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Prediction of the Cardiovascular System on the Basis of an Assessment of Repeated Extreme Values Heartbeat Intervals and Times to Achieve them in the Light of Short-term and Long-term Relationships

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Abstract

A procedure for predicting large (with a record of more than a certain high threshold Q) Q-interval heart rate, which is a combination of the transformation of the original series of signals to a number of time to reach a predetermined threshold changes and the method of a large re-range prediction with a record of more than Q (Q-event) on the basis of estimate the probability WQ (t; Δt) that during the time DELTA.t will be at least one Q if an interval of time t until the last Q -Events came Q-event. This procedure allows you to speed up the implementation of the process of constructing the forecast and increase its reliability.

Keywords: Cardiovascular system; Forecasting; Heartbeat intervals; Records; Assessment

Introduction

In recent years, the problem of the study of rare (extreme) event attracted a lot of attention [1-3]. Generally, rare events with values much higher than the average value are considered to be independent, as the typical time between them is very large. However, in recent years it has become increasingly clear that this assumption is not always satisfied. To quantify rare events is usually the interval time between the appearance of successive events above (or below) a certain threshold Q. This is investigated as a function of the probability distribution of these repeated intervals (return intervals), as well as their long-term dependence (autocorrelation, conditional periods and reps etc.). In the numerical analysis, definitely not considered very high thresholds the Q, which provide a good statistical estimates of repeat intervals, and then try to extrapolate these results to the very high thresholds for which statistics are very poor.

For independent sets of data repeated intervals are independent and (according to Poisson statistics) is exponentially distributed. Clustering of rare events indicates the existence of a certain memory in repeated intervals, and, as shown by recent studies [4-6], this type of memory is a sequence of long-term dependency of time series Long-term memory may be: (i) a linear (ii) or nonlinear (iii) for linear and nonlinear characteristics of some other process characteristics. In the first case, which is often called "monofraktal" (linear) the autocorrelation function of the $C_x(s)$ of input data decreases with time s power law $y_{n-k} : y_{k-1}, y_{n-k+1}, ... y_{n-1},$ and exponent gamma fully It describes the correlation between the records (extreme values). In this case, as repeated intervals, and records have long-term correlations and their distribution on a large scale is characterized by a stretched exponential exponential gamma c, but on a small scale are subject to a power law with an exponent γ-1 [4,6,7]. Such phenomena are observed in long-term climate records [4] and volatility (variability) of the financial records of [5], despite the fact that the volatile memory comprises non-linear and, therefore, relates to the case (iii).

In the second case, when the records form a "multifractal" linear autocorrelation function $C_x(s)$ vanishes for s>0, and the records are characterized by non-linear multifractal correlations that cannot be described by a single exponential. With the generation of a multiplicative random cascade (multiplicative random cascade-MRC) in [8] that the non-linear correlations inherent in such a time series provide statisticians repeated intervals peculiar effect, which manifests itself in submission to a power law probability density functions (probability density functions-PDFs), the autocorrelation function (autocorrelation functions - ACFs), and repeated periods of conditional (conditional return periods-CRPs), which contradicts the properties of independence and monofractal in the presence of long-term correlations in the original data. [2] Exhibitors corresponding power laws essentially depend on the selected threshold level, i.e., repeated intervals will have different behavior at high and low thresholds. Consequently, direct extrapolation of the laws governing repeated intervals with low thresholds would not be lawful for a quantitative description of repeated intervals with large rapids.

In [9], based on 24-hour Holter monitoring data shows that the linear and non-linear long-term memory, inherent in repeated intervals heart, leading to a power law changes PDF. As a result, the power law will satisfy the probability $W_Q(t;\Delta t)$ that Δt. of time units that have elapsed since the last re-interval with an extreme event (record) larger than the threshold Q (Q-short interval), there will be at least a Q-interval if for t time units until the last Q-Q-interval appeared heartbeat interval.

In this paper, prediction of large (with a record of more than a certain high threshold Q) re Q heartbeat interval is carried out using the procedure of forecasting [9] with repeated intervals statistics estimates [10] and with the preliminary selection of repeat Q-intervals with persistent (steadily increasing) records on the basis of conversion [11] of the original signals (in this case repeated Q-intervals) in a time to reach a predetermined change threshold.

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1. Prognosis large repeated intervals heart with a great record. Preexisting repeated intervals forecasting strategy is based, as a rule, short-term pre-history, and were based on the construction of the training sample (precursors) $y_{n-k}: y_{k-1}, y_{n-k+1}, \ldots\ldots y_{n-1}$, consisting of the events preceding the extreme events $y_n > Q$. These strategies are based mainly on two approaches. In the first approach considers the big events with the appropriate precursors and their frequencies, which are determined based on the posterior probability $P(y_{n,k}=y_n>Q)$ In the second approach considers all the precursors of $y_{n,k}: y_{n-k}, y_{n-k+1}, \ldots\ldots y_{n-1}$, which is preceded by some record y_n, and calculates the probability $P(y_n > Q \mid y_{n,k})$, while $y_{n,k}$ considered a precursor of extreme events $y_n>Q$ [12,13]. The second approach is more comprehensive because it takes into account information precursors of all the events, thus providing additional information about the studied ranks contained in the short- and long-term correlations of the original data [14,15].

A more direct way of dealing with the study of the problem is proposed in [12] a method in which the precursor is sought prior to the consideration of extreme events and with the highest probability of a generation of alarm (alarm) of the appearance of such a precursor. For physiological extreme events (records) that appear in the nonlinear complex systems (which, in particular, relates cardiovascular system), the said precursor may not be representative due to the fact that many other precursors may be of comparable probability to determine a second interval following During the extreme event y_n. In this case it is advisable to generate an alarm signal in accordance with a preliminary estimate of the probability P with which there are extreme events exceeding the threshold Q_p. Selecting Q_p usually carried out optimally, minimizing the total loss associated with the forecast errors, including false alarms and disturbing events (artifacts), with a preliminary specification of losses from a false alarm and a disturbing event (which can vary greatly in different tasks [12]).

In this regard, [9] developed a third approach to the problem of predicting large repeated intervals, requiring less information and therefore more convenient than the conventional approach. This approach, which uses non-volatile memory and named [9] RIA-approach (return intervals appkoach), based on the use of statistics repeated intervals and very useful, in particular, in the study of records having nonlinear(Multifractal) long-term memory. PDF-based assessments repeated intervals size r, consisting of events with a value greater than Q (briefly, this PDF is designated $P_Q(r)$; Properties of $P_Q(r)$; are considered in [11] estimates) obtained two values, it is essential to predict the record (extreme events) with a value greater than Q (Q-short event) that appears after the last Q-events. The first of these variables, the expected number of $\tau_Q(t)$ time units, after which you receive the following Q-event will take place as soon as the t time units after the last Q-events. By definition, $_Q(0)$. τ is equivalent to the period of repetitive intervals R_Q Q-events (Q-short interval). In general, $\tau_Q(t)$ associated with $P_Q(r)$ ratio:

$$\tau_Q(t) = \frac{\int_t^{\infty}(r-t)P_Q(r)dr}{\int_t^{\infty}P_Q(r)dr} \quad (1)$$

and $\tau_Q(t)$ for multifaraktalnyh data satisfies the scaling relation

$$\tau_Q(t) \sim t^{\xi(Q)} \quad (2)$$

PDF to repeat $r>r_0$ size intervals denoted briefly by $P_Q(r|r_0)$. Generalization values $\tau_Q(t)$ on Q events included in repeated intervals size $r>r_0$ (summarized these events will be denoted by $Q(r_0)$ Events), leads to the concept of magnitude $\tau_Q(t|r_0)$ in which the definition of Q-event replaced to $Q(r_0)$-event. Figure 1a and 1c of [9] shows the value of the global $\tau_Q(t)$ and conditional $\tau_Q(t|r_0)$ the magnitude of the expected temporary units until the next event, their numerical values obtained for the MRC-models: (a) $R_Q=10$ and (c) for $R_Q=70$. The values of r_0 only considered when $r_0=1$, $r_0=3$. From Figure 1, it follows that $\tau_Q(t)$ satisfies a power:

$$\tau_Q(t) \sim \left(t/R_Q\right)^{\xi(Q)}, \quad (3)$$

where the exponent ξ(Q) decreases with increasing Q(ξ=0.6 for $R_Q=10$ and ((ξ=0.47 for $R_Q=70$) Conditional expected number of time units $\tau_Q(t|r_0)$ for $r_0=1$ may also be described by a power law. about the same exponential $\xi(Q,r_0)$, as well as the global value of ξ(Q). On the contrary, the value for $r_0>3$ $\tau_Q(t|r_0)$ significantly deviates from the power law for small values of the argument t/R_Q. For large values. t/R_Q, corresponding $\tau_Q(t|r_0)$ graphics for both values $r_0=1$ and $r_0=3$ close to collapse (merge) $W_a(t,\Delta t)$ is the probability that the time Δt for the units following the last Q-event will be at least one heartbeat interval Q-, if for t units of time before the last Q-event event appeared interval. This value is related to $P_Q(r)$ ratio:

$$W_Q(t;\Delta t) = \int_t^{t+\Delta t} P_Q(r)dr \Big/ \int_t^{\infty} P_Q(r)dr \quad (4)$$

Since the value of $W_Q(t;\Delta t)$ is limited by the number 1 when $t/R_Q \to 0$, it can satisfy the power law only if $\frac{t}{R_Q} > (\delta(Q)-1)\Delta t/R_Q$ and written as [9]:

$$W_Q(t;\Delta t) = \frac{(\delta(Q)-1)\Delta t/R_Q}{t/R_Q + (\delta(Q)-1)\Delta t/R_Q} \quad (5)$$

Figure 1c and 1d shows graphs for W_Q records MRC-model, characterized the power spectrum of the form 1/f 1 when $R_Q=10$ and $R_Q=70$, respectively. For such records PDF is better described by a gamma distribution than the power law, significantly deviate from it on a large scale, to obtain an analytical expression for the W_Q in this case is very difficult. Empirically [9] shows that the best estimate for W_Q obtained in this case, if the denominator of the fraction (5) is replaced by t/R_Q at $(t/R_Q)^{1-\varepsilon} c\, \varepsilon = 0.15$ which leads to the estimate:

$$W_Q(t;\Delta t) = \frac{(\delta(Q)-1)\Delta t/R_Q}{(t/R_Q)^{1-\varepsilon} + (\delta(Q)-1)\Delta t/R_Q} \quad (6)$$

For large t/R_Q there are strong finite-dimensional effects that manifest themselves especially at high R_Q (Figure 1d). These finite-dimensional effects are reduced with a decrease in R_Q and with increasing length *l* of the time series, understating the denominator in (5), and thereby artificially inflating assessment W_Q.

The simplest forecast is obtained by choosing the estimate (6) with a high probability of a fixed value Δt=1. These results agree well with the corresponding results for the model MRC. To build a more accurate prediction [9] propose an algorithm, providing a comparison W_Q assessments at various fixed values of Q_p and calculating the relevant risk probabilities. For a fixed value of Q_p determined by two indicators: sensitivity (sensitivity) Sens, who correctly predicted the share harakteriruet Q-Events and specified index (specifity) Spec, which characterizes the proportion correctly predicted not Q-events. Larger values and Sens Spec provide a better prognosis. To increase the efficiency of use of the forecast analysis using the reception signal operator (receiver operator characteristic), called the ROC-analysis, according to which plotted by Sens Spec for all possible values of Q_p. By opredelnie $Q_{|p}=0$, when Sens=1 Spec=1 and 0, while $Q_p=1$ when Sens=0 and Spec=1. At $0<Q_p<10$ curve ROC extends from the top left to the bottom right corner on the plane (Sens, Spec). When there is no memory in Sens+Spec=1 data and the ROC curve is a straight line connecting both of the angle (dashed lines in Figure 2 [9]). General PP forecast accuracy measure 0<PP<1, it is an integral over the ROC

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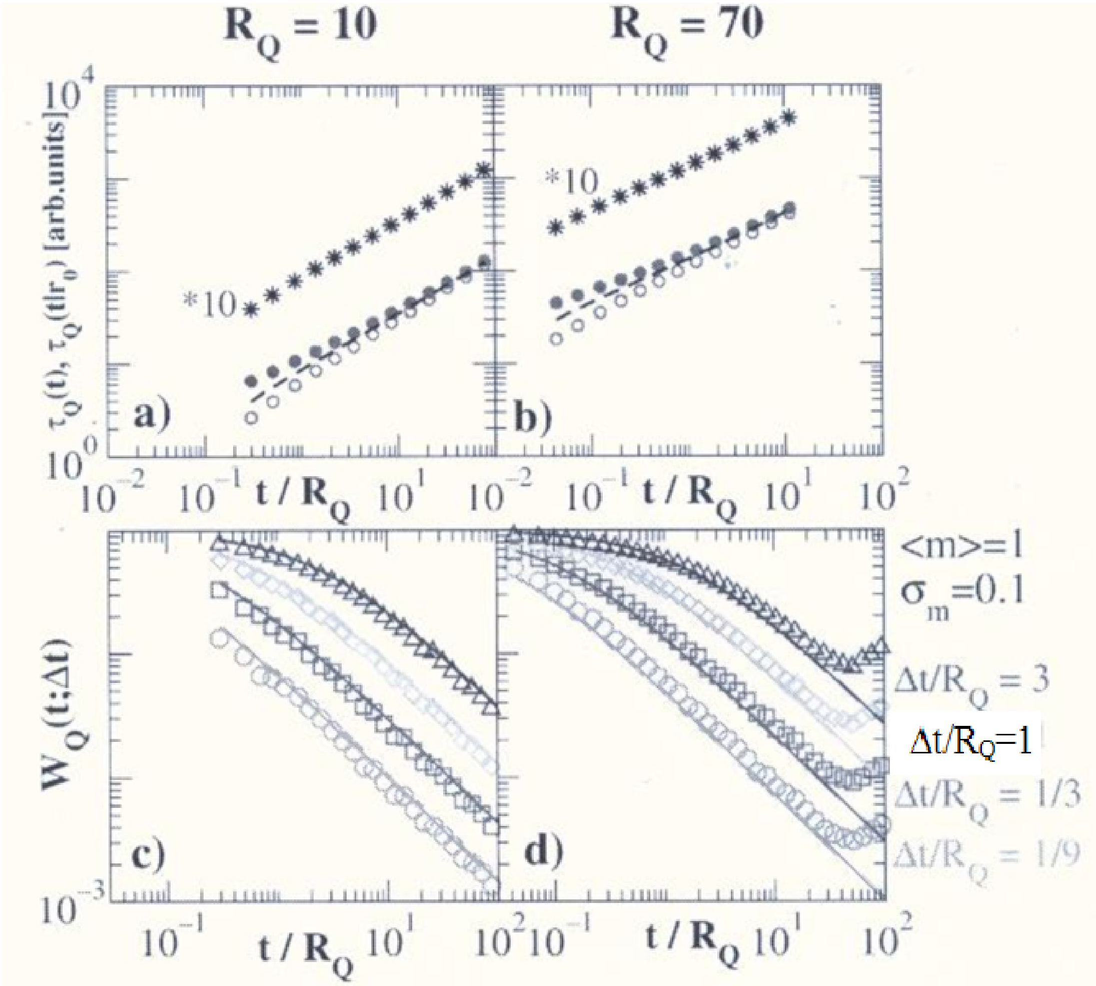

Figure 1: The values of global $\tau_Q(t)$ and the value of the conditional $\tau_Q(t|r_0)$ the expected time units until the next event.

curve, which is equal to 1, with absolutely tochnom forecast and equal to ½ for random data. To estimate the probability of risk can be used to "teach" a sample or model of the observed records of Records as the MRC-model. The traditional technique of recognition given patterns (templates, standards), so-called recognition PRT-technique (pattern recognition technique), based on short-term memory, built a database of all possible patterns $y_{n,k}$ from a previous event with a sliding window, which divides full sample records possible values y_i the l levels with the same number of values, so that the total number of patterns is equal to l^kl. Then, for each pattern precursor $y_{n,k}$ estimated probability $P(\mathbf{y}_n>Q|\ y_{n,k})$ that exceed the following event yn Q. The main difficulty here is the need for multiple settings in order to find the optimal values of parameters l and k, resulting in high accuracy of the forecast. In an alternative RIA-techniques using non-volatile memory, the probability $W_Q(t;\Delta t)$ is determined from the observed records using equation (1.4), or analytical expression (6). As shown in [9] RIA-approach to forecasting Q-intervals, which does not require the limited ispolzuyumyh statistics, it gives in all cases the best result.

Figure 2 [9] has shown that when R_Q=10, both approaches provide similar results in three representative cases, patterns of k=2, k=3 and k=6, and for R_Q=70 ROC-curve is systematically located above the RIA-curve, especially near Sens=1. Experimental studies suggest [9] that the PRT-forecasts using the "training" of the observed sample records are usually more accurate than forecasts obtained through records MRC-model. The reason for this is the limited ability to MRC-model for describing the dynamics of short-term heart rate intervals, including individual variations in the physiological regulation. In this regard, the high sensitivity of RIA-techniques results in significantly fewer false alarms than PRT-technique.

Thus, the use in the study of records in non-volatile memory heartbeat intervals inherent in events that appear after the last Q-events, has the undoubted advantage compared with PRT-technique, using only short-term memory. RIA- approaches main disadvantage is that it typically cannot predict the events of the first Q-cluster event, a large number of heartbeat intervals t used when W (t; Δt) becomes low. However, due to multifractality records in clusters of extreme events, benefit from better than expected, following the first event in the cluster Q-events, and from the reduction of false alarms in the RIA-approach is much higher than the loss of the weak predictability of the first event in the cluster Q-events that confirmed ROC-analysis. In addition,

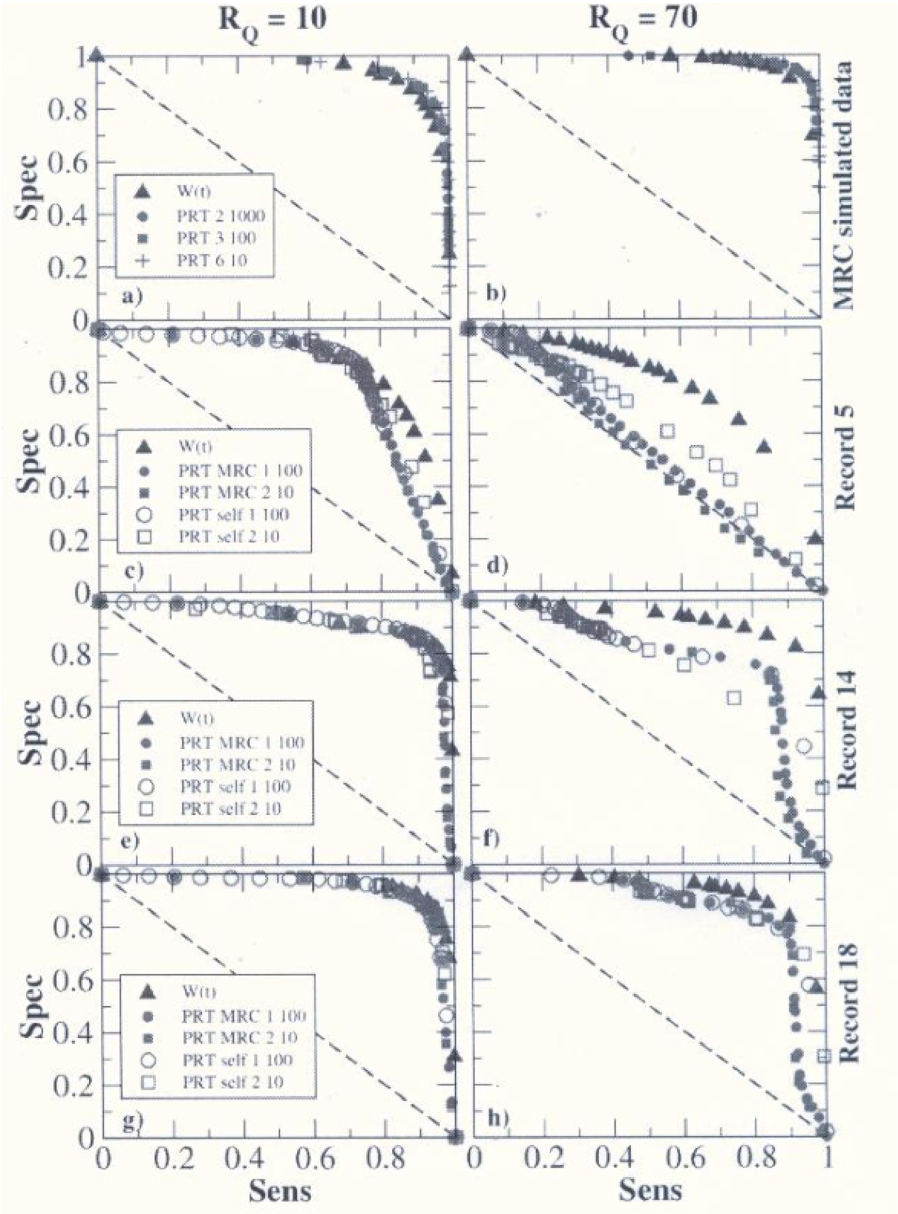

Figure 2: Graph Spec Sens depending on all possible values of Q_p.

RIA-intensive approach does not require the use of multiple training procedures and test patterns facilitating its numerical implementation compared to PRT-approach.

To improve the efficiency Q-event prediction obtained RIA-method, we will use a combination of this method with the method of achieving change threshold [10]. The basis of this method is necessary the original signal into a number of time to reach the threshold of change p [16]. It allows, firstly, the aggregate signal without loss of significant information about it, and secondly, not predict the next signal value, and the time in which the signal change exceeds the known threshold p. Prediction made two-layer perceptron. Consequently, the original signal is converted as follows:

$$x(t)-\{x_1,x_2,....x_n\}\rightarrow x'=\{x_1^{'},x_2^{'},....x_n^{'}\}, \quad (7)$$

$$\left|\left(x_{i+1}-x_{i-1}\right)\right|x_i \geq p,\ p>0,\ i=1,...N'-1, \quad (8)$$

$$\left|\left(x_{i+1}^{'}-x_{i-1}^{'}\right)\right|x_i^{'} \geq p,\ p>0,\ i=1,...N'-1, \quad (9)$$

$$\tau=\{\tau_1,\tau_2,...\tau_{N'-1}\},\tau_{i+1}^{'}-\tau_i^{'},\ i=1,...N'-1 \quad (10)$$

where N-number of samples in the original signal, x'-converted signal, in which left only the values relative difference between the intervals is greater than the threshold p, N-number of samples in the transformed signal, τ-number time to reach a predetermined change threshold, where each value means the time it took the signal to exceed the threshold p changes. Furthermore, this method enables a combined prediction, which includes:

1) assessment for the x' next value $x_{N'+1}^{'}$;

2) assessment for the next value $\tau\tau_{N'+1}; \tau$;

3) Compare sing $\left(x'_{N'+1} - x'_{N'}\right)$ and sing $\left(x'_{N'+1} - x'_{N'}\right)$

The agreement marks the differences $(\tau_{N'+1} - \tau_{N'})$ and $x'_{N'+1} - x'_{N'}$ svidetelst- It exists on the persistence (sustainable growth) as the values x'_i, and the time $\tau_i = \tau'_{i+1} - \tau'_i$ between the values of x'_{i+1} and x'_i. When applied to the records (extreme events) heart which means a steady growth of Records and the intervals between consecutive records

The transformation (7) - (10) with the replacement of (9) to

$$\left(x'_{i+1} - x'_i\right) / x'_i \geq p,\ 0 < p < 1 i = 1, \ldots, N' - 1 \quad (9)$$

You can apply for the pre-selection of records in the heart of the above Q-range forecasting process at large Q-based RIA-technology that will speed up the last procedure and increase the reliability of the proqnosis.

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