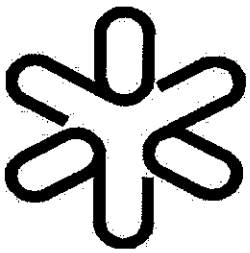

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Epileptic activity recognition in EEG recording

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Abstract

We apply Approximate Entropy (ApEn) algorithm in order to recognize epileptic activity in electroencephalogram recordings. ApEn is a recently developed statistical quantity for quantifying regularity and complexity. Our approach is illustrated regarding different types of epileptic activity. In all segments associated with epileptic activity analysed here the complexity of the signal measured by ApEn drops abruptly. This fact can be useful for automatic recognition and detection of epileptic seizures.

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I. INTRODUCTION

One of the main problems in the physics of complex systems is how to define a measure that can diagnose the kind of dynamics characterizing a given system. The potential applications of such a measure are enormous. Recently, a measure of complexity so-called approximate entropy (ApEn) has been introduced by S.M. Pincus [1,2]. This measure is a quantification of regularity in time series data, motivated by applications to relative short, noisy data sets. It has been applied to a diversity of physiological signals [3–6]. We will apply it here to electroencephalogram (EEG) signals in order to identify epileptic seizures (ES).

Usually, the discrimination between different dynamics in nonlinear chaotic systems will mean establishing an adequate set of invariant measures, such as: fractal spectrum, Lyapunov exponents, Kolmogorov entropy, etc. [7–9]. These measures have been developed to characterize nonlinear dynamical systems and their blind application to experimental time series may easily produce spurious results [10,11]. Even for low dimensional chaotic systems a huge amount of clean data are needed for a reliable estimation of these measures (about 10^d where d is the embedding dimension [12]). Thus, long stationary time series of EEG signals are required by those methods. In most cases, the stationarity of the signal is usually taken for granted, although this condition may not be satisfied when we deal with EEG signals [13]. Thus, these methods have poor discrimination power. Moreover, they are not useful for an accurate temporal localization of transient events in EEG recordings [14,15].

The traditional clinical application of the EEG is in the identification of ES, where the background activity is interrupted by sharp-waves, spikes, or spike-wave complexes [16–19]. The morphology of these sharp transients has been correlated with different types of ES [20]. For this reason, methods used to detect seizures, based solely in the morphology aspect, require a big data base of morphology aspects in order to make a precise identification, as any epileptic pattern not present in the data base would not be identified.

In contrast, the approach presented here is able to characterize the different types of ES

using short portions of signals. We shall apply a criterium for characterization based on the loss of complexity during the seizure, due to synchronous discharge of large groups of neurons. In fact, the loss of complexity associated with all types of ES has been corroborated by some researchers, who have found low correlation dimension for EEG signals recording during seizure [21–24], while normal EEG signals can be described better as linearly filtered noise [25].

In the present effort, we shall not try to establish the existence of chaos or estimate invariant measures of ES in EEG recording. We compute a complexity measure to quantify the regularity of the dynamics underlying the EEG. The complexity measure is computed by the ApEn algorithm that uses sliding temporal window. It should be remarked that this complexity measure is not invariant [1]. This is a very useful property because, when dealing with EEG signals, it is difficult to obtain a long transient for a reliable estimation of the invariant measure.

The detection and spatial localization of epileptic activity are particularly valuable in dealing with focal epilepsy, specially when surgical treatment is indicated [26]. The methodology presented here uses a short interval (about 1 seconds of standard clinical EEG) to identify epileptic activity. An effective temporal localization is useful for the spatial estimation of the epileptogenic focus [26,27].

We organize our presentation as follows: in Sec. II we review some ideas concerning the method of quantification of regularity, i.e. the approximate entropy algorithm. We describe also the procedure used to record the EEG signals. In Sec. III we present our results regarding the EEGs of patients with epilepsy. Finally some conclusions are drawn in Sec. IV.

II. METHOD AND DATA

A. Approximate Entropy algorithm

We shall present briefly the ApEn method for measuring complexity or regularity of the time series. We assume that the EEG signal is a stroboscopic sequence of N measurement $\{v(t_0), v(t_0+\tau_s), \ldots, v(t_0+N\tau_s)\}$ made at intervals τ_s. We construct a sequence of vectors using time delay embedding [28], which uses a collection of coordinates with time lag to create a vector in d dimensions,

$$\mathbf{v}(n) = (v(t_n), v(t_n-\Delta), \ldots, v(t_n-(d-1)\Delta)), \tag{1}$$

where $\Delta = n\tau_s$, $(n \in \mathcal{N})$, is the time lag or delay.

Now, we define the distance $d[\mathbf{v}(i), \mathbf{v}(j)]$ between vectors $\mathbf{v}(i)$ and $\mathbf{v}(j)$ as the maximum difference in their respective scalar components. For each $i \leq N-(d-1)\Delta$, we use the sequence $\mathbf{v}(1), \mathbf{v}(2), \ldots, \mathbf{v}(N-(d-1)\Delta)$ to construct,

$$C_i^d(r) = \frac{1}{N-(d-1)\Delta} \sum_j \theta(r - d[\mathbf{v}(i), \mathbf{v}(j)]) \ , \tag{2}$$

where $\theta(x)$ is the step function ($\theta(x) = 1$ if $x > 0$, and 0 otherwise). $C_i^d(r)$ is a measure, *within a tolerance* r, of the regularity (or frequency) of patterns similar to a given pattern i of length $d \times \Delta$. Now we define

$$\Phi^d(r) = \frac{1}{N-(d-1)\Delta} \sum_i \ln\left[C_i^d(r)\right]. \tag{3}$$

Then, $ApEn(d,r)$ is defined by

$$ApEn(d,r) = \lim_{N\to\infty}\left[\Phi^d(r) - \Phi^{d+1}(r)\right]. \tag{4}$$

Given N data points, we implement (4) by defining the *statistics* [4]:

$$ApEn(d,r,N) = \Phi^d(r) - \Phi^{d+1}(r). \tag{5}$$

Thus, the ApEn measures the logarithmic likelihood that sets of patterns that are close for d observations remain close on the next incremental comparisons. We can see easily that in the limit $r \to 0$, and $d \to \infty$, Eq. (4) is the Kolmogorov-Sinai entropy [29].

Three input parameters d, r, and N, must be fixed to compute $ApEn(d, r, N)$: d is the dimension of the compared vectors, r is effectively a filter, and N is the number of data points. Studies based on both theoretical analysis and clinical applications [4,30] suggest that for $d = 1$ and 2, values of the parameter r between 10% to 25% of the standard deviation (SD) of the signal produce good statistical validity of the ApEn. For ApEn computation the number of N of data points is tipically between 75 and 5000.

B. Clinical Data

As control group we have taken the EEG recordings from ten normal individuals, males. between 26 and 47 years old, free of a past history or current symptoms of psychopathology. The recordings have been obtained under wakefulness, with the individuals physically and mentally at rest, and closed eyes. For the epileptic group, we considered EEG recordings from 6 male and 2 female, between 5 and 39 years old, showing evident paroxysmal discharges. Three of the patients present clinical history of partial seizure, two of generalized seizure, and three of partial seizure that turns into generalized. These patients were examined under one of the following conditions: in the basal conditions of the normal patients, spontaneous or induced sleep, and hyperventilation. These EEG recordings were previously examined by a clinical specialist in order to make sure that they were free of artefacts.

The recordings have been obtained using a standard clinical device (International 10/20 Systems) connected to the scalp, a reference electrode being placed at the patient's nose. The data was amplified and filtered using a low-frequency cut-off of 0.1 Hz, and high-frequency cut-off of 50 Hz. The data was stored on magnetic tape and then digitized off-line at 256 Hz with 8 bit digitizer. In order to test the method in the case of presence of artefacts, we considered also two additional EEG recordings: channel Fp1 from a normal

individual during eyes-blink, and channel O1 from a patient with focal epilepsy during interictal activity at sleep stage I-II. These recordings have been obtained in the same conditions above mentioned, but with 102.5 Hz of sampling frequency.

III. RESULTS

We compute $ApEn(2, r, N)$ using a slide window with $N = 250$, with overlap of 220 samples, for different values of parameter r. We found that $r = 0.25 \times \mathrm{SD}$ is a useful choice for our applications. In all cases the time lag used corresponds to one sample ($\Delta = \tau_s$).

The ApEn algorithm, with the parameters above mentioned, was applied to EEG recordings of both the control group and the epileptic group. In the epileptic group the characterization of epileptic seizures was illustrated regarding all available situations: during epileptic activity from patients with focal epilepsy, generalized epilepsy, and partial seizures that turn into generalized. It is important to use a great variety of epileptic pattern in order to guarantee a good performance in clinical monitoring.

A representative sample of our results is given in Fig. 1. At the top of the Fig. 1 we can see the channel F8 of the EEG recording from a patient with generalized epilepsy, the seizure presenting sharp waves. At the bottom of the same figure is displayed the corresponding ApEn. We can clearly see huge sharp decrease of the ApEn at the points where epileptic activity occurs. This decrease in the ApEn is due to a complexity decrease in the EEG during the seizure, as many authors have reported using other techniques. At the top of the Fig. 2 is presented the EEG from a healthy subject, at the bottom the corresponding ApEn. In contrast with the case of epileptic signals, the ApEn does not fall below 0.5. The variations of the ApEn take into account the different degrees of complexity registered in the EEG of the healthy subject.

From the eight patients of the epileptic group, we selected 122 time epochs of epileptic activity, and a mean value of the ApEn is calculated for each epoch. Each epoch has 730 data points corresponding to 17 windows. Table I shows the minimum and the maximum mean

values of ApEn registered in the EEG recording of each patient. The values are between 0.27 to 0.43. The mean value of ApEn for each patient during all epochs are shown in the third column of Table I. Table II shows the mean value of ApEn for EEG recording of ten subjects of the control group (only F4 and F8 have been considered in the calculations). In this case, the ApEn values are between 0.6 to 1. Thus, it may be possible to devise a technical device that uses the crossing of threshold for the automatic detection of ES.

At the top of Fig. 3 we can see the channel O1 of a patient with focal epilepsy at sleep stage I-II. The segment was recorded with 102.5 samples per second, and presents interictal activity (spike-wave complexes in this case). As we can see at the bottom of Fig. 3, the concomitant ApEn drops in essentially the same form as shown at the bottom of the Fig. 1. This means that the present method is robust both with respect to the behavioral state of the patients, and the morphologic patterns of the epileptic activity.

We tested the method in an interesting situation related to the problem of false positives. In some cases decrease in the ApEn could arise from other sources like eyes-blink, motion artifacts, etc. At the top of Fig. 4, we show the EEG signal of the channel Fp1 from a healthy subject (vigilia, closed eyes). This signal was recorded with 102.5 samples per second, and presents several eyes-blink. In this case, decreases in the ApEn are observed, indicating that the signal with eyes-blink has also low complexity. However, the decrease of the ApEn in this case is less than in the epileptic activity case (see Fig. 3 for comparison). This means that the ApEn can discriminate false positives from the true positives. In the cases illustrated in the figures 3 and 4, the ApEn was computed using $N = 125$ with overlap of 110 samples. This smaller number of points introduces a slight increase in the ApEn values in comparison with the other calculations.

IV. DISCUSSION AND CONCLUSIONS

We have presented here an alternative method for characterizing and detecting ES. We applied it in the characterization of epileptic activity in nine patients. Different kinds of

epilepsy, different time intervals for the same patient, and different epileptic patterns have been analysed. In all cases an effective characterization of the seizure has been possible. Thus, the main advantage of the methodology presented here is its robustness in the characterization of different types of epileptic patterns.

Another remarkable facet of the present technique is that we use only about 1 second of standard clinical recording in order to characterize the loss of complexity associated with the seizure. This is an important fact because, when we deal with EEG signal, it is difficult to obtain a long transient for a reliable estimation of the invariant measures. Thus, the problems associated with the nonstationarity of the EEG signals are avoided.

We conclude that the ApEn provides an effective temporal localization of a great variety of ES, using a relative small amount of data. In dealing with focal epilepsy, the high temporal resolution is particularly valuable because it improves the possibility of localizing and monitoring the epileptic focus activity using a multi-channel EEG recording [27]. The computational burden is significantly low, and can be implemented on-line, with the acquisition of the signal, in cases requiring many hours of EEG recording for a reliable diagnosis.

For most normal subjects analysed here, we found a greater complexity in channel F8 than in the channel F4, as we can see in Table 2. This fact indicates that the ApEn is a very useful quantity for characterizing the complexity of EEG from a short portion of the EEG.

V. ACKNOWLEDGMENTS

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TABLES

patients	ApEn min. value	ApEn max value	$\langle ApEn \rangle$	SD
0358 G	0.37	0.43	0.40	0.022
1072 G	0.28	0.39	0.32	0.030
1126 P	0.34	0.39	0.36	0.027
1211 P	0.27	0.40	0.35	0.030
1741 P	0.30	0.35	0.32	0.017
1176 P→G	0.32	0.36	0.34	0.017
0748 P→G	0.27	0.30	0.28	0.019
0857 P→G	0.30	0.38	0.33	0.040

TABLE I. ApEn (min, max, mean value, SD) for eight patients with epilepsy. Only segments with paroxismal discharges have been considered in the calculations.

patients	$\langle ApEn \rangle$	SD	$\langle ApEn \rangle$	SD
0317	0.749	0.011	0.839	0.011
0420	0.658	0.007	0.694	0.007
1053	0.646	0.008	0.764	0.010
1066	0.669	0.008	0.628	0.008
1359	0.745	0.013	0.797	0.012
1377	0.802	0.013	0.941	0.009
1949	0.723	0.006	0.753	0.019
0450	0.589	0.005	0.675	0.040
0624	0.649	0.008	0.679	0.007
0949	0.689	0.008	0.709	0.010

TABLE II. ApEn (mean value and SD) for ten normal subjects. Only two channels have been considered, F4 on the left, and F8 on the right. We can see that the ApEn in F8 is greater than the ApEn F4 in nine out of ten subjects.

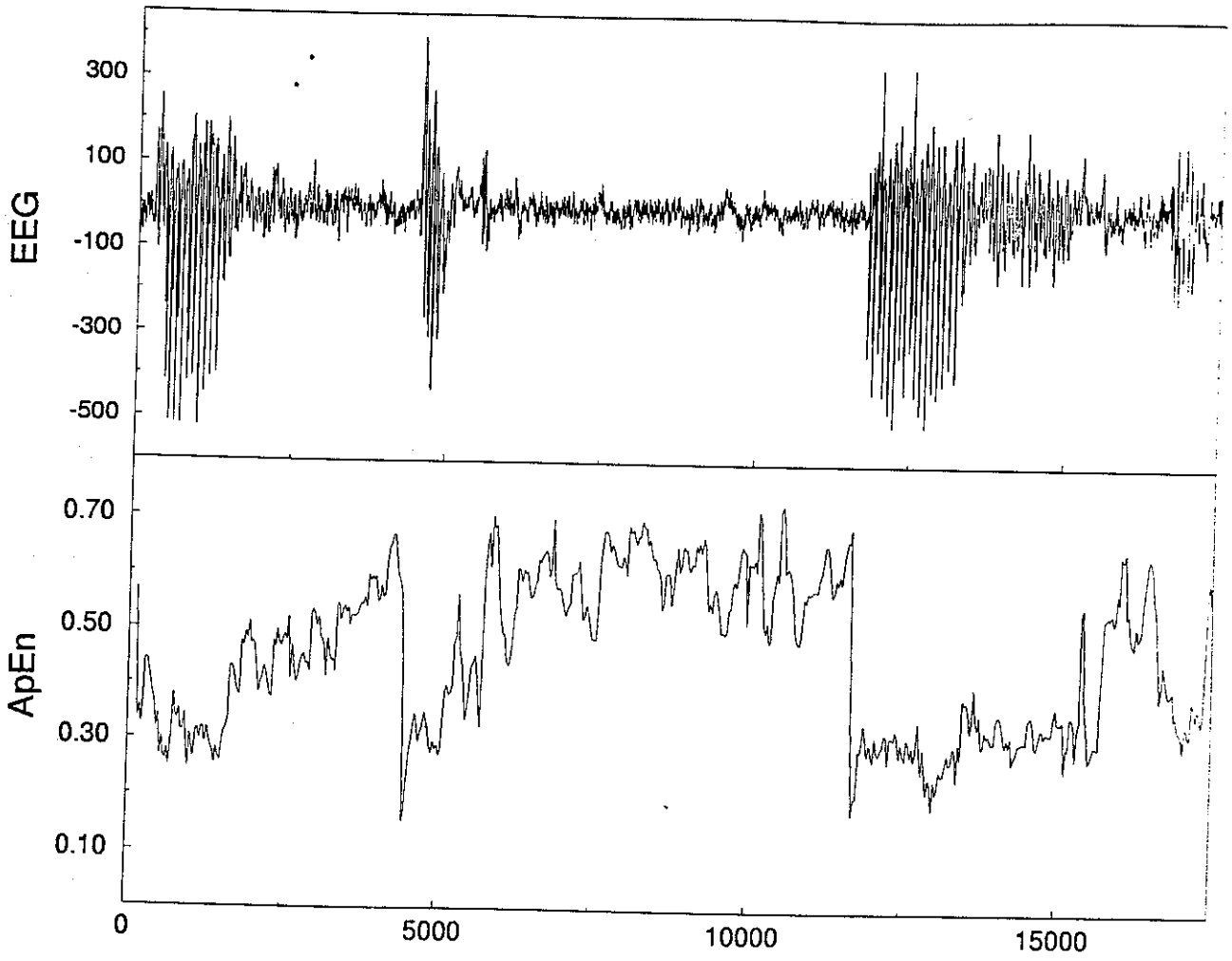

FIG. 1. Top: about 70 seconds of EEG recording from the patient 1072 with generalized epilepsy (channel F8). Bottom: the corresponding ApEn using $d = 2$, $r = 0.25\times$ SD, and $N = 250$ (with overlap of 30 samples).

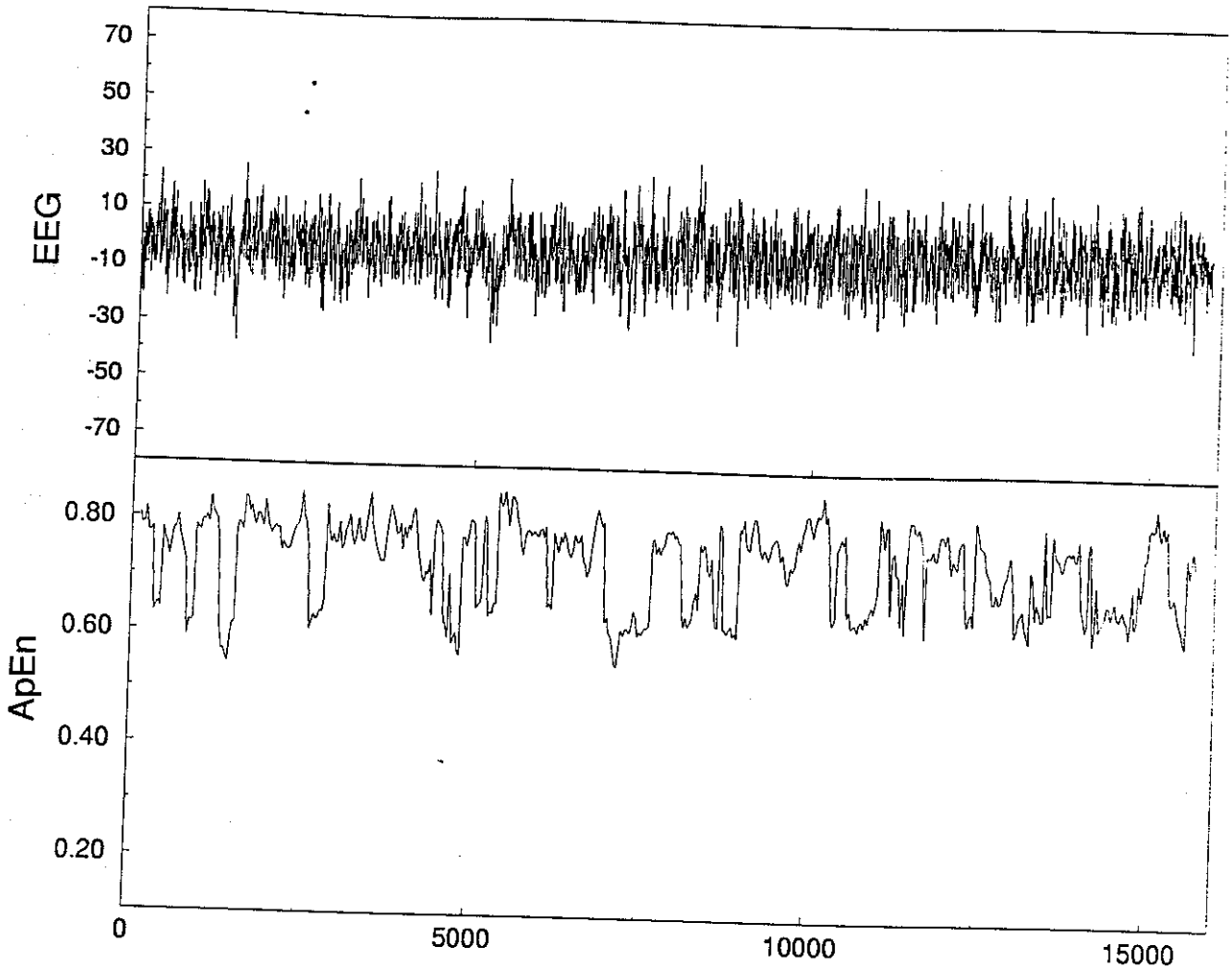

FIG. 2. Top: about 65 seconds of EEG recording from the healthy patient 1949 (channel F8). Bottom: the corresponding ApEn using the same parameters d, r, and N of Fig. 1.

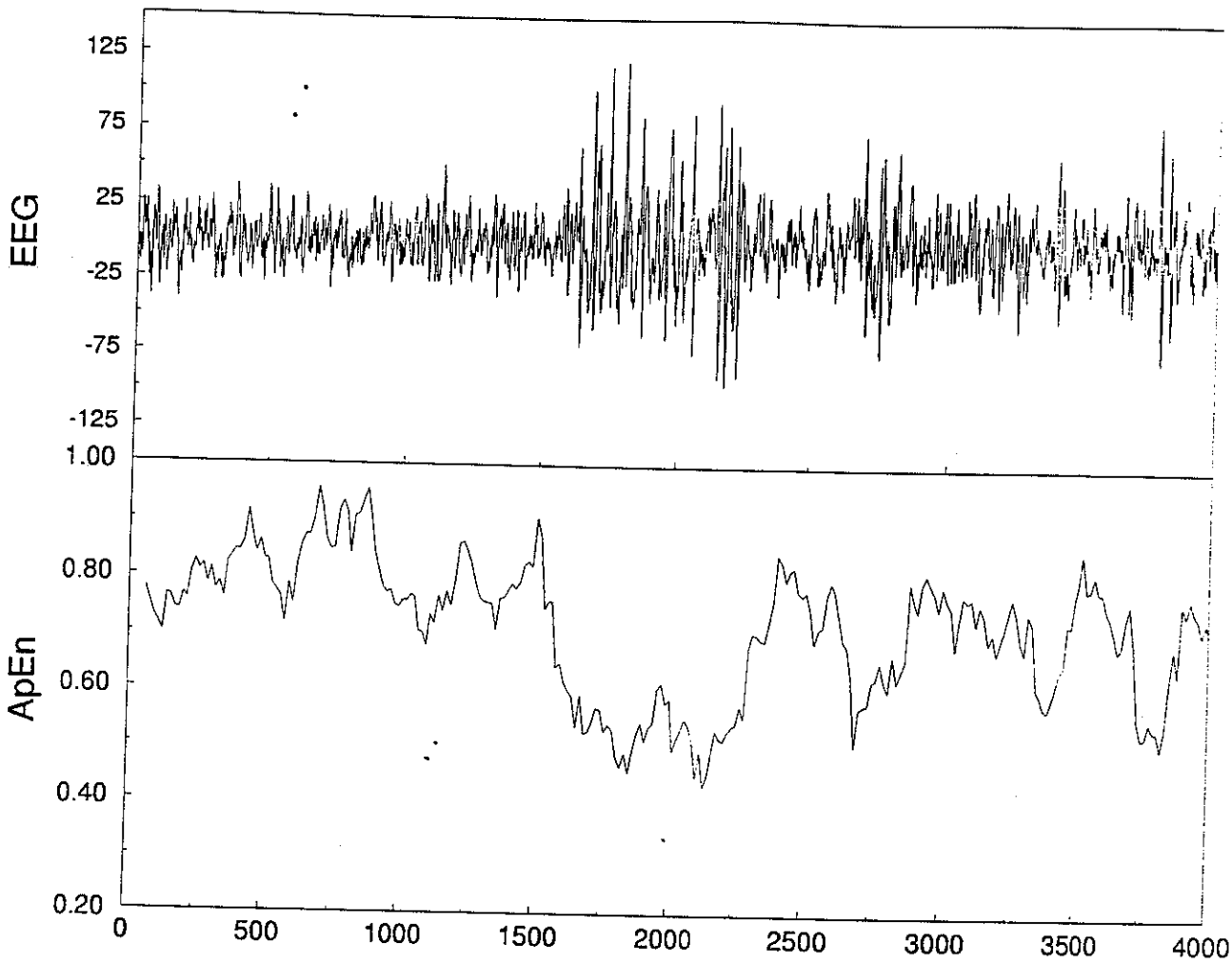

FIG. 3. Top: about 40 seconds of EEG recording from the patient 1002 with focal epilepsy (channel O1). Bottom: the corresponding ApEn using $d = 2$, $r = 0.25\times$ SD, and $N = 125$ (with overlap of 110 samples).

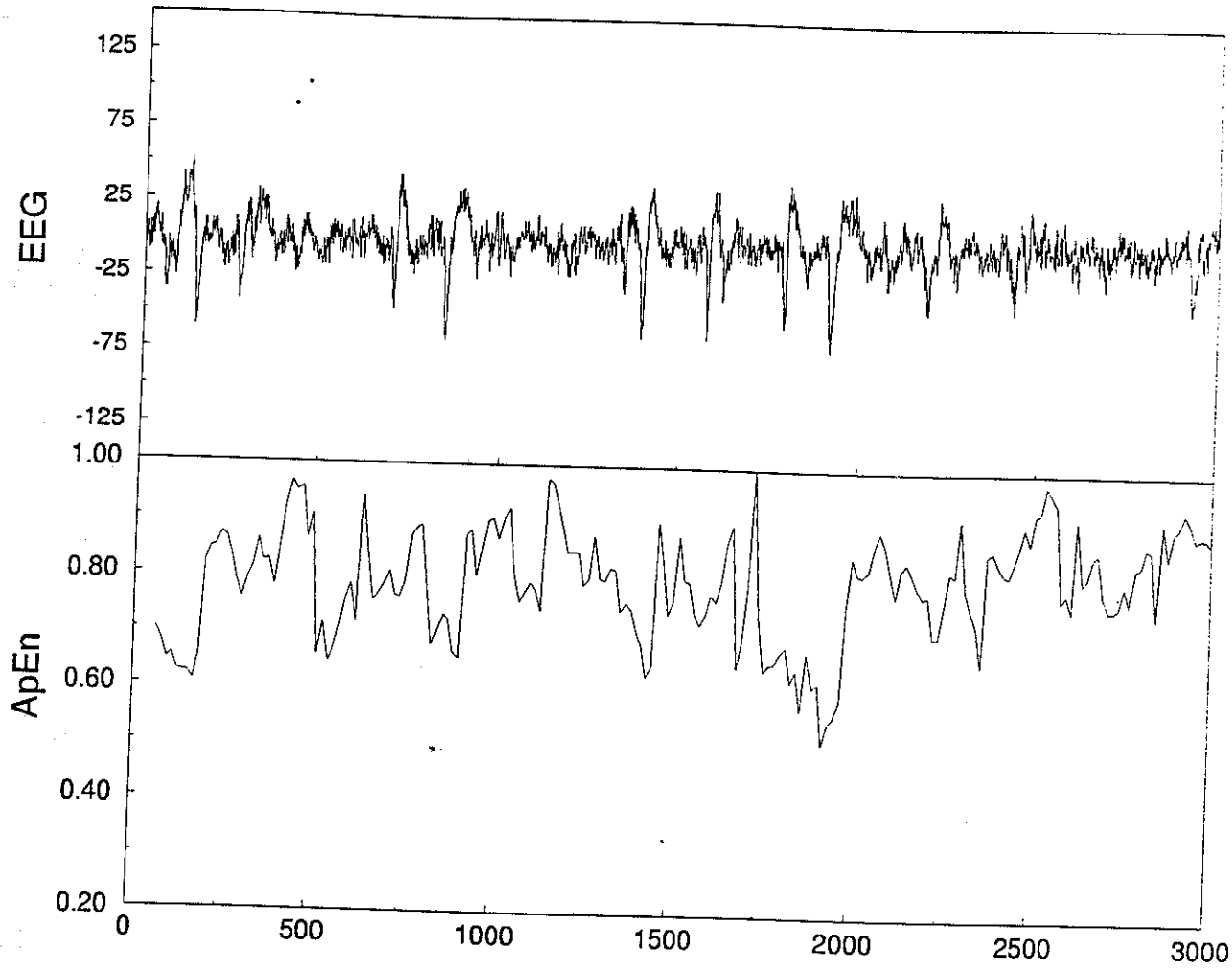

FIG. 4. Top: about 30 seconds of EEG recording from the healthy patient 1003 (channel Fp1) with evident eye-blinks. Bottom: the corresponding ApEn using the same parameters d, r, and N of Fig. 3.