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A new approach to detect congestive heart failure using sequential spectrum of electrocardiogram signals

Chandrakar Kamath *

Electronics and Communication Department, Manipal Institute of Technology, Manipal 576104, India

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ABSTRACT

The aim of this study is to evaluate the discriminative power of sequential spectrum analysis of the short-term electrocardiogram (ECG) time series in separating normal and congestive heart failure (CHF) subjects. The raw ECG time series is transformed into a series of discretized binary symbols and the distribution of mono-sequences (i.e., tuples containing only one type of symbol '0' or '1') is computed. The relative distribution of mono-sequences containing only one type of symbol constitutes binary occupancy for that symbol in the sequential spectrum. The quantified approximate entropies of the binary occupancies in the sequential spectra are found to have potential in discriminating normal and CHF subjects and thus can significantly add to the prognostic value of traditional cardiac analysis. The statistical analyses and the receiver operating characteristic curve (ROC) analysis confirm the robustness of this new approach, which exhibits an average accuracy, average sensitivity, average positive predictivity, and average specificity, all 100.0%.

1. Introduction

Despite numerous recent advances in the field of medicine, congestive heart failure (CHF) has been difficult to manage with in clinical practice and mortality rate has remained high [1]. As a consequence the development of new methods and measures of mortality risk in CHF, including sudden cardiac death, is still a major challenge. Besides this, there is a need to reach remote and under served communities with life saving healthcare. A reliable automated classification system combined with high-speed communication can resolve this issue. This work is an attempt to develop such an automated system to discriminate between normal and congestive heart failure subjects.

Physiological data more often show complex structures, which cannot be quantified or interpreted using linear methods. The classical nonlinear methods suffer from the disadvantage of dimensionality. Further, there are not enough samples in the time series to arrive at a reasonable estimate of the nonlinear measures. From this point of view it is advisable to resort to methods, which can quantify system dynamics even for short time series, like the symbolic dynamics. The prime advantages of symbolic dynamics are the following: if the fluctuations of the two data series are governed by different dynamics then the evolution of the symbolic sequences is not related. The resulting symbolic sequences histograms give a reconstruction of their respective histories and provide a visual representation of the dynamic patterns. In addition, they may be used as a basis to build statistics to compare the regions that show different dynamical properties and indicate which patterns are predominant. Thus methods of symbolic dynamics are useful approaches for classifying the underlying dynamics of a time series. Parameters of time domain and frequency domain often leave these dynamics out of consideration. Besides computational efficiency, symbolic methods are also robust when noise is present. However, it is always advisable to filter any noise in the data series prior to the application of the proposed symbolic method. The process of symbolization can be used to represent any possible variation over time, depending on the number of symbols and the sequence lengths used. This is a very powerful property because it does not make any assumptions about the nature of the signals/patterns (e.g., it works equally well for both linear and nonlinear phenomena).

Symbolic time series analysis has found application for the past few decades in the field of complexity analysis, including astrophysics, geomagnetism, geophysics, classical mechanics, chemistry, medicine and biology, mechanical systems, fluid flow, plasma physics, robotics, communication, and linguistics [2]. To be specific, in medicine, various implementations of symbolic sequences have been used to characterize encephalography (EEG) signals to understand the interaction between brain structures during seizures [3]. Under mechanical systems, symbolic methods were applied to combustion data from internal combustion engines to study the onset of combustion instabilities [4] and in multiphase flow data-symbolization were found to be useful in characterizing and monitoring fluidized-bed measurement signals [5]. Symbolic dynamics, as an approach to investigate complex

* Tel.: +91 0820 4294139.
E-mail address: chandrakar.kamath@gmail.com

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systems, has found profound use in the analysis of heart rate variability signals [6–10]. However, there is hardly any literature where symbolic dynamics is applied for analysis of ECG signals.

There are many ways symbolic dynamics can be used for analysis of time series and all of them require coding, i.e., converting the time series into symbolic series. The differences in symbolic methods are usually in their coding procedure or used complexity indices. In this contribution we employ sequential spectrum [11] as the symbolic method and approximate entropy [12–14] as a measure of complexity of the sequential spectrum to classify ECG signals obtained from standard Holter recordings from PhysioNet database [15] into normal and CHF subjects. The rationale behind the application of sequential spectrum and approximate entropy measures is that both are suitable for short-term segments of the ECG signal. Receiver operating characteristic (ROC) plots were used to evaluate the ability of these complexity measures to discriminate normal from CHF subjects. Both the approximate entropy measures ($ApEn_0$: approximate entropy of the binary occupancies of symbol '0' and $ApEn_1$: approximate entropy of the binary occupancies of symbol '1') yielded excellent results with an average accuracy, average sensitivity, average positive predictivity, and average specificity, all, 100.0%.

The remainder of this paper is organized as follows: Section 2.1 explains the data used and the basic data pre-processing. Section 2.2 introduces the symbolic dynamics transformations and concepts of mono-sequences, binary occupancy and sequence spectrum of ECG signals. Approximate entropy measure is discussed in Section 2.2.3. In the next two sections approach to statistical analysis is presented. Experimental results are discussed in Section 3. Finally a conclusion part is presented.

2. Methods and materials

2.1. ECG records

All the ECG records used are from the benchmark PhysioNet databases [15]. The work involves 18 ECG records from normal sinus rhythm (Fantasia database-fanatasia and MIT-BIH normal sinus rhythm (NSR) database-nsrdb) and ECG records of 15 subjects with severe CHF (NYHA class 3–4) from BIDMC congestive heart failure (CHF) database-chfdb. The Fantasia database includes 20 young (21–34 years) and 20 elderly (68–85 years) healthy subjects. Both young and elderly groups include equal number of men and women. The NSR database includes 5 men, aged 26–45 years, and 13 women, aged 20–50 years. The CHF database includes 11 men, aged 22–71 years, and 4 women, aged 54–63 years. For sake of comparison and validation, two groups Group-I and Group-II are constituted as explained below. A normal sinus rhythm database is formed with two sub-groups, with 10 records each: (1) Normal-1, with 8 records from Fantasia (f1o01–f1o02; f1o07; f1o09–f1o10; f2o04; f2o06; f2o08) and 2 records from NSR (16265 and 16273) databases; (2) Normal-2, with 8 records from Fantasia (f1o03–f1o06; f1o08; f2o01–f2o03) and 2 records from NSR (16420 and 16483) databases. Likewise, a CHF database is formed with two sub-groups, each with 7 ECG records: (1) CHF-1 (chf01–chf07) and (2) CHF-2 (chf08–chf10, chf12–chf15). Group-I includes Normal-1 and CHF-1 sub-groups, while Group-II includes Normal-2 and CHF-2 sub-groups. Since factors like age differences and differing male-to-female ratios between compared groups will have an impact on the results, when statistical analyses are carried out, the above grouping is done to match gender and age between Group-I and Group-II. From each record the modified limb lead II is only considered for analysis. The resolution is 200 samples per mV. The sampling frequency of normal sinus rhythm signal from Fantasia is 250 Hz, while that of NSR is 128 Hz and that of CHF signal is 250 Hz. Since the sampling frequency does influence upon the calculated indices it is necessary to have the same sampling frequency for all the records. For this reason ECG signals from NSR database are first re-sampled at 250 Hz. Then each record is divided into segments of equal time duration (14 s), with 3500 samples/segment in both normal sinus rhythm and CHF database. The reason for choosing 3500 samples/segment is explained in Section 3. A total of 6912 segments from normal sinus rhythm and CHF database are analyzed. All the records are normalized before analysis. Also the signals from Fantasia database are comparatively noisy and hence we use an 8-point moving average filter out this high-frequency noise.

2.2. Symbolic dynamics and sequential spectrum

2.2.1. Static transformation and dynamic transformation

Symbolic dynamics, as an approach to investigate complex systems, facilitates the analysis of dynamic aspects of the signal of interest. The concept of symbolic dynamics is based on a coarse-graining of the dynamics [3]. That is the range of original observations or the range of some transform of the original observations such as the first difference between the consecutive values, is partitioned into a finite number of regions and each region is associated with a specific symbolic value so that each observation or the difference between successive values is uniquely mapped to a particular symbol depending on the region into which it falls. The former mapping is called static transformation and the latter dynamic transformation. Thus the original observations are transformed into a series of same length but the elements are only a few different symbols (letters from the same alphabet), the transformation being termed symbolization. A general rule of thumb is that the partitions must be such that the individual occurrence of each symbol is equiprobable with all other symbols or the measurement range covered by each region is equal. This is done to bring out ready differences between random and nonrandom symbol sequences. The transformations into symbols have to be chosen context dependent. For this reason, we use complexity measures on the basis of such context-dependent transformations, which have a close connection to physiological phenomena and are relatively easy to interpret. This way the study of dynamics simplifies to the description of symbol sequences. Some detailed information is lost in the process but the coarse and robust properties of the dynamic behavior are preserved and can be analyzed [3].

2.2.2. Mono-sequences, binary occupancy and sequential spectrum of ECG signals

In this study, we use dynamic transformation approach for the symbolic dynamics [4]. Such a differenced symbolization scheme is relatively insensitive to extreme noise spikes in the data. In this approach arithmetic differences between adjacent data points of the ECG signal define the symbolic values. We symbolize the positive difference as a '1' and the negative difference as a '0' as shown in the equation below.

$$S_i = \begin{cases} 1 & \text{if } x_i - x_{i-1} \geq 0 \\ 0 & \text{if } x_i - x_{i-1} < 0 \end{cases} \quad (1)$$

After symbolization the next step is to partition the symbol sequence into windows of width W symbols each. It is sliding window technique and if the shift is smaller than W, then the consecutive windows overlap. The next step is the construction of temporal patterns in each window, by the identification of short ordered sequences of only one type of symbol (0 or 1), termed tuples or mono-sequences, from the symbol series by gathering groups of symbols in the temporal order. The mono-sequence $Nx0$ (or $Nx1$), is a homogeneous sub-sequence containing N (N = 1,2,. . .,W), only one type of symbol S = 0 (or 1). The lengths of the mono-sequences