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A computer method for identifying patterns in electroencephalogram signals

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A computer method is developed for identifying patterns in electroencephalogram (EEG) signals. An EEG numerical signal is transformed into a symbolic series. The simple transformation used here studies the variations between two successive values of the signal. Then, this series is analysed with a symbolic correlation function based on probabilities without bias. The use of large windows, e.g. 1 hour, allows the identification of weak signals hidden by the specific ones. An application of this method to the sleep analysis of a healthy adult shows a periodicity modulo 10 in all derivations. A possible neurophysiological meaning is presented in the discussion.

Introduction

Although the first report concerning the human electroencephalogram (EEG) appeared 70 years ago [1], the nature of EEG is still in investigation for fundamental research in neurology as well as for applied research in medicine. Computer methods allow quantitative analyses of recorded channels, and in particular identifications of patterns in the EEG signals. For example, the alpha patterns related to a certain event [2], e.g. a sensory stimulus, are studied by methods of EEG frequency and time-frequency analysis; see e.g. [3]. The understanding, recognition and treatment of epilepsy may be analysed by searching and characterizing the preictal, ictal and postictal patterns or by detecting seizure disorders; see e.g. [4–7]. Insomnia may be associated with particular alpha patterns; see e.g. [8]. Finally, a new sleep classification, independent of the Rechtschaffen and Kales system [9], is investigated by determining a limited set of quasi-stationary segments in the four main frequency bands delta, theta, alpha and beta; see e.g. [10–12].

A new computer method is proposed for identifying weak patterns which are hidden by the specific EEG signals. In EEG sleep, the classical specific signals of a healthy subject comprise 5–6 cycles of about 90 min containing the four stages of non-REM (rapid-eye-movement) sleep and REM sleep [13,14]. The four stages of non-REM sleep are: stage 1 (drowsiness) with irregular alpha waves (between 8 and 13 Hz) and some rhythmic theta waves (between 4 and 7 Hz); stage 2 with theta waves associated with sleep spindles (between 12 and 14 Hz), vertex sharp waves and K complexes; stage 3 with delta waves (less than 4 Hz) associated with spindles, vertex spikes and K complexes; and stage 4 with mainly high-voltage delta waves. REM sleep has low-voltage irregular waves.

In order to reveal weak patterns, the method developed is based on three properties:

- transformation of the EEG signal into a symbolic series according to a property of the electrical activity, here the variations between two successive values of the signal;
- analysis of this series with a symbolic correlation function based on probabilities without bias; and
- data analysis with large recorded windows (several minutes), in contrast with the methods searching specific signals with windows of a few seconds, typically between 1 and 4 s.

An application of this method to the sleep analysis of a healthy subject shows a periodicity modulo 10 in all derivations.

Method

Definition of a symbolic correlation function

An EEG signal can be associated with a series $x(t) = x_0, \ldots, x_{n-1}$ of n numerical values function of the time and expressed in μVolt [15], x_i being the ith value in $x(t)$. This numerical series $x(t)$ is transformed into a symbolic series $a(t) = a_0 \ldots a_{m-1}$ of m letters function of the time on a given alphabet A, a_i being the ith letter in $a(t)$.

The simple transformation studied here analyses the increase I and the decrease D between two successive values x_i and x_{i+1}.

$$a_i = \begin{cases} \mathrm{I} & \text{if } x_{i+1} > x_i \\ \mathrm{D} & \text{otherwise} \end{cases}.$$

This transformation leads to a symbolic series $a(t)$ with $m = n - 1$ letters on the 2-letter alphabet $A = \{\mathrm{D,I}\}$. The

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symbols I and D could roughly be associated with activation and inactivation, respectively, of neurones.

Let t, $t \in \{1,\ldots t_{\max}\}$, be the occurrence time of a letter a' after a letter a, $a,a' \in A$. In order to correct the side effect induced by the end of the symbolic series $a(t)$, the total number of letters studied in $a(t)$ is equal to the constant $m_{\max} = m - t_{\max} - 1$, i.e. independent of t [16]. The correlation function $F_{a,a'}(t)$, also noted a_a' (for simplicity), is then the function $t \rightarrow F_{a,a'}(t)$ giving the occurrence probability that the letter a' occurs at the time t after the letter a in the symbolic series $a(t)$

$$F_{a,a'}(t) = \frac{1}{m_{\max}} \sum_{i=0}^{m_{\max}-1} h_a(i) h_{a'}(i+t),$$

with $h_a(i) = \begin{cases} 1 & \text{if the letter in the position } i \text{ is } a \\ 0 & \text{otherwise.} \end{cases}$

Notes:

i $\sum_{a,a' \in A} F_{a,a'}(t) = 1 \quad \forall t.$

ii In a random series in which the two letters a and a', $a,a' \in A$ and $a \neq a'$, are generated with equiprobability, i.e. $P(a) = P(a') = 1/2$, then:
   (a) for $t > 1$, $F_{a,a'}(t) = P(a) \times P(a') = 1/4$ $\forall a,a' \in A$ (independence of two events); and
   (b) for $t = 1$, the two events are obviously not independent:
   - $F_{a,a}(1) = 1/6$ $\forall a \in A$ (one of six possibilities for $a_i a_{i+1}$ with three successive values x_i, x_{i+1} and x_{i+2});
   - $F_{a,a'}(1) = 1/3$ $\forall a,a' \in A$ (two of six possibilities for $a_i a'_{i+1}$).

iii The definition of the correlation function $F_{a,a'}(t)$ differs from the classical one of $A_{a,a'}(t)$, which is defined for $t \in \{0,\ldots,m-1\}$ by:

$$A_{a,a'}(t) = \sum_{i=0}^{m-1} h_a(i) h_{a'}(i+t),$$

such as the discrete Fourier transform (DFT) of the correlation function is the product of the Fourier transforms of the two signals whose one is conjugate:

$$\mathrm{DFT}\left[A_{a,a'}(t)\right] = \bar{H}_a(f) H_{a'}(f),$$

where $H_a(f)$ is the Fourier transform of $h_a(i)$. If $a = a'$ then the correlation function is called autocorrelation function and its Fourier transform is equal to the power spectral:

$$\mathrm{DFT}\left[A_{a,a}(t)\right] = |H_a(f)|^2.$$

The definition of $F_{a,a'}(t)$, contrary to the classical one of $A_{a,a'}(t)$, leads to probabilities without bias by correcting the side effect induced by the end of the symbolic series, i.e. there is no probability decrease when t increases. Therefore, the function $F_{a,a'}(t)$ is more suitable for revealing weak periodicities and local maxima.

iv Similar transformations, i.e. from numerical data into symbolic ones, have already been proposed, e.g. transformation into binary sequences for computing in EEG series different measures, such as the Kolmogorov complexity, the information content and the fractal dimension [4].

The correlation function a_a' is represented as a curve as follows:

i the abscissa shows the time t of the letter a' after the letter a, by varying t between 1 and $t_{\max} = 100$;

ii the ordinate gives the probability $F_{a,a'}(t)$ in the symbolic series $a(t)$.

On the alphabet $A = \{D,I\}$, there are $2^2 = 4$ correlation functions: D_D, D_I, I_D, I_I. The results given in this paper only concern the activation autocorrelation function I_I.

Data acquisition

The EEG data are obtained from a continuous record of more than 6 h 30 min in the night sleep of a healthy adult (Service de Neurologie, Neuropsychologie et Explorations fonctionnelles des Epilepsies des Hôpitaux Universitaires de Strasbourg). The record is sampled at 128 Hz (s^{-1}) and leads to $n = 3\,000\,000$ observations ($128 \times 3\,600 = 460\,800$ observations per hour) for the 20 derivations {FP1,F3,C3,P3,O1,F7, T3,T5,FP2,F4,C4,P4,O2,F8,T4,T6,FZ,CZ,PZ,OZ}. The positive and negative values of the data are given in μVolt distributed around 0 μVolt and with a sensibility at 0.1 μVolt.

Generally, the computer methods analyse the EEG signals after detection and rejection of the artefacts, such as electromyography and movement artefacts. The EEG-artefact processing is a difficult problem which is treated by several techniques such as prefiltering (wide and narrow range bandpass filters) and neural network systems for eliminating noise or for simplifying the wave recognition; see e.g. [17–19]. However, all these techniques may lead to a lost of information which can alter the spectral analysis [20]. In contrast, the approach developed here, which considers a great number of observations for identifying weak patterns, needs neither artefact processing nor window selection. The law of large numbers applied in the correlation function destroys the specific signals for revealing the common and weak signals (not detailed).

Results

Preliminary data analysis

Table 1 gives basic statistics with $n = 3\,000\,000$ observations of the 20 EEG signals. As expected with the calibrated recording, all 20 EEG signals have a mean equal to 0.0 (at the sensibility level) and a skewness very close to 0: each signal has a symmetrical distribution around 0 μVolt.

Table 1. Basic statistics of the 20 EEG signals obtained with n = *3 000 000 observations.*

	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
FP1	0.0	48.7	−361.5	364.2	0.0	4.7
F3	0.0	41.1	−360.9	359.5	0.1	5.1
C3	0.0	20.7	−351.6	203.4	−0.2	5.3
P3	0.0	21.3	−217.3	264.7	0.1	5.1
O1	0.0	40.8	−364.5	373.1	−0.1	5.7
F7	0.0	41.6	−359.5	371.7	−0.2	5.2
T3	0.0	38.2	−358.1	386.6	−0.2	6.1
T5	0.0	40.2	−358.2	359.5	−0.1	4.8
FP2	0.0	49.0	−361.7	361.0	0.1	4.7
F4	0.0	40.7	−359.4	357.9	0.2	5.2
C4	0.0	21.9	−278.4	242.6	−0.1	5.1
P4	0.0	26.1	−297.5	322.2	0.0	5.2
O2	0.0	43.5	−370.1	378.3	−0.1	6.0
F8	0.0	43.4	−358.4	372.2	−0.2	3.7
T4	0.0	37.3	−358.5	357.1	−0.1	4.9
T6	0.0	41.5	−358.9	369.3	−0.1	4.9
FZ	0.0	45.5	−360.5	384.1	0.1	4.5
CZ	0.0	21.1	−210.9	245.5	−0.1	3.6
PZ	0.0	19.6	−218.1	251.0	0.3	5.7
OZ	0.0	41.2	−387.4	389.6	−0.1	7.4

Several classical statistical parameters reveal the variability of the 20 EEG signals (table 1):

- a standard deviation with a lowest value of 19.6 for PZ and a highest value of 49.0 for FP2;
- a minimum with a lowest value of −387.4 for OZ and a highest value of −210.9 for CZ;
- a maximum with a lowest value of 203.4 for C3 and a highest value of 389.6 for OZ; and
- a kurtosis different from 0 for all the signals which do not follow a standard normal distribution.

Furthermore, the direct observation of an EEG recording does not allow the recognition of an obvious and simple pattern which is common to the 20 signals. Figures 1 (a,b) given as an example with two window recordings (about 8 s) at different times (each figure containing only two signals for readability reasons), present a 'random' aspect which contrasts with the periodicity observed in figure 2.

Identification of a periodicity modulo 10

Unexpectedly, and in contrast to the directly observed variability, the increase/decrease transformation of the numerical signal P4 and its analysis by the autocorrelation function I_I with all the observations (n = 3 000 000), identify a periodicity modulo 10 with the following properties (figure 2):

- local maximal values of the function at t around 1, 11, 21, etc. up to 91 traducing the persistence of this periodicity during about 0.78 s (about 10 waveforms) after its generation;
- a maximal value at t = 1 with a probability equal to 0.381 and a local maximum at t = 21; and
- a continuous decrease between t = 1 and 6 leading to a minimal value at t = 6 with a probability equal to 0.201.

Note that all these statistical properties observed with the autocorrelation function $F_{I,I}(t)$, would be reduced mainly to a frequency peak in 1/10 = 0.1 with the classical spectral analysis.

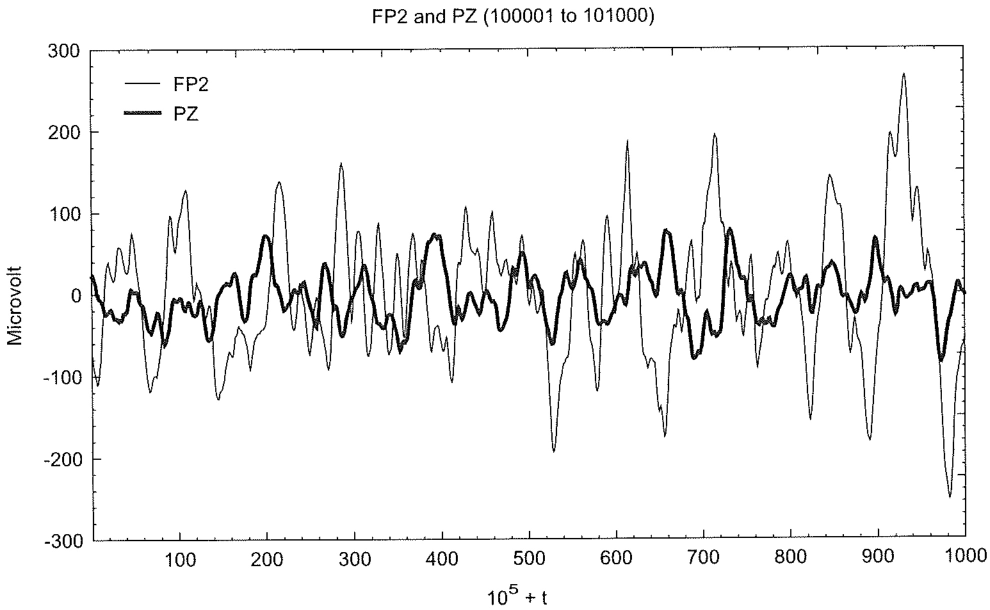
Statistical significance of this periodicity modulo 10

The statistical significance of this periodicity modulo 10 is evaluated as follows:

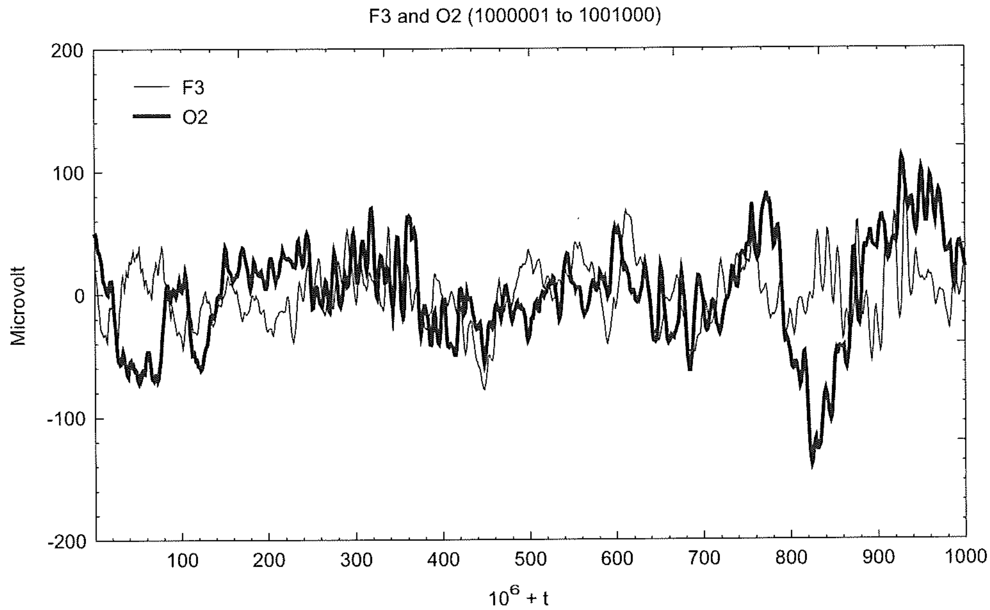
i There is no periodicity in the random case. Indeed, if the autocorrelation function I_I is applied in a random series in which the two letters D and I are generated with equiprobability, i.e. $P(\mathrm{D}) = P(\mathrm{I}) = 1/2$, then it presents a horizontal line equal to $1/4 = 0.25$ for $t > 1$ and a minimum equal to $1/6 \approx 0.166$ at $t = 1$ (see note ii in Definition of a symbolic correlation function). The random case with the autocorrelation function I_I has no periodicity, no unique maximal value and no maximal value at $t = 1$.

ii If the n = 3 000 000 observations in the signal P4 are randomly permutated, then the curve shape of the autocorrelation function I_I is identical to the random one (figure 3). Note also that the probability values of the autocorrelation function are close to the random case meaning that the letters I and D, i.e. the increase and the decrease between two successive values x_i and x_{i+1}, have approximately the same occurrence probabilities.

iii The periodicity modulo 10 also exists in different epochs of the signal P4. For example, if the n = 3 000 000 observations of P4 are divided into three successive epochs of 1 000 000 observations, i.e. from 1 to 1 000 000 (figure 4(a)), from 1 000 001 to 2 000 000 (figure 4(b)) and from 2 000 001 to 3 000 000 (figure 4(c)), the autocorrelation functions I_I applied in these three



a



b

Figure 1. Absence of an obvious and simple pattern which is common to the 20 signals in direct observation. (a) An example with the signals FP2 and PZ in a recording window (about 8 s). The horizontal axis represents the time t, $t \in \{10^5+1,\ldots,10^5+1000\}$ *with a time unit equal to 1/128 s. The vertical axis represents the values of FP2 and PZ in microvolt. (b) An example with the signals F3 and O2 in a recording window (about 8 s). The horizontal axis represents the time* t, $t \in \{10^6+1,\ldots,10^6+1000\}$ *with a time unit equal to 1/128 s. The vertical axis represents the values of F3 and O2 in microvolt.*

epochs also reveal this periodicity. This result can be related to the law of large numbers which implies stable frequencies with a great number of observations [21].

iv Very unexpectedly, this periodicity modulo 10 is present in all the 20 EEG signals (figures 5(a–t)). However, all these periodicities do not have exactly the same features. The periodicity modulo 10 is attenuated with four signals F3, F4, FZ and CZ (figures 5(b,j,q,r) respectively) with local maxima of the autocorrelation function up to 51 traducing a persistence of this periodicity during about 0.39 s (about five waveforms) instead of 0.78 s (see above).

The maximum value is always observed at $t=1$ with the highest probability (0.397) for FZ and OZ and with the lowest probability (0.369) for P3 (not shown in figures 5(a–t) for readability reasons). The minimum value is observed at t around 6 with the highest probability (0.213) for F4 (figure 5(j)) and with the lowest probability (0.197) for T6 (figure 5(p)).

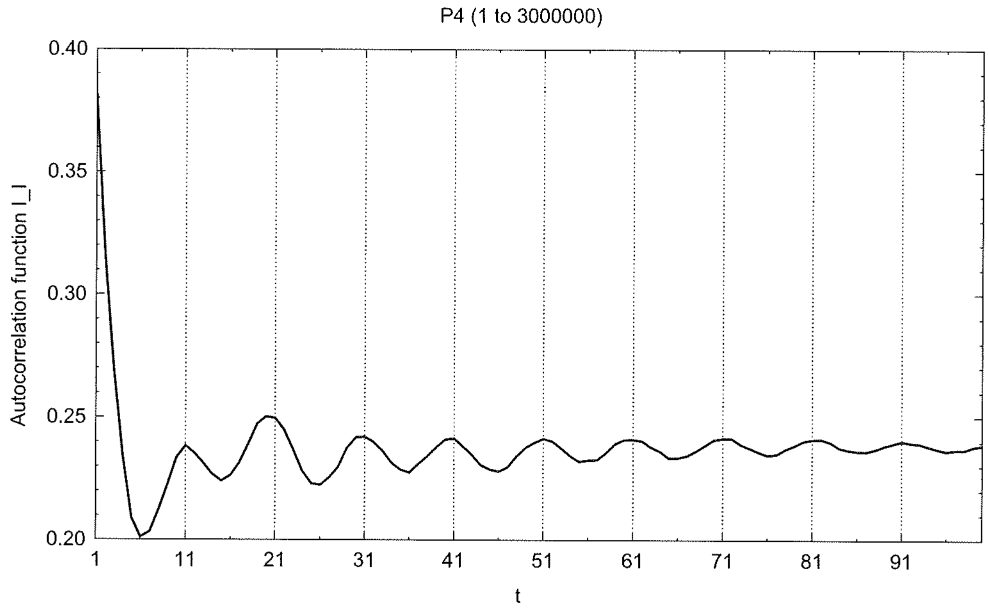


Figure 2. Identification of a periodicity modulo 10 in the signal P4 with n = *3 000 000 observations. The horizontal axis represents the time* t, t∈*{1,. . .,100} with a time unit equal to 1/128 s, between the two letters I with* $I = \{x_{i+1} > x_i\}$ *and* x *in microvolt. The vertical axis represents the autocorrelation function I_I.*

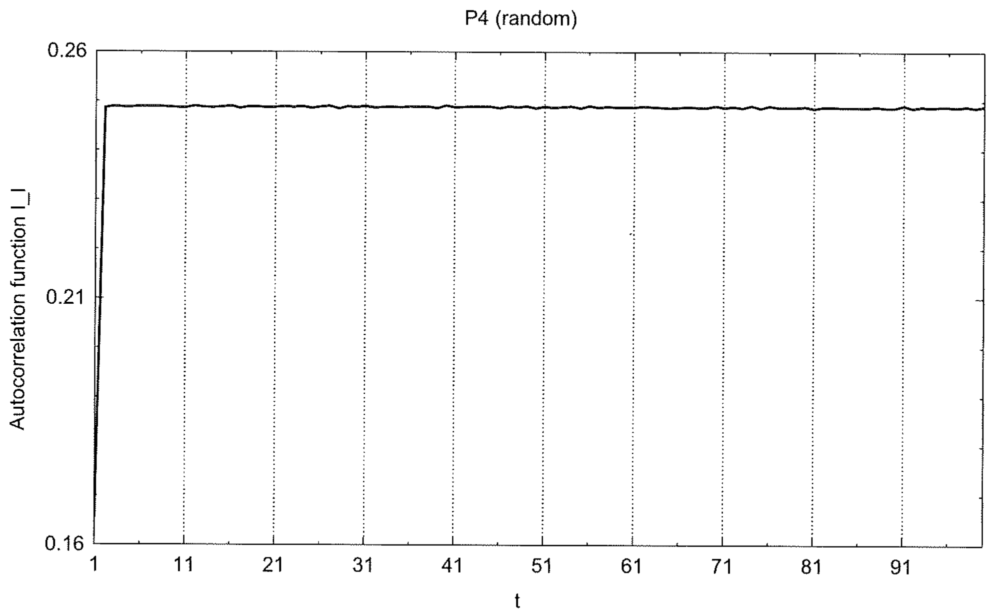


Figure 3. Loss of the periodicity modulo 10 in the signal P4 after random permutations of n = *3 000 000 observations. The autocorrelation curve shape is identical to the random one with a horizontal line close to 1/4 = 0.25 for* t > *1 and a minimum close to 1/6* ≈ *0.166 at* t = *1 (see note ii in Definition of a symbolic correlation function). The horizontal axis represents the time* t, t∈*{1,. . .,100} with a time unit equal to 1/128 s, between the two letters I with* $I = \{x_{i+1} > x_i\}$ *and* x *in microvolt. The vertical axis represents the autocorrelation function I_I.*

Discussion

The main purpose of this work is the development of a new computer method for identifying weak patterns in EEG signals, e.g. periodicities. The method developed is simple and based on three properties:

- transformation of the EEG signal into a symbolic series according to the variations between two successive values of the signal;
- analysis of this series with a symbolic correlation function based on probabilities without bias; and
- data analysis with large recorded windows (several minutes).

Other methods are based on a principle of transformation of the EEG signal in order to reduce the complexity of the waveform [22], in particular transformation methods into binary sequences (e.g. [4]) and

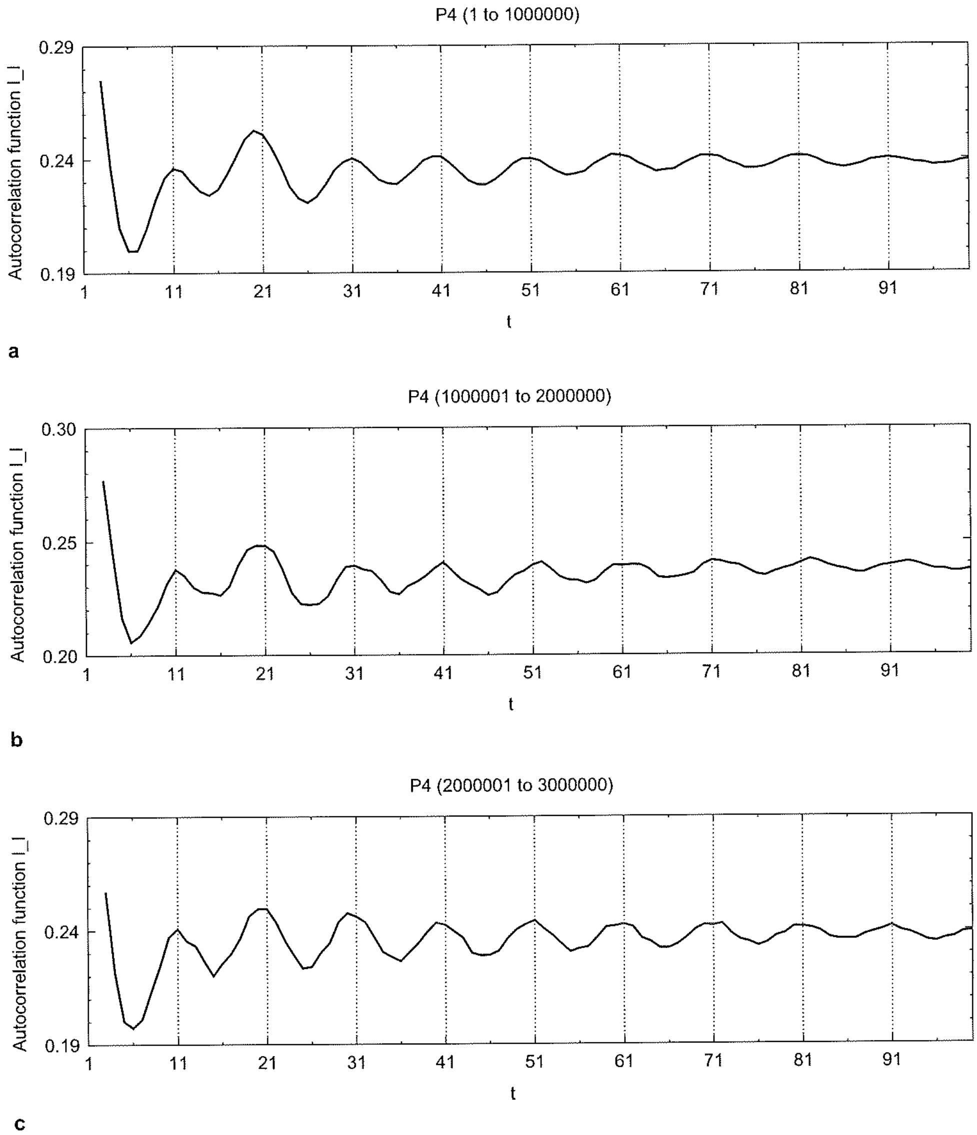


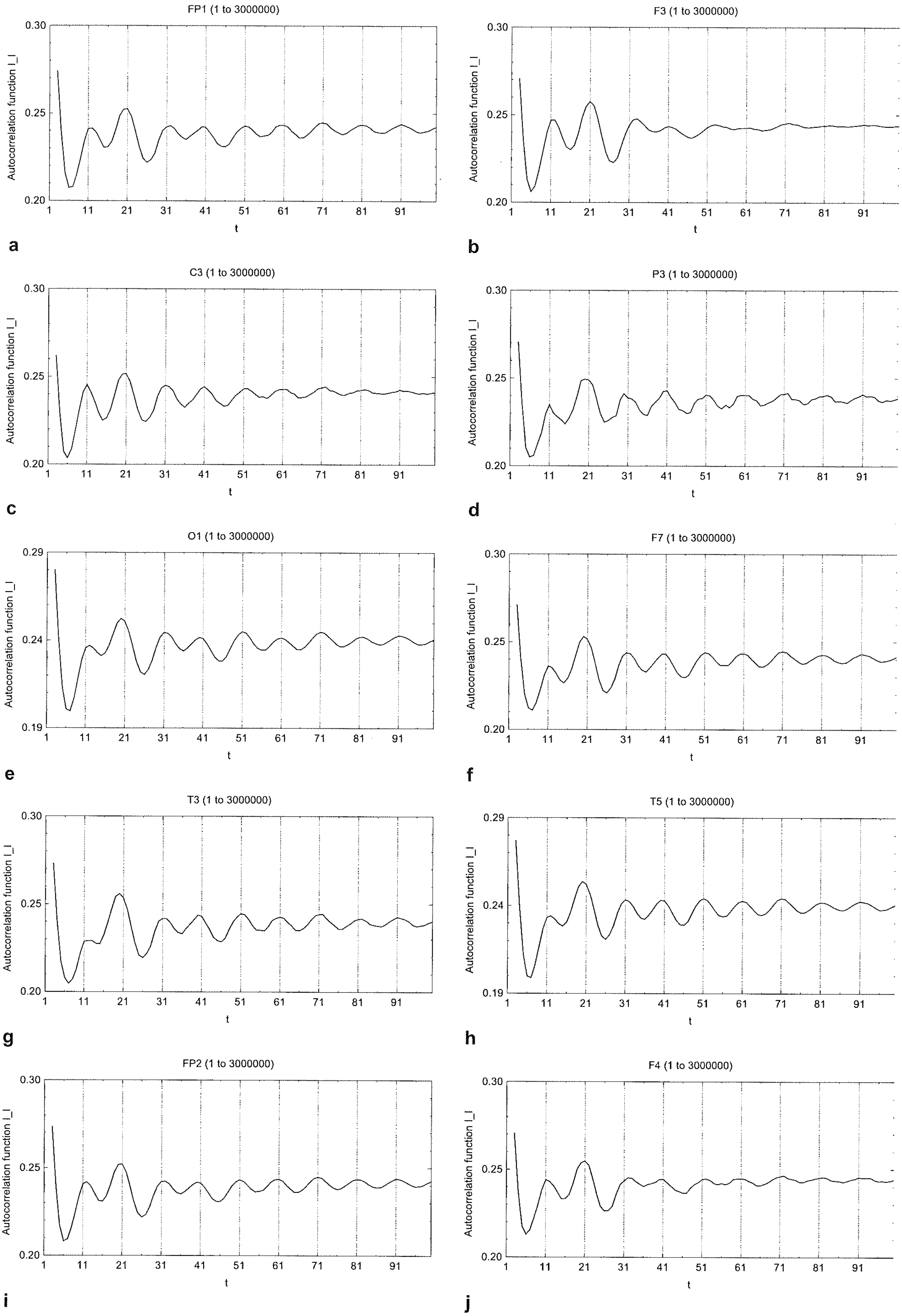
Figure 4. Periodicity modulo 10 in the signal P4 with an epoch of 1 000 000 observations from (a) 1 to 1 000 000; (b) 1 000 001 to 2 000 000; and (c) 2 000 001 to 3 000 000. The horizontal axis represents the time t, $t\in\{3,\ldots,100\}$ *(for readability reasons) with a time unit equal to 1/128 s, between the two letters I with* $I=\{x_{i+1} > x_i\}$ *and* x *in microvolt. The vertical axis represents the autocorrelation function I_I.*

Fujimori's method (reviewed in [23]) which transforms a simple waveform by a single measured value in the corresponding frequency, while the spectral analysis results in a wider distribution in frequencies.

A few other transformations have been tested with this correlation function definition, but without success. For example, the intensity level of the value x_i, instead of its variation, has been considered by dividing the frequency band, for example from -400 to 400 μVolt into ranges of 50 μVolt and by associating a given letter a_i^j, $j \in \{1,\ldots,16\}$, on the 16-letter alphabet $A=\{a^1,\ldots,a^{16}\}$ to the value x_i such as $-400+50(j-1) \leqslant x_i < -400+50j$. The 16 autocorrelation functions $a^j\_a^j$ applied in this symbolic series do not reveal any patterns (data not shown).

Neurophysiological interpretation of this periodicity modulo 10 must be carried out with caution as the results are observed with a unique recording of one adult. For deducing new properties in the EEG signals, these results must be confirmed with other records, investigation of which is not the aim of this paper.

However, in this study, the periodicity which is observed in a large continuous record (about 6 h 30 min) in the night sleep of a healthy adult and in its different epochs, could be associated with a weak and non-random sleep signal hidden by the specific ones (mentioned in Introduction). A periodicity modulo 10 leads to a frequency of 12.8 Hz which belongs to the frequency band of alpha waves. Therefore, this periodicity could traduce the presence of alpha waves during the sleep, for every sleep stage and in all derivations. For almost all derivations, the persistence time of this periodicity is about 0.78 s after generation.


FP1 (1 to 3000000)
F3 (1 to 3000000)
C3 (1 to 3000000)
P3 (1 to 3000000)
O1 (1 to 3000000)
F7 (1 to 3000000)
T3 (1 to 3000000)
T5 (1 to 3000000)
FP2 (1 to 3000000)
F4 (1 to 3000000)
Autocorrelation function I_l
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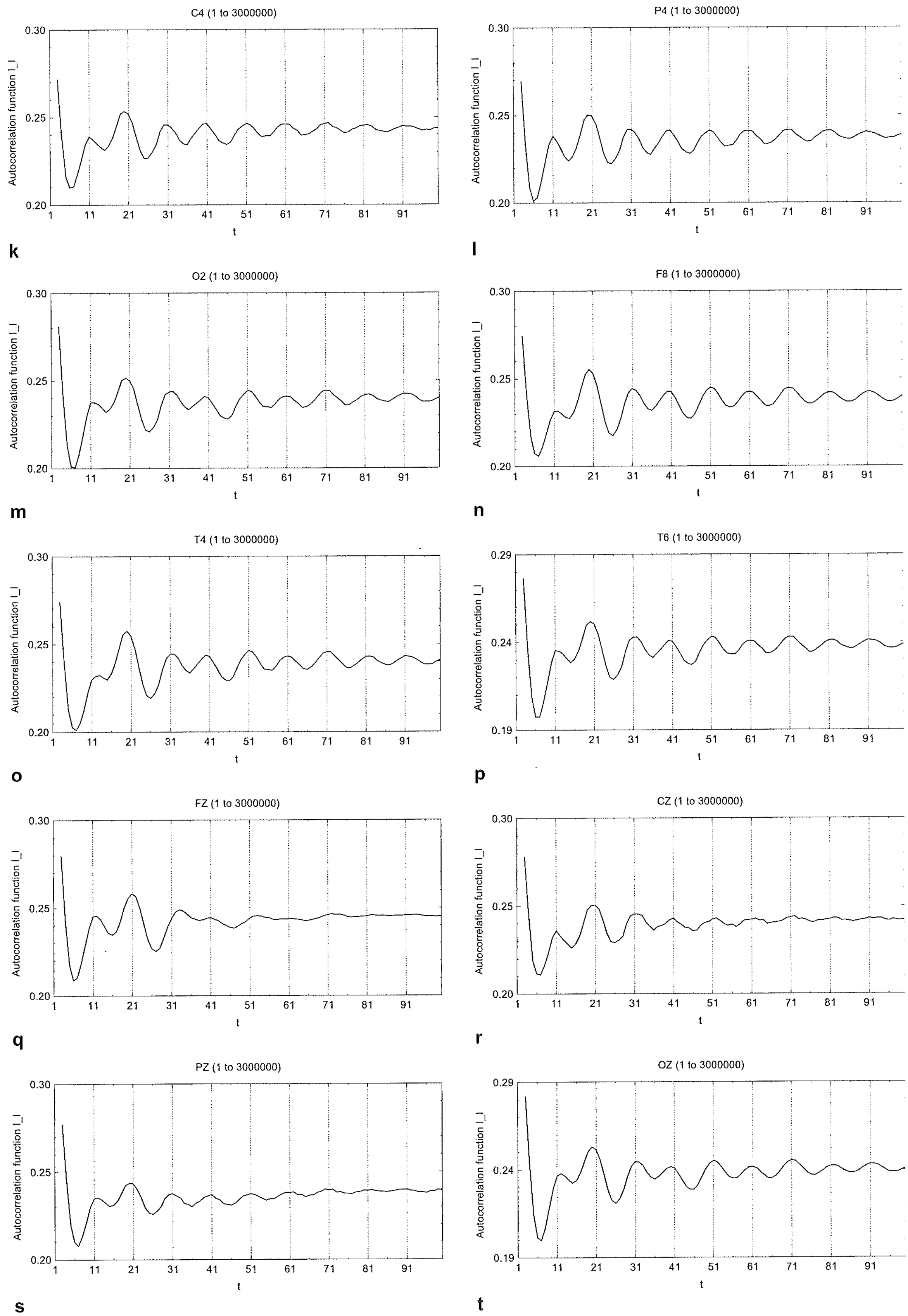

Figure 5. Periodicity modulo 10 in the signal (a) FP1; (b) F3 (c) C3; (d) P3; (e) O1; (f) F7; (g) T3; (h) T5; (i) FP2; (j) F4; (k) C4; (l) P4; (m) O2; (n) F8; (o) T4; (p) T6; (q) FZ; (r) CZ; (s) PZ; and (t) OZ.

This observation of alpha waves during sleep can be related with previous similar reports. It has been initially described with a mixture of delta waves in the unipolar C4 recording in psychiatric patients such as schizophrenia and depression [24], fibrositis syndrome [25], etc. Also, it has been reported in healthy subjects in NREM sleep and to a lesser degree though, in REM sleep [26], and in occipital and parietal derivations [27].

The principle of transformation of the EEG signal into a word on a given alphabet also allows the use of text algorithms (reviewed in [28]) for identifying new EEG patterns.

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References

1. Berger, H., 1929, Uber das Elektrenkephalogramm des Menschen. *Archiv für Psychiatrie und Nervenkrankheiten,* **87,** 527–570.
2. Niedermeyer, E., 1993, The normal EEG of the waking adult. In *Electroencephalography: basic principles, clinical applications and related fields,* third edition, edited by E. Niedermeyer and F. H. Lopes da Silva, (Baltimore: Williams and Wilkins), p. 131.
3. Quian Quiroga, R., and Schürmann, M., 1999, Functions and sources of event-related EEG alpha oscillations studied with the Wavelet Transform. *Clinical Neurophysiology,* **110,** 643–654.
4. Petrosian, A., 1995, Kolmogorov complexity of finite sequences and recognition of different preictal EEG patterns. *Proceedings of the 8th IEEE Symposium on Computer-Based Medical Systems,* June 9–10, 212–217, Lubbock, Texas: IEEE Computer Society Press).
5. Klatchko, A., Raviv, G., Webber, W. R. S., and Lesser, R. P., 1998, Enhancing the detection of seizures with a clustering algorithm. *Electroencephalography and Clinical Neurophysiology,* **106,** 52–63.
6. Beun, A. M., van Emde Boas, W., and Dekker, E., 1998, Sharp transients in the sleep EEG of healthy adults: a possible pitfall in the diagnostic assessment of seizure disorders. *Electroencephalography and Clinical Neurophysiology,* **106,** 44–51.
7. Sartoretto, F., and Ermani, M., 1999, Automatic detection of epileptiform activity by single-level wavelet analysis. *Clinical Neurophysiology,* **110,** 239–249.
8. Schneider-Helmert, D., and Kumar, A., 1995, Sleep, its subjective perception, and daytime performance in insomniacs with a pattern of alpha sleep. *Biological Psychiatry,* **37,** 99–105.
9. Rechtschaffen, A., and Kales, A., 1968, A manual standardized terminology, techniques and scoring system for sleep stages of human subjects. Public Health Service, NIH Publication N° 204, US Government Printing Office, Washington, DC.
10. Hirshkowitz, M., and Moore, C. A., 1994, Issues in computerized polysomnography. *Sleep,* **17,** 105–112.
11. Hasan, J., 1996, Past and future of computer-assisted sleep analysis and drowsiness assessment. *Journal of Clinical Neurophysiology,* **13,** 295–313.
12. Kaplan, A., Röschke, J., Darkhovsky, B., and Fell, J., 2001, Macrostructural EEG characterization based on nonparametric change point segmentation: application to sleep analysis. *Journal of Neuroscience Methods,* **106,** 81–90.
13. Broughton, R. J., 1987, Polysomnography: Principles and applications in sleep and arousal disorders. In *Electroencephalography,* second edition, edited by E. Niedermeyer and F. Lopes da Silva, (Baltimore: Urban and Schwarzenberg).
14. Carskadon, M. A., and Rechtschaffen, A., 1989, Monitoring and staging human sleep. In *Principles and practice of sleep medicine,* edited by M. H. Kryger, T. Roth and W. C. Dement, (Philadelphia: Saunders).
15. Gevins, A. S., 1987, Correlation analysis. In *Methods of Analysis of Brain Electrical and Magnetic Signals (Handbook of Electroencephalography and Clinical Neurophysiology, revised series, vol. 1),* edited by A. S. Gevins and A. Rémond, (Amsterdam: Elsevier).
16. Arquès, D. G., and Michel, C. J., 1987, A purine-pyrimidine motif verifying an identical presence in almost all gene taxonomic groups. *Journal of Theoretical Biology,* **128,** 457–461.
17. Sadasivan, P. K., and Dutt, D. N., 1994, Minimization of EOG artefacts from corrupted EEG signals using a neural network approach. *Computers in Biology and Medicine,* **24,** 441–449.
18. Saastamoinen, A., Pietila, T., Varri, A., Lehtokangas, M., and Saarinen, J., 1998, Waveform detection with RBF network–application to automated EEG analysis. *Neurocomputing,* **20,** 1–13.
19. Robert, C., Guilpin, C., and Limoge, A., 1998, Review of neural network applications in sleep research. *Journal of Neuroscience Methods,* **79,** 187–193.
20. Nuwer, M. R., 1988, Quantitative EEG: I. Techniques and problems of frequency analysis and topographic mapping. *Clinical Neurophysiology,* **5,** 1–43.
21. Arquès, D. G., and Michel, C. J., 1990, A model of DNA sequence evolution. Part 1: Statistical features and classification of gene populations. Part 2: Simulation model. Part 3: Return of the model to the reality. *Bulletin of Mathematical Biology,* **52,** 741–772.
22. Ktonas, P. Y., and Gosalia, A. P., 1981, Spectral analysis vs. period-amplitude analysis of narrow band EEG activity: a comparison based on the sleep delta-frequency band. *Sleep,* **4,** 193–206.
23. Uchida, S., Matsuura, M., Ogata, S., Yamamoto, T., and Aikawa, N., 1996, Computerization of Fujimori's method of waveform recognition. A review and methodological considerations for its application to all-night sleep EEG. *Journal of Neuroscience Methods,* **64,** 1–12.
24. Hauri, P., and Hawkins, D. R., 1973, Alpha-delta sleep. *Electroencephalography and Clinical Neurophysiology,* **34,** 233–237.
25. Moldofsky, H., Scarisbrick, P., England, R., and Smythe, H., 1975, Muskuloskeletal symptoms and non-REM sleep disturbance in patients with "fibrositis syndrome" and healthy subjects. *Psychosomatic Medicine,* **37,** 341–351.
26. Scheuler, W., Stinshoff, D., and Kubicki, S., 1983, The alpha-sleep pattern. Differentiation from other sleep patterns and effect of hypnotics. *Neuropsychobiology,* **10,** 183–189.
27. Dumermuth, G., Lange, B., Lehmann, D., Meier, C. A., Dinkelmann, R., and Molinari, L., 1983, Spectral analysis of all-night sleep EEG in healthy adults. *European neurology,* **22,** 322–339.
28. Crochemore, M., and Rytter, W., 1994, *Text algorithms.* (New York: Oxford University Press).