Data-driven Multiscale Tsallis Complexity: Application to EEG Analysis

Young-Seok Choi

Abstract—This work proposes a data-driven multiscale based quantitative measures to reveal the underlying complexity of electroencephalogram (EEG), applying to a rodent model of hypoxic-ischemic brain injury and recovery. Motivated by that real EEG recording is nonlinear and non-stationary over different frequencies or scales, there is a need of more suitable approach over the conventional single scale based tools for analyzing the EEG data. Here, we present a new framework of complexity measures considering changing dynamics over multiple oscillatory scales. The proposed multiscale complexity is obtained by calculating entropies of the probability distributions of the intrinsic mode functions extracted by the empirical mode decomposition (EMD) of EEG. To quantify EEG recording of a rat model of hypoxic-ischemic brain injury following cardiac arrest, the multiscale version of Tsallis entropy is examined. To validate the proposed complexity measure, actual EEG recordings from rats (n=9) experiencing 7 min cardiac arrest followed by resuscitation were analyzed. Experimental results demonstrate that the use of the multiscale Tsallis entropy leads to better discrimination of the injury levels and improved correlations with the neurological deficit evaluation after 72 hours after cardiac arrest, thus suggesting an effective metric as a prognostic tool.

Keywords—Electroencephalogram (EEG), multiscale complexity, empirical mode decomposition, Tsallis entropy.

I. INTRODUCTION

ELECTROENCEPHALOGRAM (EEG) has been exploited in connection with functional brain mechanisms as a potential tool for the identification of brain disorder such as hypox-ic-ischemic brain injury, epileptic seizure and so on [1]. Despite the effectiveness of EEG as a clinical diagnostic tool, most interpretations are based on subjective measures such as visual inspection, limiting precise interpretation. Thus, the need for objective measures gives rise to the development of quantitative EEG measure to uncover neurological states [2]. Recently, quantitative EEG analyses based on novel signal processing techniques have shown promising results for analyzing brain rhythm following hypoxic-ischemic brain injury after cardiac arrest [3], [4].

Among those, information theoretic analyses have been successfully used to quantify complexity or irregularity of injured brain rhythm [5]. These studies founded on assumption that the larger information content of EEG, the better neurological status of brain. More recently, it has been reported that informative content in EEG spans and varies over multiple frequencies through injury and recovery phases. Thus the single

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scale based entropy measures are lacking in reflecting the changing dynamics over multiple scales in EEG.

To address this obstacle, we present a multiscale framework of entropy measure by incorporating intrinsic mode functions (IMFs) from the empirical mode decomposition (EMD) into computing entropies. EMD, which has been recently introduced as a data-driven technique, is known as appropriate for analyzing non-stationary and nonlinear time-series [6]. It decomposes a time-series into narrow band components, called IMFs, by empirically identifying the physical time scales intrinsic to the signal. Thus, due to the potential of EMD, it has been gradually used to analyze physiological signals such as EEG [7]. Unlike the single scale based entropy measures, we compute entropy using the probability distributions of the IMFs at each scale, followed by averaging over multiple scales. Thus, we develop the multiscale complexity measures which are applied to well-known Tsallis entropy due to their simplicity and effectiveness. We showed the performance of the multiscale Tsallis entropy by comparing the conventional single scale based one in characterizing bursts. In addition, we demonstrate that the performance of the multiscale Tsallis entropy by correlating the measure of the neurological outcomes for the experimental animal subjects.

II. DATA-DRIVEN MULTISCALE COMPLEXITY

A. Empirical Mode Decomposition

In [6], a data-driven decomposition method which is appropriate for nonlinear and non-stationary time series has been developed. By an iterative scheme, EMD extracts the finest oscillation from the series, called as an IMF. The extracted IMFs exhibit the oscillatory patterns with different frequency.

An IMF has to meet the following two criteria: 1) the number of extreme and zero crossings are either equal or differ by at most one, and 2) the mean value of the envelope defined by the local maxima and local minima is zero.

Here, we describe the principle of EMD as follows. Let $s(i)$ denote the raw sampled EEG signal. Then EMD is composed of the followings:

1. Identify all the local maxima and minima of $s(i)$.
2. Interpolate between local maxima and minima respectively, getting an upper envelope $e_u(i)$ and a lower envelope $e_l(i)$.
3. Compute the mean between $e_u(i)$ and $e_l(i)$, i.e., $\mu(i) = [e_u(i) + e_l(i)]/2$.
4. Subtract the mean from the original signal $d(i) = s(i) - \mu(i)$.

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5. Repeat steps 1-4 until $d(i)$ satisfies the above two criteria to be an IMF. If $d(i)$ satisfies conditions, it becomes the first IMF that contains the finest temporal scale in the signal. Also denote as $d_1(i)$.

6. Compute the residue $r_1(i) = s(i) - d_1(i)$.

7. Iterate through steps 1−6 with $r_1(i)$ instead of $s(i)$ until the residue satisfies some stopping criterion. A commonly used stopping criterion is the sum of difference.

After the whole process, the EEG signal $s(i)$ is represented as

$$s(i) = \sum_{k=1}^{K} d_k(i) + r_K(i) \tag{1}$$

where K is the number of all extracted IMFs, $d_k(i)$ is the K-th IMF, and $r_K(i)$ is the final residue. The last residue can be considered as the last IMF.
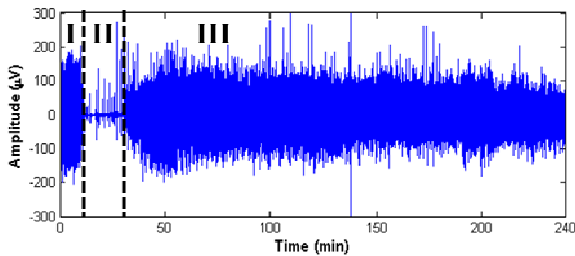

Fig. 1 Raw EEG recording of a rat during brain injury and recovery after asphyxia cardiac arrest. A 4 hour compressed signal capturing the entire experiment is presented. (I) 10 min baseline, (II) 7 min brain injury after cardiac arrest and silent period, and (III) EEG recovery

B. Multiscale Complexity

Here, we utilize the distribution of the time-varying individual oscillatory components obtained in (1), i.e., $d_k(i)$, in evaluating the multiscale complexities. To cope with the temporal evolution of complexities, EEG recording is divided into a number of segments using a sliding temporal window, leading to a time dependent entropy measure [3]. For a given $\{s(i) : i = 1,...,N\}$, a sliding temporal window $w \le N$ and a sliding interval $\Delta \le w$ are defined. Then, the n-th sliding window of the raw EEG signal are defined by

$$\mathbf{s}_n(i) = \{s(i); i = 1+n\Delta,...,w+n\Delta\} \tag{2}$$

where $n = 0,1,\cdots,[(N-w+1)/\Delta]$ and $[x]$ denotes the integer part of x.

Then, we incorporate EMD to utilize the underlying time-varying oscillatory components in EEG recording. Let assume EEG is decomposed by a sifting process, yielding totally IMFs and one residual which is considered as (K+1)-th mode. A set of IMFs, $\mathrm{De}[\mathbf{s}_n(i)]$, is obtained from the EEG signal in a sliding window

$$\mathrm{De}[\mathbf{s}_n(i)] = [\mathbf{d}_n^1, \mathbf{d}_n^2,...,\mathbf{d}_n^{K+1}] \tag{3}$$

where $\mathbf{d}_n^k = [d_k(i) : i = 1+n\Delta,...,w+n\Delta]$, $k-1,...,K+1$ are the k-th IMF after EMD on then n-th sliding window.

In order to compute the probability distributions of the IMFs, $\mathbf{d}_n^k$ is partitioned into M disjoint intervals $\{I_m, m=1,...,M\}$ spanning the range between the minimum and maximum IMF with $l_1 = \min\{\mathbf{d}_n^k\}$ and $l_M = \max\{\mathbf{d}_n^k\}$ where $l_1 < l_2 < \cdots < l_M$. Using the above definitions, a set of disjoint intervals $\{I_m = [l_m, l_{m+1}], m=1,...,M-1\}$ is obtained by binning $\mathbf{d}_n^k$. Next, $p_n^k(m)$ is the probability that the IMF belongs to the interval I_m in k-th IMF $\mathbf{d}_n^k$. It is computed as a ratio of number of samples of $\mathbf{d}_n^k$ within I_m and the total sample number of $\mathbf{d}_n^k$.

To evaluate multiscale based complexity, we incorporate the probabilities of each IMF into well-known Tsallis entropy measure as

$$\mathrm{Tsa}^k(n) = \frac{1}{q-1}\left(1 - \sum_{m=1}^{M} p_n^k(n)^q\right) \tag{4}$$

where $k = 1,...,K+1$, $0 \le p_n^k(m) \le 1$ and $\sum_{m=1}^{M} p_n^k(m)$. The following averaged complexities over all scales lead to the multiscale complexity measure, which is given by

$$\mathrm{Multiscale\ Tsa}(n) = \sum_{k=1}^{K+1} \mathrm{Tsa}^k(n). \tag{5}$$

III. EXPERIMENTS

EEG signals were recorded from rats during experiments in rodents subjected to controlled periods of normal circulation and asphyxial cardiac arrest with the goal of assessing brain dynamics following such an injury. The experimental model of brain injury by cardiac arrest has been approved by animal Care and Use Committee of the Johns Hopkins Medical Institutions [9]. This rat model has been previously validated to study multiple aspects of calibrated brain injury after asphyxial cardiac arrest, including the physiologic parameters, short-term and long term neurobehavioral outcomes, EEG recovery, and histology.

Nine adult male Wistar rats (300 $\pm$ 25g) were used. Anesthesia was induced with 4% halothane in 50% N2:50% O2. A 10 min of baseline trend was recorded including 5 min washout period to ensure that halothane did not influence the EEG. Subsequently, 7 min asphyxia was induced by stopping and disconnecting the ventilator and clamping the tracheal tube. The duration of cardiac arrest was determined by the mean arterial blood pressure being below 10 mmHg. Cardio Pulmonary Resuscitation was carried out by chest compression until return of spontaneous circulation which was decided a spontaneous the mean arterial blood pressure greater than 60 mmHg. Selected rats received hypothermia therapy.

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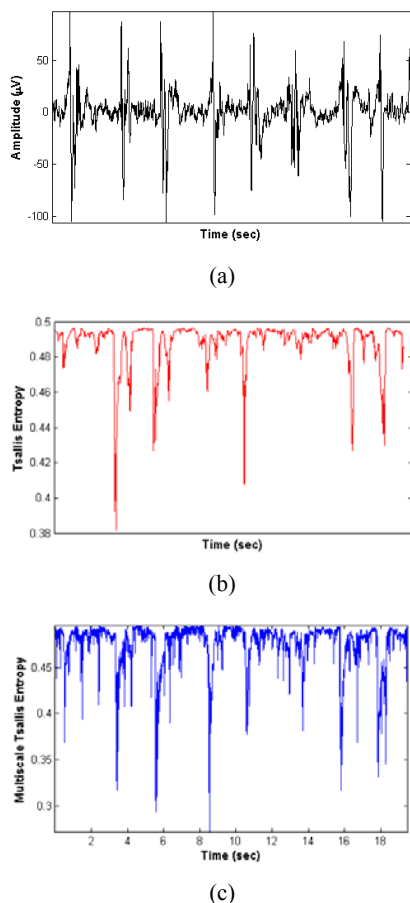Vol:9, No:5, 2015

(a)

(b)

(c)

Fig. 2 Real EEG recording of burst suppressions and time evolutions
of Tsallis entropy and multiscale Tsallis entropy. (a) Real EEG
recording of early recovery phase at 50 min. (b) Time evolution of
Tsallis entropy. (c) Time evolution of multiscale Tsallis entropy

The signals were digitalized using CODAS, a data acquisition package (DATAQ Instruments INC., Akron, OH). A sampling rate of 250 Hz and a 12 bit resolution of A/D converter were used for digitization of the data. All rats were resuscitated and neurological outcome was evaluated by neurological deficit score (ranging from 0 = worst to 80 = best) consisting of level of arousal, cranial nerves and sensory motor assessments, reflexes, and occurrence of clinically appreciable seizures [8]. The neurological deficit score was calculated by an independent observer 72 h after asphyxial cardiac arrest injury. Fig. 1 shows the EEG recording for a rat during brain injury and recovery after cardiac arrest. The raw EEG signal can be divided into three periods as follows: (I) 10-min baseline, (II) 7-min CA and silent phase, and (III) recovery. From Fig. 1, it is obvious that the amplitude of EEG decreases after CA injury and followed by gradual increase in recovery period. However, it is difficult to clearly discriminate difference between the pre-injury and the various recovery phases by visualization alone. Even more difficult would be to objectively compare different injury grades or the effects of hypothermia therapy. Limits of visual investigation stress the need for a reliable quantitative approach to study EEG's.
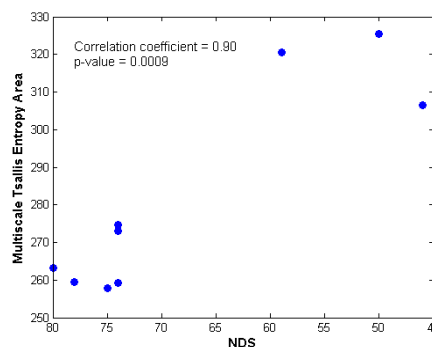

Fig. 3 Correlation between multiscale Tsallis entropy and NDS.
Pearson correlation coefficients and the corresponding p-value were
calculated

To show the inherent oscillatory components of EEG, EMD was carried out, and the resulting IMFs and corresponding power spectral densities are shown in Fig. 3. Figs. 2 (a)-(c) show the EMD results of three 10 s segments of EEG recording at various phases in Fig. 1 as follows: EEG recordings in baseline, 50 min, and 180 min, respectively.

For evaluating the multiscale complexities, the following parameters were used: sliding temporal window length with 10 s, sliding interval with 10 s, and M=20. In addition, when computing Tsallis entropy, we choose $q = 3$. To test the capability of the multiscale Tsallis entropy for detecting burst, we calculated the Tsallis entropies (multiscale and gross scale) for the burst pattern of EEG shown in Fig. 2 (a). This burst was obtained from real EEG recording of a rat. Tsallis entropy in Fig. 2 (b) underestimates some bursts (at 2, 9, and 14 s), whereas the multiscale Tsallis entropy (Fig. 2 (c)) shows its specificity for detecting the bursts. Recently, Tsallis entropy based measure, namely, Tsallis entropy area, has been introduced as a promising marker for quantifying burst suppression of EEG [4]. Along this line, we calculated the Tsallis entropy areas (multiscale and gross scale). Fig. 3 reveals that the multiscale Tsallis entropy area is relevant with neurological deficit score. Hypothesis testing using a Student-t distribution (n=9) reveal that the multiscale entropies is correlated to neurological deficit score.

IV. Conclusion

We presented a new framework for quantifying complexity in EEG over multiple time scales. Conventional Tsallis entropy measure has been successfully applied in prognosticating the degree of neurological states. However, it has limitation in de-scribing complexity spanned over different scales. Here, evaluation of Tsallis entropy using probability distribution of intrinsic oscillatory mode at each scale, followed by averaging over multiple scales results in an effective measure for assess multiscale complexity in EEG. Through experimental study, the multiscale Tsallis entropy is more proficient for detecting spikes and bursts in EEG than the single scale based one. To conclude, in order to provide a more effective prognostic metric for hypoxic-ischemic brain injury following cardiac arrest, the multiscale complexity framework can be used as a real-time

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indicator of neurological status.

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