LEGIBILITY NOTICE

LA-UR -89-3192

LA-UR--89-3192

DE90 000692

TITLE MONITORING CHAOS OF CARDIAC RHYTHMS

AUTHOR(S) GOTTFRIED MAYER-KRESS, CNLS

SUBMITTED TO "BIOTECH USA", PROCEEDINGS OF THE 6th ANNUAL INDUSTRY CONFERENCE AND EXHIBITION, OCTOBER 2-4, 1989, SAN FRANCISCO, CA.

Los Alamos National Laboratory
Los Alamos, New Mexico 87545

Monitoring Chaos of Cardiac Rhythms

Gottfried Mayer-Kress, Ph. D.

Mathematics Department, University of California at Santa Cruz

The Santa Fe Institute, 1120 Canyon Rd. Santa Fe, NM 87501

Center for Nonlinear Studies, Los Alamos National Laboratory

MS-B258, Los Alamos, NM 87545

Abstract

Chaos theory provides a new paradigm in monitoring complexity changes in heart rate variability. Even in cases where the spectral analysis only shows broad band characteristics estimations of dimensional complexity parameters can show quantitative changes in the degree of chaos present in the interbeat interval dynamics. We introduce the concept of dimensional complexity as dynamical monitoring parameter and discuss its properties in connection with control data and data taken during cardiac arrest. Whereas dimensional complexity provides a quantitative indicator of overall chaotic behavior, recurrence plots allow direct visualization of recurrences in arbitrary high dimensional pattern-space. In combination these two methods from non-linear dynamics exemplify a new approach in the problem of heart-rate monitoring and identification of precursors of cardiac arrest. Finally we mention a new method of chaotic control, by which selective and highly effective perturbations of nonlinear dynamical systems could be used for improved pacing patterns.

Biography:

Gottfried J. Mayer-Kress, is visiting assistant professor at the Mathematics Department of the University of California at Santa Cruz and research colaborator of the Santa Fe Institute and the Center for Nonliner Studies at the Los Alamos National Laboratory. He holds a Diploma in theoretical physics from the University of Hamburg, West Germany and a Ph. D. in theoretical physics from the University of Stuttgart. His work was centered at chaotic aspects of synergetics and applications of chaos theory to biological, medical and socio political systems and arts.

In: "Biotech USA", Proceedings of the 6th annual industry conference and exhibition, October 2-4, 1989, San Francisco

Introduction

A basic feature of recent methods in nonlinear dynamics is a geometrical view of temporal processes. From an observed time series of, say, interbeat intervals, a sequence of multidimensional vectors is reconstructed. These vectors can be interpreted as patterns in the observed time signals. With the methods from chaos theory it is possible to operate in this space of temporal patterns with geometrical and quantitative methods (see e.g. [5]). In this contribution we want to discuss the concept of fractal dimension and also the concept of close recurrences of patterns, which might diagnostically indicate some significant regularity in the heart rate dynamics.

Below we give a brief overview of the concepts of dynamical dimension estimates and then describe the methods we have used to obtain an unbiased estimate of dominating dimensional complexity parameters and the detailed structure of the scaling properties of reconstructed attractors.

Assume we are measuring a single variable discrete time-series $x(t_m) = x_m$. In the current context x_m would correspond to an interspike interval or instantaneous heart rate. Then we can reconstruct vectors $\vec{x}_m$ in a n-dimensional state space through time delay coordinates: $\vec{x}_m = (x_m, x_{m-k}, x_{m-2k}, \ldots, x_{m-(n-1)k})$, where m runs from $(n-1)k+1$ to the number n_{data} of data points and k is the time delay. The successive sequence of points $x_m, x_{m-k}, x_{m-2k}, \ldots, x_{m-(n-1)k}$ can be viewed as a temporal finite pattern of the signal. The embedding dimension n determines the length of the pattern, the delay time k determines the degree of detail or fines tructure that is resolved in the pattern. Periodic behavior in the signal can be identified by closed loop in pattern space, which can be visualized if the embedding dimension is not greater than three. Chaotic solutions are seen geometrically as structured, non-repeating orbits in the reconstructed pattern state space.

Here and in the following figures we want to illustrate our method with the help of the two different heart rate signals (control set and ischemia) of figs. (1, 2). The time delay for the reconstruction should be chosen in a way that the coordinates of $\vec{x}_m$ are maximally independent. We use the concept of mutual information content [3] to determine the optimal delay time. In figure 3 we plot the mutual information content of three different heart condition as a function of delay time. For the dimension calculation we have chosen a delay of 9 beat intervals. The increase in mutual information content from the control to ischemia indicates a decrease in chaos for the transition to pathology.

From the data vectors $\vec{x}_m$, we select a subset of equally spaced (in time) reference vectors $\vec{\xi}_j$. For each of the n-dimensional reference vectors, we determine the local gauge function $N_{\vec{\xi}_j}(r)$, which counts the number of data points in a neighborhood of $\vec{\xi}_j$ of size r. In a log-log-representation this function typically exhibits a scaling region over which a slope can be defined. This means that we have: $log N_{\vec{\xi}_j}(r) \ = \ log\ c(\vec{\xi}_j) + d_{\vec{\xi}_j} log\ r$ where $c(\vec{\xi}_j)$ is a position dependent scale factor. This slope is then interpreted as the pointwise dimension $d_{\vec{\xi}_j}$ of the system at point $\vec{\xi}_j$ (see e.g. [4], [7], [8], [9], [11]).

From theoretical arguments we know that the estimation of the dimension value itself would require a much large data set. But we think that especially in bio-medical applications it might be useful for diagnostic purposes to compare significant relative changes in the "dimensional complexity parameter" ([8], [9]) even for relatively small data sets. Similar arguments are also used in connection with spectral analysis. In order to minimize the bias in dimension estimates, we introduced an algorithm which determines the fit-range, goodness of fit (GF), and the estimated dimension automatically for each reference point and for each embedding dimension [9].

Dynamics of Dimensional Complexity

Since our reference points are sampled at equal time intervals, we obtain a sequence of dimension values that reflects the temporal ordering on the attractor although the dynamics itself is chaotic and recurrences are quasi random. It is possible through our method to localize the specific regions on a reconstructed attractor responsible for significant changes in the apparent local dimensionality.

In figs. 4, 5 we plot the pointwise dimension obtained in this way as a function of the reference point for the time series shown in figs. 1, 2. The dynamics of the dimensional complexity parameter confirms the evidence from the mutual information content: The average of the pointwise dimensional complexity as a measure for the degree of chaos in the system decreases, as the heart goes from the control state to ischemia. In the control state we estimate a dimensional complexity $d \approx 7.7 \pm 1.5$ compared to a value of $d = 5.2 \pm 2.5$ in the ischemic state. We also can observe that in the latter we have a clear structure in the dimensional complexity series with minimal values below $d \approx 2$.

The method of estimating the point wise dimension at a sequence of time instances is equivalent to probing the attractor at different geometrical locations. We think that this information is very helpful in associating changes in the com plexity of the dynamics with geometrical features of the reconstructed data set; it offers stronger insights into the characteristics of the system.

Recurrence Plots

The time dependent pointwise dimension or crowding index give us information about the scaling behavior in a n dimensional neighborhood of the reconstructed system at a given point in time. As mentioned above, we are only interested in the contribution of those points of the system, which are not temporarily too close, but revisit the neighborhood after some elapsed recurrence time. From the dimensional complexity alone we cannot deduce any information about the time in which those recurrences take place. It would be possible that a large number of recurrences are generated through some localized small scale dynamics of the system. Then it could take the system a very long time before it visits the same neighborhood again. In other, more regular types of attractors, the recurrence could occur in periodic time intervals. In distinction to random systems we can identify conditions of a chaotic attractor under which relatively short recurrences are frequent. For some applications it might be interesting to obtain quantitative information about the dynamics of those recurrences. A very elegant way of representing this information was introduced in [1]. We have modified the original method slightly for computational and visualization purposes.

From a (reconstructed) vector time series $\vec{x}_m, m = 1, \ldots, n_{data}$ we compute the distances $\Delta_{m,l}$ between each of the vectors $\vec{x}_m, m = 1, \ldots, [\frac{n_{data}}{2}]$ and the vector $\vec{x}_{m+l}$ shifted in time by an amount of l, for $l = 1, \ldots, [\frac{n_{data}}{2}]$. We now can define a threshold distance $\epsilon > 0$ and define the recurrence times $T_R(m, \epsilon)$ through the condition: $\Delta_{m,T_R(m,\epsilon)} \leq \epsilon$. In the graphical representation of these functions we observe the periodic structures of the signal in the recurrences (see fig. 6). We obtain more complete information about recurrences at different distances ϵ by plotting the graph of $\Delta_{m,l}$ either in a three dimensional representation or with the help of color coding. Note that each of these reconstructed vectors can be represented as a pattern in the time series, and therefore this method might be helpful in the context of pattern analysis of scalar signals.

Besides estimating the fractal dimension of heart rate data and examining recurrences in pattern space, recent efforts have tried to extract dynamical equations from the observed time series (see e.g. [2]). The parameters obtained in this way for the reconstructed model are of limited accuracy because of factors like limited observation time/resolution, stationarity etc.

Having an approximate model of the healthy heart dynamics now allows us to test the response of the heart rate dynamics to external pacing generated by the reconstructed model equations This pacing would have to be aperiodic with characteristic features optimized for maximal "resonant" response. This type of approach has been successfully applied ([6], [10]) in a general context. We suspect that this concept of chaotic stimulation might have possible applications in cardiac pacemakers with the goal to reverse (under minimal eletro-chemical perturbations) the transition to cardiac arrest.

Acknowledgements:

I would like to thank James E. Skinner, Clara Carpeggiani, Carole Landisman and Keith Fulton for providing the heart rate data.

References

[1] J.P. Eckmann, S. Oliffson Kamphorst, D. Ruelle, Europhysics Letters, 4,973-977, (1987)

[2] J.D. Farmer, J. Sidorowich, "Exploiting Chaos to Predict the Future and Reduce Noise", Reviews of Modern Physics, (1989)

[3] A.M. Fraser, H.L. Swinney, Phys. Rev. **A 33**, 1134-1140, (1986)

[4] P.Grassberger, I. Procaccia, "Measuring the Strangeness of Strange Attractors", Physica **9D**, 189, (1983)

[5] H. Haken, "Advanced Synergetics", Springer, Berlin 1983

[6] A. Hübler, E. Lüscher, "Resonant Stimulation and Control of Nonlinear Oscillators", Naturwissenschaften 76, 67(1989),

[7] G. Mayer-Kress, (ed.), "Dimensions and Entropies in Chaotic Systems", Springer Series in Synergetics, Vol 32, Springer Verlag Berlin, Heidelberg 1986

[8] G. Mayer Kress, S.P. Layne, "Dimensionality of the Human Electroencephalogram", Proc. of the New York Academy of Sciences conf. "Perspectives in Biological Dynamics and Theoretical Medicine", A.S. Mandell, S. Koslow (eds.) Annals of the New York Academy of Sciences, Vol. **504**, New York, 1987

[9] G. Mayer-Kress, F. E. Yates, L. Benton, M. Keidel, W. Tirsch, S.J. Pöppl, K. Geist, "Dimensional Analysis of Nonlinear Oscillations in Brain, Heart and Muscle", Mathematical Biosciences **90**, 155-182, 1988

[10] G. Mayer-Kress, A. Hübler, "Time Evolution of Local Complexity Measures and Aperiodic Perturbations of Nonlinear Dynamical Systems," submitted to "Quantitative Measures of Complex Dynamical Systems," N. B. Abraham (ed.), Plenum, NY., 1989

[11] J. P. Zbilut, G. Mayer-Kress, P. Sobotka, M. O'Toole, J. X. Thomas, "Chaotic Heart Rate Dynamics in Isolated Perfused Rat Hearts," to appear in Biol. Cybernetics

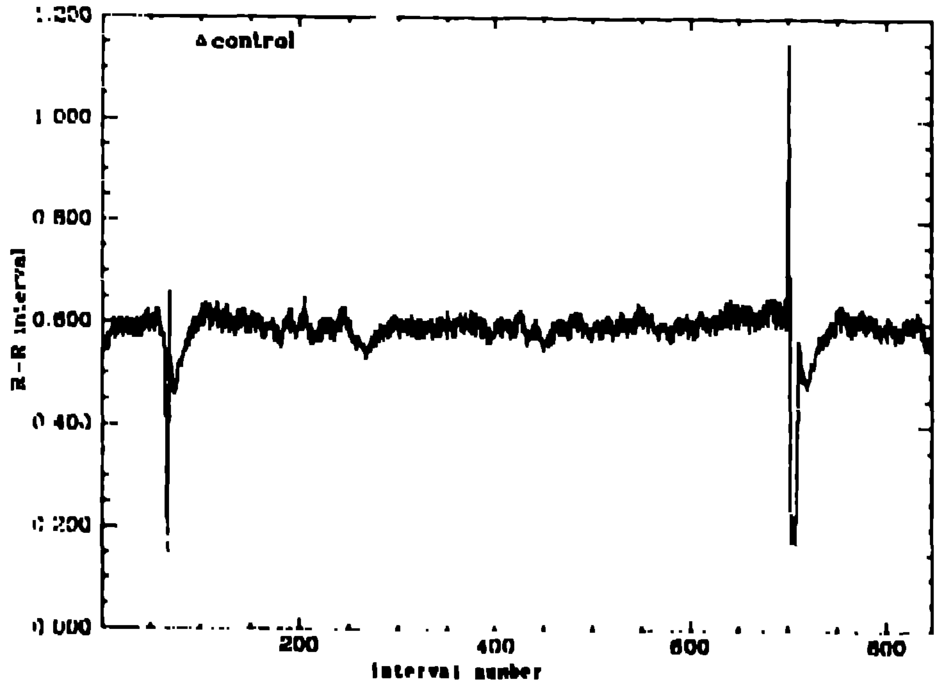

Figure 1: An 8 minute file of R R intervals recorded from the standard heart lead (surface lead) of a pig. The data set represents within-subject control conditions in which the animal is alert and awake.

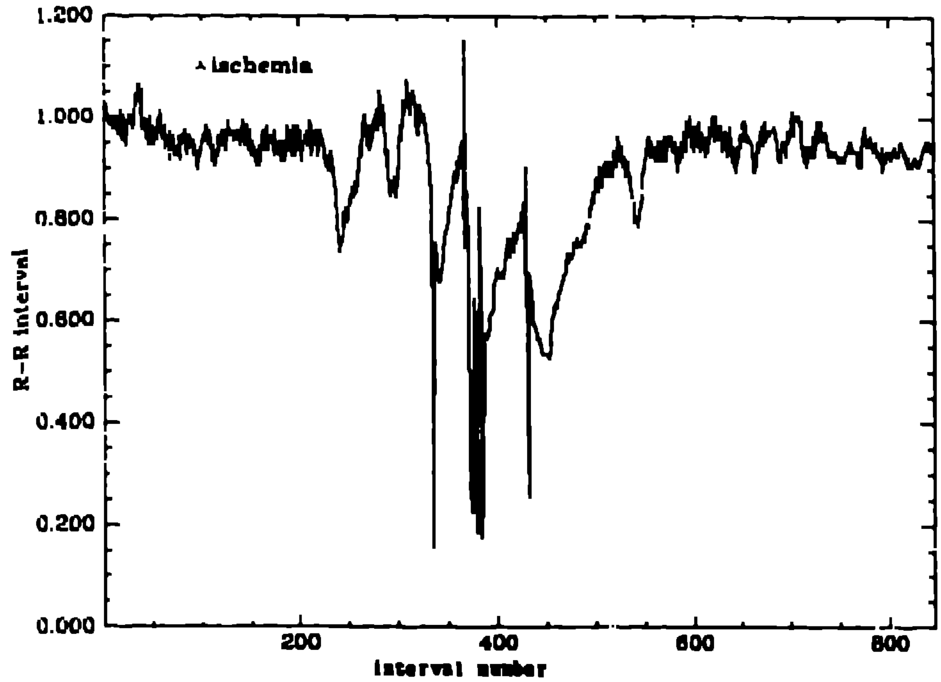

Figure 2: An 8 minute file of R-R intervals recorded from the standard heart lead of the same pig. The data set represents test conditions of 100of the left anterior descending artery of the heart (LAD). Recording taken on the same day as the other files.

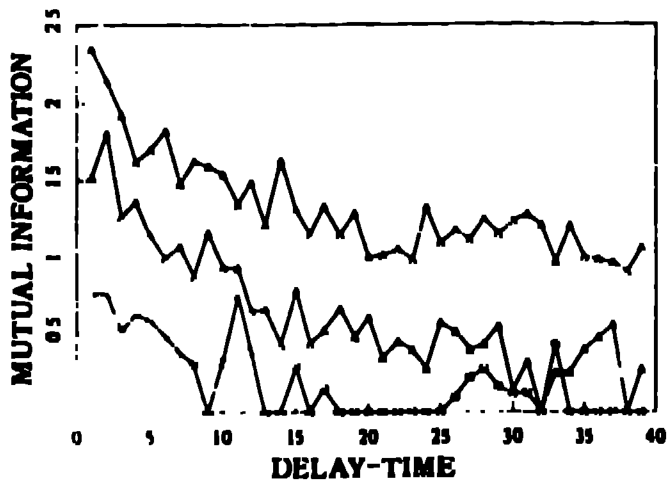

Figure 3: Mutual information content of R-R interval signals of healthy control (bottom curve), 50% occlusion (middle curve), and ischemia (top). This seems to indicate a loss in chaotic complexity during the transition to a pathological state.

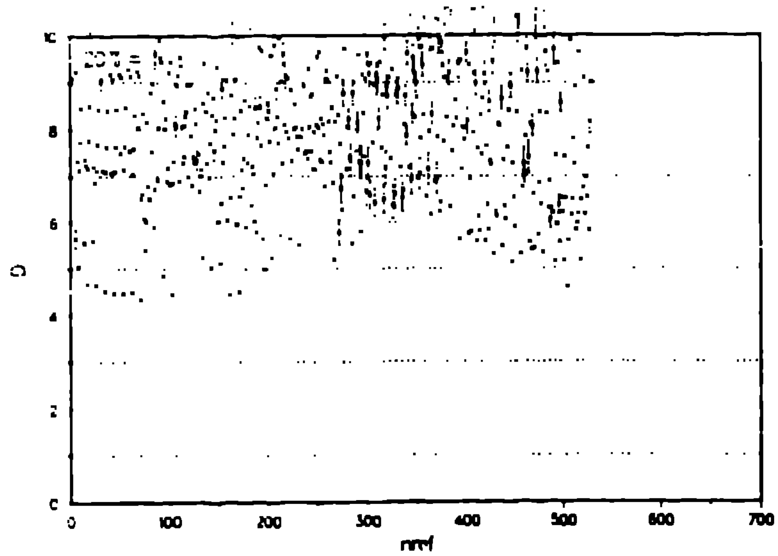

Figure 4: Time series of pointwise dimension values for the heart rate signal of fig. 1 (control state). From the $n_{data} = 847$ skalar data points we reconstruct a vector time series with a time delay of $k = 9$. Under these conditions we obtain $n_{vec} = 669$ vector data points $\vec{x}_m$ in a 20- dimensional embedding space. Out of those we choose the first $n_{ref} = 650$ vectors as reference vectors $\vec{\xi}_j$. To avoid points which are temporally very close we don't count vectors $\vec{x}_m$ in a neighborhood of $\vec{\xi}_j$ whenever $| m - j\nu | \leq 3$. For this data file we have to reject 264 reference vectors due to insufficient scaling behavior.

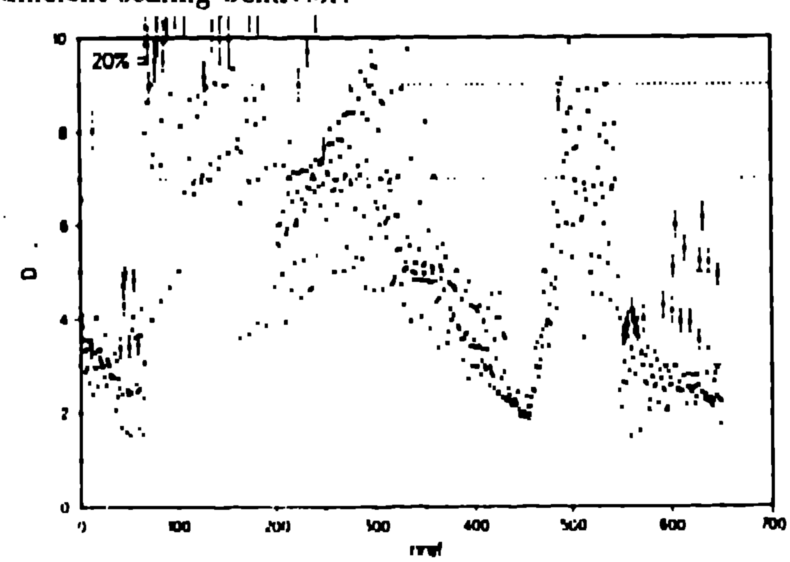

Figure 5: Same as in fig. 4 for the data of fig. 2 (ischemia). The numerical parameters are basically the same. For this file we only have to reject 103 reference vectors indicating a lower degree of chaos.

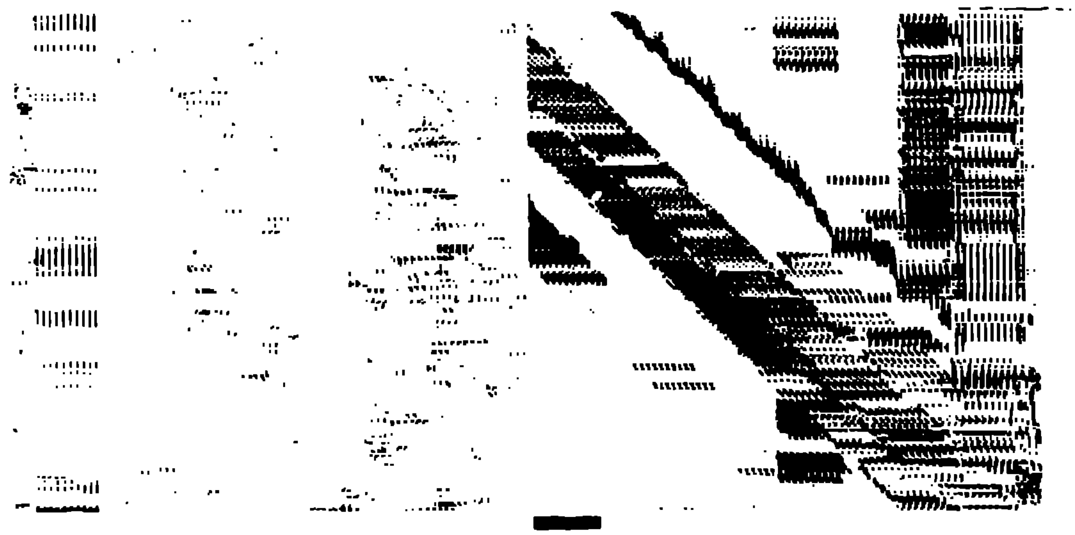

Figure 5: Recurrence plot $\Delta_{m,T_R(m,\epsilon)}$ for the data of fig. 1 (left) and 2 (right). In horizontal direction we have the time index m, in vertical direction we have the time shift l between the two vectors, whose separation is computed. Periodic structures in the signal is represented by horizontal lines. Vertical lines indicate clustering properties of the reconstructed signal. Diagonal lines indicate relaxation type oscillations.