Time Order in Brain Chaos

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Introduction

In recent studies (Keidel, Tirsch, & Pöppl, 1987; Rensing, An der Heiden, & Mackey, 1987), it has been pointed out that the bioelectrical activity of the central nervous system (CNS) is not maintained in a steady state but shows oscillations, exhibiting a well-ordered change of activity and synergy in time. Cyclic alterations of the spontaneously active human nervous "network" are responsible for these rhythms and oscillations with various period lengths (Brenner & Schaul, 1990; Koepchen, Hilton, & Trzebski, 1980; Scheuler, Rappelsberger, & Schmatz, 1988). Numerous mathematical models have been developed in the last years for the interpretation of the self-organized rhythmical behavior of biological (Mackey & Glass, 1977; Carpenter, 1983) and social systems (Brunner & Tschacher, 1991). Here some of the deterministic nonlinear models will be considered.

A detailed review of the mathematical approaches in brain dynamics is given by Dvorak and Holden (1990). Nonlinear models for analyzing the complex time structure of CNS signals could enlarge our insight into the functioning of the brain, especially the mutual interaction of various brain subsystems. In contrast, classical linear models which are based on stationary processes, study brain dynamics merely from a stochastic framework. Spectral analysis provides a good example of the classical model; the analysis is based on the assumption that the EEG is generated by the superposition of an infinite number of harmonic and linear periodic oscillators. It will be illustrated in the sequel that interesting aspects of CNS functioning are lost by adopting a linear stochastic framework.

By applying methods of nonlinear dynamical system theory, it will be attempted to model the underlying dynamical system (Farmer; 1982; Mayer-

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Kress & Holzfuss, 1987; Nicolis, 1987). The solution of the basic question how many equations are needed to describe the observed process, amounts to the estimation of the dimensionality of the underlying dynamical system. Dimensionality can be estimated under the assumption that the investigated one-dimensional time series is derived from synergetic systems and is showing a deterministic chaotic behavior. The estimation of the dimension provides information about the number of active coherent modes modulating the corresponding physiological processes in the brain. These variables may also be related to behavioral and personality variables. This nonlinear model may be described by a system of several nonlinear coupled differential equations in which different system states depend on the choice of system parameters. This approach may lead to a better interpretation of the EEG signal, as the generation of certain signal structures is performed by means of selected modes and system parameters. The introduction of such mathematical models of time order in bioelectrical activities would enrich our knowledge about the CNS considerably and possibly present a new basis for the assessment of brain dysfunctions.

Nonlinear dynamical analysis has found an important application domain in the bioelectrical activity of the brain; this gave rise to statements as "the EEG may be more than white noise," and "the EEG reflects deterministic chaos" (Basar, 1990). This new approach in brain research makes an essential contribution to our knowledge about the functioning of the brain. As a one-dimensional projection of a high-dimensional complex dynamical system, the EEG signal may play a causal role in the excitation of the brain via sensory organs or internal arousal, and in information processing and storage in the brain (Adey, 1966, 1974; Landfield, 1976). The introduction of the "running" dimensional analysis makes it possible to disclose temporal alterations (nonstationarities) in the signal's complexity and to discern transitions from low- to high-dimensional brain chaos. The modeling of the observed cyclic alterations in the dynamics of the signal may be performed by the interaction of two or more nonlinear oscillators functioning as interrelated partners in an overlaying system. A model of such a central pattern generator has been proposed by Bay and Hemami (1987).

The goals of the present paper are (a) to demonstrate a temporal order in the main frequency range of two prominent CNS oscillators such as EEG and tremor; (b) to present a systematic relationship between cyclic alterations of spectral density and dimensional complexity of the EEG; (c) to propose a neural approach which may explain the observed correlations; and (d) to gain insight into the functioning of the CNS by nonlinear modeling.

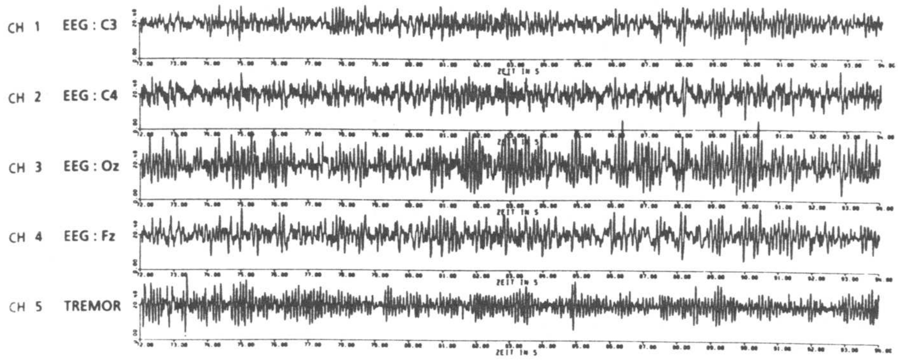


Figure 4.1
22-s section of a 4-min record of EEG activity and physiological finger tremor (from Tirsch, Keidel, & Pöppl, 1988)

Materials and Methods

Eight healthy students in an awaked state with eyes closed were investigated. Simultaneous unipolar scalp-EEG recordings were obtained from left and right motor cortex (C3/C4), from mid-frontal (Fz) and mid-occipital regions (Oz) corresponding to the 10/20 system and referred to linked earlobes. Simultaneous recordings of physiological finger tremor were made by gripping an accelerometer between the right thumb and forefinger with maximal force. All signals were continuously recorded for 4 minutes and A/D converted using a sampling rate of 500 Hz.

When visually inspecting the temporal structure of the recordings, only vague information about short-term fluctuations in the bioelectrical activity can be established (see Figure 4.1). Underlying systematic oscillatory changes in neuronal activity are quite below the perception thresholds of the human cognitive system and can only be detected by appropriate computer-assisted procedures.

Linear Spectral Analysis

As a classical method of time series analysis, spectral analysis was applied to 10-s periods taken from a 4-min epoch of CNS signals. After low-pass filtering of 50 Hz and elimination of linear trends, each segment of 2.56 s duration overlapping each other by 1.28 s was subjected to Fast Fourier Transformation. The segmental spectra were averaged according to the segmentation algorithm of Welch (1967). Frequency resolution was 0.391 Hz, upper frequency limit 31.28 Hz. In a subsequent analysis the band-related spectral power was computed in the following frequency bands: subdelta (0.4–1.5 Hz), delta (1.5–3.5 Hz), theta (3.5–7.4 Hz), alpha (7.4–12.5 Hz), beta1 (12.5–19.5 Hz) and beta2 (19.5–25 Hz).

Nonlinear Dynamical Analysis

Geometrical Reconstruction of "Strange Attractors"

In contrast to the preceding analysis which describes the spectral properties of the signal and is based on the superposition of harmonic and linear periodic oscillators, procedures and measures were introduced that characterize the local structure of the posttransient phase–space orbits, i.e., the so-called "strange attractors."

The dynamical approach described here expresses the measured time series of the CNS signal as trajectories in a multidimensional phase–space. A trajectory is a mathematical description of a sequence of values derived from a state variable of a dynamical system which can be described by state equations. Hence, starting from some initial conditions, an orbit is generated on which the system's trajectories move and tend to terminate in an attractor. In the most simple case, this can be a limit cycle with a very regular structure; in other cases, when the activity of the system appears to be random but is actually deterministic, a strange (or chaotic) attractor with a more complicated and rather highly fractured structure may be obtained.

Based on a geometrical view of the underlying dynamical process, a technique was developed by which a single scalar time series can be interpreted as the one-dimensional projection of a multidimensional phase–space trajectory of an (unknown) nonlinear dynamical system. This technique of geometrical reconstruction (Packardt, Crutchfield, Farmer, & Shaw, 1982; Takens, 1981) is a basic tool for the characterization of a dynamical chaotic system.

Let the variable $y(t_i)$ with $i = 1, \ldots, N$ represent the time series of the bioelectrical activity of the CNS, e.g., the EEG signal derived from one lead on the scalp. Under the assumption that the metric properties of the original and reconstructed attractor will be the same and that the dynamics of the signal may be described by a set of d variables which are obtained from the time series by introducing a time lag τ, one can reconstruct a phase–space vector of the "embedding" dimension d. The general form of such a phase–space vector is given by:

$$\vec{y}(t_i) = \{y(t_i), y(t_i + \tau), y(t_i + 2\tau), \cdots, y(t_i + (d-1)\tau)\}.$$

It can be derived from the equation that the instantaneous state of the system is represented by a point in the multidimensional phase–space. With increasing discrete time index from 1 to N, the consecutive data points describe a geometrical object on which the trajectories of the system move. The reconstructed phase trajectories, the "attractors" from the time series, can be drawn as phase portraits in different projections. Their shape corresponds to the dynamics of the system and depends markedly on the time lag τ. Various values of τ are possible in practical applications. In order to find a suitable time delay, the mutual information content of the time series is calculated, as explained in the next subsection.

Mutual Information Content

Several procedures have been proposed to estimate time delays in nonlinear systems. In addition to functions of autocorrelations, the mutual information content has been calculated frequently. The measure describes the relation between input and output of nonlinear systems, providing the amount of information about a random vector coupled with another vector. Based on Shannon's information theory (Shannon & Weaver, 1948) and on Shaw's (1985) idea to predict a time series vector at time $t+\tau$ if the measurement at time t is known, a procedure was developed which computes the average amount of mutual information (Fraser & Swinney, 1986; Mars & Van Arragon, 1982). For the four-dimensional discrete case, this measure is given by:

$$I = \sum_{i,j,k,\ell=1}^{M} F_{xyzv}(x_i, y_j, z_k, v_\ell) \times \ln \frac{F_{xyzv}(x_i, y_j, z_k, v_\ell)}{F_x(x_i) \cdot F_y(y_j) \cdot F_z(z_k) \cdot F_v(v_\ell)},$$

in which

$F_x(x_i)$ is the relative frequency of realization x_i derived from time series $x(t)$;

$F_y(y_j)$ is the relative frequency of realization y_j derived from time series $x(t+\tau)$;

$F_z(z_k)$ is the relative frequency of realization z_k derived from time series $x(t+2\tau)$;

$F_v(v_\ell)$ is the relative frequency of realization v_l derived from time series $x(t + 3\tau)$;

F_{xyzv} is the joint relative frequency of (x_i, y_j, z_k, v_ℓ);

M is the total number of cells.

When constructing an "attractor" from limited time series, the method enables us to determine the optimal time delay. The latter value is obtained when the mutual prediction reaches the first minimum; for this optimal time delay, the phase-space coordinates are approximately uncorrelated and independent.

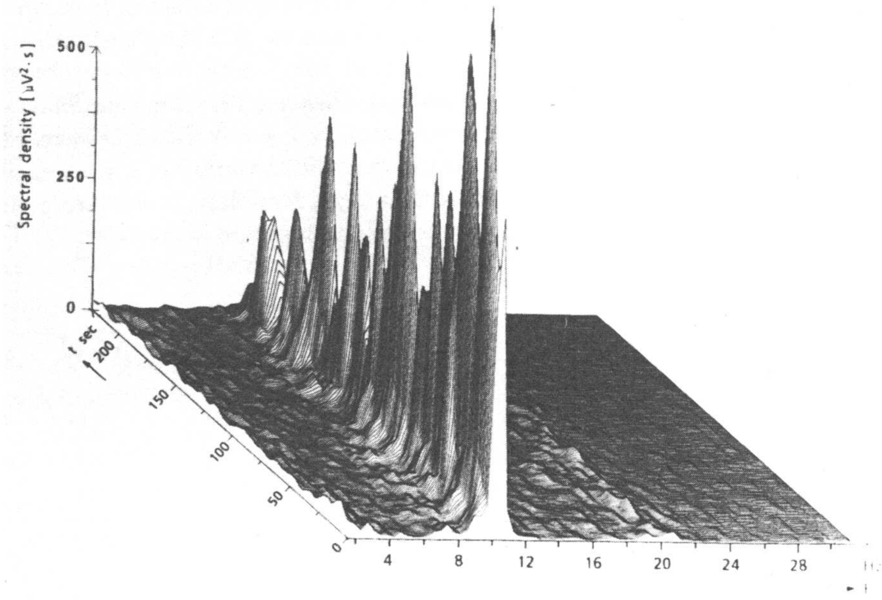


Figure 4.2
Pseudo-3D spectrogram of "running" auto-power derived from a 4-min epoch of EEG Oz. The spectral frequency in 77 increments of 0.4 Hz is indicated on the abscissa. The time or the number of shifts in seconds is drawn on the Z-axis

Dimensional Analysis

The basic idea for the characterization of chaotic dynamical systems is to calculate the dimension of their attractors measuring their self-similar structure. Initial reports on this subject were published by Farmer (1983). The measure is widely used in the field of nonlinear dynamical analysis to estimate the number of independent variables needed to model the dynamical process. The dimensionality is also a measure of complexity related to the number of active coherent modes modulating the process, and enables to discriminate between deterministic and random activity. To compute the dimensionality of an attractor, the procedure of Grassberger and Procaccia (1983) was applied utilizing the scaling structure of the attractor. It can be quantified by measuring the spatial correlation between pairs of random points $(\vec{y}_i, \vec{y}_j)$ on the attractor. This requires the introduction of an additional concept: the correlation integral, representing the number of pairs of phase–space vectors separated by distances less than a prior defined value. The general form of this integral is:

$$C(r) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \Theta\left(r - |\vec{y}_i - \vec{y}_j|\right),$$

in which

N is the number of sample points;

Θ is the Heaviside function:

$$\Theta(x) = 0 \text{ if } x \leq 0;$$
$$\Theta(x) = 1 \text{ if } x > 0;$$

r is the distance;

$\vec{y}_i$ is the phase–space vector.

First, we choose a reference point $\vec{y}_i$ in the phase–space. Next, all possible distances $|\vec{y}_i - \vec{y}_j|$ from the remaining $N-1$ points are computed. By means of the Heaviside function, all the data points within a given distance r from the reference point are counted. By repeated application of this procedure to all data points, the correlation integral is determined. For a large number N of data points and for small distances r, this function has the following scaling property which is due to the exponential divergence of trajectories:

$$C(r) \sim r^D,$$

in which D is the correlation dimension.

One can show that the correlation exponent is a useful measure of the local structure of a strange attractor (Grassberger & Procaccia, 1983). The correlation dimension D is obtained as the slope of a regression line fitted through the scatter diagram of the two logarithmic variables C and r, using the region with relevant scaling behavior. The whole procedure is performed by considering successively higher values of the embedding dimension. For a sufficiently large value the dimension of the attractor will be obtained as the saturation value of this procedure. Following the theorem of Takens (1981), the embedding dimension should be greater than $|2D + 1|$.

This approximation method, which is routinely used in several fields, is limited by the finite precision of the fitting procedures and the finite length of the time series. Because biosignals are almost never completely stationary over a long time, care must be taken in selecting the appropriate number of data points. Although analysis of long-term series requires much computation time, the evaluation of small data sets can result in underestimation of the dimensionality.

"Running" Analysis

In contrast to conventional analysis techniques consisting in the consecutive evaluation of defined periods, we introduced the "running" technique. This technique by which systematic oscillatory changes in the signal's activity can be detected more clearly was developed in analogy to earlier described "running" computations of, among other things, correlation coefficients (described by Keidel, 1976). It enables a sliding shifting of a defined period like a "running" analysis window over the whole record length, using a selected time shift Δt. An extensive description of this procedure as applied to spectral analysis is given by Tirsch et al. (1988).

Results

"Running" Spectral Analysis versus Dimensional Analysis Derived from EEG Data

Applying the "running" technique to spectral analysis of a 4-min EEG epoch with a window length of 10 s and time shifts of 1 s produces 230 spectral densities. After smoothing with an autoregressive low-pass filter, the resulting spectra are drawn as chronospectrograms as shown in Figure 4.2. The dominant power in the alpha-range and the pronounced rhythmic variations in power densities with periods of about 30–40 s appearing during the analysis of 4 minutes are easily observed.

Analogous to the "running" spectral analysis (Tirsch et al., 1988), a "running" computation of dimensional complexity was introduced as reported earlier (Keidel, Tirsch, & Pöppl, 1990b). In the upper graph of Figure 4.3,

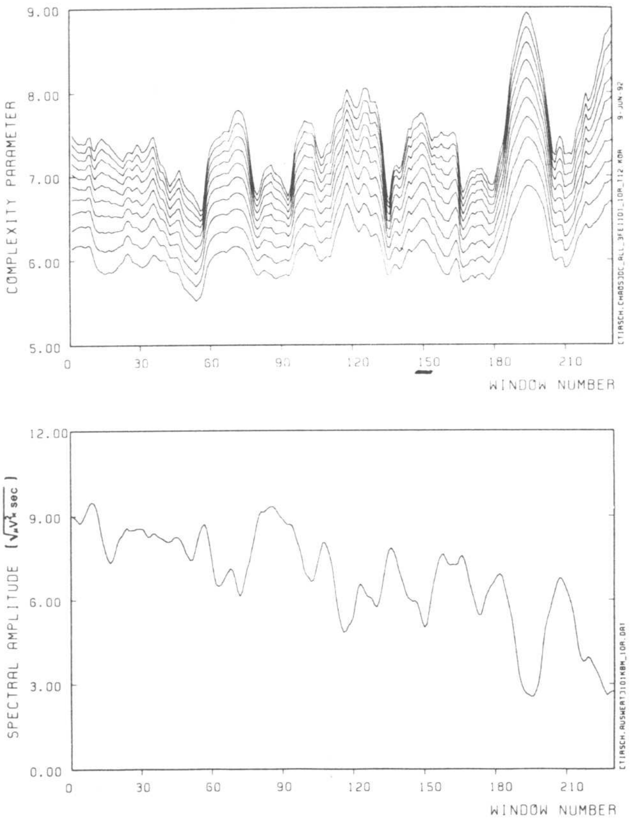


Figure 4.3

Synopsis of "running" dimensional and spectral analysis derived from the same EEG epoch as in Figure 4.2

Explanation:

Upper graph: Smoothed time courses of complexity over 230 windows with embedding dimension from 11 up to 20. Time delay is 24 ms. Length of analysis window is 10 s using time shifts of 1 s.

Lower graph: Time series of spectral amplitude in the alpha-band (7.5–13.5 Hz). Note the reciprocal behavior of the two graphs indicating that an increase of complexity causes a decrease of spectral density, and vice versa.

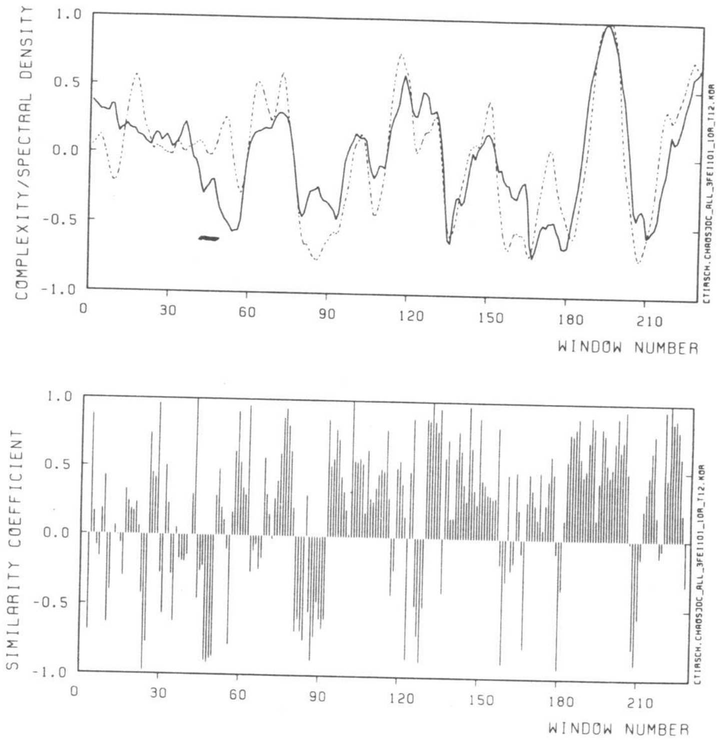


Figure 4.4

Relationship between "running" dimensional and spectral analysis derived from the same EEG recording as in Figure 4.2

Explanation:

Upper graph: Normalized time series of complexity (embedding dimension = 16, τ = 24 ms) and inverted spectral density in the alpha-band (dashed line).

Lower graph: Time series of 74 positive and 31 negative coefficients describing the similarity between the two graphs at each time increment. Note the high degree of correlation between the two methods of analysis.

the results of applying the "running" technique to dimensional analysis are illustrated for the same 4-min EEG epoch as above. The window number for each of the 230 sliding computations of dimensional complexity is drawn on the abscissa (time shift is 1 s; window length is 10 s; 5000 data points are used). The embedding dimension increases from 11 up to 20. The numeric range of complexity is comparable with specific EEG findings in recent literature (Mayer-Kress & Layne, 1987b; Mayer-Kress, Yates, Benton, Keidel, Tirsch, & Pöppl, 1988). In contrast to consecutive analysis, the rhythmic variation of complexity is more distinct (upper graph of Figure 4.3).

The time course of the band-related spectral density in the alpha-band derived from the same EEG data is shown below. Comparing the cyclic structure of the two graphs, a relationship between dimensional complexity and spectral density is evident. This correlation is demonstrated more clearly in Figure 4.4. For this purpose the time courses of the complexity according to the embedding dimension of 16 and of the inverted spectral density were normalized between −1 and +1 and superimposed (upper graph).

The inverted spectral density, represented by the dotted line, clearly follows the cyclic alterations of the dimensionality. In order to quantify the similarity of the two graphs, a simple procedure was introduced which is based on the quotient of slopes of the two regression lines fitted along the two curves. The result of this technique is shown in the lower diagram, where the derived similarity coefficients are represented by columns. The number of positive similarities indicates a high degree of correlation between dimensional complexity and inverted spectral density. The high degree of congruence between the two graphs can also be confirmed by the application of a sine wave fitting technique that considers the temporal order of systematic cyclic changes in complexity and inverse spectral density. The optimal fit which represents the endogenous auto-rhythm within the time series was determined by a least-square procedure which minimizes the residual variance matching various sine functions with stepwise increasing period lengths (Tirsch et al., 1988).

In Figure 4.5a the time series corresponding to an embedding dimension of 16 is drawn together with the optimal sine waves that correspond to the fits of first and second order; in the same way the time series of noninverted spectral density in the alpha-band is presented (see Figure 4.5b). Comparing the results of sine wave fitting derived from the two methods of analysis, the period durations of either the first or second fit are nearly identical, indicating a 40 or 41 s periodicity and a nearly identical temporal order of the two time series.

To determine whether the observed conformity in temporal order is also valid for other data sets, the procedure as described before was applied to the EEG data of 7 subjects corresponding to the same mid-occipital derivation as in the previous case. In Table 4.1 the period lengths corresponding to the time series of complexity and spectral density are illustrated. A matched paired t-test was applied to the data sets of the Table, indicating a nonsignificant

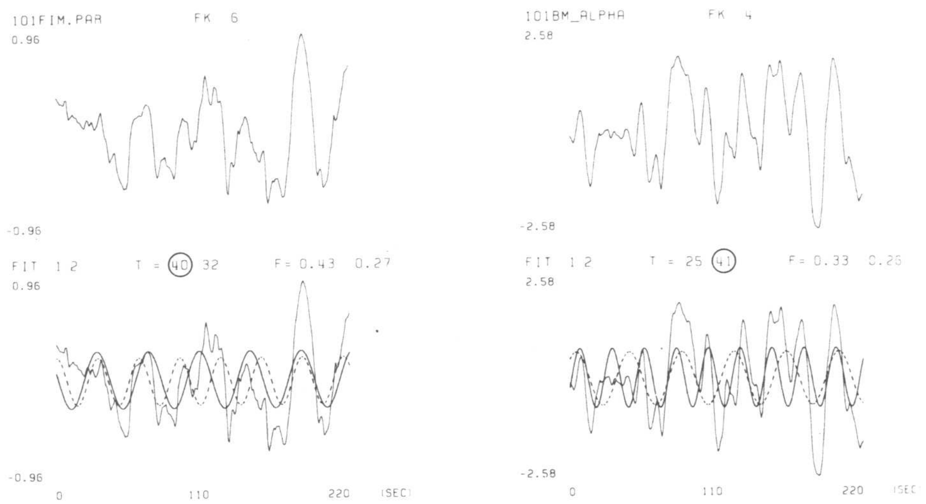


Figure 4.5
Results of sine wave fitting technique

Explanation:

(a) Left upper graph: Time series of complexity (d=16) derived from the same EEG recording as in Figure 4.2.

Left lower graph: Optimal fit of sine waves of first (T = 40 s) and second order (T = 32 s, dashed line).

(b) Right upper graph: Time series of spectral density.

Right lower graph: Optimal fit of first (T = 25 s) and second order (T = 41 s, dashed line). Note that period durations derived from complexity are nearly identical to those from spectral density.

Table 4.1

Comparison of Period Lengths Derived from Sine Wave Fitting Technique Applied to the Time Series of Complexity and Spectral Density

	Period length derived from: (a) complexity (wave fitting)	(b) alpha-power (7.5–13.7 Hz)
Subject	T_1 (s)	T_2 (s)
1	42	41
2	31	32
3	32	34
4	44	40
5	40	40
6	38	45
7	39	42
Averages	38.0	39.14

difference between the two sets of period lengths.

Tremor Data

To obtain long lasting recordings of oscillations of physiological finger tremor the subjects were lying in a supine position; their right arm was supported. The chronospectrogram shows the widely described frequency dominance of tremor oscillations in the alpha range (7.5–13.7 Hz), as can be verified in Figure 4.6. As demonstrated for EEG data previously, the time course of the chronospectrogram is well structured with "slow" oscillations of about 30–40 s in the same range.

Figure 4.7 demonstrates the relationship between complexity and spectral density. Despite various discordances between 30 and 60 s, a high degree of correlation between the two graphs is revealed. Moreover, the observed correlation can be confirmed by the sine wave fitting technique shown in Figure 4.8. The agreement is also apparent when the corresponding endogenous rhythms represented by 3 fits with period lengths ranging from 29 to 74 s are considered.

Discussion

The approach of a "running" spectral analysis of long-term recordings of human CNS signals enabled us to detect rhythmic variations in neuronal activity and to demonstrate that the CNS is not maintained on a static level but operates in an oscillatory mode. Period lengths ranging from 20 s to 70 s, most frequently of 40 s, were observed. Various other investigations have reported

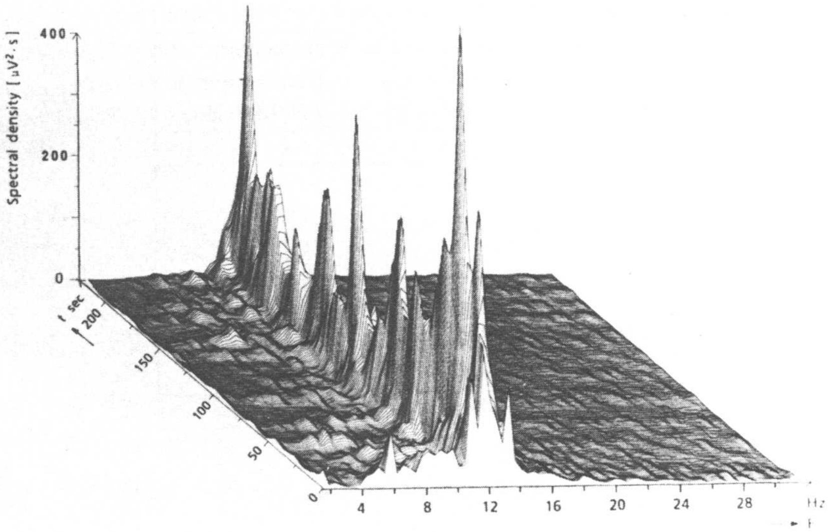
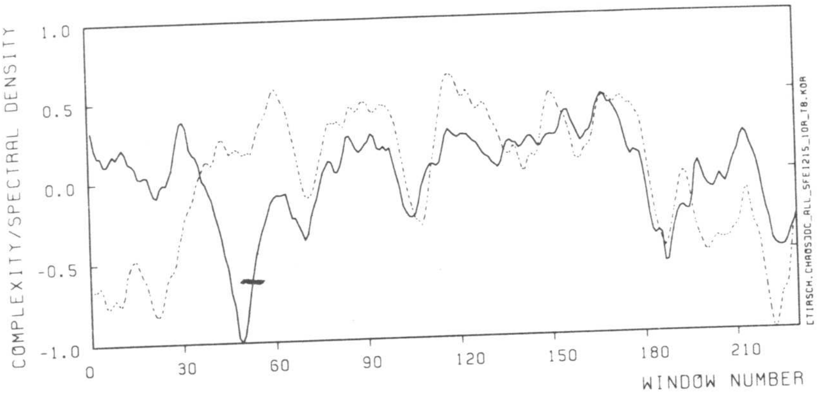


Figure 4.6
Pseudo-3D spectrogram of "running" auto-power derived from a 4-min epoch of finger tremor. Note the rhythmic variations in power densities with periods of approximately 30-40 s during an analysis of 4 min

similar periodicities of approximately one minute (Lips, Schultz, & Pichmayr, 1987; Scheuler, Rappelsberger, Schmatz, Pastelak-Price, Petsche, & Kubicki, 1990; Terzano, Parrino, & Spaggiari, 1988).

In earlier investigations (Keidel, 1990; Keidel, Tirsch, & Pöppl, 1989a; Keidel, Tirsch, Pöppl, & Radmacher, 1990; Keidel, Czettritz, Tirsch, Weinmann, Bax, & Eckardt, 1990; Tirsch et al., 1988), we demonstrated that these periodicities play an important role in the cortical (EEG) and spinal output of the brain corresponding to muscle and finger tremor as mechanical correlates of the motoneuronal activity. The introduction of a sliding or "running" analysis of long-term recordings of such signals enabled us to disclose a well-ordered temporal pattern of rhythmic change in the spectral density and coherence of neurobiological signals. We assumed that a power increase in the main frequency range may be due to an underlying increase in synchronization or coupling strength of neuronal elements generating the derived signals. Consequently, the "network" of the CNS may be more ordered and hence, less complex in case of high spectral density, and vice versa. Thus, we hypothesize



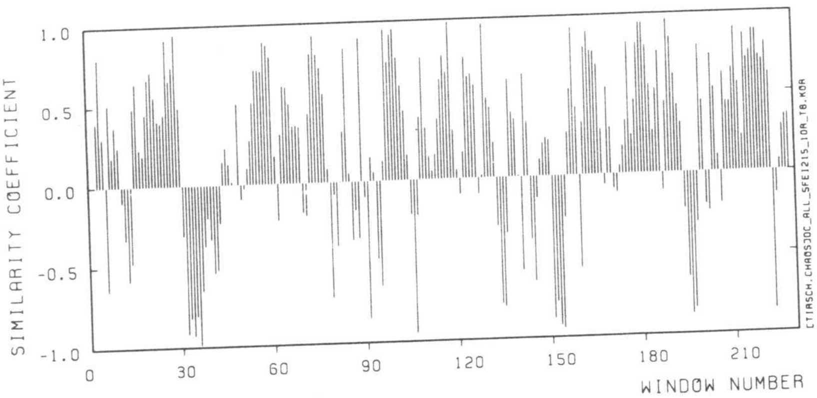


Figure 4.7

Relationship between "running" dimensional and spectral analysis derived from the same tremor recording as in Figure 4.6

Explanation:

Upper graph: Normalized time series of complexity (embedding dimension = 16, τ = 16 ms) and inverted spectral density in the alpha-band (dashed line).

Lower graph: Time series of 81 positive and 27 negative similarity coefficients. Note the high degree of correlation between the two methods.

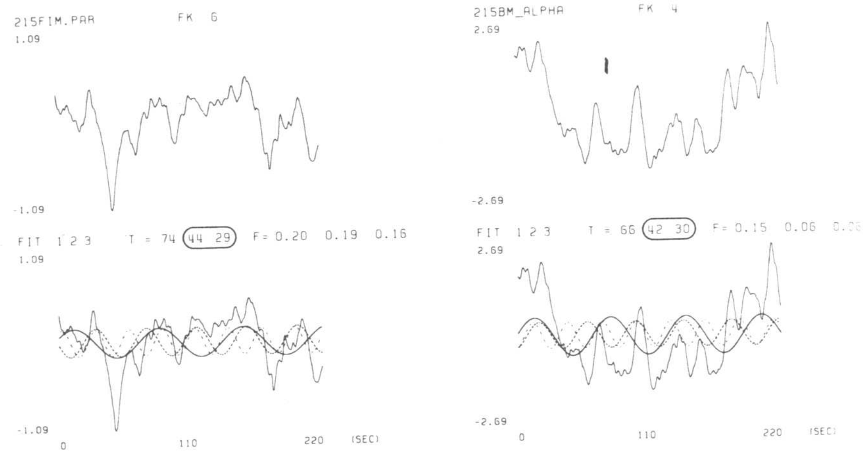


Figure 4.8
Results of sine wave fitting technique

Explanation:
(a) Left upper graph: Time series of complexity (d = 16) derived from the same EEG recording as in Figure 4.7

Left lower graph: Optimal fit of sine waves of first (T = 74 s), second (T = 44 s, dashed line) and third order (T = 29 s, dashed line).

(b) Right upper graph: Time series of spectral density.

Right lower graph: Optimal fit of first (T = 66 s), second (T = 42 s, dashed line) and third order (T = 30 s, dashed line). Note that period durations derived from complexity are nearly identical to those from the spectral density.

Decrease of dimensional complexity implies: –increase of order of the underlying system –increased neuronal synchronization –increase of in-phase coherent oscillators (subsystems) –increase of spectral density and coherence
Increase of dimensional complexity implies: –decrease of order of the underlying dynamical system –increased neuronal desynchronization –increase of out-of-phase incoherent oscillators –decrease of spectral density and coherence

Figure 4.9

Model of interpretation according to the observed inverse covariation between dimensional complexity and spectral density of human neurobiological signals

an inverse relationship between cyclic dynamics of dimensional complexity and spectral density or coherence during long-term analysis of such recordings.

In an application of the "running" dimensional analysis to the activity of two prominent neuronal oscillators, such as EEG and tremor, the temporal pattern of dimensional complexity was found to display an inverse relationship with simultaneously computed spectral power changes. The correlation is relatively high. A former conventional successive analysis, as reported by other groups, failed to elucidate this correlation. The results indicate that the band-related dominant spectral density of the signal increases with decreasing dimensionality or increasing order of the dynamical system. This may be caused by an enhanced neuronal synchronization or subsystem coherence causing a lower complexity of the CNS (see Figure 4.9).

These observations agree with the conclusions of Farmer, Ott, and Yorke (1983) who suggested that the dimensionality of a dynamical system is related to the number of active coherent modes modulating the underlying physical process. Similarly, Mayer-Kress et al. (1988) concluded that an increase in dimensionality could correspond to an increase in the number of independently or incoherently oscillating subsystems or modes. This number may correspond to the number of independent frequencies in the spectrum quantified by spectral analysis in the area of linear systems. On the other hand, the reduced dimensionality could reflect an enhanced "synergetic self-organization," described by Haken (1977), which synchronizes some of the subsystems and leads to transitions from "high-dimensional" to "low-dimensional" chaos (Babloyantz & Destexhe, 1986; Basar, 1983; Keidel, Tirsch, Pöppl, & Radmacher, 1990). The existence of such transients seems to be an intrinsic property of the CNS which might be necessary for information processing (Basar, Basar-Eroglu, Röschke, & Schutt, 1989). It could be argued that, analogous to computer technology, the brain switches from a *parallel* processing mode (with high EEG complexity, but low spectral density and low coherence of the desynchronized EEG) to a *central* processing mode (with lower complexity resulting in a fairly low dimensionality, but higher spectral density and coherence within the synchronized EEG). These aspects and their psychophysiological relevance are discussed by Keidel, Tirsch, and Pöppl (1989b).

The fact that two basically different methods of analysis applied to the same data sets of both EEG and tremor reveal an identical order in temporal oscillations may support the hypothesis that there exists an oscillatory neuronal structure such as the "common brainstem system" with its "dynamic specificity." This system is represented by the "formatio reticularis" as an arousal system (Langhorst, Schulz, Lambertz, Schulz, & Camerer, 1980) which functions as a central "master network." Similar ideas with respect to faster oscillating mechanism in the short period range like the alpha rhythm are described in the thalamic pacemaker model (Nicolis, 1987) and the model of an "internal clock" (Treisman, 1984). Studies by Moruzzi (1964; Moruzzi & Magoun, 1949) have shown that the reticular formation of the brainstem has the ability to modulate the global level of cortical excitability. Following his considerations it could be argued that the reticular formation operates as an ascending (to the cortex) and descending (to the spinal cord) activation controller, involving various other oscillating structures. This system of ascending and descending influences may simultaneously drive cortical (EEG) and spinal (tremor) neuronal assemblies which will then become coupled oscillators with their own rhythms (Basar, 1983), thereby causing the observed cyclic transients in dimensionality and spectral density in the circa 1-min range. As an alternative explanation, the possibility of a self-generating rhythmicity caused by a nonlinear coupling of different oscillators in the brain and spinal cord could be considered. Similar models for EEG and EP activity are described by Achimowicz (1990).

Conclusions and Prospects

The introduction of a sliding or "running" analysis of long-term recordings of CNS signals enabled us to disclose a temporal order of systematic changes in spectral density and dimensional complexity of CNS signals and thus to gain insight into the functioning of the CNS. The results indicate that the CNS periodically alters the level of activity, complexity, and degree of synergy between different processing structures and subsystems.

The functional significance of the observed periodicities in the brain's activity is not yet elucidated completely. Various hypotheses could be put forward to explain the periodicities. Besides some reset or gating mechanism, a continuous tuning of the responsiveness of the CNS to external (or internal) stimuli may lead to the maintenance of a certain mid-level of excitability by avoiding habituation of sensory evoked or motor induced alterations in the

CNS complexity; especially as sensory evoked excitation may be encoded in interneuronal coupling strength, as the studies of Engel and Singer (1990) have shown. A general neural model of attention processes was formulated by Ventriglia (1990).

The transient periods of high complexity of the brain and low coherence between different brain areas may allow a (fast) parallel information processing, e.g., in different sensory channels, because numerous cognitive processes would be executed simultaneously. Intermediate short periods of a central information processing mode with a high coupling strength between different brain structures (including hemispheres and subcortical–cortical connections) resembling a lower complexity of the brain may facilitate the data transfer to (and retrieval from) "higher" association areas or between the hemispheres.

As our results demonstrate an inverse covariation between EEG power and EEG complexity, it can be expected that in psychophysiological studies an event-related desynchronization or synchronization may be accompanied by an increase or decrease of the correlation dimension. Because of the revealed ordered nonstationarity within the spontaneous EEG activity, the validity of event-related studies can be increased if the evoked single trial data are acquired time locked to identical complexity levels and are averaged selectively. Bearing this approach in mind, it might turn out in future research of long-term monitoring that various psychological functions such as cognition, vigilance, attention, perception, and motor performance demonstrate an oscillatory behavior which is related to the endogenous circa 1-minute rhythm of the transients in the brain's complexity.

The modeling of the functioning of the CNS with respect to its oscillatory behavior may have some practical aspects, e.g., in the field of bionics and neurocomputing, or in computer-modeling of neuronal networks. Recently, the role of neuronal oscillations in primate visual systems took on a prominent place in modeling visual perception and cognition (Eckhorn, Reitboeck, Arndt, & Dicke, 1990; Engel, König, Gray, & Singer, 1990; Van Essen, Anderson, & Felleman, 1992). Thus, the implementation of such a synergetic strategy which causes an ordered cyclic change in coupling strength between single elements or subsystems, may enhance the efficacy of the overall function of the entire network. Moreover, the nonlinear modeling of CNS signals suggests a prominent role in determining nonlinear characteristics which are closely related to different physiological or patho-physiological states and which cannot be disclosed by conventional analyses. An additional important aspect is that the study of time order of CNS signals may help to disclose temporal "dynamic" disorders related to CNS dysfunctions in many diseases. In the neurological and psychiatric field these diseases may be caused, for example, by disconnections syndromes, by altered states of consciousness, or by mental disturbances such as psychoses.

Finally, in clinical applications of the procedures described here, it may appear that "lesions" *in time* become evident earlier than "lesions" *in structure* or *substrate* which at present form the common basis of current diagnostic and therapy concepts. Thus, the new approach of nonlinear modeling and studying the time order of CNS signals may present a powerful tool in brain diagnostics in the future.

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