# Neural chaos and schizophrenia

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**Abstract.** Recent data indicate that random-like processes are related to the defects in the organization of semantic memory in schizophrenia which is more disorganized and less definable than those of controls with more semantic links and more bizarre and atypical associations. These aspects of schizophrenic cognition are similar to characteristics of chaotic nonlinear dynamical systems. In this context, the hypothesis tested in this study is that dynamic changes of electrodermal activity (EDA) as a measure of brain and autonomic activity may serve as a characteristic which can be used as an indicator of possible neural chaotic process in schizophrenia. In the present study, bilateral EDA in rest conditions were measured in 40 schizophrenic patients and 40 healthy subjects. Results of nonlinear and statistical analysis indicate left-side significant differences of positive largest Lyapunov exponents in schizophrenia patients compared to the control group. This might be interpreted that the neural activity during rest in schizophrenic patients is significantly more chaotic than in the control group. The relationship was confirmed by surrogate data testing. These data suggest that increased neural chaos in patients with schizophrenia may influence brain processes that can cause random-like disorganization of mental processes.

**Key words:** EDA — Lyapunov exponent — Schizophrenia — Chaos

## Introduction

The theory of nonlinear dynamical systems and chaos theory deal with deterministic systems that exhibit complex and seemingly random-like behavior. This interdisciplinary area of science influenced also research in physiology because of the complexity of living systems (Freeman 1991, 2000, 2001; Elbert et al. 1994; Weng et al. 1999; Dokoumetzidis et al. 2001). The values of the measured properties of many physiological systems look random and their determinants are often unknown because of high complexity of the factors affecting the phenomena under consideration in physiological research (Elbert et al. 1994; Freeman 2000; Dokoumetzidis et al. 2001; Korn and Faure 2003). Main idea of randomness relies on the concept that every complex system has a large number of degrees of freedom which cannot be directly observed and are manifested through the system's fluctuations (Freeman 1991, 2000, 2001; Elbert et al. 1994; Dokoumetzidis et al. 2001). Recent research shows that the chaotic deterministic dynamical systems display the random-like behavior often indistinguishable from pure random processes (Elbert et al. 1994; Dokoumetzidis et al. 2001). Although the roots of the chaos theory are in the work of the French mathematician Henry Poincaré (1854–1912) (Peterson 1993), the main results of this interdisciplinary research in the field of physiology are relatively new (Freeman 1991, 2001; Elbert et al. 1994). In this context the concept of self-organization has been proposed because the chaotic dynamics tends to produce a spontaneous order and patterns of organization in the physiological systems (Elbert et al. 1994; Dokoumetzidis et al. 2001; Freeman 2001; Korn and Faure 2003). The self-organization patterns typically are linked to instability states that may enable a new mode of behavior. The sudden phase

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transitions called bifurcations represent a form of system's behavior which is deterministic and in the state space of the system's behavior is compressed to a subset called the attractor (Elbert et al. 1994; Dokoumetzidis et al. 2001; Freeman 2001). In the physics state (or phase) space means the abstract multidimensional space in which every possible state of the system corresponds to a unique point in the space that may be visualized by state space diagram (Fig. 1). The number of dimensions or parameters of this space represents degree of freedom of the system and every dimension may be represented as axis. For example, mechanical system may be described by all possible values of position and momentum or in the thermodynamics states or phases of a chemical system may be described as function of pressure, temperature or composition (Elbert et al. 1994; Dokoumetzidis et al. 2001). Complex macrosystem such as living organism may be therefore described by many state functions such as temperature, blood pressure, electrical activity, for example EEG, ECG, electrodermal activity (EDA) and also other physiological, behavioral or cognitive characteristics (Elbert et al. 1994).

Recent findings suggest that methods of chaos theory may represent a useful experimental tool and theoretical model

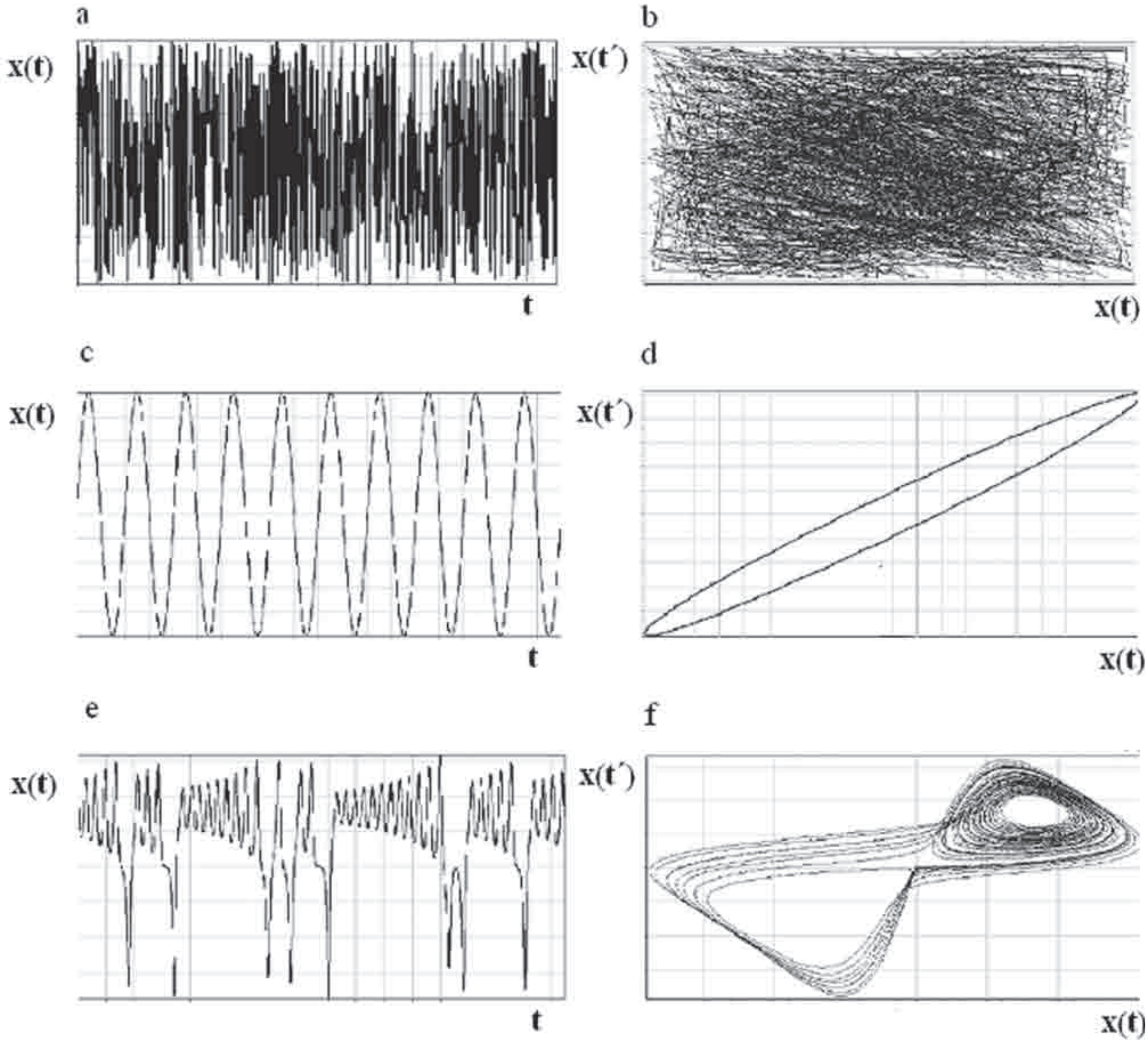


**Figure 1.** Examples of signals and states space diagrams. a) White noise is a random phenomenon and its state space diagram is expanded to the state space (b); c) sine oscillations, for example mathematical pendulum, have elliptic trajectory in the state space (d); e) typical chaotic signal which leads to the well-known Lorenz attractor (f). t, time; x, time-dependent variable; $t' = t + \tau$ ($\tau$ is time delay).

for the study of the complex systems such as the human brain (Gottschalk et al. 1995; Huber et al. 1999; Melancon and Joanette 2000; Bob 2003, 2007; Korn and Faure 2003; Paulus and Braff 2003; Bob et al. 2006; Breakspear 2006). One of the aims for using this method is understanding of critical sensitive periods (as possible bifurcation points) related to initiation of new trends in the system's evolution that later emerge as very different macroscopic patterns of neural activity and mental processes (Freeman 1991, 2000; Elbert et al. 1994; Globus and Arpaia 1994; Meyer-Lindenberg et al. 2002; Korn and Faure 2003). In the brain, the critical sensitive periods are linked to a large number of complex and interlinked neural states which lead to extreme instability with respect to competition of many possible behavioral patterns (Freeman 2000; Korn and Faure 2003).

On a cognitive level the random-like complexity is related to the defect in the organization of semantic memory in schizophrenia which is more disorganized and less definable than those of controls with more semantic links and more bizarre and atypical associations (Davis et al. 1995; Paulsen et al. 1996; Vinogradov et al. 2002). Other studies examined textual analyses of the semantic processing and found that schizophrenic speech is less predictable, more repetitious, and often violates the rules of normal discourse (Manschreck et al. 1979, 1981; Hoffman et al. 1982; Goldberg and Weinberger 2000). These findings and clinical experience indicate seemingly random patterns in the disorganized cognition in schizophrenia although it is characterized by a complex lawfully mediated behavior (Leroy et al. 2005). These processes are probably closely related to information overload caused by defective attentional filtering and frontal lobe executive dysfunction (Hotchkiss and Harvey 1990; McGrath 1991; Goldberg and Weinberger 2000). Hypothetically it may be explained as random-like chaotic behavior in the neural systems. This pathological information processing might lead to a failure to inhibit activities of irrelevant neural assemblies (Vaitl et al. 2002; Olypher et al. 2006) and pathologically increased neural complexity characterized by an amount of independently active neural assemblies. The explanation is in accordance with findings that chaotic states in deterministic structure of the system occur when the neural process involves a large number of complex interlinked and simultaneously active states which lead to self-organization and high complexity (Korn and Faure 2003). It is also in accordance with recent data which suggest that chaotic processes likely emerge in a wide variety of cognitive phenomena and might be linked to pathophysiological changes in schizophrenia and other mental disorders (Gottschalk et al. 1995; Huber et al. 1999; Melancon and Joanette 2000; Bob 2003, 2007; Korn and Faure 2003; Paulus and Braff 2003; Bob et al. 2006; Breakspear 2006). From this point of view, pathophysiology of schizophrenia may be related to underlying chaotic neural process mainly in the frontotemporal and limbic structures, which might determine dynamics of schizophrenia and development of the disease (Paulus and Braff 2003; Breakspear 2006). One of the sensitive measures of specific pathophysiological changes during pathogenesis of schizophrenia is EDA (Dawson and Schell 2002; Williams et al. 2002; Schell et al. 2005; Zahn and Pickar 2005; Bob et al. 2007). These findings strongly suggest that EDA may help to predict treatment outcome and that specific electrodermal dysfunctions may carry prognostic information regarding subsequent symptoms, as well as social and occupational outcome in medicated patients (Dawson and Schell 2002). For example, the typical results of these studies are that heightened EDA typical for schizophrenia also in medicated patients was significantly correlated with poor short-term symptomatic recovery and that heightened EDA was associated with more disorganized symptoms which suggest that specific patterns of mental and semantic disorganization could be reflected in EDA records (Dawson and Schell 2002; Schell et al. 2005). These results strongly suggest that when arousal increases beyond the level needed to initiate attention and problem solving it leads to interference in cognitive processing and impaired ability to discriminate between relevant and irrelevant information that cause mental disorganization (Dawson and Schell 2002; Schell et al. 2005). Recent evidence indicates that EDA is governed by limbic modulation influences and correlates with amygdala activity, but also other structures such as ventromedial and dorsolateral prefrontal cortices, anterior cingulate gyrus, parietal lobe, insula and hippocampus in EDA modulation are involved (Mangina and Beuzeron-Mangina 1996; Phelps et al. 2001; Critchley 2002). Typical for EDA is that it reflects activity within the sympathetic axis of the autonomic nervous system and serves as a sensitive index of sympathetic activity (Dawson et al. 2000; Critchley 2002). Nonlinear measures calculated from EDA thus may serve as characteristics that can be used as an indicator of possible chaotic process in neural systems in comparison of schizophrenic patients with normal control group.

## Materials and Methods

In the present study we used measurement during rest to reveal possible underlying nonlinear neural dynamics in 40 adult schizophrenic outpatients of University Hospital (mean of age 28.1, age range 20–35) and 40 healthy control subjects randomly selected from general population (mean of age 23.8, age range 20–35) with given informed consent from all the participants. The 22 males and 18 females from schizophrenia group, and the 17 males and 23 females from the healthy control group with comparable (predominantly high school) education took part in the study. Schizophrenic patients had diagnosis of paranoid schizophrenia. All the schizophrenia patients were in partial remission. Their treatment at the time of the recruitment was based on antipsychotic medication. Exclusion criteria were organic illnesses involving the central nervous system, substance, and/or alcohol abuse, mental retardation and significant extra-pyramidal symptomatology. Two of the authors of this article independently reexamined the patient's diagnoses according to DSM-IV criteria (American Psychiatric Association 1994). All the participants were strongly right-handed according to Waterloo Handedness Questionnaire (Elias et al. 1998).

### *EDA measurement*

During rest conditions, the EDA was recorded bilaterally using two channels SAM unit and Psylab software (Contact Precision Instruments) connected to personal computer. Measurement was performed in a quiet room, with room temperature of about 23°C. During experiment the participant sat in a comfortable chair. The measurement was performed using two pairs of Ag/AgCl electrodes (8 mm diameter active area) filled with electro-conductive-paste that were attached to medial phalanges of the index and middle finger of each hand. After 5 min long resting state with closed eyes, experimental EDA recording with closed eyes during rest began and takes time 2 min.

### *Data analysis*

Practical approach to study of the complex dynamical systems is the method called time series analysis. A postulate of this method is that every dynamical system, for example the human brain and its functions, is governed and determined by a number of independent variables, similarly as a function may be determined by one (for example y = f(x)) or more independent variables. Nevertheless, any real measurement performed on the system cannot provide information about all the variables because the system with high complexity such as the human brain is multidimensional. Time series analysis therefore represents mathematical approximation that enables reconstruction of certain variables underlying multidimensional dynamics from data values obtained from the system during the time (Kantz and Schreiber 1997). The data values may provide for example psychophysiological measure performed on the system during an experiment. Because observational data reflect only a few real independent variables of a system, the approximation of the dynamical system behavior therefore uses a finite number of (mathematically reconstructed) variables to approximate states of the system. The multidimensionality of the dynamical system is therefore approximated by embedding dimension that represents dimensionality contained (or embedded) in the data. In the cases of electrophysiological signals the embedding dimension is often in the range from 1 to 4.

The analysis of the EDA time series in resting state was performed using the software package Dataplore valued as one of the most and well known software for the time series analysis. 120 s EDA records were divided on 4 s intervals (including 4000 datapoints) which represent sufficiently long time series and also satisfy criteria for signal stationarity (Elbert et al. 1994). In the data analysis by common technique mutual information, false nearest neighbours, embedding dimension and largest Lyapunov exponents were calculated (Kantz and Schreiber 1997). false nearest neighbours technique utilizes geometric principles for the finding of embedding dimension which determines reconstruction of underlying chaotic dynamics by means of largest Lyapunov exponents (Kantz and Schreiber 1997). For all these dimensions, the analysis gives the Lyapunov exponent whose set equal to the number of state variables. The spectrum of Lyapunov exponents describes the rates at which information about the process grows or decays in time. The largest Lyapunov exponent describes the nature of the system and indicates whether neighboring points in the state space characterizing the states of the system diverge for a chaotic system (positive largest Lyapunov exponent), converge for a stable predictable deterministic system (negative largest Lyapunov exponent), or the distance between the neighboring points remain unchanged for stable repetitive system (zero largest Lyapunov exponent) (Kantz and Schreiber 1997). The finding of appropriate embedding dimension of the state space is also needed for the finding of the neighboring points in the multidimensional state space and excluding the false neighbours. The largest Lyapunov exponent therefore describes underlying dynamics that may result to unpredictability and information loss or increased predictability of the system's behavior. In the state space largest Lyapunov exponent is defined using two close trajectories which represent two very similar states at the beginning of the system's development. In the case of chaos, the trajectories diverge during the time and a very little difference between the states results to very significant differences and information loss in the future (Fig. 2).

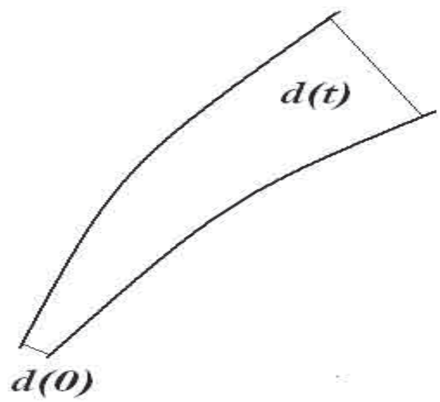


**Figure 2.** Positive largest Lyapunov exponent is characterized by divergence of two close trajectories *d(0)* in the state space representing two very similar states at the beginning of the system's development. In the case of chaos trajectories diverge to *d(t)* and it leads to information loss. The Lyapunov exponent $\lambda$ is defined by formula $d(t) = d(0)exp(\lambda t)$.

In the nonlinear data analysis we have reconstructed the neural dynamics from the EDA time series using the Takens' embedding theorem (Kantz and Schreiber 1997). The embedding theorem states that an attractor equivalent to the original attractor of the system that produce the experimentally measured signal may be reconstructed from a dynamical system of $n$ variables $x_1, x_2, x_3,..., x_n$ using the so-called delay coordinates:

$$x(t_1) = [x(t_1),x(t_1 + \tau),...,x(t_1+(d - 1)\tau]$$
$$x(t_2) = [x(t_2),x(t_2 + \tau),...,x(t_2 + (d - 1)\tau]$$
$$x(t_i) = [xi(t), x(t_i + \tau),...,x(t_i + (d - 1)\tau]$$

from a time series $x(t_i)$ where $d$ is the embedding dimension.

The purpose of the time-delay embedding is to reconstruct multidimensional state space that is equivalent to the multidimensional state space determining the state of the system. For examination of the time delay $\tau$, the first local minimum of the average mutual information has been used (Kantz and Schreiber 1997).

A difference between degree of chaos measured by positive largest Lyapunov exponents calculated according to Briggs' algorithm (Briggs 1990) between the groups was assessed in a statistical evaluation that included means, SD (standard deviation) and $t$-test for independent samples.

In addition, the same analysis using the surrogate data was performed. The basic idea of the surrogate-data testing is to first perform the nonlinear analysis on the actual experimental time series. The resulting value of the nonlinear measure is then compared with the same calculations performed on the set of suitable control surrogate signals constructed from the original time series that are linearly filtered Gaussian white noises which have the same mean, the same variance, the same autocorrelation function and the same power spectrum as the original sequence but nonlinear phase relations are destroyed (Kantz and Schreiber 1997). The null hypothesis that the original data represent linearly filtered Gaussian white noises can be rejected if the results of the same calculations performed on the actual and surrogate time series are statistically significantly different. In this case, the results cannot be understood as a consequence of the linear data properties. Surrogate data techniques thus permit the statistical testing of nonlinearities in a system's dynamics.

## Results

The results show that dynamic changes measured by largest Lyapunov exponents calculated from EDA records discriminate between the groups of schizophrenic patients and normal controls, because schizophrenic patients display significantly higher largest Lyapunov exponents on the left side (Table 1). The results of nonlinear data analysis and descriptive statistics indicate the chaotic behavior of neural dynamics during rest because of positive largest Lyapunov exponents in the both groups. With respect to surrogate testing the data also show that the neural dynamics in schizophrenic patients is on the left side during rest significantly more chaotic than in the healthy controls (Table 1, Fig. 3).

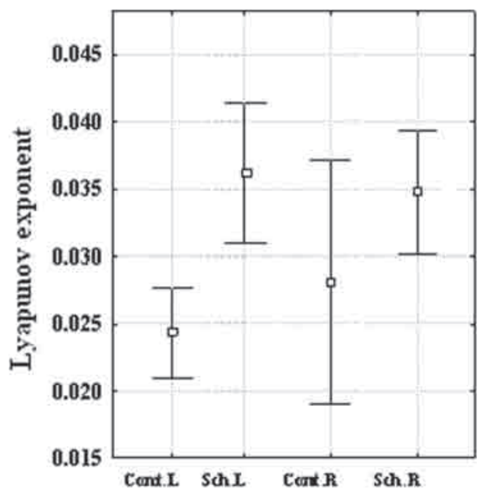


**Figure 3.** Means and standard deviation of calculated positive largest Lyapunov exponents (in bits) for schizophrenic (Sch.) patients and the normal control subjects (Cont.) on the right (R) or left (L) side.

**Table 1.** Descriptive statistics of positive largest Lyapunov exponents and results of surrogate data testing

| | Mean Lyap. Cont. | SD | Mean Lyap.-Sch. | SD | $t$-test Cont.-Sch. | Lyap. O.-S. Cont. | Lyap.O.-S. Sch. |
|---|---|---|---|---|---|---|---|
| Left | 0.024232 | 0.012101 | 0.035953 | 0.018342 | −3.506872* | −14.3471 | −13.7425 |
| Right | 0.027932 | 0.027751 | 0.034831 | 0.016913 | −1.412791 | −11.7321 | −12.8413 |

$t$-test Cont.-Sch., $t$-value of statistical test for controls and schizophrenic patients; Lyap.O.-S., $t$-test value between positive largest Lyapunov exponents calculated from original and surrogate time series; SD, standard deviation; * $p < 0.001$ ($p < 0.05$ for absolute $t$-value 2 or higher); Embedding dimension was 1 for all calculated largest Lyapunov exponents; with the aim to compare a degree of chaos between the groups, rare values of negative or zero largest Lyapunov exponents were excluded.

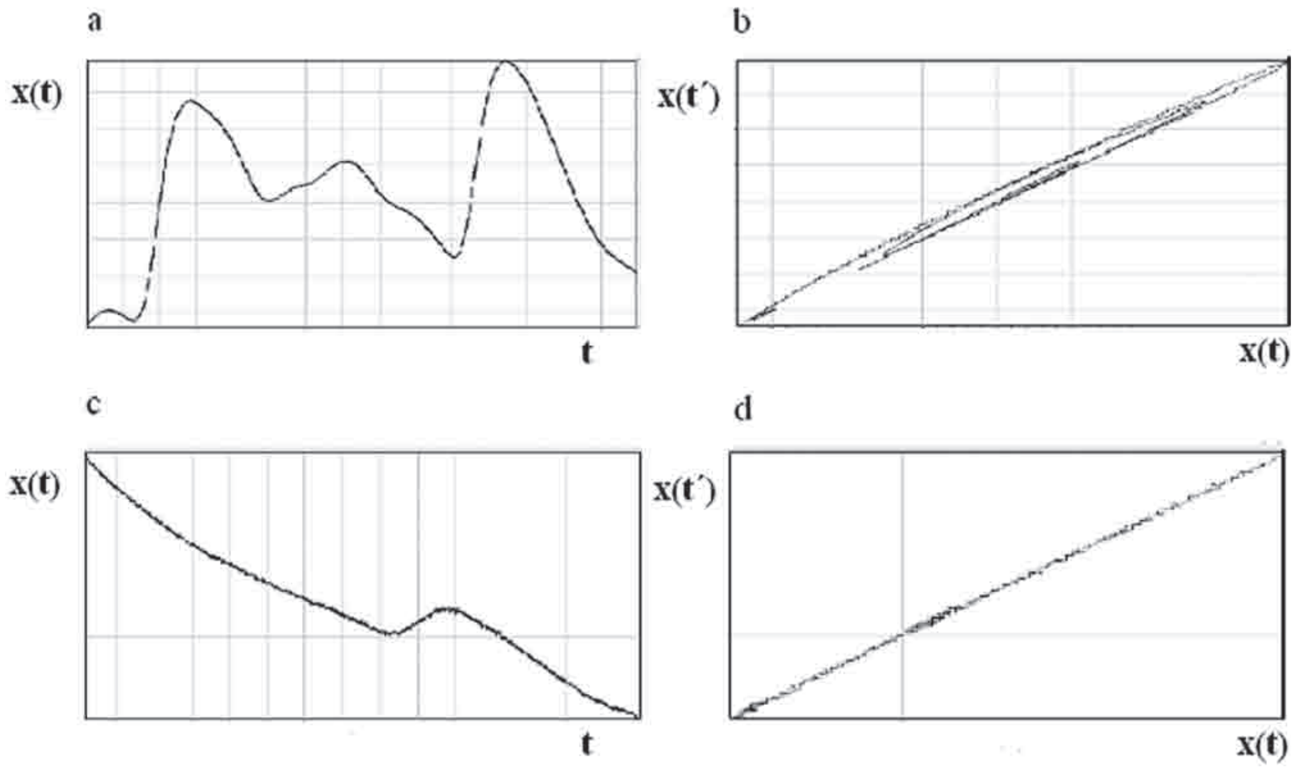


**Figure 4.** Examples of signals and state space diagrams: a) electrodermal activity (EDA) (denoted as x($t$)) on the left side in a schizophrenic patient (largest Lyapunov exponent $\lambda = 0.0608$) and its state space diagram $t' = t + \tau$ (b); c) EDA on the left side in a healthy control subject ($\lambda = 0.0141$) and its state space diagram (d).

Examples of the state space diagrams for the schizophrenic patients and for the healthy controls are in the Fig. 4. Surrogate data analysis confirms that original data do not represent linearly filtered Gaussian white noises because the results of nonlinear data analysis applied to experimental and surrogate data values are highly statistically different (Table 1). This implicates that the results cannot be explained from the linear data properties and give evidence of nonlinear neural dynamics as measured by EDA.

## Discussion

A methodological contribution of this study is the application of the method of nonlinear data analysis and surrogate data testing to EDA which at this time according to web of science and PubMed search is not in the scientific literature. With respect to surrogate data testing reported in this study, EDA manifests evidence of nonlinear dynamics in the nervous system which can distinguish specific changes of mental states and may detect specific nonlinear disturbances in schizophrenia. At this point, the results are in accordance with reported data that suggest specific nonlinear processes as related to schizophrenia (Paulus and Braff 2003; Breakspear 2006). Crucial aspect of the chaos theory that may throw new light to schizophrenia pathology is the underlying chaotic deterministic dynamics that may produce complex and seemingly random patterns in a system's behavior. From this point of view, the findings of this study suggest that increased neural chaos in patients with schizophrenia may influence brain processes that can cause random-like disorganization of mental processes.

The significantly higher largest Lyapunov exponents on the left side correspond to findings that indicate left-side temporal-limbic dysfunction in schizophrenia (Flor-Henry 1969; Gruzelier and Venables 1974; Gruzelier 1983, 1993; Hugdahl 2001). The neurobiological processes related to increased chaoticity may be related to asymmetry of limbic functioning and overactivation most probably in the left hemisphere that may cause emotional dysregulation and random-like behavior of mental processes. These changes in normal asymmetry of the temporal lobe in schizophrenia might be due to a disruption of the neurodevelopmental processes involved in hemispheric lateralization (Shirakawa et al. 2001). The findings also provide evidence for discussion of the significance of unbalanced hemispheric activation and related disruptions of integrative brain activity as a biological substrate for schizophrenia (Garcia-Toro et al. 2001; Dawson

2004; Fingelkurts et al. 2006; Bob et al. 2007). Together these findings suggest that dynamic changes in EDA, indicating nonlinearities of limbic modulation influences are present in the patients with schizophrenia differently than in the healthy controls and may represent significant factor in the pathophysiology of schizophrenia.

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## References


Bob P. (2003): Dissociation and neuroscience: history and new perspectives. Int. J. Neurosci. **113**, 903–914

Bob P. (2007): Chaotic patterns of electrodermal activity during dissociated state released by hypnotic abreaction. Int. J. Clin. Exp. Hypn. **55**, 435–456

Bob P., Šusta M., Procházková-Večeřová A., Kukleta M., Pavlát J., Jagla F., Raboch J. (2006): Limbic irritability and chaotic neural response during conflicting stroop task in the patients with unipolar depression. Physiol. Res. **55** (Suppl. 1), 107–112

Bob P., Susta M., Glaslova K., Pavlat J., Raboch J. (2007): Lateralized electrodermal dysfunction and complexity in patients with schizophrenia and depression. Neuro Endocrinol. Lett. **28**, 11–15

Breakspear M. (2006): The nonlinear theory of schizophrenia. Aust. N. Z. J. Psychiatry **40**, 20–35

Briggs K. (1990): An improved method for estimating Liapunov exponents of chaotic time series. Phys. Lett. A **151**, 27–32

Critchley H. D. (2002): Electrodermal responses: what happens in the brain. Neuroscientist **8**, 132–142

Davis A. V., Paulsen J. S., Heaton R. K., Jeste D. V. (1995): Assessment of the semantic network in chronic schizophrenia. J. Int. Neuropsychol. Soc. **1**, 132

Dawson K. A. (2004): Temporal organization of the brain: neurocognitive mechanisms. Brain Cogn. **54,** 75–94

Dawson M. E., Schell A. M. (2002): What does electrodermal activity tell us about prognosis in the schizophrenia spectrum? Schizophr. Res. **54**, 87–93

Dawson M. E., Shell A. M., Filion D. L. (2000): The electrodermal system. In: Handbook of Physiology (Eds. J. T. Cacioppo, L. G. Tassinary and G. C. Bernston), pp. 200–223, Cambridge University Press, Cambridge, MA

Dokoumetzidis A., Iliadis A., Macheras P. (2001): Nonlinear dynamics and chaos theory: Concepts and applications relevant to pharmacodynamics. Pharm. Res. **18**, 415–426

Elbert T., Ray W. J., Kowalik Z. J., Skinner J. E., Graf K. E., Birbaumer N. (1994): Chaos and physiology: deterministic chaos in excitable cell assemblies. Physiol. Rev. **74**, 1–47

Elias L. J., Bryden M. P., Bulman-Fleming M. B. (1998): Footedness is better predictor than handedness of emotional lateralization. Neuropsychologia **36**, 37–43

Fingelkurts A. A., Fingelkurts A. A., Kaplan A. Y. (2006): Interictal EEG as a physiological adaptation. Part II. Topographic variability of composition of brain oscillations in interictal EEG. Clin. Neurophysiol. **117,** 789–802

Freeman W. J. (1991): The physiology of perception. Sci. Am. **264**, 34–41

Freeman W. J. (2000): Mesoscopics neurodynamics: from neuron to brain. J. Physiol. (Paris) **94**, 303–322

Freeman W. J. (2001): Biocomplexity: adaptive behavior in complex stochastic dynamical systems. BioSystems **59**, 109–123

Globus G. C., Arpaia J. P. (1994): Psychiatry and the new dynamics. Biol. Psychiatry **32**, 352–364

Goldberg T. E., Weinberger D. R. (2000): Thought disorder in schizophrenia: a reappraisal of older formulations and an overview of some recent studies. Cognit. Neuropsychiatry **5**, 1–19

Gottschalk A. M., Bauer M. S., Whybrow P. C. (1995): Evidence of chaotic mood variation in bipolar disorder. Arch. Gen. Psychiatry **52**, 947–959

Hoffman R. E., Kirstein L., Stopek S., Cicchetti D. V. (1982): Apprehending schizophrenic dicourse: a structural analysis of the listener's task. Brain Lang. **15**, 207–233

Huber M. T., Braun H. A., Krieg J. C. (1999): Consequences of deterministic and random dynamics for the course of affective disorders. Biol. Psychiatry **46**, 256–262

Hotchkiss A. P., Harvey P. D. (1990): Effect of distraction on communication failures in schizophrenic patients. Clin. Res. Reports **147**, 513–515

Kantz H., Schreiber T. (1997): Nonlinear Time Series Analysis. Cambridge University Press

Korn H., Faure P. (2003): Is there chaos in the brain? II. Experimental evidence and related models. C. R. Biol. **326**, 787–840

Leroy F., Pezard L., Nandrino J. L., Beaune D. (2005): Dynamical quantification of schizophrenic speech. Psychiatry Res. **133**, 159–171

Manschreck T. C., Maher B. A, Rucklos M. E., White M. T. (1979): The predictability of thought disordered speech in schizophrenic patients. Br. J. Psychiatry **134**, 595–601

Manschreck T. C., Maher B. A., Ader D. N. (1981): Formal thought disorder, the type token ratio and disturbed voluntary movement in schizophrenia. Br. J. Psychiatry **139**, 7–15

Mangina C. A., Beuzeron-Mangina J. H. (1996): Direct electrical stimulation of specific human brain structures and bilateral electrodermal activity. Int. J. Psychophysiol. **22**, 1–8

McGrath J. (1991): Ordering thoughts on thought disorder. Br. J. Psychiatry **158**, 307–316

Melançon G., Joanette Y., Bélair J. (2000): Chaos, brain and cognition: toward a nonlinear order? Brain Cogn. **42**, 33–36

Meyer-Lindenberg A., Zeman U., Hajak G., Cohen L., Berman, K. F. (2002). Transitions between dynamical states of differing stability in the human brain. Proc. Natl. Acad. Sci. U.S.A. **99**, 10948–10953

Olypher A. V., Klement D., Fenton A. A. (2006): Cognitive disorganization in hippocampus: a physiological model of the disorganization in psychosis. J. Neurosci. **26**, 158–168

Paulus M. P., Braff D. L. (2003): Chaos and schizophrenia: does the method fit the madness? Biol. Psychiatry **53**, 3–11

Peterson I. (1993): Newton's Clock: Chaos in the Solar System. W. H. Freeman, New York

Paulsen J. S., Romero R., Chan A., Davis A. V., Heaton R. K., Jeste D. V. (1996): Impairment of the semantic network in schizophrenia. Psychiatry Res. **63**, 109–121

Phelps E. A., O'Connor K. J., Gatenby J. C., Gore J. C., Grillon C., Davis M. (2001): Activation of the left amygdala to a cognitive representation of fear. Nat. Neurosci. **4**, 437–441

Schell A. M., Dawson M. E., Rissling A., Ventura J., Subotnik K. L., Gitlin M. J., Nuechterlein K. H. (2005): Electrodermal predictors of functional outcome and negative symptoms in schizophrenia. Psychophysiology **42**, 483–492

Vinogradov S., Kirkland J., Poole J. H., Drexler M., Ober B. A., Shenaut G. K. (2002): Both processing speed and semantic memory organization predict verbal fluency in schizophrenia. Schizophr. Res. **8**, 171–181

Vaitl D., Lipp O. V., Bauer U., Schüler G., Stark R., Zimmerman M., Kirsch P. (2002): Latent inhibition in schizophrenia: Pavlovian conditioning of autonomic responses. Schizophr. Res. **55**, 147–158

Weng G., Bhalla U. S., Iyenga, R. (1999): Complexity in biological signaling systems. Science **284**, 92–96

Williams L. M., Bahramali H., Hemsley D. R., Hartus A. W. F., Brown K., Gordon E. (2002): Electrodermal responsivity distinguishes ERP activity and symptom profile in schizophrenia. Schizophr. Res. **59**, 115–125

Zahn T. P., Pickar D. (2005): Autonomic activity in relation to symptom ratings and reaction time in unmedicated patients with schizophrenia. Schizophr. Res. **79**, 257–270

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