Physica A 185 (1992) 433–438
North-Holland

PHYSICA A

Spatio-temporal dynamics of human EEG

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1. Introduction

Electroencephalogram (EEG) – recording of spontaneous brain electrical activity resulting from collective dynamical behaviour of the neural mass – was traditionally treated as a random signal and processed by stochastic methods like spectral analysis. Qualitatively new views were opened by approaches derived from synergetics, non-linear dynamics and theory of deterministic chaos introduced into EEG research in the last six years (see refs. [1, 2], and references therein). In this approach the EEG signal is supposed to be a deterministic signal generated by chaotic dynamics of finite and even low-dimensional dynamical system evolving on its strange attractor. Processing EEG data consists then of the reconstruction of a hypothetical strange attractor from experimental data and computations of relevant dynamical/topological invariants (fractal dimensions, Lyapunov exponents, Kolmogorov entropy). The goal of this treatment is using measures of complexity and chaos for characterization of brain processes reflected in the EEG signal, i.e. developing new tools for computerized EEG analysis with applications in psychiatry, neurology and pharmacology of psychoactive drugs.

EEG signals can be simultaneously registered from several locations on the scalp (16, 32, 64). Two ways of reconstructing the "brain attractor" are presently used:

One-channel reconstruction. A one-dimensional ("one-channel") EEG signal registered from a particular location on the scalp is considered as a smooth projection of n-dimensional chaotic dynamics on the strange attractor. An n-dimensional trajectory is reconstructed using the time-delay method based

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on the theorem of Takens [3] and dynamical invariants are computed from this (reconstructed) n-dimensional data.

Multi-channel reconstruction. An n-channel EEG recording (typically $n = 8$, 16) registered from the whole scalp or its selected subarea is considered as an n-dimensional dynamical trajectory and dynamical invariants are computed directly from it. This approach is inspired by proposition of Eckmann and Ruelle for spatially extended systems [4].

Correlation dimension

In both types of "EEG attractor" reconstruction the correlation dimension (CD, Renyi dimension of order 2) [5] is a dynamical invariant computed by a majority of researchers. Albeit many papers on CD of EEG were published (see refs. [1, 2], and references therein) no systematic study has been performed yet and results from various laboratories are hardly comparable because of non-standardized conditions on physiological, technical and numerical levels. This does not mean, however, that this approach is not promising. CD, or more precisely its estimates, are sensitive to physiological or pathological conditions in which relevant EEGs were recorded. (See ref. [1] for references and discussions.)

EEG: spatio-temporal phenomenon

One serious theoretical objection appers when we analyze in details the above mentioned types of "EEG attractor" reconstruction: EEG is a spatio-temporal signal and this fact is ignored applying any of the above mentioned approaches (either one- or multi-channel reconstruction) separately. It would be more plausible to study EEG in its full spatio-temporal dynamics. This "many-dimensional" problem, however, requires large computers and large amounts of data to obtain reliable estimates of relevant measures of complexity and chaos.

Orthonormal decomposition and linear complexity

Orthonormal decomposition we consider as the first step to studying EEG spatio-temporal dynamics: Let us denote a registered multi-channel EEG as a spatio-temporal function $U(r, t)$, where r is the space and t the time coordinate. Suppose it can be decomposed in the following way:

$$U(r, t) = \sum a_i(t)\, \Psi_i(r)\,, \tag{1}$$

where $\Psi_i(r)$ are spatial modes and $a_i(t)$ are uncorrelated time-dependent coefficients. Solution of (1) leads to the eigenvector–eigenvalue problem for

the EEG signal correlation matrix and it is known in pattern recognition theory as the Karhunen–Loeve expansion [6]. In our case the spatial modes are given by eigenvectors of a 16×16 or 32×32 EEG signal correlation matrix. "Significance" of a particular mode (i.e. its portion in total energy of dynamics) is given by its eigenvalue. Structure of the modal decomposition we can characterize by "linear complexity" measure (LC):

$$\mathrm{LC} = -N \Big/ \sum \log \sigma_i \,,$$

where σ_i are eigenvalues of the EEG signal correlation matrix and N is a proper normalization constant.

2. Results

At least the first four modes, explaining 65%–85% of the total data variance, are universal for various human healthy subjects in a broad variety of physiological conditions (fig. 1).

The modal structure, quantified by LC, is sensitive to changes of physiological conditions. In an experiment a dose of alcohol was administered to several healthy volunteers. The concentration of ethanol in blood was traced and a

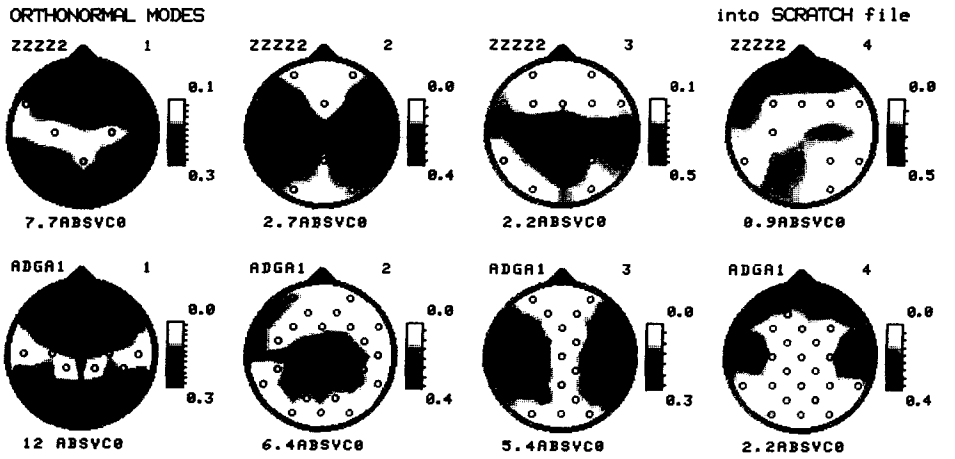

Fig. 1. Orthonormal modes 1–4 of two various subjects' multi-channel EEG (vertex view to the head, the open circles illustrate positions of electrodes). In subject 1 (upper part) a 16-channel and in subject 2 (lower part) a 32-channel EEG recording was decomposed. Both subjects are healthy volunteers, the first a 20 year old female, the second a 29 year old male, both in a state of relaxed vigilance with closed eyes.

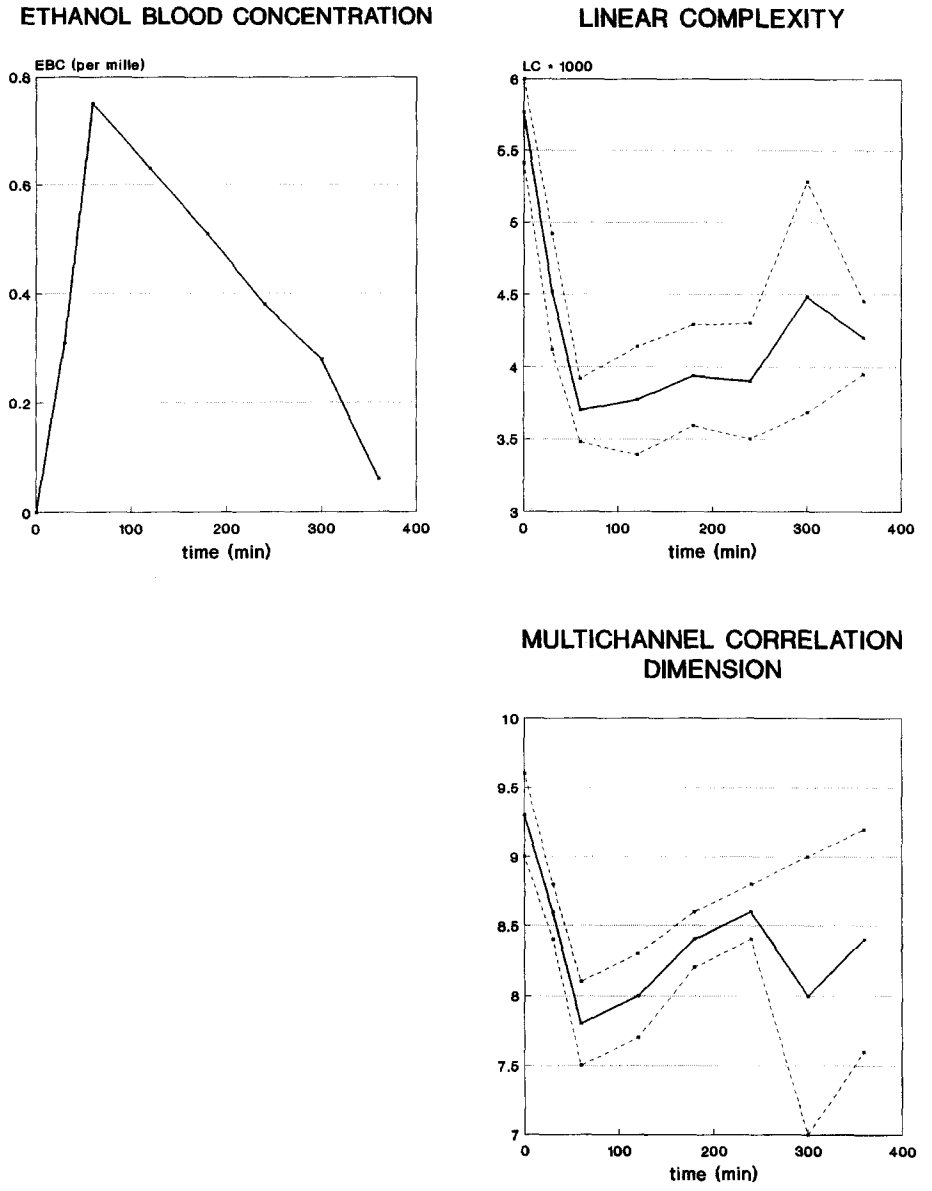

Fig. 2. Changes of spatio-temporal EEG dynamics induced by a dose of alcohol to a healthy volunteer (43 year old female): alcohol causes a decrease of complexity of 16-channel EEG dynamics detectable at both the linear (linear complexity – the upper right graph) and nonlinear level (multi-channel correlation dimension – the lower right graph). Compare the time course of ethanol blood concentration (the upper left graph) with those of LC and CD. The dashed lines illustrate standard deviations of presented complexity measures given by natural variance of the EEG signal.

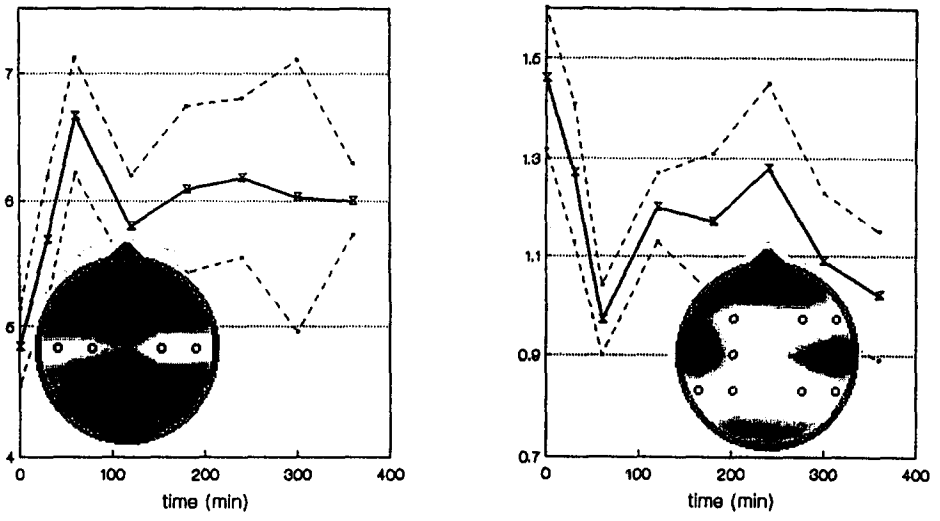

Fig. 3. Alcohol has no influence on the shapes of the EEG spatial modes but induces changes of their eigenvalues – compare the time course of ethanol blood concentration (the left graph of fig. 2) with those of eigenvalues of mode 1 (the left graph) and of mode 4 (the right graph). The standard deviations are illustrated by dashed lines.

16-channel EEG recorded before and several times after alcohol administration. Changes of the ethanol blood concentration are reflected in changes of the modal structure of spatio-temporal EEG dynamics: alcohol induces a decrease of the multi-channel EEG linear complexity, i.e. a higher degree of spatial EEG coherence. The dominance of modes 1–3 increases at the expense of the other modes (figs. 2, 3).

These changes are detectable by multi-channel CD as well (fig. 2).

3. Conclusion

The novel dynamical approach to EEG analysis is promising and the results obtained are very encouraging. A final answer on its applicability in neurologic and psychiatric diagnostics, however, can be obtained only from many systematic studies. Several of them are currently under way in the authors' laboratory.

Acknowledgement

Large computational experiments in this project are performed within the

framework of the IBM Academic Initiative in Czechoslovakia, which is gratefully acknowledged.

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