Available Online at http://www.journalajst.com

ASIAN JOURNAL OF SCIENCE AND TECHNOLOGY

ISSN: 0976-3376

Asian Journal of Science and Technology
Vol. 6, Issue 05, pp. 1455-1457, May, 2015

RESEARCH ARTICLE

MULTI SCALE ANALYSIS OF CARDIOVASCULAR VARIABILITY

***Butta Singh**

Department of Electronics and Communication Engineering, Guru Nanak Dev University, Regional Campus, Jalandhar, Punjab, India

ARTICLE INFO

Article History:
Received 07th February, 2015
Received in revised form
18th March, 2015
Accepted 29th April, 2015
Published online 31st May, 2015

Key words:
Cardiovascular Variability,
Multiscale Analysis,
Multiscale Entropy

ABSTRACT

Cardiovascular variability refers to the beat-to-beat alterations in RR intervals of electrocardiogram (ECG) and a decrease in its value or abnormalities in its patterns have been used as a measure for predicting the future coronary events. Multiscale entropy (MSE) is a will developed complexity measure to quantify the concomitant effect of the cardiovascular regulating mechanisms at different time scales. This paper investigate the performance of MSE to classify the normal healthy and cardiac subjects. Lead-II ECG was acquired from 10 healthy (average age 31 years) and 10 acute myocardial infarction (AMI) subjects (average age 48 years). The study confirms that the time scales has a significant effect on MSE based cardiovascular variability.

Copyright © 2015 Butta Singh. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

Cardivascular variability is beat to beat variation in heart rate (i.e. in RR intervals) under resting conditions (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). Figure 1 shows the variation in three RR intervals of an ECG signals. These beat to beat variations occur due to continuous changes in the sympathetic and parasympathetic outflow of autonomic nervous system to the heart. Cardiovascular variability is the result of interaction among complex feedback mechanisms in the cardiovascular system. Therefore, as the feedback mechanisms are degraded by diseases, the cardiovascular variability diminishes (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996; Singh *et al*., 2011). The average value of heart rate in normal individuals in the resting state is around 72 beat per mimute, varies in the range of 60-90 bpm in a day. The heart rate may be increased by slow acting sympathetic activity or decreased by fast acting parasympathetic activity. The balance between these two opposite acting branches of the autonomic nervous system, is referred to as the sympathovagal balance. The pboblems encounters in clinical applications of cardiovascular variability includes: i) Significant inter-patient variation within similar groups, it is difficult to ascribe definite values of cardiovascular variability metrics to delineate pathology from normal behaviour. Ii) ECG recordings, especially during an exercise, stress and surgical conditions, are exposed to artifacts. The source of artifacts can be due to technical problems, biological events and errors in the automatic detection. The presence of ECG artifacts represents an important error source which must be dealt with before cardiovascular variability analysis. Factors Influencing cardiovascular variability quantification are age; gender; circadian rhythm; blood pressure; respiration; alcohol/smoking; body position; physical fitness; food ingestion; medication and body mass index etc (Acharya *et al*., 2006).

The analysis of cardiovascular variability can be done by three methods: Time domain, Frequency domain and Non Linear methods (Acharya *et al*., 2006; Singh *et al*., 2014). Statistical techniques are applied to quantify the cardiovascular variability in time domain and the parameters include; SDNN - Standard deviation of the RR intervals; SDSD- Standard deviation of successive RR interval differences; RMSSD- Root mean square of successive RR interval differences; NN50 – Number pairs of RR intervals differing by 50 ms; pNN50 – Percentage of NN50. The frequency components of cardiovascular variability are analyzed using many methods. Fast Fourier Transform (FFT) is one of the commonly employed methods.

****Corresponding author: Butta singh***
Department of Electronics and Communication Engineering, Guru Nanak Dev University, Regional Campus, Jalandhar, Punjab, India

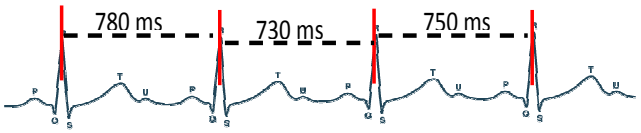

Fig 1. Variation in RR intervals referred as cardiovascular variabilitv

The power spectrum is subsequently divided into three frequency bands Table 1; VLF- (0.001 to 0.04) Hz, LF- (0.040 to 0.15) Hz and HF- (0.15 to 0.4) Hz (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). Normative data of frequency domain cardiovascular variability parameters are shown in Table 2.

Table 1. Cardiovascular variability parameters in frequency domain

Frequency bands	Frequency	Mediated by
Very low frequency (VLF)	0.001-0.04 Hz	Possibly renin- angiotensin system
Low frequency (LF)	0.04-0.15 Hz	Parasympathetic and sympathetic influences
High Frequency (HF)	0.15-0.4 Hz	Parasympathetic influence
LF/HF ratio		Sympatho-vagal balance

Table 2. Normative frequency domain perameters

Parameters	Values (mean ± SD)
LF (ms^2)	1170 ± 416
HF(ms^2)	975 ± 203
Total(ms^2)	3466 ± 1018
LF (n.u.)	54 ± 4
HF(n.u.)	29 ± 3
LF/HF ratio	1.5 ± 2.0

(Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). Cardiovascular system is comprised of multiple subsystems that exhibit both highly nonlinear deterministic, as well as, stochastic characteristics, and subject to hierarchical regulations. Since the linear parameters of cardiovascular variability do not provide adequate information on the complexity that lies inside beat-to-beat variability, the application of complexity based nonlinear techniques is appropriate (Singh and Singh, 2012). Approximate entropy (ApEn), sample entropy (SampEn), Poincare plot, Fractral analysis are the well developed non linear techniques to quantify the cardiovascular variability (Hoyer *et al*., 1997; Singh and Singh, 2013).

Cardiovascular control is composed of numerous regulatory systems interacting across multiple time scales. Short-term neural regulation is fast that is carried out by sympathetic and parasympathetic activities of autonomic nervous system. whereas vasomotor control, chemoreflex regulation and thermoregulation are relatively sluggish and hormonal control even more slower (Costa *et al*., 2002; Singh and Bharti, 2015). Therefore cardiovascular variability cannot be completely characterized on a single time scale, and RR interval time-series have a complex temporal structure with multiscale correlations Multiscale entropy (MSE) developed by Costa *et al.,* has become a promising technique for measuring the complexity of finite length time series at different timescales (Costa *et al*., 2005).

The objective of this study is to evaluate the performance of MSE to classify the normal healthy and cardiac subjects.

II Data

This study involves 10 healthy (average age 31 years) and 10 acute myocardial infarction (AMI) subjects(average age 48 years). All subjects refrained from alcohol, coffee and smoking for 24 h prior to this study. No participant was addicted to drugs, taking any medication or involved in endurance training. This study was performed at rest in the supine position and the subjects were kept quiet in a natural environment. The subjects were allowed to normal breathing during the whole study. The data were acquired on Biopac MP100 system. The ectopic free RR interval with length N=1000 of two groups were derived from Lead-II ECG recordings having a sampling frequency of 500 Hz.

III Methods

Multiscale Entropy

For a given time series with N data points, multiple coarse-grained time series are constructed by averaging a successively increasing number of data points within non-overlapping windows of increasing length, τ. Each element of the coarse-grained time series is calculated as:

$$y_j^{\tau} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i$$

Where τ represents the scale factor and $1 \le j \le N/\tau$. The length of each coarse-grained time series is N/τ. For scale-1, the coarse-grained time series is simply the original time series. For each coarse-grained time series, SampEn is calculated with predefined parameters m and a threshold value equal to r times the standard deviation of original time series, and then plotted as a function of the scale factor τ. SampEn is a "regularity statistic." It "looks for patterns" in a time series and quantifies its degree of predictability or regularity. Where m specifies the length of patterns and r is the tolerance threshold for accepting similarity between these patterns.

RESULTS AND DISCUSSION

In cardiovascular system or neurosciences analysis, a wide consensus has been reached. A decrease in the complexity with respect to the normal case is in most instances bounded to a pathological condition. To evaluate the performance of MSE to classify the normal healthy and cardiac subjects, entropy par meters of controlled group (healthy subjects) and AMI subjects are calculated at time scales varies from 1 to 10 Table 3. At scale -1, average MSE was 1.5311for helthy subjects and 1.5239 for AMI subjects. The decrease in entropy of RR interval time series of healthy subjects (Figure 2) on large time scales indicates that the coarse-grained time series become gradually less complex than those corresponding to shorter time scale. Whereas increase in entropy of RR interval time series of AMI subjects on large time scales reflects the increase in complexity of time series. Thus, it is not only the specific values of the entropy measure but also their dependence on time scale needs to be taken into account to better describe the physiologic mechanism.

Table 3. Avearge MSE values of 10 healthy and 10 AMI subjects at various time scales varrrying from 1 to 10

Subjects	γ=1	γ=2	γ=3	γ=4	γ=5	γ=6	γ=7	γ=8	γ=9	γ=10
Healthy	1.5311	1.5156	1.5083	1.5065	1.5043	1.5009	1.4907	1.4931	1.491	1.4983
AMI	1.5239	1.5649	1.5732	1.5708	1.574	1.5693	1.5717	1.5725	1.5748	1.575

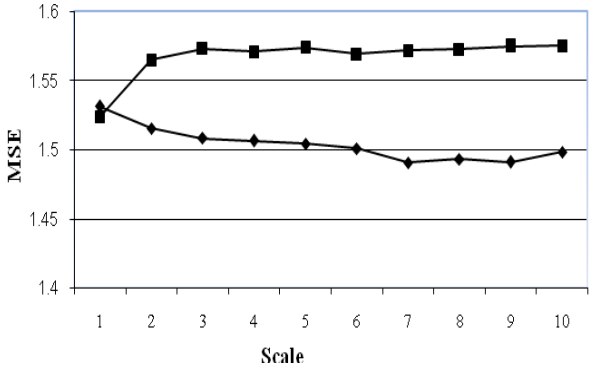

Figure 2. Effect of temporal scales on MSE of healthy (♦) and AMI subjects (▪)

Conclusion

This study confirms that the time scales has a significant effect on MSE based cardiovascular variability. Physiologic complexity is associated with the capacity of living systems to adjust to an everchanging environment, which requires integrative multiscale functionality. In contrast, under free-running conditions, a sustained decrease in complexity reflects a reduced ability of the system to function in certain dynamical regimes possibly due to decoupling or degradation of control mechanisms.

REFERENCES

Acharya, U.R., Joseph, K.P., Kannathal, N., Lim, C.M. and Suri, J.S. 2006. Heart rate variability: a review. *Medical and Biological Engineering and Computing,* 44(12): 1031–1051.

Costa, M., Goldberger, A.L. and Peng, C.K. 2002. Multiscale entropy analysis of complex physiological time series. *Physical Review Letters.* 89(6): 068102(1)-068102(4).

Costa, M., Goldberger, A.L. and Peng, C.K. 2005. Multiscale entropy analysis of biological signals. *Physical Review.* 71(2): 021906(1)- 021906(18).

Hoyer, D., Schmidt, K., Bauer, R., Zwiener, U., Kohler, M., Luthke, B. and Eiselt, M. 1997. Nonlinear analysis of heart rate and respiratory dynamics. *IEEE Engineering in Medicine and Biology.* 16: 31–39.

Merati, G., Reinzo, M.D., Parati, G., Veicsteinas, A. and Castiglioni, P. 2006. Assessment of autonomic control of heart rate variability in healthy and spinal-cord injured subjects: contribution of different complexity based estimators. *IEEE Transaction on Biomedical Engineering.* 53(1):.43–52.

Singh, B. and Bharti, N. 2015. Software tools for heart rate variability analysis. International Journal of Recent Scientific Research. 6(4): 3501-3506.

Singh, B. and Singh, G. 2013. Evaluation of multiscale entropy based HRV for ectopic beats. *10th IEEE International Conference on Information Technology: New Generations (ITNG) Las Vegas.* 706-711.

Singh, B., Singh, D. 2012. Modified multiscale entropy in HRV for automatic selection of threshold value *r. Int. J. Medical Engineering and Informatics.* 4(1): 55–65.

Singh, B., Singh, D., Jaryal, A.K. and Deepak, K.K. 2011. Ectopic beats in approximate entropy and sample entropy-based HRV assessment. *International Journal of Systems Science,* 43(5): 884-893.

Singh, M., Singh, B. and Banga, V.K. 2014. Effect of ECG sampling frequency on approximate entropy based HRV. *International Journal of Bio-Science and Bio-Technology.* 6(4): 179-186.

Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology 1996. Heart rate variability-standards of measurement, physiological interpretation and clinical use. *European Heart Journal.* 17: 354-38, 1996

****