Approximate Entropy (ApEn) based Heart Rate Variability Analysis

Amritpal Singh¹* and Jashandeep Kaur²

¹School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara - 144411, Punjab, India; apsingh1.ppu@gmail.com
²Lovely Professional University, Phagwara - 144411, Punjab, India

Abstract

Heart Rate Variability (HRV) has been established as a vital index for diagnostics and prognosis of a number of pathological conditions. Moreover, HRV is a proven indicator of autonomic balance. As HRV is a result of multiple responses acting at various time scales, these interactions need to be quantified. In this paper, a complexity measure called ApEn is utilized to quantify the complexity of HRV. This method is tested on age stratified standard Fantasia database from Physionet. It is observed that young subjects show higher HRV complexity than the older ones. The effect of tolerance threshold ‘r’ is also evaluated on the HRV complexity estimation of young and old subjects. Further, for r≥0.10, the complexity of HRV is higher for young subjects but the trend is reverse for r<0.10. Therefore, it is concluded that the tolerance threshold ‘r’ should be carefully selected for the complexity analysis of HRV.

Keywords: Approximate Entropy, Autonomic Nervous System, Complexity, Heart Rate Variability

1. Introduction

Heart rate variability is one of the simple and widely accepted measures by cardiologist for both clinical and research use as reveals the cardiac health and Autonomic nervous system. Heart rate variability is defined as a physiological process of determining variability in time gap between consecutive heart beats. Heart rate variability is regulated by sinoatrial node having two parts sympathetic and parasympathetic nodes and is a natural pacemaker of human body. Beat-to-beat analysis of HRV provides an important information regarding cardiovascular tone non-invasively. The analysis of HRV is a noninvasive diagnostic tool that provides significant prognostic information in cardiology for both physiological and psychophysiological processes. HRV is the result of modulation of both cardiac parasympathetic and sympathetic outflow to the sinus node in the heart. HRV is affected by a number of physiological and psychophysiological processes. These include body position or postural stress, mental stress, exercise, moderate hypotension, controlled respiration, and in various diseases like diabetes mellitus, myocardial infarction etc. In it has been mentioned that HRV is capable to discriminate amongst post myocardial infarction cardiac arrest (MI-CA) survivors from further post MI patients. HRV index is furthermore capable to measure autonomic dysfunction of diabetic patients.

Over the last ten years, indices of HRV have arisen as a pronounced predictive pointer of extensive range of cardiovascular diseases. Invasive and non-invasive approaches have been established over a period of time to examine HRV. The invasive approaches utilize outer stimulus, viz., drugs to stimulate or block one of the branches of Autonomic Nervous System (ANS) thereby altering the autonomic balance. This is in turn leads to changes in HRV. Non-invasive methods include signal processing techniques for time domain, frequency domain and Time-frequency analysis of HRV. For analysis of HRV, RR intervals (time between successive R-peaks) series obtained from electrocardiogram (ECG) signal is usually analyzed. Non-invasive ways of assessing HRV is
grounded on natural beat-to-beat measurement of heart rate. Statistical methods are used for analyzing HRV time-domain. Various parameters like SDNN, SDSD, RMSSD, SDNN index etc. are used for the time-domain analysis of HRV. Frequency domain approaches comprise parametric and non-parametric power spectral estimation to assess Very Low Frequency (VLF), Low Frequency (LF) and High Frequency (HF) power bands. LF/HF ratio is an important index to assess sympathovagal balance. Since, HRV is due to non-linear interactions between number of physiological processes, linearity is a limitation of these time and frequency domain methods, a number of non-linear methods like Poincare’ indices, Entropy, generalized and phase synchronization and the methods based on chaos theory have emerged as better tools to analyze HRV. As the non-stationarity of RR interval series (tachogram) limits the use of frequency domain methods based on spectral analysis, new time-frequency techniques have been developed over the time. These include methods like short time Fourier transform, orthonormal basis portioning, wavelet transforms, Wigner ville distribution etc. Using these methods, it is possible to analyze the HRV in time-frequency domain to know how energy of the signals vary with respect to both time as well as frequency. Since, HRV is a result of complex interactions originating from different physiological processes, the complexity of HRV needs to be analyzed.

In this paper, analysis of HRV is performed on age stratified standard Fantasia database from Physionet. This data contains 20 young subjects (21 - 34 yrs.) and 20 old subjects (68 - 85 yrs.) strictly vetted healthy subjects, those experienced 120 mins of uninterrupted supine resting position, whereas, continuous electrocardiogram (ECG), and respiration signals were recorded. In addition, the measurements also included an uncalibrated continuous Arterial Blood Pressure (ABP) waveform. The paper is further distributed in three sections where Section 2 explains the methods used for spontaneous HRV complexity estimation, database used, pre-processing technique employed on the data, Section 3 contains results and discussion followed by conclusion in Section 4.

2. Methods

2.1 Sample

The Fantasia dataset consists of 20 young and 20 old subjects recorded for HRV studies who watched the ‘Fantasia’ movie while being recorded. The complexity study was performed on this standard database available at Physionet for each young and old subject. 1000 samples for each RR interval series were used for analysis.

2.2 Data Pre-processing

Since, the ECG waveforms is a quasi-periodic waveform, a non-linear algorithm developed using empirical mode decomposition is utilized to detect the R-peaks from the ECG waveform. This method is based on the decomposition of original multicomponent waveform into subsequent Intrinsic Mode Functions (IMFs) of unique instantaneous frequency each. This is a data driven method unlike wavelet transformation which decomposes the input signal based on a pre-defined kernel. The ectopic beats were physically removed using the zero degree interpolation technique. The tachogram (RRi series) formed using successive R-R peaks for a typical subject is as shown in Figure 1. The RRi series was normalized according to the following equation:

$$RRI_n = \frac{RRI_t - \frac{1}{N} \sum_{i=1}^{N} RRI(t)}{\frac{1}{N} \sum_{i=1}^{N} RRI(t)}$$  (1)

where, N=Number of samples, i corresponds to sample. Beat-to-beat RRi series was utilized for approximate entropy calculation of each subject.

2.3 Complexity Analysis using ApEn

For finding sample entropy of a given discrete time series with N number of sample data points an array of N-m+1 is formed, here m is defined as embedding dimension. Every array comprises of m consecutive points and each
one of the array act as a template for template matching purpose with all datasets. In order to find maximum distance between them and also resulting in formation of conditional vectors having next close value of the position after our selected template set under a pre-decided threshold level referred to as “r” (tolerance also). This process also comprises of template matching with itself also and hence giving rise to bias problem that is log0 (zero) condition. In the next step, these conditional vectors are arranged as data sets and then conditional probabilities are drawn from each conditional vector. ApEn is defined as:

\[ ApEn(m,r) = \frac{\sum_{i=1}^{N-m+1} \ln \left( \frac{C_i^m(r)}{N-m+1} \right) - \sum_{i=1}^{N-m} \ln \left( \frac{C_{i+1}^{m+1}(r)}{N-m} \right)}{N-m} \]  

where, \( C_i^m(r) \) and \( C_{i+1}^{m+1}(r) \) is the conditional probability that the distance between the two vectors lie within the threshold \( r \) for window length \( m \) remains within \( r \) for window length \( m+1 \) respectively.

2.4 Variation of tolerance threshold ‘r’

Nevertheless, a suggested range of ‘r’ has been suggested as (0.1–0.25) times the standard deviation of the HRV time series, in some cases ‘r’ within this range may lead to incorrect conclusions in analyzing complexity of a time series. In this paper, ‘r’ is varied from 0 to 0.34 in steps of 0.02 and the variation of mean and SD of ApEn is analyzed of HRV for young and old subjects.

3. Results and Discussion

Figure 2 shows the variation of mean value of ApEn over 20 young and 20 old subjects as a function of tolerance threshold ‘r’ where \( r \) is varied from (0.1–0.34) times the standard deviation. It is evident from the results shown in Figure 2 that for \( r \geq 0.10 \), the complexity of HRV in young subjects is higher than the older ones as depicted by higher ApEn values for young subjects than the old subjects. This is physiologically also correct as the variability in young subjects is more than the older ones. But, as the \( r \) decreases from 0.10, the trend reverses. Figure 3 shows the variation of SD of ApEn over 20 young and 20 old subjects as a function of tolerance threshold ‘r’ where \( r \) is varied from (0.1–0.34) times the standard deviation. It is evident from the results shown in the Figure 3, that except for \( r < 0.02 \), the ApEn (SD) is higher in the case of young subjects.

4. Conclusion

Interactions between multiple physiological processes affects the heart rate variability under different physiological conditions. These complex interactions need to be quantified in order to decipher the functioning of autonomic control system. In this paper, the complexity of HRV is analyzed using an information domain indices called ApEn. The analysis was performed on the age stratified data. It is concluded that the complexity of HRV is higher in younger subjects than the older ones. However, the algorithmic parameters like tolerance threshold ‘r’ affects these findings. Therefore, the analysis was conducted over a complete spectrum of ‘r’ and it is emphasized that the selection of ‘r’ is critical for such complexity analysis using ApEn as the trend reverses for certain values of the tolerance threshold ‘r’ that leads to misleading conclusion about the true nature of complexity of HRV in younger and older subjects.
5. References

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