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Complex systems method approach to the ECG analysis

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***Abstract*-Q-statistics combined with multi-fractal structure investigation and log periodicity evidence have been used here in the analysis of time series of ECG records for a common pathology, arrhythmia. We observe that q-distributions of filtered or de-noised data differ from them of direct data, so those procedures affected the state of the system, getting out of the sight part of statistical and dynamical information. In the other side the multi fractal structure does not change significantly, so as expected, in the diagnostic sense common filters have no important implication. Next, the q-Gaussians were found useful to describe the overall statistics of the events, specifically in the sense of in-homogeneity for characteristic parameters as amplitude of the R and S electro-signal and the period of occurrences. In our case study of ECG records in arrhythmia pathology, log-periodic behaviour was found in the trends of R and S amplitude dynamics. Traces of log-periodicity were obtained in the decoration of q-Gaussians fitted to the distribution too. Thus, hierarchical self-organisation behaviour and their effect could become part of detailed diagnostic or therapeutic procedures. We observe that different multi fractal structure characterize different signals registered from different points. Bringing together all those findings, we admit that those methods will reveal more information from the series in ECG and perhaps for others bio-signals.**

***Index Terms*— medical physics, multi fractals, discrete scale of invariance, log-periodic, Tsallis statistics.**

I. INTRODUCTION

Electrocardiogram (ECG) is a graphical interpretation of the electrical activity of the heart. It consist of billions micro signals generated from the contraction of the cells in heart muscle. The registration is realized by measurement of

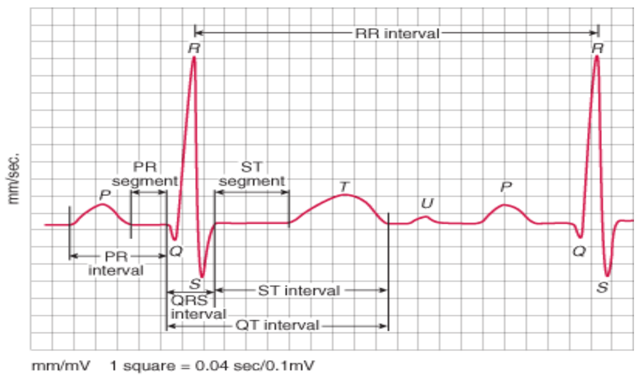

Fig1. Elements of ECG.

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voltage in different part of the human body, usually in 12 points. The standard ECG waveform has two main components: polarization and depolarization. The P wave and QRS complex denote atrial and ventricular depolarization, respectively. The ST segment, T wave and the U wave account for ventricular re-polarization. Consistent ECG interpretation requires a systematic approach based on well-known parameters. So, the rate is normal at the values 60-100, and pathologic otherwise, for example bradycardia has the rate less than 60 and tachycardia higher than 100. It can easily understand by measurement of the occurrence of cardiac cycles (P-QRS-UT). Other important elements are the time intervals found on the ECG series and morphologies of the waves. The pathology of premature ventricular complex (PVC) is characterized by the premature occurrence of a QRS complex that is generally longer than 120 milliseconds in duration. Premature atrial beats generally have an abnormal looking P wave that comes early, a narrow complex QRS that resembles a normal beat, and usually (although not always) a compensatory pause following the PAC. 1st Degree AV Block is a prolongation of the PR interval. It usually results from AV nodal dysfunction. The normal PR interval is 120 - 200 ms. In the elderly, the upper rate of normal is 220 ms. In the case above, the PR interval is approximately 300 ms, suggesting first degree AV block and so on. All of them are routinely scrutinized by doctors and specialized physicians using respective analysis. According to the nature of ECG signals generation and registration, the system as a whole with any doubt is complex and therefore particular treatment of complexity could be helpful. In this aspect there are dedicated papers on the multi-fractal properties of ECG data series [1], and other suggestion to apply complex system methods. In fact, physiologic time series contain hidden information related to an extraordinary complexity that characterizes physiologic systems, and so has fueled growing interest in applying techniques from statistical physics for the study of living organisms [2]. Here we propose to consider distribution of the amplitudes of each wave as another important output rich with information, the self-organization behavior especially in the sense of presence discrete scale of the invariance. Another aspect of this consideration is related to the possible effect of the routinely filtering or de-noising original data.

II. SOME STATISTICAL AND DYNAMICAL PROPERTIES UNDER COMPLEXITY PARADIGM.

Let we brief here some specific elements of statistics in complex systems that usually are found in the out-of-equilibrium state [7],[8], hence not appropriate for ordinary statistical treatments. Quite similar with the optimization of classical (Boltzmann-Gibbs, Shannon) entropy $S_{Boltzman} = -kp_i \log_2 p_i$ in equilibrium states, for complex systems C.Tsallis has proposed to maximize a specific entropy $S_q^T = \frac{1}{q-1}\left[1-\sum_{i=1}^{w} p_i^q\right]$ [9],[10],[11] under appropriate constraints, to obtain the distribution or for other statistical mechanics consideration. If the state under analysis has the mean of a variable x definite, the distribution found in this way results to be a q-exponential function namely $e_q(-\beta(x-\mu) = \alpha\{1-\beta(1-q)(x-\mu)\}^{\frac{1}{1-q}}$, and moreover if q-variance of the variable x is defined, distribution is a q-Gaussian [9],[11] in the form $e_q(-\beta(x-\mu)^2) = \alpha\{1-\beta(1-q)(x-\mu)^2\}^{\frac{1}{1-q}}$. Q-calculation of specific moments (mean, variance etc.,) is in the form $x_n = \int p_q x^n dx$. Here q-parameter is labeled “q_{stat}” and measure the distance from the equilibrium as in the limit q→1 the classical entropy is recovered. In Tsallis statistics a triplet of parameters, the sensitivity parameter (q_{sens}), the relaxation parameter (q_{relax}) and the stationary parameter q_{stat} are significantly more important [7]. Q_{sens} estimate the sensitivity to the initial condition and in some special case it measures the rate of the entropy production. It is found using relationship $\frac{1}{1-q_{sens}} = \frac{1}{\alpha_{\min}} - \frac{1}{\alpha_{\max}}$ where $\alpha_{\min,\max}$ are the singularity point of the fractal power function of the structure [9]. Multi-fractal property consists in the local power law behavior in any point say $X(n+a) - X(n) \sim a^{h(n)}$ where h(x) is called the singularity exponent. The ensembles of point having the same h exponent produce the fractal dimension D(h), that identify the (logarithmic) ratio of the change in the detail to the change in the scale [3]. Closely related to it is the multi fractal spectrum $f(\alpha)$ that measures the density of the local similarity in scaling $\rho_\alpha(\varepsilon) = a^{-f(\varepsilon)}$ where ε is a local size [4]]. We will consider this last twice: to help estimation of the sensitivity parameter in Tsallis triplet and to directly evaluate self-affinity property of time series considered. Q_{relax} is estimated from the relaxation rate and generally is calculated from the q-exponential fitted to the time autocorrelation function of the series. Another important feature of complex systems is the discrete scaling property, that is, for physical observable F we have $F(\lambda x) = \lambda^\alpha F(x)$ which hold only for some discrete value of λ [12]. The time behavior in this case is theoretically predicated to be a log periodic function [12] of a non-homogenous variable $x = t - t_c$ where t_c is a critical time, like critical points in physics, when the regime is expected to change drastically. Log-periodic forms encompass global and local scaling features [12]. We will use the form $I = I_0 + a * x^m + bx^m \cos[\omega \log(x) + \varphi] + cx^m \cos[2\omega \log(x) + \varphi]$ that has been introduced from us for other systems as more easily to fit [16], but essentially it is the same as the general form used initially [12]. The presence of the log-periodic behavior is considered an argument for self-organization with discrete scale of invariance structure. Next, related to q-distributions prescribed above, in some systems where self-organization behavior for some hierarchic level occurs, a log periodic term is reported to decorate the q-Gaussian distribution [14]. The general form of this perturbation is proposed $f(X) \sim e_q(-X)\left\{w_0 + w_1 \cos\left[\frac{2\pi}{\ln(1+\alpha)} \ln\left(1+\frac{X}{Ta}\right)\right]\right\}$ where X is an energy-like function or variable [14]. The fit of the empiric distribution to q-Gaussians or q-exponentials will suffer generally from the difficulty of optimization of the cost function, but it could be realized using nonlinear least square techniques if parameters-domains are carefully selected according to the theoretical view. In the case of log periodic functions different and combined methods are usually needed [17]. We made use of parametric (Jakobson) derivative combined with preliminary Lomb periodogram, and finally applied a genetic procedure that produce an acceptable fit of the dynamics with log-periodic functions in similar cases[15],[16]. Those two preliminary procedures are not displayed here as they only helped us to facilitate the calculation. But in their own they are very important for a rigid physical consideration.

III. Q-STATISTICS, MULTI-FRACTALS AND COMPLEX BEHAVIOR ON ECG SIGNALS.

In this analysis we used a data set form physionet.org that belongs to pathological syndrome known as arrhythmia and include original and filtered signal. Filtering was reported on the database as realized by a routine standard procedure as in all ECG diagnostics [6],[8]. From physical point of view we can assume that pathologies could affect all parameters at once, but in practice one of them will be measured and analyzed for specific tasks. According to the pathological symptom, different types of signal modification are possible

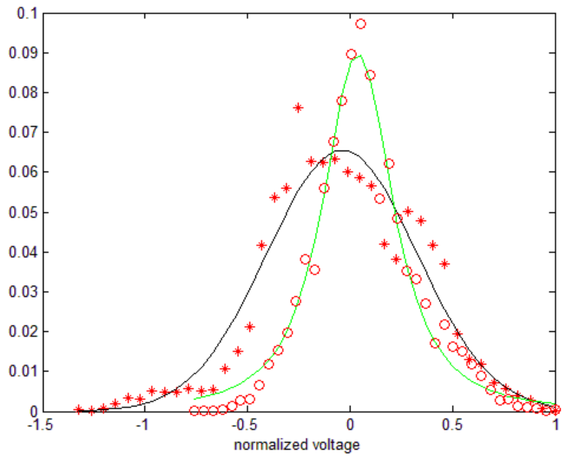

Fig2. Fits of the ECG signals. q-Gaussian of original signal (black) and filtered signal (green). By markers, real points

and typically cardiac cycle occurrence modification, wave amplitude modification or combined ones [4],[8]. It means that the distribution of the amplitude will be somewhat skewed, and the time occurrence typically irregular. Those new properties are measured here using q-Gaussian distribution, multi fractal spectrum analysis and log-periodic dynamics respectively. Amplitude and frequency modifications separately, will report other first order or

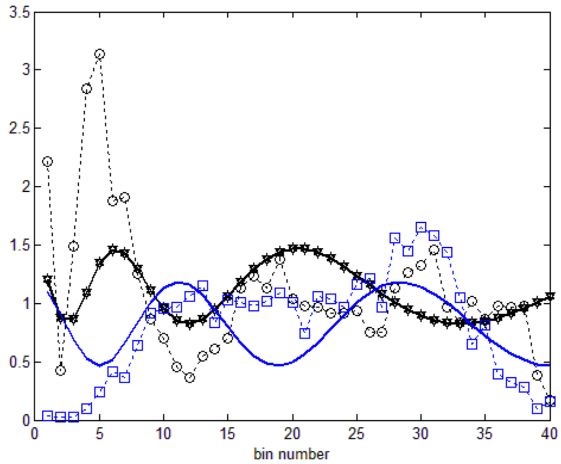

Fig3. Decoration of q-Gaussians with log-periodic term. Blue, filtered, black, orginal. By markers, real raport

accompanying functional disorders in all the chain of heart activity that affect the electrical response from the tissues. So far self-similarity of the signals will evaluate the nature of such changes. If changes are smooth and so the power spectrum is concave and continues, they could be just normal fluctuations, otherwise, they signal physiologic problem or failure, hence multi fractal spectrum is full of information [5]. It seems that in-conscientiously an ECG analyst considers this property in the sense of resemblance of signals to diagnosis heart problems. Original data as a rule are too noisy and filters are necessarily applied but they can possibly hide information too. In standard techniques of filtering and de noising, this special care is balanced with the purpose of the rapid diagnostics. In the following we will compare q-statistics results for the original and standard filtered ECG to deal with secondary information presence. Next, we'll focus in some view for general analysis using different series produced by original one to read the statistical and dynamical

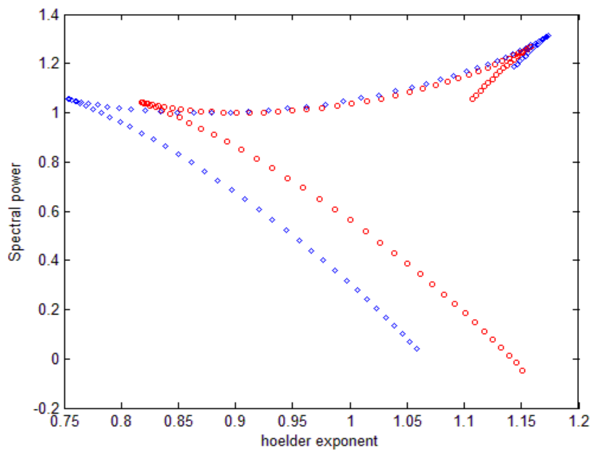

Fig4. Multi fractal spectrum. Red markers, filtered data, blue markers original (noisy)

state and time evolution behaviour. If multi fractal structures produce a concave smooth shape, the estimation of the $q_{sensitive}$ will make possible an appropriate evaluation of the entropy production in system that is the dynamics of the system starting from the point considered. If this will be realized just in time, it is possible to say what is the most probable near future of the patient. Comparing the two ECG signals we see that q_{stat} change remarkably and so do the goodness of fit. We obtain $q_{stat.}$~1.703 in filtered signals as they are read form doctors, and 2.23 for q-Gaussian modified by a log-periodic term (Fig2). We found q=1 for the normal q-Gaussian in the bin size as optimized using Scot rule, but in this case the fit is very sensitive to the histogram optimization so we reject it, and we keep the value 1.7 found in for bin size optimized empirically, using a medium value between Freedman-Diaconics and Scot bin size. In the original data we see that the decoration is approached with a

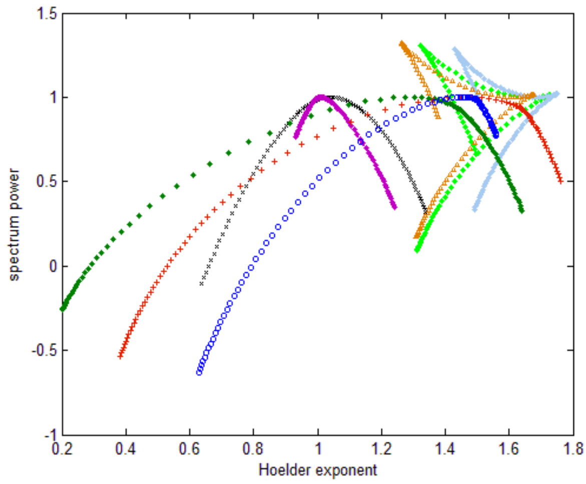

Fig 5. Different behavior of multi-fractal spectrum and distribution

log-periodic-like term using the voltage as energy like parameter (Fig3). Up now we observe that filtered and original data have different statistical characteristics under q-statistics approach. In the sense of self-affinity of amplitudes, we read from the multi-fractal analysis (Fig4) that filtering process does not affect the signal and all two functions of power spectrum are similar and report a physiologic failure [4].

In the filtered data the decoration of the q-Gaussians does not follow log periodic behavior in the trend thus the procedure of the filtering seems to eliminate elements on the signals that are related with hierarchic organizational behavior. Q-Gaussians reflect the nature of the symmetry on signals and meanwhile filtering highlights specific ECG information to be processed in the diagnostics, it seems to hide elements of such symmetry, causing two q-distribution to have quite different stationary q-parameter. To better understand those effects we've reconsidered the signal from pathological situation of arrhythmia, but now gathered from many point of registration type MLII and V2 as explained in data base source [6]. The first is "modified lead II", a bipolar lead parallel to the standard limb lead II, but acquired using electrodes placed on the torso (a requirement for long-term ECG monitoring). V2 is a precordial lead that is roughly orthogonal to MLII. These two leads are favored for many recordings, since MLII yields high-amplitude normal QRS complexes in most subjects, and V2 usually offers a nearly optimal frontal-plane projection of any ectopic beats that happen to be of low amplitude in MLII. Here, the q-Gaussians fitted to each distribution on particular series are found different. For example we obtain q_{stat}~1.358 in MLII records and q_{stat}~1.119 for V2 registration that report quite different distance from the equilibrium and so on. Signals reaching electrodes from different points are modulated differently affecting directly the distribution. So it consist to a valuable information for the overall complex behavior of heart electricity. In this case the parameter (electro signal) that belongs to a most un-stationary state could be evaluated as an indication reporting perhaps a specific aggravation. Next, as is shown in Fig5, from 5 such series we observe that the multi fractal structure produce smooth and concave power spectrum function, while for other 3, the multi-fractal structure report a near to chaotic regime or abrupt changes on the electro-signal. Again the distributions have two small peaks accounting for the R and S waves' amplitude, like in Fig2. For full registration taken in the standard points {II,V1,aVF,CS12,CS34,CS56,CS78,CS90}, we obtained from the q-Gaussians fitted the values q_{stat}=[**1.8690** 1.4228 1.7934 1.7605 1.0000* **1.9575** 1.4987 **1.8097**]. It is clear that the distance from the stationary is remarkable distinguishable, so we can judge that the most possible clinically disturbed parts are they that affect the electro-signals recorded in [**II, CS56, CS90]** etc. Moreover, in series recorded in the points {V1,aVF,CS12,CS34, CS78 }, one can evaluate directly the q-sensitive $\frac{1}{1-q_{sens}}=\frac{1}{\alpha_{\min}}-\frac{1}{\alpha_{\max}}$ because the multi fractal spectrum is smooth and convex, hence the extrapolation was approached very well by polynomial shape whereof $\alpha_{\min,\max}$ were obtained (Fig5). Accordingly, we can estimate the dynamics of the system using q_{sens} as measure of the sensitivity form initial condition or entropy production rate in actual state. Again, it will support valuable information to the specialists for diagnostics and therapeutic uses.

IV. TIME BEHAVIOUR OF PEAKS FOR R AND S –WAVES AND THEIR DYNAMICS

In this section we considered two amplitudes in R and S ridges neglecting all intermediary points including T and U waves. There are usually 200 points in between two successive R waves, so the number of points in the new series was reduced

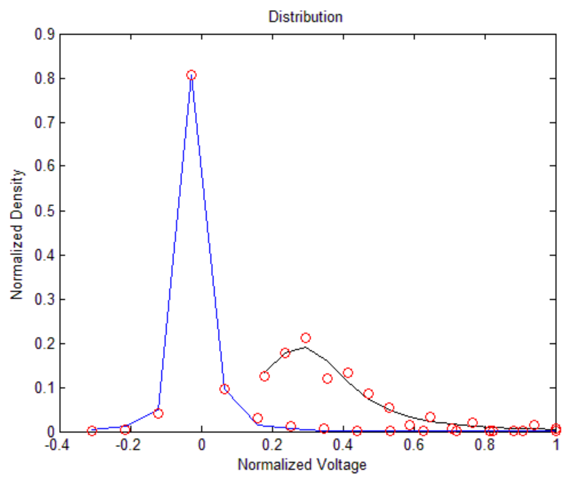

Fig6. Distribution for R and S amplitude

by a factor 100. To cut the R and S amplitude we filtered firstly using the threshold at 0.5 mV according to the general assumption for R and S wave amplitudes. Q-statistical analysis is performed over this new series to read the level of stability of the sates. It is logical to check the stability first and after that to use those finding for further step analysis. Now from q-functions fitted to the empiric distribution for the series of R and S-waves amplitudes the statistical q-parameter was obtained at 1.703 and 1.78 respectively, wherefrom we immediately see that q_{stat} >5/3. Therefore the two signals report "exited states" since they are in a zone of infinite variance in the sense that, if we add more records, the variance will add up (Fig6). We briefly conclude that the dynamical state of R and S wave were found different, and moreover they belong to stable distributions but with variance and mean indefinite. In mathematical sense these values do not converge, but in truncated distributions indefinite seems a more meaningful term as compared with "infinite" so we keep it even here. In the physiological approach the respective processes seems to be governed from unbalanced mechanisms of polarization-depolarization, and those changes are measured by q_{stat} read form q-distributions. Adding to that we observe that the series consist on data that belong to a high non-stable processes characterized by indefiniteness of some statistical variables. Extending our view in the medical view, it seems more convenient that a physician needs to treat the patient dynamically until a more stable distribution will be

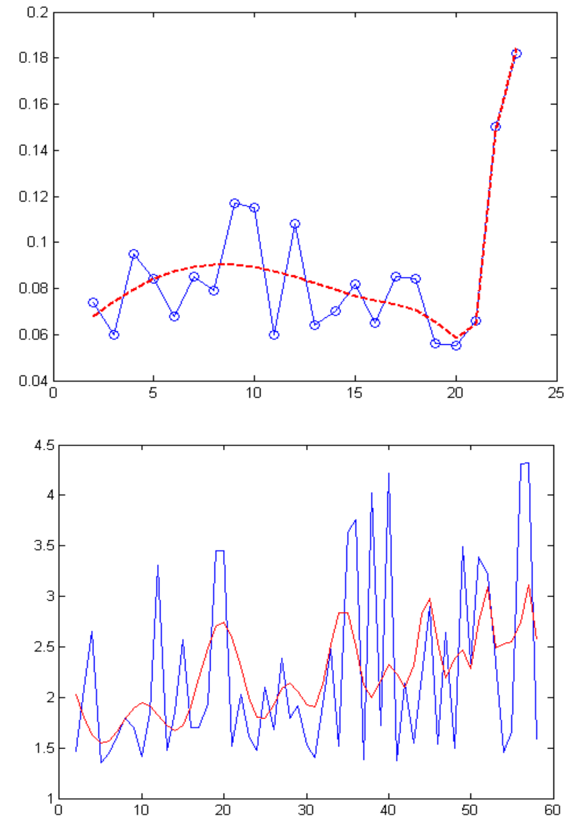

Fig7. Dynamics of R-amplitudes : change of the regime expected to occur in the future.

reached (on the zone of q_{stat}<5/3) and all of this could be monitored using q-distributions as in this paragraph. For our extended view, this far-from the equilibrium state is full of dynamics, and it is reasonable to search for DSI self-organization behavior. It will be worthy to consider time processes even other than standard cycle (P-QRS-TU) so new series of averaged amplitudes among few successive

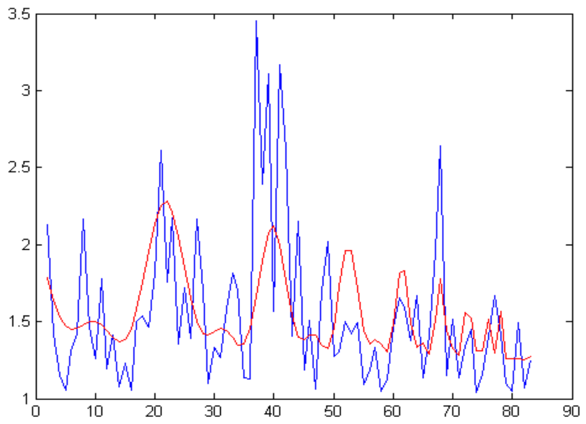

Fig8.Relaxation of the amplitude

neighbors are used. In those lasts the quantitative analysis is questionable because the number of R,S-amplitudes is not large enough, so it would be considered only qualitatively, but in concrete consideration it is possible to administer series with many points improving the analysis. To this purpose we checked the dynamics of the amplitudes (R ands) for 8 signals for the same patient as in the preceding paragraph. We find a good log periodic fit in some cases that will be related to possible presence of DSI self-organization. In this case we've considered the evolution of the amplitude

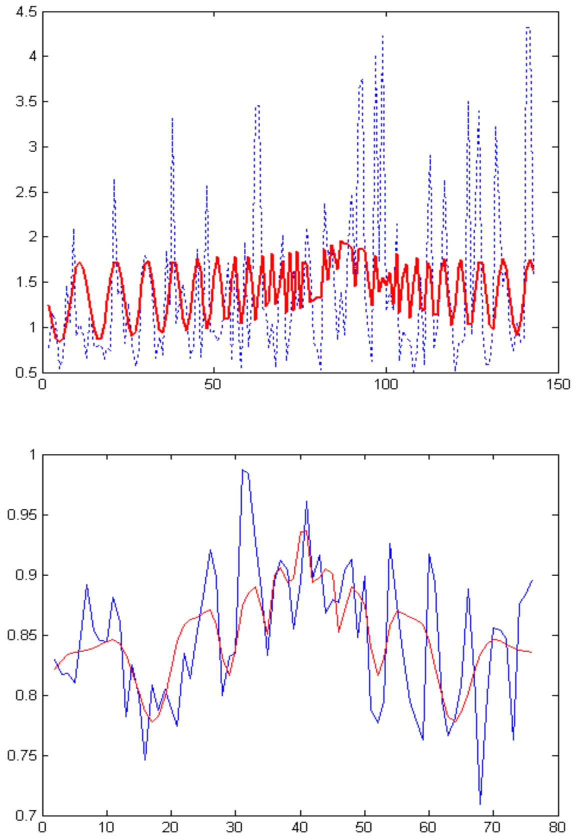

Fig.9. Evidences form fitted log-periodic curves(black line) . Above, amplitude in arrhythmia regime, below, changing of arrhythmia stage.

and tried to fit the dynamics with a log periodic shape of the form used recently [15],[16]

$$I(t) = I_0 + B(t-t_c)^m \begin{bmatrix} 1 + C\cos(\omega(\log(t-t_c)+\varphi_1)) \\ + D\cos(2\omega(\log(t-t_c)+\varphi)) \end{bmatrix}$$

where t_c is the critical time. It will represent the moment where remarkable change in the physiological behavior of the organ are possible to occur. In the pathologic sense this could be the moment when the patient is more probably to become suddenly better or get even worse, hence it will bring another

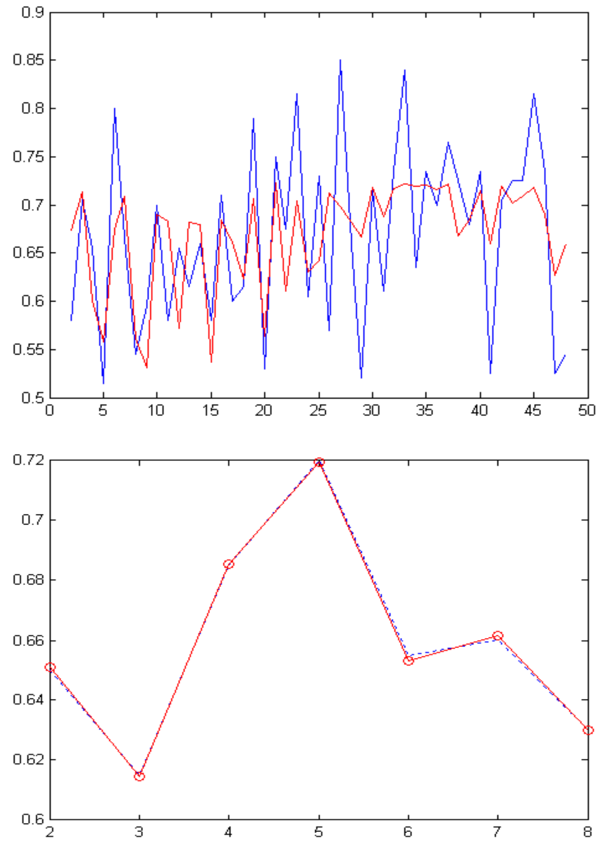

Fig.10. Evidences from log-periodicity (black line). Above, non-homogenous cycles, up-left, below fitted log-periodicity for long time events

information if dynamical treatment/observation is conducted to the patient. Physically it consists in a symmetry broken point, so another regime will top follow. In the statistical sense this is the moment when the extreme event is highly probable to occur. Remember that similar with other DSI systems, this critical term should not be confused with deterministic notation that is the time when the extreme event or change in the regime will occur. This last could not be known with certainty in the DSI approach [18],[19], but ht probability to occur if not yet realized is maximal in this point. To get the fit, here we proceeds with pre-selecting time interval [t_i,t_f] that will produce the best log-periodic approach, that is, the critical value and critical time will be reproduced within a admissible accuracy. In appropriate time intervals the fit was found admissible indicating the presence of the DSI behavior. In this case some short comments are possible, telling that even non specialized staff could read the result as follow. In Fig7 the amplitude of R-ECG has entered a self-organizing phase and remarkable changes will occur in the near future as read from the critical time t_c. In the series of Fig8, the change is coming more smoothly. In Fig9 there are many other cases where log-periodic approach gives interesting results. The analysis is extended in the frequency of occurrence too. Here we produce novel series in some small groups to see what the sequential behavior that is , if a disturbing process is repeated in time. In this case we do not care roughly in amplitude fit but in the rhythmic fit. In fig 9 and 10 are selected some pictures of log-periodic fit that reveal the interior timing of arrhythmic behavior in the sense of the appropriate large time (many cycles) where a specific event will be eventually repeated or reproduced with some similarity.

V. Conclusions

Complex system approach in the study of ECG could improve the reading and understanding of the bio-electric signals generated from heart activity. The first application could be in the framework improvement in some sense on filtering procedures and techniques. Here q-statistics can be used as control tool when dealing with fluctuation's de-trending process. Second, important information for dynamics of the system can be read form q-analyses, especially if in this regard the overall state is not far from the equilibrium. In the other cases, q-analyze combined with multi-fractal consideration will help to keep calculation un-contaminated from fake assumption. The last application herein, but not the last in general, could be the analysis of the amplitude evolution for each wave and the timing process on the cycles using log periodic approach. This may help even not qualified person (nurse for example) to follow up the patient dynamics and to report it. It is quite natural to extend this view for other bio-signals.

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