

TSALLIS ENTROPY BASED SEIZURE DETECTION

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ABSTRACT

This paper presents EEG signal analysis using Tsallis entropy and then it will make available for comparison with any another method along with KNN classification. Electroencephalogram (EEG) remains the most immediate, easy and rich source of information for accepting phenomena related to brain electrical activities [1]. Important information, about the state of patient under observation, must be extracted from calculated DSD (Decimated signal diagonalization) bispectrum[2]. For this aim, it is useful to delineate an assessment index about the dynamic process associated with the analysed signal. This information is measure by means of entropy, since the degree of order or disorder of the recorded EEG signal will be replicated in the obtained DSDbispectrum[3]. Tsallis entropy is better than Shannon one because it maximizes the probabilities of the events of the interest through the selection of the entropic index, and so it permits to detect in more perfect way, spikes related to epileptic seizure. Then, the signals are classified using K Nearest Neighbour classifier.

KEYWORDS: EEG, Entropy, DSD, Bispectrum, K Nearest Neighbour.

INTRODUCTION

EEG is a non-invasive testing method which contains a lot of information about the state of a patient's health. It also contains very useful information relating to the different physiological states of the brain and thus is a very effective tool for understanding the complex dynamical behaviour of the brain. The EEG recordings are visually inspected by highly trained professionals for detecting epileptic seizures. This information is then used for medical diagnosis and possible treatment strategies. Clearly, this is a very time consuming process and is very costly. A lot effort has been devoted for developing automated seizure detection techniques which might help not only to speed up this process but also reduce the amount of data needs be stored[4].

Entropy is a measure of order or disorder in a dynamical system. Tsallis entropy (TsEn) plays a central part in nonextensive statistical mechanics. It is successful at relating systems with long range exchanges, multiracial space time constraints, or long term memory effects. EEG spikes, bursts and continuous or merged rhythms may be differentiated with the help of Tsallis statistics [5]. The spikes can distinguish using K Nearest Neighbour classifier. K Nearest Neighbour Classification is a pattern recognition algorithm.

In case of KNN we can consider the characteristics of each signal in our set as a different dimension in some space and take the value of an observation for this characteristic as its coordinate in that dimension. We can consider the similarity of two points to be the distance between them in this space under some appropriate metric. The algorithm decides that the points from the training set are similar enough to be consider for choosing the class to predict for a new observation is to pick the k closest data points to the new observation as well as to take the most common class among these, thus called the K Nearest Neighbour algorithm[6].

PROPOSED METHODOLOGY

Procedure steps: The steps of proposed methodology as follows,

- 1] EEG signal: The input EEG signals are obtained from the benchmark dataset.
- 2] Tsallis entropy: In this stage Tsallis entropy is calculated using formula.

- 3] Spectrum Display of Extracted Signal: After calculating entropy values the extracted signal will be display in the form of spectrum.
- 4] K-NN Classification: The spikes of extracted signal can be distinguishing using K Nearest Neighbour classifier.

BLOCK DIAGRAM

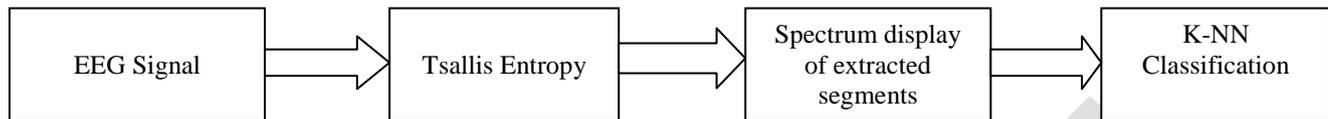


Fig 1: Block diagram of methodology.

A. EEG SIGNAL

Electroencephalogram (EEG) signals are brain activities recorded using electrodes that placed on the scalp. In this case, the EEG signals are obtained from the benchmark dataset. The dataset contain online data which will be downloaded through physionet.org. It will contain number of folders contains patients information and EEG signal. In our paper we process on downloaded data form physionet.org and real data form hospital. The downloaded data consist of EEG signal between 23 test point and real data will consist of 17 test point out of which 14 test points are taken, two eye blinking and one ground test point are ignored[7,8].

B. TSALLIS ENTROPY

Entropy provides a measure of the quantity of the information content of a random variable in terms of the minimum number of bits per symbol required to encode the variable. Entropy is an indicator of the amount of randomness or uncertainty of a discrete random process. Entropy can be used to calculate the theoretical minimum capacity or bandwidth required for the storage or transmission of an information source such as text, image, music, etc.[9].

Entropy is measure of order or disorder in a dynamical system according to information theory. Tsallis entropy is better than Shannon. The diagonalization technique that extracts all of the relevant peak constraints, namely, the complex frequencies and amplitudes, $\{\omega_k, d_k\}$, using a windowing process on the EEG signal $[\omega_{min}, \omega_{max}]$. [1]

$$c_n = \sum_{k=1}^K d_k e^{-j\omega_k n \tau} \quad (1)$$

Therefore, the time signal consists of N points, and τ is the sampling time. A time signal is processed to get a low-resolution spectrum by discrete Fourier transform (DFT). This spectrum is divided into $M = N/ND$ windows $[\omega_{min}, \omega_{max}]$ containing at most 200 data points (ND). A new signal is generated for each window by zeroing the content exterior the window and then recentering the window at zero. The inverse DFT is performed to convert the frequency data back into the time domain. Therefore, the decimated band-limited signal is obtained

$$c_n^{bld} = \sum_{k=1}^K d_k e^{-j\omega_k n \tau D}, \quad \text{Im } \omega_k < 0 \quad (2)$$

And the sampling time is increased by a factor of M yielding $\tau D = M\tau$.

This signal is diagonalized to extract the spectral parameters for the matrix overlapping U_0d , U_1d , and U_2d of eigenvalues problem. For each of the M signals a diagonalization procedure is implemented, then

$$c_{1n}^{bld} = \sum_{k=1}^K d_{1k} e^{-j\omega_{1k} n \tau_D} \rightarrow U_1 B_{1k} = u_{1k} U_0 B_{1k} \quad (3)$$

$$c_{2n}^{bld} = \sum_{k=1}^K d_{2k} e^{-j\omega_{2k} n \tau_D} \rightarrow U_2 B_{2k} = u_{2k} U_0 B_{2k} \quad (4)$$

The ω_{1k} and ω_{2k} are extracted from the eigenvalues $u_{1k} = e^{-j\omega_{1k} \tau}$ and $u_{2k} = e^{-j\omega_{2k} \tau}$, and the frequencies are

$$\omega_{1k} = \frac{1}{\tau_D} \angle(u_{1k}) \quad (5)$$

$$\omega_{2k} = \frac{1}{\tau_D} \angle(u_{2k}) \quad (6)$$

While the amplitudes are,

$$d_{1k} = (0|\omega_{1k})^2 = (C_1^T B_{1k})^2 = \left(\sum_{n=0}^{K-1} B_{n1k} C_{1n}^{bld} \right)^2 \quad (7)$$

$$d_{2k} = (0|\omega_{2k})^2 = (C_2^T B_{2k})^2 = \left(\sum_{n=0}^{K-1} B_{n2k} C_{2n}^{bld} \right)^2 \quad (8)$$

$$C^T = [c_0^{bld}, \dots, c_{M-1}^{bld}]$$

After calculating the cross amplitude as

$$D_{kk} = B_{1k}^T U_0 B_{2k} \sqrt{d_{1k} d_{2k}} \quad (9)$$

We build the bispectrum as

$$A(F_1, F_2) = \sum_{1k, 2k} \text{Im} \left\{ \frac{D_{kk}}{\omega_{1k} - 2\pi F_1} \right\} \text{Im} \left\{ \frac{D_{kk}}{\omega_{2k} - 2\pi F_2} \right\} \quad (10)$$

The EEG signal consists of many random components that make unpredictable its time trend. With reference to (7), we calculate the entropy, in according to theory of Shannon, in this way

$$H = - \sum_n P_n \log_2 P_n \quad (11)$$

Where P_n is the probability of distribution of the peaks in the bispectrum relatively to the frequency range measured, that is

$$P_n = \frac{|A(f_1, f_2)|}{\sum_{\Omega} |A(f_1, f_2)|} \quad (12)$$

with $\Omega = [0-70]$ Hz as interval of interest for brain activity, selected by implementation of a Notch filter to eliminate the supply frequency at 50 Hz, and a low-pass filter to cancel frequencies >70 Hz.

The Shannon entropy is not appropriate for an accurate analysis, because, the trend of entropy is very variable and this can mislead to error. Shannon entropy assumes certain tradeoff between the contributions from the tails and the main mass of this distribution. It is good to control this tradeoff. For this purpose, more generalized entropy formalism was proposed in

$$TE = \frac{1 - \sum_n p_n^q}{q - 1}. \quad (13)$$

Tsallis entropy is a measure that depends on power of probability, and this has the effect to impose a control: for $q < 1$ the rare events are privileged, while for $q > 1$ the salient events are privileged. Tsallis entropy degrades to conventional Shannon entropy when the entropic index q converges to 1. For our purpose, that is to identify abnormalities in the EEG record, and values of $q > 1$ are chosen because we want to emphasize the probability to have a peak to dominant frequency in bispectrum. The peak to dominant frequency of the signal allows detecting the dominant brain activity and an epileptic seizure too [10].

C. SPECTRUM DISPLAY OF EXTRACTED SIGNAL

After calculating entropy values the extracted signal will be display in the form of spectrum. The EEG spectrum contains some characteristics waveforms that fall primarily within four frequency band:

- Delta waves are as theta waves except their frequency range is 0.5-3.5Hz.
- Theta waves have frequencies ranging from 3 to 8Hz. They are present in the EEG of newborns or adults who have disease or injury.
- Alpha waves have frequencies ranging from 8 to 13Hz. They are usually present in normal human at rest with closed eyes & not subjected to external stimulus.
- Beta waves have frequencies ranging from 14 to 30Hz and mainly occur when the subject is exposed to external stimulus.

D. KNN CLASSIFIER

The spikes of extracted signal can be distinguishing using K Nearest Neighbour classifier. The algorithm decides the points from the training set are similar enough. The class are choose to predict for a new observation, then to pick the k closest data points to the new observation and to take the most common class among these.

In KNN classifier, the class of x is found by following procedure.

- a) Determine the k instances which are nearest to the class x based on the distance measure.
- b) The next step is to allow this k instances to vote to find the class of x.

Classifier of the signal data using K Nearest Neighbour clustering technique finds the centroids and these centroids are plotted on cluster plot . The details of the function are as below.

Class = knnclassify (Sample, Training, Group)

Classifies the rows of the data matrix sample into groups, based on the grouping of the rows of training. Sample and Training must be matrices with the same number of columns. Group is a vector whose distinct values define the grouping of the rows in Training. Each row of Training belongs to the group whose value is the corresponding entry of Group. KNNclassify assigns each row of Sample to the group for the closest row of Training. Group can be a numeric vector, a string array, or a cell array of strings. Training and Group must have the same number of rows. KNNclassify empty strings in Group as missing values, and ignores the corresponding rows of Training. Class indicates which group each row of Sample has been assigned to, and is of the same type as Group [11].

RESULT AND DISCUSSION

Entropy calculation and knnclassification for online dataset signal.

STEP 1: Take any input EEG signal. In our paper we take the EEG signal from physionet.org website. The dataset containing EEG is in the form of .edf, which is converted into MATLAB file. Each dataset contains 23 recording signals according to test points. Here we take signal between F7 and T7 point.

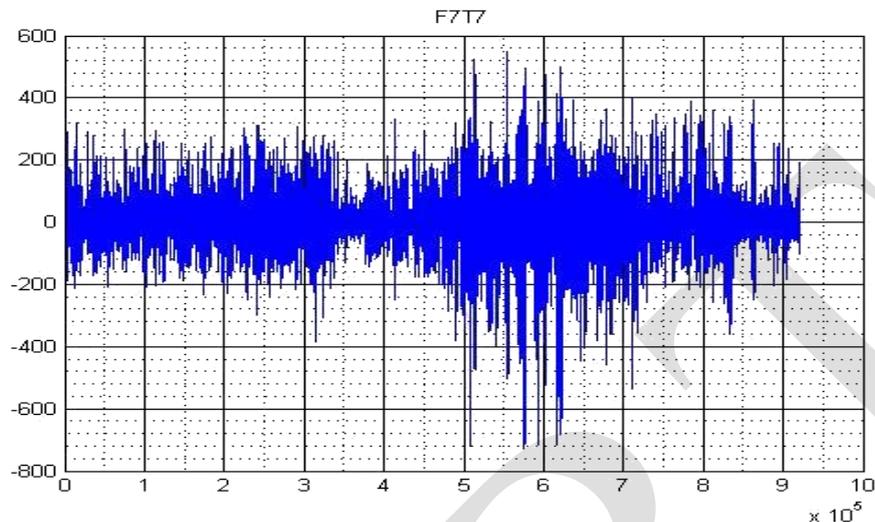


Fig2: Input EEG Signal

STEP2: The entropy of above signal is calculated using the formula,

$$TE = \frac{1 - \sum_n p_n^q}{q - 1}$$

Where, q=10 is to be taken.

STEP3: The calculated entropy is saving in (.mat) file.

STEP4: Then the signal is given to knn classify. Using function

`C=knnclassify(sample,traingset,targets)`

Where, C is variable use for saving output. If c==0 signal is normal else seizure.

For our given input signal value of c==0, so the signal is normal.

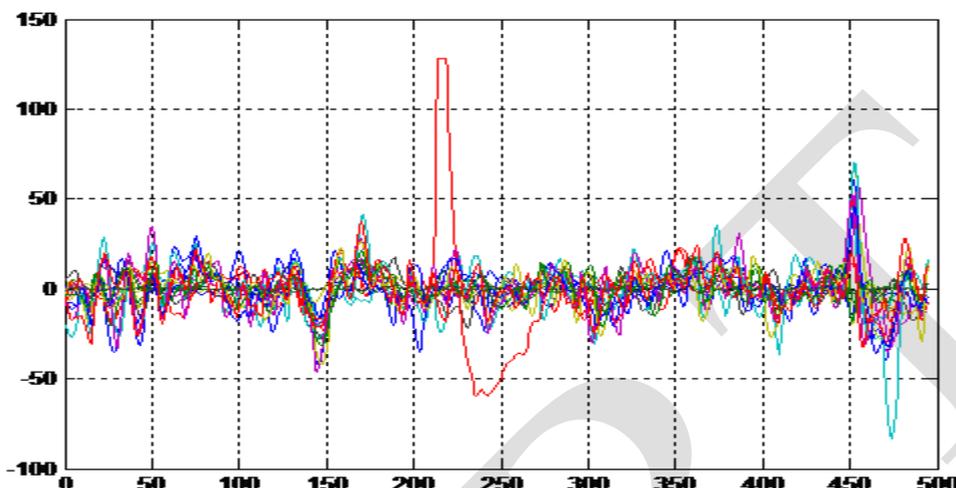
Tabulated result of weighted frequencies for 5online datasets using proposed method

Sr.No	Patients Dataset No.	Ground Truth	KNN classifications
1	Dataset 2	Normal	Normal
2	Dataset 4	Normal	Seizure
3	Dataset 5	Normal	Normal
4	Dataset 3	Seizure	Seizure
5	Dataset 1	Seizure	Seizure

Limitation: There may be possibility that ground truth results and KNN classification results are not same.

Entropy calculation and KNN classification for real dataset signal from hospital.

STEP 1: Take any input EEG signal. In our paper we take the EEG signal from real dataset taken from hospital. Each dataset contains 17 recording signals according to test points. Here we take 14 recording signals out of which we take one signal.



STEP2: The entropy of above signal is calculated using the formula,

$$TE = \frac{1 - \sum_n p_n^q}{q - 1}$$

Where, q=10 is to be taken.

STEP3: The calculated entropy is saving in (.mat) file.

STEP4: Then the signal is given to knn classify. Using function

C=knnclassify(sample,traingset,targets)

Where, C is variable use for saving output. If C==0 signal is normal else seizure.

For our given input signal value of C==1, so the signal is seizure.

Tabulated result of weighted frequencies for 5 real datasets using proposed method

Sr.No	Patients Dataset No.	Ground Truth	KNN Classifications
1	Dataset 2	Normal	Normal
2	Dataset 4	Normal	Seizure
3	Dataset 5	Normal	Normal
4	Dataset 3	Seizure	Normal
5	Dataset 1	Seizure	Seizure

CONCLUSION

The purpose of this research was to analysis Tsallis entropy is better than Shannon one because it maximizes the probabilities of the events of the interest through the choice of the entropic index and so it permitsto detect, in a more accurate way, spikes related to epilepticseizure.

REFERENCE

- 1) Aimé Lay-Ekuakille, Senior Member, IEEE, Patrizia Vergallo, Giuseppe Griffo, Francesco Conversano, Sergio Casciaro, Shabana Urooj, Member, IEEE, Vikrant Bhateja, Member, IEEE, and Antonio Trabacca, "Entropy Index in Quantitative EEG Measurement for Diagnosis Accuracy", *IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT*, VOL. 63, NO. 6, JUNE 2014.
- 2) A. Lay-Ekuakille, G. Vendramin, and A. Trotta, "Robust spectral leak detection of complex pipelines using filter diagonalization method," *IEEE Sensors J.*, vol. 9, no. 11, pp. 1605–1614, Apr. 2010.
- 3) Aimé Lay-Ekuakille, Senior Member, IEEE, and Patrizia Vergallo, "Decimated Signal Diagonalization Method for Improved Spectral Leak Detection in Pipelines", *IEEE SENSORS JOURNAL*, VOL. 14, NO. 6, JUNE 2014.
- 4) Hasan Ocak, "Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy," *Mechatronics Engineering Department, Kocaeli University, 41380, Kocaeli, Turkey, 2009.*
- 5) D. Zhang, X. Jia, H. Ding, D. Ye, and N. V. Thakor, "Application of Tsallis entropy to EEG: Quantifying the presence of burst suppression after asphyxial cardiac arrest in rats," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 4, pp. 867–874, Apr. 2010
- 6) Murugappan Murugappan, Nagarajan Ramachandran, Yaacob Sazali "Classification of human emotion from EEG using discrete wavelet transform" *School of Mechatronic Engineering, Universiti Malaysia Perlis (UniMAP), Perlis, Malaysia. J. Biomedical Science and Engineering, 2010, 3, 390-396 JBiSE doi:10.4236/jbise.2010.34054 published Online April 2010*
- 7) R. Martins, S. Selberherr, and F. A. Vaz, "A CMOS IC for portable EEG acquisition systems," *IEEE Trans. Instrum. Meas.*, vol. 47, no. 5, pp. 1191–1196, Oct. 1998.
- 8) Maryann D'Alessandro and Rosana Esteller, Senior Member, "Epileptic Seizure Prediction Using Hybrid Feature Selection Over Multiple Intracranial EEG Electrode Contacts: A Report of Four Patients", *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, VOL. 50, NO. 5, MAY 2003 603.
- 9) "Advanced Digital Signal Processing and Noise Reduction" *Fourth Edition Professor Saeed V. Vaseghi. Professor of Communications and Signal Processing Department of Electronics & Computer Engineering Brunel University, London, UK.*
- 10) S. Tong, A. Bezerianos, Y. Zhu, R. Geocadin, "Monitoring brain injury with tsallis entropy," *Dept. of Biomedical Engineering, Shanghai Jiaotong University, Shanghai, China, 1 Dept. of Biomedical Engineering, Johns Hopkins School of Medicine, Baltimore, USA.*
- 11) Mahfuzah Mustafa, Mohd Nasir Taib, Zunairah Hj. Murat and Norizam Sulaiman "Comparison between KNN and ANN Classification in Brain Balancing Application "via Spectrogram Image *Journal of Computer Science & Computational Mathematics, Volume 2, Issue 4, April 2012 17*