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Analysis of Forecasting Methods Makes it Possible to Use Dynamic Series with Short-Term and Long-Term Correlation Dependencies of Heartbeat Intervals

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Annotation

Using the example of repeated heartbeat intervals, we analyze the effect of short-term and long-term dependencies of initial data on the dynamics of emissions at a given threshold and provide a comparative analysis of the effectiveness of the pattern method (PRT) and the interval statistics method (RIA) of predicting the dynamic series of repeated intervals of a monofractal and multifractal nature.

Keywords: *Time series; Heartbeat intervals; Repeated intervals; Mono and Multifractals; Efficiency Analysis*

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Introduction

In the past 20-30 years, it has been shown that dynamic series with fractal properties are generated by a number of heterogeneous complex systems, in particular, physiological systems with inherent different autonomously adjustable rhythms, for example, heart rhythms [1,2]. There are two main classes of fractal dynamic series used in the description of random processes formed by complex systems [3]. The first class includes monofractal dynamic series represented by dynamic series formed by means of spectral transformation and reflecting only the linear component of the long-term dependence of the process generated by the complex system being analyzed. The second class includes multifractal time series represented by time series formed with the help of a multiplicative cascade, which can also reflect the nonlinear component of the long-term dependence. These classes of models use, respectively, a different amount of information about the long-term dependence of the observed values, time series, which can affect the quality of forecasting [4,6]. On the other hand, this increase in the amount of information used requires the involvement of additional computational resources, which is not always justified from the point of view of the result obtained. The relevance of using information with short-term and long-term dependencies, and accordingly, the optimal choice of a forecasting method is determined by the properties of the studied dynamic series.

In [1, 7, 8], it was shown that physiological signals possess multifractal properties inherent in the phenomenon of turbulence and can be effectively modeled by multiplicative cascades. These properties are very stable and undergo significant changes only in cases of cardiac dysfunction of the cardiac function and depend directly on age [9-12]. They are also very dependent on physical activity and on changes in sympathetic and vagal regulation, such as pharmacologically induced changes in sympathetic activity [13].

Modern studies of physiological data show that the variability of physiological values is more characteristic of young and healthy organisms. A decrease, on the contrary, indicates aging or pathological changes. It was possible to establish that the dynamics of physiological processes occurring in the human body is chaotic and can be described from the perspective of the theory of nonlinear dynamic systems. Numerous publications are devoted to the analysis of the chaotic behavior of the heart rhythm, and in a number of works, the randomness of the heart rhythm is associated with the activity of the parasympathetic nervous system [7,8,11].

It would be wrong to associate all pathological changes in the cardiovascular system (CVS) with the development of randomness and an increase in the frequency of the heart rhythm. However, the timely registration of chaotic rhythm behavior should expand diagnostic capabilities and reduce the risk of a patient's deterioration or sudden death. Based on the analysis of rhythmograms, it was found that, in most cases, indicators of chaotic behavior complement the diagnostic picture obtained by the methods of spectral correlation analysis. Along with this, there are identified implementations that are characterized by significantly different estimates of randomness indicators for similar values of the spectral power density of the rhythmogram and comparable values of the sample pulse dispersion. This fact clearly indicates a greater, compared with the traditionally recorded parameters, the sensitivity of the indicators of chaotic conduction to certain states of the CVS and confirms the feasibility of research conducted in this direction.

In this article, using the example of repeated heartbeat intervals, we analyze the effectiveness of using short-term and long-term correlation dependencies in predicting emissions of dynamic series with fractal properties.

1. Factual processes with short-term and long-term dependencies.

The concept of multifractality is closely related to the concepts of short-term dependence (ShTD) and long-term dependence (LTD). The presence of such dependencies is shown for a number of random processes both in technical systems and for processes of natural origin. In particular, the presence of LTD of some physiological processes is shown [1].

The classic sign of the presence of a LTD in a stationary random process S (t) is the infinite characteristic correlation time T_k, at which the integral of the autocorrelation function (ACF)

$$C(\tau) = lim_{T\to\infty}\frac{1}{T}\int_0^T [S(t)-\bar{S}][S(t-\tau)-\bar{S}]2\tau$$

($\bar{S}$ - is the average value of the process) diverges [14]:

$$(T_{kt} = \int_0^t C(\tau)\xrightarrow[t\to\infty]{}\infty$$

For a wide class of stationary fractal LTD -processes, a power-law approximation of ACF is used [15].

C(τ)~τ^(-γ) (1)

where - γ is the parameter that determines the decay rate of the ACF. At the same time as the main characteristics of the LTD for such processes the H Hurst index is used, associated with the parameter γ by the expressionH=1-γ/2. To estimate the Hurst index of a LTD process, fluctuation analysis is usually used [16]. When analyzing long-term realizations of real processes, the stationarity condition is often not satisfied. To analyze such processes, a method of fluctuation analysis was proposed with the exception of the trend (Detrended fluktuation analysis-DFA) [16,17].

As applied to the discrete time series Si, the DFA method consists of two stages. At the first stage, the profile (cumulative sum) of time series elements S_i is calculated.

$Y_K=\sum^{K}_{(i=1)} (S_i-\bar{S})$, which is then subdivided into N_s=]N/S[segments of equal duration, consisting of S counts each ( ]·[- operator taking the whole part). To solve the problem of non-multiple record length and window size, two-pass approximation is used, performed in different directions, starting with the first and last samples, respectively.

At the second stage, the trend is removed from the data by calculating the polynomial approximation P_v (k) of the time fragment S_i in each window v, after which the fluctuation function is detected

$$F^2(s,v) = \frac{1}{S}\sum_{k=1}^{S}\{Y[(v-1)S+k]-P_v(k)\}^2$$

The resulting fluctuation function is calculated by averaging over all windows v

$$F(S) = \left\{\frac{1}{2N_S}\sum_{v=1}^{2N_S}F^2(s,v)\right\}^{1/2} \qquad (2)$$

Asymptotic representation is performed for the fractal LTD process

$$F(s)\sim s^H \qquad (3),$$

Where - H is the Hurst exponent. The uncorrelated process corresponds to H=0.5, the region 0<H<0.5 corresponds to a negative correlation, and the region 0.5<H<1 is positive. In this case, for processes with a power attenuation of the ACF, the following relation is satisfied for the Hurst index:

$$S_{min}:\forall s>s_{min},\ \ H=\alpha\neq 05\ ,\ \alpha=const \qquad (4)$$

("⍰" и "∀" – mean, respectively, "exists" and "for any").

In contrast, for the ShTD process.

$$S_{min}:\ \forall s>s_{min} \qquad H=0,5 \qquad (5)$$

For the characteristics of ShTD and LTD in terms of moments of higher orders as well as fractional moments, the method MF-DFA (Multifractal Detrended Fluctuation Analysis) or MDFA was proposed in [17], within which a family of fluctuation orders q is calculated:

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}[F^2(v,s)]^{q/2}\right\}^{1/q} \qquad (6)$$

For the fractal non-stationary LTD process, we can write:

$$S_{min}:\ \forall s>s_{min}\ F_q\ (s)\sim s^{H(q)} \qquad (7),$$

Where *H(q)* is called the generalized Hurst index for the random process S_i. The process for which H(q) = H = const is called monofractal; if there is a dependence of H on the moment q, the process is called multifractal.

With the distribution of generalized Hurst exponents H (q), it is possible to draw a conclusion about the monofractality of the process under study with H(q)=H=const (regardless of q) and its multifracatality with H(q)≠const, as well as the presence of ShTD when asymtomotive relations (7) are fulfilled for small S_min or the presence of DVB with considerable S_{min} values in the ratio (7).

In the latter case, it is necessary to verify the fulfillment of relations (7) with $S > 10^3$, since MF-DFA can introduce distortions with $S < 10^3$ [18].

The presence in the random ShTD process (and in particular the LTD) significantly affects the statistics of intervals between process exceeding a given threshold Q. These classes of processes were not previously considered in the well-known reviews of classical statistics of intervals, in particular in [19-21]. Therefore, recent results with respect to statistics of intervals between exceeding fixed thresholds Q for mono- and multifractal processes deserve special attention [4,22].

2. A multiplicative probabilistic cascade algorithm for generating multifractal data.

For illustrative purposes, the LTC is commonly used in two common classes of continuous processes [23]. The first class involves the monophthalic process of the lineas long term correlations (LTC) with the autocorrelation function (ACF) at (1) $C(S) \sim s^{-\gamma}$ $(0 < \gamma < 1)$, terminating the subgroup law , and the only exhibitor.

$h=1-(\gamma|2)$, describing the fluctuations in the time of the shaft S. The LTC-process can be generated silently by means of a Fourier filters technique [14].

The second section involves the multifractal process. In addition to the recordings of monofractals, all fluctuations of the record for multifactals are required for an infinite number of exhibitors h(q) in the moment of momentum, representing the effect of nonlinearity.

The multiplicative random cascade-MRC model is commonly used for multi-fractal record generators [24]. In the process, the data is obtained by an iterative path, where the number of points found doubles to each iteration. *(n = 0)*, runs from one value $(X_1^{(0)})$, such that $(X_1^{(0)}) = 1$. In the nth terms, $X_i^{(n)})$, i = 1,2,…2^n, are obtained from the recurrent affinity.

Initial isotopic iterations from a single value noun. In the n-th, it is derived from the recombinant correspondence

$X^{(n)}_{(2l-1)} = X_l^{(n-1)} \cdot m^{(n)}_{(2l-1)}$и $X^{(n)}_{2l} = X_l^{(n-1)} \cdot m_{2l}^{(n)}$,

Where $m^{(n)}_{(2l-1)}$ and $m^{(n)}_{(2l)}$ are non-equilibrium singular distributions, given by RADDOM equivalently distributed sensors (0, 1) the odd sheets.

Function riska as a prediction of riska.

An important characteristic in forecasting is an estimate of the probability W_Q (t,Δt) of one or multiple exceeding the random process value of a fixed threshold Q during the interval Δt (starting from the current moment), which can be expressed in terms of the density of the intervals P_Q (t) between the elevations Q threshold [3]:

$$W_Q(t;\Delta t) = \frac{\int_t^{t+\Delta t} P_{Q(r)} dr}{\int_t^{\infty} P_{Q(r)} dr} = \frac{C_Q(t+\Delta t) - C_Q(t)}{1 - C_Q(t)} \approx \frac{P_Q(t)\Delta t}{1 - C_Q(t)}, \qquad (8),$$

Where t is the time elapsed since the previous threshold was exceeded; $C_Q(t) = \int_{-\infty}^{t} P_Q(r)dr$;

Where r is the distance between two consecutive records.

The approximation by the right-hand expression in (8) is performed under the condition Δt≪t and in some cases allows us to obtain an analytical expression for W (t, Δt). In particular, when P_Q (t) can be approximately described by a generalized gamma distribution, which is a generalization of the Erlang distribution, widely used in queuing theory, the dependence W (t, Δt) is a power function [25]. The power character can also be shown analytically for a wide class of multifractal data synthesized by the MRC method [4,5].

The method of forecasting emissions of time series based on the risk function (8), which uses long-term memory, is called the return approach (RIA) approach [2].

In the case of a multifractal process obtained by the MRC – model with a zero value and a unit variance of normally distributed multipliers, for three representative values of records of heartbeat intervals R_Q = 10,70 and 500, the distribution density function (PDF) of r lengths of intervals exceeding Q is subject to a power law [4].

$$P_Q(r) \sim (\frac{r}{R_Q})^{-\delta(Q)} \qquad (9)$$

Where δ(Q) decreases with increasing Q, in particular, δ(Q)=1.6 when R_Q = 10δ(Q)=1.4 when R_Q = 70 and δ (Q) = 1.25 when R_Q = 500. Some deviations from the law (9) are observed for large values of the argument r/R_Q, which is especially evident in multifractal records in the presence of linear correlations [5,6] and least of all in multifractal records in the absence of linear correlations [4]. For MRC-records with a 1/f power spectrum, these deviations are fairly well approximated by the gamma distribution

$$P_Q(r) \sim (\frac{r}{R_Q})^{-\delta(Q)} \cdot \exp\left(-\frac{cr}{R_Q}\right) \qquad (10)$$

Where c≈1/400. Due to the effects of finite sizes, additional deviations may appear for large values of R_Q.

For a monofractal process withH=0.8, when $r > R_Q$, the relation is approximately fulfilled [22]

$$\ln\,[P_Q(r)] \sim (\frac{r}{R_Q})^{-\gamma} \qquad (11)$$

where γ-corresponds to the exponent ACF of the random process $C(s) \sim s^{-\gamma}$. When $r < R_Q$ the ratio is

$$P_Q(r) \sim (\frac{r}{R_Q})^{-1-\gamma} \qquad (12)$$

The quality of the last approximation is satisfactory for practical purposes, at least for 0.5 < H < 0.8, and at the same time it is theoretically consistent with H → 1, when γ → 0 and the probability density takes on a power-law character [18].

To extract more information from the memory of repeated intervals, conditional repeated intervals are considered, i.e. only those Q-intervals, which is preceded by an interval of fixed size r_0. The probability density of such intervals is denoted $P_Q(r|r_0)$. For uncorrelated data, conditional PDFs collage into one single power curve showing the PDF independence from the r_0 condition.

For data with long-term correlations, weak deviations from the unconditional distribution are observed, so conditional intervals preceding for example the fourth bin (after the first three bins of size $L_Q/2$, $L_Q/4$ and $L_Q/8$) will have a wider distribution than for $r_0 = L_Q$ (2) (first bin). The conditional probability density distributions $P_Q(r|r_0)$ are shown in Fig. 1 for those following the intervals of the first bin (contour markers) and the fourth bin (filled markers).

Additionally, it is possible to take into account information about the value of the previous interval between outliers by switching to the conditional probabilities $W(t;\Delta t|r_0)$ obtained from formula (8) with the replacement of $P_Q(r)$ by $P_Q(r|r_0)$, while for the first bina conditional probability $W(t;\Delta t/r_0)$ can be estimated as

$$W(t;\Delta t/r_0) \approx W(t;\Delta t), \quad \Delta t \ll t < 10R_Q \qquad (13)$$

The value of W_Q (t; Δt), defined by formula (8) is limited to 1 as $t/R_Q \to 0$ and therefore it can satisfy the power law only if $t/R_Q > (\delta(Q)-1)\cdot\Delta t/R_Q$, and is written taking into account (9) in this case as [2]:

$$W_Q(t;\Delta t)=[(\delta(Q)-1)\cdot\Delta t/R_Q]/[(t/R_Q)+(\delta(Q)-1)\cdot\Delta t/R_Q] \quad (14)$$

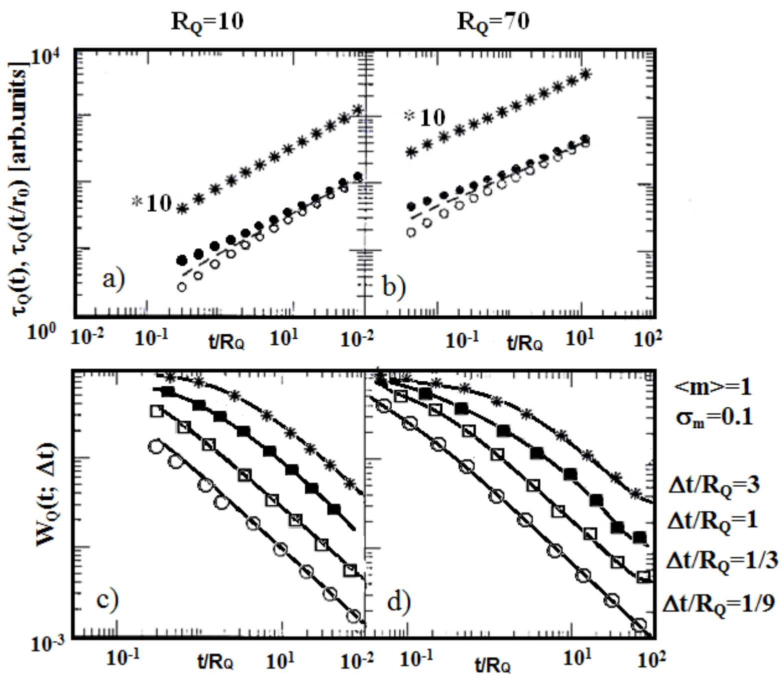

Figure 2

Figure 2 (c) and 2 (d) from [2] show the W_Q values for the MRC model with a power spectrum of the form 1/f for R_Q = 10 and R_Q = 70 , respectively. For such records, PDF is better described by the gamma distribution than by a power law, deviating significantly from it on a large scale, and therefore in this case it is very difficult to obtain an analytical expression for W_Q. Empirically, in [2] it was shown that the best estimate for W_Q in this case is obtained if in the denominator of the fraction (12) replace t/R_Q to $(t/R_Q)^{1-\varepsilon}$ with ε = 0.15 with ε = 0.15, which leads to assessment

$$W_Q(t;\Delta t) = \frac{(\delta(Q)-1)\Delta t/R_Q}{(t/R_Q)^{1-\varepsilon}+(\delta(Q)-1)\cdot\Delta t/R_Q} \quad (15)$$

For large t/R_Q, strong finite-dimensional changes occur, which are especially pronounced with large R_Q (Figure 2 (d)). These effects weaken with increasing R_Q and increasing the length L of the time series. In this case, the denominator in (14) is underestimated, and thus the W_Q estimate is artificially inflated.

Another measure of the quality of prediction using long-term memory is the expected number τ_Q (t) of time units, after which the next Q-event will appear (i.e., a record with a value greater than Q) as soon as t time-units have passed after the last Q-event. By definition, τ_Q (0) is equivalent to the period R_Q (the average value of the lengths of all repeated intervals with records greater than Q). In the general case, τ_Q (t) is related to the probability density function (PDF) of P_Q (r) by

$$\tau_Q(t) = \frac{\int_t^{\infty}(r-t)P_Q(r)dr}{\int_t^{\infty}P_Q(r)dr} \quad (16)$$

Figure 2 (a) and 2 (b) show the global τ_Q (t) and the conditional τ_Q (t|r_0) expected number of time units after the expiration of which the following Q-events obtained from the data, a generated MRC model with a power spectrum of the form 1/𝑓 (a) for R_Q = 10 and (b) for R_Q = 70 ("o" for r_0 = 1 and for r_0>3). The dashed lines denote the values τ_0 (t)

From figure 2 it follows that τ_0 (t) satisfies the power law

$$\tau_Q(t) \sim (t/R_Q)^{\xi(Q)} \quad (17),$$

Where the exponent ξ(Q) decreases with increasing Q (ξ = 0.6 for R_Q = 10 and ξ = 0.47 for R_Q= 70). The conditional expected number of time units τ_Q (t|r_0) for r_0 = 1 can also be described by a power law with approximately the same exponent ξ(Q,r_0), as the exponent ξ (Q,) for the global value τ_Q (t). On the contrary, for r_0 > 3, τ_Q (t|r_0) significantly deviates from the power law for small values of the variable t|R_Q. For large values of t/R_Q, the graphs of the function τ_Q (t/r_0), corresponding to the values r_0= 1 and r_0 > 3, are close to collapse (merge).

An interesting fact, noted in [4], is the presence of linear long-term correlation in repeated intervals for multifractal data with the absence and presence of linear correlations. This is due to the fact that linear and nonlinear correlations present in the original data have a significant contribution to the linear correlation of repeated intervals, so that even in the absence of any linear correlations in the original data, repeated intervals can have long-term correlations.

Figure 2 (a, b) - expected value of time units τ_Q (t) and conditional expected value τ_Q (t|r_0) ("o" for ξ = 1, and for r_0 > 3) the appearance of the next Q – event after t intervals heartbeats that have passed since the last occurrence of a Q event in the MRC data model, characterized by a 1 / 𝑓 power spectrum, for R_Q = 10 and R_Q = 70, respectively; dashed lines represent τ_Q (t); (c,d) - values of the function.

W_Q (t;Δt):(c)) for R_Q = 10 and (d) for R_Q = 70 for those MRC records where the symbols (○), (□) and (◊) correspond to the estimates for Δt/R_Q equal to 1/9, 1/3, 1 and 3, respectively, for the MRC records obtained at L = 221 and testing of N = 150 systems, while the approximations for W(t;Δt) are calculated by the formula (15) .

4. Comparative analysis of methods for predicting emissions of time series with fractal properties using short-term or long-term information

The simplest forecast is obtained by choosing the estimate (12) with a high probability with a fixed value Δt=1. The results obtained are in good agreement with the corresponding results for the MRC model. To build a more accurate prediction, an algorithm is proposed in [2], which involves comparing the estimates of W_Q with different fixed values of Q_P and calculating the corresponding risk probabilities. For a fixed value of Q_P, two indicators are defined: sensitivity (sensitivity) Sens, which characterizes the proportion of correctly predicted Q events and the specific (sencificity) Spec, which characterizes the proportion of correctly predicted non-Q events. Larger Sens and Spec provide better prediction.To improve the forecast efficiency, analysis using the receive-signal operator (recuver operator characteristic), the so-called ROC analysis, is used, according to which the Sens and Spec plot is plotted for all possible Q_P values. By definition, Q_P = 0 when Sens = 1 and Spec = 0, while Q_P = 1, when Sens = 0 and Spec = 1. When 0<Q_p < 1, the ROC curve extends from the upper left corner to the lower right corner on the plane (Sens, Spec).

If there is no memory in the data, Sens + Spec = 1 and the ROC curve is a straight line connecting the two angles indicated (dashed lines in Fig. 3 [9]). The general measure of forecast accuracy, PP, 0 <PP <1, is represented by the integral over the ROC graft, which is equal to 1 with absolutely accurate prediction and equal to ½ for random data. To estimate the probability of risk, you can use the "reverse" sampling of observed records in the form of an MRC model. In the traditional technique of recognition of specified patterns (patterns, standards), the so-called PRT-recognition technique (pattern recognition technique), based on short-term memory, a database of various patterns $y_{n,k}$ is built from to the previous messages with a sliding window that divides full sample of possible values of records y_i on l levels with the same number of values, so that the total number of patterns is l^{κ}. Then, for each precursor pattern $y_{n,k}$, the probability $P(y_n>Q/y_{n.k})$ is estimated that the next event y_n exceeds Q. The main difficulty here is the need to repeatedly adjust to find the optimal values of the parameters l and k leading to high prediction accuracy. In an alternative RIA-technology using long-term memory, the probability W_Q (t;Δt) is determined from observable records using equation (8) or the analytical expression (13). As shown in [2], the RİA-approach to predicting Q-intervals, which does not require the limitedness of the statistics used, gives the best result in all cases. In fig. 3 [2] it is shown that with R_Q =10 both approaches give approximately the same results in three representative cases of the patterns k = 2, k = 3 and k = 6, and for R_Q = 70 the ROC-curve of the systematic is located above the RİA curve in the vicinity Sens = 1. Experimental studies show [2] that PRT forecasts using a “training” sample of observed records are, as a rule, more accurate than forecasts obtained using records of a synthetic MRC model.

The reason for this is the limited ability of the MRC model to describe the short-term dynamics of heartbeat intervals, including individual variations in physiological regulation. In this regard, the high sensitivity of the RIA-technology leads to a significantly smaller number of spurious signals than the PRT-technology. In Fig.3. ROC curves reflect the efficiency of forecasts obtained from MRC records, characterized by 1/f power spectrum: (a) for R_Q=10 and (b) for R_Q=70, based on PRT technology with k = 2 (•), k = 3 (□) and k = 6 (+) and RIA-technique (Δ)□_ using formula (13). Similar curves are presented in fig. (c) - (h) for three presented records of heartbeat intervals, with the ROC-curves shown for k = 1 (o) and k = 2 (□) for patterns obtained by MRC model for k = 1 (o) and for patterns obtained by directly observable values for k = 2 (□). Figures 3 (a) and 3 (b) show the ROC-curves reflecting the effectiveness of the prediction of a significant MRC model, the records of which have a linear correlation, with a 1/f power spectrum obtained with $l=2^{21}$ and with R_Q=10 and R_Q=70. From these figures it follows that in these cases, the statistics of excellent (compared to records obtained directly from the observed data), the forecast efficiency in both cases is very high and the forecasts are comparable with each other. In fig. 3 (c) - (h) shows the ROC-curve obtained by the three presented values of the records 5,14,18 (out of 20 records) heartbeat intervals. These figures also show the corresponding results obtained by the PRT technique on the observed records, while the “training” was performed on 10 records selected at random from the remaining 17 records. The figure shows that in all three records considered, both the ROC curve and the RIA-technology give fairly well-comparable forecasts at R_Q=10, and at R_Q=70, the RIA-forecasts in all three cases exceed the accuracy characterized by ROC curves, especially near Sens values = 1.

At the same time, PRT forecasts based on “training” in observable records are better than forecasts trained in model records. The reason for this fact is a fairly good degree of learning statistics and the limited ability of the MRC model to represent the short-term dynamics of heartbeat intervals, including the presence of individual variations of physiological regulation.

Accordingly, at high values of the Sens indicator, the RIA forecasts have significantly lower values of the false alarm indicator Spec than the PRT forecasts.

In a practical test of predicting the dynamics of a random process using the estimate W(t;Δt;r_0), we compare the results obtained using empirical estimates of P_Q (r/r_0) for the first four bins of r_0 values and similar characteristics obtained on the basis of the MRC model, moreover, for the first bean we will use approximation (13). In this case, the criterion of the quality of the work of the method will be understood as the areas obtained under the ROC-curves in the plane (C, D), where C=Spec and D=Sens (Fig. 4) [15].

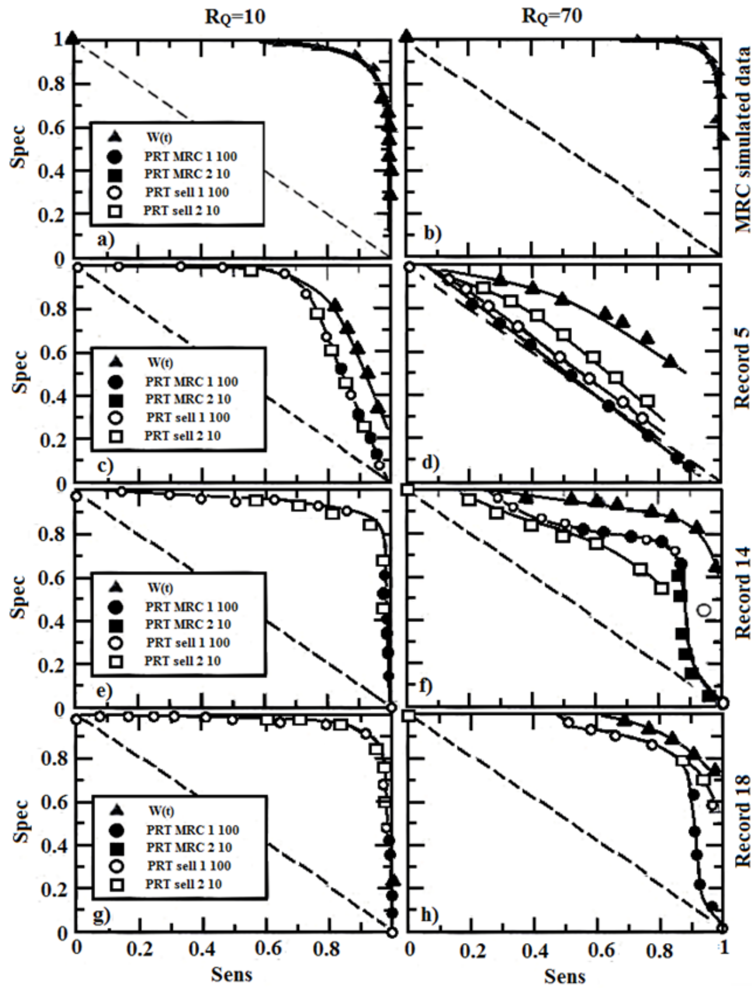

Figure 3

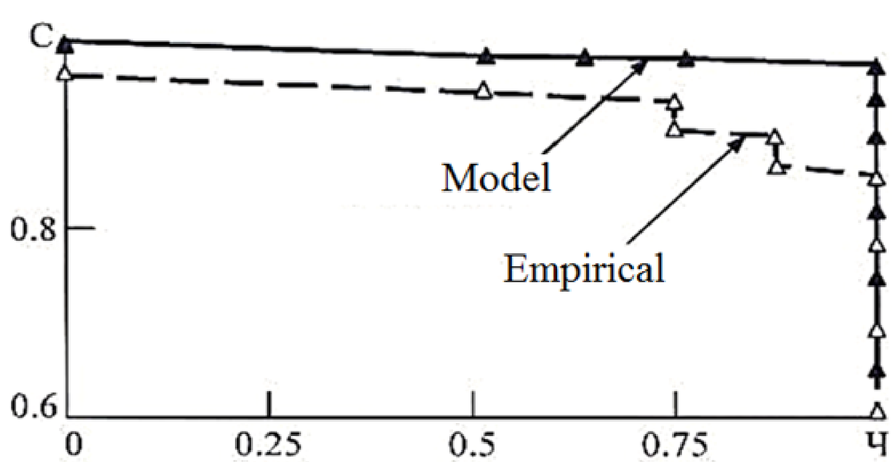

Figure 4

From figure 4 that the ROC curve for estimating W(t;Δ|r_0, obtained using the P_Q (r/r_0), characteristics approximation, for the multifractal model (Figure 1), shown in Fig. 4 with a solid line, for all threshold values are higher than the ROC curve obtained using the empirical estimate P(r|r_0) for real data (dashed line). The area bounded by two curves characterizes the resulting gain.

Conclusions

1. The efficiency of prediction of dynamic series with multifractal properties is much higher than the series with monofractal properties, which indicates the importance of the non-linear component of dependence in the source data
2. Linear and nonlinear correlations present in the original data contribute to linear correlations of repeated heartbeat intervals, so repeated intervals can have long-term correlations even in the absence of linear correlations in the original data.
3. When using information about both short-term and long-term dependence, with equal values of the false alarm probability (Spec), approximately equal probabilities of correct prediction (Sens) are achieved.
4. Use in the study of records in the heartbeat intervals of long-term memory inherent in events occurring after the last Q-event (RIA-approach) has an undoubted advantage over the PRT-technology that uses only short-term memory.
5. The main disadvantage of the RIA-approach is that it usually cannot predict the first event in a cluster of Q-events with a large number t of used heartbeat intervals, at which W(t;Δt) becomes low. However, due to the multifractality of records in clusters of extreme events, the gains from the best predictions following the first event in the Q-events cluster and from the reduction of false alarms in the RIA-approach significantly exceed the losses from the weak predictability of the first events in the Q-events cluster, which is confirmed by ROC analysis. In addition, the RIA-approach does not require intensive use of training procedures and repeated testing of patterns, which facilitates its numerical implementation in comparison with the PRT-approach.
6. Additional accounting of information on the value of the previous interval between outliers can be obtained by moving to the main probabilities W(t;Δt|r_0), calculated on the basis of conditional probabilities P(r|r_0).
7. It is necessary to take into account that the indicated conclusions were obtained under the assumption that there is no noise in the initial data. The effectiveness of PRT and RIA prediction methods in the presence of source data noise and noise immunity of both methods require separate consideration. The results obtained in this direction will be presented by us in subsequent works.

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