Classifying Simulated and Physiological Heart Rate Variability Signals

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Abstract

The main intention of this contribution is to sketch our way of analysing the 50 time series from the 2002 Computers in Cardiology challenge. The task to cope is to discriminate simulated and physiological heart rate variability signals. Our approach for doing this is rather simple: We exclude time series which show non-physiological behaviour. The methods applied serve to quantify the distribution of the RR-intervals, the circadian beat-to-beat variability as well as the beat-to-beat dynamics. Using cut-offs for these parameters, both time series groups can be discriminated clearly. Thus, the intricate interdependencies of variations in heart rate variability data on different scales are still difficult to simulate, such that even an experienced observer may be misled easily.

To demonstrate the suitability of our methods not only for characterising simulated and physiological data, an outline of further applications shall be given.

1. Introduction

Physiological data very often show complex structures which cannot be interpreted immediately. Therefore, the simulation of such time series seems to be extremely sophisticated. However, the classification of physiological and simulated heart rate variability (HRV) time series should be possible. The data analysed here are the 50 time series from the challenge organised by PhysioNet [1] and Computers in Cardiology 2002. The main intention of this contribution is to sketch our way of discriminating both types of time series and demonstrate further applications of our methods in risk stratification.

2. Methods

HRV analysis is often difficult due to excessive artefacts and arrhythmias. While occasional ectopic beats are treated successfully by most preprocessing methods, more complex arrhythmias or arrhythmias which are similar to normal HRV fluctuations may remain untreated. Therefore, the preprocessing of the data shall be dealt with separately in the subsection below.

2.1. Data preprocessing

Ectopic beats in the tachogram are usually characterised by a short coupling interval followed by a pause with a longer RR-interval than the preceding sinus rhythm or by a short coupling interval only without a pause. Simple percentile exclusion rules consider these facts; when the current value of the tachogram differs from its predecessor by more than a certain percentage, the current value and its successor are marked as not normal. The advantage of this filter is the very simple rule. However, the disadvantages are rarely considered [2]. Therefore, we developed an adaptive filtering algorithm [3] which is superior to simple percentile rules. A MATLAB implementation of this filtering algorithm is freely available [4].

The disadvantage associated with standard linear parameters in HRV analysis [5] is the limited information about the underlying complex system, whereas the nonlinear description suffers from the curse of dimensionality. Mostly, there are not enough points in the (often non-stationary) time series to reliably estimate these nonlinear measures. In addition to standard parameters, we therefore favour the measures of complexity which characterise quantitatively the dynamics even in rather short time series [6,7].

2.2. RR-interval distribution

A standard measure to quantify the histogram, i.e. the density distribution of the RR-intervals, is the triangular index HRVi [5]. It is the integral of the density distribution (number of all RR-intervals) divided by the maximum of the density distribution. This measure expresses the overall HRV measured over 24 hours and is mainly influenced by lower-frequency processes. A major advantage of this parameter lies in its relative insensitivity to the quality of the investigated HRV time series. In this study, however, the Shannon entropy of the histogram was used [7]. As shown in [8], the Shannon entropy in combination with other parameters is a better predictor of a high arrhythmia risk than the standard HRV measurement in patients who survived a myocardial infarction.

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2.3. Circadian variability changes

To quantify the circadian variability changes, we used the parameter 'pNNl10', the percentage of NN-interval (filtered RR-intervals) differences lower than 10 milliseconds. This parameter was calculated for successive 5-minutes windows – the standard deviation of these values over 24 hours is a suitable measure to identify day-night variability changes. Obviously, there are several other parameters to quantify these changes, e.g. 'cvNN' - the coefficient of variation [7].

2.4. Beat-to-beat dynamics

Heart rate variability reflects the complex interactions of many different control loops of the cardiovascular system. As far as the complexity of the sinus node activity modulation system is concerned, a predominantly nonlinear behaviour has to be assumed. Thus, the detailed description and classification of dynamic changes using time and frequency measures is often not sufficient. Therefore, we have introduced new methods of nonlinear dynamics, derived from symbolic dynamics, to distinguish between different states of autonomic interactions [6,7]. The first step of this approach is the transformation of the time series into symbol sequences with symbols from a given alphabet. Some detailed information is lost in this process, but the coarse dynamic behaviour can be analysed.

The transformations into symbols have to be chosen on a context-dependent basis. For this reason, measures of complexity have been developed on the basis of such context-dependent transformations, which have a close connection to physiological phenomena and are relatively easy to interpret.

By comparing different kinds of symbol transformations, we found that the use of four symbols, as explained in eq. (1), is appropriate for our purpose.

$$s_i(x_i) = \begin{cases} 0: & \mu & < x_i \le & (1+a)\mu \\ 1: & (1+a)\mu & < x_i < & \infty \\ 2: & (1-a)\mu & < x_i \le & \mu \\ 3: & 0 & < x_i \le & (1-a)\mu \end{cases} \quad \text{, i=1,2,3,.} \quad (1)$$

The time series $x_1,x_2,x_3,...,x_N$ is transformed into the symbol sequence $s_1,s_2,s_3,...,s_N$, where s_i is an element of the alphabet $A=\{0,1,2,3\}$. The transformation into symbols refers to three given levels, where μ denotes the mean beat-to-beat interval and a is a special parameter, here chosen to be 0.05; we tested several values of a from 0.05 to 0.08. However, the resulting symbol sequences did not differ significantly.

There are several quantities that characterise such symbol strings. Here, the frequency distribution of words of length 3 is analysed, i.e. substrings which consist of three adjacent symbols, leading to a maximum 64 different words (bins). This is a compromise between retaining important dynamic information and having a robust statistics to estimate the probability distribution. The beat-to-beat dynamics in this paper, finally, was quantified with the parameter 'wsdvar' which measures the variability of the words occurring [7].

3. Results

Our approach to discriminating between simulated and physiological time series is rather simple: We exclude time series which show non-physiological behaviour. The first decision rule is

"The distribution of the RR-intervals is too narrow!", which was quantified by the Shannon entropy of the histogram. Time series with entropy values less than 2.8 were excluded (RR-series with the numbers 10, 27, 28, 36, 42, 45). The second rule is

"No circadian beat-to-beat variability changes", quantified by the 24h variability of the parameter 'pNNl10'. Time series with pNNl10 values less than 0.07 are set to be simulated (RR-series with numbers 2, 3, 4, 11, 17, 19, 25, 26, 29, 31, 43, 44, 49 were detected).

The final decision for the remaining time series was made using the symbolic dynamics approach. The simulated time series showed a lower word variability than the physiological one, which was quantified by the parameter 'wsdvar'. As clearly visible in Fig. 1, the simulated time series (filled spheres) have a lower beat-to-beat dynamics than all physiological heart rate time series (open spheres). Hence, the last decision rule is

"A decreased beat-to-beat dynamics".

Using this rule, the last three simulated time series remaining could be detected. As obvious from Fig. 2, the last three simulated time series all have a sufficiently broad density distribution (even if it is skewed in rr37) and show circadian changes in HRV. HRV is decreased for faster heart rates and increased for a slower one. All other simulated time series did not fulfil these simple rules.

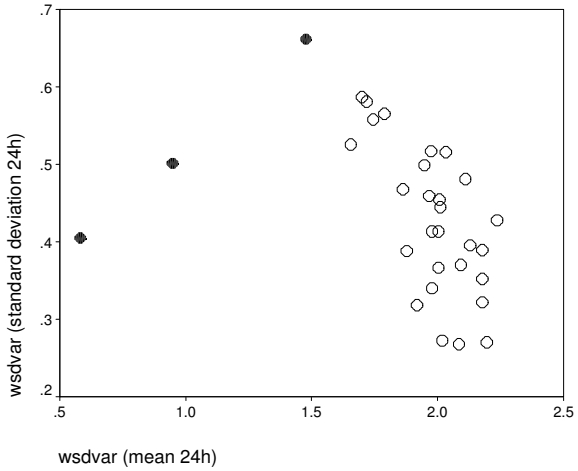

Figure 1. The symbolic dynamics parameter wsdvar - mean value vs. standard deviation over 24 hours.

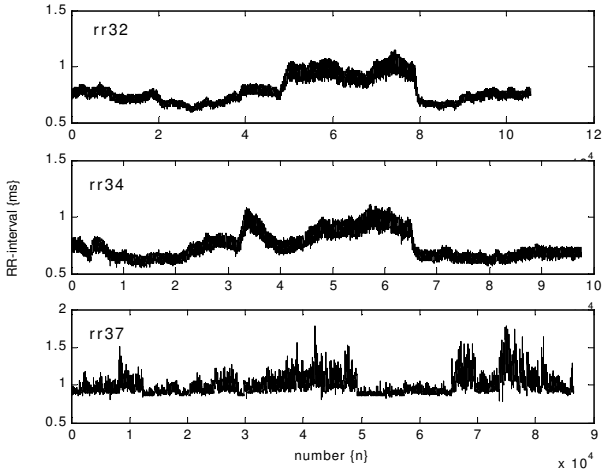

Figure 2. The remaining (not detected) simulated series before the last decision rule: rr32, rr34 and rr37.

4. Discussion

This contribution presents our way of discriminating the 50 simulated and physiological heart rate variability time series from the 2002 Computers in Cardiology challenge. Our approach to doing this was rather simple: We excluded time series which showed non-physiological behaviour. The methods we applied served to quantify the distribution of RR-intervals, the circadian beat-to-beat variability as well as the beat-to-beat dynamics. Using cut-offs for these parameters, both time series groups could be discriminated clearly. The cut-offs were subjectively chosen based on the knowledge of the normal ranges of the used parameters. Moreover, it was an act of instinct which parameter to choose first. So, we are sure that there are a lot of ways to discriminate both groups of time series. At least with our parameters, however, it was impossible to distinguish between the groups using one parameter only. This is exactly what we got in earlier studies [8]. Several parameters are necessary to quantify the complexity of HRV signals. To our knowledge, the best way for analysing such complex physiological data is to calculate time and frequency domain parameters as well as parameters which describe the dynamics in the time series. The advantage of doing this was demonstrated in [7,8] as well as in an animal model of Mas-deficient mice [9]. Symbolic dynamics is a useful tool in several fields of complexity analysis in science. Moreover, it is a method with a very close connection to physiological phenomena and relatively easy to interpret. It also yields promising results for the prediction of life-threatening cardiac events which were measured in implanted cardioverter defibrillators [10,11]. To sum up, the intricate interdependencies of variations in heart rate variability data on different scales are still difficult to simulate, such that even an experienced observer may be misled easily.

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