Synergetics in Psychology: Patterns and Pattern Transitions in Human Change Processes

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Abstract. Synergetics has arrived in psychology. More than this – it has proven to be an inspiring research paradigm for investigating and modelling complexity and dynamics of mental, behavioural, and social phenomena. The evolution of human systems is characterized by features as circular causality, the emergence and dynamics of order parameters, order transitions, and critical instabilities. Psychotherapy research was one of the most productive fields for empirical research on self-organization in psychology. Referring to several studies on psychotherapy processes we will demonstrate that human development and learning generate some kind of order. They are chaotic in a strict sense, i.e., they can be characterized by low-dimensional, complex, and changing dynamics. Empirical studies used different data sources, coding methods, and time scales and focused on synchronization, non-stationarity, and local instabilities of psychotherapeutic processes. Referring to the concept of order transitions, synergetics offers an explanation to what is called "sudden changes" in psychotherapy. Empirical evidence also exists for coordinated order transitions in the dynamics of subjective experiences and brain activity, measured by repeated fMRI scans. During the treatment of patients with obsessive-compulsive disorder (OCD), transitions started by the destabilization of current patterns and hence by critical fluctuations. The most important change rates of neuronal activity in different brain areas occurred during cognitive-affective order transitions.

Keywords: Synergetics, psychology, order transitions, psychotherapy research, brain dynamics

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1 Introduction

Synergetics describes, measures, and explains processes of pattern formation and pattern transition in complex nonlinear systems. Although Hermann Haken developed it in the field of quantum optics (laser physics) and applied it firstly to other physical phenomena like the emergence of convection patterns in fluids, he noticed quite early that its principles and the mechanisms of self-organization hold for true independently of the matter of the systems they occur in [1]. Synergetics is thus not only a theory of pattern formation in physics; it is a general theory of structures and a conceptualizing module for modelling and thinking in quite different disciplines. Its general concepts, equations, and mathematical formalisms successfully founded the perhaps most important transdisciplinary framework and connecting pattern of modern science.

In terms of the structuralistic concept of theories and theory dynamics [2], synergetics provides a theory kernel which applies successfully to many phenomena in the natural sciences and the humanities [3]. Beginning from models of pattern formation in physics, chemistry, and biology, Hermann Haken early applied it also to brain dynamics (e.g., [4, 5]). He thereby gave rise to the insight that the brain is perhaps the most interesting example of a complex, self-organizing system. More than 10^{11}nonlinear interconnected neurons create a dynamic meganetwork of neuronal networks with emerging and submerging synchronizations, nearly instantaneous adaptability and flexibility with ever changing pattern formation working "at the edge of chaos", and realizing combined (activating and inhibiting) feedback mechanisms following the principles set forth by synergetics [6, 7].

In contrast to early presentations of synergetics, when the listing of examples synergetics was applied to jumped from biological structures and brain dynamics to macro-sociology (where synergetics modelled the change of opinions and attitudes of large populations by the master equation, [8]), later on mental and behavioural phenomena were introduced into the set of examples, too [9, 10]. It became evident that the paradigm of self-organization would be a very promising approach to psychology. The laws and principles of synergetics helped for a deeper understanding of neural, mental, and behavioural processes. Fruitful interdisciplinary cooperation in modern psychology was underpinned by the unifying terminology, formalism, and modelling tools of synergetics.

When taking a closer look at psychological phenomena like perception, learning, decision making, thinking, feeling, or social interaction and behaviour coordination in dyads or groups, we can appreciate that they are dynamic in nature and characterized by specific "Gestalts". They can be described by synergetic features such as

- order and order parameters, in many cases also hierarchies of order parameters,
- enslaving of system components by order parameters,
- coordination (competition or cooperation) of order parameters,
- order transitions (non-equilibrium phase transitions) with symmetry breaking,

– critical instabilities and fluctuations during the emergence of new or changed patterns,
– multistability,
– hysteresis,
– circular causalities between the components of a system, and
– circular causality from the bottom (relative micro-level of a system) to the top (relative macro-level of a system) and from the top to the bottom.

In consequence, synergetics has successfully been applied to many topics in psychology:

General psychology

– motoric coordination (e.g. [11–14])
– perception (e.g., [15, 16])
– decision making (e.g., [3, 17])
– memory (ekphorisation as a spontaneous self-organizing process of neural networks triggered by internal and external stimuli, former system states, and boundary conditions, e.g., [33, 18])
– learning (e.g., [9, 19, 20])
– intentionality of cognition and action processes (e.g., [21, 22])
– dynamics of emotions (e.g., [3, 23])
– creativity and innovation (e.g., [24])
– speech recognition and speech acquisition (e.g., [25])
– the emergence of phenomenal consciousness (e.g., [3])
– the dynamics of the „self“ (e.g., [3, 26])

Developmental Psychology

– child development (e.g., [23, 27])
– assimilation and accommodation of schemata (e.g., [27])

Social psychology

– dyadic interaction (patient-therapist, mother-child) (e.g. [28, 29])
– attitude change (e.g., [8, 30])
– group dynamics (e.g., [3, 31–33])
– stability and instability of collective behaviour (e.g., [30, 34])

Clinical psychology

– etiology of mental disorders (e.g., [35, 36]),
– mental disorders as dynamical diseases (e.g., [35, 37–39]),
– psychotherapy (process-outcome-research, feedback and monitoring) (e.g., [3, 40–43])

Management / organizational psychology (e.g., [3, 44]).

Looking back to the last three decades, synergetics gave some important inspirations to modern academic psychology: First, it introduced a “thinking in complexity" [45] on mental and social phenomena. Since after World War II positivism and linear causality had become the dominating paradigm, complexity had been ruled out from psychological modelling. Second, concepts of time and dynamics were integrated into psychological thinking. Even though it seems quite obvious that things evolve in time and that they are not "being" but "becoming", the important tools for thinking in dynamics and for nonlinear time series analysis had to be imported to psychology from the outside – from the theory of self-organization and dynamic systems. Third, synergetics introduced a fruitful research paradigm to psychology by consequently relating models to empirical testing. The complexity of hypotheses increased noticeable, since not only differences between experimental conditions or pre-post-differences were in the focus of interest, but specific dynamic patterns, emerging dynamics, and contra-intuitive phenomena. Fourth, synergetics gave rise to a specific ,,imago hominis" accentuating the autonomy of individuals (in contrast to focussing on their dependency of external input) but without forgetting the social context of interpersonal synchronization and cooperation. Finally, synergetics turned psychology back to its own history by connecting it to its roots in "Gestalt psychology" and other traditional approaches.

The Gestalt psychology of the early 20^{th} century was concerned with patterns ("Gestalts") of perception, thinking, behaviour, and interaction (e.g., group dynamics, [46]). Psychologists like Wolfgang Köhler (e.g., [47]), Wolfgang Metzger (e.g., [48]), Max Wertheimer, Kurt Lewin (e.g., [46]) and others can be seen as predecessors of modern complexity research in psychology [49] . Another precursor of self-organization theory is Jean Piaget's equilibration theory of action-cognition patterns (schemata) describing assimilation-accomodation-cycles of schemata [50] by using input from the inner and outer environment as disturbing stimulation. Another historical line – anthropological medicine – accentuated concepts of circular causality. The "Gestaltkreis" integrates feedback loops between sensorial and actional systems on the one side, and individual and environmental systems on the other side (ecosystemic approach) [51] .

2 Dynamic Patterns in Psychotherapy

One of the prominent topics of applied synergetics in psychology is human development during psychotherapy, which has become an important field of research similar as laser physics did in the early steps of synergetics. One of the reasons is that psychotherapy is an intensive learning and development process integrating cognitive, affective, and behavioural systems. Stable, dysfunctional patterns of processing are destabilized in order to give rise to new patterns and the deformation of potential landscapes and thereby creating changed mental attractors. In such a way, self-organizing processes can very well be studied in psychotherapy research.

One of the basic questions is whether therapy-related dynamics of behaviour, cognition, and emotion manifest some kind of order or not. If this is not the case, we would expect irregularity or white noise. But if psychotherapy was a self-organizing process, one would expect some kind of complex dynamic order – in other words: deterministic chaos. The term "deterministic chaos" refers to complex dynamic structures in time signals generated in "real world systems" by deterministic or – more realistic – by combined deterministic and stochastic processes [52–54]. The term "chaos" covers a large spectrum of dynamic patterns between irregularity on the one hand and regularity and order on the other hand. One consequence with specific relevance to psychotherapy is a fundamental limitation of predictability and of linear controllability of processes. Another consequence is the distinctive individuality of processes; any notion of superposition of dynamics within or between individuals (systems) cannot be maintained meaning that concepts like "standard tracks" or "normative processes" are inappropriate to describe psychological phenomena.

2.1 Patients and Measurement Procedure

To investigate the hypothesis of ordered dynamics in psychotherapeutic change processes we used the data from daily self-assessments of 149 patients (average age: 34.3 years, 92 female, 57 male) during in-patient psychotherapy in a psychiatric hospital. The self-ratings were collected through an Internet-based device, the so called Synergetic Navigation System (SNS, [42]). In the last years, Internet-based real-time methods like the SNS were successfully used in research and practice for process monitoring and ambulatory assessment [55, 56]. Real-time monitoring allows for the optimization of therapy processes [57, 58] and offer detailed insights into process-related patterns. Every day, patients completed the Therapy-Process Questionnaire (TPQ) provided by the SNS. The TPQ is a self-assessment tool for patients undergoing in-patient or out-patient psychotherapeutic treatment. The study described here made use of the in-patient version with 23 items, grouped into 5 scales [59].

Most of the patients were categorized to three ICD-10 diagnostic groups: F30 (affective disorders), F40 (neurotic stress-related and somatoform disorders), and F60 (specific disorders of personality, esp. F60.3, emotionally unstable personality disorder, referred to as borderline type in other classification systems). On average, the TPQ was completed by patients during 97 days (SD: 50.3). The number of days defines the length of the time series and roughly corresponds to the days of hospital treatment. 5.1% of the entries were missing; the missing values were restored by a cubic spline function implanted in the SNS. Figure 1 gives an example of the 5 time series of a patient, corresponding to the 5 subscales of the TPQ.

The measurement series of all 149 patients were joined together, resulting in 5 artificial time series with a length of n = 14,425 points (one time series for each subscale of the TPQ). Different durations of hospital stay were not counterbalanced, i.e., patients with longer treatments hold a greater fraction of the resulting artificial time series.

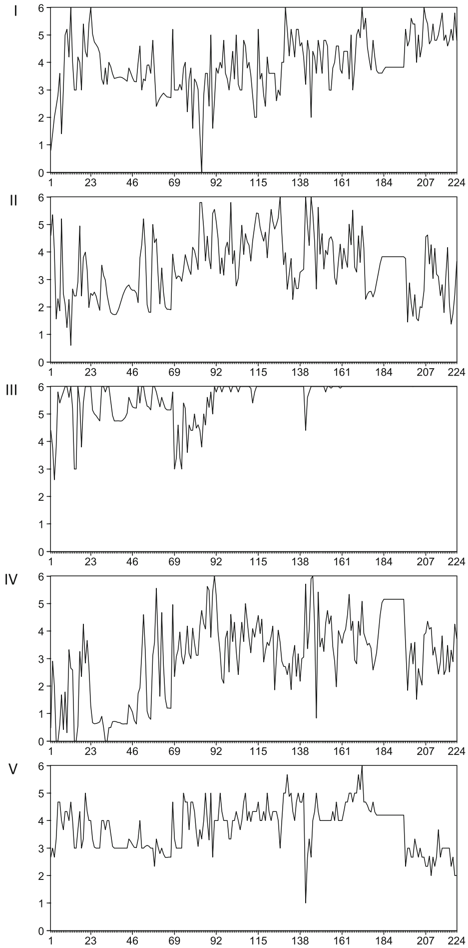

Fig. 1. Example of time series from TPQ scales (factors). Factor I: Therapy progress; Factor II: Complaints and problem pressure; Factor III: Relationship quality and trust in therapists; Factor IV: Dysphoric affects; Factor V: Relationship with fellow patients / ward atmosphere. All scales were normalized to a range from 0 to 6. (Female patient, 25 years old; diagnosis: F33.10 major depressive disorder, recurrent; 224 measurement points = days).

2.2 D2 and Pointwise D2 (PD2)

Fractal dimensionality of a time series estimates the number of independent system components or subsystems whose interaction creates the system dynamics. The dimensionality of an attractor corresponds to the degrees of freedom of the generating system and can be seen as an indicator of its complexity.

There are several definitions and methods for calculating fractal dimensionality. A well known method for empirical time series is the D2 algorithm, which is based on the embedding of a time series in a reconstructed phase space whose dimensions were created by time-delay coordinates [60]. The method calculates a correlation integral [61, 62] by a counting algorithm over all Euclidean distances between vector points within the phase space. The estimate of the D2 correlation dimension results from a diagram which plots D2 against increasing numbers of embedding dimensions. In case of saturation, D2 estimates converge to a fixed value with increasing embedding dimensions (for details see [3] pp. 484-489, [54] pp. 208-214). While D2 provides a complexity estimation of the attractor of the whole process, the pointwise D2 (PD2) portrays the possible changes of dimensional complexity over time (non-stationarity). D2-estimates are taken from vector point to vector point and can be portrayed in a PD2 to time diagram [63, 64].

2.3 Surrogate Data Analysis

When there is no saturation of D2 estimates for increasing time-delay embedding dimensions, this theoretically means that the process under consideration does not entail systematic order. In practice, however, the hidden dynamic order of the data has to correspond to the resolution of the measurement scale and to the length of the time series. If the scale is too coarse grained and by this, the corresponding m-dimensional phase space doesn't include a sufficient number of m-dimensional voxels, even ordered time series will cover the phase space and fail any D2 convergence. On the other hand, time series without sufficient measurement points n ($n \ll$ number of available voxels in the phase space) cannot cover the phase space, even if they result from pure randomness (white noise). Here, the pseudo-evidence of saturation would erroneously reject the null-hypothesis of no existing dynamic structure. In both cases the procedure fails to differentiate between randomness and order.

A random series only covers the entire phase space (resulting in no D2 saturation with increasing numbers of embedding dimensions) if the time series is long enough. In a 10-dimensional embedding space, only 10 levels of a measurement scale result in 10^{10} possible voxels or data constellations within the phase space. If a diced time series wanted to cover the entire phase space, the series would have to include at least the same number of measurement points. If the time series is too short for covering the phase space, it is possible to calculate finite correlation dimensions even for randomness. Safely backing up D2 or PD2 analyses therefore requires surrogate data testing [65] which tests for nonlinearity or chaos in a given time series [66] .

Surrogate time series preserve some characteristics of the original time series while others are changed. A simple surrogate can result from shuffling the values of the series, leading to a random surrogate. The dynamic structure vanishes but the series maintains distribution characteristics as mean, median, or variance. In applying complexity estimates, the surrogate differs from the original time series. If not, the original itself seems to be only a random arrangement of values. Generally, surrogate data sets are created by different procedures in order to obtain or destroy specific statistic distributions and dynamic features

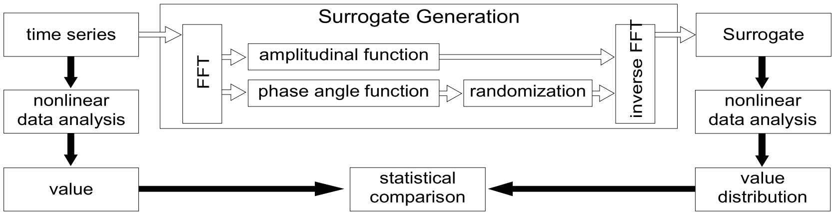

Fig. 2. Procedures of surrogate data analysis, based on statistical comparisons of dynamic features resulting from nonlinear time-series analysis (e.g., fractal dimensionality). The distribution of the features of a large number of surrogates is compared against the feature of the original time series. In case of FFT surrogates, linear autocorrelations and the frequency spectrum of the time series are retained in the surrogates while nonlinear features are destroyed by the procedure of phase angle randomization. Surrogate data tests will thus be indicative for nonlinearity. Depending on the null hypothesis under consideration, surrogates can be generated by quite different methods.

of the data. A surrogate corresponds to a specific null-hypothesis. Eliminating nonlinear qualities should result in the effect that the nonlinearity and chaoticity of the original is discarded. By this, the crucial part in surrogate data testing is the algorithm for surrogate generation.

More sophisticated than random surrogates is the surrogate production by applying a Fast Fourier Transformation (FFT) [66–71]. The time series is submitted to a Fourier-analysis with randomization of the resulting function phase angles. When the spectral density function and the randomized phase angle function are subsequently used to generate a surrogate via Fourier synthesis, the surrogate retains the frequency spectrum of the original time series but has lost its nonlinear features. It seems to be the result of a linear stochastic process. Linear correlations within the data are preserved, whereas nonlinear qualities are lost. A surrogate data test using such kind of surrogates tests for nonlinearity, which is a prerequisite for chaotic dynamics (Figure 2). Calculations were performed with GChaos 19.0 (www.complexity-research.com), a nonlinear analysis program written by one of the authors (G. Strunk).

2.4 PD2 of TPQ Factor Dynamics and D2-Differences Between Original Time Series and FFT-Surrogates

The time series of the factors of the TPQ were analyzed by the PD2 algorithm. We adopted Skinner's [63] criterion of at least 75% valid measurement points for the calculation and interpretation of the PD2 for all 5 factors (Table 1). This implies that the majority of the processes is suitable for interpretation as ordered dynamics instead of being a stochastic processes.

The arithmetic means of the PD2 range from 0.947 to 5.187 and are indicative for low-dimensional chaotic processes. Large standard deviations (as compared to the means of PD2) result from the variability in the PD2 dynamics which

I Therapy Progress	% valid time points in PD2	88.72%	
	PD2 AM±SD	0.947	±2.263
	surrogate data test D2: t (p)	113.070	(<0.001)
II Complaints and Problem Pressures	% valid time points in PD2	77.49%	
	PD2 AM±SD	2.650	±3.662
	surrogate data test D2: t (p)	89.103	(<0.001)
III Relationship Quality and Trust in Therapists	% valid time points in PD2	87.80%	
	PD2 AM±SD	3.239	±2.940
	surrogate data test D2: t (p)	54.681	(<0.001)
IV Dysphoric Affect	% valid time points in PD2	90.61%	
	PD2 AM±SD	1.114	±2.420
	surrogate data test D2: t (p)	100.368	(<0,001)
V Relationship with Fellow Patients	% valid time points in PD2	81.70%	
	PD2 AM±SD	5.187	±2,803
	surrogate data test D2: t (p)	42.043	(<0,001)

Table 1. PD2 of TPQ factor time series and surrogate data test of D2 using FFT surrogates of TPQ factor time series (see Figure 1; TPQ: Therapy Process Questionnaire). The time series of the 5 factors of 149 patients were joined together, resulting in 5 artificial time series with a length of n = 14,425 points. 30 FFT surrogate time series were generated for each factor dynamics to produce a distribution of D2 estimates. Maximum embedding dimension was 15. The table presents the percentage (%) of valid PD2 values, the arithmetic mean (AM) and the standard deviation (SD) of the PD2s of the 5 empirical (original) time series, and the t- and p- values of the surrogate data tests.

refer to different levels of fractal dimensionality between patients, but also to the nonstationarity of the dynamics and hence to phase transitions during treatment.

FFT surrogates from the time series of TPQ factors were used for a comparison to the original time series. Since the PD2 scaling range was not sufficiently large for surrogates (which results in insufficient valid measurement points), the surrogate test is based on the D2 algorithm. 30 FFT surrogate time series were generated per TPQ factor to obtain statistical distributions of the D2 values, which served as a reference for comparison with the original time series by t-tests. The greatest number of embedding dimensions in the time-delay phase space was 15. For surrogate time series lacking D2 saturation, the average D2 estimates were used to compare embedding dimensions from 10 to 15. For results see Table 1.

When nonlinear dynamic structures are destroyed by producing FFT surrogates, one expects significantly increased fractal complexity of the surrogates. This hypothesis could be confirmed: all t-tests were highly significant ($p < 0.001$). The data represent a nonlinear dynamic structure.

The hypothesis of chaoticity and nonlinearity of psychotherapeutic processes was corroborated once again. Calculating fractal dimensionality via PD2 results in saturation of the mean PD2 estimates in low-dimensional ranges. The PD2's high standard deviation is an indicator of non-stationary processes (phase transitions). The crucial point is validation through FFT surrogate testing which is methodically rigorous and discriminating, because it not only contains means and variances of the surrogate time series used for comparison but also their frequency spectrums. Only nonlinear characteristics are removed, providing the basis for statistically significant D2 complexity differences.

3 Order Transitions in Human Dynamics

3.1 Patient-Therapist Interaction

In psychotherapy research there has been a rapid rise in interest in the study of patterns of change. In the sense of synergetics, these patterns correspond to the order parameter dynamics of the process. If the prerequsites for self-organized order transitions are given, they should occur with only small external driving forces or even without any additional input. Indeed, discontinuous transitions of dynamic patterns were found in the social dynamics of psychotherapies and in the social dynamics of groups.

In a study on the dynamics of the therapeutic relationship [28, 72] we used the method of Sequential Plan Analysis, which is a development of the hierarchical plan analysis proposed by Grawe and Caspar [73] . By "plans" here one understands more or less conscious and verbally or non-verbally communicated intentions and/or self-presentations in a social situation. Patient's and therapist's interactional behavior was analysed on the basis of video recordings. The construction of a hierarchical plan analysis leads to an idiographic categorical system for the observation of the patient-therapist interaction. Two complete therapies (13 and 9 therapy sessions, resp.) were encoded with a sampling rate of 10 seconds. At this measuring frequency, a psychotherapy process of 13 sessions was represented by multiple time series of about 3,800 measurement points, and a therapy of 9 sessions by time series of about 2,900 points.

Nonlinearity was proven by surrogate data tests [65] using random surrogates and FFT-based phase-randomized surrogates. Then the time series were analysed by methods which are sensitive to the nonlinearity as well as the non-stationarity of processes. The methods of PD2 [64] and of the Local Largest Lyapunov Exponents [74] were used to identify phase-transition like discontinuities. Following the evolution of PD2 dimensionalities, both therapies realized non-stationarities, and both therapies showed periods of strongly synchronized (with correlations from 0.80 to 1.00) and anti-synchronized PD2-processes (with correlations from -.80 to -1.00) between patient and therapist (Figure 3). Quite similar and even more pronounced dynamical jumps could be identified in the development of the Local Largest Lyapunov Exponents (LLLE) (Figure 4), representing changes in the chaoticity of a time signal [28]. Most of the discontinuities of the LLLE were exactly synchronized between patient and therapist. Obviously both persons create a dynamic self-organizing communication system, which enables and triggers the individual change processes of the patient.

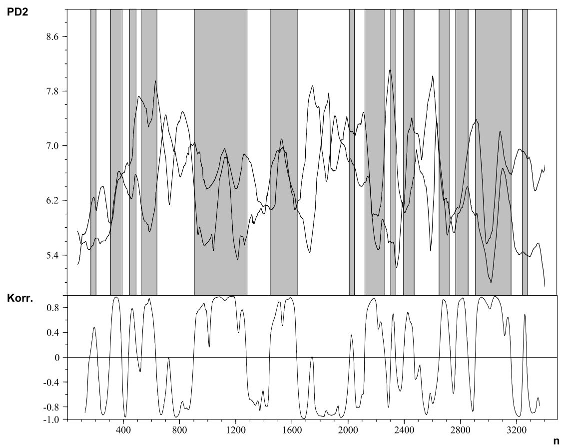

Fig. 3. Dynamics of PD2 of patient and therapist from one of the two therapies under consideration (13 sessions, 3,800 measurement points). A smoothing was realized by a gliding window of 100 PD2 values. The lower part of the figure represents the correlation between the two PD2 dynamics, with correlations calculated in a gliding window of 100 points. Periods of strong positive correlations are marked by a grey background, periods of strong negative correlations are marked by a white background.

These results receive support from nonlinear coupling measures between the time series of the interaction partners. Pointwise Transinformation as well as Pointwise Coupling Conditional Divergence [75, 76] were applied to the data, and both indicate changing and time-dependent coupling strengths between the time series of the interacting persons. There is no priority of the therapist's influence on the patient, or vice versa. Constituting the circular causality of psychotherapeutic self-organization, this finding contradicts the classical opinion where the input from the therapist supposedly determines the patient's output.

The converging results corroborate the hypothesis of (i) nonlinearity and deterministic chaos realized in therapeutic change dynamics and interaction, (ii) spontaneous order transitions in these processes, and (iii) synchronization and synchronized order transitions between patient and therapist. Furthermore there are some studies that focus on self-organized synchronization between patient and therapist at different time scales and with different methods [29, 77–79].

3.2 Group Dynamics

The method of Sequential Plan Analysis was not only applied to patient-therapist interaction, but also to the microdynamics of group interaction [3]. In a group of five persons a creativity and problem solving task was to be solved within 2 $\frac{1}{2}$ hours (creation of ideas, rules, and physical handicraft realisation of a prototype board game from different materials). Similar to the psychotherapy study the sampling rate was 10 seconds. The superordinate plans which could be identified

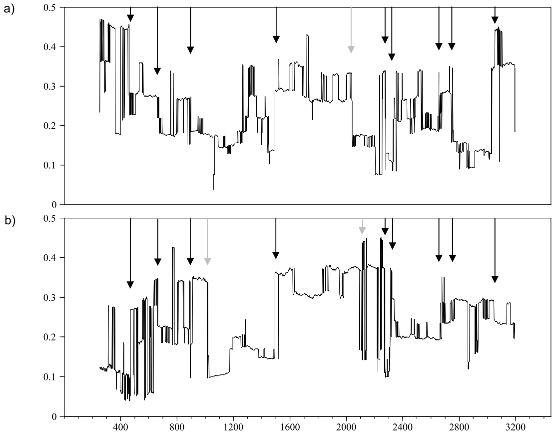

Fig. 4. Synchronized jumps in the dynamics of Local Largest Lyapunov Exponents (black arrows) during a therapy of 13 sessions (3,800 measurement points). Grey arrows indicate not clearly synchronized changes. (a) therapist, (b) patient. For the patient, the embedding was realized in a 6-dimensional phase space, constructed by 3 plans (time series) at the top of the plan hierarchy with each time series represented by two time delay coordinates, $x(t)$ and $x(t-\tau)$. For the therapist, the embedding was realized in a 8-dimensional phase space, constructed by 4 plans (time series) at the top of the plan hierarchy with each time series represented by two time delay coordinates, $x(t)$ and $x(t-\tau)$. LLLE estimates were calculated in a gliding window of 500 points by the algorithm of Rosenstein et al. [74].

for all five persons were (1) spontaneity and emotional engagement vs. shyness, restricted behaviour, and orientation to social norms, (2) engagement in the group interaction and in positive social climate, (3) task orientation. Length of time series was about 810 coding points. D2 as well as mean PD2 estimates saturated at a fractal dimensionality of about 5 for all categories. The embedding of the time series was realized by two ways: (1) The phase space was constituted by the three dimensions of superordinated plans with five trajectories representing the five group members, or (2) the phase space was constituted by the five persons with three trajectories representing the time course of the three plans (additional embedding dimensions result from time delay coordinates). In both cases PD2 results show an evolving pattern of quasi-attractors with changing complexity, and LLLEs (algorithm from [74]) portray chaoto-chaotic phase-transitions with clear-cut interpersonal jumps – similar to the dyadic interaction of the psychotherapy study.

3.3 Sudden Changes Reflect Order Transitions in Psychotherapy

Phase-transition-like phenomena characterize the short-term as well as the long-term evolution of cognitive, affective, and social systems. In psychotherapy, sudden changes seem to be a universal and robust phenomenon. A substantial percentage of patients experience discontinuously shaped changes. Sudden gains, especially if they occur early in the therapy process, uphold until the end of treatment or seem to be a necessary prerequisite for successful treatment [77, 80–82]. However, the mechanisms underlying such discontinuous shapes of symptom severity and other change markers are still not well understood challenging classical views of linear input-output-functions or dose-to-effect-relations. It is an anomaly of conventional psychotherapy science which postulates that specific factors of treatment cause the therapeutic effect in a linear way (or in a damped function related to the dose). Consequently, explanations tried to provide evidence for changes in relevant factors occurring before symptom changes, such as cognitive restructuring in the pre-gain-sessions of cognitive therapy [82]. Others have disputed this interpretation and have argued on behalf of common factors such as positive expectations, induction of hope, or positive therapeutic relationship [83, 84]. Kelly et al. [80] did not find any factors, such as changes in self-esteem, attribution style, concurrent psychological treatment or psychotropic medication to precede sudden treatment gains.

Actually, in psychotherapy research there are no adequate theoretical models explaining discontinuously shaped transitions in a fundamental way, still employing the idea of being uniquely reactive to external input like instructions, (minor) interventions, or therapeutic techniques. Synergetics, on the contrary, provides a model predicting that once system dynamics has reached an instability point, phase transitions are likely to occur. There are specific prerequisites for self-organized pattern transitions, such as (i) the existence of a system with nonlinearly interacting components or subsystems, (ii) the existence of one or several control parameters driving the system out of the actual stability state, and (iii) relatively stable boundary conditions. If the conditions for self-organized order transitions are met – that is to say, the instability point draws closer – a nonlinear shift-like change will be the consequence of the slightest additional external input. One of the predictions of the model is the occurrence of critical fluctuations just before a system undergoes such qualitative changes of pattern formation.

To investigate the above mentioned phase-transition-like phenomena in psychotherapy, we used the data from daily self-assessments of 18 patients with obsessive-compulsive disorder (OCD; ICD diagnosis: F42; average age: 32.2 years, SD = 9.6; 9 female, 9 male). The therapies were realized in a day-treatment center at Munich. Mean duration of treatment was 61 days (SD = 12.5, range from 37 to 88 days). Exposure with response prevention (ERP) was the principal cognitive-behavioural intervention of the therapy. ERP is a therapeutic procedure in the treatment of OCD, where patients are confronted with symptom provoking stimuli but abstain from performing compulsive rituals (e.g., cleaning).

Similar to the study we reported in chapter 2, the self-ratings were done by the Synergetic Navigation System (SNS, [42]). Every day, patients completed the Therapy-Process Questionnaire (TPQ) provided by the SNS. Two times per week, patients filled out the Yale-Brown Obsessive Compulsive Scale (Y-BOCS) provided by the SNS. The Y-BOCS is a self-assessment scale for obsessions and compulsions [85]. In order to compare individual change dynamics to ERP we related the individual symptom severity trajectories to the onset of ERP.

Building on the earlier finding that phase transitions (here referred to as order transitions) in self-organizing systems are introduced by critical fluctuations and instabilities [3, 86], a measure of dynamic complexity was calculated on the time series resulting from daily self-ratings in order to identify non-stationarity and critical instabilities in short time series. In contrast to statistical variance, this complexity measure identifies jumps, volatility and pattern complexity of signals. It is used for the analysis of discrete time series data with a known data range (for the algorithm see [87]). Dynamic complexity combines a fluctuation measure and a distribution measure in a multiplicative way. The fluctuation measure is sensitive to the amplitude and frequency of changes in a time signal, and the distribution measure scans the scattering of values – or system states – realized within the theoretical range of possible values – or system states. In order to identify nonstationarity, the dynamic complexity is calculated within a window of 7 data points (= 7 days) moving over the time series of each patient.

The processes of each patient (see Figure 5 for an example) are evidence for increased dynamic complexity of the subscales and most of the items of the TPQ just before or during sudden changes, which are characterized by the steepest gradient (decrease) of the Y-BOCS curve. Significant decrease of symptom severity (Y-BOCS) takes place before (!) the most important therapeutic intervention – exposure with response prevention (ERP) – of the treatment process was started, a result in line with the theory of synergetics and findings across several disciplines.

Figure 6 aggregates the dynamics of all 18 patients. For each patient, the individual ERP-onset was defined at $t = 0$, and the trajectories of the total Y-BOCS scores were related to this event. In 72% of the 18 cases, the steepest gradient of symptom change was located before ERP-onset. Figure 6 illustrates that the mean trajectory of the z-transformed individual total scores of the Y-BOCS has its steepest change gradient before ERP starts (t = -4 days), and symptom severity reaches a significantly reduced level at the day of ERP onset at $t = 0$ ($T(17) = 3.07$; $p = 0.007$).

The same procedure was accomplished with the mean dynamic complexity signal of all items of the TPQ, calculated within a moving window of 7 data points. This complexity signal was related to ERP-onset as well. Figure 6 illustrates the mean z-transformed complexity signal of the change processes of the 18 subjects. Besides a complexity peak at the beginning of treatment, which may be interpreted as an initial instability period representing individual doubts and varying degrees of working intensity at the start of the treatment process, the most important peak occurred three days before the steepest gradient of symptom reduction was realized and about 7 days before ERP-onset ($T(17) = 2.48$, $p = 0.026$). In terms of synergetics, this corresponds to the assumed critical instabilities accompanying order transitions of a self-organizing system.

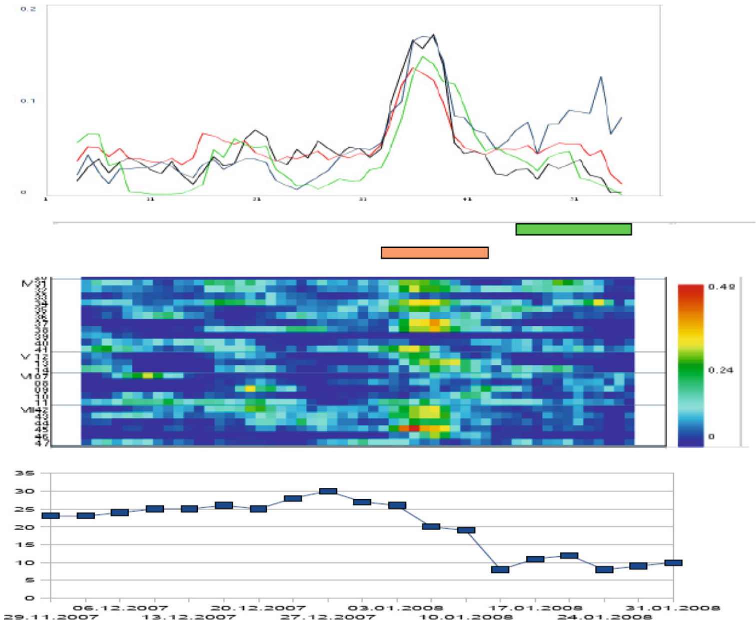

Fig. 5. Order transition in the therapy process of a patient with OCD (64 days = measurement points). Brown bar: critical instability (period of statistical significance of increased dynamic complexity). Green bar: Period of ERP. The curves at the top of the diagram represent the dynamic complexity of factors of the TPQ: Factor I: Therapy progress (blue), Factor II: Complaints and problem pressure (black), Factor IV: Dysphoric affects (red), and "getting new insights and perspectives", which is a factor from a former factor analysis. Below the complexity-resonance-diagram where the intensity of dynamic complexity is translated into colours. Yellow, orange, and red correspond to high complexity values. The lower part of the diagram represents the course of the Y-BOCS which was completed two times per week. The steepest gradient of symptom reduction was realized during the period of critical instability.

4 The Self-organizing Brain

The human brain is one of the most fascinating complex systems. Since function corresponds to structure and vice versa, structural changes can be understood as functional self-organization of neural populations. Changes of synaptic coupling strengths and network configurations (re-wiring patterns) follow the synchronized co-activity of neurons. Perception, action and transition of action patterns, decision making, and cognitive, behavioural, as well as emotional learning are generated by principles of self-organization [3, 6, 7, 86]. At a neuronal level they correspond to and are based on nonlinear brain dynamics. The emergence of order parameters and the occurrence of phase transitions can be described and measured on psychological as well as on neuronal levels.

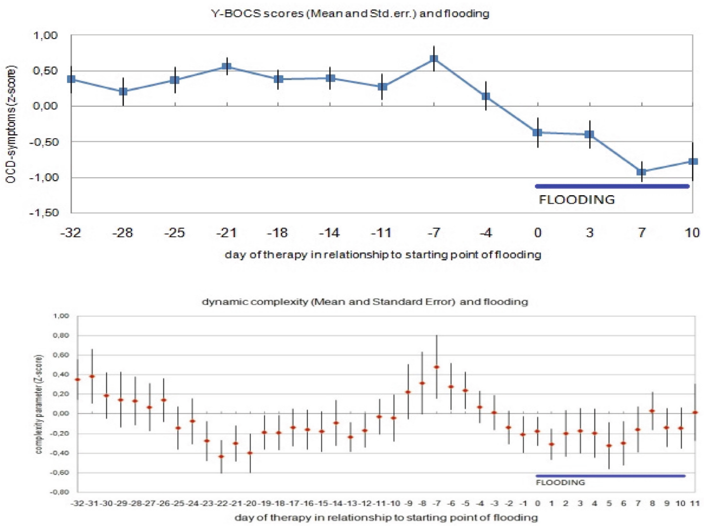

Fig. 6. Mean course of symptom severity (Y-BOCS, z-transformed) (upper part), and mean course of dynamic complexity (z-transformed), normalized in relation to the beginning of ERP during the behavior therapy of 18 OCD patients (day treatment center Munich). Vertical bars: standard error.

4.1 Brain Correlates of Gestalt Perception

One of the phenomena modelled by synergetics is Gestalt perception – the emergence of percepts and the switching of ambiguous visual patterns (e.g., Necker cube or stroboscopic alternative motion). These processes of Gestalt perception constitute the link between Gestalt psychology and actual mathematical modelling in synergetics [88]. The binding of different perceptual features or components to coherent structures or "qualia" seems to be due to synchronization processes of extended brain regions and converging integrative areas [89]. "Pattern perception is pattern formation" – as Hermann Haken puts it into pointed words.

Tallon-Baudry et al. [90, 91] measured enhanced gamma-band activity (30-50 Hz) in the EEG of the primary and secondary visual cortex while subjects identified a triangle from the offered stimulus material. This could be a fingerprint of corresponding neuronal synchronization processes. The activity occurred when subjects saw a real object (triangle) or a figural illusion of the object (Kanizsa-triangle), but not if the same geometrical components could not be composed to a true Gestalt. The research group of Basar-Eroglu and Stadler [92] measured increased gamma-band activity in EEG during states of perceptual switching triggered by stroboscopic alternative motions. To summarize: Perception of multistability is one of the multifold cognitive processes giving rise to 40 Hz enhancement in the cortex, and coherent oscillations reflect an important mechanism of feature binding in the visual cortex which corresponds to the emergence of a neuronal order parameter. Changing order parameter dynamics during different cognitive activities was shown by Schupp et al. [93]. Mental imagery of an object could be differentiated from its concrete perception. The dimensional complexity of prefrontal EEG was increased during sensory imagery compared to the real perception of the same object [94].

4.2 Neuronal Activity During Motoric Instability and Motoric Order Transitions

The well-known movement coordination paradigm modelled by Haken, Kelso, and Bunz [12] was used to demonstrate neuronal correlates of instability and symmetry breaking processes in the motoric brain. The order parameter in this finger movement experiment is the relative phase of the index fingers of both hands. Metronome-pacing – with movement frequency as the control parameter – triggers the system from parallel (out-of-phase) to mirror (in-phase) movement. Meyer-Lindenberg et al. [95] showed that the emergence of patterns in open, non-equilibrium systems like the brain is governed by their (in-)stability in response to small disturbances. Transitions could be elicited by interference at the neuronal level. Functional neuroimaging (PET) identified premotor (PMA) and supplementary motor (SMA) cortices as having neuronal activity linked to the degree of behavioural instability, induced by increasing frequency of the finger movement. These regions then were transiently disturbed by transcranial magnetic stimulation (TMS) of different intensity, which caused sustained and macroscopic behavioural transitions from the less stable out-of-phase to the stable in-phase movement, whereas the stable pattern could not be affected. Moreover, the intensity of the disturbance needed (a measure of neuronal stability) was correlated to the degree of the control parameter (movement frequency) and thereby to the behavioural stability of the system.

4.3 Coordinated Order Transitions of Mental and Brain Dynamics

A fMRI-study[5] investigated order transitions of brain activity related to subjective experiences of patients during their psychotherapy process [41, 96]. Repeated fMRI scans were related to the degree of stability or instability of the ongoing dynamics (measured by the dynamic complexity of daily TPQ-ratings). The time series of dynamic complexity were averaged over the items of the TPQ,

[5] Multi-center study of the Ludwig-Maximilians-University Munich, University Hospital of Psychiatry (PD Dr. O. Pogarell, Dr. S. Karch, Dr. Ch. Mulert), Hospital of Psychosomatic Medicine Windach/Ammersee and Day Treatment Center Munich/Westend (Dr. I. Tominschek, Dipl. Psych. S. Heinzel, Prof. Dr. M. Zaudig), University Hospital Vienna/Astria, Clinic of Psychiatry (Prof. Dr. M. Aigner, Prof. Dr. G. Lenz, Dr. M. Dold, Dr. A. Unger), MR Centre of Excellence, Medical University Vienna/Austria (Prof. Dr. E. Moser, PD Dr. Ch. Windischberger). The study was coordinated by G. Schiepek.

and the maxima of these dynamics were used as an indicator of the most intensive fluctuation periods and the discontinuous transition(s) during the therapies. Real-time monitoring by the Synergetic Navigation System allows for the identification of stable or unstable periods and by this for a decision on the appropriate moments of fMRI acquisitions. Wherever possible, fMRI measurements were realized shortly before or after these transitions.

3 or 4 scans were realized during each of the psychotherapy processes of 9 patients and compared to the scans of 9 healthy controls without therapy. The study included patients with obsessive-compulsive disorder (OCD) of the washing/contamination fear subtype (DSM IV: 300.3), without co-morbid psychiatric or somatic diagnoses. All patients except for one were drug naïve. Patients were matched to healthy controls.

OCD seems to be an appropriate model system for synergetic studies in clinical psychology, since the pathological order parameter is quite evident, the disease has an obvious and often stable time course, and therapeutic order transitions – if they do occur at all – are easy to be observed. OCD-specific functional neuroanatomy is partially known. It includes an integrated network of cortico-striato-thalamo-cortical feedback-loops and limbic structures (amygdala, hippocampus, insular cortex, anterior cingulate cortex) [97, 98].

The visual stimulation paradigm of the study used symptom provoking, disgust provoking, and neutral pictures. The disgust and the neutral pictures were taken from the International Affective Picture System, whereas the OCD-related pictures were photographed in the home setting of the patients, showing specific and individual symptom provoking stimuli [41, 96]. Here we refer on the contrast of individualized symptom provoking pictures vs. neutral pictures.

Results from a Single Case. For illustrative purposes we report on the results of a single case. It is a female patient, whose fMRI scans were taken three times during the 59 days of their hospital stay at days 9, 30, and 57. The matched healthy control was also scanned three times at identical time intervals as the patient. The second acquisition was done after an intensive period of critical instability of the TPQ-based time series, but just before ERP started. The instability maximum of the patient's process was the precursor of an important personal decision to divorce from her husband. (Her OCD symptoms had developed in the context of a long-lasting marital conflict.) This decision was the essential order transition of the therapy.

Indeed, the most pronounced changes in brain activity occurred from the first to the second fMRI scan, whereas BOLD response differences from the second to the third session were only slight. The changes from the first to the second scan perhaps represent the neuronal correlates of her personal order transition (decision to divorce) related to the resolution of a severe personal conflict. Not only these changes occurred before the ERP procedure was introduced but also a marked symptom reduction took place (measured by the Y-BOCS) (Figure 7).

The alternations of brain activity during this period involved widespread areas, e.g. medial frontal brain regions including anterior cingulate cortex, superior

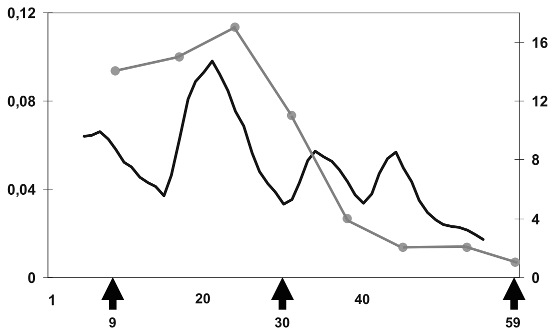

Fig. 7. The course of the Y-BOCS of a female patient (completed once per week; grey line). The steep gradient of symptom reduction in the middle of the hospital stay is preceeded by an intensive period of critical instability of therapy-related self-ratings. Black curve: Mean dynamic complexity of the items of the TPQ. Black arrays indicate the days when fMRI scans were realized. ERP started 2 days after the second fMRI scan.

and middle frontal gyrus, inferior frontal and precentral gyrus, superior temporal gyrus, superior parietal lobe, cuneus, thalamus, caudate nucleus in both hemispheres, as well as the right fusiform gyrus (Figure 8). The OCD-associated BOLD responses of the second and third session revealed only small differences (Figure 8). Slightly enhanced responses were found during the second session compared to the third session in the precuneus and the inferior parietal lobe. The middle frontal gyrus, the left inferior parietal lobe, the cuneus, the superior and middle frontal gyrus, and the cingulate gyrus responded slightly stronger during the third session compared to the second session. In the healthy control to the patient, no such changes of brain activity took place between the scans.

Thalamic and basal ganglia activation is part of the dorsolateral-caudate-striatum-thalamus circuitry of OCD. Especially the caudate nucleus takes a role within the executive dysfunction model of compulsions [99], and its activity has been found to be reduced after treatment (e.g., [100]).

The function of the anterior cingulate cortex is interesting with regard to synergetics. The cingulate cortex comprises various functions like somatosensoric integration, mediation of affective and cognitive processes, control of attention, and processing of painful stimuli. Additionally, it plays an important role as conflict monitoring system: it is sensitive to ambiguous or conflicting information [101, 102], is involved in decision making [103, 104], and its activation is predictive to treatment outcome in depression [105]. This is true especially for the dorsal (cognitive) structures of the ACC. By this, its activity could be an indicator of symmetry states of brain functioning, which are characterized by two or more dynamic patterns or attractors in competition. In the present case, the ACC activation at the beginning of the therapy could be either part of the pathology or could be indicative for the critical instability of the cognitive-affective system of the patient, preparing her important decision. The second

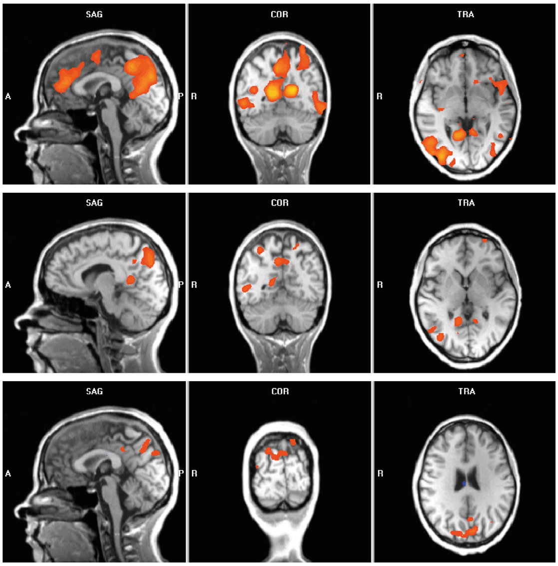

Fig. 8. Brain activation patterns of a patient with OCD (washing/contamination fear) during psychotherapy. BOLD signals from a 1.5 Tesla fMRT scanner. Top: first scan (9^{th} day of hospital stay; $x = 0$, $y = -55$, $z = -2$; $p(\text{uncorr}) < 0.001$). Middle: second scan (30^{th} day of hospital stay; $x = 8$, $y = -54$, $z = -5$; $p(\text{uncorr}) < 0.001$). Bottom: third scan (57^{th} day of hospital stay; $x = 0$, $y = -85$, $z = 26$; $p(\text{uncorr}) < 0.001$). Activations during the presentation of individual symptom provoking pictures contrasted to activations during the presentation of standard neutral pictures. The brain activations before the order transition (first scan) (medial frontal brain regions including anterior cingulate cortex, superior and middle frontal gyrus, inferior frontal and precentral gyrus, superior temporal gyrus, superior parietal lobe, cuneus, thalamus, caudate nucleus, right fusiform gyrus) are markedly reduced at the second and third scan.

fMRI measure was conducted during a local minimum of critical fluctuations. Whether the impressive change in cingulate activation could be attributed to a changed critical symmetry state of the neuronal self-organization before vs. after the phase transition or to changes in symptom severity cannot be decided within a single case study, but seems to be an interesting question for further research.

Results from the Sample of OCD-Patients. Similar results were to be seen in the whole sample of all 9 patients [96]. In order to quantify the changes of neuronal activity over the fMRI scans, 8 brain regions were identified that are important in OCD-related neuronal processing: the anterior and medial cingulate cortex as well as the supplementary motor area (CC/SMA), the dorsolateral prefrontal cortex (DLPFC) right and left, the insula right and left, the parietal cortex right and left, and the cuneus.

When interscan-intervals including order transitions (OT) were compared to intervals without order transitions (NOT), the changes of the number of signifi-

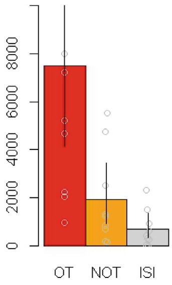

Fig. 9. Differences in order transition intervals for patients (OT: order transitions, red), non-order-transitions for patients (NOT: non-order-transitions, yellow) and inter-scan-intervals (ISI) for healthy controls (grey). Y-axis: mean voxel number differences between scans. 95%-confidence intervals of the means were bootstrapped with R's boot.ci function using 10,000 resamples and the "bca" type of confidence intervals.

cant voxels for the contrast between individualized symptom provoking pictures and neutral pictures show increased BOLD responses during OT in all relevant brain regions. The healthy controls received no therapy so that any distinction between intervals with and without order transitions has no importance. By this, in healthy subjects functional changes were averaged across all inter-scan-intervals (ISI). Figure 9 illustrates the changes in significant voxels averaged for the 8 brain areas of OT and NOT (patients), and ISI (controls). Activation rates and change rates were significantly higher for patients compared to controls.

The differences between order transition intervals (OT) of the patients (mean voxel number difference: 7480, SD: 6835) and non-order-transition intervals (NOT) of patients (mean voxel number difference: 1900, SD: 1968) reached significance. In addition, the number of activated voxels differenced significantly between order transition intervals of patients and the inter-scan-intervals (ISI) of the controls, whereas the differences between the NOT intervals of patients and the inter-scan-intervals (ISI) of the controls were quite similar. For each of the 8 brain regions we identified, pronounced differences occurred between OT and NOT and even more clearly for OT vs. ISI, but not for NOT vs. ISI. The most pronounced differences were realized in the CC/SMA, the DLPFC left, DLPFC right and insula right. The differences in the area of the cuneus and the left parietal cortex did not reach significance because of the NOTs' wide confidence intervals. The high individual variability is partly the result of distinctly differing change patterns in patients as well as therapy processes.

An additional result concerns the intercorrelations of the involved brain areas. When comparing correlations before and after order transitions, the difference is striking, independent of where the order transitions were located in the course of therapy. The mean intercorrelation of the brain areas changed from 0.73 (SD: 0.09) to 0.33 (SD: 0.33) (p of the difference < 0.001). In addition to the decline in correlation, a differentiation of intercorrelations occurred which is reflected in an increase in variation (standard deviation of the intercorrelations increased from 0.09 to 0.33). This could be taken as an indicator of a decreased network-synchronization of OCD-specific brain areas before and after order transitions.

To conclude: Most patients showed clearly recognizable order transitions in different brain areas. Changes in the activity of brain areas outside of order transitions were considerably weaker, similar to the differences between fMRI scans of the healthy controls which did not undergo psychotherapy and by this did not experience any dynamic changes. The strong connection between cognitive-affective order transitions and BOLD responses reversely validate the operationalization of order transitions by the maximum of dynamic complexity of the time series gained from daily self-assessments by the Synergetic Navigation System.

5 Perspectives

Order or phase transitions indicate the spontaneous emergence of collective patterns or qualitative pattern shifts in complex non-equilibrium systems. Based on an empirically sound transfer of this and other concepts from synergetics to human systems functioning, psychotherapy can now be interpreted as the procedural creation of conditions conducive to biological, mental, and social self-organization processes [3]. This opens new perspectives for basic and applied research, but also for the treatment of mental disorders. New developments in the real-time monitoring of human change processes by internet-based devices with integrated nonlinear analysis methods like the Synergetic Navigation System offer effective means of therapy feedback and therapy control [57, 106].

Other encouraging developments concern invasive and non-invasive brain stimulation which applies to neurological diseases as Parkinsonian or essential tremor, chronic tonal Tinnitus, but hopefully also to psychiatric disorders as OCD or mayor depression [107]. The difference between new technologies of stochastic phase resetting applying mathematical tools and concepts of synergetics at the one hand and high frequency stimulation at the other is that high stimulation frequencies mimic tissue lesions by a blocking effect on the stimulated target. However, learning and un-learning needs the activity of neuronal cell populations. New technologies are demand-controlled and are activated only during certain stimulation intervals. Its effect is a desynchronization of pathologically synchronized populations of neurons, using multi-site coordinated reset (CR) stimulation [107] or nonlinear delayed feedback stimulation [108]. Both methods counteract abnormal interactions and detune the macroscopic frequency of the collective oscillators – that is the abnormally established order parameters of neuronal synchronization. Thereby they restore the naturally varying frequencies of the individual oscillatory units. Neurons get in the range of physiological functioning and can engage in changing and varying synchronization patterns. In consequence, the coupling strengths connecting synapses (synaptic weights) are changed and a long term rewiring of neuronal networks is reached. Changed function triggers the emergence of healthy attractors and by this changes the structure of neuronal networks. For therapeutic effects on chronic Tinnitus see [109].

In the future technologies of non-invasive brain stimulation could be combined with a SNS-based psychotherapy for the optimization of self-organizing changes in therapeutic processes.

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