Changes in the Hurst exponent of heartbeat intervals during physical activities

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The fractal scaling properties of the heartbeat time series are studied in a controlled ergometric regime using the Hurst rescaled range R/S analysis. The long-time "memory effect" quantified by the value of the Hurst exponent $H > 0.5$ is found to increase during progressive physical activity at healthy subjects in contrast to those having stable angina pectoris (SAP), where it is decreasing. We argue that this finding may be used as a useful new diagnostic parameter for short heartbeat time series.

The output of many physiological systems, such as the normal human heartbeat time series, are extremely inhomogeneous and nonstationary. They fluctuate in an irregular and complex manner, even under resting conditions. The presence of scaling properties suggest that the regulatory systems are operating far from equilibrium and application of fractal analysis may provide a new approach to recognize diseased states by studying changes in the scaling properties. It has been observed that fractal scaling is degraded in some diseased states [1, 2, 3].

The heart rate variability (HRV) under controlled physical activity is not well studied [4, 5]. The time series of heartbeat intervals (RR intervals), used in various analyses, are usually holter type data or data from steady state measurement. The conventional statistical analysis of the ambulatory ECG (Holter) records is, however, limited. The great wealth of data about the dynamics of the heart that is contained in such records is usually reduced to characterize only the mean heart rate and the presence and frequency of some abnormal electrocardiographic complexes. The analysis of long-time correlations is largely ignored. One possible reason for this is that in the study of twenty four hour HRV, in a natural setting, the subjects are constantly changing their level of physical activity. These changes are unpredictable and the comparison of such time series are difficult. However, some heart diseases, such as stable angina pectoris (SAP), are clearly visible only under physical activity. That has given
us a reason for investigating the scaling properties of heartbeat intervals in a various well defined ergometric regimes.

Fluctuations in RR intervals during one of our ergometric measurements are shown in Fig.1. Both time series look very similar and we cannot say, without knowing, which one is from a healthy and which one is from a SAP individual.

Different self-similar time series can be classified into random or non-random series by estimating their Hurst exponent \[6\]. In order to determine the long-time dependencies in time series of RR intervals during controlled physical activity, we apply the rescaled range (R/S) method \[7\], to estimate the Hurst exponent. In fact, we are interested in the capability of the R/S method to distinguish the patients with SAP from the healthy subjects. For a heartbeat
time series data of length \( N \) \{ \( u(n), n = 1, \ldots, N \) \}, where \( u(n) \equiv RR(n) = t(R_{n+1}) - t(R_n) \) is the \( n^{th} \) RR interval defined as a difference in time position for R-wave peaks, we calculate the running means \( \overline{u}(n) \) for a given \( n \) and the accumulated deviations from the mean \( X(l,n) \), \( l=1,\ldots,n \):

\[
\overline{u}(n) = \frac{1}{n} \sum_{k=1}^{n} u(k),
\]

\[
X(l,n) = \sum_{k=1}^{l} [u(k) - \overline{u}(n)].
\]

The range \( R(n) \) is the distance between the minimum and the maximum value of \( X \), and is rescaled by dividing it by the standard deviation \( S(n) \):

\[
R(n) = max_l X(l,n) - min_l X(l,n),
\]

\[
S(n) = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (u(k) - \overline{u}(n))^2}.
\]

The rescaled range (R/S) is a dimensionless quantity and for large \( n \) it is expected to show a power law dependence:

\[
R(n)/S(n) \sim n^H,
\]

where \( H \) is the Hurst exponent. If the time series is long enough, the relationship between the fractal dimension \( D \) and the Hurst exponent \( (H) \) is

\[
D = 2 - H.
\]

The time series of RR intervals can be divided into three distinct categories: \( H<0.5, H=0.5 \) and \( H>0.5 \). The case \( H=0.5 \) correspond to random or uncorrelated RR intervals. If \( H > 0.5 \), the RR intervals are persistent and characterized by long-time correlations or ”memory’ effects on all time scales. The strength of the persistence increases as \( H \) approaches 1.0. The impact of the present on the future can be estimated through the correlation function \( (C) \)

\[
C = 2^{(2H-1)} - 1.
\]

Most of natural phenomena show persistent behavior with \( H \sim 0.7 \) \[7, 8\]. The time series with \( H < 0.5 \) is antipersistent, which means that RR intervals are negatively correlated.
Program | Belt angle (°) | Belt velocity (km/h)
--- | --- | ---
P1 | 10 | 2.7
P2 | 12 | 4
P3 | 14 | 5.5
P4 | 16 | 6.9
P5 | 18 | 8

Table 1: Defined regimes in ergometric measurement: Bruce protocol.

The time series of RR intervals in our controlled ergometric measurement (Fig.2) had a time duration of about 15 min. (≈ 2000 beats). This type of measurement is used as a routine in everyday clinical diagnostic procedure, because some heart diseases, such as SAP, usually become transparent under physical activities.

The ECG ergometric data were digitized at sampling time of 1 ms by the WaveBook 512 (Iotech. Cal. USA), and transferred to a computer for further analysis. The RR interval series was passed through a filter that eliminates noise and artefacts. All R-wave peaks were first edited automatically, after which a careful manual editing was performed by visual inspection of the each RR interval. After this, all questionable portions were excluded manually, and only segments with > 90% sinus beats were included in the final analysis. The location of the R-wave peaks was determined with a resolution of 1 ms.

Each measurement consists of stationary state part (pretrigger Pt), few stages of running (P1-P4) on an inclined belt and a period of relaxation (Re). Different regimes of physical activity are defined according to the standard Bruce protocol (Table 1), with a time duration of 3 min for each program. The pretrigger part has a variable duration and is limited for analysis to the first 30 sec in each measurement. The relaxation period is restricted to 6 min.

The R/S analysis was performed on four separated regimes: stationary state Pt, running programs P1, P2 and relaxation Re. Patients were divided in two groups: one with the evidence of ischemic ST-segment depression of more than 1 mV (SAP subjects), and the control group of healthy subjects. Selection of subjects was performed by a cardiologist according to the generally accepted medical knowledge. Before starting with the R/S calculation, we performed a polynomial regression (trendline) fit on the original RR interval data, in order to compensate for the global nonstationarity in the data caused by the physical
Figure 2: RR intervals in an ergometric measurement. The global nonstationarity as result of physical activity is clearly seen. Pt correspond to stationary state measurement, P1-P4 to running stages on a belt with increasing intensity, and Re to a relaxation period after stopping the moving belt.
Figure 3: (a) Typical shape of HRV in the ergometric measurement, (b) RR intervals in Program 1 with 3rd degree polynomial regression trendline, (c) deviations from the polynomial trendline, (d) R/S results for deviation signal in comparison with random data result (H=0.5).

activity. The R/S calculation was performed on the deviation of the original RR intervals from the trendline. The main steps are shown in Fig.3 for P1 regime. The procedure adopted here is to calculate R/S for a box of n elements, starting with the first two elements. In each next step one more element is added, and R/S is calculated for the wider box. The process is continued until the box of length N (the whole data set) is reached. The Hurst exponent H is evaluated as a slope of the least-square fit line on log(R/S) vs. log(n) plot. In this way, we preserve the ordering of RR intervals during calculation.

The average Hurst exponent H in four analysed regimes, with corresponding statistical error bars are shown in Fig.4, for healthy and SAP subjects. It
includes 14 independent measurements on 7 healthy + 7 SAP subjects.

The Hurst exponent H exceeds 0.5 in all cases and ranges from 0.6–0.9 depending on the regime type. For RR intervals in the Pt regime, H for both healthy and SAP subjects is about 0.7 and we cannot distinguish them. The situation is different in regimes under physical activity. The difference between healthy/SAP subjects is clearly seen in the P1–P2 program of controlled running, in our analysis. The Hurst exponent for healthy subjects increases with increased running intensity, while H for SAP subjects decreases in the same (P1–P2) regimes. Our time series are too short for reliable connection of the scaling exponent with the fractal dimension. However, if the scaling exponent reveals the complexity of the underlying pattern, we may say that the complexity of the RR pattern in running is decreased in the healthy heart, but increased in the sick heart. The conclusion is opposite from what it would be expected in a stationary state measurement [3]. It could be connected with the heart reaction on well defined excitation. The healthy heart restricts flexibility according to restrict outside condition: well defined excitation – well defined reaction. The sick heart, under well defined excitation, probably produces ”mess” in the reaction, and a more complex pattern of fluctuation.

In the relaxation part, which is a recovery period after running, the Hurst exponents for healthy and SAP subjects are moving towards each other and to the values found in the Pretrigger state (Pt).

These preliminary results of the R/S analysis show a clear separation in the value of the Hurst exponent under controlled physical activity. Further studies in larger populations are needed to confirm this result. If the found trend would continue on larger statistics, the Hurst R/S method could be useful in separating SAP subjects from healthy ones, especially in borderline cases where clinical diagnosis cannot be set from ECG measurement only.

In conclusion, we have shown that fluctuations in heartbeat time series in a controlled ergometric regimes exhibit fractal properties when analysed by a rescaled range method (Fig.4). The rescaled range (R/S) for ergometric measurements is very well described by the Hurst empirical law $R/S \sim n^H$, for $2 \leq n \leq 400$, where the Hurst exponent $H > 0.5$ increases for healthy subjects, in contrast to SAP subjects where it is found to be decreasing, during progressive physical activity.

References
Figure 4: Average Hurst exponents with corresponding $1\sigma$ error bars for different regimes of ergometric measurement; Pretrigger (Pt), Program 1 (P1), Program 2 (P2) and Relaxation (Re). Dots are for healthy subjects, and squares are for SAP subjects.
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