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Wavelet Entropy and Complexity Analysis for Drinkers' EEG

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Abstract: This paper investigates the influence of alcohol on brain complexity. Considering electroencephalogram (EEG) has the nonlinear dynamics characteristic of time-varying and non-stationary, the wavelet entropy (WE) analysis is introduced. The EEG data of drinkers' and normal people's is analyzed using the wavelet entropy. The results show that the EEG wavelet entropy of drinkers' is markedly greater than the EEG wavelet entropy of normal people's, The EEG complexity of drinkers' is higher and the brain of drinkers' is in a more chaotic state. *Copyright © 2013 IFSA.*

Keywords: EEG, Wavelet transform, Wavelet entropy, Complexity.

1. Introduction

Drunk driving is the major reason for traffic accidents. The regularity of drinkers' brain function change is an interesting topic. Generally, dizziness, tinnitus and show response especially for emergency, are typical symptoms after drinking. Brain is composed of a huge amount of nerve cells and each nerve cell connects to other nerve cells, making brain a complex non-linear system. Complexity can reflect the regularity of dynamic systems. The behaviour of various systems is different, and thus the regularity of the behaviour from these systems is also different. Complexity is capable of describing these differences and then further discriminating these systems.

Electroencephalogram (EEG) is a non-invasive, low-cost and effective technique for examining electrical activity of the brain and diagnosing brain diseases in clinical setting [1]. EEG is a type of non-stationary time series signal. It's hard to analyze EEG by linear method, such as time domain analysis and frequency domain analysis because of the no-regularity caused by nonlinear and nonlinear and non-stationary factors. Therefore non-linear analysis methods could better facilitate opening out the characteristics and mechanisms of EEG [2].

With the rapid development of non-linearity theory, complexity analysis is becoming a popular field for studying nonlinear dynamics of EEG time series. Although different methods have provided indirect evidence for synchronization EEG processes [3, 8], a tool for a quantitative evaluation of the complex EEG signal synchronization and its temporal dynamics is still lacking. In information theory, 'entropy' represents the irregularity of systems, and many complexity concepts are related to entropy. Entropy is a concept handling predictability and randomness, with higher values of entropy always related to less system order and larger randomness [4]. Several recent studies measured entropy in drinkers' EEG time series. Approximate entropy (ApEn) was first put forward by Pincus et al.

[5]. In [6], an ApEn-based epileptic EEG detection system using artificial neural networks was studied. These methods are based on information theory, such as permutation entropy (PE), ApEn, and other ones based on chaos theory. SampEn was an improved algorithm based on approximate entropy (Richman et al. 2000) [7].

PE and ApEn are better in distinguishing the EEG between drinkers and the control, but they can't be used for on-line analysis due to too much time-consuming. ApEn's counting process adopts Heaviside function, which is very sensitive to the threshold value and phase space dimension, and vulnerable to noise interference. It lacks relative consistency and the result shows much dependence on data length. SampEn displays relative consistency and less dependence on data length. Nevertheless, the similarity definition of vectors in SampEn is based on Heaviside function as in ApEn. Due to the inherent flaws of Heaviside function, problems still exist in the validity of the entropy definition, especially when small parameters are involved. To overcome these limitations, Wavelet entropy (WE) [13] (Osvaldo A. Rosso et al. 2001), a new nonlinear dynamic analysis method, can be used for analyzing the short time signal. WE algorithm needn't consider any parameters during the process of calculation. It can reduce the influence of noise, reflect the signal's confusion degree of frequency components and provide the dynamics characteristics. And it is simple and possesses both time-frequency limitations and robustness.

In this paper, we investigate the influence of alcohol on brain complexity based on wavelet entropy. The work is organized as follows. Section 2 introduces wavelet entropy method. Section 3 WE performances to the nonlinear signals are discussed. In Section 4, by calculating the wavelet entropy of drinkers' and normal people's EEG signal, we analyze the complexity of drinkers' and normal people's EEG signal. Finally, Section 5 draws the conclusions.

2 Wavelet Entropy

2.1. Wavelet Transform

Wavelet analysis [9, 10-12, 14] is a signal processing method, which relies on the introduction of an appropriate basis and a characterization of the signal by the distribution of amplitude in the basis. If the wavelet is required to form a proper orthogonal basis, it has the advantage that an arbitrary function can be uniquely decomposed and the decomposition can be inverted (Mallat, 1989). The wavelet is a smooth and quickly vanishing oscillating function with good localization in both frequency and time. A wavelet family $\psi_{a,b}(t)$ is the set of elementary functions generated by dilations and translations of a unique admissible mother wavelet $\psi(t)$:

$$\psi_{a,b}(t) = |a|^{-1/2}\psi(\frac{t-b}{a}),\ a \in R, a \neq 0, b \in R, \quad (1)$$

where a, b are the scale and translation parameters, respectively, and t is time. As the scale parameter increases, the wavelet becomes wider. Thus, one has a unique analytic pattern and its replications at different scales and with variable time localization.

The continuous wavelet transform of a signal $S(t) \in L^2(R)$ (the space of real square summable functions) is defined as the correlation between the function $S(t)$ with the family wavelet $\psi_{a,b}(t)$ for each a and b:

$$(W_\psi S)(a,b) = |a|^{-1/2}\int_{-\infty}^{+\infty} f(t)\psi(\frac{t-b}{a})dt = \langle S, \psi_{a,b} \rangle, \quad (2)$$

For a special election of the mother wavelet function $\psi(t)$ and for the discrete set of parameters, $a_j = 2^{-j}$ and $b_{j,k} = 2^{-j}k$ with $j,k \in Z$ (the set of integers) the family

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^j t - k) \quad j,k \in Z, \quad (3)$$

constitutes an orthonormal basis of the Hilbert space $L^2(R)$ consisting of finite-energy signals. The correlated decimated discrete wavelet transform provides a non-redundant representation of the signal and its values constitute the coefficients in a wavelet series. These wavelet coefficients provide full information in a simple way and a direct estimation of local energies at different scales. More-over, the information can be organized in a hierarchical scheme of nested subspaces called multi-resolution analysis in $L^2(R)$. In the present work, orthogonal cubic spline functions are employed as mother wavelets. Among several alternatives, cubic spline functions are in a suitable proportion with smoothness and numerical advantages and they have become a recommended tool for representing natural signals.

In the following, the signal is assumed to be given by the sampled values $S = \{s_0(n), n = 1, \ldots, M\}$, corresponding to a uniform time grid with sampling time ts. For simplicity the sampling rate is taken as ts = 1. If the decomposition is carried out over all resolutions levels, $N = \log_2 M$, the wavelet expansion will be:

$$S(t) = \sum_{j=-N}^{-1}\sum_{k \in Z} C_j(k)\psi_{j,k}(t) = \sum_{j=-N}^{-1}\gamma_j(t), \quad (4)$$

where wavelet coefficients $C_j(k)$ can be interpreted as local residual errors between successive signal approximations at scales j and j + 1, while $\gamma_j(t)$ is the residual signal at scale j. It contains information of the signal S(t) corresponding to frequencies $2^{j-1}\omega_s \le |\omega| \le 2^j \omega_s$.

2.2. Wavelet Energy

Since the family $\{\psi_{j,k}(t)\}$ is an orthonormal basic for $L^2(R)$, the concept of energy is linked with the usual notions derived from Fourier theory. Then, wavelet coefficient are given by $C_j(k) = \left\langle S, \psi_{j,k}(t) \right\rangle$, and the energy of a signal at each scale $j = -1, -2, \cdots, -N$, will be

$$E_j = \|\gamma_j\|^2 \sum_k |C_j(k)|^2, \tag{5}$$

The energy at each sampled time k will be

$$E(k) = \sum_{j=-N}^{-1} |C_j(k)|^2, \tag{6}$$

In consequence, the total energy can be obtained by

$$E_{tot} = \|S\|^2 = \sum_{j<0} \sum_k |C_j(k)|^2 = \sum_{j<0} E_j, \tag{7}$$

For the j[th] scale, the wavelet energy ratio is considered as a normalized value

$$p_j = \frac{E_j}{E_{tot}}, \tag{8}$$

The wavelet energy ratio vector $\{p_j\}$ represents energy distribution in a time-scale, which gives a suitable tool for detecting and characterizing singular features of a signal in time-frequency domain. Clearly, $\sum_{j=-1}^{-N} p_j = 1$.

2.3. Wavelet Entropy

Entropy gives a useful criterion for analyzing and comparing a probability distribution. It provides a measure of information of any distribution. According to the entropy theory and wavelet energy ratio defined above, wavelet entropy is defined as

$$S_{WT} = S_{WT}(p) = -\sum_{j<0} p_j \cdot \ln[p_j], \tag{9}$$

To some extent, wavelet entropy can represent the degree of order/disorder of the signal, so it can provide useful information about the underlying dynamical process associated with measured signals. A signal generated by a totally random process can be taken as representing a very disordered behavior. This kind of signal will have a wavelet representation with significant contributions from all frequency bands. In addition, it is expected that all contributions will be of the same order. Consequently, the relative wavelet energy will be almost equal for all resolution levels and the wavelet entropy will take the maximum value.

3. WE Performances for the Nonlinear Signals

In order to study the wavelet entropy's performance of mutation detection and sequence complexity measuring about the nonlinear time series, we construct the following ideal nonlinear time series.

$$y_{n+1} = uy_n(1 - y_n),\ y \in [0,1], \tag{10}$$

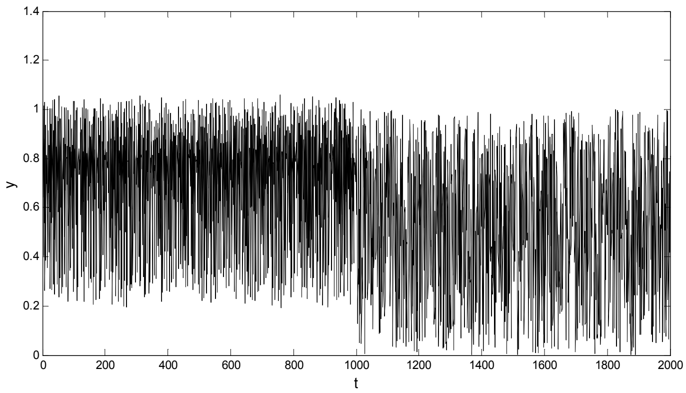

Fig. 1. Curve of nonlinear time series with Gaussian white noise.

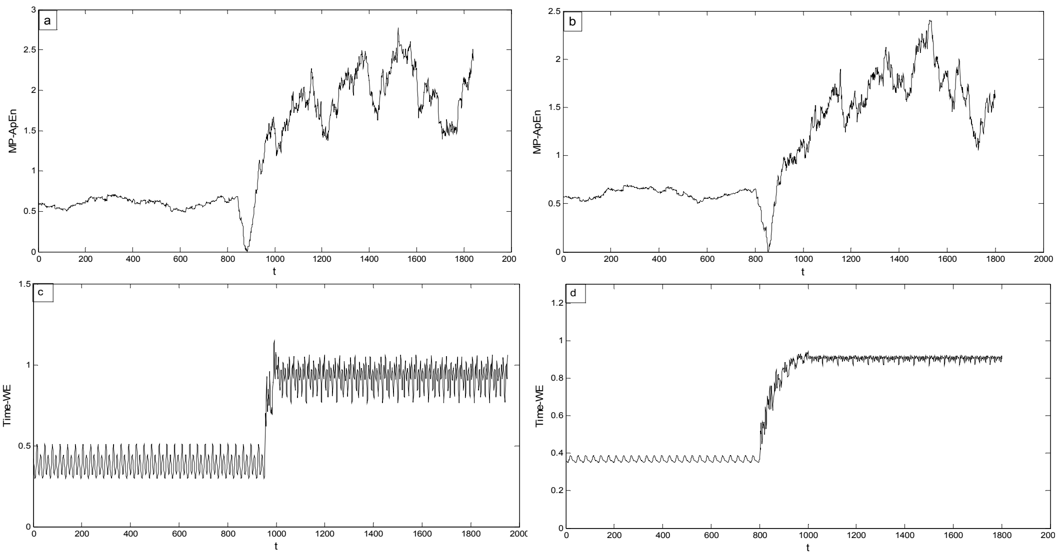

Fig. 2. Entropy curves of nonlinear noised time series. MP-ApEn curve: (a) Sliding window length L=50, step 1; (b) L=200. Time-WE curve: (c) Time evolution window length L=50, step 1; (d) L=200.

In the equation (10), y0=0.8, u=3.8. we introduce the Gaussian white noise into nonlinear ideal time series in the foundation of equation (10). The Gaussian white noise with noise ratio for 2 db, and the amplitude for 0.2.

To study the performance of wavelet entropy for measuring the complexity of nonlinear time series with Gaussian white noise, we calculate MP-ApEn and Time-WE of the noised nonlinear time series. The MP-ApEn and Time-WE curves are shown in Fig. 2. In order to test the efficiency of wavelet entropy algorithm in the complexity analysis of time series, we select the length of ApEn sliding window and WE time evolution window is 200, and separately calculate the average entropy value when the data of the series are at $1 \le t \le 1000$ and $1000 < t \le 2000$. Meanwhile, we count the average computing time. The parameters of ApEn, m=2, r=0.26*std (y). Results are shown in Table 1, ATApEn means the average computing time of ApEn, and ATWE means the average computing time of WE. ApEns1 or WEs1 means $1 \le t \le 1000$ paragraph sequence entropy, and ApEns2 or WEs2 means $1000 < t \le 2000$ paragraph sequence entropy. As shown in Table 1, the entropy of $1 \le t \le 1000$ is smaller than $1000 < t \le 2000$ .Comparing the average computing time of WE and ApEn used in the operation of the series, the WE calculation time is significantly faster than the ApEn at the same conditions.

Table 1. The entropy and calculating time of nonlinear series.

	$ApEn_{s1}$	$ApEn_{s2}$	AT_{ApEn}/s	WE_{s1}	WE_{s2}	AT_{WE}/s
Nonlinear	0.3997	1.5563	9.673	0.3416	0.5948	2.196

4. Application

4.1. Experiment Data

The experimental data were taken from a public EEG database. The experiments were performed on 122 subjects. The tested people are made experiments 120 times respectively [15] (Zhu Guohun et al., 2011). In the experiment, the tested people's heads are placed with 64 conductive poles, the sampling frequency is 256 Hz and recording data period is 1 second in every experiment. Because the data of EEG in data concentration is incomplete, some experiment data are not in the database, therefore, with the requirements of examples analysis and in order to ensure the comparability of analysis results, 30 drinkers' and 30 normal people's EEG completely data are random selected in the dataset, as two data sets of this research analysis. Firstly, we calculate the sampling data of 64 conductive poles that are got in single at the 40th stimulation experiment, and analyze the results. Then, we choose drinkers numbered co2a0000364 and normal people numbered co2c0000337 in the same 10 times irritant experiments. We calculate WE and analyze EEG data of FP2 conductive pole. FP2 electrodes were located at the upper part of the eyes.

4.2. Experiment Results

The EEG data was selected from the 60 tested people. Among the 60 tested people, there are 30 drinkers and 30 normal people. We calculate all 64 electrodes' wavelet entropy to get the average value, draw drinkers' and normal people's average wavelet entropy curve of 64 conductive poles shown in Fig. 3.

As shown in Fig. 3, including 64 conductive poles, the drinkers' EEG wavelet entropy is widely greater than normal people's. The wavelet entropy of every conductive pole of drinkers' or normal people's is Inconsistent. The different degree of EEG wavelet entropy between drinkers and normal people is also clear at the same conductive pole.

In order to analyze WE's obvious differences of two groups of EEG data on the same electrode, we choose alcoholic numbered co2a0000364 and normal people numbered co2c0000337. Let them stay in the same experiments 10 times to get the FP2 electrode's EEG data, and calculate WE of drinker and normal people at FP2 electrode in every experiment, then get the wavelet entropy that listed in Tab.2. WE of the jth experiment is denoted WEj, $j = 0, 1, 2, \cdots, 9$.

As in Table 2, the WE of drinker's EEG data on FP2 electrode is markedly greater than normal people's. The corresponding entropy curve is shown in Fig. 4. We can find that entropy curves become more and more stable with more experiments.

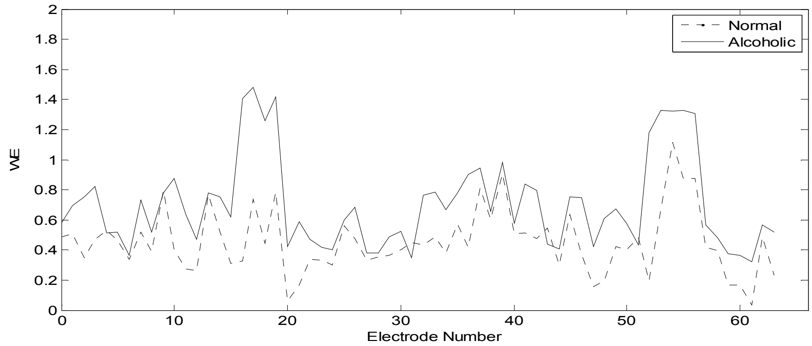

Fig. 3. WE curves of 64 conductive poles of drinkers' and normal people.

Table 2. WE of FP2 electrode.

Brain state	WE_0	WE_1	WE_2	WE_3	WE_4	WE_5	WE_6	WE_7	WE_8	WE_9
Normal	0.5076	0.4316	0.2012	0.4271	0.3629	0.1429	0.4310	0.3885	0.3890	0.4293
Alcoholic	0.6952	0.6199	0.5215	0.4798	0.5872	0.4948	0.6003	0.5888	0.5609	0.5820

4.3. Results Analysis

Through the comparison and analysis of EEG complexity by wavelet entropy on drinkers and normal people, we verify that the feasibility of the wavelet entropy in measuring the complexity of living examples. Analyzing the two figures, we can get that the EEG wavelet entropy of drinkers is markedly greater than the EEG wavelet entropy of normal people. Compared with normal brain, the drinkers' will be with highly complexity and neuronal activity is increased because of stimulation of alcohol. All results can properly reflect the dynamics nature and changes of brain signals. For the changes between drinker's and normal people's EEG wavelet entropy at the same electrode point, from Fig. 9, at CP1, CP5 and CP6 electrode points, the increasing trend of WE is obvious larger. So these parts are more sensitive to alcohol.

The method, using WE to analyze the complexity of EEG signal, makes a contribution to detect drunken driving and help hospitals with alcoholism. However, the EEG reference data is incomplete, we should try our best to choose the part of data which is much more complete to compute and analyze. Observing Fig. 4, under the case of fewer experiments, the fluctuation of WE curve is larger. With more and more experiments carried out, more and more objects chosen, wavelet entropy trends to be stable. It shows that when wavelet entropy is used on object in practice, because of limits of experiment times and less random data got, the fluctuation of wavelet entropy is strongly, and then leading the accuracy of experiment to reduce. The problems need to be solved in the future.

5. Conclusions

In this paper, we introduced the wavelet entropy to analyze and measure the EEG complexity of drinkers' and normal people.

1) Wavelet decomposition can reduce the influences of noise. WE model dimension m and threshold value r, have no influence on the result. WE can accurately measure the chaos of linear and nonlinear time series.

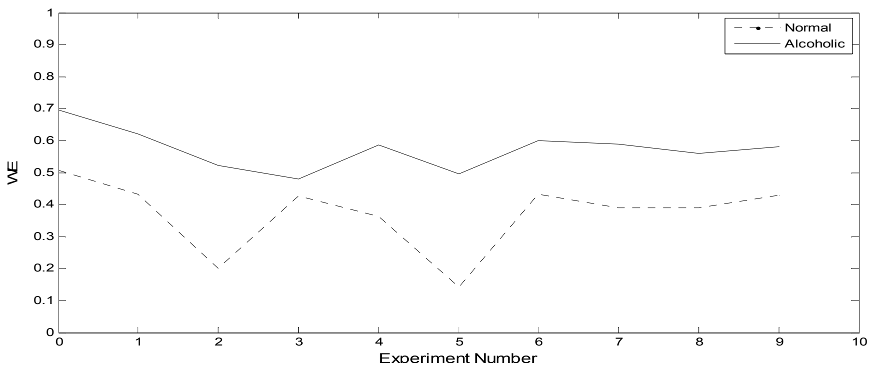

Fig. 4. WE curve of FP2 electrode of drinkers' and normal people.

2) Comparing and analyzing drinkers' (or alcoholics') and normal people's EEG, the WE of drinkers' is widely larger than that of normal people's. In other words, the complexity of drinkers' brains is higher than that of normal people's. This makes a contribution to studying the states and complexity of drinkers' brains.

3) Considering that drinkers' intoxication levels and sensitive degree for alcohol are all different, we will introduce fuzzy analysis method, such as fuzzy entropy, based on quantitative WE analysis in future works. We will do systematic fuzzy classification of the drunken degree and alcohol sensitive degree of drinkers', and reveal the changing rules of drinkers' EEG complexity with more details.

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References

[1]. C. Stam, J. Pijn, P. Suffczynski, F. Lopez da Silva, Dynamics of the human alpha rhythm evidence for non-linearity, *Clin Neurophysiol*, 1999, Vol. 110, Issues 10, pp. 1801–1813.

[2]. D. Duke, W. Pritchard, Measuring chaos in the human brain, *World Scientific*, Singapore, 1991.

[3]. H. D. I. Abarbanel, Analysis of observed chaotic data, *Springer*, New York, 1996.

[4]. N. Kannathal, M. Choo, U. Acharya, P. Sadasivan, Entropies for detection of epilepsy in EEG, *Computational Methods Programs Biomed*, Vol. 80, 2005, pp. 187–194.

[5]. S. M. Pincus, Approximate entropy (ApEn) as a complexity measure, *Chaos*, Vol. 5, Issue 1, 1995, pp. 110-117.

[6]. V. Srinivasan, C. Eswaran, N. Sriaam, Approximate entropy-based epileptic EEG detection using artificial neural networks, *IEEE Transactions on Information Technologies Biomed*, Vol. 11, Issue 3, 2007, pp. 288–295.

[7]. J. S. Richman, J. R. Moorman, Physiological time-series analysis using approximate and sample entropy, *American Journal of Physiology: Heart and Circulatory Physiology*, Vol. 278, Issue 6, 2000, pp. H2039–H2049.

[8]. G. Jingming, T. Kao, C. Hsia, L. Yunfu, Alter action detection and recovery for medical and surveillance systems, *International Journal of Innovative Computing, Information and Control*, Vol. 9, Issue 4, 2013, pp. 1389-1408.

[9]. H. Ocak, Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy, *Expert Systems with Applications*, Vol. 36, 2009, pp. 2027-2036.

[10]. K. Miyanishi, T. Yamaguchi, M. Fujio, K. Inoue, EEG Analysis During Sleep by Using Morphological Local Pattern Spectrum, *ICIC Express Letters*, 2013, Vol. 7, Issue 5, 2013, pp. 1469-1474.

[11]. L. Zhi, W. Yan, Classification of Sound Types in Border Monitoring System Based on Wavelet Transform, *ICIC Express Letters, Part B: Applications*, 2012, Vol. 3, Issue 1, 2012, pp. 127-132.

[12]. S. Mallat, A theory for multi resolution signal decomposition: The wavelet representation, *IEEE Transactions on Pattern And Machine Intelligence,* Vol. 11, Issue 7, 1989, pp. 674–693.

[13]. O. A. Rosso, J. Yordanova, E. Basar, Wavelet entropy: a new tool for analysis of short duration brain electrical signals, *Journal of Neuroscience Methods,* Vol. 105, Issue 1, 2001, pp. 65-75.

[14]. Q. Tian, N. Yamauchi, An Approach Based on Wavelet Analysis and Hidden Markov Models for Behavior Understanding, *ICIC Express Letters, Part B: Applications*, Vol. 3, Issue 6, 2012, pp. 1645-1650.

[15]. Z. Guohun, Y. Li, P. Wen, Evaluating function connectivity in alcoholics based on maximal weight matching, *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Vol. 15, Issue 9, 2011, pp. 1221-1227.