Dynamic Features of the Normal Heart Rate Variability

T Šmuc, I Marić, G Bosanac, D Gamberger, N Bogunović, G Krstačić*

Rudjer Bošković Institute
*Institute for Cardiovascular Prevention and Rehabilitation,
Zagreb, Croatia

Abstract

The set of new features focussed primarily on different dynamic properties of the heart rate variability was defined and investigated within the scope of CinC 2002 challenge. The objective of the challenge was finding differences in heart rate variability between real and artificial heart beat signals.

Among a larger number of features, several turned out to have high discriminative value: a) inter/intra signal power spectrum similarity; b) adjacent RR-interval changes; c) short range deceleration-acceleration ratio; d) complexity of dynamical states and state transitions.

Combined in a voting scheme this set of features showed large correlation (agreement) in attribution of signals, resulting in a very high classification accuracy on the challenge set.

1. Introduction

Clinical importance of the heart rate variability (HRV) became apparent in the late 80's when it was confirmed that HRV is strong and independent predictor of mortality following an acute myocardial infarction.

According to the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [1] there are two main groups of methods for measuring HRV:

a) time domain methods
b) frequency domain measures

Standard measures falling in time domain methods mainly deal with standard deviation of intervals or differences between adjacent intervals, counts of pairs of significantly different adjacent intervals and indices, which express integral properties of these measures. Standard frequency domain measures are total power and powers of the spectrum of the entire signal in distinct frequency parts of the spectrum. We have soon discovered that in order to obtain more reliable predictions some new measures will be needed. Therefore, with the exception of the power spectrum similarity measure, other measures described in this work were devised independently of the standardized measures given in [1]. New dynamic measures could be put in the category of rhythm pattern analysis methods, and are related to heart rhythm changes on the short scale of 2 to 10-20 consecutive heartbeats.

We have used MIT-BIH Normal Sinus Rhythm Database [2], as a set of control samples in developing classification features. In Section 2, all the features are explained in detail, together with illustrative results.

2. Methodology

In order to produce discriminative features and a classifier for the task of distinguishing synthetic heart beat signals from the real ones, we also needed a set of representative synthetic signals. This fact forced us to build our own artificial heart beat signal generator. Improvements in artificial generator were made based on features discovered through the analysis of real signals and artificial signals generated by the current version of the signal generator. Reciprocally, new features for the classifying task were devised as our heart rate signal generator was improved.

At the start of this process simple features as standard deviation of heart rate, or distributions of heart rate intervals were sufficient to discriminate artificial signals. As the generator improved, features describing dynamics and rhythm patterns seemed to be most promising for distinguishing between real and artificial signals.

In the rest of the article we use vector $\{\mathbf{x}\}=(x_1, x_2, \ldots x_i, \ldots x_N)$ as a notation for the signal of 24 hour recording of RR-interval lengths. Other numerical entities and their notation will be introduced and described within subsections devoted to the particular method.

In the following parts of the section we will briefly describe features that were found to have high discriminative value for the classification task.

2.1. Inter/intra signal power spectrum similarity

Fourier power spectrum of the part or entire signal is one of the standard features for describing HRV. Most of the artificial signals of the challenge test set, originating from the same generator, express highly similar power spectrum, despite seemingly different footprint in the time domain. Similarly, real signals express significant variability of the spectra. Additionally, power spectrum during the day is different from the power spectrum over the night (intra signal difference). The similarity of two spectra for the signals from the same generator, as well as similarity of day-night spectra were one of the first features we have detected as important for the classification task.

2.2. Adjacent RR-interval changes

The complexity of adjacent or consecutive interval changes was studied using two mutually related measures: histogram of mean adjacent RR-interval changes with respect to RR-interval length and distribution of states characterized by specific RR-interval length and RR-interval difference.

Let us consider a series of consecutive R-R interval lengths $\{\mathbf{x}\}=(x_1, x_2, ...x_i, ...x_N)$, where x_i represents the length of the i-th RR-interval. If we divide all RR-interval lengths into J discrete channels we can determine mean adjacent RR-interval change for RR-interval length falling in the j-th channel (first measure) as:

$$<\Delta rr_j>=\sum_{i}^{N-1}(x_{i+1}-x_i)/N_j : \qquad (rr_j^l < x_i \le rr_j^u)$$

where N_j is the total number of RR-intervals satisfying $rr_j^l<x_i\le rr_j^u$ condition.

Similarly, if we divide all RR-interval lengths into J discrete channels and divide all adjacent RR-interval differences into K discrete channels we can determine density for the specific (j,k) channel (second measure) as:

$$d(rr_j,\Delta rr_k)=\sum_{i}^{N} v_i / N$$

$$v_i=\begin{cases}1 & \text{if } (rr_j^l < x_i < rr_j^u)\wedge(\Delta rr_k^l < x_{i+1}-x_i < \Delta rr_k^u)\\ 0 & \text{otherwise}\end{cases}$$

where:

N - total number of RR-intervals in the

x_i - length of i-th RR-interval

rr_k^l, rr_k^u- lower and upper range limits for the j-th channel of R-R interval lengths

Δrr_k^l, Δrr_k^u- lower and upper range limits for the k-th channel of adjacent R-R interval differences

$d(rr_j, \Delta rr_k)$ - density of states in the (j,k) channel

Both measures strongly emphasize the difference between real and synthetic signals. Fig. 1 shows that average differences for the real signal are small and positive for shorter R-R intervals and larger and negative for longer intervals. This illustrates typical difference between the $<\Delta rr_j>$ measure for the great number of real and synthetic signals in the challenge test set. Fig. 2 shows a 3-D distribution of state densities $d(rr_j , \Delta rr_k)$.

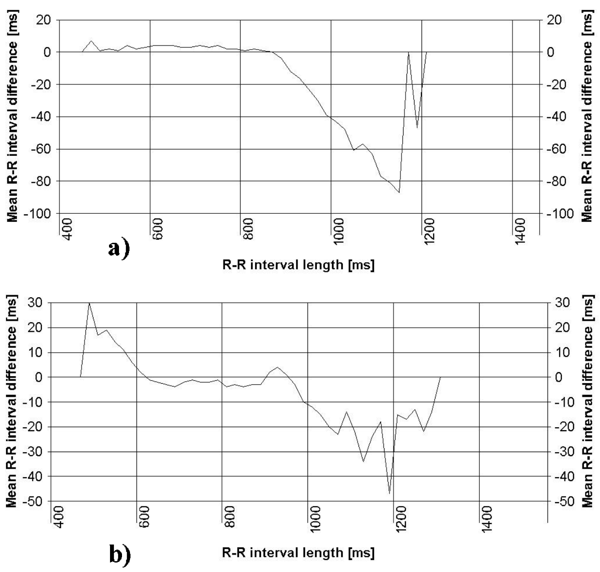

Figure 1. Piece-wise linear interpolation of 2-D histogram representing average differences related to R-R interval lengths $<\Delta rr_j>$ for the real signal (a) and for the synthetic signal (b).

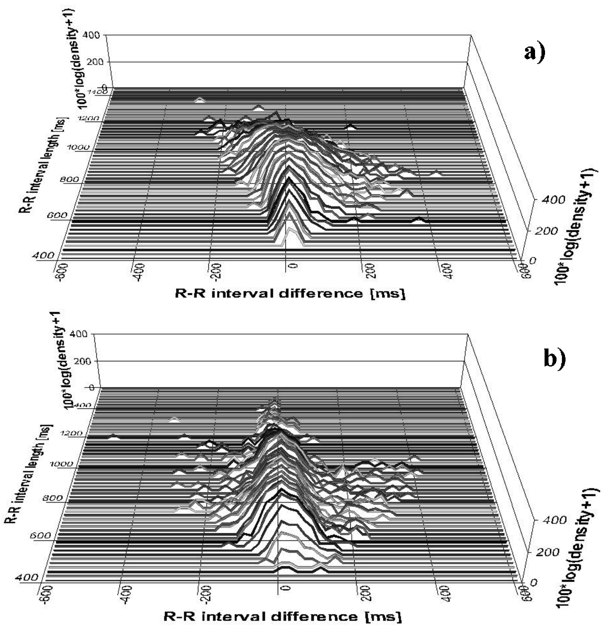

Figure 2. 3-D histogram of dynamic states $d(rr_j ,\Delta rr_k)$ for the real (a) and synthetic signal (b).

From Fig. 2 one can again observe a characteristic asymmetric distribution (for the real signal) of differences of the adjacent R-R intervals changes, from generally positively displaced differences at shorter interval lengths to predominantly negative differences at longer interval lengths. This behavior is not present in the synthetic signal.

2.3. Short range deceleration-acceleration ratio

This feature deals with heart rate dynamics over the short range of beats, averaged for the whole signal. We have defined average acceleration and deceleration of the heart as:

Acceleration

$$<\Delta x^- >_n = (\sum_{i=1}^{N-n} | x_{i+n} - x_i |_a)/N_a; \qquad \forall i \,|\, (x_{i+n} < x_n)$$

Deceleration

$$<\Delta x^+ >_n = (\sum_{i=1}^{N-n} | x_{i+n} - x_i |_d / N_d; \qquad \forall i \,|\, (x_{i+n} > x_n)$$

where:

$N_d = \Sigma_i$ (1) if (x_{i+n}>x_i) - total number of decelerating states.

$N_a = \Sigma_i$ (1) if (x_{i+n}<x_i) - total number of accelerating states.

Indices a and d in the equations above stand for acceleration and deceleration, while N_a and N_d stand for the number of pairs of intervals i and $i+n$ that satisfy either (x_{i+n}<x_i) or (x_{i+n}>x_i) criterion. Average deceleration $<\Delta x^+>_n$, and acceleration $<\Delta x^->_n$, are defined as conditional sums of interval length differences for each index n. When studying real signals from MIT normal sinus rhythm database, we have found that ratio $<\Delta x^+>_n/<\Delta x^->_n$ of all the signals has similar pattern for shorter periods (number of beats, i.e. indices $n \in [2,10]$). Figure 3 shows distributions of $<\Delta x^+>_n/<\Delta x^->_n$ ratios (in the form of box plots for each index n) for all the signals from MIT-BIH normal sinus rhythm database. One must notice that all the signals have this ratio higher than 1 for $n \in [2,10]$, meaning that normal heart, on average, decelerates faster than it accelerates.

This finding was confirmed on the test set of CinC 2002 challenge, where this criterion has produced almost clear division among real and synthetic signals. Figure 4 shows distributions of $<\Delta x^+>_n/<\Delta x^->_n$ ratios for real and synthetic signals of the CinC 2002 challenge test set. Another important insight from the plot is that distribution of ratios for the synthetic signals is more uniform, which is the consequence of almost constant value of $<\Delta x^+>_n/<\Delta x^->_n$ ratio (generally around 1) for all the synthetic signals. Thus, mean value and variance of $<\Delta x^+>_n/<\Delta x^->_n$ ratios for indices $n \in [2,10]$ can be used as independent and sufficient criteria for perfect classification of real and synthetic signals of CinC 2002 challenge test set.

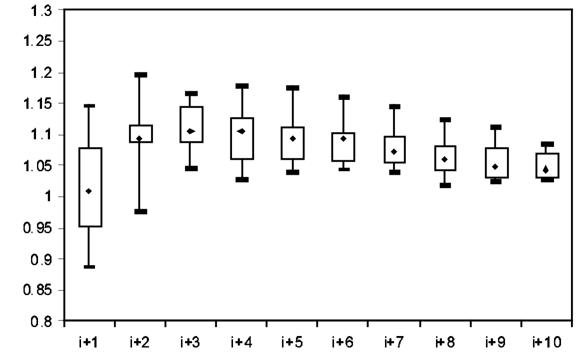

Figure 3. Distributions of deceleration vs. acceleration ratios for the training set - normal sinus rhythm database.

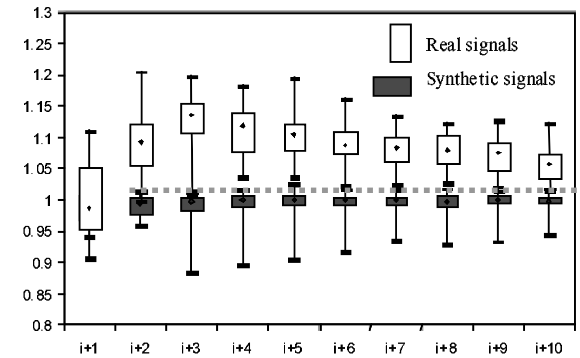

Figure 4. Distributions of deceleration vs. acceleration ratios for the CinC 2002 challenge test set.

2.4. Complexity of dynamical states and transitions

One way to express the complexity of the heart rate variability is through observing simple patterns of simultaneous acceleration (contraction of RR-interval lengths), deceleration (extension of RR-interval lengths) and constant heart beat or stagnation. In that respect, one has to determine all possible RR-interval segments of consecutive acceleration, deceleration and stagnation. For each signal we determine the number of different segments with respect to their length, expressed in the number of consecutive beats, density of such segments in the signal and densities of transitions between different segments. Thus, each segment is uniquely characterised by its length (number of consecutive RR-intervals) and by its dynamical trend (acceleration, deceleration, and stagnation).

The analysis starts with transforming the real RR-intervals time series into the series of numbers 0, 1 and 2. This transformation gives signal description in symbolic segments, which are subsequently enumerated. The transformation rule is described by:

$$s_i = \begin{cases} 0, \; if\,(x_{i+1}-x_i) = 0, \; stagnation\ (S) \\ 1, \; if\,(x_{i+1}-x_i) < 0, \; acceleration\ (A) \\ 2, \; if\,(x_{i+1}-x_i) > 0, \; deceleration\ (D) \end{cases}$$

where $\{x_i\}$ is the original R-R time series, and $\{s_i\}$ a transformed one. Unique segments are represented by a pair of numbers (s_i, ns), where ns stands for number of RR-intervals in the same dynamics (S, A or D). Finally, we enumerate all (s_i, ns) states in the signal and determine their total number and number of transitions to other states. Using the transformation and analysis described above, we determine basic complexity of heart rate dynamics with respect to S, A or D. Each signal is characterised by the unique picture of dynamical states and state transitions. Figure 5 presents transformed RR-interval series into dynamic states and transitions for the real and synthetic signal. Number of distinct dynamic states and diversity of transitions in 24-hour heart rate signal turned out to be an important feature for distinguishing real from artificial signals. On the horizontal axis are qualitative dynamic descriptors (S, A, D) while vertical axis gives the number of repetitive events, ns. Real RR-interval series has a maximum of 16 subsequently accelerating intervals, i.e. the biggest dynamical state number is (1,16), while the biggest dynamical state for the synthetic signal is (1,8). The net composed of transitions from one dynamical state to another gives a clear distinction between real and synthetic signals. Real heart dynamics apparently expresses more complex behavior in the acceleration phases than the synthetic simulation.

3. Conclusions

Dynamical features developed during the CinC 2002 challenge and described in this article, have high discriminative value with respect to the classification task of the CinC 2002 challenge. They also seem to emphasise one of the interesting aspects of heart rate variability - short range dynamic complexity. Main findings of this work can be summarised in the following: HRV of the normal healthy heart is on average characterised by different complexity in the acceleration phase and deceleration phase. This seems to be the consequence of the genuine characteristic of the normal HRV: on the average, human heart seems to express faster deceleration and slower acceleration on a short range of up to 10 heart beats. Whether these findings could be employed in analysing specific heart related diseases or problems, could be worth exploring.

Acknowledgements

We express gratitude to the organizers, for their efforts in assembling this and all previous challenges, and especially to Physionet for running the very important web-site for all those doing the research in this field.

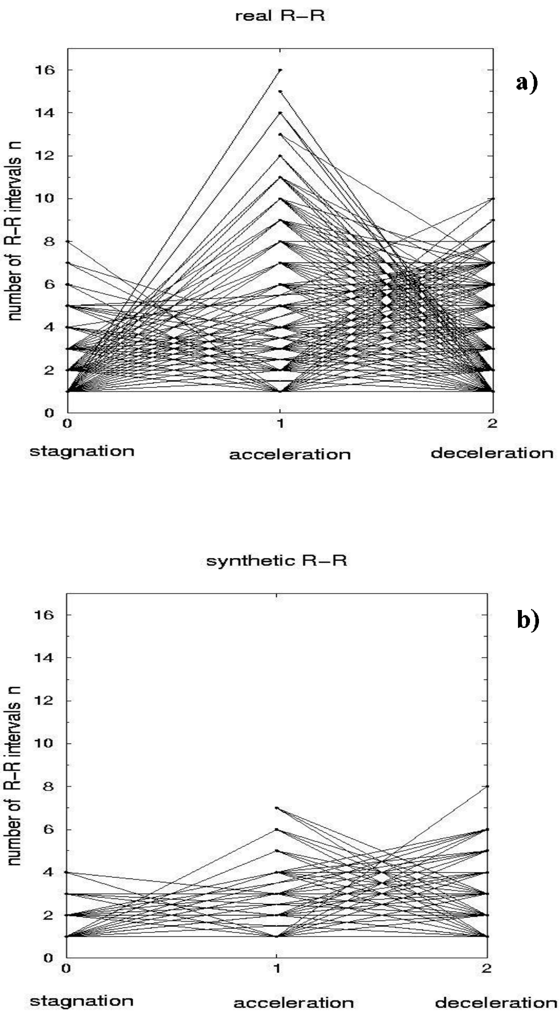

Figure 5. Dynamic states and transitions of the real (a) and synthetic (b) RR-interval series.

References

[1] Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology. Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. European Heart Journal 1996;17:354-381.

[2] The MIT-BIH Normal Sinus Rhythm Database. http://www.physionet.org/physiobank/database/nsrdb/.

[3] RR interval time series modeling: A challenge from PhysioNet and Computers in Cardiology 2002;http://www.physionet.org/challenge/2002/.

Address for correspondence:
Tomislav Smuc
Rudjer Boskovic Institute
Bijenicka 54,
10000 Zagreb, Croatia
E-mail address: smuc@rudjer.irb.hr