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The identification of critical fluctuations and phase transitions in short term and coarse-grained time series—a method for the real-time monitoring of human change processes

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Abstract We introduce two complementary measures for the identification of critical instabilities and fluctuations in natural time series: the degree of fluctuations F and the distribution parameter D. Both are valid measures even of short and coarse-grained data sets, as demonstrated by artificial data from the logistic map (Feigenbaum-Scenario). A comparison is made with the application of the positive Lyapunov exponent to time series and another recently developed complexity measure—the Permutation Entropy. The results justify the application of the measures within computer-based real-time monitoring systems of human change processes. Results from process-outcome research in psychotherapy and functional neuroimaging of psychotherapy processes are provided as examples for the practical and scientific applications of the proposed measures.

Keywords Critical fluctuation · Distribution of time series data · Nonstationarity of processes · Phase transitions · Real-time monitoring

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1 Introduction

Human change processes are characterized by the nonlinearity as well as the nonstationarity of their dynamics. Nonlinearity is based on nonlinear system functions and describes the nonproportionality of input and output of systems as well as chaotic behavior. Nonstationarity generally indicates a change in descriptive statistics such as [moving] average and variance over time. Additionally, in dynamic processes like human change processes, nonstationarity also implies the changing of classical invariants of complex systems like chaoticity (e.g., measured by Lyapunov exponents) and complexity (e.g., measured by the Correlation Dimension).

Examples of the manifestation of nonlinearity and nonstationarity are: movement and behavior patterns, cognitions and emotions; social interaction in dyads and groups; the dynamics of the peripheral and central nervous system; or dynamical diseases (an der Heiden 1992; Kantz et al. 1998; Kelso 1995; Kruse and Stadler 1995; Nowak and Vallacher 1998; Popovych et al. 2006; Schiepek and Perlitz 2009). This especially holds true for intentional or supervised change processes such as decision making (Haken 1996), learning (Freeman 2000; Vetter et al. 1997), or therapy processes (Haken and Schiepek 2006; Hayes et al. 2007a,b; Kowalik et al. 1997; Schiepek et al. 1997; Strunk 2005). The nonstationarity of such processes corresponds to discontinuous phase transitions produced by the nonlinear mechanisms of the underlying complex systems. Phase transitions are almost necessarily accompanied by critical instabilities that precede and enable such transitions (Haken 2002, 2004).

Since phase transition-like phenomena and critical instabilities seem to be ubiquitous in human change processes, there should be means for their identification not only in completed but also in ongoing processes like medical or psychological treatments. Utilizing this identification, interventions

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could be placed at the right moments, and perhaps episodes or relapses of mental disorders (like major depression or schizophrenia) could be prevented. Real-time monitoring is a promising technology for the optimization of psychotherapy processes, as has been demonstrated by practical experience and empirical studies (Haken and Schiepek 2006; Lambert et al. 2001; Tominschek et al. 2008; Whipple et al. 2003). By using real-time feedback, therapists are able to identify "off track" processes and early deteriorations in the treatment and also to correct them within the ongoing process. Worsening rates were reduced, drop-outs were prevented, and "on track" processes could be optimized and abbreviated (Asay et al. 2002; Whipple et al. 2003).

In typical clinical practice, patients submit feedback over the course of psychotherapy sessions (e.g., once a week with irregular intervals), and the evaluation is based on a visual inspection of the resulting time series. If data are available, comparisons are made to data of reference patients. No further mathematical analyses are conducted. However, given the evidence for critical instabilities and phase transitions in psychotherapy processes (e.g., Kowalik et al. 1997), which seem to be necessary conditions for treatment success and efficacy (reviews on actual studies: Haken and Schiepek 2006; Schiepek and Perlitz 2009), ongoing analyses for the identification of such phenomena are necessary. This requires continuous and equidistant measures, which can be analyzed by the methods described below. For the purpose of real-time data acquisition and analysis we developed an internet-based device that allows for daily ratings (or other intervals), using the Therapy Process Questionnaire (Haken and Schiepek 2006) or other questionnaires, in combination with different outcome measures. This internet-based system—which we call the *Synergetic Navigation System*—gives a continuous feedback on the turbulences and instabilities of self-organization processes and can be implemented in clinical practice and in process-outcome research. Further along in this article, we will discuss some findings related to the *Synergetic Navigation System*. Actual applications of this system are approved by the Ethics Committee of the Paracelsus Medical University Salzburg, and all the patients have provided signed informed consent.

Nonetheless, even time series produced by daily patient feedback are short, when compared with data sets produced by physiological or physical experiments. Given treatment periods of several weeks or months, outpatient or inpatient treatments include 40–150 measurement points. In addition, important discontinuities or treatment responses (so-called "rapid early responses") often occur during the first weeks of the process (Ilardi and Craighead 1994). As we have seen, the duration of critical periods like phase transitions of cognitive, behavioral, and affective patterns with their correlated critical instabilities is usually days, and often less than two weeks. In addition, most questionnaires in psychology and psychotherapy are based on 5-point, 7-point, or 11-point Likert scales, or on visual analog scales transformed to a 0–100 range, so the time series are not only short, but also coarse.

Therefore, the aim of this article is to introduce two newly developed measures and to discuss their ability to identify nonstationary phenomena and critical instabilities in short and coarse-grained time series data. In the following sections, we first present and discuss the algorithms for the computation of the two measures. Then we test the measures' ability to identify critical instabilities by correlating their results from the Feigenbaum Scenario of the Verhulst system with the positive Lyapunov exponent as well as the Permutation Entropy (Bandt and Pompe 2002) for the same scenario. A second test is performed to check the scalability of the measures for short time series. Practical applications of the measures are discussed in the last part of the article.

2 New measures for critical fluctuations

In the following we will propose two newly developed measures to identify nonstationary phenomena and critical instabilities in short and coarse-grained time series. Both measures are used for the analysis of discrete time series data with known theoretical data range. Let x_t represent the value of a variable measured at time t on the basis of a constant and discrete time base (e.g., one observation per day). Values are represented on the basis of a constant unit with theoretical data range s between the theoretical minimum $x_{\min}$ and the theoretical maximum $x_{\max}$ of x. The fluctuation measure F is sensitive to the amplitude and frequency of changes in a time signal, and the distribution measure D 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 two measures are calculated within a window of data moving over the time series.

2.1 Fluctuation intensity

The fluctuation algorithm is applied to segments of discrete time series. These segments are defined by the width of a moving window that can be arbitrarily fixed. The window runs over the whole time series and results in a continuous fluctuation intensity measure F. All measurement points within the window are subdivided into periods with cutoff points defined by changes in slope (points of return k). Trends can be: "increasing," "decreasing," or "no change" (Fig. 1). The difference between the values x_n at the points of return k is taken irrespective of the sign—in absolute terms: $y_i = |x_{n_{k+1}} - x_{n_k}|$—and is divided by the duration of the period (i.e., the number of data points within the period from one point of return k to the next one $k+1$). Thus, the change rate is related to its duration, and F is sensitive to the frequency

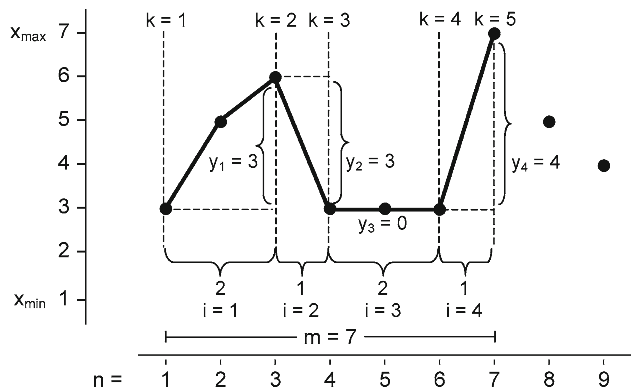

Fig. 1 Explication of the fluctuation intensity algorithm. In this example, the F-value is calculated as follows: The first contributor is between $k = 1$ and $k = 2$ a difference of 3 (since $x_1 = 3$, $x_3 = 6$), divides by 2 (2 is the number of intervals between $k = 1$ and $k = 2$. The next contributor is between $k = 2$ and $k = 3$ a difference of 3, divided by only one interval. Next is a difference of 0 divided by 2 intervals (remains 0),and the last difference between $k = 4$ and $k = 5$ is 4, divided by 1. So we sum up $3/2 + 3/1 + 0/2 + 4/1 = 8.5$. This sum is divided by the maximum of possible fluctuation, which is in this case (with the greatest number of points of return $k = 1$ to $k = 7$, and $s = (x_{\max} - x_{\min}) = 7 - 1 = 6$): 6/1 + 6/1 + 6/1+ 6/1 + 6/1 + 6/1 = 36. $F = 8.5/36 = .23611$

as well as to the amplitude of the fluctuation. These fractions within the window are summed. In order to normalize the fluctuation intensity, the result is divided by the greatest possible fluctuation, which is given by the maximum amount of change within a minimum duration. This is the sum of the differences between the lowest and the greatest value of the available range between one measurement point and the next. The formula results in a normalized fluctuation intensity $0 \leq F \leq 1$:

$$F = \frac{\sum_{i=1}^{I} \frac{y_i}{(n_{k+1} - n_k)}}{s(m-1)} \tag{1}$$

with

- $y_i = |x_{n_{k+1}} - x_{n_k}|$
- x_n nth value of the time series
- k points of return (number of changes in slope of the data sequence)
- i periods between points of return
- I total number of such periods within the window
- m number of measurement points within a moving window
- m–1 number of intervals between all measurement points of a window
- $s = x_{\max} - x_{\min}$ with $x_{\min}$ smallest value of the scale, $x_{\max}$ largest value of the scale.

One can immediately derive that $\sum_{i=1}^{I} \frac{y_i}{n_{k+1} - n_k} \leq s(m-1)$, so $0 \leq F \leq 1$, see Fig. 1.

Note that $s(m-1)$ is the window area expressed in units of t and x and that s is not the data range but the theoretical range of the scale.

2.2 Distribution

The degree of distribution D represents another aspect of critical instabilities. Whereas F is at its maximum when the dynamics of the data jump between the minimum and maximum values with large and regular frequency, instabilities are often characterized by irregularities, resulting in quite different system states. In the extreme case, the values should be irregularly and chaotically distributed over the range of the measurement scale. As a result, the degree of distribution, D, measures the deviance of the data values from an ideal equal distribution over the range or measurement scale. As in the calculation of F, we use a moving window running over the whole process and thus consider the values over the entire process. For the distribution measure, the order of values within the moving window is irrelevant, and so we first sort the values in ascending order. Let x_i be the values of a variable x at the sorting position i within the moving window X, which is given by:

$$X = \{x_1, x_2, x_3, \ldots, x_m\} \quad \text{with} \quad x_1 \leq x_2 \leq x_3 \leq \cdots x_m$$

In the following calculation, this sorted window is compared with an artificial data set of equally distributed values. These artificial data consist of the same number m of values arranged in ascending order in equally spaced intervals between the theoretical minimum and maximum of the scale. The interval I is given by $I = s/(m-1)$, $s = x_{\max} - x_{\min}$ and the artificial data set Y is given by:

$$Y = \left\{y_1 = I^*1, y_2 = I^*2, y_3 = I^*3, \ldots, y_m = I^*m\right\}$$

If the data in X are equally distributed within the data range, then differences between values at different positions in X must be equal to the differences in Y at the same positions. To give an example, if X is perfectly equally distributed within the data range, then $\delta_{Y \cdot 2-1} = y_2 - y_1 = \delta_{X \cdot 2-1} = x_2 - x_1$. Generally, the aberration Δ_{ba} of X from the ideal given in Y can be calculated for the positions a and b as follows:

$$\Delta_{ba} = \delta_{Y \cdot b-a} - \delta_{X \cdot b-a} \quad \text{with} \quad \delta_{Y \cdot b-a} = y_b - y_a$$
$$\text{and} \quad \delta_{X \cdot b-a} = x_b - x_a$$

In total, the aberration Δ^* is given by the following permutation of a and b.

$$\Delta^* = \sum_{c=1}^{m-1} \sum_{d=c+1}^{m} \sum_{a=c}^{d-1} \sum_{b=a+1}^{d} \Delta_{ba} \Theta(\Delta_{ba})$$

The two outer sums are permutations of all combinations of c and d within the window. The inner sums of a and b are representing all combinations of positions within the interval given by c and d.

$\Theta(\Delta_{ba})$ is the Heaviside step function, resulting in 1 if Δ_{ba} is a positive number, and 0 if not. So, only positive aberrations are considered, because negative aberrations always result in positive ones at other positions.

The distribution measurement D is therefore given by:

$$D = 1 - \sum_{c=1}^{m-1} \sum_{d=c+1}^{m} \sum_{a=c}^{d-1} \sum_{b=a+1}^{d} \frac{\Delta_{ba}\Theta(\Delta_{ba})}{\delta_{Y.ba}} \tag{2}$$

One can see that D is normed so that $0 \leq D \leq 1$, and high values of D are the results of equally distributed measures of x within the moving window.

2.3 Reasons for the introduction of the methods

Two questions arise when considering the benefits of these methods: First, why not use classical variance as a measure of varying degrees of fluctuations? The answer is: variance measures the average of squared distances of the values from their arithmetic mean, irrespective of frequency, distribution, slope or other properties. Variance is therefore not sensitive to the shape or the "Gestalt" of the time series, as are F or D. Variance represents the amplitude of fluctuations, but not the frequency or the sequence of the system states. The dummy sequences in Fig. 2 illustrate this.

A second question that arises is: why not use well-known methods from chaos theory, which were developed to identify nonstationarities within chaotic processes, such as the Pointwise Correlation Dimension (PD2: Skinner et al. 1994; Strunk and Schiepek 2006), the Local Largest Lyapunov exponent (LLLE: Kowalik and Elbert 1995; Kowalik et al. 1997; Rosenstein et al. 1993; Strunk and Schiepek 2006), or the Entropy Rates (Kowalik et al. 1997)? All of these methods require much longer sets of data points than used in the fluctuation and distribution indices. They are calculated within moving windows or by distance counts (including at minimum several hundred measurement points), but require sequences longer than the time series available in our applications (e.g., <200 in psychotherapy processes). In addition, these well-known measures require highly resolved data, which is not required for the F and D measures.

3 Tests for validity and scalability

To test the validity of our measures, we compare their results with results from other methods with known validity. Additionally, we test the scalability of the measures by assessing the stability of results in cases in which the calculation is based on very short data sets.

3.1 Methods

In order to investigate the applicability of the methods even for short moving windows, we produced an artificial data set using the well-known iterative logistic map, or Verhulst dynamics $x_{n+1} = rx_n(1 - x_n)$. It is the simplest system producing deterministic chaos with a period-doubling scenario on the way to full chaos. Continuous increase of the growth parameter $r(0 \leq r \leq 4)$ results in the so-called Feigenbaum Scenario. We increased the parameter r from 3.10 to its maximum of 4.00 by steps of .001, and produced 100 data points for each of the resulting 901 sequences (Fig. 3a). The data set of each sequence was z-transformed in order to avoid differences in variance between the sequences.

We used two different reference measurements with known validity in order to compare these with results from F and D.

First, we used a recently developed complexity measure for time series in order to compare it with the F and D measure—the Permutation Entropy (h) introduced by Bandt and Pompe (2002). Like F and D, it is a complexity measure for natural, real-world time series without restricting parametric assumptions and with high tolerance for noise. Given the logistic map, Permutation Entropy behaves like the positive Lyapunov exponent (Fig. 3b, g). The Permutation Entropy is calculated by studying the frequency distribution of dynamic patterns within a given data set. In our case, the data set is given by the moving window. Patterns are constructed from the data in the moving window on the basis of so-called words with a given word length n. All possible words of length n within the moving window are investigated, and values within a word are recoded in rank order numbers ranging from 0 to $n - 1$. Therefore $n!$ rank number patterns can theoretically be found within a data set with no ties. So, Permutation Entropy depends on the window width and the word length n. Permutations of word length 6 are calculated for different window widths and compared using product moment correlations with F and D for the same window widths.

Second, the positive Lyapunov exponent is calculated directly from the equations of the logistic map for each parameter value throughout the Feigenbaum Scenario. The Lyapunov exponent can be interpreted as a "gold standard." It is a well-known measure which is sensitive to the degree of instability and the identification of phase transitions in complex systems. The positive Lyapunov exponent is compared with F and D using product moment correlations.

In summary, we have produced 901 sequences of the Feigenbaum Scenario for the logistic map with different parameters. For each sequence F, D, Permutation Entropy of word length 6 (h_6) and the Lyapunov exponent were calculated. Product moment correlations between the measurements are interpreted as validity coefficients. Significance of these validity coefficients is presented. Significant validity

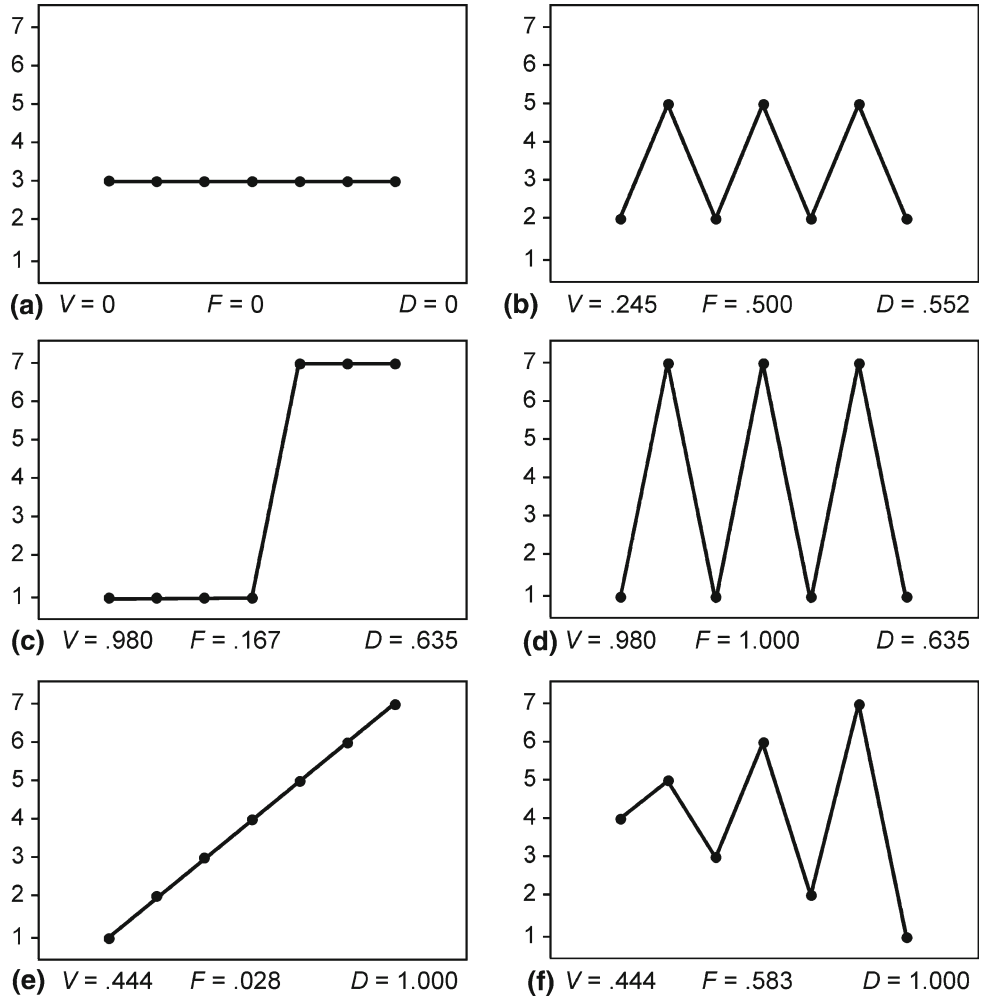

Fig. 2 Variance score (V), degree of fluctuation (F), and degree of distribution (D) of 6 dummy sequences. The ordinate corresponds to a 7-point Likert scale. The variance score V is the ratio between the variance and the greatest possible variance in this case ($s^2 = 10.29$), and thus normalized between [0, 1], as are F and D. **a** In the case of a horizontal line all three scores have the same result: 0. **b** Periodic alternation: F and D are more sensitive than V. **c** The system jumps from one stable state to the other, but without fluctuations. Therefore, F remains small. **d** The sequence realizes the same values as in **c**, but now by manifesting strong fluctuations. F is sensitive to this, V and D do not differ from **c**. **e** and **f** have the same variance, whereas the differences in the shape of the time series are evident. The fluctuation is more accentuated in **f** than in **e**

coefficients above .6 are interpreted as substantially high and above .8 as almost perfect.

Additionally, in order to investigate the scalability of the measures we have repeated all calculations using different window lengths. In every case the sequences from the logistic map consisted of 100 data points. The largest window width included 100 data points, the shortest 7 data points.

3.2 Results

As seen in Fig. 3, the F measure does what it should do: high frequency and high amplitude changes of x_n correspond to increased F values. It should be noted that the most pronounced values of F are not seen during the phases of chaotic dynamics, but during the period 2 oscillation. Bifurcation cascades of higher periodicity and chaotic dynamics reveal smaller differences between subsequent values (from x_n to x_{n+1}) than the period 2 oscillation, with its big jumps from x_n to x_{n+1}. Close inspection of the time series provides evidence that during periods of extreme chaoticity, x_n repeatedly moves around fixed values (between .6 and .7) and thus is restricted to reduced amplitudes. Consequently, F is negatively correlated to the degree of chaoticity indexed by the Lyapunov exponent (Fig. 3b, c and d, Table 1).

In contrast, D increases when chaos increases (Fig. 3e, f). This is because the available range of $x_n (0 < x_n < 1)$ successively widens and a greater number of possible values are observed (increased density). Before full chaos appears at $r = 4.00$, x_n is restricted to certain areas of the available range—especially during early stages of the period-doubling cascade (Fig. 3a).

The specific patterns of F and D following the period-doubling scenario, the successive degrees of chaoticity and the "window of order" at $r = 3.85$ remain stable when the window width is reduced from 100 (including all data points of every sequence) to 20 and also from 20 to 7.

Table 1 gives the validity coefficients for F and D along with the Permutations Entropy (h_6) and the positive Lyapunov exponent. For all window length, D is highly positively correlated with h_6, which was calculated at a window lengths of 100 data points in all comparisons. Validity coefficients of D in comparison with h_6 range between .929 ($P < .001$)

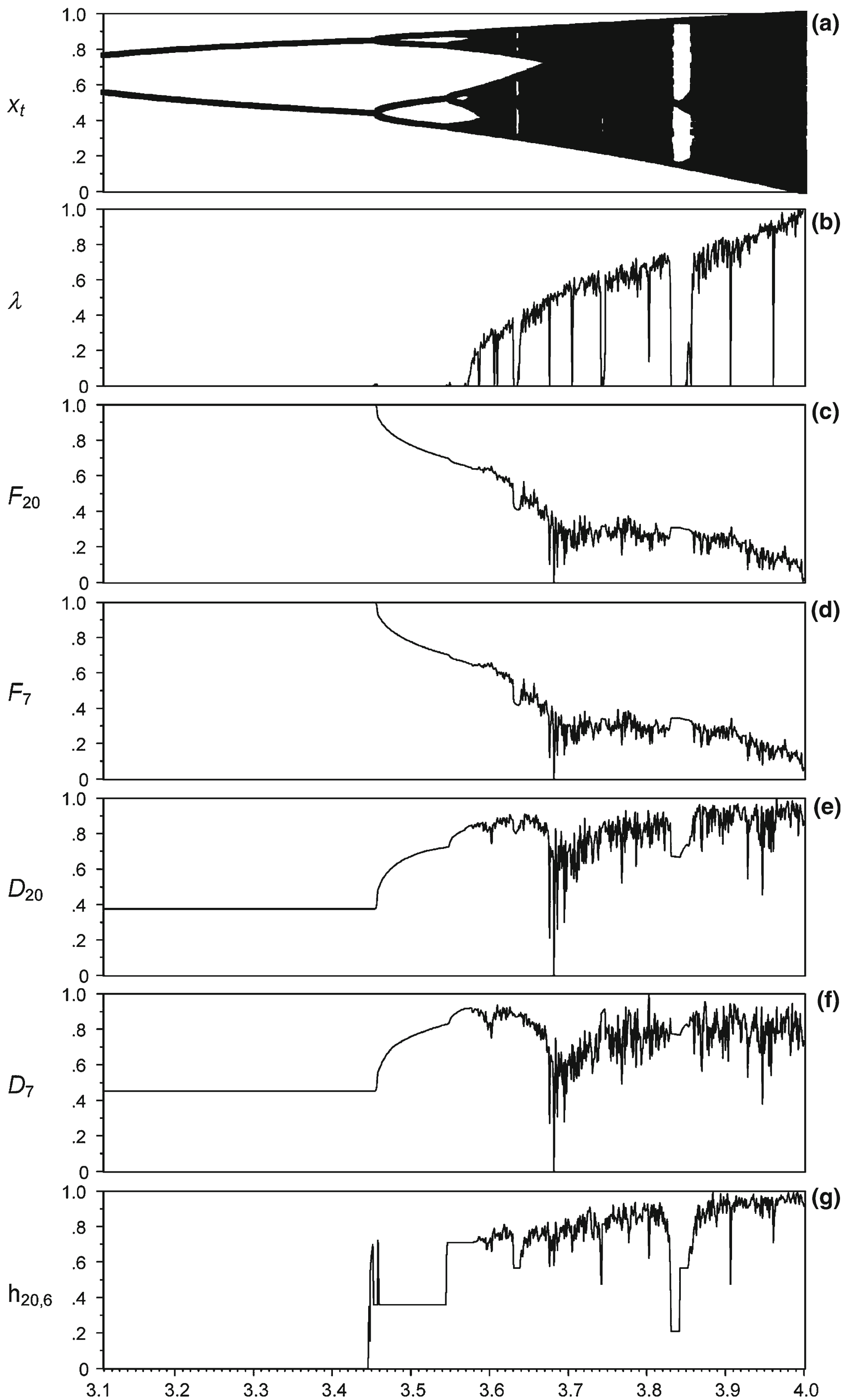

Fig. 3 Method comparison. **a** The logistic map produced time series of 100 data points for increasing steps of r (starting from 3.10 up to 4.00, step width = .001, resulting in 901 sections). Data are z-transformed within each sequence, resulting in époques of time series with identical variance. **b** Positive Lyapunov exponents, calculated directly from the equations of the logistic map. **c** and **d** F-values produced by moving windows of width 20 and 7. **e** and **f** D-values produced by moving windows of width 20 and 7. **g** Permutation Entropy with word length 6 for moving windows of width 20

Table 1 Validity- and scalability-testing. Correlations of distribution D, fluctuation F with Permutation Entropy h of word length 6 (h_6) and positive Lyapunov exponent calculated at different window widths (100, 80, 60, 40, 20, 10, down to 7)

Window	Correlation with $h_{6(\text{window}=100)}$		Correlation with Lyapunov exponent		
	D	F	D	F	h_6
100	.929	−.936	.809	−.875	.928
80	.927	−.935	.805	−.875	.925
60	.922	−.935	.796	−.875	.919
40	.914	−.935	.781	−.875	.904
20	.883	−.936	.728	−.875	.843
10	.797	−.937	.601	−.876	.604
7	.722	−.938	.499	−.876	–

F seems to be very robust against the reduction of the calculation windows

at window length 100 and .722 ($P < .001$) for a 7 data point window. Also, the correlation with the positive Lyapunov exponent shows the validity of the measure but is not as distinct as in the comparison with the Permutation Entropy. Validity coefficients of D in comparison with the positive Lyapunov exponent range between .809 ($P < .001$) at window length of 100 and .499 ($P < .001$) for the 7 data point window.

For all window length, F is negatively correlated with both $h_6(-.936, P < .001)$ and positive Lyapunov exponent ($-.875$, $P < .001$). As can be seen from Table 1, the validity coefficients are only slightly influenced by the window length and are high for both comparisons.

To conclude: (1) When compared to the Permutation Entropy and the positive Lyapunov exponent fluctuation, F and distribution D have been shown to be valid measures. (2) This validity is present even for very short window widths and short time series. (3) F and D are sensitive to two complementary aspects of dynamic complexity (F to the amplitude and frequency of "jumps" between subsequent measurement values, D to the distribution of values over a given range of values).

4 Examples for practical applications

In the following, we present some examples for practical and research applications of the F and D measure.

4.1 Fluctuation and distribution resonance diagrams

In order to get a summary of an empirical system including all variables (time series) measured in parallel—for example, the items of a questionnaire—only the significant peaks of the fluctuation or distribution time series are marked in a diagram including all this items. First, the data series of F and D are z-transformed. By applying thresholds given by the confidence intervals of $P < .05$ or $P < .01$, significant periods of the time series are identified. Taking for example all items of a questionnaire, periods of critical instability are identified and specified for the different subscales. Figure 4 gives an example using the Therapy Process Questionnaire (TPQ) of Haken and Schiepek (2006). The column-like structures are easily identified in the practice of real-time change monitoring.

4.2 Enhanced F and D measures correspond to transitions as indicated by Recurrence Plots

A practical application of F and D measures is demonstrated in a comparison with the results of the Recurrence Plots of the natural time series of $N = 94$ inpatient psychotherapy processes. Data were acquired by using the Therapy Process Questionnaire during a process-outcome study at the University Hospital of Aachen (Germany). The method of Recurrence Plots (Eckmann et al. 1987) identifies recurrent sequences of a single or of several time series and indicates this recurrence in a time-by-time-plot. The identification is based on the embedding of time series within phase spaces defined by time-delay coordinates. Where no recurrent patterns can be identified, the plot has no dots. The resulting empty stripes in the dot plot indicate pattern transitions or critical instabilities (Webber and Zbilut 1994). In consequence, they should correspond to the columns in the Fluctuation or Distribution Resonance Diagrams, which indeed is true in many clinical cases of psychotherapy processes (Fig. 4). The correlation between the histograms resulting from summing the dots in corresponding Fluctuation Resonance Diagrams and Recurrence Plots of the same process should be negative. This was true for the 94 psychotherapy processes of the previously mentioned study. The mean correlation over all cases was $-.34$(SD $= .21$, $P < .001$). When the histograms were allowed to "lock in" by adjusting them with a small correction in their relative position (only lag of 1, 2, or 3), the mean correlation was $-.45$(SD $=$ .19, $P < .001$).

4.3 Fluctuation and distribution fit to the dynamics of treatment processes

An example of a female patient with Obsessive Compulsive Disorder (OCD) illustrates the clinical applicability of the F and D measure. She started an inpatient treatment in a psychosomatic hospital after being impaired by OCD symptoms for about four years. Her problems were contextualized within an autonomy conflict concerning her marriage. During her hospital stay, she decided to divorce her husband

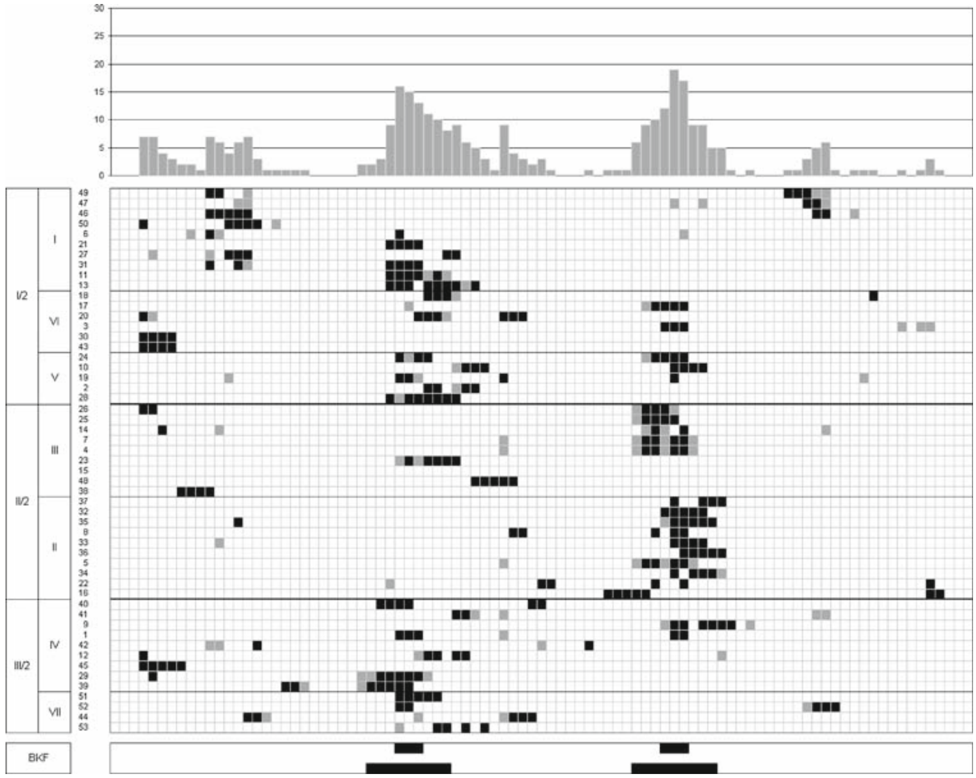

Fig. 4 A Complexity Resonance Diagram of a psychotherapy process. The time series data were produced by daily ratings of a patient (diagnosis: Major depression) who answered the Therapy Process Questionnaire (TPQ, Haken and Schiepek 2006) every day of his hospital stay. Subscales resulted from a factor analysis of the 53 items which was realized with the data of $N = 94$ psychotherapy processes: (I) experience of progress, confidence, and self-efficacy during the ongoing therapy, (IV) insight and development of new perspectives, (V) intensity of therapeutic work and intrinsic motivation, (III) social climate and interpersonal relations to other patients, (II) quality of the therapeutic relationship, (IV) dysphoric emotions and self-relatedness, (VII) symptom severity. *Gray dots* correspond to a significance level $< .05$, *black dots* correspond to a significance level $< .01$. As can be seen, two periods of critical instability include partially different subscales of the TPQ, which represent different aspects of experiencing the psychotherapy process

after a couples' therapy session. As a consequence of this decision, she reported feelings of not only pity, but also of anger. Interestingly, the period before this critical event and her decision was characterized by intensive and increased complexity in her daily ratings of therapy-related feelings and cognitions (Fig. 5). In this case, a variation of the TPQ specifically developed for OCD patients was used for the process monitoring. The averaged F as well as the average D measure of all items (time series) indicated a significant peak in the period 0–4 days before her fateful decision at the 28th day of hospital stay. We hypothesized that the system was destabilized before a phase transition-like phenomenon took place. The phase transition concerned a pattern of several components: finishing an important and long-term subliminal decision process, becoming aware of different emotions (like anger), and finally, of a clear-cut symptom reduction, represented by the course of the Y-BOCS (Fig. 5). The Y-BOCS (Yale-Brown Obsessive Compulsive Scale, Goodman et al. 1989) is a commonly used symptom score for obsessions and compulsions, and in this case was administered weekly. It should be noted that the Y-BOCS symptom reduction started 4 days before the crucial decision date. The peaks of F and D occurred 8 and 6 days before this date, respectively. Results from single case studies like this indicate that the measures F and D are applicable to the data produced in studies on human change processes.

Since the Synergetic Navigation System, which integrates the F and D measures for purposes of real-time data analysis, is part of the everyday routine practice in some hospitals, continuously growing data sets are available on psychotherapeutic change practice. For example, from the inpatient treatment center of the Psychiatric University Hospital Salzburg (35 treatment places) alone, we got a sample of about 180 cases with 50–200 data points each (daily ratings from the TPB and a written diary), from the one and a half years of SNS-based practice (Spring 2008 to Fall 2009). Judging by this, the ancient distinction between large-N-studies with only pre-post-assessments and single case studies with so-called "intensive" or time series designs is vanishing. Of course, more cases are needed in order to draw clinical conclusions,

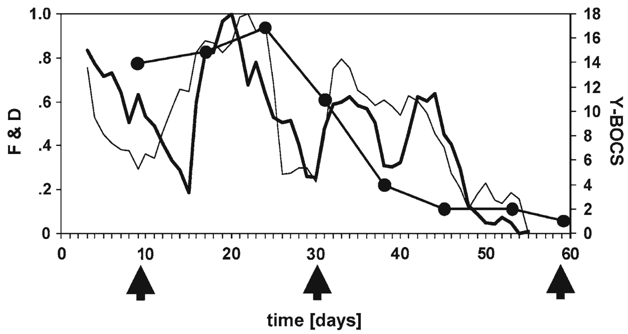

Fig. 5 Time series results from a female patient with obsessive compulsive disorder. *Black dots* and *line*: The course of the Y-BOCS scores of a patient with OCD (washing/contamination fear) during a hospital stay of about 8 weeks (ratings once a week, scale at the right side). Treatment was psychotherapy (combined behavioral and systemic therapy). *Bold black line*: fluctuation F. *Thin black line*: distribution D. F and D were averaged over all 45 items of the TPQ-OCD (a variation of the TPQ for the monitoring of OCD treatment). The F and D values are based on time series resulting from daily TPQ-ratings and calculated within a moving window of 7 days. The resulting F and D values are normalized to values from 0 to 1 (scale at the *left side*). X-axis: Days of hospital stay. *Black arrows* indicate the days where fMRI sessions took place. From the figure, one can see that the downward trend in the Y-BOCS is closer to the date of crucial decision (i.e., 4 days before the intervention at the 28th day) than for the measures D (6 days before) and F (8 days before)

but this concept of data sampling in psychotherapeutic routine practice offers new possibilities for data mining.

4.4 Fluctuation and distribution correspond to changing patterns of brain activity

Since F and D indicate critical instabilities in self-organizing processes, they can be used as time markers for appropriate fMRI scans in hypothesis-driven brain studies on psychotherapy. There is an increasing interest not only in the outcome of, but also in what is going on during human change processes at the brain level. In one of our studies we used functional brain imaging to search for correlates of stable and instable periods of psychotherapy dynamics. fMRI with an individualized symptom provocation paradigm was applied repeatedly (3–4 scans) during the treatment process of nine patients with obsessive-compulsive disorder (OCD, subtype: washing/contamination fear) and nine matched healthy controls. Data of the whole sample are prepared for publication.

A preliminary single case study has already been published (Schiepek et al. 2009): The brain activity of a female OCD patient was investigated during the treatment process by repeated functional MRI. In Fig. 5, the days where fMRI sessions took place are marked by black arrows. The stimulation was done by (a) visual symptom provocation (individual pictures taken from the patient's home context), (b) disgust provoking, and (c) neutral pictures. The disgust and the neutral pictures were taken from the International Affective Picture System (Lang et al. 1997/2001). The phase transition that was prepared by the salient peak of fluctuation and distribution not only changed the dynamics of the psychotherapy process but also the patient's brain activity pattern. The comparison of OCD-specific brain responses at the beginning of the therapy and the second fMRI measurement (activations during the presentation of OCD-related pictures > activations during the presentation of neutral pictures) revealed clearly reduced activity of the medial frontal gyrus/anterior cingulate cortex, superior and middle frontal gyrus, inferior frontal/precentral gyrus, superior temporal gyrus, superior parietal lobe/cuneus, the thalamus and caudate nucleus in both hemispheres, as well as the right fusiform gyrus during the second session. The OCD-associated BOLD responses of the second and third sessions at the end of therapy produced only small differences. The specific changes in the neural patterns of the patient were controlled by a healthy subject who was confronted with the identical stimuli during fMRI scans taken at identical time intervals.

In the future of bio-psychological research in psychotherapy, it will be of great importance to bridge the gap between brain data (functional brain imaging, neuro-biochemistry) on the one side and psychological measures of the dynamics on the other. Methods such as the Synergetic Navigation System will play an important role in psychological imaging within this integrated research program.

5 Discussion

Human change processes are nonlinear, complex, and nonstationary by nature. In order to identify nonstationary phenomena and critical instabilities in short and coarse-grained time series data, we introduced two newly developed measures. The first measure (F) represents the fluctuation intensity of a given discrete time series. The second measure (D) characterizes the distribution of the time series data over the scale range. Both measures are calculated within a moving window, in order to identify nonstationary changes in the underlying time series. We have tested the validity of both measures by comparing their results with results from Lyapunov exponents and from Permutation Entropy for the Feigenbaum Scenario of the logistic map. Results demonstrated a strong correlation of the newly-proposed measures with both Lyapunov exponent and Permutations Entropy. Correlations between D and the two reference measures remain sufficiently high even for short moving windows with only 10 data points. F seems to be valid even for shorter moving windows with only 7 data points.

Additionally, we discussed examples of practical and research applications of the two measurements. These examples highlight the usefulness of nonlinear methods integrated in real-time monitoring systems for the analysis and optimization of human change processes. Since F and D, together with other measures like Permutation Entropy and Recurrence Plots, are integrated in the Synergetic Navigation System, an internet-based real-time monitoring system of human change processes, these methods contribute to a better understanding of the learning and development of complex biological and mental systems.

At the moment, the usefulness of real-time monitoring systems is becoming more evident, since these systems are applied in everyday practice of psychotherapeutic and psychosomatic treatments (inpatient as well as outpatient treatments). The internet-based technology offers new ways of process diagnostics, introduces the dimension of "time" into psychological and psychiatric research, and provides an "early warning system" for helpful and creative as well as possibly dangerous phase transitions in human self-organization processes. F and D are crucial for the analysis of the time series that are made available by such monitoring systems.

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