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Characterization of EEG—A comparative study

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Summary The Electroencephalogram (EEG) is a representative signal containing information about the condition of the brain. The shape of the wave may contain useful information about the state of the brain. However, the human observer cannot directly monitor these subtle details. Besides, since bio-signals are highly subjective, the symptoms may appear at random in the time scale. Therefore, the EEG signal parameters, extracted and analyzed using computers, are highly useful in diagnostics. Chaotic measures like correlation dimension (CD), largest Lyapunov exponent (LLE), Hurst exponent (*H*) and entropy are used to characterize the signal. Results indicate that these nonlinear measures are good discriminators of normal and epileptic EEG signals. These measures distinguish epileptic EEG and alcoholic from normal EEG with an accuracy of more than 90%. The dynamical behavior is less random for alcoholic and epileptic compared to normal. This indicates less of information processing in the brain due to the hyper-synchronization of the EEG. Hence, the application of nonlinear time series analysis to EEG signals offers insight into the dynamical nature and variability of the brain signals.

As a pre-analysis step, the EEG data is tested for nonlinearity using surrogate data analysis and the results exhibited a significant difference in the correlation dimension measure of the actual data and the surrogate data.

1. Introduction

Computer technology has an important role in structuring biological systems. The explosive growth of high performance computing techniques in recent years with regard to the development of good and accurate models of biological systems has contributed significantly to new approaches to fundamental problems of modeling transient behavior of biological system.

The importance of the biological time series analysis, which exhibits typically complex dynamics, has long been recognized in the area of nonlinear analysis. Several features of these approaches have been proposed to detect the hidden important dynamical properties of the physiological phenomenon. The nonlinear dynamical techniques are based on the concept of chaos and it has been applied to many areas including the areas of medicine and biology.

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The study of human brain activity by means of the electroencephalogram (EEG) has profited from recent advances in the field of nonlinear time series analysis. In the past, the EEG has been characterized by using indices initially derived for the study of deterministic dynamical systems [1]. This new approach has provided a better insight about the way in which the brain works. Nonlinear methods have shown their ability to excel the traditional spectral techniques, tracing changes in the signal that would have remained undisclosed otherwise. Most of the studies undertaken hitherto have been carried out in one single EEG channel, whose nonlinear characteristics were calculated to test for differences among groups of healthy and diseased subjects [2—4] or different sleep stages [5].

Until about 1970, EEG interpretation was mainly heuristic and of a descriptive nature. Although several papers have discussed quantitative techniques to assist in EEG interpretation [6] in clinical terms the situation remained unchanged. In 1985, Babloyantz et al., have used certain nonlinear techniques to study the slow wave sleep signal [7—9]. Since that time, applications of EEG to several research areas have significantly increased and (potential) clinical applications have been reported such as the prediction of epileptic seizures [10,11], characterization of sleep phenomena [12], encephalopathies [13] or Creutzfeldt—Jakob disease [14] and monitoring of anaesthesia depth [15,16].

In a neuronal network such as the brain, nonlinearity is introduced even on the cellular level, since the dynamical behavior of individual neurons is governed by threshold and saturation phenomena. Moreover, the hypothesis of an entirely stochastic brain can be rejected due to its ability to perform sophisticated cognitive tasks. For these reasons, EEG appears to be an appropriate area for nonlinear time series analysis techniques. Jing and Takigawa [17] applied correlation dimensions techniques to analyse EEG at different neurological states. Lehnertz and Elger [18] used correlation dimension technique to test whether a relationship exists between spatio-temporal alterations of neuronal complexity and spatial extent and temporal dynamics of the epileptogenic area. Martin et al. [19] showed that techniques developed for the study of nonlinear systems can be used to characterize the epileptogenic regions of the brain during the interictal period. In particular, recordings from epilepsy patients have often attracted researchers' attention and they have used nonlinear techniques for analysis [20—22]. Epilepsy is a pathological condition characterized by spiky patterns in continuous EEG and seizure at times. The aim of our study is to compare dynamical properties of EEG signals of healthy subjects with epileptic and alcoholic subjects.

2. Materials

2.1. Data selection

The EEG data for analysis were obtained from two different sources, one for epileptic seizure analysis and other for alcoholic subjects EEG analysis. EEG recordings of control and alcoholic subjects were obtained from the University of California, Irvine Knowledge Discovery in Databases (UCI KDD) Archive. There were 122 subjects and each subject completed 120 trials where different stimuli were shown. The electrode positions were located at standard sites (Standard Electrode Position Nomenclature, American Electroencephalographic Association 1990). Zhang et al. [23] describes in detail the data collection process. The recorded EEG were sampled at 256 Hz. We have chosen 30 data sets each from control and alcoholic group for our analysis.

For epileptic data analysis, data were obtained from the EEG database available with the Bonn University. Two sets each containing 30 single channel EEG segments of 23.6-s duration, were composed for the study. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. In addition, the segments fulfilled the stationarity criterion tested using surrogate data analysis. The surrogate data analysis performed on the EEG data is described in Section 3.4. Set A consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open. Set E is chosen for our study that contained EEG obtained from five patients diagnosed with epilepsy. Set E contains data recorded during seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, digitized with a sampling rate of 173.61 Hz and 12 bit A/D resolution. Sample recordings of normal and epileptic EEG is given in Fig. 1.

3. Method

3.1. Correlation dimension

Correlation dimension is one of the most widely used measures of fractal dimension. Here we adapt

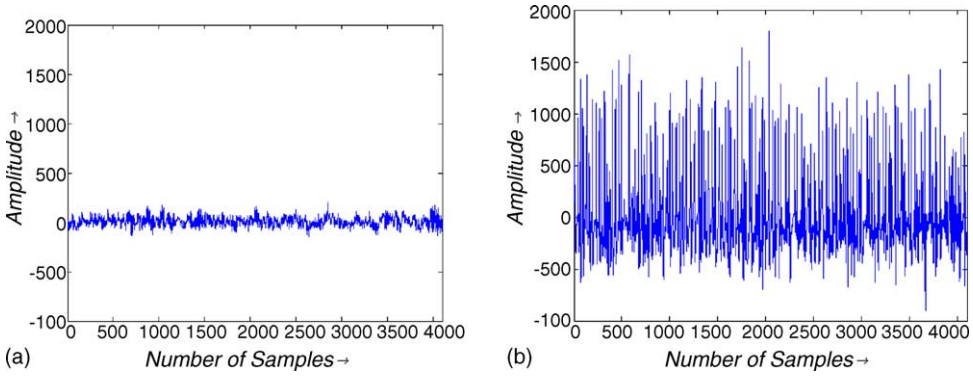

Fig. 1 (a) Normal EEG signal and (b) epileptic EEG signal.

the algorithm proposed by Grassberger and Procaccia [24]. The idea is to construct a function $C(r)$ that is the probability that two arbitrary points on the orbit are closer together than r. This is done by calculating the separation between every pair of N data points and sorting them into bins of width dr proportionate to r. A correlation dimension can be calculated using the distances between each pair of points in the set of N number of points, $s(i, j) = |X_i - X_j|$. A correlation function, $C(r)$, is then calculated using,

$$C(r) = \frac{1}{N^2}(\text{Number of pairs of } (i, j) \text{ with } s(i, j) < r).$$

Correlation dimension was calculated using the fundamental definition:

$$D_{\text{corr}} = \text{CD} = \lim_{r \to 0} \frac{\log(C(r))}{\log(r)} \tag{1}$$

The accuracy of the nonlinear time series analysis lies in the selection of optimum embedding dimension [25]. Embedding theorems defined by Takens [26] and Sauer et al. [27] states that for a strange attractor of fractal dimension D, the embedding using time delay coordinates is one to one if $m \geq 2D + 1$ or $m \geq D_{\text{corr}}$, where D_{corr} is the correlation dimension. But the limitation on the applicability of the theorems are that the measure D and D_{corr} are not known. For practical applications, it is best to apply the Grassberger and Procaccia algorithm [24] and calculate the D_{corr} for various embedding dimension. Then the minimum embedding dimension of the attractor for one to one embedding is $m + 1$, where m is the embedding dimension above, which the D_{corr} saturates. In this work, we have calculated D_{corr} with an embedding dimension varying from 3 to 10 for all the subjects. The graph of D_{corr} versus embedding dimension is shown in Fig. 2. From the graph, it can be seen that D_{corr} saturates after the embedding dimension of 9. So, we have chosen the embedding dimension of $m + 1 = 10$ for analysis. The software used for analysis is CDA Pro Data analyzer [28].

3.2. Hurst exponent (H)

Hurst Exponent is the measure of the smoothness of a fractal time series based on the asymptotic behavior of the rescaled range of the process. In time series analysis of EEG, Hurst exponent H is used by Dangel et al. [29] for characterize the non-stationary behavior of the sleep EEG episodes. The Hurst exponent H is defined as:

$$H = \frac{\log(R/S)}{\log(T)} \tag{2}$$

where T is the duration of the sample of data and R/S the corresponding value of rescaled range. The above expression is obtained from the Hurst's generalized equation of time series that is also valid for Brownian motion. If $H = 0.5$, the behavior of the time-series is similar to a random walk. If $H < 0.5$, the time-series cover less ''distance'' than a random walk. But if $H > 0.5$, the time-series covers more ''distance'' than a random walk. H is related

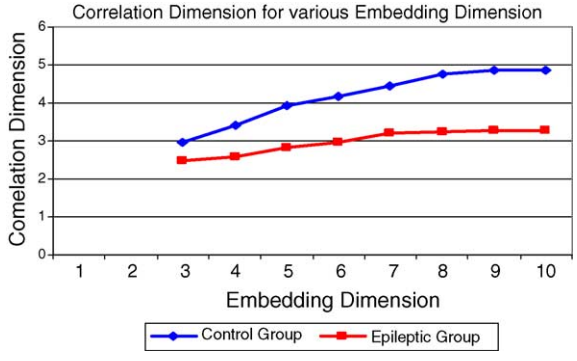

Fig. 2 Variation of correlation dimension for different embedding dimension.

to the fractal dimension D given by:

$$H = E + 1 - D \tag{3}$$

where E is the Euclidean dimension.

3.3. Largest Lyapunov exponent (LLE)

Lyapunov exponent (λ) is a quantitative measure of the sensitive dependence on the initial conditions. It defines the average rate of divergence of two neighboring trajectories. An exponential divergence of initially nearby trajectories in phase space coupled with folding of trajectories, to ensure that the solutions will remain finite, is the general mechanism for generating deterministic randomness and unpredictability. Therefore, the existence of a positive λ for almost all initial conditions in a bounded dynamical system is widely used definition of deterministic chaos. To discriminate between chaotic dynamics and periodic signals, Lyapunov exponents (λ) are often used. It is a measure of the rate at which the trajectories separate one from other. The trajectories of chaotic signals in phase space follow typical patterns. Closely spaced trajectories converge and diverge exponentially, relative to each other. For dynamical systems, sensitivity to initial conditions is quantified by the Lyapunov exponent (λ). They characterize the average rate of divergence of these neighboring trajectories. A negative exponent implies that the orbits approach a common fixed point. A zero exponent means the orbits maintain their relative positions; they are on a stable attractor. Finally, a positive exponent implies the orbits are on a chaotic attractor.

The algorithm proposed by Wolf et al. [30] is used to find Largest LE (LLE) from EEG data. For Given the time series $x(t)$ for m dimensional phase space with delay coordinate t, that is a point on the attractor is given by:

$$\{x(t), x(t+t), \ldots, x(t+(m-1)t\}$$

We locate nearest neighbor to initial point:

$$\{x(t0), x(t0+t), \ldots, x(t0+(m-1)t\}$$

And denote the distance between these two points as $L(t_0)$. At a later time t_1, initial length will evolve to length $L'(t_1)$. The mean exponential rate of divergence of two initially close orbits is characterized by:

$$\lambda = \frac{1}{t_M - t_0} \sum_{k=1}^{M} \log_2 \frac{L'(t_k)}{L^{'}(t_{k-1})} \tag{4}$$

In implementation of this program, the following set of numerical parameters has to be chosen:

$$P = \{m,\ t,\ T,\ S_{\max},\ S_{\min},\ \mathrm{th}_{\max}\}$$

where m is the embedding dimension, t is delay, T being evaluation time ($=t_{k+1} - t_{k-1}$) and $S_{\max}$, $S_{\min}$ are the maximum and minimum separations of replacement point respectively and thmax is the maximum orientation error. According to Das et al. [31] an embedding dimension between 5 and 20 and a delay of 1 should be chosen when calculating LLE for EEG data. In our analysis we have chosen an embedding dimension of 10 and delay of 5.

3.4. Entropy

Entropy is a thermodynamic quantity describing the amount of disorder in the system. From an information theory perspective, the above concept of entropy is generalized as the amount of information stored in a more general probability distribution. The theory was supported by the contributions of Shannon, Renyi and Kolmogorov. In this work we adapt the entropy measure defined by Kolmogorov known as Kolmogorov-Sinai entropy [32]. Entropy is determined from the embedded time series data by finding points on the trajectory that are close together in phase space (i.e., have a small separation s_{ij}) but which occurred at different times (i.e., are not time correlated). These two points are then followed into the future to observe how rapidly they move apart from one another. The time it takes for point pairs to move apart is related to the so-called Kolmogorov entropy, K, by $\langle t_{\mathrm{div}} \rangle = 2^{-Kt}$ where $\langle t_{\mathrm{div}} \rangle$ is the average time for the pair to diverge apart and K is expressed in bits per second. Entropy reflects how well one can predict the behavior of each respective part of the trajectory from the other. Higher entropy indicates less predictability and a closer approach to stochasticity.

3.5. Surrogate data analysis

The purpose of surrogate data is to test for any nonlinearity in the original data [33]. Surrogate signal is produced by phase randomizing the original data. It has similar spectral properties as of the given data. The surrogate data sequence has the same mean, the same variance, the same autocorrelation function and therefore the same power spectrum as the original sequence, but phase relations are destroyed. In the case of data shuffling, the histograms of the surrogate sequence and the reference sequence are identical. The random phase

spectrum is generated by using any of the three methods described below.

1. *Random phase*: here the complex phase values of the Fourier transformed input signal are chosen randomly.
2. *Phase shuffle*: here the phase values of the original spectrum are used in random order.
3. *Data shuffle*: here the phase values of the original spectrum are used in random order and the sorted values of the surrogate sequence are substituted by the corresponding sorted values of the reference sequence additionally.

4. Results

The complex phase values of the Fourier transformed input signal is used to produce the surrogate data set of the EEG data under consideration. Surrogate data sets are generated for 20 sets of control and epileptic EEG signals. The correlation dimension measure is calculated for each surrogate set and the actual data and the result is shown in Table 1. It can be seen that the values of the correlation dimension of the original and the surrogate dataset are distinct and they differ by more than 50%. This rejects the null hypothesis and hence the EEG data considered are nonlinear.

Table 2 shows results of nonlinear time series analysis of EEGs during seizures. From each EEG-recording we have computed the chaotic quantifiers described in Section 2. Correlation dimension, the parameter that quantifies the variability of the time series is computed for embedding dimensions 3—10 (Fig. 2). The optimal embedding dimension is chosen by the saturation of the correlation dimension as given by Takens [26]. From the graph it can be seen that D_{corr} saturates after the embedding dimension of 9. So we have chosen the embedding dimension of $m+1=10$ for analysis. A one to one embedding can be obtained for any value of the delay time $\tau>0$ for infinite amount of noise free data. However, both too small and too large values for τ will cause failures of the reconstruction in case of observed finite noisy time series. The optimal τ is determined using mutual information function $I(\tau)$ [34]. Mutual information function for normal and epileptic EEG is given in Fig. 3a and b respectively. It can be clearly seen that the mutual information $I(\tau)$ reaches its first minimum at $\tau=5$ for both cases.

Table 1 Result of surrogate data analysis

	Control group	Epiletic group
Original data	4.8748	3.2921
Surrogate data	2.2421	1.5429
Difference (%)	54	53.12

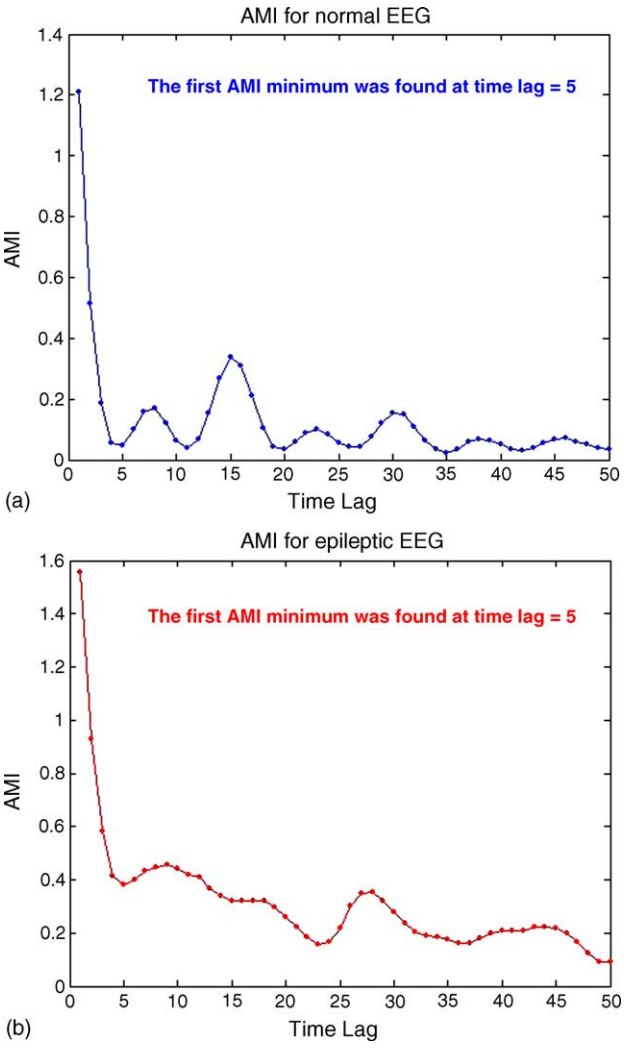

Fig. 3 (a) AMI for normal EEG (b) AMI for epileptic EEG.

Table 2 Results of chaotic measures of control and epileptic group

	Control group	Epileptic group	*P*-value
CD	4.9248 ± 0.3667	3.3892 ± 0.2582	0.0001
LE	0.204 ± 0.0156	0.2152 ± 0.0319	0.0891
Hurst	0.3248 ± 0.0588	0.3563 ± 0.0614	0.0474
Entropy	0.6252 ± 0.0713	0.4672 ± 0.0474	0.0001

Table 3 Results of chaotic measures of control and alcoholic group

	Control group	Alcoholic group	*P*-value
CD	4.8768 ± 0.16	3.9407 ± 0.1422	0.0001
LE	0.2036 ± 0.0278	0.1845 ± 0.034	0.0493
Hurst	0.3155 ± 0.0588	0.247 ± 0.0701	0.0001
Entropy	0.6033 ± 0.039	0.4926 ± 0.0474	0.0001

Hence, the optimal embedding delay τ_{opt} is chosen as 5 for our analysis.

The results show that the correlation dimension of epileptic activity is less as compared to that of nonepileptic activity. The results are in support of the studies [10,11] on dimension analysis of EEG that epileptic seizures are emergent states with reduced dimensionality compared to nonepileptic activity. This concept finds support in the observations [18] that neuronal hyper-synchrony underlies seizures; a phenomenon during which the number of independent variables required to describe the system is smaller than at other times. Thus, correlation dimension measure allows for distinguishing the epileptic and control groups. The results are supported by statistical analysis using t-test ($P < 0.0001$) indicating extreme statistical significance. A similar situation is observed for the Lyapunov Exponent. The seizure is characterized by a drop in the value of the maximum Lyapunov exponent. And also our results support the existence of chaos in the EEG signals by the presence of positive Lyapunov exponent and finite Kolmogorov entropy [10,35,36].

The Hurst exponent that characterizes the nonstationary behavior of the signals is calculated. From Table 2, it can be seen there is clearly a negative correlation between the values of correlation dimension and hurst exponent. This is the expected behavior of a stochastic system with power-law spectra, $D_2 = \max(1 - H_2, M)$, where M is the embedding dimension. Increase in the value of the Hurst exponent indicates less complexity and more synchronization. This is in accordance with our other results that the brain exhibit less chaotic behavior during a seizure. According to Sleigh et al. [37], the changes in entropy of the EEG are expected to indirectly coarsely measure changes in the entropy occurring within the cerebral cortex itself. Hence, the decrease in entropy during seizures, indicate less of information processing by the brain. This is supported by our results for entropy shown in Table 2.

Table 2 also depicts the result of statistical analysis between the control group and epileptic pathological groups. It is found that the measures CD, LE and Entropy are significantly lower ($P < 0.0001$ for CD and entropy, $P < 0.08$ for LE) in the seizure group than the control group. Similar results are exhibited by increase in Hurst exponent ($P < 0.04$) for epileptic group. This suggests a decreased complexity in the epileptic EEG. This is the indication that there are less independent, parallel, functional processes active in the epileptic group than the control group.

Our studies on the alcoholic EEG (Table 3) shows decreased value of correlation dimension, Lyapunov exponent, entropy and increased value of Hurst exponent. Hence, the complexity of the signal reduces. The results obtained show a distinct difference in the measures between the control group and the alcoholic group ($P < 0.001$). Thus the chaotic measures described can be used distinguish the alcoholic EEG from the normal EEG. The alcoholic EEG exhibit more complexity compared to the epileptic EEG. This is indicated by the correlation dimension values of normal 4.9248 ± 0.3667, alcoholic 3.9407 ± 0.1422 and epileptic 3.3892 ± 0.2582. The same trend is observed for Lyapunov exponent, entropy and Hurst exponent. This indicates that there is less thinking processes in the brain for alcoholic group as compared to the control group but more compared to the epileptic group.

5. Conclusion

The study shows clear difference in dynamical properties of electrical activity of the brain in normal, alcoholic and epileptic subjects. Tables 2 and 3 show that the CD, LLE and H decreases for alcoholic subjects compared with the normal subjects. This indicates that the dynamical behavior is less random during the alcoholic states. Also, the same tables show during the epileptic seizure the EEG signal becomes less random. The results show that, the alcoholic EEG is more complex than the epileptic seizure signal. Hence, the EEG is less complex compared to the normal, indicating reduction in active neuronal process in the brain.

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