CHAOS PARAMETERS FOR EEG ANALYSIS

J. Ulbikas, A. Čenys
Semiconductor Physics Institute, Goštauto 11, 2600 Vilnius, Lithuania
O. P. Sulimova
Institute of Higher Nervous Activity and Neurophysiology, Russian Academy of
Sciences, Moscow, Russia

Abstract

The possibility to apply nonlinear dynamics methods for the EEG time series
analysis is investigated. Problems related with the estimation of the chaos
parameters from the physiological data are discussed.

INTRODUCTION

During the last two decades, development of the chaos theory has introduced
new approaches for understanding the nature of oscillatory phenomena. Numerical
methods of the chaos theory dealing with complicated temporal behaviour in
nonlinear equations appear to be ideally suited for many experimental systems
exhibiting erratic data. Biological systems exhibiting very complicated behaviour
are among them. Large number of investigations implementing nonlinear dynamics
methods for the analysis of human and animal electroencephalograms (EEG)
analysis have been presented [1, 2, 3]. However, an increasing enthusiasm for
the application of the nonlinear dynamics methods to real EEG data also meets
some scepticism. This is related with the reliability and interpretation of the
obtained results. Algorithms for the estimation of chaos parameters contain some
unavoidable arbitrariness. The basic concepts "attractor" and "fractal dimen-
sion" were introduced assuming stationarity of the dynamic system, therefore,
application of these concepts in situation of biological systems can be incorrect.
Nevertheless, Babloyantz and Destexe [1] pointed out that stationarity of the EEG
could be detected for sleeping patients or patients in rest. They have calculated
and classified dimensionality of the EEG signal in different stages of sleep and
have also tried to estimate dimension for the awaked patient EEG. However, it
was noted that error bars in these calculations were very large and were related

with the nonstationarity of the recorded biological signal and insufficient number of experimental points.

Therefore, although reliability of the estimated parameters is very important in theoretical research, we propose a phenomenological approach which can be useful in physiological practice. In this phenomenological approach, chaos parameters are to be calculated from the EEG data using standard algorithms. The results, however, are treated only as numbers for the quantitative description of the system in different situations. This approach requires subtle repetition of the experimental situations. The obtained values cannot be considered as dimensions, entropies, or other chaos parameters of the attractor due to the nonstationarity of the biological signal. However, it is possible that they can be successfully used to describe and to classify different states of the brain activity [1]. In this study we have applied this approach for the EEG analysis based on nonlinear dynamics methods. To find out sensitivity of different algorithms with specific modifications experimental data were recorded under the same conditions but under the influence of different external factors.

ALGORITHMS

Specifics of the biological systems requires modifications of standard nonlinear dynamics algorithms. The main problems of the nonlinear analysis when applying it to biological signals can be summarized as follows: a) high level of random noise in the biological data. The applied nonlinear dynamics methods should be robust to the noise influence; b) short experimental data sets due to the low frequencies of the biological signals. Short realizations cause large error bars in the estimation of the chaos parameters; c) nonstationarity of the biological systems. For example, the brain activity is influenced by a great variety of external factors having different characteristic times; d) spatially extended character of the system. It is well known that different parts of the brain core are responsible for the different brain functions. Interrelations of different parts of the brain can also give very useful information about the brain activity under different external conditions, moreover in detecting the dominant regions.

Dynamical nature of analysed time series is an additional problem when applying nonlinear dynamics algorithms to experimental data. Few years ago were showed [8] that for the noisy and short time series, standard chaotic dynamics algorithms can give spurious results, i.e. they can indicate the presence of the nonlinear dynamics in completely random systems. Recently, the surrogate data

2

techniques have been developed to distinguish the chaotic systems from the linearly correlated noise [8]. We have used the method of so called "surrogate" data sets generation [9] to check the dynamic nature of the used in calculations EEG records. The obtained difference between the dependence of $\nu(M)$ for the original data set and the surrogate signals ensemble gives strong evidence of the nonlinear structure in the EEG data.

In our study we have used two chaos parameters, namely, the correlation exponent, which is an analogue of the correlation dimension [4] and the chaotic interrelation parameter [5]. The correlation dimension is the most popular characteristic of experimental chaotic systems. The chaotic interrelation parameter allows one to estimate nonlinear correlations between different regions of the spatially extended systems.

The first step in calculating both parameters is reconstruction of the high dimensional state space from the scalar data recorded in the experiment. Delay vectors are the most widely used method for reconstructing the high dimensional state space [6]. From the experiment we have EEG data as a discrete time series $(x_1, x_2, .., x_i, ..., x_N)$ for each probe on the scalp. Here $x_i \equiv x(t+i\tau)$, t is the initial time, and τ is the sampling time. The M-dimensional phase space is reconstructed from a single observable $x(t)$ by means of the M-dimensional vectors:

$$x_i^M \equiv x(t), x(t + \tau), ..., x[t + (M - 1)\tau]. \tag{1}$$

The same procedure can be applied for each probe of the EEG data $x(t), y(t)....$

The delay τ is a free parameter in this method. The Takens theorem suggests that theoretically the choice of this parameter is not important. In practice, however, it is crucial to choose a good value of τ due to the noise and the short time series. It is shown that the most effective sampling frequency for biological signals is in the range of $100 - 500Hz$ [1, 2].

The correlation dimension is calculated by the Grassberger-Procaccia algorithm [4] from the scaling properties of the correlation integral:

$$C^M(\varepsilon) = N^{-1/2} \sum_{i \neq j} \Theta(\varepsilon - \| x_i^M - x_j^M \|) \sim \varepsilon^{\nu(M)} \tag{2}$$

Here $\| x_i^M - x_j^M \|$ defines the distance between points in the M-dimensional space and Θ is the Heaviside function. Correlation dimension is to be estimated as a saturating value of the exponent for large enough M. In our experiments, as is typical of biological systems, the nonsaturating behaviour of $\nu(M)$ was observed.

3

We suppose that this behaviour is related with the unavoidable presence of the random noise in EEG data.

The algorithm for determining the correlation dimension from the noisy data was suggested in [7]. The main idea is to find the linear part of the plot $\nu(M)$ vs M in the range of large values of M. This line is extended until it intersects the line $\nu(M) = M$. The needed correlation dimension of the underlying attractor is determined by the intersection point. This method is valid, however, if the slope of the function $\nu(M)$ is small enough. This was not always the case in our calculations, and we can not treat the obtained values as a correlation dimension. This is the reason why we call the parameter used in our study the correlation exponent.

For the quantitative characterisation of nonlinear correlations in signals generated from different brain regions, we have chosen a parameter introduced in [5]. According to this method nonlinear interrelation between two signals x and y is estimated from the dependence of conditional dispersion σ_{xy}^M on ε:

$$\sigma_{xy}^M(\varepsilon) = \left(\frac{\sum_{i \neq j} \parallel x_i^M - x_j^M \parallel^2 \Theta(\varepsilon - \parallel x_i^M - x_j^M \parallel)}{\sum_{i \neq j} \Theta(\varepsilon - \parallel x_i^M - x_j^M \parallel)} \right)^{1/2} \tag{3}$$

Thus signals x and y are interrelated, if the conditional dispersion dependence on ε reduces with the decrease of ε, and are not interrelated when σ_{xy}^M does not depend on ε. Conditional dispersion σ_{xy}^M can be calculated only in the interval $(\varepsilon_{min}, \varepsilon_{max})$. The value of ε_{max} is determined by the attractor size, while the value ε_{min} depends on the number of points in the time series. Even for the interrelated signals, σ_{xy}^M does not depend on ε for large ε. This dependence begins at some ε_0. Therefore, $K_{xy} = \varepsilon_0 / \varepsilon_{max}$ can be chosen as a parameter of the interrelation. Another important feature of the parameter K_{xy} is that, due to definition of the conditional dispersion, this parameter is not symmetric to the interchange of the signals x and y.

DATA AND RESULTS

The encephalographic signals were recorded from the standard contact configuration of the electrodes attached by conductive paste to the scalp. The EEG signal was in the microvolt range and was amplified by several orders of magnitude before recording. The artefacts often originate from slight movements of the electrodes and from the contraction of muscles below the electrodes. The standard probe position is an international 10-20 system. Most of the experiments with

4

EEG signals were performed using this system. In our study, EEG signals were registered from fourteen channels of the unipolar 10-20 Jasper registration scheme shown in Fig. 1. The ear electrode was used as an indifferent joint contact. The frequency range of the recorded EEG was $0.4-30Hz$, while the sampling frequency was $100Hz$. Registration time of the single EEG record was up to 25 minutes. In the calculations, pieces of the realization of $N = 2^{12}$ points were used. Two realizations for each person with and without the applied external factor (the so-called deceptive experiment), other experimental conditions being the same, were recorded.
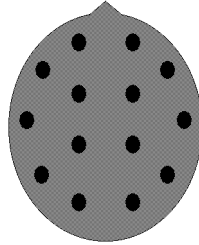

Fig. 1. Location of the scalp probes during experiment.

For the brain activation, two standard external factors were used: light to the open eyes and hands action. In addition we have studied uncommon factor - influence of the millimeter waves irradiation of nonthermal intensity. In the last case, the electromagnetic field with the wave length of $7.1mm$ and the output power of $5mV/cm$ was applied on the hand using an optical fiber.
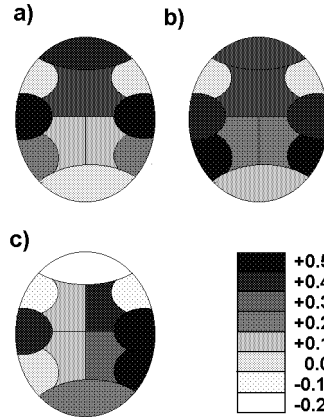

Fig. 2. Mapping of the differences of the correlation exponent ν calculated from experiments with and without an external factor: a) light to the eyes, b) hands action, c) microwaves irradiation.

5

The main idea of the phenomenological approach for physiological tests is to compare the calculated results for the brain in rest of the healthy patient and the same results but under the influence of some external factor or pathological state. If one detects some differences, this can be an evidence of the influence of the external factor. It is also expected that different external factors influence different brain regions. For better visualization, mappings were constructed using differences between the values of the correlation exponent ν calculated from the realization under an external factor and without it. The example of such a mapping is shown in Fig. 2. As can be seen from Fig. 2, mappings are different for different stimulus. The dark areas represent regions of the brain in which ν is higher under the influence of the external factor. A standard presumption is that a higher correlation exponent value manifests an increasing degree of the brain activation [1, 2], and vice versa. As can be seen from Fig. 2, most of the areas of the brain under the influence of external factors exhibit a higher activation level than that for the brain in rest. Moreover, the obtained mappings are noticeably different for different external factors. The mappings obtained in our experiments for standard external factors shows the highest brain activation level in the same brain areas as that obtained from biological experiments using typical physiological tests.
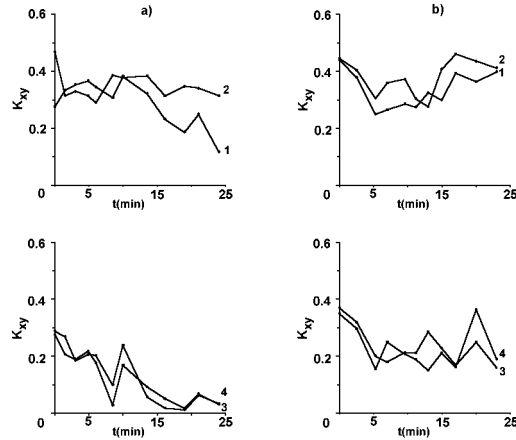

Fig. 3. The time dependence of the nonlinear interrelation parameter K_{xy} for a) EEG recorded for the patient under microwave irradiation, b) the patient in rest. The interrelation is calculated between the different brain regions: 1 - right frontal and right occipital regions, 2 - left and right frontal regions, 3 - left and right occipital regions, 4 - right frontal and left occipital regions.

Therefore, we suppose that the correlation exponent is more or less an adequate quantity describing the brain activation level. More interesting mappings were

6

obtained for the uncommon factor, the millimetre electro magnetic waves of the nonthermal intensity. Obtained activation of the brain and nonsymetrical configuration of brain activation mapping can be related with the brain reaction to the millimeter wave irradiation.

Similar information about changes in brain activity was found in the measurements of the time dependencies of the interrelation parameter K_{xy} between different brain areas under millimetre waves irradiation (Fig. 3a) and the patient in rest (Fig. 3b). Slight decrease of K_{xy} under irradiation for right - left occipital, and occipital - frontal regions of the brain can be an additional prove of the brain reaction to irradiation of the waves of the millimetre range.

CONCLUSIONS

The proposed phenomenological approach of the application of nonlinear dynamics methods is demonstrated to be promising for the development of new physiological testing techniques. Despite large problems related with the experimental data recording under real clinical conditions, the modified nonlinear dynamics methods are sufficiently sensitive for application them in physiological diagnostics. Our experiments with the different external factors have shown that it is possible to separate different brain activity stages using nonlinear dynamics methods. Of course, there is still a long way for checking new methods on real data to the physiologically reliable result, but we hope that this study will give some impetus for the analysis of the physiological system dynamics.

ACKNOWLEDGEMENTS

REFERENCES

1. Babloyantz A., Salazar J. M., Nicolis C., *Evidence of chaotic dynamics of brain activity during the sleep cycle, Phys. Lett.* A, **111A**, p. 152, 1985.

2. Mayer-Kress G., Layne S. C., *Dimensionality of the human electroencephalogram, In: Perspectives in Biological Dynamics and Theoretical Medicine,* Ann. N. Y. Acad. Sci., p. 504, 1987.

3. Layne S. P., Mayer-Kress G., Holzfuss J., *Problems associated with dimensional analysis of electroencephalogram data*, In: *Dimensions and entropies in chaotic systems*, Berlin: Springer-Verlag, p. 246, 1986.

4. Grassberger P., Procaccia I., *Characterization of strange attractors*, *Phys. Rev. Lett.*, **50**, p. 346, 1983.

5. Čenys A, Lasienė G., Pyragas K., *Estimation of interrelation between chaotic observables*, *Physica* D, **52**, p. 332, 1991.

6. Packard N. H., Crutchfield J. P., Farmer J. D., Shaw R. S., *Geometry from a time series*, *Phys. Rev. Lett.*, **45**, p. 712, 1980.

7. Čenys A, Lasienė G., Pyragas K., *Correlation dimension of noisy strange attractors*, *Lith. Phys. Coll.*, **30**, p. 274, 1990.

8. Theiler J., Eubank S., Longtin A., Galdrikian B., Farmer J. D., *Testing for non linearity in time series: the method of surrogate data*, In: *Proc. of the IUTAM Symposium and NATO Advanced Research Workshop on interpretation of Time Series for Nonlinear Mechanical Systems,* University of Warwick, Coventry, p. 1, 1991.

9. J. Ulbikas, A. Čenys, D. Žemaitytė, G. Varoneckas, *Correlations in the heart rate data, Nonlinear Analysis: Modeling and Control,* **2**, Vilnius, IMI, p. 137, 1998.