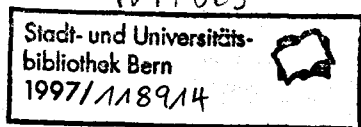


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Non-Linearity and Chaos in the Course of Psychoses – An Empirically Based Classification of Dynamics

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Summary

The paths of psychoses (mainly schizophrenic) were examined on the base of daily ratings of psychoticity in 14 long-term patients. Measures of non-linear dynamical properties of the disease process can be derived from these time series. We applied forecasting methods combined with statistical surrogate data tests and Lyapunov exponents. With this methodology, we assessed the class of dynamics expressed in the course of symptoms: eight out of fourteen patients present non-linear courses, of which 6 show signs of chaoticity; four time series can be modelled linearly as auto-regressive processes; two cases are classified as random. Thus, a considerable subset of our cases seem corroborative of Ciompi's "chaos theory of schizophrenia" which states that productive symptoms may be generated by a chaotic dynamical system of few non-linearly coupled variables. Yet, on the grounds of the present sample, no clear relation between phenomenological descriptors of patients and their dynamical classifications can be established.

Clinical observation gives ample evidence of how heterogeneous the courses of psychotic illnesses can be in the medium and long run. Classical descriptions of schizophrenia in psychiatry since Kraepelin and Bleuler therefore have commonly emphasised the processual character of this disorder. From this tradition a bundle of theories and models emerged which set out to classify the paths of psychosis (Ciompi, 1988; Strauss et al., 1985). But this tradition of studying the *psychotic process* is to a large extent either tied to qualitative-descriptive phenomenology or to cross-sectional empirical research. In their overview Häfner & Maurer (1991, p. 154) state that the field is still suffering from an "extreme shortcoming of longitudinal research."

In this paper we consider psychotic symptomatology from a longitudinal perspective by making use of empirical methods of time series analysis and modelling; this perspective is based on dynamical systems theory. Our starting point will be a discussion of psychoses as "dynamical disorders": we sug-

gest that psychotic and non-psychotic behaviour can essentially be distinguished by the kind of dynamical regime or equilibrium realised. In the interdisciplinary field of dynamics two focal concepts are currently discussed (the phenomenon of self-organisation and the regime "deterministic chaos"); the relevance of either concept for psychiatric research will be highlighted. Finally, we will present the results of an investigation of empirical data on the paths of psychoses; this is accomplished by nonlinear techniques which have become available recently.

It seems inadequate to label psychosis *per se* as "chaotic," "nonlinear" or by any such attribute; even the narrower concept of schizophrenia probably represents different heterogeneous types of disorders (Andreasen & Olsen, 1982). Additionally, schizophrenia may manifest itself differently at each systems level. In the context of our study we see the option of statistically assessing the course of each single patient by the method of time series analysis; this makes it an idiographic study as claimed by phenomenology. We also restrict ourselves to statements about a specific systems level (i.e., the level of psychopathological time courses of 200 to 800 days); under these constraints we think it is possible to differentiate types of psychotic dynamics on an empirical basis. Finally we will compare this differentiation with phenomenological and diagnostic descriptions of our cases.

The Concept of Dynamical Diseases

The concept of dynamical diseases (Glass & Mackey, 1988) is based on the axiom that psyche, body, and social world may be subdivided into *systems*, which themselves consist of interacting components (cf. Bunge, 1979). In the respective basic disciplines psychology, biology and sociology this axiom has been elaborated especially by cybernetics. Recently the various attributes of *complex* systems (Nicolis & Prigogine, 1977) render the systems view a valuable heuristic principle especially in the field of psychiatry (Schiepek & Tschacher, 1995). In its application to psychosocial systems, however, the question of which components make up the system is far from trivial (Tschacher, 1990). Pragmatically we assume that researchers' biases (e.g., conventions of scientific disciplines) participate in determining the components. Thus, a system in psychiatry is never entirely the reflection of the objective world, but must also be viewed as the construction of an observer (Böker & Brenner, this book).

The interaction of components results in a dynamics characteristic of the system. In mental, social and biological systems this dynamics is often a state

of equilibrium (in cybernetics: a loop with negative feedback). But the counterpart to homeostatic dynamics is also found: in random, turbulent or unpredictable behaviour (e.g., positive feedback amplifying small deviations). Whatever dynamics a concrete system may exhibit, the concept of dynamical diseases assumes it to be essential for any dysfunction that the interaction of system components is altered. Pathological behaviour evolves out of healthy behaviour by way of a bifurcation (a phase transition between two different dynamical regimes, cf. an der Heiden, 1992). A bifurcation is also found if an unordered complex system spontaneously evolves into an ordered state; this emergent phenomenon of pattern formation is studied in self-organisation theory and synergetics (Haken, 1983).

The dynamical concept of disorder prepares for no dichotomous judgement between "sick" and "healthy," but assesses "illness" to be merely a different way of functioning in the same system. Therefore, no ontological quality is ascribed to illness (disorder), rather, it is seen as a process deviating from normal. Additionally in complex systems there may exist a tendency to fixate recurring or enduring dynamics morphologically, which explains the increasing stability of chronic states (cf. Bischof, 1990). Insofar dynamical diseases may secondarily become "imprinted" into a substrate and manifest themselves in structural changes.

Put formally, we may start from *stochastic dynamical systems*. They can be symbolized by a differential equation with a stochastic term $F(t)$ describing external fluctuations that act on the system:

$$\mathbf{x}'(t) = N(\mathbf{x}(t), \mu) + F(t) \quad (1)$$

$\mathbf{x}(t)$ 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 state 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 .

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

- (a) $F(t) \gg N(\mathbf{x}(t), \mu)$: If the noise or random term is much larger than the deterministic part of the equation, system (1) becomes a more or less pure stochastic process. A special case is the temporally weighted noise of a moving average (MA) process.
- (b) $F(t) \ll N(\mathbf{x}(t), \mu)$: We get a deterministic system capable of producing equilibrium states ("attractors"). Examples of attractors are point attractors (the equilibrium is a constant, e.g., the mood of a well-balanced person); periodical attractors are oscillating equilibria: for instance the mood

of some manic-depressive persons. Point attractors can be realised by systems with linear or nonlinear N , while all equilibria of higher complexity necessarily stem from nonlinear systems. The class of chaotic attractors has been widely discussed in recent years and seems relevant for many applications. Chaotic behaviour eludes long term forecasting by showing turbulent, mixing behaviour (Rössler, 1976; Abraham & Shaw, 1984), which is hardly captured by a common notion of homeostasis; it can nevertheless be shown that these attractors must be counted among those dynamical structures that – all in all – increase order.

- (c) $N(x(t), \mu)/F(t) = R$: A combination of both former classes is predominant in empirical research, namely “noisy” deterministic systems (in our data with a signal-to-noise ratio of $9 > R > 0.6$). Here a further distinction is close at hand:
 - (c₁) N is nonlinear. Nonlinear dynamical systems are prerequisite for chaos and self-organisation.
 - (c₂) N is linear. The time series may then be modelled by an autoregressive (AR) process.

Dynamics and Psychodynamics

We have now reached a point where we can put forward our content hypothesis: psychotic episodes may be understood as manifestations of a chaotic system. Clues to this point are given in studies of Ciompi and coworkers (Ciompi et al., 1992). Schmid (1991) points to the consequences of scale invariance (an attribute of chaotic fractal attractors) for a multi-level approach to schizophrenia. The significance of the dynamical finding (chaotic process (c₁) vs. noise (a)) for the understanding of the underlying (psychobiosocial) system is outlined in Steitz et al. (1992); elaborating this former formulation we hold the following assignment to be useful:

Pure stochastic systems (a), whose time series do not show serial structure, possess high sensitivity for fluctuating environmental stimuli. In our study this poses a fundamental null hypothesis since environmental influences on psychoticity are not controlled for in our field data (rigorous control is possible only under experimental circumstances and as such incompatible with the acquisition of long and relevant time series). (a)-systems are suggested by behavioural theories (operant and classical conditioning) which take behaviour as largely under the control of external stimuli. In this case the dynamics of a system does not primarily result from its intrinsic properties.

Table 1. Patient population studied according to demographic and disorder-related criteria. Grouping was achieved by cluster analysis of the variables "vocational training", "attribution (of the cause of the disorder)", "high-EE" (expressed emotions in family), "social relations" (to persons outside the ward).

Patient (sex)	age	vocational training	diagnosis	extent of psychopath.	attribution	rehabilitation	high-EE	social relations
56 (m)	18	drop-out	schizophrenia	large	intrinsic	good	yes	no
54 (f)	32	university	schizophrenia	very large	intrinsic	bad	yes	no
58 (f)	26	completed	borderline	large	extrinsic	bad	yes	no
51 (f)	23	completed	schizophrenia	large	extrinsic	bad	yes	no
13 (f)	23	drop-out	schizophrenia	large	extrinsic	good	yes	no
53 (m)	24	completed	schizophrenia	large	extrinsic	good	no	no
47 (f)	20	drop-out	schizophrenia	very large	extrinsic	bad	no	no
24 (m)	27	drop-out	borderline	large	extrinsic	good	yes	yes
41 (f)	18	none	adolesc. psychosis	small	extrinsic	good	yes	yes
62 (m)	20	completed	schizoaffective	moderate	extrinsic	good	no	yes
57 (f)	26	drop-out	schizophrenia	large	intrinsic	bad	no	no
34 (m)	25	drop-out	schizophrenia	large	extrinsic	bad	no	no
48 (f)	37	completed	schizophrenia	large	intrinsic	good	no	yes
19 (f)	29	completed	schizophrenia	large	intrinsic	good	no	yes

Table 2. Scale for daily ratings of psychotic derealisation (psychoticity).

- 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 derealisation and/or depersonalisation: surroundings or oneself appear unreal, strange, changed. Thought disturbance: absent-mindedness, 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

Chaotic dynamics (c_1), on the other hand, point to the existence of a internally controlled, low-dimensional system unfolding relatively autonomously from environmental fluctuations. Empirical evidence of (c_1)-systems would be a validation of the dynamical disease concept for psychoses. In a complex network given by a person and all of his numerous cognitive, social, and biological interactions, we understand the emergence of a low-dimensional sys-

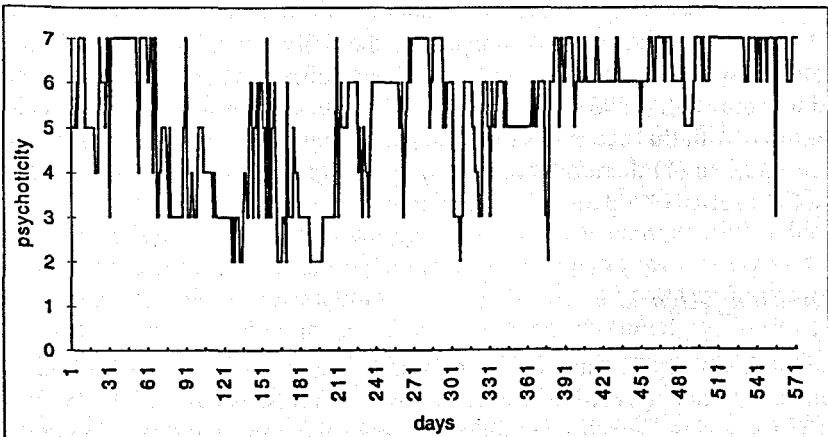


Figure 1. Plot of a time series (patient 47) of daily psychoticity ratings over a period of 572 days.

tem as a process of self-organisation. In the context of psychotherapy theories such systems seem compatible with psychoanalytical, cognitive, or systemic theories.

Methods

Subjects

We studied patients treated at the *Soteria Bern*; as a small therapeutic residential community, specialised for persons experiencing a first psychotic manifestation, this is based on ideas of milieu therapy and affect logic (Ciompi, 1991; Aebi et al., 1993 a). The prerequisite for inclusion in our sample was that a patient's daily manifestation of psychotic symptomatology could be observed almost completely for a long enough period of time (at least 200 days). Thus, the subjects did not constitute a random sample, but a population of long-stay Soteria patients.

Patients were assessed by two independent observers for their phenomenological characteristics, which were rated on the basis of detailed personal and interactional knowledge of the patients. The description of 14 patients is presented in Table 1.

Time Series Data

The longitudinal course was mapped by the daily rating of a patient's psychoticity by Soteria staff members. A seven-point scale was used, as described in Aebi et al. (1993 b, see Table 2). The course of psychotic derealisation measured with this scale was the focus of our interest. The state vector $\mathbf{x}'(t)$ after equation (1) therefore contains only one (global) variable. An example of a time series of a patient is depicted in Figure 1.

Forecasting Algorithm

The methodology of time series analysis has progressed considerably in recent years; linear (ARIMA-) models (Box & Jenkins, 1976), which have been in use for several decades, are more and more accompanied by nonlinear models (Tong, 1990). The rapid extension of nonlinear methods is important, especially in the context of innovative system theoretical approaches as self-

organisation theory and chaos theory, which start out from nonlinear interactions within a system.

Our data sets are characterised by relatively short time series lengths, few steps of the scales; and probably high measurement error, which altogether is typical for psychosocial data acquisition. Therefore, methods that try to estimate the dimensionality of fractal attractors fail to be applicable (Steitz et al., 1992). For our study we decided to implement the nonlinear forecasting algorithm (NFA) proposed by Sugihara and May (1991). It can be shown that the NFA is robust concerning the restraints for data quality just mentioned (Scheier & Tschacher, 1994).

We continue with a short description of the NFA. First, the time series is divided into two halves; the first half is a "library" that can generate forecasts. In order to do that, the state space (or "phase space") of embedding dimension m is reconstructed using the method of Takens (1981). Each state of the system is described as one point in state space. Forecasting temporal development thus addresses the question of which point in state space is next approached by the system. On the grounds of axioms of dynamical systems theory (e.g., Rosen, 1970) it may be assumed that neighbouring points ("neighbours") in state space may change in a similar way if the system is deterministic.

For any time series measurement documented in our patients we may forecast the future development of any given state. The accuracy of this forecast may be defined as the correlation of expected development (extrapolated on the basis of next neighbours in the "library" data) with actual development (as realised in the second half of the time series). Figure 2 charts such correlations derived via NFA from the data set of Figure 1. As can be seen, the correlation value for time step 1 ("next day") is around 0.7. A forecasting period of five days, however, no longer yields a valid prognosis (the correlation has decreased to about 0.15 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 some "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 from zero; a deterministic-chaotic system acts according to sensitive dependence on initial conditions (the definition of chaos: Bergé et al., 1984) by giving a trajectory of prognoses that resembles the one depicted in Figure 3: short-term predictability with non-predictability in the longer run is a basic sign of deterministic chaos.

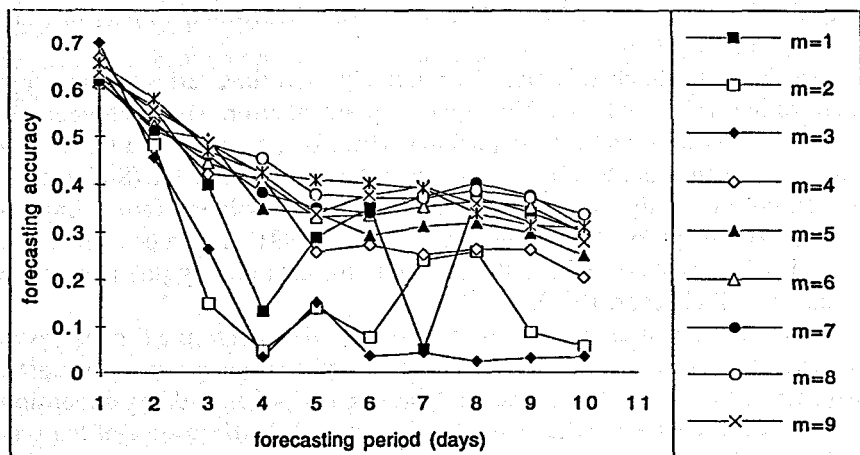


Figure 2. Courses of forecasting accuracies computed with the Sugihara-May algorithm (NFA), embedding dimensions from 1 to 10, based on the data of Figure 1.

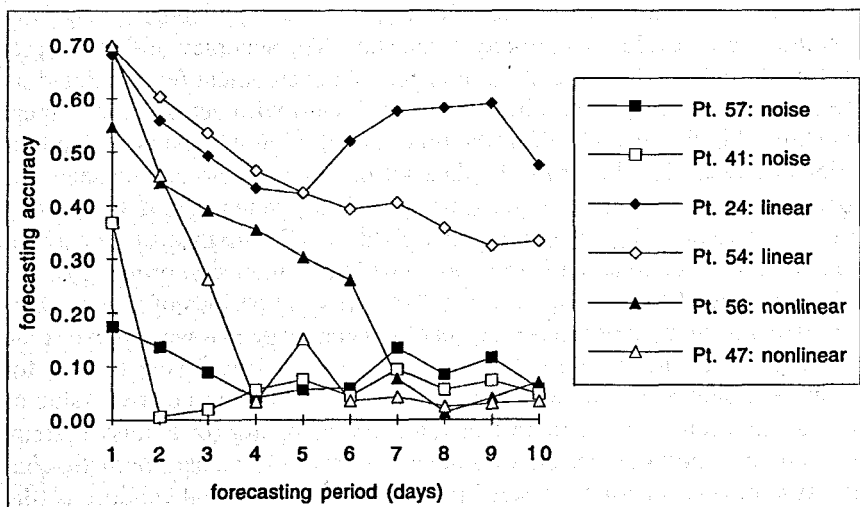


Figure 3. (c₁)-systems, (a)-systems, (c₂)-systems: courses of forecasting accuracies for six exemplary psychosis time series.

Surrogate Data Method

We use the method of surrogate data in order to evaluate the statistical significance of our time series classification with the NFA. The method is described at length in Theiler et al. (1992) and Scheier and Tschacher (1994), so that we may introduce it here by a short example: first we compute a discriminating statistic with the forecasting method NFA, say the forecasting accuracy for the period "one day." This value in the time series of Figure 2 is about $r = 0.70$ (see Fig. 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); in this way we gain a *distribution* of discriminating statistics. Thus we can test if the empirical time series can be discriminated from a population of surrogate data.

Tests were employed in two ways: first, we tested if empirical time series can be predicted better than random; secondly, we fit autoregressive models to the original data, used the various realisations of models as surrogate data sets and examined if empirical data can be forecast better than their linear models. Thus, the surrogate data method allows us to test two null hypotheses:

Null hypothesis (1): The time series behaves like a string of random numbers as far as forecastability is concerned, i.e., is an (a)-system according to the classification given above. Here surrogates can be generated by scrambling the original data: time series length, mean, and standard deviation remain the same, but serial dependency is eliminated.

Null hypothesis (2): The time series to be examined behaves like a linear autoregressive process, is a (c₂)-system. Surrogate data in this test are different realisations of an AR(1) model of the time series.

The rejection of both null hypotheses indicates that a certain time series contains nonrandom serial structure and is nonlinear.

Lyapunov Exponents

These "characteristic exponents" count among the ergodic measures of a dynamical system (Eckmann & Ruelle, 1985), i.e., signify invariants of systems dynamics. The largest Lyapunov exponent is an indicator for divergence of neighbouring trajectories in state space. Divergence (> 0) points to entropy production and sensitive dependence from initial conditions, in other words, deterministic chaos. Calculating is sensible if the testing of null hypotheses (1) and (2) shows that the course of a psychosis can be understood as a non-

linear (c_1)-system. then gives an indication of whether there is nonlinearity in the sense of deterministic chaos. We used the algorithm after Wolf et al. (1985).

Cluster Analyses

Finally we clustered the various descriptors of 14 empirical time series in order to find out about the subgroups in these cases. We used hierarchical cluster analyses with appropriate correlation coefficients (Pearson- r for the NFA- and surrogate data; Goodman-Kruskal-Gamma as the distance metric for phenomenological data) (Wilkinson, 1989). For analysing the latter data the ratings had to be quantified – we therefore “translated” the ordinal scales (e. g., the scale “attribution” was quantified in this way: intrinsic = 1; extrinsic = -1).

Results

Different groups of psychotic courses can already be seen in visual inspection as soon as the 14 data sets are assessed by the NFA. Two courses in each group, respectively, are presented in Figure 4. The first group of courses yields forecasting curves that resemble those of chaotic-deterministic systems (denoted as “nonlinear” in the legend of Figure 4). The discussion of the population dynamical time series in Sugihara and May (1991) corresponds to our finding of a variable amount of noise in our nonlinear time series, which reduces one-day forecasts to values of between 0.92 (approx. 10% noise) and 0.4 (approx. 60% noise). These time series are probably (c_1)-systems. Further time series can be characterised as random data sets ((a)-systems, “noise” in Fig. 4) or autoregressive processes ((c_2)-systems, “linear”). This last group of psychoses shows no significant change in forecasting accuracy over time.

These results are supported by the significance tests on the null hypotheses of the surrogate data method. In Table 2 we listed the forecasting accuracies after Sugihara and May for the psychoses time series and the effect measures for null hypotheses (1) and (2). The table shows that eight out of fourteen patients (57%) have nonlinear dynamics. Four time series are best modelled as autoregressive linear processes. Two cases are classified as random. The results of significance tests are summarised under the heading “model” in Table 2.

Table 3. Results of the non-linear forecasting method NFA and related significance tests. "Forecasting accuracy": the degree of predictability of a time series (maximum NFA correlation between forecast one day ahead and actual data); "forecasting decline": mean forecasting accuracy one day ahead *minus* mean forecasting accuracy five days ahead; "I": value of the largest Lyapunov exponent; "Ho(1)": noise effect measure from test of the first null hypothesis; "Ho(2)": linearity effect measure (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 (**). This table is grouped according to cluster analysis of the data included in the table.

62	0.790	0.422	0.024	12.22**	0.98	AR
54	0.696	0.229	0.014	17.13**	1.23	AR
24	0.852	0.408	0.002	11.97**	0.87	AR
51	0.920	0.288	0.142	11.28**	1.90	nl
13	0.661	0.269	0.104	10.84**	1.72	AR (nl?)
47	0.698	0.344	0.27	15.27**	2.18*	nl
34	0.479	0.325	0.004	11.64**	2.28*	nl (AR?)
48	0.472	0.364	0.02	4.70**	2.18*	nl (AR?)
56	0.578	0.206	0.372	9.26**	6.66**	nl
19	0.671	0.326	0.243	5.13**	2.33**	nl
53	0.757	0.45	0.214	4.59**	3.42**	nl
58	0.358	0.123	0.117	2.72**	8.16**	nl
41	0.477	0.113	0.002	1.66	4.91**	noise (nl?)
57	0.174	0.005	0.021	0.80	5.26**	noise

The largest Lyapunov exponents are also given in Table 2; they support our classification made on the basis of significances since nonlinear courses show the highest values. Thus, at least in six cases we may assume that clear signs of chaotic dynamics are present.

The values listed in Table 2 were analysed for internal structure by cluster analysis. This resulted in three subgroups or clusters, which are graphically indicated in the table by spaces. The three qualitatively distinguished types of courses differentiated by the tests of the surrogate data method are suggested by cluster analysis as well. The transitions between the groups of linear, nonlinear, and noisy systems are not clear-cut, though.

Phenomenological descriptors were quantified and then clustered in the same manner. The result of this analysis is again illustrated by graphical groupings in Table 1. We find that the three dynamical clusters are not congruent with phenomenological clusters. This incompatibility also turns up in correlational analyses (which cannot be detailed here): no significant correlations are found to exist between phenomenological and quantitative-dynamical variables in our 14 cases.

Discussion

In our opinion a number of central questions concerning schizophrenia and psychosis research can only be answered by longitudinal studies. In this paper we treated the basic question of which kind of dynamics reigns psychotic courses: Is the unpredictable and seemingly turbulent sequence of daily symptomatology the expression of a nonlinear system or does it simply reflect environmental fluctuations? In the former case we might approach schizophrenia and similar psychoses on a new foundation, i. e., by interpreting them as dynamical diseases. A palette of methods and phenomena would then be accessible to psychiatry, especially those developed and refined in the field of dynamical science, of synergetics and chaos theory (Tschacher et al., 1992). The validity of such an approach has recently been questioned for different reasons in the case of schizophrenic psychoses (as opposing bipolar depression) (Emrich & Hohenschutz, 1992).

Our investigation actually presents clear evidence to the point that a larger proportion of the psychoses we studied show *nonlinear time courses*. This is the (to our knowledge) first time that the validity of the concept of dynamical diseases could be established on statistical grounds in this important area of psychopathology. Additionally, we succeeded in showing by the estimation of Lyapunov exponents that most of the nonlinear courses may be interpreted as expressions of low-dimensional chaos. This applies to at least six out of eight nonlinear cases. Reversely, this interpretation is supported by the fact that in linear and noisy data sets of our population exponents do not deviate significantly from zero.

The context of the paths of psychopathology measured under field conditions is influenced by many factors, i. e., is high-dimensional. We therefore may assume that nonlinear dynamics is a reflection of the eigen-activity of the psychobiological system "psychosis" which is embedded in the social milieu "Soteria." We see this as an example of *self-organisation*, by which a nonlinear chaotic system is contrasted against a complex environment by an emergent process of pattern formation.

Phenomenology

Our studies have so far not resulted in a congruence between dynamical clustering and groups gained by clinical phenomenological descriptions. The most interesting chaotic courses (i. e., the (c₁)-systems with positive) are mainly schizophrenic psychoses (in one case – Pt. 58 – a borderline disorder).

But we find among these courses favourable and unfavourable paths of the disorder as well; in respect to social interaction and insight into the illness (attribution) the 58 "chaotic" patients are heterogeneous, too.

The same applies to a prognosis we held to be plausible a priori: the less severe a psychosis (as in a borderline disorder), the noisier should be its course. In other words, (a)-systems indicate environmentally contingent behaviour. Our results do not readily support this idea: one of the (a)-systems is generated by a schizophrenic disorder (see Pt. 57 in Table 1). Altogether we think that hypotheses on the connection of dynamics and phenomenology are yet to be generated by correlative-heuristic methods. General statements about this issue must remain vague also due to the small number of cases available at the present time.

We might infer different conclusions from the fact that diagnoses of single patients do not correspond well with dynamical parameters. On the one hand, it is certainly desirable to accommodate diagnoses to path characteristics more than is done in standard taxonomies. A more valid diagnostic system should evolve in this way. On the other hand, our preliminary results encourage idiography which we see not as a method of hermeneutics alone. Each person develops his/her own dynamics; psychoses are private and "creative" phenomena, too, and therefore cannot be subsumed under a category completely (Scharfetter, 1990).

Outview

Time series data of the length reported here, especially with regular daily ratings, are probably rare; they were acquired through observations under special conditions in the course of years. Nevertheless, a number of optimisations are desirable: if scales were more differentiated the course of psychoses could be investigated more thoroughly and reliably (our research group has therefore advanced to data acquisition with multiple time series in the meantime). The topic of the interaction of different symptoms (say, positive and negative symptoms) in schizophrenic disorders has stimulated various incompatible theories which equally draw upon cross-sectional correlational studies (Maurer & Häfner, 1989). We think it is evident that these theories can be further discussed only by applying finer temporal resolution in the sense of multiple time series analysis.

If – as now seems justified – we may count a considerable proportion of psychoses among the dynamical disorders, cross-sectional research approaches even in large samples must in principle leave the essence of these psychoses in the dark. We adopt the opinion of Strauss et al. (1985, p.295): "... the issues of sequence and patterns cannot be neglected indefinitely: they poten-

tially hold answers for too many crucial questions." Beyond this, we think it is time to advocate the theory of dynamical systems as a methodology to be used within psychiatry and psychology. The consequences of a dynamical view will be far-reaching; they not only concern the theory but also the therapy of these disorders.

Chaos does not mean total uncontrollability (as is suggested by colloquial language), but increasing unpredictability combined with short-term determination. Thus, therapeutic intervention can contain a moment of "chaos control": the time span between intervention and evaluation (which guides new interventions) should be chosen accordingly (Mayer-Kress, 1992). The question of dealing with complex systems may be approached also in the context of synergetics; applications to clinical psychology are already being discussed (Kruse & Stadler, 1990; Schiepek et al., 1992; Tschacher, 1990). Psychosis is then understood as a dynamical pattern generated by a self-organising system (i. e., as the attractor of a dynamical disease); theoretically, there are different ways of restituting the dynamics to non-psychotic regions of state space. First, with gradual variation of the environment ("control parameters") the attributes of attractors change in an often discontinuous manner. Second, if other "non-pathological" attractors continue to exist there is an opportunity to drive the system into the basins of these attractors by single interventions or perturbations, i. e., even without changing control parameters. Functioning in these attractors then has to be stabilised structurally in the sense of relapse prevention.

In the future a more systematic and fundamental elaboration of a dynamical intervention theory will have to be developed. We hope to have stimulated such an endeavour with the present article.

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