# Scaling analysis of heartbeat under the influence of external stimulation and disease

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Clinicians usually describe the normal activity of the heart as regular sinus rhythm. However, recent evidences indicate that heartbeat intervals fluctuate in a very complex and irregular manner even for healthy people at rest. That is why heart rate variability (HRV) has attracted the interest of many scientists in recent years as a tool for better understanding of the mechanisms of the heart, and its reaction to perturbations.

Conventional techniques usually label complex fluctuations in the heartbeat series as "noise" to distinguish them from the "true" signal, thus focusing on the averaged quantities only. But with the development of new methods in statistical physics it has been found that this highly complex behavior of the heartbeat series revealed hidden scaling properties.

The point-to-point (auto)correlation function is defined by

$$C_n = \langle u_i \cdot u_{i+n} \rangle = \frac{1}{N-n} \sum_{i=1}^{N-n} u_i \cdot u_{i+n}$$

| | | |
|---|---|---|
| uncorrelated data | $C_n = 0$ | n>0 |
| short-range correlations | $C_n \sim e^{-n/n_x}$ | |
| long-range correlations | $C_n \sim n^{-\gamma}$ | $0<\gamma<1$ |

## Scaling exponent

The scale-invariance relation is expressed in the following way

$$f(x) = \lambda^{-\alpha} f(\lambda x)$$

If long-range correlations exist in the data, then the fluctuations will possess a scaling property, and behave as a power-law of scales.

$$F(n) \sim n^{\alpha}$$

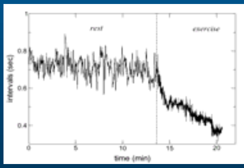
| | | |
|---|---|---|
| uncorrelated data | $\alpha=0.5$ | |
| correlated data | $\alpha>0.5$ | $\alpha = 1 - \gamma/2$ |
| anticorrelated data | $\alpha<0.5$ | |

## Effects of external stimulation on the scaling of HRV

The non-linear interaction between the parasympathetic (PS) and sympathetic (SS) branches of the autonomic nervous system is the mechanism which is responsible for the complex behavior of the heartbeat. The response of these systems is highly sensitive to external stimuli. Such stimulation can be either physical activity or the influence of disease or drugs.

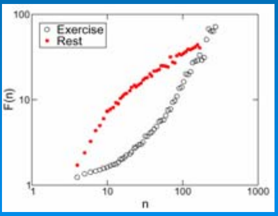
## The effect of physical activity on scaling

The records we use in this project are peripheral arterial tone (PAT) signals, that measure the magnitude of changes in arterial blood flow in the fingertip. An example of interval series obtained by detecting successive peaks in PAT signal in rest and exercise stages is shown below.




It can be seen that the two regimes of rest and exercise posses different statistical properties like mean and variance. Thus we may ask the question whether the intrinsic dynamics is also different in these two regimes.

We apply DFA separately on rest and exercise stages of the same person.

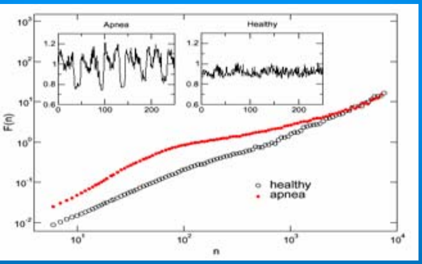



We should pay attention to the fact that the curves presented on the graph are not straight lines over the whole region as it supposed to be according to the power-law relation. Instead we observe the crossover phenomenon, i.e. there is a transition between different scaling exponents when crossing from small scales regime to large scales regime. We note the scaling exponent on small scales as $\alpha_1$ and the scaling exponent large scales as $\alpha_2$.

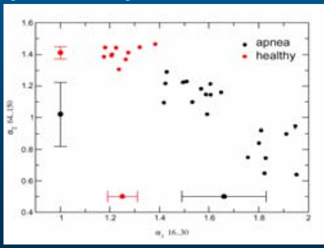
## Determining apnea epochs using scaling techniques

Sleep apnea is a breathing disorder characterized by interruptions of breathing during sleep. Standard methods for detecting sleep apnea are based on respiration monitoring which is generally expensive. But a number of studies during recent years have hinted at the possibility of detecting sleep apnea using electrocardiogram (ECG). The ECG signal shows a characteristic R-peak, which is easily detectable. We focus on the interbeat signal constructed from the intervals between successive R-peaks.

Due to the periodicity in the RR series for apnea patients we see a crossover in the fluctuation function.



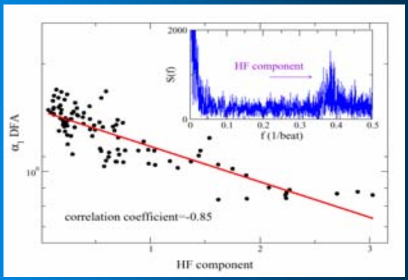

Scaling techniques can also be applied to the magnitude and sign of the RR series increments. We average the fluctuations from all apnea regimes and from all healthy regimes that were detected by human experts on the basis of respiration monitoring. The figure below shows the scaling exponents calculated from the fluctuations of the sign series. Each point in the graph stands for a patient.



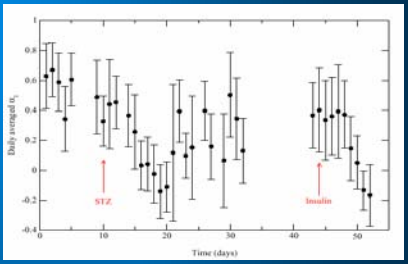

According to the error bars, apnea and healthy subjects are completely separated, but surprisingly for the apnea group we observe two sub-groups. This can be related to the fact that there are two different types of apnea known to medicine.

## Evolution of a disease by scaling techniques

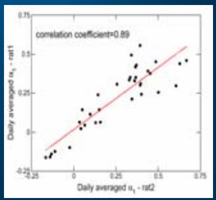
It was established that scaling techniques can be indicative of heart disease. We study the progress of diabetes in rats using two independent properties - the scaling exponent and the high frequency (HF) component. The HF component in the power spectrum of the RR series is associated with breathing. The scaling exponent for small scales $\alpha_1$ is probably affected by the heartbeat oscillations induced by breathing as well. We found that there is strong correlation between the changes of both parameters caused by the development of diabetes in the rats.




The picture below shows daily averaged and standard deviations of the scaling exponent in the course of time.




In the treatment, STZ induction was used to transform the rats to diabetic. Following the administration of STZ, we observe a decrease in $\alpha_1$ indicating the evolution of the disease. After a long period insulin was given to the rats, stabilizing the value of $\alpha_1$. When insulin treatment was stopped, $\alpha_1$ decreased again.




A similar behavior of $\alpha_1$ was observed for different genetically identical rats, as reflected by the high correlation in the presented figure.