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Differentiation of Heart Rate Time Series from Electroencephalogram and Noise

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Abstract**—**Analysis of heart rate variability (HRV) has become a popular non-invasive tool for assessing the activities of autonomic nervous system. Most of the methods were hired from techniques used for time series analysis. Currently used methods are time domain, frequency domain, geometrical and fractal methods. A new technique, which searches for pattern repeatability in a time series, is proposed for quantifying heart rate (HR) time series. These set of indices, which are termed as pattern repeatability measure and pattern repeatability ratio are able to distinguish HR data clearly from noise and electroencephalogram (EEG). The results of analysis using these measures give an insight into the fundamental difference between the composition of HR time series with respect to EEG and noise.

Keywords**—**Approximate entropy, heart rate variability, noise, pattern repeatability, and sample entropy.

I. Introduction

TIME series analysis methods are used to quantify physiological data for classification and identification of different pathological conditions. Variability of electroencephalogram (EEG), heart rate (HR), human gait dynamics and blood pressure (BP) are some of the physiological signals that are analyzed using time series analysis techniques [1]-[3].

Heart rate variability (HRV) refers to the variation in the rate at which sino-atrial (SA) node triggers over time. Analysis of HRV is a powerful tool for the estimation of autonomic nervous system (ANS) activity, as the rate of pulsation of SA node is controlled by ANS. 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 [4]-[11].

The EEG is a recording of the electrical activity of the brain from the scalp. The EEG has a very complex pattern, which is much more difficult to recognize than the electrocardiogram (ECG). EEG seems to be affected by the mental activity and health condition of person [1], [12].

The physiological signals mentioned above are not periodic and it looks like random noise. Various techniques are employed to differentiate these physiological signals from random noise [13]. These data mining methods include time domain, frequency domain, geometrical and non-linear methods. Considering the variety of measures used for HRV analysis, European society of cardiology and the North American society of pacing and electrophysiology had set up a committee, and they submitted recommendations on standardization of the indices used for heart rate variability analysis [14]. 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 analyzing a particular group of diseases and others may fit for another group [15].

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 living systems. It is found that the system generating the physiological signals is nonlinear and the signals are nonstationary. Nonlinear methods are able to describe more details of these processes [15]-[16]. Measures which can quantify complexity, irregularity or randomness are, approximate entropy [17], sample entropy [18]-[19] and multiscale entropy [20]-[21]. Sample entropy (SampEn) and approximate entropy (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. Multiscale Entropy (MSE) takes into account of 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 distinguish the set of elements, which constitute the HR from EEG time series and noise. The study was intended to propose measures meant specifically for the quantification of the variability of heart rate time series, which is independent of data length. The results of analysis using these measures give the fundamental reason for the difference in the values of various established indices for HR data, EEG data and noise.

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II. Materials and Methods

Electrocardiogram (ECG) was recorded from healthy volunteers, using BIOPAC(TM) equipment and converted to heart rate time series using ACQKnowledge software available along with the system. The sampling rate was 200 Hz. The proposed indices were computed for HR data of normal healthy subjects, and different noise files and HR data of MIT-BIH normal sinus rhythm database available at www.physionet.org. This database includes long-term ECG recordings of subjects referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). Subjects included in this database were found to have had no significant arrhythmias; they include 5 men, aged 26 to 45, and 13 women aged 20 to 50. SampEn and ApEn values for the above mentioned groups were also computed for record length of 4000 points. The following section explains the details of the proposed indices. The EEG data for the experiment was also recorded using the same equipment at same sampling rate for five minutes. The subjects were instructed to relax in a lying position with eyes closed throughout the entire recording session in order to minimize eye movement artifacts.

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. *Pattern repeatability ratio (m, n)* is expressed as,

$$PRR(m,n) = PRM(m) / PRM(n)$$

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

B. Testing with HR Data and Noise

The proposed indices, PRM (1), PRM (2) and PRR (2, 1), were computed for the HR data files in the MIT-BIH normal sinus rhythm database and compared with that of the healthy volunteers, for a record length of 4000 points. The proposed measures were computed for EEG data of healthy volunteers and for noise files of physionet, for the same length. The effect of duration of the HR data, noise and EEG on the proposed indices was studied with increasing window size.

TABLE I
Proposed Indices for the Various Groups

Groups	*PRM (1)*	*PRM (2)*	*PRR (2,1)*
	Mean ± SD	Mean ± SD	Mean ± SD
HR (Healthy Volunteers)	79.8 ± 25.7	1158.2 ± 510.7	14.1 ± 2.5
HR (MIT-BIH data)	71 ± 23.8	920.6 ± 361.8	12.8 ± 1.7
Noise	3997.2 ± 7.1	3999 ± 0	1.0005 ± 0.002
EEG	3992.22 ± 9.5365	3999 ± 0	1.0017 ± 0.0024

III. Results and Discussion

The computed values of the proposed measures for healthy volunteers under study, the MIT-BIH normal sinus rhythm

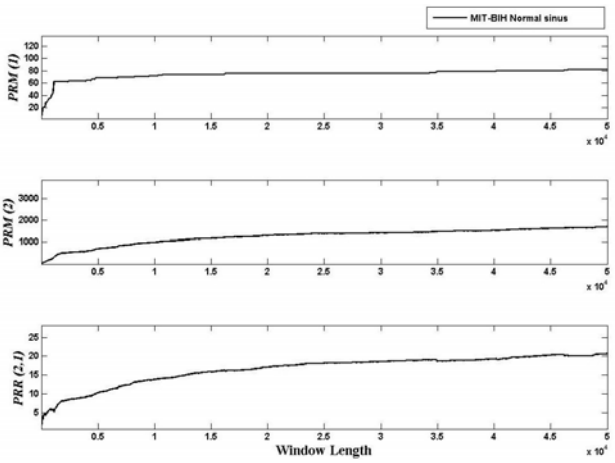

Fig. 1 The effect of record length on various indices for 12 hours MIT-BIH normal sinus rhythm data

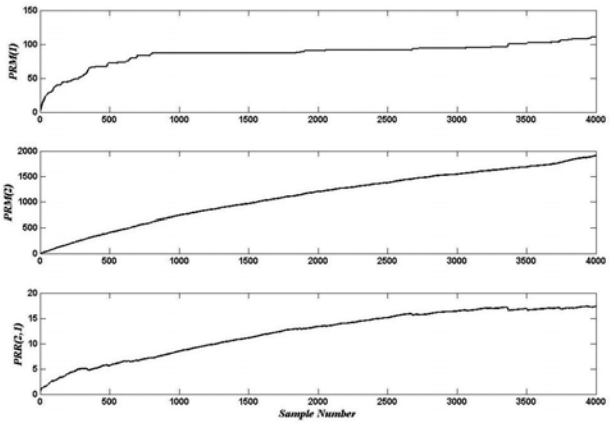

Fig. 2 The effect of record length on various indices for normal healthy volunteers

data, noise and EEG time series are tabulated in Table I. It can be noted that, for noise data, the values of the measures are at

extreme level indicating no pattern repetition. The values of these measures for EEG time series and noise are comparable. Hence the proposed measures distinguish HRV time series from noise and EEG time series, as the indices are beyond comparison.

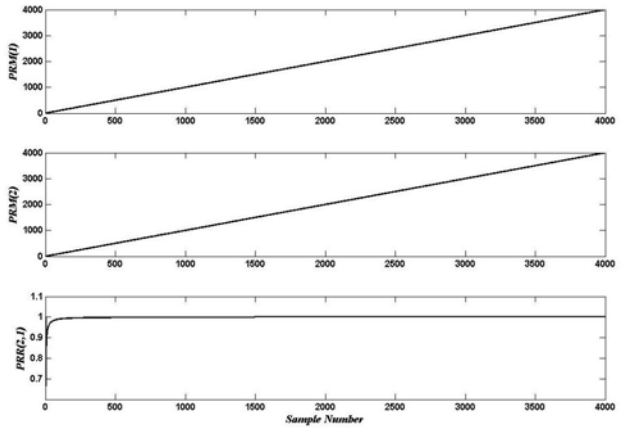

Fig. 3 The effect of record length on various indices for noise

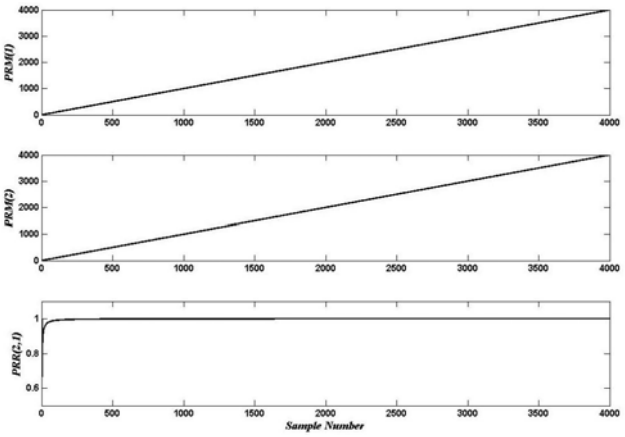

Fig. 4 The effect of record length on various indices for EEG

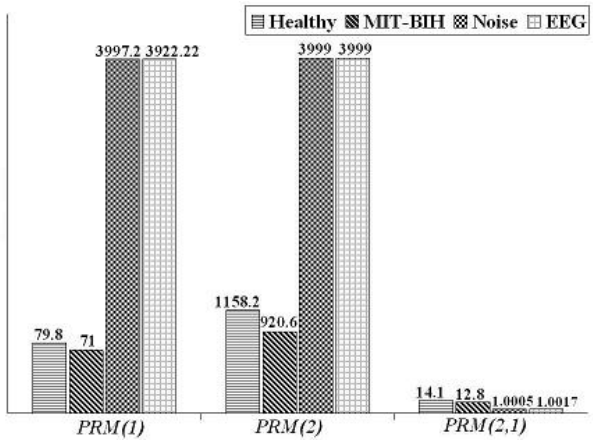

Fig. 5 Comparison of proposed measures for HR time series (healthy and MIT-BIH), noise and EEG

TABLE II
SAMPEN AND APEN FOR THE VARIOUS GROUPS

Groups	ApEn	SampEn
	Mean ± SD	Mean ± SD
HR (Healthy volunteers)	1.3113 ± 0.267	1.4392 ± 0.273
HR (MIT-BIH data)	0.8392 ± 0.191	0.9221 ± 0.207
Noise	1.713 ± 0.217	1.823 ± 0.291
EEG	1.0423 ± 0.3810	1.1125 ± 0.4282

The effect of length of the data on PRM (1), PRM (2) and the PRR (2, 1) are shown in Fig. 1 for 12 hours MIT-BIH normal sinus rhythm data. It can be seen that the indices reach almost a steady value after 1000 samples. In the case of HR data of the healthy volunteers also, the sample number at which the steady state occurs is comparable with that of the MIT-BIH normal sinus rhythm data. The variation of the indices for noise and EEG are shown in Fig. 3 and Fig. 4 respectively. It can be seen that, for noise data and EEG time series, the indices PRM (1) and PRM (2) go on increasing with the window size. But PRR (2,1) is saturated immediately indicating proportional increase in PRM(1) and PRM(2). This suggests that proposed measures are highly dependant on the length of data in the case of noise and EEG.

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). Fig. 5 shows the graphical representation of Table I, for better visual interpretation of the result.

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, in the case of HR data. These measures reach a plateau around window length of 1000 points. If the average heart rate is taken as 70 beats per minute, this sample number 1000 corresponds to an approximate duration of 15 minutes. It can be inferred from Fig. 1 that almost all the distinct values, PRM (1), of the heart rate time series Xt, occur in duration of about 15 minutes in the case of healthy subjects. In another study we found that the time duration required to reach the plateau is around 3000 points for diabetic patients [23]. Hence the analysis is done with 4000 points providing some tolerance. We suggest that in the established linear and nonlinear HRV analysis techniques also this time span of recording may be considered as the minimum standard. We propose this as most of the elements in the sample set in the time series appear within this duration and any further increase in time duration produce negligibly small increase in the number of HR values in sample set.

It can be seen from Table II that SampEn and ApEn values do not show much difference between HR data and noise and EEG. Moreover, the new indices for the MIT-BIH normal sinus rhythm database are comparable with that of the healthy volunteer group, which confirms the robustness and reproducibility of the measure. Most of the established indices are dependent on the length of the time series [12]. The

advantage of the new measures is that they are independent of the duration of HR data, above a record length of one hour.

IV. Conclusion

In a given heart rate time series, it is found that the instantaneous heart rate values are distinct and they are the members of a limited sample set whereas in noise time series, the sample set is made of non-repeating values. This confirms that although heart rate time series looks like random noise, it is totally different and distinguishable from noise. In EEG time series also the repetition of elements is very less and is comparable with noise. So HR data can be easily distinguished from EEG and noise. One of the important features of the proposed measure is that they are independent of length of HR data, if the duration of record is above one hour. As this measure is specially suited for HRV analysis, it can be used for characterizing ANS activity at various pathological conditions.

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