Structure of heart rate asymmetry: deceleration and acceleration runs

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Abstract
A family of new heart rate asymmetry measures is introduced, namely deceleration and acceleration runs, as well as entropic measures summarizing their distribution. We introduce the theoretical run distribution for shuffled data and use it as a reference for interpreting the results. The measures defined in the paper are applied to actual 24 h Holter ECG recordings from 87 healthy people, and it is demonstrated that the patterns of accelerations are different from those of decelerations. Acceleration runs are longer and more numerous: all runs of accelerations, with the exceptions of lengths 3 and 4, are more numerous than those of decelerations. These findings are reflected in the difference between the entropic measures for acceleration and deceleration runs: for 74 subjects the acceleration-related entropic parameter is greater than that of decelerations ($p < 0.001$). For shuffled data there is no difference in the above parameters, and there are more short runs and fewer long runs than in physiological data. The influence of the measuring equipment resolution is also discussed.

Keywords: heart rate variability, heart rate asymmetry, decelerations and accelerations, monotonic runs, Shannon entropy

1. Introduction
Heart rate variability (HRV), understood as the variation in the length of the $RR$ intervals, has been the subject of intensive study for many years. It has two major goals: the first one is exploratory, and the second one is practical. A lot has been learnt about the cardiovascular system from studying HRV, and some of its methods have found their way to the clinic (Task Force of the European Society of Cardiology and the American Society of Pacing and Electrophysiology 1996, Seely and Macklem 2004, Bauer et al 2006a).
HRV can be loosely divided into variance-based methods (like measuring SDNN, descriptors of the Poincaré plot or spectral methods), complexity-based methods (symbolic dynamics and other entropic methods) (Piskorski et al 2010) and a class of mixed methods, which have properties of the above two, such as detrended fluctuation analysis (DFA) (Kantelhardt et al 2001, Seely and Macklem 2004), or phase-rectified signal averaging (PRSA) (Bauer et al 2006a, 2006b).

Heart rate asymmetry (HRA) is a physiological phenomenon by which the contribution of decelerations to short-term variability is statistically significantly greater than that of accelerations, and the contribution of accelerations to long-term and total variability is greater than that of decelerations (Guzik et al 2006, Piskorski and Guzik 2007, Guzik and Piskorski 2010).

The presence of HRA is one of many proofs that show that the RR interval time series is time irreversible. The irreversibility problem was studied e.g. by Costa et al (2005) or Porta et al (2008, 2009). In these papers irreversibility parameters were defined; it was established that the RR interval time series is time irreversible, and the degree of irreversibility was related to the physiological/pathological state of the organism. HRA as defined by Guzik et al (Guzik et al 2006, Piskorski and Guzik 2007) and to some extent by Porta et al (2008, 2009), as well as the approach introduced in the present paper, concentrates on the quantitative and qualitative difference between accelerations and decelerations and tries to find the structures generating asymmetry, rather than establishing the presence and extent of time irreversibility.

In what follows we develop a novel method based on monotonic runs of heart rate decelerations and accelerations which uncovers another aspect of HRA. The known HRA descriptors were variance based (Guzik et al 2006, Piskorski and Guzik 2007), and the ones defined here are based on counting statistics. We show that in a real RR interval time series from an ECG recording, the distribution of runs of decelerations is consistently and unidirectionally different from that of accelerations.

2. Runs of decelerations and accelerations

In this section, we define the monotonic runs, consider the shuffling probability distribution of these runs and define entropic parameters summarizing the run distribution in physiological and shuffled order.

2.1. Definition of monotonic runs

Let us define an RR time interval time series as

\[ RR_n = (RR_1, RR_2, \ldots, RR_n), \]

and the derivative run of differences

\[ \Delta = (\delta_1, \delta_2, \ldots, \delta_{n-1}), \]

where

\[ \delta_i = RR_{i+1} - RR_i. \]

The deltas can be positive, negative or can be equal to zero. Let us define the following mapping of the RR time series to a symbolic time series with three values

\[ \text{sgn}(\delta_i) = \begin{cases} + & \text{if } \delta_i > 0, \\ - & \text{if } \delta_i < 0, \\ 0 & \text{if } \delta_i = 0. \end{cases} \]

Using this we can define the monotonic runs.
Structure of heart rate asymmetry

Figure 1. The partitioning according to runs for a short fragment of a tachogram. The runs are given as DRi and ARi; the Ni symbols stand for neutral runs which may break the deceleration/acceleration runs. Full gray circles denote beginnings of deceleration runs and full black circles mark the beginnings of acceleration runs—these can be thought of as reference points for the respective runs.

Table 1. Some examples of monotonic runs.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Run</th>
</tr>
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<tbody>
<tr>
<td>AR1</td>
<td>0 - +</td>
</tr>
<tr>
<td>AR5</td>
<td>+ - - - - - +</td>
</tr>
<tr>
<td>DR2</td>
<td>- + + -</td>
</tr>
<tr>
<td>DR8</td>
<td>- + + + + + + 0</td>
</tr>
</tbody>
</table>

Definition 1. A deceleration run of length i (DRi) is a segment of the symbolic time series which begins and ends with either a - or a 0 and consists of i consecutive + signs.

Definition 2. An acceleration run of length i (ARi) is a segment of the symbolic time series which begins and ends with either a + or a 0 and consists of n consecutive - signs.

Table 1 presents a few examples of monotonic runs.

This partitioning divides the mapped RR interval time series into disjoint deceleration and acceleration runs, with some neutral (no change) runs in between. These neutral runs mainly depend on the sampling frequency—this problem is discussed in more detail in section 5. An example of such a partitioning is presented in figure 1.

2.2. Shuffling distribution of monotonic runs

In the previous studies, we used data shuffling as a way to check whether HRA is a real physiological phenomenon or just an artifact of the applied method (Guzik et al 2006, Piskorski and Guzik 2007). In this paper, we use this procedure for two reasons: the first, which is identical to the above, is to check whether the results obtained here are real physiological phenomena, and the second is to provide a reference value for the distributions found in physiological time series. In other words, the results obtained for physiological time series will be compared to their shuffling distributions. This will prove to be highly physiologically interpretable.

Let $X'$ be a random variable with a continuous distribution function $f(x)$ and $X = (x_1, x_2, \ldots, x_n)$ be a vector of $n$ independent observations of $X'$. Using the results derived by
Levene and Wolfowitz (1944), we can write the following formula for the expected number of runs in this vector:

\[
E(\mathbf{r}_i^k, n) = n \frac{i^2 + 3i + 1}{(i + 3)!} - 2 \frac{i^3 + 3i^2 - i - 4}{(i + 3)!},
\]

where \( i \leq n - 2 \), \( k = D, A \),

\[
i \leq n - 2, \quad k = D, A,
\]

where \( i \) is the length of the run, \( D \) stands for deceleration and \( A \) for acceleration. There obviously is

\[
E(\mathbf{r}_i^D) = E(\mathbf{r}_i^A).
\]

This model of shuffling assumes that the samples come from a continuous random process, which entails that the probability of a tie is 0. The RR interval time series is measured with a finite resolution device, so, inevitably, there will be ties which will lead to the occurrence of runs which are neither decelerating nor accelerating. The incidence and distribution of these neutral runs depend on many factors, the two most important of them being the resolution of the measuring device and the process which generates the data. The first of these factors is known, the other is not. In further analysis, we show that the bias introduced by the final resolution measurement is small and can be ignored.

### 2.3. Estimating distributions of runs

Formula (5) can be rewritten in a form which has a simple and suggestive physiological interpretation, namely we can write down the formula for the probability that a beat belongs to a run \( \mathbf{r}_i^k \):

\[
p_{i,k} = \frac{E(\mathbf{r}_i^k, n)}{n} \times i.
\]

This formula can be understood as the proportion of the considered, shuffled RR time series realized as run \( \mathbf{r}_i^k \).

The estimator for the probability/proportion (7) in a real recording may be defined as

\[
\hat{p}_{i,k} = \frac{\text{(number of } \mathbf{r}_i^k \text{)} \times i}{n}.
\]

The finite precision of the measuring device will introduce bias to this estimator which will underestimate the proportions. Formula (8) can be used to estimate the run distributions for other generating processes, even if their mathematical form is unknown, like the process generating the RR interval time series in the physiological order. In the following sections, we will use estimation (8) for data in both physiological and shuffled order.

### 2.4. Entropic measure of the runs of decelerations and accelerations

In this subsection, we define a summary parameter for the run distribution which can be partitioned into deceleration- and acceleration-related parts. The idea is similar to the construction of the asymmetric contributions to variance (Guzik et al. 2006, Piskorski and Guzik 2007). Since the runs are counted and form a probability distribution, a natural candidate for such a measure is Shannon entropy. This measure can be used to summarize probability distributions and, since it is additive, it can easily be partitioned into deceleration- and acceleration-related parts (Denker et al. 1998).
Using (8) for the case of perfect measurement (no ties), we can write down the sum of probabilities (or proportions) connected with decelerations and accelerations in the following way:

$$\max_{i} D \sum_{i=1}^{\max(i)} p_{i,D} + \max_{j} A \sum_{j=1}^{\max(j)} p_{j,A} = 1,$$

(9)

where \( \max(i)D \) is the maximum length of the deceleration run in the studied time series, and \( \max(i)A \) has a corresponding meaning for accelerations. Using this we can write the expression for the Shannon entropy for the probability distribution that a specific \( RR \) interval belongs to a specific run,

$$H_R = - \max_{i} D \sum_{i=1}^{\max(i)} p_{i,D} \cdot \ln p_{i,D} - \max_{j} A \sum_{j=1}^{\max(j)} p_{j,A} \cdot \ln p_{j,A}.$$  

(10)

In (10) base \( e \) is used, but obviously any other base will work as well. This formula has two parts—the first depends only on decelerations, the other only on accelerations. So we can define

$$H_{DR} = - \max_{i} D \sum_{i=1}^{\max(i)} p_{i,D} \cdot \ln p_{i,D},$$

(11)

and

$$H_{AR} = - \max_{j} A \sum_{j=1}^{\max(j)} p_{j,A} \cdot \ln p_{j,A}.$$  

(12)

From equations (5) and (6), for the shuffling distribution, we have

$$p_{i,D} = p_{i,A},$$

(13)

from which

$$H_{DR} = H_{AR} = H_{ShR}.$$  

(14)

This can be used as a null-hypothesis for the following statistical tests.

If the above entropic measures are used with a real \( RR \) interval time series measured with a finite precision, a third element connected with neutral runs, \( H_{NR} \), can be introduced,

$$H_R = H_{DR} + H_{AR} + H_{NR},$$

(15)

with

$$H_{NR} = - \max_{i} N \sum_{i=1}^{\max(i)} p_{i,N} \cdot \ln p_{i,N}.$$  

(16)

In this way each \( RR \) interval is accounted for and contributes to \( H_R \) by being part of either a deceleration, acceleration or a neutral run. For more discussion of the neutral runs and their relation to sampling frequency, see section 5.

This third part (\( H_{NR} \)) could be distributed equally between the deceleration and acceleration runs or just ignored, since, as shown below, it is small at high sampling frequencies and will not influence the statistical results.
3. Materials and methods

3.1. Materials

The group consisted of eighty-seven 24 h Holter recordings from healthy subjects (41 men); the mean age was 35 ± 7.4 years. The participants were healthy volunteers who underwent careful history taking, physical examination and resting 12-lead ECG. They were all in sinus rhythm, between 55 and 90 beats min⁻¹, showed no signs of myocardial ischemia, strain or infarction, atrial or ventricular hypertrophy, conduction abnormalities, fascicular or bundle branch blocks, had no common channelopathies like the Brugada syndrome or the LQT syndrome, and had normal blood pressure (< 140/90 mmHg). No volunteer reported any chronic disease or acute disease within the last 3 months or taking any medications, including oral contraceptives by female volunteers within the last 2 weeks. None of the volunteers was doing endurance training. There was no predefined scenario for the activities during the day on the day of the recording and participants were free to do whatever they wanted or needed to do.

The Holter recordings were made with the Digi-Trak Plus Recorder (Philips Medical Systems, Bothell, USA) with the sampling frequency of 200 Hz and the R peak resolution of 5 ms. The recordings were analyzed with the Zymed 1810 (Philips Medical Systems) software. The beats were classified according to their origin and nature (sinus, ventricular, supraventricular, artifact) and the resulting RR intervals were exported to a text file along with the classifications. Only recordings in which the number of ectopic beats and artifacts did not exceed 1% of the whole recording were used in further analysis. Out of the original group of 90 subjects, 3 were excluded because they did not fulfill this criterion. The mean length of the recording was 1313 ± 48 min.

3.2. Methods

Each RR interval time series was partitioned into deceleration and acceleration runs. Runs of all lengths were counted separately for decelerations and accelerations. The obtained numbers of runs for successive run lengths were compared between decelerations and accelerations with the nonparametric, paired Wilcoxon test. Parts of entropy were calculated separately for decelerations and accelerations according to formulae (11) and (12) and compared with the nonparametric, nonpaired Wilcoxon test. These calculations were performed for data in the original order as well as for shuffled data. For clarity, the results are presented as mean ± standard deviation, even though nonparametric tests were used. The sample size considerations are the same as those presented by Piskorski and Guzik (2007) for variance-based HRA descriptors.

All the data-analytic tasks were performed with the use of in-house software written in Python (Python Software Foundation, www.python.org, Wolfeboro Falls, NH, USA) and the statistical analyses were performed with the R statistical package (version 2.9; The R Foundation for Statistical Computing, www.r-project.org, Vienna, Austria). This study was approved by the Poznan University of Medical Science Bioethical Committee.

4. Results

4.1. Run lengths

The runs of all lengths were counted for both decelerations and accelerations. The distributions are shown and compared with Wilcoxon’s test in figure 2. The numbers of runs of lengths 3 and 4 were not significantly different for decelerations and accelerations. For all the
other lengths, there were significantly more runs of accelerations than decelerations. This phenomenon was especially visible for the longer runs. The longest run recorded in the group was an acceleration run of 24; the longest deceleration run was 19. Altogether, there were 1940 runs above length 10 and 7 runs above 20 for accelerations; the respective numbers for decelerations are 463 above length 10 and 0 above 20. The average longest run for accelerations was $15.43 \pm 3.39$ and for decelerations it was $12.54 \pm 2.24$. The difference between the longest runs is statistically significant ($p < 0.05$). In shuffled data the maximum run is 9 for both decelerations and accelerations and the means of maximum runs are $6.99 \pm 0.64$ for decelerations and $6.99 \pm 0.62$ for accelerations. This difference is not statistically significant. Clearly, the acceleration runs are longer than deceleration runs and both are longer than the runs found in shuffled data. This is visible in figures 2 and 3 which compare the runs of decelerations and accelerations in original recordings to those found in shuffled data. There are fewer short runs in original data than in shuffled data, but there are more long runs in original data than in shuffled data—see figure 3.

4.2. Runs’ entropy

The deceleration-related part of entropy is statistically significantly smaller than the acceleration-related part ($p$ value $< 0.001$) and both are greater than the entropy of the shuffling distribution (14). The numerical results are $H_{DR}: 1.04 \pm 0.1$; $H_{AR}: 1.12 \pm 0.12$, $H_{SR}: 0.94 \pm 0.01$ for both accelerations and decelerations.

Out of the 87 analyzed recordings, in 74 (85%) cases the acceleration-related part of entropy is greater than that of decelerations, with no ties. The formulae for both parts of entropy are exactly the same ($(11), (12)$) so this is caused by the data structure: if the structures for accelerations and decelerations were the same, the probability of one being
Figure 3. Comparison of deceleration and acceleration runs for the healthy subjects with the run distribution for shuffled data. It can be seen that physiological runs are less numerous for the short runs and more numerous for the long runs. Note the change of scale on the y axis between the panels.

Figure 4. Comparison between parts of entropy for the deceleration and acceleration runs as well as between the two types and the shuffling run distribution-related entropy. For comparison, the theoretical value of shuffling entropy is shown ($H_{\text{ThrSh}}$). This is slightly greater than most of the shuffled data results because of the finite measurement bias. For details, see the text. For the interpretation of the box-and-whiskers lengths, see the caption of figure 2.

In the shuffled data, there were 43 (49%) cases for which the acceleration-related part of entropy is greater than that of decelerations, with no ties. The binomial test leads to the conclusion that there is no difference between the entropies ($p = 1$). The results are presented in figure 4.
5. **The role of device resolution**

In this section, we study the influence of the resolution of the measuring equipment on the acceleration and deceleration runs and the entropy parts. To this end we use two techniques: first, we remove the ties in the $RR$ interval time series by adding Gaussian noise; second, we downsample the series to the resolution of 10 ms (corresponding to 100 Hz).

### 5.1. Ties removal

To study the bias introduced by finite measurement, we added $N(0, 10^{-9} \text{ ms})$ noise to the studied $RR$ interval time series. The standard deviation of the noise was well below the resolution of the measuring device. We repeated this procedure until we obtained time series with no ties. For those time series, after shuffling, we obtained results which were equal to the theoretical values following from formulae (5), (7), (11) and (12) to the sixth decimal place. This shows that the difference between the theoretical value and shuffled data is indeed caused by the finite resolution measurement. The relative error between the biased entropy parts and theoretical values for shuffled data was 2% for both decelerations and accelerations.

### 5.2. Downsampling to 10 ms resolution

To study the effect of lower sampling frequency, we lowered the resolution of the $RR$ interval time series to 10 ms, which corresponds to 100 Hz. Since the original ECG lines were not available, we could only do this by rounding, using the odd–even rule for the least significant digit (Bevington and Robinson 2003).

In the downsampled time series in the original order, the average longest deceleration run was $11.04 \pm 2.19$ and the average longest acceleration run was $12.91 \pm 2.82$. The Wilcoxon test yields a statistically significant difference between the longest runs at 200 and 100 Hz for both decelerations and accelerations, with $p < 0.005$. In the shuffled order, the average longest deceleration run was $6.86.04 \pm 0.63$ and the average longest acceleration run was $7.03 \pm 0.71$. The difference between the two sampling frequencies for shuffled data is not significantly different, which follows from the low probabilities of long runs in shuffled data predicted by formulae (5) and (7). It can be concluded that lower sampling frequencies underestimate the number of long runs.

Figure 5 shows the influence of sampling frequency on the entropic parameters for the data in the original order. It is clear that the lower sampling rate underestimates the values of these parameters as there are more neutral runs. The numerical values for the 100 Hz time series are as follows: $H_{\text{DR}} 100 \text{ Hz } = 0.955 \pm 0.153$, $H_{\text{AR}} 100 \text{ Hz } = 1.007 \pm 0.172$. The observation that $H_{\text{AR}} > H_{\text{DR}}$ is still true and statistically significant (see figure 5).

The entropy parts for shuffled data differ between the 200 and 100 Hz cases ($H_{\text{DR}} 200 \text{ Hz } = 0.944 \pm 0.007$ and $H_{\text{DR}} 100 \text{ Hz } = 0.935 \pm 0.016$). The difference between the entropy parts at both frequencies is statistically significant ($p < 0.05$, Wilcoxon test).

6. **Discussion**

In this paper, we have analyzed one aspect of the structure of heart rate asymmetry, i.e. the distribution of runs of accelerations and decelerations. It turns out that runs of accelerations are more numerous for almost any length of run and that runs of accelerations are longer—the longest runs are exclusively acceleration runs.
We have defined entropic measures which are able to summarize the distribution of deceleration and acceleration runs separately and give us the possibility of comparing those distributions. In this paper, we have shown that the acceleration-related part of entropy is greater than that of decelerations. Also, both acceleration and deceleration run-related parts of entropy for data in natural order are clearly greater than acceleration/deceleration run-related entropy for shuffled data.

This result can be mathematically interpreted as follows. Entropy (10) is of the Shannon type; this type of entropy assumes its maximum value for the uniform distribution and the minimum value of zero for the binomial distribution, i.e., a distribution in which one result is certain and the probabilities of all other results are zero (Denker et al. 1998). In our case, the acceleration-related part of entropy (12) is greater, which is due to the fact that overall there are more acceleration runs and also that there are more long acceleration runs. The run distribution for shuffled data has many more short runs and much fewer long runs than any of the entropies for data in the physiological order. Therefore, this distribution is closer to the binomial, delta-shaped distribution and consequently should have a lower value. This is exactly what was found in this study. We can hypothesize that the greater the acceleration/deceleration run entropy part, the more long runs the corresponding distribution has. On the other hand, the more short runs in a recording, the more it resembles the delta distribution and the lower the value of the entropic parameters. This should be studied in more detail in a separate study.

The first suggestions that the number of accelerations is greater than that of decelerations came from the analysis of the Porta index, which shows the contribution of decelerations to all changing beats of sinus origin. Physiologically, the Porta index is <50%, which means that decelerations in general are less numerous than accelerations (Porta et al 2008, 2009). This is
in perfect agreement with the results reported in this paper. It is much more difficult to relate our findings to the results of research based on the approach proposed by Costa et al. (2005), since the parameter measuring time irreversibility in this line of research is not expressed in terms of accelerations and decelerations.

The method presented in this paper has some similarities to other HRV methods—the most important are those in which the RR interval time series is mapped onto a symbolic series and this simplified time series is analyzed. Methods in which such a step is taken include symbolic dynamics (Voss et al. 1996, Guzzetti et al. 2005), linguistic analysis (Yang et al. 2003), some approaches to approximate and sample entropy (Pincus 1991, Cysarz et al. 2006) or ternary coding of the differentiated series (Cammarota and Rogora 2007). In these approaches symbolic series are formed on the basis of a certain criterion, like being over/under a certain threshold or being an accelerating or decelerating beat, and the patterns in these symbolic series are summarized, usually with an entropic measure. In the above approaches, the symbolic series is divided into constant length segments (sometimes called ‘words’). This division occurs either once or is repeated a few times with different segment length for each run of the method and/or a different starting/ending point.

The partition of the RR time series into segments in the monotonic run method presented here is performed on the basis of a clearly defined physiological criterion. Also, we try to avoid discussing the time series in such mathematical terms as complexity theory or chaos theory. We do use the notion of Shannon entropy, but our only purpose in doing so is to summarize the whole distribution with one number which can be divided into deceleration- and acceleration-related parts. In this way, it is similar to SDNN² and its parts (Guzik et al. 2006, 2010, Piskorski and Guzik 2007). Of course, this does not exclude the possibility of using the measures defined here for more advanced complexity analysis.

The monotonic run method offers a glimpse into the microstructure of heart rate and its patterns. The mechanisms influencing HRV modify spontaneous depolarization of cardiac cells within the sinus node (the primary pacemaker in human heart) by changing the electrical transmembrane potential produced by different concentrations of various ions such as sodium, potassium or calcium (Klabunde 2005). The sympathetic and parasympathetic nervous systems are behind most of the mechanisms regulating the momentary heart rate. Heart rate acceleration can be caused by an increased sympathetic tone, reduced parasympathetic drive or be an effect of both. Similarly, heart rate decelerations can be caused by a reduction in sympathetic activity, augmentation of parasympathetic tone or both. The balance between these two branches of the autonomic system can be modulated by a number of reflexes (e.g. baroreflex or peripheral and central chemoreflexes), hormones (e.g. catecholamines from suprarenal glands, thyroxine and triiodothyronine from thyroid, insulin from pancreas), substances (e.g. glucose, adenosine, lactic acid), physical factors (e.g. temperature) and random effects (noise, pain, fear, joy, exercise). Some other features of the autonomic effects like different delays in response of sinus node to changes in sympathetic and parasympathetic tones or completely different chemical transmitters (norepinephrine versus acetylcholine) for these nervous systems should also be considered. Further, there are various oscillations in the cardiovascular system, like more or less regular breathing with usually different duration of inspiration and expiration, sighs, which are less common than normal breathing but are still repeated phenomena, changes in vascular tone (the so-called Meyer waves), day-to-night variation in light intensity, tides or winds, etc. Thus, it appears that it is not easy to identify which of the above listed factors or mechanisms is directly responsible for the momentary heart rate acceleration or deceleration.
It is almost certain that the findings reported in this paper are the result of the sympathetic–parasympathetic interaction, but of course, for now this is only a hypothesis. It is possible that some of the explanation lies in the respiratory sinus arrhythmia, though the longest runs are much longer than a single breath cycle and the asymmetry seen in them is unlikely to be caused by this phenomenon. Furthermore, asymmetry is not observable for run lengths 3 and 4, which are usually near the breathing cycle length. Carefully planned physiological and clinical studies, including various blockades and manoeuvres as well as analyzing the day–night sub-periods, should be performed before a more concrete hypothesis is made.

The comparisons for run lengths were performed for the original and shuffled RR intervals. It is possible to normalize the runs with the use of (8); however, in the case of the data presented in this paper, this procedure did not change the statistical significance levels, and the conclusions were the same as for not-normalized data. We believe that using the numbers of runs rather than their normalized values made the discussion clearer.

Sampling frequency is an important factor in studying monotonic runs. Higher resolutions lead to fewer neutral runs and consequently to better expression of long and very long runs and higher entropy part values.

The run method has potential for clinical applications: it was reported that the rate of deceleration runs is reduced in post-infarction patients with increased risk of mortality during a 2 year follow-up (Guzik et al 2009, Guzik and Piskorski 2010).

The most important finding reported in this paper is a new aspect of heart rate asymmetry; the runs of accelerations are more numerous and longer than those of decelerations in 24 h long recordings.

Acknowledgments

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