Dynamical Analysis of Schizophrenia Courses

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In order to assess the working hypothesis that schizophrenia may be viewed as a nonlinear dynamical disease, we examined the long-term psychoticity dynamics of 14 patients. The data consist of daily ratings of psychopathology observed for 200 or more consecutive days in each patient. We implemented nonlinear dynamical analysis methods with a potential of being applicable even to relatively short and noisy time series: two different forecasting approaches combined with surrogate methods that allow statistical testing in each single case. The resulting classification of dynamics gives evidence that eight patients show nonlinear evolutions of symptom courses. Four cases can be modeled linearly, two as random processes. Thus, a larger proportion of the schizophrenic psychoses we studied shows nonlinear time courses. In this way the validity of the concept of dynamical diseases could be supported on statistical grounds in this important area of psychopathology. The nonlinear view—a low-dimensional nonlinear system generating psychotic symptoms—may provide the foundation for a more parsimonious theory of schizophrenia compared to traditional multicausal models. In several of the nonlinear cases we also observed the qualitative "fingerprint" of deterministic chaos: a decay of deterministic features of the course of disorder with time. © 1997 Society of Biological Psychiatry

Key Words: Chaos, dynamical disease, forecasting, self-organization, schizophrenia, synergetics

Introduction

In psychiatry, a profound interest in the processual character of schizophrenia (Ciompi 1989; Strauss et al 1985) faces a neglect of quantitative longitudinal research. Thus, in the face of dynamical theories of the subject matter, empirical research is still tied to cross-sectional designs and hypotheses. It appears that there is a definitive incongruence of theory and methodology in this field in

that the crucial importance of time is stressed in theory and ignored in empirical studies. Häfner and Maurer (1991) express this same opinion by stating that psychiatry is still suffering from an "extreme shortcoming of longitudinal research."

In the last three decades the new interdisciplinary research program of nonlinear dynamical systems theory has gained much momentum as a unifying paradigm in the natural sciences. In this context two focal concepts, self-organization and chaotic dynamics, are prominent. The former states that complex systems of any kind may tend to produce order and pattern spontaneously if systems are permeated by fluxes of matter, energy, or information (Haken 1988; Nicolis and Prigogine 1977). Self-organized

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patterns typically evolve via instability points where a system enters a new mode of behavior. Sudden phase transitions (bifurcations) may thus be followed by phases of stable dynamics (dynamical equilibria, attractors). Equilibrium does not imply static equilibrium, or a steady state (Abraham and Shaw 1992). The concept of chaotic dynamics, for example, addresses a type of dynamical equilibrium that has received much attention recently. Chaos stands for a class of deterministic behaviors in a system which, while fully determined and stable (i.e., compressing phase space to a subset, the attractor), nevertheless shows unpredictable courses within a short period of time (Rössler 1976; Bergé et al 1984). Thus, chaos is a strange phenomenon: it entails order and uncertainty at the same time. The functionality of this Janus-faced dynamics for cognitive information processing (providing for continuity and creativity) has been stressed by several authors (e.g., Nicolis 1986; Skarda and Freeman 1987).

Both concepts—self-organization and chaos—have increasing impacts on psychology and psychiatry (Haken and Stadler 1990; Tschacher 1990; Tschacher et al 1992). Globus and Arpaia (1994) point out that the nonlinear dynamical model leads to a topological representation of disorders and has the potential to yield a new paradigm for psychiatry (see also Mandell and Seltz 1992). The new dynamical approach appears to be relevant to psychiatry in several respects: (1) Brain function can be modeled deductively by connectionist computer simulations; the resulting neural nets have many of the attributes of nonlinear dynamical systems. Compared to the symbol processing approach of traditional artificial intelligence (AI) they promise to yield more appropriate models of the actual neuronal networks of the brain. (2) Brain dynamics may be modeled in an inductive, data-driven way by nonlinear time series analysis. Many studies have been conducted by employing dimensionality measures of the electroencephalogram (EEG) to estimate the chaoticity of the electrical behavior of the cortex (e.g., Mayer-Kress and Layne 1987). (3) The concept of dynamical diseases (Glass and Mackey 1988; an der Heiden 1992) is based on a system's view of psyche, body, and social world. This concept implies that behind symptoms we may find the processing of a dynamical system. Then, disorder is equivalent to a significant change of a system's dynamical regime such that pathological behavior evolves out of healthy behavior by way of a bifurcation (a phase transition between two different dynamical regimes). In psychiatry, mainly bipolar depression and schizophrenia have been viewed from this angle (Gjessing 1932; Gottschalk et al 1995). (4) Techniques of nonlinear time series analysis are becoming available for the investigation of symptomatology ratings. There is a growing palette of methods

suitable even for noisy data with restrictions due to time series length and resolution (Scheier and Tschacher 1994).

In this paper we will address the last two points of this list; our hypothesis concerning schizophrenia claims that psychotic episodes may be understood as manifestations of a nonlinear, possibly chaotic system, i.e., schizophrenic psychoses are considered to be dynamical diseases (Schmid 1991; Ciompi et al 1992). Furthermore, the limitations of standard chaos detecting methods discussed in Steitz et al (1992) caused us to adopt a new kind of methodology capable of distinguishing nonlinearity from noise and noisy linear processes.

Hypotheses

The system-under-study of this paper is the hypothetical dynamical system that generates psychotic symptoms. In formal notation, we assume to observe data of a stochastic dynamical system. We put aside the possibility of a system showing high levels of dynamical noise resulting in non-stationary time series; non-stationarity would make any modeling effort suspect.

The system may be symbolized by a differential equation with a stochastic term $F(t)$ describing external fluctuations that act on the system:

$$\dot{x}(t) = N(x(t),\mu) + F(t). \tag{1}$$

$x(t)$ is a vector of the state variables of the system dependent of time t (state variables are all m phenomenological descriptors of the system, thus spanning a phase space of dimension m). N is the (linear or nonlinear) function that determines the temporal change of state variables. The function itself depends on the environment of the system expressed by a set of control parameters μ).

(1) lends itself to the following simple classification of qualitatively distinct dynamical systems:

(a) $F(t) \gg N(x(t),\mu)$: If the noise or random term is much larger than the deterministic part of the equation, system (1) describes a more or less stochastic process. This would mean that the time series shows no evidence of a dynamical disease.

(b) $F(t) \ll N(x(t),\mu)$: We get a deterministic system capable of producing dynamical equilibria ("attractors"). Point attractors and periodic attractors can be realized by systems with linear or nonlinear N, while chaotic dynamical equilibria are necessarily derived from nonlinear systems.

(c) $\sigma^2(N(x(t),\mu))/\sigma^2(F(t)) = R$: A combination of the above cases is predominant in most empirical time series reflecting noisy deterministic systems with some signal-to-noise ratio R, which is expressed using the variances σ^2 of the

deterministic and stochastic terms of (1). Here a further distinction can be made by using statistical tests:

(c_1) N is nonlinear. If a positive Lyapunov exponent exists, the system is chaotic (with some degree of contamination with observational noise).

(c_2) N is linear. The time series can be explained as linearly correlated noise, and should therefore be modeled by, e.g., an autoregressive moving average process (ARMA).

We will classify empirical data on psychoses according to this differentiation. The goal of our classification is to disentangle the different dynamical sources of variation (i.e., linear autoregressive (AR) or moving average (MA), white or colored noise components) in our time series. This classification must be seen as an effort to estimate attributes of (1) on the basis of discrete data. Purely stochastic systems (a) whose time series do not show serial structure pose a first null hypothesis since environmental influences on symptoms are not controlled for in our field data (rigorous control is possible only under experimental circumstances and as such is incompatible with the acquisition of long and relevant time series). (a)-systems are suggested by behavioral theories (operant and classical conditioning) which view psychotic behavior as largely under the control of external stimuli; the dynamics of an (a)-system does not result from a system's intrinsic properties: We would not speak of a dynamical disease in this case at all.

Nonlinear and chaotic dynamics (c_1) on the other hand point to the existence of an internally controlled, possibly low-dimensional system unfolding relatively autonomously from environmental fluctuations. Empirical evidence of (c_1)-systems (and obviously of (b)-systems, also) would be a validation of the dynamical disease concept of schizophrenia.

Methods

Subjects and Variables

We studied patients treated at "Soteria" in Bern, a therapeutic residential community specialized for persons experiencing a first psychotic manifestation. The only prerequisite for inclusion in our sample was that a patient's daily manifestations of psychotic symptomatology could be observed for a long enough period of time (at least 200 consecutive days). Thus because of methodological constraints our sample consists of 14 long-term Soteria residents (10 diagnosed schizophrenic, two schizoaffective, one schizophreniform, one brief psychotic disorder).

The longitudinal course of symptoms was mapped by

1: relaxed, well-balanced, calm
2: unsteady, anxious, nervous, irritated
3: restless, tense, loaded, aggressive
   or
   depressive, cross, down-hearted, sad
   or
   ambivalent, irresolute
4: intimidated, agitated, confused, labile, loose associations
5: phenomena of derealization and/or depersonalization: surroundings or oneself appear unreal, strange, changed. Thought disturbance: absentmindedness, pressure of thought, breaks of thought
6: ideas of reference, delusional projections, delusions: incorrigible convictions of oneself and the world contradict reality and experiences of others
7: hallucinations: perceptual experience without objective source of stimulation. Inexistent stimuli are heard, seen, felt, smelled. Catatonic phenomena: motor blockage, compulsive posture, stereotypy, mannerism, movement storm

Figure 1. Abbreviated manual for the daily rating scale (variable measured: psychotic derealization in schizophrenia).

daily ratings of a patient's psychoticity by Soteria staff members. A seven-point scale was used (Figure 1; Aebi et al 1993) by which the course of psychotic derealization was measured. Reliability of ratings was established during a period of six weeks of training, resulting in an interrater agreement of .70 (Kendall's tau).

The measurement process can be seen as the mapping of a continuous variable "psychotic derealization" in schizophrenia onto a set of seven equidistant categories of the rating scale. In order to arrive at an appropriate formulation of the state vector $x(t)$ after equation (1), the empirical time series must be unfolded by the method of time delays (Takens 1981). Thus we obtain an embedding in a space of m dimensions where the course of the system is represented as a trajectory (a sequence of states). Actually, the trajectories that result from our empirical time series are approximations of the hypothesized continuous trajectories of the schizophrenic processes. Examples of time series and trajectories of two patients are depicted in Figure 2.

Additional to symptom ratings we recorded the dosages of psychoactive drugs patients of our sample received. For an overview of subjects see Table 1.

Time Series Analyses

The methodology of time series analysis has progressed considerably during the last years; linear (ARMA) models (Box and Jenkins 1976) which have been in use for several decades are more and more accompanied by nonlinear models (Tong 1990). This is essential for innovative system theoretic approaches like self-organization theory (synergetics) and chaos theory.
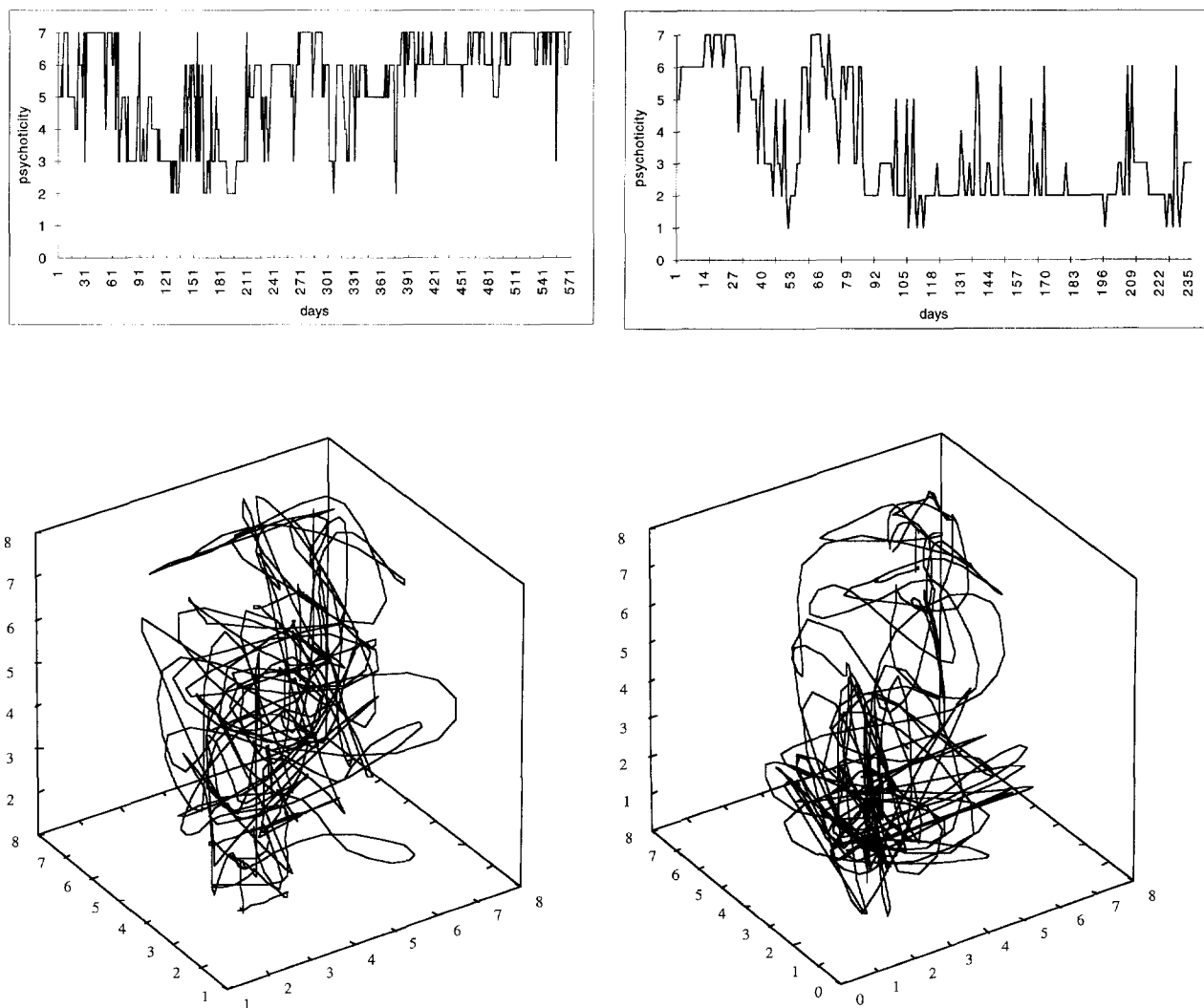
Figure 2. Time series plots and phase plots of psychoticity ratings (left: patient 47; right: patient 57). The phase plots are embedded in $m=3$ by the method of time delay vectors ($\tau = 10$ days).

Our data sets are characterized by relatively short time series lengths ($200 < n < 770$), few steps of the scales (resolution of measurement <3 bits), and varying degrees of measurement noise and dynamical noise; taken altogether, this is typical of psychosocial data acquisition.

One of the main points of this paper is that psychiatric time series like the schizophrenia data presented here can be analyzed with appropriate dynamical measures. Most recent studies applying dynamical methods to psychological and psychopathological time series (e.g., Ciompi et al 1992; Redington and Reidbord 1992; Gottschalk et al 1995) use the "classical" methods of nonlinear time series analysis, namely calculations of fractal dimensions and Lyapunov exponents. These methods, however, can not be applied to short and noisy time series with low resolution (Ruelle 1990; Steitz et al 1992; Rapp 1993; Scheier and

Tschacher 1994). Thus, they are not used in this study. We concentrated on new methodological approaches which have been shown to remain applicable when only short and noisy time series are available. These approaches are nonlinear forecasting algorithms combined with statistical tests.

The rating scale used to assess psychoticity enforces a discretization to seven categories as mentioned above. Nevertheless, the measured variable—psychotic derealization in schizophrenia—is assumed to be a continuum. Thus, our data are not merely symbol strings of observed symptoms. The theory of a continuum of progressive derealization marked by a number of diverse symptoms is detailed in Ciompi (1982) and elsewhere (Conrad 1958; Scheflen 1981; cf, factor analytical views: Kay and Sevy 1990).

Table 1. Description of Subjects Included in the Study[a]

Patient	Sex	Age (years)	n (days)	Average neuroleptic dosage	Average psychoticity	Previous admissions	DSM-IV code	Diagnostic impression
53	m	24	212	158.6	2.43	None	295.3	Paranoid schizophrenia; persecutory delusions
56	m	18	503	91.3	3.28	None	295.3	Paranoid schizophrenia; religious delusions, voices, echopraxia
47	f	20	572	502.3	5.37	None	295.1	Schizophrenia, disorganized type, anergia, irrelevant affect
58	f	26	291	15.9	3.59	None	295.3	Paranoid schizophrenia; persecutory delusions
51	f	23	222	190.5	4.13	1	295.1	Schizophrenia, disorganized type; poor premorbid adaptation
19	f	29	203	228	2.78	1	295.4	Schizophreniform disorder
34	m	25	762	102.9	2.26	None	295.1	Schizophrenia, disorganized type; suicide 1/90
48	f	37	207	112.7	1.82	Approx. 10	295.7	Schizoaffective disorder, depressive type
54	f	32	681	23.8	2.92	None	295.2	Catatonic schizophrenia; mutism, mannerisms, voices
13	f	23	326	409.3	6.03	2	295.3	Paranoid schizophrenia; voices, inappropriate affect
24	m	27	234	4.1	4.01	1	295.3	Paranoid schizophrenia; delusions of persecution, jealousy, voices
62	m	20	227	57.6	3.27	3	295.7	Schizoaffective disorder, bipolar; paranoid ideation
57	f	26	236	239.1	3.43	None	295.3	Paranoid schizophrenia; somatic delusions, suicide 10/91
41	f	18	297	0	1.73	None	298.8	Brief reactive psychosis; after social stress, emotional ambivalence

[a]n, number of daily symptom ratings; Average neuroleptic dosage, mg chlorpromacine equivalents; Average psychoticity, according to ratings; DSM-IV code, clinical diagnostic impression.

Forecasting Algorithm 1

An essential property of a system is the way in which its temporal evolution is determined. How may we classify the rules that influence the system's behavior? A direct way to accomplish this would be a measure of the determinism inherent in the system. One such measure of determinism is the forecastability of a system, given time series observations of its behavior (Sugihara and May 1990).

First, a time series is divided into two halves; the first half is a "library" that can generate forecasts. In order to do that, a system's phase space of embedding dimension m is reconstructed from the time series using the method of Takens (1981). Each state of the system is represented by one point in phase space. Forecasting temporal development thus addresses the question of which point is next approached by the system. On the grounds of axioms of dynamical systems theory it must be assumed that neighbors in phase space change in a similar way if the underlying system is deterministic.

In this way we can forecast the future development of any given state documented in our patients. The accuracy of forecasting can be defined as the correlation of expected development (extrapolated on the basis of next neighbors in the "library" data) with actual development (as realized in the second half of the time series). Figure 3 charts such correlations derived via a non-parametric version of the

Sugihara-May algorithm from the data sets of Figure 2 and the other patients. As can be seen in patient 47, the correlation value for time step 1 ("next day") is approximately 0.7. A forecasting period of 4 days, however, no longer yields a valid prognosis (the correlation has decreased to below 0.1 at an embedding dimension of $m = 3$).

The change of forecasting accuracy for increasing periods of time is characteristic for the kind of time series that has been mapped—we achieve a "fingerprint" of the system's dynamics. A linear autoregressive system, for instance, yields no decrease of correlations, but a constant positive value of forecasting accuracy; a random generator in a computer (or a noisy system, respectively) shows no correlations deviating significantly from zero; a chaotic system acts according to sensitive dependence on initial conditions (the definition of chaos) by giving a trajectory of prognoses that resembles patient 47: short-term predictability with non-predictability in the longer run is a basic sign of deterministic chaos.

SURROGATE DATA METHOD. One possible way to classify a system would be to describe the system's "fingerprints" by visual inspection. But superposition of different source processes may lead to erroneous classification. We therefore chose a more systematic statistical procedure which estimates if there is a significant difference of the
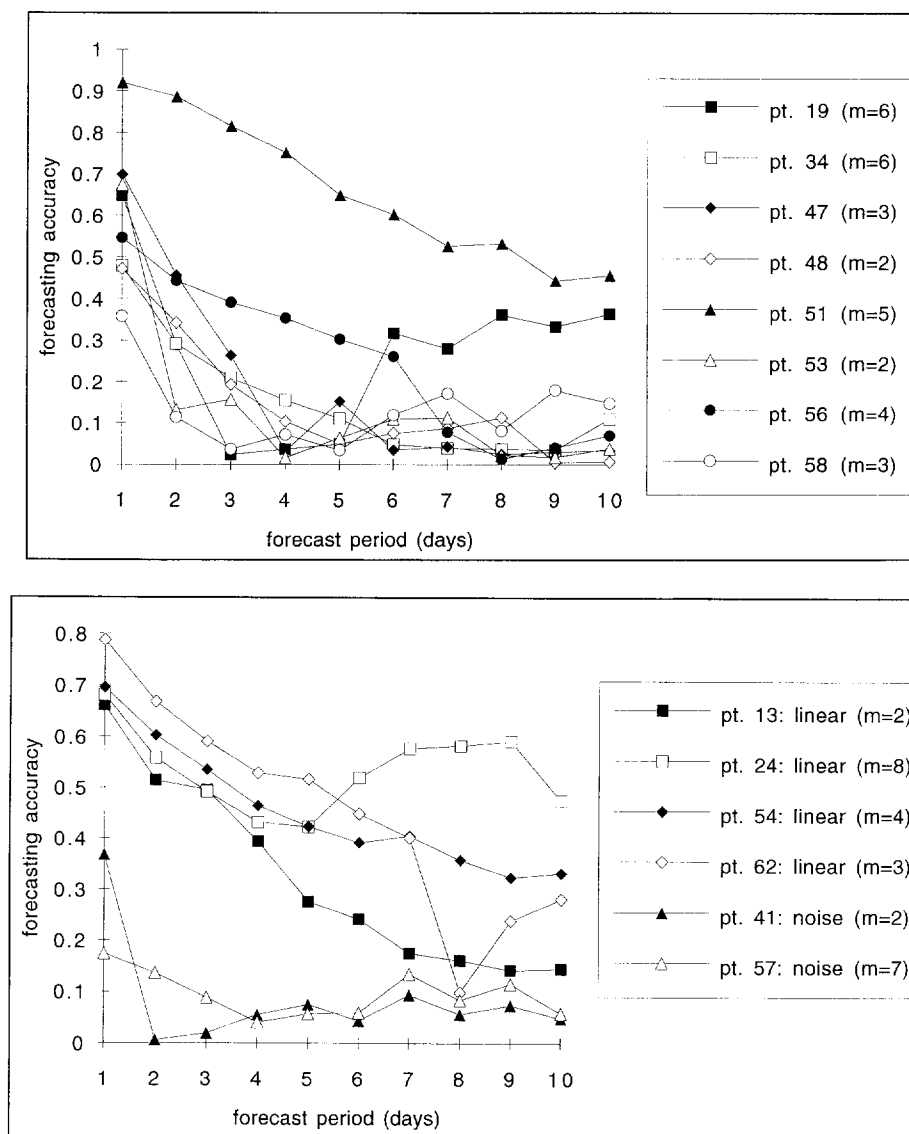
Figure 3. Courses of forecasting accuracies computed with the Sugihara-May algorithm for the patients. In each course the optimal embedding dimension m is chosen. The top chart shows patients with courses classified as nonlinear. The bottom chart shows patients with courses classified as linear or noisy.

index system's determinism and the determinism of archetypal artificial systems, so-called surrogates.

We used this method of surrogate data to evaluate the statistical significance of our time series classification via forecasting accuracies. The method is described at length in Theiler et al (1992) and Scheier and Tschacher (1994): first we compute a discriminating statistic with the above forecasting method (we exploited the forecasting accuracy for the period "one day" as a marker of determinism; e.g., $r = 0.70$ for patient 47 in Figure 3). Then we determine the respective values for a number of surrogate data (i.e., artificially generated "time series," that are identical with the measured data according to mean, variance, and length, but represent other types of serial determinism). In this way we gain a distribution of discriminating statistics so that we can test if the empirical time series can be discriminated from a population of surrogate data as far as determinism is concerned.

Tests were employed in two ways: first, we tested if empirical time series can be predicted better than random; second, we fitted linear autoregressive models to the original data, used the various realizations of these models as surrogate data sets, and examined if empirical data can still be forecast better than their linear models. Thus, this surrogate data method allows us to test two null hypotheses: null hypothesis (1): The time series behaves like a

string of random numbers, i.e., is an (a)-system according to the classification given above. null hypothesis (2): The time series examined behaves like a linear autoregressive process—a (c_2)-system.

The rejection of both null hypotheses indicates that a certain time series contains nonrandom serial structure and is not linear-autoregressive.

Forecasting Algorithm 2

This second forecasting algorithm is similar to the Sugihara-May algorithm. It was designed to allow for a distinction of noise vs chaos (NVC). For each m-dimensional state vector of a time series one single closest neighbor in phase space is determined. In order to control for spurious correlations, neighbors in temporal vicinity of the to-be-predicted state are excluded from computation. In cases where there is still more than one equidistant neighbor, the computer routine uses the first nearest neighbor found. The evolution of this neighbor serves as a predictor. Application to every state vector of the data set yields a distribution of prediction errors (Kennel and Isabelle 1992).

SURROGATE DATA METHOD (NVC). Kennel and Isabelle suggest using surrogate data sets which have the same length, mean, variance, and power spectrum as the original time series. These surrogates test for "linearly correlated noise" as detailed in Theiler et al (1992).

Surrogates are generated by randomizing the phase of the discrete Fourier transform of the original data. Then the distribution of prediction errors of the original data is compared to the distributions of surrogate prediction errors by a nonparametric test (Mann-Whitney U). For large enough numbers of prediction values, a standard normal distributed z-statistic is obtained (see Table 2). In short, we introduce another null hypothesis: null hypothesis (3): The time series behaves like a string of random numbers with a power spectrum identical to the original data ("linearly correlated noise").

In several computer experiments we could confirm the ability of the two forecasting methods to distinguish random (a)-systems, linear stochastic (c_2)-systems and nonlinear deterministic (c_1)-systems reliably (Scheier and Tschacher 1994). We found that discrimination is maintained under conditions of noise (up to 70%) and short time series (in some cases with less than 200 points of measurement). Computer experiments also show that this method is robust when a continuous variable is discretized so that data resolution is artificially reduced to a few categories (Scheier and Tschacher 1995). We found consistently that lowered data quality leads to more conservative estimations, which helps avoid false positive re-

Table 2. Results of Nonlinear Forecasting and Related Significance Tests[a]

Patient	Forecasting accuracy	Noise test	Linearity test	NVC	Model
53	0.757	4.59**	3.42**	−5.12**	Nonlinear
56	0.578	9.26**	6.66**	−8.32**	Nonlinear
47	0.698	15.27**	2.18*	−12.55**	Nonlinear
58	0.358	2.72**	8.16**	−7.12**	Nonlinear
51	0.92	11.28**	1.9	−2.9**	Nonlinear
19	0.671	5.13**	2.33*	−3.45**	Nonlinear
34	0.479	11.64**	2.28*	−1.88	Nonlinear
48	0.472	4.70**	2.18*	−3.16**	Nonlinear
54	0.696	17.13**	1.23	0.47	AR
13	0.661	10.84**	1.72	0.66	AR
24	0.852	11.97**	0.87	1.09	AR
62	0.79	12.22**	0.98	−0.23	AR
57	0.174	0.8	(5.26**)	0.77	Noise
41	0.477	1.66	(4.91**)	2.33*	Noise

[a]Forecasting accuracy, the degree of predictability of a time series (maximum correlation between forecast one day ahead and actual data after Sugihara and May); Noise test, noise effect measure from test of the first null hypothesis; Linearity test, linearity effect measure for the second null hypothesis; NVC, noise vs chaos effect measure for third null hypothesis (effect measures are values under a standard normal distribution; e.g., 1.96 [*] is significant at a 5% error level [both sides], 2.58 at the 1% level [**]); Model, classification according to coefficients [Noise: (a)-systems; AR: (c_2)-systems; Nonlinear: (c_1)-systems.

sults. In short, we simulated the application of rating scales like the ones we used for the observation of psychotic derealization in schizophrenic subjects.

Rejection of null hypotheses (1)–(3) suggests that the time series tested is neither noise, a linear-autoregressive process, nor colored noise (e.g., a general ARMA process). Thus, we may follow by exclusion that the time series has significant nonlinear components.

Results

Qualitatively different groups of psychotic courses can be distinguished by visual inspection of the 14 data sets as assessed by the Sugihara-May algorithm (Figure 3). The first group of courses yields forecasting curves that resemble those of chaotic-deterministic systems (denoted as "nonlinear" in the legend of Figure 3). As in the original publication of Sugihara and May (1990) we found varying degrees of noise in our nonlinear time series that reduce one-day forecasts to values of between 0.92 and 0.4. These time series are probably (c_1)-systems. Further time series can be characterized as random data sets ((a)-systems, "noise" in Figure 3) or autoregressive processes $((c_2)$-systems, AR). This last group of psychoses shows less change in forecasting accuracy over time.

The impression obtained by visual inspection of forecasts is supplemented by the significance tests on the null hypotheses of the surrogate data methods. In Table 2 we list the forecasting accuracies after Sugihara and May and

the effect measures for null hypotheses (1) and (2). Tests of null hypothesis (3) derived from the NVC method support these findings. Table 2 shows that eight out of 14 patients (57%) present nonlinear dynamics. Four time series are best modeled as (AR and/or MA) linear processes. Two cases are classified as random. In cases that seem unclear after visual inspection (e.g., is the fingerprint of pt. 13 nonlinear?), we classify according to the statistics. To quote another example: Pt. 41 shows some forecastability one day ahead, but is diagnosed as colored noise by the NVC. This course could be modeled by a moving average process, and is therefore not counted as nonlinear. The results of significance tests are summarized under the heading "model" in Table 2.

Neuroleptic medication is one of the most influential parameters in psychopathological courses of treated patients. For this reason we tested whether there was any indication of an influence of drugs on the classification given in Table 2. We computed the average daily neuroleptic dosage (mg chlorpromacine equivalents) for each patient that is positively correlated ($r = 0.69$) to the level of psychoticity (see Table 1). There is no significant correlation of dosage (nor of average psychoticity) with a "nonlinear vs other" subgrouping of patients.

Discussion

Our goal is to contribute to a dynamical systems approach in psychiatry and clinical psychology. With Strauss et al (1985) we hope that "...the issues of sequence and patterns cannot be neglected indefinitely: they potentially hold answers for too many crucial questions." Furthermore, we are convinced that the concepts of self-organization, chaos and complex dynamics have great explanatory power for psychopathology and schizophrenia research. But as empirical scientists we also think that the years of systems theoretical conceptualizations (for an overview see Tschacher et al 1992) should finally be accompanied by longitudinal empirical studies. Even if "dynamics is the essence of psychiatry" (Freeman 1992) there will be no dynamical systems paradigm in this field without much more empirical work.

In the field of nonlinear dynamics we encounter growing skepticism about the method of dimension analysis as a tool to detect chaos in empirical data (Ruelle 1990). Even many of the EEG findings reported in recent years are probably based on spurious effects (Rapp 1993). So to us it seems all the more clear that correlation dimension is not an adequate parameter for the description of psychopathology ratings and psychological data. We therefore investigated and tested alternative methods of data reduction—forecasting algorithms combined with surrogate data statistics—which are more appropriate tools for

modeling nonlinearity in noisy empirical data. A further advantage of this statistical "bootstrap approach" is that more and more specific null hypotheses can be generated (e.g., the static nonlinear filter surrogates mentioned in Theiler et al [1992]). Furthermore, various discriminating statistics may be defined that map other attributes or invariants of time series, e.g., Lyapunov exponents or measures of entropy (Wales 1991; in the context of psychotherapy research (Tschacher and Scheier 1995), we implemented surrogate tests using algorithmic complexity (Rapp et al 1991).

The application of surrogate methods to psychoticity time series of 14 psychiatric patients is reported here. We found evidence to the point that a larger proportion of the psychoses we studied shows nonlinear time courses. This supports the validity of the concept of dynamical diseases on statistical grounds in this important area of psychopathology (for earlier work in this field see Gjessing 1932; Cronin 1973). Additionally, our investigations are compatible with the hypothesis that schizophrenia may be characterized by chaotic evolutions. Since direct proof of deterministic chaos in relatively short empirical time series is unattainable (Scheier and Tschacher 1995) we can not assess the chaoticity of the schizophrenia courses we studied. Yet, visual inspection of forecasting accuracies (Figure 3) shows that the decay of predictability typical of chaos (but also of some MA processes) is present in several cases. In most of these cases, though, alternative hypotheses (especially, linearly correlated stochasticity of ARMA processes) can be rejected.

Which conclusions can be drawn from these results? The finding that in schizophrenia symptoms are generated by a nonlinear dynamical system is good reason to assume that a precise understanding of the disorder is possible. We think it is probable that few variables coupled nonlinearly can sufficiently explain the unfolding of symptoms in many cases. The solution to the problem of schizophrenia may not lie in adding still more causal factors to an additive multicausal theory of this disease. An adequate nonlinear theory will be more parsimonious.

Quite obviously, we do not yet have this theory at our disposal; we know little of the character of the nonlinearly coupled variables mentioned. They may be biological, psychological, or social (or some blend of the three phenomenological domains). Until now, we found no phenomenological parameters that could link nonlinear dynamical models to other descriptors (such as severity of symptoms, outcome variables, medication). For example, we found no simple relation between average doses of neuroleptics used by patients and their dynamical classifications. There probably is no general theory of schizophrenia even in similar cases but rather individual instantiations of a dynamical disease. Schizophrenia may be a

wide class of (c)-systems with idiosyncratic parameters in each instance.

Several dynamical views of psychiatric disorders have been put forward recently. Globus and Arpaia (1994) assume that there is a splitting of the brain's tuning (i.e., in technical terms, a change of control parameters causing phase transitions in a self-organizing system). Malattunement may thus distort the topology of the cognitive system. Hoffman and McGlashan (1993) propose that parasitic foci emerge in neuronal networks and produce the positive symptoms of schizophrenia. Our view on psychosis takes another direction which is due to the different data levels used (neural net modeling vs empirical psychopathological data): we try to reconstruct the schizophrenia attractor from phenomenological observations.

Our findings also complement evidence of an increase of dimensional complexity in the EEG of schizophrenic persons (Koukkou et al 1993). Results appear to be antagonistic (few degrees of freedom in schizophrenia courses on one side, increase of degrees of freedom in the EEG on the other); but the increased number of neuronal cell assemblies activated in schizophrenics may reflect the cognitive and emotional impairment, which in turn leads to the phenomenological derealization dynamics discussed in our study. The neurophysiological and the longitudinal clinical picture can be seen as two different views of the same dynamical disease.

From the phenomenological point of view, normal functioning is realized by a stable fixed point (a point attractor). The fixed point damps out any psychotic fluctuation (caused by, say, sensory deprivation) within a short time and restores the system to nonpsychotic regions in phase space. In order to become schizophrenic an individual must cross one or more critical points in parameter space; at these points once stable variables become endowed with positive eigenvalues and tend to emerge as the new organizing forces in the system. If three or more competing unstable variables simultaneously emerge they may cause the system to show chaotic dynamics (Haken

1983). The crossings of critical points are called phase transitions or bifurcations (Abraham and Shaw 1992).

If this scenario is valid for individuals at the edge of psychosis, we should be able to observe typical bifurcational phenomena like oscillating stages and period doubling as prodromal signs of an episode. Furthermore, a fixed point about to degenerate looses its restoring capacity gradually, which leads to a phenomenon termed "critical slowing down" in dynamics. Thus, our theory makes several predictions which should be accessible empirically if it is possible to acquire reliable data from the initial stages of schizophrenia.

The consequences of a dynamical view not only touch on theory but also on clinical issues. Chaos, as is demonstrated by forecasts, does not entail a total loss of controllability (as is suggested by colloquial language), but short-term determinism combined with increasing unpredictability. Thus, therapeutic intervention can contain a moment of chaos control in the sense that the time span between intervention and evaluation (which guides new interventions) should be chosen accordingly. Thus, chaotic regimes dictate a certain time horizon for interventions. Compared to periodic attractors chaos is even easier to handle because small inputs to control parameters can stabilize favorable behavior which in the chaotic attractor may already be present as unstable orbits (Ott et al 1990; Pyragas 1992).

Controlling chaos and complexity traditionally is the main problem in any psychiatric and psychotherapeutic endeavor. Due to the concepts of nonlinear dynamics there is increasing promise that an adequate theoretical framework may come within reach to help tackle this problem.

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