Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state

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We compare dynamical properties of brain electrical activity from different recording regions and from different physiological and pathological brain states. Using the nonlinear prediction error and an estimate of an effective correlation dimension in combination with the method of iterative amplitude adjusted surrogate data, we analyze sets of electroencephalographic (EEG) time series: surface EEG recordings from healthy volunteers with eyes closed and eyes open, and intracranial EEG recordings from epilepsy patients during the seizure free interval from within and from outside the seizure generating area as well as intracranial EEG recordings of epileptic seizures. As a preanalysis step an inclusion criterion of weak stationarity was applied. Surface EEG recordings with eyes open were compatible with the surrogates’ null hypothesis of a Gaussian linear stochastic process. Strongest indications of nonlinear deterministic dynamics were found for seizure activity. Results of the other sets were found to be in between these two extremes.

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I. INTRODUCTION

The theory of deterministic chaos deals with complex dynamical systems that are characterized by the fact that they can be rather simple to describe, e.g., by a set of nonlinear differential equations, but can show a complicated, often erratic, temporal evolution [1]. Nonlinearity as a necessary condition for such chaotic behavior is present in many dynamical systems found in nature. For a neuronal network such as the brain, nonlinearity is introduced even on the cellular level, since the dynamical behavior of individual neurons is governed by threshold and saturation phenomena. Moreover, the hypothesis of an entirely stochastic brain can be rejected due to its ability to perform sophisticated cognitive tasks. For these reasons, the electroencephalogram (EEG) appears to be an appropriate area for nonlinear time series analysis (NTSA) techniques, the practical spin-off from the theory of deterministic chaos [2].

The structure of the brain, however, is highly complicated. Furthermore, the EEG always results from a huge number of individual neurons, each interacting with its neighboring neurons as well as with remote neurons whose electric potentials are not included in the measurement. It is therefore questionable whether EEG time series, particularly those of short duration, can carry enough information to reveal dynamical properties of the underlying system brain. Many studies are known from the literature in which NTSA techniques were applied to different kinds of EEGs from humans, such as recordings from healthy volunteers at rest [3–10], sleep [11–13], during periods of cognitive activity [14–17], under the influence of low doses of ethanol [18] or anesthetics [19], or from patients with diseases like Alzheimer’s [16,20], Parkinson’s [21,22], Creutzfeldt-Jakob [23], depression [24], and schizophrenia [25] mostly during cognitive activity and in comparison against healthy control subjects. In particular, recordings from epilepsy patients have often attracted researchers’ attention [9,26–41]. This is due to outstanding features of actual seizure activity and, moreover, to the medical indication to perform recordings invasively in epilepsy patients, which offers a unique view of the dynamical system human brain.

Interpretations of results ranged from “evidences for chaotic attractors” underlying the alpha rhythm [7], sleep recordings [11], or epileptic seizures [33,35,40], to the conclusion that EEG data of healthy volunteers “may be more appropriately modeled by linearly filtered noise” [15]. In between these two extremes, authors concluded significant indications of nonlinearity but no indication of low dimensionality or determinism [3–5,8,13]. Besides the aim of finding a certain dynamical model for the EEG, it was furthermore investigated if relative changes of the calculated quantities are capable of differentiating between different physiological brain states [14,15,17], increasing insight into brain dysfunction [9,16,21–25] or even of yielding information useful for diagnostic purposes [26,28–30,34]. The anticipation of impending epileptic seizures is a further challenging aspect that was investigated by a number of studies [31,36–39]. Nevertheless, it remains uncertain whether the aforementioned varying results indeed reflect different dynamical features of brain electrical activity, or whether they must instead be attributed to differences in parameters of the respective algorithms and recording setups. Thus the aim of our study is to compare dynamical properties of brain electrical activity from different extracranial and intracranial recording regions and from different physiological and pathological brain states, using fixed analysis parameters. Apart from the different recording electrodes used for extracranial and intracranial EEG registration, all other recording parameters were fixed. Some of the morphological characteristics of the different EEG time series under investigation, which are obvious to an expert’s eye, will be sketched in the following.
EEG time series recorded extracranially during the relaxed state of healthy subjects with eyes closed show a predominant physiological rhythm, the so-called alpha rhythm in a frequency range of 8–13 Hz, an activity which is most pronounced at the back of the head [42]. In contrast, broader frequency characteristics are obtained for open eyes. EEG time series are also recorded intracranially in humans, however only in the framework of a presurgical evaluation of focal epilepsies. In this context the implantation of electrodes is carried out to exactly localize the seizure generating area which is termed the epileptogenic zone [43]. During a seizure free interval the EEG recorded from within the epileptogenic zone is often characterized by intermittent occurrences of so-called interictal epileptiform activities. Investigation of these steep, sometimes rhythmic high amplitude patterns in EEG recordings contributes to a localization of the epileptogenic zone. Fewer and less pronounced interictal epileptiform activities can be found at recording sites distant from the epileptogenic zone. Finally, the EEG recorded during epileptic seizures, termed ictal activity, is almost periodic and of high amplitude, resulting from hypersynchronous activity of large assemblies of neurons.

We tested indications of deterministic and/or low-dimensional structures in the aforementioned EEG time series against the null hypothesis that these properties are compatible with a Gaussian linear stochastic and stationary process that was passed through a monotonic static but a possibly nonlinear measurement function. To this end, a nonlinear prediction error [44] and an estimate of the correlation dimension [45] were calculated in a reconstructed state space [46] for both the original EEG time series and an ensemble of surrogate time series [47]. To reduce the probability of rejections of this null hypothesis, due solely to nonstationarity, EEG segments were chosen under an inclusion criterion of weak stationarity.

II. METHODS

A. Data selection and recording techniques

Five sets (denoted A–E) each containing 100 single-channel EEG segments of 23.6-sec duration, were composed for the study. These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. In addition, the segments had to fulfill a stationarity criterion described in detail in Sec. II B. Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme (cf. Fig. 1). Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from our EEG archive of presurgical diagnosis. For the present study EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone (cf. Fig. 2). Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity. Here segments were selected from all recording sites exhibiting ictal activity.

All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference [omitting electrodes containing pathological activity (C, D, and E) or strong eye movement artifacts (A and B)]. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. Band-pass filter settings were 0.53–40 Hz (12 dB/oct.). Exemplary EEGs are depicted in Fig. 3.

B. Steps of analysis

1. Surrogate time series

For each time series \( s = 39 \) surrogate time series were generated using the technique of Schreiber and Schmitz [47]. This iterative amplitude adjusting scheme results in surrogates that consist of the original sample values and have power spectra “practically indistinguishable” [47] from those of the original time series. The underlying null hypoth-
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FIG. 3. Exemplary EEG time series from each of the five sets. From top to bottom: set A to set E (denoted EEG-a to EEG-e). Amplitudes of surface EEG recordings are typically in the order of some µV. For intracranial EEG recordings amplitudes range around some 100 µV. For seizure activity these voltages can exceed 1000 µV.

2. Weak stationarity criterion

The probative force of a rejection of the surrogates’ null hypothesis for deterministic and/or low-dimensional structure is limited, since stationarity is included in this null hypothesis. On the other hand, this particular property allows one to use surrogates in a test for nonstationarity. Here we propose such a test as a preanalysis step that eventually reduces the probability of rejections of the null hypothesis due to nonstationarities.

EEG-time series and respective surrogates were each divided into \( n = 16 \) nonoverlapping subsegments (length \( N^\ast = 256 \)). For each subsegment (\( j = 1, \ldots, n \)) the average deviation of amplitudes

\[
m_j^\ast = \frac{1}{N^\ast} \sum_{i=1}^{N^\ast} |x_i - \bar{x}|
\]

(where \( \bar{x} \) denotes the mean of the respective subsegment) and the center frequency

\[
m_j^w = \frac{2}{N^\ast} \sum_{i=1}^{N^\ast/2} \omega_i S(\omega_i)
\]

(where \( S \) denotes the amplitude of the Fourier transform of the respective subsegment) were calculated. The fluctuation of these properties among subsegments was quantified using the average deviations

\[
F^w = \frac{1}{n} \sum_{j=1}^{n} |m_j^w - \bar{m}^w|,
\]

\[
F^s = \frac{1}{n} \sum_{j=1}^{n} |m_j^s - \bar{m}^s|,
\]

where the overbar denotes mean of all 16 subsegments. As an inclusion criterion, both \( F^w \) and \( F^s \) of the original time series were required to range within the distribution calculated from the respective surrogate ensemble, i.e., both values must neither exceed the maximum nor fall below the minimum of the surrogate distribution.

3. Estimate of an effective correlation dimension

Using delay coordinates \( x_t = (x_{t}, x_{t+\tau}, \ldots, x_{t+(m-1)\tau}) \) [46] and the correlation sum

\[
C(\varepsilon,N) = \frac{2}{(N-T)(N-T-1)} \sum_{i=0}^{N-1} \sum_{j=i+T}^{N-1} \Theta(\varepsilon - \|x_i - x_j\|)
\]

[where \( \Theta \) is the Heaviside step function, \( \Theta(a) = 0 \forall a \leq 0 \) and \( \Theta(a) = 1 \forall a > 0 \)] the correlation dimension \( D_2 \) is defined [45] by

\[
D_2 = \lim_{N \to \infty} \lim_{\varepsilon \to 0} d(\varepsilon,N),
\]

where

\[
d(\varepsilon,N) = \frac{\partial \ln C(\varepsilon,N)}{\partial \ln \varepsilon}.
\]

From these definitions it follows that a true correlation dimension cannot be calculated from time series of finite length and limited accuracy. An estimation of an effective correlation dimension, however, can be obtained for those time series where a quasiscaling behavior of \( d(\varepsilon,N) \) is found at least for a limited range of the hypersphere radius \( \varepsilon \) [50]. The applied steps of analysis and the choice of parameters follow Ref. [36], and use the algorithm described in Ref. [51]. With a fixed time delay (\( \tau = 1 \) sampling time), \( d(\varepsilon,N) \) was calculated for a range of embedding dimensions (\( m = 1, \ldots, 25 \)) using the maximum norm and applying a Theiler window [52] (\( T = 5 \) sampling times). The range of \( \varepsilon \)
was chosen to match the resolution of the analog-to-digital converter, and divided into 128 intervals. A “quasiscaling region” \([e_1, e_u]\) is defined by

\[
e_u = \max\{e\mid d(e, N)|_{m=1} > 0.975\},
\]

\[
e_1 = \min\{e\mid d(e, N)|_{m=25} - d(e, N)|_{m=25}\}
\]

\[
\leq 0.05d(e, N)|_{m=25}.
\]  

(8)  

(9)  

If \(e_u\) and \(e_1\) existed, and the number \(N_r\) of \(e\) values in \([e_1, e_u]\) was greater than or equal to 5, the estimate

\[
D_{2,eff} = \frac{1}{N_r} \sum_{e=e_1}^{e_u} d(e, N)|_{m=25}
\]  

(10)  

was computed. If no quasiscaling existed or if \(D_{2,eff} \geq 7.2 \approx 2 \log N\) (cf. Ref. [53]), \(D_{2,eff}\) was set to an arbitrary value of \(D_u = 10\).

4. Nonlinear prediction error

For each reference point \(x_i\) \((i = 1, \ldots, N-m)\) in a reconstructed state space (embedding dimension \(m = 6\) and time delay \(\tau = 8\) sampling times) a fixed number \(k = 5\) of nearest neighbors \(\{x_j\}_{j=1, \ldots, k}\) was used to perform an \(H\)-step prediction:

\[
\tilde{x}_{i+H} = \frac{1}{k} \sum_{j=1}^{k} x_{j+H}.
\]  

(11)  

The difference between the actual \(x_{i+H}\) and predicted translation \(\tilde{x}_{i+H}\) is the local prediction error

\[
e_{i, \tilde{x}_{i+H}} = |x_{i+H} - \tilde{x}_{i+H}|.
\]  

(12)  

The local prediction error for the mean of the time series \(\bar{x}\) is

\[
e_{\bar{x}} = |x_{i+H} - \bar{x}|,
\]  

(13)  

where \(\bar{x}\) is an \(m\)-dimensional vector that carries the mean in each of its component. Finally the nonlinear prediction error \((P)\) is calculated from

\[
P = \frac{R(e_{\bar{x}}, \tilde{x}_{i+H})}{R(e_{\bar{x}}, \bar{x})},
\]  

(14)  

where \(R\) indicates the root mean square. For a nearest neighbor search for every reference point \(x_i\), a Theiler window \((T = 25\) sampling times\) was applied to its own trajectory segment and to neighboring trajectory segments: In a first step, vectors with indices \(\{-T, \ldots, i-1, i+1, \ldots, i+T\}\) were discarded. In a second step, out of a group of nearest neighbors passing the first step but closer to each other in time than \(T\), only the one nearest to \(x_i\) was included. The second step is important to ensure that information for the \(P\) is gathered from multiple adjacent trajectory segments rather than from only one trajectory segment (cf. Refs. [48,49]). The prediction horizon \(H\) was set to 65 sampling times. The parameter values reported were obtained from preanalysis with regard to an optimum differentiation between nonlinear deterministic and linear stochastic model systems. In order to meet the requirements of the respective statistics, we chose all parameters independently for both \(P\) and \(D_{2,eff}\).

5. Levels of null hypothesis testing - Statistical methods

All following steps of analysis were carried out for \(P\) and \(D_{2,eff}\). In the following, \(M\) stands for any of the two measures. The null hypothesis was tested on two levels: on one level for every individual EEG segment, and on a second level for each of the five sets of EEG segments. On the individual level the null was rejected if \(M^{EEG}\) ranged outside the distribution calculated from all of its surrogates \(\{M^{Sur_{i=1, \ldots, s}}\}\). For a given set and measure, let \(R_{min}\) be the number of rejections of the null hypothesis which were caused by the fact that \(M^{EEG}\) was smaller than the minimum of \(\{M^{Sur_{i=1, \ldots, s}}\}\). To rate a given number of rejections of the null hypothesis, the probability \(p_{min}\) to find \(R_{min}\) or less rejections on a set of \(n = 100\) time series just by chance was calculated as

\[
p_{min} = \sum_{k=0}^{R_{min}} (\binom{n}{k} \left(1 - \frac{1}{s+1}\right)^k \left(1 - \frac{1}{s+1}\right)^{n-k}).
\]  

(15)  

In complete analogy, we calculated the probability \(p_{max}\) to find \(R_{max}\) or less rejections that were caused by the fact that \(M^{EEG}\) exceeded the surrogates’ maximum.

On the set level one surrogate per EEG segment was used. In accordance with Ref. [3], values of \(\{M^{EEG}\}\) and \(\{M^{Sur}\}\) were used as paired observations for a nonparametric Wilcoxon signed rank test. In order to ensure that the choice of \(D_u\) did not influence results of the null hypothesis testing on the set level, the Wilcoxon test was carried out with different values of \(D_u\).

III. RESULTS

Figure 4 depicts results of exemplary EEGs. Table I and Fig. 5 summarize the results of all EEG segments and sets. On the individual level, sets E and D exhibited highest and second highest \(R_{min}\) values for both \(P\) and \(D_{2,eff}\). For all sets, the use of \(P\) led to higher \(R_{min}\) values than the use of \(D_{2,eff}\). This was particularly true for sets B and C, for which the strongest discordance between the two measures was found: while for \(P\) both \(R_{min}\) values were significant, they were both nonsignificant for \(D_{2,eff}\). Concordance was found only for set A: here none of the two measures led to significant \(R_{min}\) values. None of the \(R_{max}\) values was significant. Segments with rejection of the null hypothesis for both \(P\) and \(D_{2,eff}\) were found in sets D and E only.

For the vast majority of segments \(D_{2,eff}\) could not be calculated, and was therefore set to \(D_u\) (cf. Table I). For sets A and B, this was the case for all EEG segments and almost all surrogates. Consequently, the null hypothesis on the set level could not be tested using \(D_{2,eff}\). For set C, only a few segments resulted in \(D_{2,eff} < D_u\), whereas most segments re-
sulted in $D_{2,\text{eff}}$, and therefore entered the Wilcoxon test as binded observations. A noteworthy number of $D_{2,\text{eff}}$ values was calculated only from EEG time series of sets D and E. These sets were the only ones that resulted in significant $p_{\text{Wilc}}$ values, so that the null hypothesis on the set level could be rejected.

Using $P$ set A was the only one for which we obtained a nonsignificant $p_{\text{Wilc}}$ value. For all other sets the null hypothesis could be rejected on the set level. Although decreasing mean values of $P_{\text{EEG}}$ were found in the set order.
TABLE I. Results for $P$ and $D_{2,\text{eff}}$ on the individual level (rows 1 and 2 and 6 and 7) and on the set level (rows 3 and 4 and 8 and 9). Values of $p_{\text{max}}$ are not listed, since all were nonsignificant. Values in row 5 denote the number of segments for which a value of $D_{2,\text{eff}}$ could be computed for the EEGs and the surrogates, respectively. The last row contains the number of segments for which the null was rejected for both measures. n.s.: values of $p > 0.05$ are assumed to be nonsignificant. $x$: no Wilcoxon test was carried out for sets A and B (see the body text).

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
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<td>$R_{\text{min}}/R_{\text{max}}$</td>
<td>4/1</td>
<td>9/3</td>
<td>14/3</td>
<td>37/0</td>
</tr>
<tr>
<td></td>
<td>$p_{\text{min}}$</td>
<td>n.s.</td>
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<td>$&lt;0.001$</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td></td>
<td>$P_{\text{Wilc}}$</td>
<td>n.s.</td>
<td>0.004</td>
<td>$&lt;0.001$</td>
<td>0.001</td>
</tr>
<tr>
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<td>-2.9</td>
<td>-7.0</td>
<td>-3.5</td>
</tr>
<tr>
<td>$D_{2,\text{eff}}$</td>
<td>$D_{\text{EEG/SUR}&lt;D_{u}}$</td>
<td>0/1</td>
<td>0/1</td>
<td>7/7</td>
<td>27/9</td>
</tr>
<tr>
<td></td>
<td>$R_{\text{min}}/R_{\text{max}}$</td>
<td>0/0</td>
<td>0/0</td>
<td>0/1</td>
<td>17/2</td>
</tr>
<tr>
<td>$P$</td>
<td>$p_{\text{min}}$</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>$&lt;0.001$</td>
</tr>
<tr>
<td></td>
<td>$P_{\text{Wilc}}$</td>
<td>$x$</td>
<td>$x$</td>
<td>n.s.</td>
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<td>$x$</td>
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<td>-3.7</td>
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</table>

IV. DISCUSSION

Our study showed clear differences in dynamical properties of brain electrical activity from different extracranial and intracranial recording regions and from different physiological and pathological brain states. Despite the assumed nonlinear deterministic nature of neuronal dynamics, a quasilinear stochastic and high-dimensional appearance of the EEG, as found for set A, consistent with results reported in Refs. [4,9,15], might originate from both the huge number of neurons included in an EEG measurement and the complicated structure of the brain. Particularly for surface EEG recordings, a further blurring of possible dynamical structures in the EEG is caused by filter processes due to different conductivities of the skull and other intermediate tissue. Certain imposed constraints in dynamics, however, might demask or further strengthen nonlinear deterministic traits of neuronal dynamics. Results found with $P$ for set B suggest that the closing of eyes might represent the imposing of such a constraint in dynamics resulting in the well-known physiological alpha rhythm. For no segment of sets A and B, however, a conclusive indication of a finite dimension or even a low dimension could be obtained. Therefore, a differentiation of the conditions of eyes closed and eyes open, such as reported in Refs. [14,16], could not be obtained. Regarding these aspects, the results of our study are in agreement with other studies carried out on surface EEG recordings of healthy volunteers [3,5,6,8,13,18], where indications of nonlinearity but not of an underlying low dimensional structure were found.

The strong indications of nonlinear deterministic structures found for set D were certainly often related to interictal epileptiform activity, as also reported in Refs. [28,29].

In summary, the null hypothesis of an underlying linear stochastic and stationary process, measured by a static and monotonic but possibly nonlinear measurement function as represented by the iterative amplitude adjusted surrogates, could be rejected for sets D and E for both $P$ and $D_{2,\text{eff}}$. For sets B and C, only the use of $P$ led to a rejection, while these sets appeared to be compatible with the null for $D_{2,\text{eff}}$. Set A was the only set which was compatible with the null hypothesis for both measures.

FIG. 5. Results for $P$ (upper panel) and $D_{2,\text{eff}}$ (lower panel) for sets A–E. For every measure and set, circles depict the mean value of $\{M^{\text{EEG}}\}$, and diamonds the mean value of $\{M^{\text{SURO}}\}$; bars on symbols are given by the ranges of these distributions. Vertical lines in between the symbols depict those values of $M^{\text{EEG}}$ for which the null hypothesis was rejected on the individual level by the fact that $M^{\text{EEG}}$ was smaller than the minimum of $\{M^{\text{SURO}}\}$. A-C-B-D-E, smallest values were still found to be higher than 0.5 (cf. Fig. 5).

A-C-B-D-E, smallest values were still found to be higher than 0.5 (cf. Fig. 5).
territorial, and the anticipation of seizures by analysis of multi-
channel EEGs recorded from epilepsy patients [31,36–39]. The results of these studies, as well as the present one, sug-
ggest that the pathological epileptic process imposes certain constraints on neuronal dynamics. Even in the absence of seizure activity these constraints appear to be reflected by nonlinear deterministic traits in the EEG, as suggested by results found for set D. Most prominently, however, this phe-

omenon was observed during seizure activity (set E). This finding is in correspondence with previous studies on intra 

cranial [29] and extracranial [9,32] recordings of epileptic seizures. Théiler [32] even a priori assumed seizure activity to be "undoubtedly nonlinear."

When comparing extracranial and intracranial recording locations, it is important to note that the latter integrate po-
tentials over a much smaller stereadian, i.e., fewer neurons contribute to the measured potentials, which furthermore are less filtered as compared to extracranial recording locations. This might explain differences in results from sets A and C. An additional and not contradictory explanation might be given by the following. Set C was measured from brain re-

gions which were proven to be nonepileptogenic but which may nevertheless participate in secondary, nonautonomous epileptic processes initiated by the epileptogenic zone.

The significant numbers of rejections \( R_{\text{min}} \) on the in-
dividual level allow two different interpretations. On the one 

hand, the sets could be assumed to have a certain distribution 
of some distinct dynamical property not included in the null 
hypothesis. Due to the limited sensitivity of the applied test 

statistics for this very property, the individual null will be 

rejected only for segments in one tail of this distribution. 

Differences of \( R_{\text{min}} \) values between sets could then be ex-

plained by different centers and widths of these distributions. 

Given the respective calculation parameters used in our 

study, both higher values and a higher intergroup variability 
of \( R_{\text{min}} \) were found for \( P \) as compared to \( D_{2,\text{eff}} \). A com-

parison between Refs. [4], and [8], as well as data reported in 

Ref. [18] show analogous results. This could be interpreted as 
a higher degree of sensitivity of \( P \) for indications of dy-

namical structures in EEG time series. The contrary conclu-

sion, i.e., a lower level of specificity, cannot of course be 

terminated.

On the other hand, the sets could consist of different sub-

sets, each containing segments of different dynamical nature. 

This idea was followed in Ref. [8], where Stam et al. con-

cluded that their "study underscores the heterogeneous na-

ture [...] of the alpha rhythm from a dynamical point of 

view." This interpretation of different subsets would discour-
age any further statistical analysis of the set level which as-

sumes the sets to be homogeneous.

Doubtlessly, sets under investigation exhibited distinct linear properties described by power spectra and amplitude distributions. However, since these properties were shared by the surrogates, they cannot account for results given here. It is important, however, to point out that a rejection of the surrogates' null hypothesis is only a necessary but not suffi-
cient criterion for nonlinearity. Surrogates that were used are stationary by construction. Therefore, even if a simple stationar-
yarity inclusion criterion was used to select the EEG seg-

ments, nonstationarity as a cause of "false" positive rejec-

tions cannot be excluded. Since this stationarity test is based on linear properties of the time series, it can neither be 

highly sensitive nor highly specific for nonstationarities of 

nonlinear dynamical systems. Nonlinear techniques calcu-

lated in a reconstructed state space such as the one proposed 
in Ref. [54] could help to overcome this shortcoming. Fur-

thermore, Kugiumtzis [55] showed that although the iterative 

amplitude adjusted surrogates are more consistent in repre-
senting the given null hypothesis than older techniques [56], 

the remaining mismatch of linear correlations of the original 

time series can still be relevant, and can cause false rejec-
tions of the null. Since these and other shortcomings weaken 

the probative force of the applied method, we only use the 

term indication rather than evidence of nonlinear determin-

istic structures.

It has become a common point of view that values of an 

estimate of the correlation dimension calculated from an un-

known dynamical system cannot be taken as a true estimate of 

a number of degrees of freedom. Particularly, our results 
geive no indication of chaos in the underlying dynamical sys-

tem brain. In a way this is to be expected, since a purely chaotic 

behavior of brain functions would consequently im-

ply that our brains' behavior is changed dramatically by each 

every arbitrary small input.

In accordance with other studies, our results show that an 

application of NTSA measures to EEG dynamics offers in-

sights into the dynamical nature and variability of the system 

brain. As a feedback for NTSA, complicated properties of 

EEG dynamics can further motivate one to improve existing 

methods and develop new methods [57].

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York, 1994).


[8] C.J. Stam, J.P.M. Pijn, P. Suffczynski, and F.H. Lopes da Silva,
[57] EEG time series are available under http://www.meb.uni-bonn.de/epileptologie/science/physik/eendata.html Contribution of further sets of EEG time series is encouraged.