short-term data) were derived for each subject by Lead-II ECG recordings on Biopac® MP150 system having sampling frequencies of 125, 250, 500, 1000, 1500 and 2000 Hz resulting in a total of 180 ectopic-free RR interval time series. The subjects were allowed to normal breathing during the whole recording.

3. Entropy Measures of HRV

Cardiovascular system is characterized by a high complexity, partly because of its continuous interactions with other physiological systems. Since this complexity, nonlinear and non stationary behavior is expected in HRV analysis. Traditional techniques of HRV analyses describe only the linear structure of the HRV, without being able to characterize the nonlinear dynamics hidden in the generation of the heart beats [14]. Therefore, HRV should be analyzed and characterized using techniques obtained from nonlinear complex dynamical system theory and chaos theory. Entropy is an invariant quantity measuring the rate of generation of information in the context of nonlinear time series analysis.

3.1. Approximate Entropy (ApEn)

ApEn is a statistical index to quantify the complexity of a signal. It has been widely adopted by many researchers especially in the field of HRV. The popularity of ApEn stems from its capability to provide quantitative information about the complexity of the experimental data that are short in data length [9**]**. ApEn measures the (logarithmic) likelihood that runs patterns that are close for *m* observations remain close on next incremental comparison. Greater likelihood of remaining close, i.e. high regularity produces smaller ApEn values [10]. While implementing ApEn, calculation requires a priori specification of two unknown parameters: *m*, the embedding dimension and *r*, a threshold, which is in effect a noise filter. Pincus [10], who developed the ApEn method, suggested that *r* should be 0.1–0.25 times, the SD of the data, and that *m* be 1 or 2 for data lengths *N* ranging from 100 to 5000 data points. Given a signal *u (1), u (2), u (3)... u (N)*, where *N* is the total number of data points. Fix *m*, a positive integer and *r*, a positive real number. For our study, we have taken *r* equal to 20% of SD and *m=2*. ApEn algorithm can be summarized as follows:

1. Form *m* vectors *X (1) to X (N-m+1)* defined by

$$X\ (i) = \left[u(i), u(i+1), \ldots . u(i+m+1) \right], \quad 1 \le i \le N - m + 1$$

2.Define the distance *d[X(i),X(j)]* between the vectors *X(i)* and *X(j)* as the maximum absolute difference their respective scalar components:

$$d\left[X(i), X(j) \right] = \max_{1,2,\ldots m} \left(u(i+k) - u(j+k) \right)$$

3. Define $v^{m}(i)$ = no of such that $d\left[X(i), X(j) \right] \le r$ from which we define

$$c_i^m(r) = \frac{v^m(i)}{N - m + 1}$$

4. Take the natural logarithm of each $c_i^m(r)$ and average it over *i*

$$\varphi^m(r) = \frac{1}{N - m + 1} \sum_{1}^{N-m+1} \ln\left(c_i^m(r)\right)$$

5. Increase the *m* to *m+1* and repeat the steps 1 to 4 and find

$$\varphi^{m+1}(r) = \frac{1}{N - m} \sum_{1}^{N-m} \ln\left(c_i^m(r)\right)$$

6. Finally calculate ApEn for the data of length of N

$$ApEn(m, r, N) = \varphi^m(r) - \varphi^{m+1}(r)$$

4. Results

In cardiovascular system and neurosciences, a wide consensus has been reached that a decrease in the complexity with respect to the normal case is in most instances bounded to a pathological condition. Various applications have considered D_2 correlation dimension, fractal dimension of the related chaotic attractor, Lyapunov exponents, etc. Other complexity measures may be applied to the data, *i.e.*, ApEn, symbolic dynamics measurements, detrended fluctuation analysis and the various measures of fractality of the signal [6]. Complexity in RR interval time series is an intriguing feature of ECG, with potential use for identification of cardiovascular state. Although various methods have been proposed for measuring physiologic complexity, uncorrelated time series are often assigned high values of complexity erroneously classifying them as complex physiological signals.

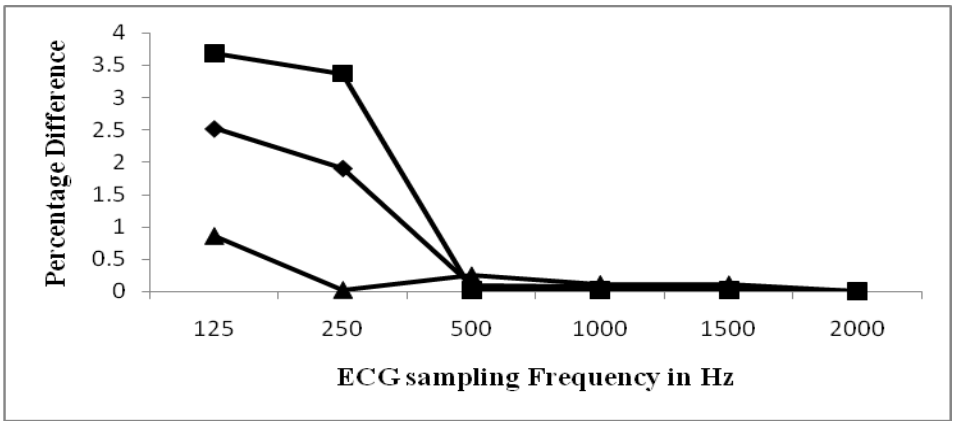
The effects of the ECG sampling frequency on the ApEn based HRV parameter was evaluated based on the percentage difference (PDs) compared with the parameters calculated from the RR interval data derived from ECG at sampling frequency 2000 Hz. When $\{X_1, X_2, \ldots X_n\}$ is obtained for ApEn based HRV parameter of the data set with a sampling frequency 125, 250, 500 1000 and 1500 Hz and X_{origin} is the corresponding parameter value at ECG sampling frequency of 2000 Hz, the percentage difference PD_k are computed as $|X_{origin} - X_k|/X_{origin} \times 100$ (%). For HRV parameter at each sampling frequency and data length of ECG signal, 150 error values were derived and used for the statistical calculations

To investigate the influence of ECG sampling frequency on, ApEn, HRV complexity measure, the ApEn based entropy of RR interval series of different lengths N = 1000 (long-term data), 500 (medium data) and 200 (short-term data) was derived. Entropies of RR interval time series derived from ECG sampled at sampling frequency 2000 Hz were taken as reference values. ApEn of RR intervals derived from ECG at sampling frequency 125, 250, 500, 1000 and 1500 Hz were computed and compared with reference values to assess the effect of ECG sampling frequency. Table 1 shows the variation in (average±Standard deviation) ApEn of RR interval time series of ten healthy subjects. Entropy measures of HRV found to be more affected by ECG sampling frequency for long term data. The percentage difference in ApEn was more than 3.5%.for long term data, more than 2.5% for medium data and less than 1% for short term data at low ECG sampling frequency of 125 Hz with respect to reference values at 2000 Hz. Percentage difference was decreases up to 0.016 % and 0.11% for long term and short term data respectively at medium ECG sampling frequency of 1000 Hz. Figure 1 shows the Percentage difference in ApEn based HRV for short term, medium and long term RR interval data. These reductions in percentage differences have been found

to be dependent on level of sampling frequency and data length. Results show that errors due to the ECG sampling frequency in ApEn can be very high at low sampling frequency.

Table 1. Effect of ECG Sampling Frequency on Average ApEn of Ten Healthy Subjects

S. No.	Sampling Frequency (Hz)	Mean±SD of ApEn			Percentage Difference		
		Data Length					
		200	500	1000	200	500	1000
1	125	1.33349±0.046	1.46807±0.101	1.53151±0.160	0.8528	2.5185	3.6846
2	250	1.34530±0.049	1.47730±0.101	1.53647±0.162	0.0252	1.9057	3.3727
3	500	1.34831±0.018	1.50743±0.052	1.58984±0.063	0.2490	0.0949	0.0163
4	1000	1.34649±0.041	1.50695±0.055	1.58981±0.063	0.1137	0.0630	0.0182
5	1500	1.34643±0.018	1.50679±0.052	1.58984±0.063	0.1092	0.0524	0.0163
6	2000	1.34496±.019	1.5060±0.052	1.59010±0.063	0	0	0



..▲.. Short Term Data (N=200), ..♦.. Medium Term Data (N=500), ..▪.. Long Term Data (N=1000)

Figure 1. Percentage Difference in ApEn based HRV of Ten Healthy Subjects with Respect to the Reference Value

5. Conclusions

An analysis of the errors due to the ECG sampling frequency in the estimation of the ApEn is described. The ECG sampling frequency produces considerable error in the ApEn estimation when the sampling frequency was low (125 Hz). This quantification results a bias in entropy measure of HRV and clinically misinterpretation. Errors in entropy measures depend upon data length of RR interval time series. Thus we have shown that the absolute entropy value estimated by the ApEn algorithm is sensitive to ECG sampling frequency and data length.

References

[1] Task Force of European society of Cardiology and the North American Society of Pacing and Electrophysiology, circulation, vol. 5, no. 93, **(1996)**.
[2] P. K. Stein, M. S. Bosner, R. E. Kleiger and B. M. Conger, American Heart Journal, vol. 25, no. 127, **(1994)**.
[3] G. G. Berntson, J. T. Bigger, D. L. Eckberg, P. Grossman, P. G. Kaufmann, M. Malik, H. N. Nagaraja, S.W. Porges, J. P. Saul, P. H. Stone and M. W. Vander-Molen, Psychophysiology, vol. 6, no. 34, **(1997)**.
[4] G. Merati, M. D. Reinzo, G. Parati, A. Veicsteinas and P. Castiglioni, IEEE Transaction on Biomedical Engineering, vol. 1, no. 53, **(2006)**.
[5] D. Singh, K. Vinod, S. C. Saxena and K. K. Deepak, Journal of Medical Engineering and Technology, vol. 3, no. 30, **(2006)**.
[6] S. Cerutti, IEEE Review in Biomedical Engineering, vol. 1, **(2008)**.
[7] S. M. Pincus, Proceedings of the National Academy of Sciences USA, vol. 88, **(1991)**.
[8] B. Singh, D. Singh, A. K. Jaryal and K. K. Deepak, International Journal of Systems Science, vol. 5, no. 43, **(2012)**.
[9] J. S. Richman and J. R. Moorman, American journal of Heart and Circulatory Physiology, vol. 6, no. 278, **(2000)**.
[10] S. M. Pincus and A. L. Goldberger, American Journal of Physiology-Heart and Circulatory Physiology, vol. 35, **(1994)**.
[11] L. Hejjel and E. Rooth, Physiological Measurements, vol. 25, **(2004)**.
[12] T. Ziemsseen, Z. Gascg and H. Ruediger, Journal of Clinical Monitoring and Computing, vol. 22, **(2008)**.
[13] S. Abboud and O. Barnea, Proceedings of IEEE Computers in Cardiology, **(1995)**.
[14] B. Singh and D. Singh, Cardiovascular Engineering and Technology, vol. 2, no. 3, **(2012).**
[15] J. F. Valencia, M. Vallverdu, R. Schroeder and R. Voss, IEEE Engineering in Medicine and Biology Magazine, vol. 6, no. 28, **(2009)**.

Authors

Manjit Singh received his bachelor degree in Electronics Engineering from Baba Banda Singh College of Engineering Fatehgarh Sahib, Punjab, India in 1998, and Masters Degree in Electronics and communication Engineering from National Institute of Technical Teacher Training and Research, Chandigarh, India in 2010. Currently he is pursuing his Ph.D. degree from Punjab Technical University Jalandhar, Punjab, India. He is working as Assistant Professor at Guru Nanak Dev University Regional Campus Jalandhar, Punjab, India. His research interest is in the area of biomedical signal processing.

Butta Singh received his Bachelor's degree in Electronics and Communication Engineering from Guru Nanak Dev Engineering College, Ludhiana, Punjab, India in 2002, Master's degree in Instrumentation and Control Engineering from Sant Longowal Institute of Engineering and Technology, Longowal, Sangrur, Punjab, India in 2005 and Ph.D. degree in Engineering from National Institute of Technology, Jalandhar, Punjab, India. He is serving as Assistant Professor in the Department of Electronics and Communication Engineering, Guru Nanak Dev University, Regional Campus, Jalandhar, Punjab, India. His professional research interests are in signal processing, in particular, applied to biomedical applications. He has published over 30 research articles in internationally reputed journals and conference proceedings.

Vijay Kumar Banga received his B.E from Punjabi University, Patiala, India , M. Tech. from Punjab University, Chandigarh, India and Ph.D. from Thapar University, Patiala. He has 18 years of academic experience & his area of Specialization includes Soft Computing, Image Processing and Autonomous Robots. Currently He is serving as Professor and Principal at Amritsar College of Engineering and Technology Amritsar, Punjab, India.