Measures of Complexity and Chaos

Edited by
Neal B. Abraham
Alfonso M. Albano
Anthony Passamante and
Paul E. Rapp

NATO ASI Series

Series B: Physics Vol. 208
COMPLEXITY AND CHAOS

N.B. Abraham, A.M. Albano, and N.B. Tufillaro
Department of Physics
Bryn Mawr College
Bryn Mawr, PA 19010-2899, USA

1. INTRODUCTION

Turbulence was one of the key phenomena that motivated the resurgence of interest in nonlinear dynamical systems. It was, after all, investigations into the mechanisms for turbulence that led Ruelle and Takens to invent the term "strange attractor" in 1971. The turbulence that is described by strange attractors is "turbulence in time" (Schuster, 1988) -- deterministic chaos, or temporal chaos in current terminology. In the past decade, a vocabulary for the quantitative characterization of temporal chaos has been developed, and has been used to describe and analyze an incredible variety of phenomena in practically all fields of science and engineering. The dimensions of strange attractors, and the entropies and Lyapunov exponents describing motions on them, have been used to analyze heartbeats and brain waves, chemical reactions, lasers, the economy, x-ray emissions of stars, flames, and fluid flow ...

Yet, this vocabulary is not sufficient to describe turbulence, for turbulence is complexity not only in time but also in space. The vocabulary needs to be enlarged to include the quantitative characterization of spatial complexity and its time evolution. So turbulence, once more, is the motivation for efforts to enlarge the scope of nonlinear dynamics to include a description of spatio-temporal complexity. These efforts include the use of modal expansions (reminiscent of the old "mode-mode coupling" theories or "dressed-mode analyses"), spatial correlation functions, coupled lattice models, and new approaches based on the analysis of topological defects.

This workshop was an effort to describe the "state of the field" of the quantitative characterization of complexity and chaos. The presentations at the workshop included in these proceedings go a long way towards that description. To enlarge the context and information for the readers, we append to this introduction a bibliography of some of the most recent references and a selection of other key articles. These are organized both by methodology and the subject to which they are applied. Further references can be found in the various chapters of this volume and in the literature citations of other works listed here. (In the following, papers appearing in this volume are followed by an asterisk).
2. CHARACTERIZING TEMPORAL CHAOS

(a) Calculational techniques, precision, error estimates

Dimensions, entropies and Lyapunov exponents have become the standard measures of temporal chaotic behavior. Of these, perhaps because of the possibility of attaching an intuitive geometric significance to them, and because of the commonly made connection between fractal attractors and chaotic behavior, dimensions have been used most frequently. This is also because the algorithms for their computation seem to be the least cumbersome. However, the relative simplicity of these methods can mask a host of possible errors and difficulties. A comprehensive review of the techniques used and the problems encountered in dimension calculations is given in Theiler's review article (Theiler, 1989).

It is now common for a chaotic time series to be described by a spectrum of dimensions, \( d_q \) \((\infty < q < \infty)\), rather than by just one. The \( d_q \)'s are a hierarchy of dimensions introduced by Grassberger (Grassberger, 1983) and by Hentschel and Procaccia (Hentschel and Procaccia, 1983). These are defined by,

\[
d_q = \frac{1}{q-1} \lim_{r \to 0} \frac{\log \sum p_i^q}{\log r},
\]

where \( p_i \) is the number of points in the \( i \)th box of a partition consisting of boxes of size \( r \) covering the attractor, typically one that is reconstructed from a time series of a single measured variable by an embedding in an m-dimensional space by the now familiar method of time delays (Packard et al., 1980; Takens, 1980; Mané, 1980). \( d_0 \) is the "fractal dimension" or the "capacity" and \( d_1 \) is the "information dimension". The "correlation dimension", \( d_2 \), is the most widely used member of the hierarchy. Alternatively, the spectrum of scaling indices, \( f(\alpha) \), is also used (Halsey et al., 1986), where the variables \((\alpha, f(\alpha))\) are obtained from \((q, d_q)\) by a Legendre transformation:

\[
\alpha = \frac{\partial [(q - 1)d_q]}{\partial q}, \quad f(\alpha) = \alpha d - (q-1)d_q.
\]

There exist a number of algorithms for calculating dimensions although that due to Grassberger and Procaccia (Grassberger and Procaccia 1983, 1983a, 1983b) for the correlation dimension remains the most widely used because it remains the easiest to implement. The Grassberger-Procaccia algorithm is often called a "fixed volume" technique as it involves counting the average number of points in a hypersphere or hypercube as function of the radius, \( r \). "Fixed mass" algorithms (Termonia and Alexandrovicz, 1983; Badil and Politi, 1985), on the other hand, involve the determination of the radius of a hypersphere that contains a given number of points, \( N \), as a function of \( N \). These numbers scale as \( R^d \) and \( N^{1/d} \), respectively. The Grassberger-Procaccia correlation integral,

\[
\log \sum p_i^n
\]

has also been modified into a statistical test for potential forecastability or hidden recurrent patterns in an observed time series (Brock and Deichert*).

Though in some cases it appears that dimensions can be reliably extracted with as few as 500 data points, the minimum sufficient number of data points, and the optimum data sampling rate and embedding delay, all depend critically on the uniformity of the strange attractor and its dimension. Sometimes a total number of points as few as \( N = 10^d \) for an attractor of dimension \( d \) can be sufficient, but various parameters of the
embedding need to be optimized. (Note that Smith (Smith, 1988) has a
proof that the lower bound of the number of points to avoid spurious
results is $N = 42^d$).

There are problems with the standard methods, however, especially when
they are used with noise-corrupted data sets of limited size and
limited precision (the only kind obtainable from experiments). Each of
these lead to different and often overlapping problems. A number of these
problems were considered in this workshop.

In constructing an embedding, one must select the sampling rate for
the data acquisition of the time series, the total length of the time
series, the delay between successive elements of an embedding vector, the
spacing in time between the first elements of successive embedding
vectors, and the total number of embedding vectors. Arbitrary selection of
these parameters can introduce significant systematic errors in the
construction or coverage, of the attractor. One key quantity appears to be
the window used in the embedding -- i.e., the time spanned by each
embedding vector. It is known that the results of dimension calculations
depend rather sensitively on this choice. Current lore suggests "rule of
thumb" criteria based on the correlation time determined from the inverse
of the bandwidth of the signal's power spectrum or the first zero,
minimum, or the decay of the envelope of the autocorrelation function.
Fraser* and Schuster* suggest improved criteria for making this choice.

Caputo* and Politi* address the problem of data requirements, Lange*
investigates systematic errors due to finite precision and noise and
proposes strategies for correcting these errors. Kostelich* presents a
procedure for decreasing the effects of noise, while Hunt*, Sayers* and
Theiler* address the problem of obtaining realistic error estimates for
the dimensions and entropies that are extracted.

Another dimension-seeking strategy is to determine an "intrinsic
dimension", a minimal embedding dimension for the time series. One
procedure is to use a singular value decomposition (Broomhead and King,
1986) to determine the smallest number of orthogonal directions needed to
describe the data. When applied locally to get an average local intrinsic
dimension, it is known to be fairly robust relative to noise (Passamante
et al., 1989). Passamante, Hediger and Farrell* discuss the use of an
information theoretic criterion to determine local dimension. Goel and
Rao* present other criteria.

Dimensions and additional topological properties of strange sets are
also obtainable from unstable periodic orbits. Some aspects of these
procedures are discussed by Schuster*, Auerbach*, Glendinning*, Smith* as
well as by Gilmore* and Solari*.

Continuously varying signals can also be characterized by smaller sets
of information. For example, a Poincaré section of a periodic signal
selects the value of the signal once every clock cycle. Externally driven
systems have well defined clock frequencies. For autonomous systems
Poincaré sections are defined by when the trajectory in the reconstructed
attractor crosses a selected hyperplane. Similar data reduction procedures
involve the study of the sequence of peak values of the signals or the
sequence of time intervals between peaks. The dimension of such a subset
is one less than the dimension of the corresponding continuous trajectory.

The logical and more sophisticated extension of these classification
schemes involves the invention of a set of symbols used to represent
different types of behavior of the system. The sequences of symbols can
be analyzed for the "syntax" and "grammar" of the "language" of the
dynamics. Conditional probabilities and the relative probability of
unique sequences can be used to define a degree of complexity and an
entropy production rate for the system. Questions of selection of a set of
symbols and enlargement of that set were addressed by Badii*, Crutchfield*
and Fraser*, among others.
It has been difficult to calculate Lyapunov exponents from experimental data principally because available procedures are not sufficiently robust against noise in experimental data. Several algorithms have been proposed by a number of investigators (Wolf, 1985; Eckmann et al., 1986; Sato et al. 1987; Stoop and Meier, 1988) but others have had their problems implementing these on experimental results. Most experimental data sets are of insufficient precision, sampling rate, or length to permit the use of these algorithms on them with consistent reliability or success. Use of the algorithms on data generated by numerical simulations are obviously more straightforward and have been more universally successful. Glover* presents a technique that calculates Lyapunov exponents more efficiently using the Poincaré sections.

Although entropies $K_q$ can be calculated by means of the same correlation integral that is used to calculate dimensions $d_q$, they have not been as widely used as dimensions, either. There are growing indications, though, that entropies may be more robust quantities than dimensions (in that they seem to be invariant under linear filtering of the data, while the dimensions are not similarly invariant [see Lange*]) and may well find more use in the future. Though the relationship between power spectra (and thus correlation functions) and entropies is not rigorously established, evidence has been consistently reported that the bandwidth of power spectra and the decay of the envelope of autocorrelation functions are excellent estimators for the entropies. Applications to measures of the complexity of symbolic sequences will increase as ways are explored to reduce the artificial complexity of continuous variables used to describe low dimensional phenomena.

It is also worth noting that internal consistency of the results can be tested since the entropy is a good estimator for the positive Lyapunov exponent (if there is only one). Furthermore, there is the Kaplan-Yorke conjecture (Kaplan, 1979) on the relationship between the dimension and the Lyapunov exponents,

$$ d_1 = j + \frac{\sum_{i=1}^{j} \lambda_i}{|\lambda_{j+1}|} $$

where $j$ is the largest integer for which $0 \leq \lambda_1 + \lambda_2 + \ldots + \lambda_j$. This seems to be particularly accurate for larger systems with only a single positive Lyapunov exponent.

(b) Routes to Chaos and a New Standard: Homoclinic and Heteroclinic Orbits, Shilnikov Chaos

Historically, once some degree of universality was assured, routes to chaos were commonly used as indicators that irregular behavior was indeed dynamical chaos. While these qualitative methods relying on changes in power spectra have fallen in disfavor when more quantitative methods can be applied, the simplicity of a new system following generic routes to chaos is still powerful when one is analyzing experimental data. Nevertheless, countless studies have shown that the universality can break down or become more complex, with truncated period-doubling sequences occurring when there are two controlling parameters rather than one. Quasiperiodicity is equally generic in reaching chaos through locking of the previously incommensurate frequencies and then period doubling of the locked conditions. Only for a few special cases does the incommensurate nature remain until chaos appears with a third frequency.

Another now common route through periodic and chaotic dynamics include sequences of symmetry breaking bifurcations (in systems described by an underlying inversion symmetry) and then gluing bifurcations that restore the symmetry with a higher degree of complexity (Hennequin et al.*).
Chaos related to homoclinic or heteroclinic orbits also seems to come in some relatively standard forms. Signatures include the similarity of the topology of successive trajectories around a topologically simple attractor even though the times for successive trajectories may differ widely. Near these homoclinic orbits there are infinite sets of periodic orbits involving different numbers of spirals. Beyond qualitative measures, it now appears that Poincaré plots of return time maps may be the best indicators of the multileaved structures created by the complex homoclinic chaos. Because of the intricate topological structure of these attractors their sensitivity to noise will also be a subject of considerable ongoing investigation. The structure in the return plots will also probably be a major source of data for studies of symbolic dynamics in the future. The new interest in the dynamics of homoclinic and heteroclinic chaos is driven by the experimental observations of such phenomena in chemical reactions (Argoul* and Arneodo*) and lasers (Arecchi* Arimondo*, Glorieux*, Weiss*).

Homoclinic orbits and coherent transients are now also an ordering feature in the study of spatial dynamics. Nikolaenko* demonstrated the importance of local homoclinic behavior in driving spatio-temporal dynamics and Newell (Newell et al., 1988) has also recently focused on the role of local coherent transients and their propagation as a governing feature of turbulence.

(c) Applications to real-world data

The large variety of fields in which dimensions, entropies, and exponents have been used to characterize complex temporal evolution is an indication of the extent to which these quantities have become elements of a scientific vocabulary that is now practically universal. The workshop saw these quantities used to characterize astrophysical data (Atmanspacher*), dendritic growth (Argoul*), electroencephalographic and electrocardiographic data (Babloyantz*), nerve fibers (Frame*), economics (Brock and Dechert*), epidemics (Schaffer*), fluids (Gollub*, Ciliberto*, Nikolaenko*, Sreenivasan), flames (Sreenivasan) and lasers (Arecchi*, Arimondo*, Glorieux*, Tamm*, Raymer*, Weiss*).

As one of the most basic applications of these methods, dimensions have been used to discriminate between chaos and noise. In many situations, it is possible to distinguish those phenomena that result from the combined effects of extremely many independent processes and which therefore may be regarded as stochastic from those that may be described as low-dimensional deterministic processes. Beyond this, dimension calculations have made possible the direct comparison of computational and experimental results.

An example of a comparison between theory and experiment that goes beyond mere matching of the dimensions of experimental data and results of numerical simulations was presented by Weiss*. He described results obtained with a laser working in a region in parameter space where its operation is described by the Lorenz equations, making it possible to make some very meticulous comparisons between theory and experiment.

(d) From data to dynamics: prediction algorithms

It is almost paradoxical that a chaotic time series, characterized by sensitive dependence to initial conditions which renders its distant future values unpredictable in practice, should be the subject of prediction algorithms (Farmer and Sidorowitz, 1987, 1988; Crutchfield and MacNamara, 1987). Yet, since it is deterministic, it is governed by a dynamical law which is discoverable, at least in principle. Badii and Sepulveda*, Crutchfield*, Mees*, Smith*, and Schuster* present various approaches to the short-term prediction problem.
3. CHARACTERIZING SPATIO-TEMPORAL COMPLEXITY

(a) Modal expansions, spatial correlation functions, coupled lattice models

The characterization of spatially complex nonlinear systems is complicated by the fact that sums of solutions are no longer themselves solutions as in the case of linear systems. The time evolution of nonlinear systems can thus no longer be simply described in terms of independently evolving modes. Nevertheless, the system can still be described by expansions over characteristic spatial modes, but one must recognize that the time evolutions of these modes are coupled.

Another alternative is the use of spatial correlation functions. One definition of turbulence, proposed by Breslo et al. (1987), is in terms of the decay of the spatial correlation function in a system with spatio-temporal dynamics which are locally chaotic. However, such a definition will clearly reject as not turbulent systems which are described by a small number of spatial modes with time-dependent amplitudes. Clearly, some intermediate approaches to characterization for systems of moderate size are still needed.

A variety of methods are used by Gollub* to characterize parametrically driven surface waves and by Oppo* to describe lasers with many transverse modes.

Another possibility of describing a spatially inhomogeneous system is to model the system on a lattice in which the dynamics at each lattice point is influenced by interactions with a few near neighbors. Coupled lattice models are discussed by Kapral*, while some problems associated with calculating dimensions for these models are presented by Politi*.

(b) Defect-mediated order-disorder transitions

Defect-mediated turbulence is emerging as a promising paradigm for studying weak turbulence in large aspect ratio systems, i.e., systems in which the size of the basic spatial structure is much less than the size of the system. The inspiration for these ideas comes from analogies with defect-mediated phase transitions in equilibrium systems.

Different theoretical approaches to defect formation in non-equilibrium systems are discussed by Coullet and Procaccia. Coullet* described the usefulness of the Ginzburg-Landau equation in understanding the essential features of defect formation, annihilation, and dynamics. Earlier applications to convective systems were supplemented by illustrations appropriate to large-aperture lasers. In contrast, Procaccia* developed a field theory which described the free dynamics and interdefect forces exhibited at finite range. Aspects of this field theory were illustrated by experimental data from electroconvecting nematics.

Several experimental examples of defect formation in far from equilibrium systems are discussed in Part III of these proceedings. Gollub* discussed the dynamics of parametrically forced surface waves which illustrate temporal chaos at small aspect ratios, and possibly a defect-mediated order-disorder transition at large aspect ratios. Defects might also be found in convective fluid systems such as those described by Ciliberto*, and in lasers with many transverse modes as discussed by Oppo*. The strongest evidence for defect-mediated transitions, however, are to be found in nematics and large aspect-ratio Rayleigh-Bénard convection.
4. PARTING SHOT

Many will continue to doubt the usefulness of quantitative measures of experimental results plagued by noise and data limitations. The work here indicates many examples where such quantitative measures can be used judiciously to confirm or deny the presence of low dimensional chaotic origins of the aperiodic behavior. Where multiple characterizations are possible, types of complexity can be distinguished and definite guidance is provided to those endeavoring to construct adequate models of the behavior.

Given the current state-of-the-art in dimension measurements, a well-defined and continuous transition from sharp to broadband spectral structure, when that is experimentally feasible, may still be one of the best practical diagnostics for the onset of chaos in physical systems.

Surely there will be increasing breadth of application of the techniques. New practitioners must be suitably chastened by the systematic errors and difficulties of interpretation, but all should be encouraged by the progress that has been made and by the additional progress which many of these articles portend.

REFERENCES (BY CATEGORY)

Complete bibliographical information is given in the alphabetical listing that follows.

Biology, neuroscience

R. E. Byers and R.I.C. Hansell, This volume.
R. E. Byers, R.I.C. Hansell, and N. Madras, This volume.
A. Destexhe, G. Nicolis, and C. Nicolis, This volume.
M. Frame, This volume.
G. W. Frank, T. Lookman, M.A.H. Nerenberg, This volume.
W. M. Schaffer and L.F. Olsen, This volume.

Books

P. Cvitanovic (1986).
H. Haken (1988).
D. Barkley and A. Cummings, This volume.
W. A. Brock and W.D. Deckert, This volume.
J. G. Caputo, This volume.
J. Fang, This volume.
M. Frame, This volume.
G. W. Frank, T. Lookman, M.A.H. Nerenberg, This volume.
A. M. Fraser, This volume.
J. N. Glover, This volume.
A. Goel, S. S. Rao, and A. Passamante, This volume.
K. Hartt and L. M. Kahn, This volume.
H. Herzl (1988)
U. Hübner, W. Klische, N. B. Abraham, and C. O. Weiss, This volume.
F. Hunt, preprint.
W. Lange and M. Möller, This volume.
M. Le Berre, E. Ressayre, and A. Tallet, This volume.
C-K. Lee and F. C. Moon (1986).
A. Passamante, T. Hediger, and M. E. Farrell, This volume.
M. G. Raymer, This volume.
D. Barkley and A. Cummings, This volume.
W. A. Brock and W.D. Dechert, This volume.
J. G. Caputo, This volume.
J. Fang, This volume.
M. Frame, This volume.
G. W. Frank, T. Lookman, M.A.H. Nerenberg, This volume.
A. H. Fraser, This volume.
J. N. Glover, This volume.
A. Goel, S. S. Rao, and A. Passamante, This volume.
K. Hartt and L. M. Kahn, This volume.
H. Herzel (1988)
U. Hübner, W. Klische, N. B. Abraham, and C. O. Weiss, This volume.
F. Hunt, preprint.
W. Lange and M. Möller, This volume.
M. Le Berre, E. Ressayre, and A. Tallet, This volume.
A. Passamante, T. Hediger, and M. E. Farrell, This volume.
M. G. Raymer, This volume.
C. L. Sayers, This volume.
W. M. Schaffer and L. F. Olsen, This volume.
Z. Su, R. W. Rollins, and E. R. Hunt, This volume.
J. Theiler, This volume.
C. O. Weiss and N. B. Abraham, This volume.

Extracting models from data
J. P. Crutchfield, This volume.
A. Mees, This volume.
H. G. Schuster, This volume.

Fluids
(See also Complexity, Turbulence)
P. Coullet, This volume.
J. P. Gollub, This volume.
B. Nicolaueno and Zhen-Su She, This volume.
C. Pérez-Garcia, E. Pampaloni, and S. Ciliberto, This volume.
I. Procaccia, This volume.
F. Takens (1981)

Fractals
(See also Chaos, Complexity, Dimensions and entropies)
B. Mandelbrot (1982).
M. A. Rubio, A. D. Dougherty, and J. P. Gollub, This volume.

Homoclinic chaos
F. T. Arecchi, This volume.
A. Arneodo, P. Coullet, and C. Tresser (1982).
S. T. Gaito and G. P. King, This volume.
Lyapunov exponents
(See also Chaos, Dimensions and entropies)

R. M. Everson, This volume.

Nonlinear optics

F. T. Arecchi, This volume.
D. Henneguin, M. Lefranco, A. Bekkali, D. Dangoisse, and P. Glorieux, This volume.
G.-L. Oppo, M. A. Pernigo, L. M. Narducci, and L. A. Lugliato, This volume.
P. Papoff, A. Fioretti, and E. Arimondo, and N. B. Abraham, This volume.
M. G. Raymer, This volume.
C. Tamm, This volume.
C. O. Weiss and N. B. Abraham, This volume.

Reviews

J. Guckenheimer and P. Holmes (1983).
Turbulence
(See also Complexity, Fluids)

F. Argoul, A. Arnéodo, J. Elzgaray, and G. Grasseau, This volume.
F. Argoul, A. Arnéodo, G. Grasseau, Y. Gagne, E. J. Hopfinger, and
S. Ciliberto, This volume.
P. Coullet, This volume.
J. Fang, This volume.
J. P. Gollub, This volume.
M. Henon (1976).
W. Li, This volume.
B. Nicolaeoko and Zhen-Su She, This volume.
G.-L. Oppo, M. A. Pernigo, L. M. Narducci, and L. A. Luglio, This
volume.
C. Pérez-Garcia, E. Pampaloni and S. Ciliberto, This volume.
A. Politi, G. D'Alessandro, A. Torcini, This volume.
I. Procaccia, This volume.
M. Schell, S. Fraser, and R. Kapral, (1982).
C. Tamm, This volume.
REFERENCES (ALPHABETICAL)


F. T. Arecchi, "Shil'nikov chaos: How to characterize homoclinic and heteroclinic behaviour", This volume.

F. Argoul, A. Arneodo, J. Elzgaray, and G. Grasseau, "Characterizing spatio-temporal chaos in electrodeposition experiments", This volume.


D. Auerbach, "Dynamical complexity of strange sets", This volume.


R. Badii, "Unfolding complexity in nonlinear dynamical systems", This volume.

R. Badii and G. Broggi, "Hierarchies of relations between partial dimensions and local expansion rates in strange attractors", This volume.


D. Barkley and A. Cummings, "Experimental study of the multifractal structure of the quasiperiodic set", This volume.


W. A. Brock and W. D. Dechert, "Statistical inference theory for measures of complexity in chaos theory and nonlinear science", This volume.


R. E. Byers and R. I. C. Hansell, "Stabilization of prolific populations through migration and long-lived propagules", This volume.
R. E. Byers, R. I. C. Hansell, and N. Madras, "Complex behavior of systems due to semi-stable attractors: attractors that have been destabilized but which still temporally dominate the dynamics of a system", This volume.

J. G. Caputo, "Practical remarks on the estimation of dimension and entropy from experimental data", This volume.

K. Chang, A. Hübler, N. Packard, "Universal properties of the resonance curve of complex systems", This volume.


S. Ciliberto, "Characterizing space-time chaos in an experiment of thermal convection.", This volume


P. Coullet, "Defect-induced spatio-temporal chaos", This volume.

J. P. Crutchfield, "Inferring the dynamic, quantifying physical complexity", This volume.


A. Destrache, G. Nicolis, and C. Nicolis, "Symbolic dynamics from chaotic time series", This volume.


R. M. Everson, "Lyapunov exponents, dimension and entropy in coupled lattice maps", This volume.


J. Fang, "Evolution of the irreversible beam dynamical variable and applications", This volume.

J. Fang, "The effects of external noise on complexity in two dimensional driven damped dynamical system", This volume.


M. Frame, "Chaotic behavior of the forced Hodgkin-Huxley axon", This volume.

G. W. Frank, T. Lookman, M. A. H. Nerenberg, "Chaotic time series analysis using short and noisy data sets: application to a clinical epilepsy seizure", This volume.

A. M. Fraser, "Measuring complexity in terms of mutual information", This volume.


S. T. Gaito and G. P. King, "Chaos on a catastrophe manifold", This volume.


P. Glendinning, "Time series near codimension two global bifurcations", This volume.

J. N. Glover, "Estimating lyapunov exponents from approximate return maps", This volume.

A. Goel, S. S. Rao, and A. Passamante, "Estimating local intrinsic dimensionality using thresholding techniques", This volume.

J. P. Gollub, "Characterizing dynamical complexity in interfacial waves", This volume.


Hao Bai-lin, "Bifurcation and chaos in the periodically forced Brusselator" (Collected Papers Dedicated to Professor Kazuhisa Tomita, Kyoto University, 1987).


K. Hartt and L. M. Kahn, "Seeking dynamically connected chaotic variables." This volume.


F. Hunt, "Error analysis and convergence of capacity dimension algorithms", preprint.


W. Lange and M. Moller, "Systematic errors in estimating dimensions from experimental data", This volume.

D. P. Lathrop and E. J. Kostelich, "Analyzing periodic saddles in experimental strange attractors", This volume.

M. Le Berre, E. Ressayre, and A. Tallet, "Phase transitions induced by deterministic delayed forces", This volume.


W. Li, "Mutual information functions versus correlation functions in binary sequences", This volume.


G. Mayer-Kress and A. Hübler, "Time evolution of local complexity measures and aperiodic perturbations of nonlinear dynamical systems", This volume.


A. Mees, "Modeling dynamical systems from real-world data", This volume.


T. Meyer, A. Hübner, N. Packard, "Reduction of complexity by optimal driving forces", This volume.


B. Niculaneko and Zhen-Su She, "Symmetry breaking homoclinic chaos", This volume.


F. Papoff, A. Fioretti, and E. Arimondo, and N. B. Abraham, "Time return maps and distributions for laser with saturable absorber", This volume.


A. Passamante, T. Hediger, and M. E. Farrell, "Analysis of local space/time statistics and dimensions of attractors using singular value decomposition and information theoretic criteria", This volume.


C. Pérez-García, E. Pampaloni and S. Ciliberto, "Amplitude equations for hexagonal patterns of convection in non-Boussinesq fluids", This volume.

A. Politi, G. D'Alessandro, A. Torcini, "Fractal dimensions in coupled map lattices", This volume.

I. Procaccia, "Weak turbulence and the dynamics of topological defects", This volume.


M. G. Raymer, "Entropy and correlation time in a multimode dye laser", This volume.


J. Ringland and M. Schell, "Pattern cardinality as a characterization of dynamical complexity", This volume.


C. L. Sayers, "Dimension calculation precision with finite data sets", This volume.

W. M. Schaffer and L. F. Olsen, "Chaos in childhood epidemics", This volume.


H. G. Schuster, "Extraction of models from complex data", This volume.

M. A. Sepulveda and R. Badii, "Symbolic dynamical resolution of power spectra", This volume.


L. P. Shil'nikov, Mat. Sbornik 77, (119), 461 (1968).


L. P. Shil'nikov, Math USSR Sbornik 6, 427 (1968).


L. A. Smith, "Quantifying chaos with predictive flows and maps: locating unstable periodic orbits", This volume.


H. G. Solari and R. Gilmore, "Relative rotation rates from driven dynamical systems", This volume.


C. Tamm, "The field patterns of a hybrid mode laser: detecting the "hidden" bistability of the optical phase pattern", This volume.


J. Theiler, "Statistical error in dimension estimators", This volume.


C. O. Weiss and N. B. Abraham, "Characterizing chaotic attractors underlying single mode laser emission by quantitative laser field phase measurement", This volume.


ADDENDUM (February, 1990)


