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Quantification of Heart Rate Variability: A Measure based on Unique Heart Rates

V. I. Thajudin Ahamed, P. Dhanasekaran, A. Naseem, N. G. Karthick, T. K. Abdul Jaleel, and Paul K. Joseph

***Abstract*—**It is established that the instantaneous heart rate (HR) of healthy humans keeps on changing. Analysis of heart rate variability (HRV) has become a popular non invasive tool for assessing the activities of autonomic nervous system. Depressed HRV has been found in several disorders, like diabetes mellitus (DM) and coronary artery disease, characterised by autonomic nervous dysfunction. A new technique, which searches for pattern repeatability in a time series, is proposed specifically for the analysis of heart rate data. These set of indices, which are termed as pattern repeatability measure and pattern repeatability ratio are compared with approximate entropy and sample entropy. In our analysis, based on the method developed, it is observed that heart rate variability is significantly different for DM patients, particularly for patients with diabetic foot ulcer.

***Keywords*—**Autonomic nervous system, diabetes mellitus, heart rate variability, pattern identification, sample entropy

I. Introduction

VARIABILITY analysis tracks the patterns of change in an individual parameter over time in order to evaluate the state of a complex system, which may be physical or biological. One such parameter is heart rate variability (HRV), refers to the variation in the rate at which sino-atrial (SA) node triggers over time. The rate of pulsation of SA node is controlled by autonomic nervous system (ANS). It is found that heart rate variability depends on various factors like gender, age, and health condition and respiration rate. Analysis of HRV is a powerful tool for the estimation of ANS activity. HRV analysis has become an important tool in the detection of cardiac and other diseases, as it is non invasive and provide prognostic information in patients [1]-[8]. Autonomic neuropathy (AN) is one of the common chronic complications of diabetes mellitus (DM). AN is associated with high mortality compared to those without it [9]-[11]. Diabetic foot ulcer (DF) is one of the preventable complications of DM. Factors contributing to the ulcer formations are, micro and macroangiopathy, neuropathy including sensory, motor, autonomic, and finally infection. AN leads to decrease in perspiration which leads to dry skin, cracks and fissures, where infection easily establish. DF is one of the most leading causes of foot amputations all over the world [12].

The heart rate data is not periodic and it looks like random noise. Various techniques are employed to differentiate the heart rate time series from random noise. These data mining methods include time domain, frequency domain, geometrical and non linear methods. Considering the variety of measures, European society of cardiology and the North American society of pacing and electrophysiology had set up a committee, and they submitted recommendation on the standardisation of the indices [13]. Although various indices are used for quantification of HRV time series, a single clinically accepted parameter which can detect various diseases is not yet identified. Certain measures may be good in analysing HRV of particular group of diseases and others may fit for another group of diseases [14].

Linear methods like conventional time domain and frequency domain methods may not be able to detect subtle but important features embedded in signals that originate from complex non linear living systems. It is found that the system generating the heart rate signal is nonlinear and the signals are nonstationary. Nonlinear methods are able to describe more details of these processes [14]-[15]. Measures which can quantify complexity, irregularity or randomness are, approximate entropy (ApEn) [16], sample entropy (SampEn) [17]-[18] and multiscale entropy (MSE) [19]-[20]. SampEn and ApEn are measures of time series regularity. SampEn(m,r,N) is the negative natural logarithm of the conditional probability that a data set of length N, having repeated itself within a tolerance r for m points, will also repeat itself for m+1 points, without allowing self matches. Low value of SampEn and ApEn indicates more self similarity in the time series. One of the differences between ApEn and SampEn is that the former allows self matches, whereas the latter does not. MSE takes into account multiple scales when calculating the entropy. These measures are pattern identification methods, which search for similar patterns in the time series.

The objective of the present work is to propose a set of measures, which can quantify the variability of heart rate time series, with certain advantages compared to existing indices.

V. I. Thajudin Ahamed, P. Dhanasekaran, N. G. Karthick, and Paul K. Joseph are with the Department of Electrical Engineering, National Institute of Technology, Calicut, Kerala, India. (email:thajudin88@gmail.com).

A. Naseem is and T. K. Abdul Jaleel are with the Department of General Medicine, and Orthopedics respectively, at Santhy Hospital, Omassery, Calicut, Kerala, India.

II. Materials and Methods

Study was conducted at Santhy hospital, Omassery, Calicut, Kerala, India, a multi specialty hospital. Patients were selected from the departments of general medicine and orthopedics. Resting conventional 12 lead electrocardiogram (ECG), blood sugar – both fasting and post prandial, blood urea, serum creatinine, serum electrolytes (Na, K, Ca, P) were done to all patients. Those who were having abnormal results, except in blood sugar were excluded. Those who were already diagnosed to have coronary artery heart disease (CAHD), those patients whose ECG showed ST-T changes suggestive of CAHD, those taking drugs which affect HRV and those with severe co-morbid conditions like renal failure, severe asthma, chronic obstructive pulmonary disease, septicemia etc., were also excluded. ECG of 10 patients each with DM and DF, and of 10 healthy volunteers, was recorded in the relaxed lying position for 60 minutes. The control group consisted of volunteers without DM, DF and any cardiac disorders. The DM and DF groups were age and sex matched with the control group. The subjects under study were in the age group of 50 -70 years (58.5±6.42) and the duration of diabetes for the patient groups was 5 -15 years. ECG was recorded using BIOPAC$^{(TM)}$ equipment and is converted to heart rate time series using ACQKnowledge software available along with the system. The sampling rate of ECG was 200 Hz. The proposed indices were computed from heart rate data of patients with DM and DF, along with that of control group and MIT-BIH normal sinus rhythm database [21]. These measures were computed for correlated noise also. The following section explains the details of the proposed indices.

A. Pattern Repeatability Ratio

The proposed new index, which is termed as *pattern repeatability ratio (PRR)*, is based on the repetition of patterns in the given data. The number of patterns, with unity pattern length, which occurs at least once in the heart rate time series, X_t, is computed. That is, the range of the sample function will contain X_i, X_j, ... Let this be termed as pattern repeatability measure with unity pattern length, and be denoted as *PRM (1)*. This computation eliminates the redundancy of repeated values. Similarly, let (X_i, X_{i+1}) occurs once or repeats in the time series X_t. The number of such distinct pairs is termed as pattern repeatability measure with pattern length two. Let this be denoted as *PRM (2)*. This index gives the number of such unique patterns, by eliminating repeated values. In general, the number of distinct sets, (X_i, X_{i+1}, X_{i+2}, X_{i+3},... X_{i+m-1}) are counted as *PRM (m)*. A shift by $\boldsymbol{c}$ in the index where $\boldsymbol{c}$ = 1, 2, 3, ... generates all pattern repeatability measures. p*attern repeatability ratio (m, n)* is expressed as,

$$PRR(m,n) = PRM(m) / PRM(n) \quad (1)$$

where *m* and *n* are the pattern lengths

B. Testing with heart rate data and correlated noise

The proposed indices, PRM (1), PRM (2) and PRR (2, 1), were tested with the MIT-BIH normal sinus rhythm database and compared with that of the control group. The effect of duration of the heart rate data on the proposed indices were also studied with increasing window size. The proposed measures were computed for the DM, DF, control group and the MIT-BIH normal sinus rhythm database for a length of 4000 data points. SampEn and ApEn values for the above mentioned groups were also computed for the same length. The indices were computed for correlated noise data also for the same length.

III. Results and Discussion

The effect of length of the data on PRM (1), PRM (2) and the PRR (2, 1) are shown in Fig. 1 for the control, DM and DF groups. It can be seen that these indices reach almost a steady value after 3000 samples, in the case of patients with DM and DF. It can also be seen from Fig. 1 that the plateau is reached at about 1000 points in the case of control group. In the case of 12 hours MIT-BIH normal sinus rhythm database also, the sample number at which the steady state occurs is comparable with that of the control subjects, which is shown in Fig. 2.

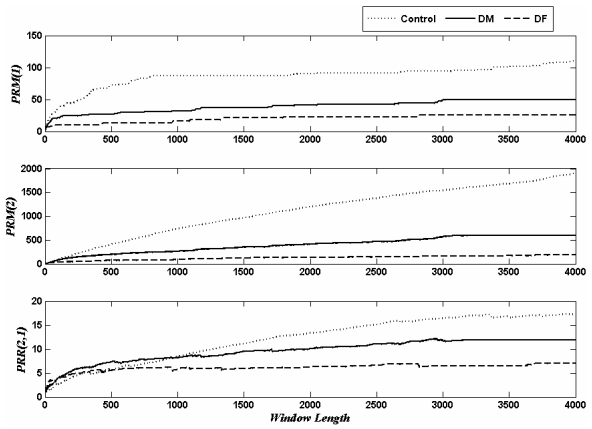

Fig. 1 The effect of record length on various indices for three groups under study

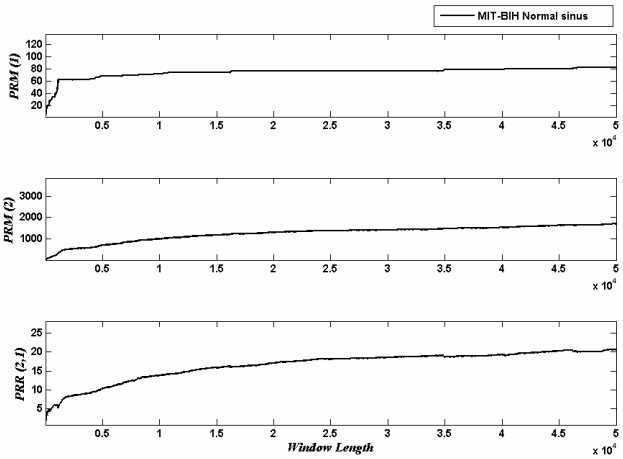

Fig. 2 The effect of record length on various indices for 12 hours MIT-BIH normal sinus rhythm data

The computed values of the proposed measures for different

groups under study and the MIT-BIH normal sinus rhythm data for 4000 points are tabulated in Table I. The paired 't' test is performed for DM and DF groups with respect to control group, and the p values are also tabulated in Table I. The variation in the mean value of the proposed indices, for the three groups, is shown in Fig. 3. The entropy measures, SampEn and ApEn for the groups of subjects under study, for the same length of data, are shown in Table II. For correlated noise with a length of 4000 points, it is observed that the values of the measures are at the extreme level indicating no pattern repetition. That is PRM (1) = 4000, PRM (2) = 3999 and PRR (2, 1) ≅ 1. Moreover these measures are highly dependant on the length of the noise data.

It is evident from the Fig. 1 and Fig. 2 that the number of elements in the sample set of HRV time series, is limited and is less than 150, which is given by the measure PRM(1).

It can be seen that there is an initial increase in the measures PRM (1), PRM (2) and the PRR (2, 1) with window size. These measures reach a plateau around window length of 3000 in the case of patient groups, and at about 1000 points in the case of control group. If the average heart rate is taken as 70 beats per minute, this sample number 3000 corresponds to an approximate duration of 45 minutes. It can be inferred from Fig. 1 that almost all the distinct values, PRM (1), of the heart rate time series X_t occur in duration of about 45 minutes. So at least 45 minutes record is required for the analysis of data using this technique, which is in between conventional short duration analysis and long duration analysis [13]. We suggest that in other measures also this time span of recording may be considered, as most of the elements in the sample set in the time series appears within this duration.

TABLE I
PROPOSED INDICES FOR THE VARIOUS GROUPS

Groups	*PRM (1)*	*PRM (2)*	*PRR (2,1)*
	Mean ± SD, p value	Mean ± SD, p value	Mean ± SD, p value
Control	79.8 ± 25.68	1158.2 ± 510.72	14.14 ± 2.47
DM	56.0 ± 19.99 p= 0.0715	574.7 ± 395.22 p= 0.0472	9.71 ± 3.52 p= 0.0272
DF	46.9 ± 34.83 p= 0.0232	425.8 ± 340.90 p = 0.0027	8.44 ± 2.86 p= 0.0001
MIT-BIH	71.0 ± 23.77	920.6 ± 361.76	12.83 ± 1.72

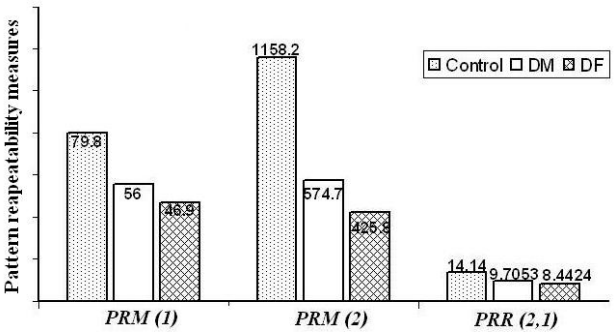

Fig. 3 Indices indicating the progression of disease

The study also has shown that diabetic patients have significantly lower values of HRV parameters, compared to control group. It can be seen from Table I that there is significant change in the proposed measures in patients with DM and DF, compared to normal, except in the case of PRM(1) for DM, as p value is 0.0715. Moreover, it can be seen from Fig. 3 that the measures are decreasing as DM progresses to DF. It is also to be noticed from Fig. 1 that, in the case of control group, the duration of HRV data required so that the proposed measures reach the plateau, is less compared to the patient group. That is, the possible distinct heart rates occur in less duration, which can be considered as a pointer towards dynamism of the ANS.

Most of the established indices are dependent on the length of the time series [13]. The advantage of the new measures is that they are independent of the duration of data, after the plateau in Fig. 1 and Fig. 2. These indices can be considered as static measures, while the duration at which plateau occurs can be considered as a dynamic measure.

TABLE II
SAMPEN AND APEN FOR THE VARIOUS GROUPS

Groups	*ApEn*		*SampEn*	
	Mean ± SD	p value	Mean ± SD	p value
Control	1.3113 ± 0.267	-	1.4392 ± 0.273	-
DM	1.0543 ± 0.420	0.0966	1.1439 ± 0.434	0.0599
DF	1.148 ± 0.348	0.1707	1.2479 ± 0.389	0.1804
MIT-BIH	0.8392 ± 0.191	-	0.9221 ± 0.207	-

It can be seen from Table II that SampEn and ApEn analysis do not show any significant variation in the ANS activity, between the patient and the control groups. The mean value of these indices is less for DM, and DF patients compared to the control group. But these values do not reflect the progression of disease from DM to DF, as measure for DF is higher than that of DM.

Results also show that the new indices for the MIT-BIH normal sinus rhythm database are comparable with that of the control group, which confirms the robustness and reproducibility of the measure. Moreover these measures distinguish HRV time series from correlated noise, as the indices are beyond comparison.

IV. CONCLUSION

In heart rate data, it is found that the instantaneous heart rate values are distinct and they are the members of a limited sample set. When resting heart rate data for duration of 45 minutes is analysed, the number of elements in the sample set is found to be around 150. As the increase in the measure is not appreciable when the record length is increased beyond 45 minutes, it can be concluded that the minimum duration of the data required for analysis is 45 minutes. The same time span of recording can be considered for the computation of other

indices also, as most of the elements in the sample set in the time series appears within this time.

The proposed indices are able to detect the changes in the ANS activity of the patients with DM and DF. It may also be noted that the effect of duration of record above 45 minutes is insignificant in these measures.

In the control group, the duration of heart rate data required so that the proposed measures reach the plateau, is less compared to the patient group. This implies that the ANS activity of the control group is more dynamic compared to the patient group.

Although heart rate time series looks like random noise, the proposed measures can easily distinguish the same from correlated noise, as the values are at the extreme level for noise data.

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