Classification of Working Memory Load Using Wavelet Complexity Features of EEG Signals

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Abstract. We investigate the use of wavelet-based complexity measures of electroencephalogram (EEG) signals to evaluate changes in working memory load during the performance of a cognitive task with varying difficulty/load levels. Extracted wavelet-complexity measures associated with four entropic measures; that is Shannon, Tsallis, Escort-Tsallis and Renyi entropies demonstrate good discrimination among seven load levels imposed on the working memory with a classification rate of up to 96% using signals recorded from the frontal lobe of the brain. The extracted measures' values show a consistent decrease in the selected channels in two frontal and occipital lobes, as the memory load increases, indicating the EEGs disorder declines while the complexity grows. This illustrates that the brain behaves in a more organized manner characterized by more order and maximal complexity when dealing with higher load levels. The growing complexity can also reflect the higher activation of neural networks involved, as the task load increases.

1 Introduction

The electroencephalogram (EEG) is a non-invasive neuroimaging technique widely used for the diagnosis of neurological dysfunctions and the understanding of cognitive processes. Practically, it can be a very effective apparatus for the understanding of the complex behavior of the brain in different cognitive states due to its high temporal resolution, relative ease of use, and a comparably low cost [1]. Each cognitive process activates local and spatial cortical networks to an extent depending on task specificity and complexity [2].

Measuring the amount of cognitive/working memory load when performing a cognitive process is of high importance for the prevention of decision-making errors, and the development of adaptive user interfaces [3]. This is necessary to avoid memory overload and maintain efficiency and productivity during tasks, especially in critical/high mental load workplaces such as persons working in the areas of air traffic control, military operations and emergency/interventional medicine.

T. Huang et al. (Eds.): ICONIP 2012, Part II, LNCS 7664, pp. 692–699, 2012.

Currently, different methods are available to measure working memory load, such as; behavioral/physiological techniques or performance-based/subjective ratings methods. Among them, EEG has been rated as the best physiological method, offering more reliability and sensitivity, when measuring memory load [4].

A range of features; mainly power spectral-based, have been applied for measuring the working memory load using EEG signals, previously [5-7]. The application of non-linear/dynamical measures in classifying different mental tasks or the comparison with the rest condition is more recent, and measures like correlation dimension (CD) [8, 9], Hurst exponent (HE), approximate entropy (ApEn) and largest Lyapunov exponent (LLE) [10, 11] have been used to measure the complexity or irregularity of the underlying brain dynamics. In [10], it is concluded that the brain reflects a lesser degree of cognitive activity (shown by less correlation dimension/complexity) when the participants are subject to sound or reflexologic stimulation compared with the normal state.

Since dynamical features had not been used in the study of measuring memory load previously and also the question of whether the complexity or order/regularity of the EEG signals change when the imposed load varies, the authors aimed at addressing these questions in [12, 13]. In these studies, features such as: spectral entropy, CD, HE, and ApEn proved to be a good discriminator of imposed memory load and indicator of higher predictability and less irregularity/more order in the brain activity when dealing with higher memory load. CD feature also showed that the brain activity dimension/complexity increases with the increase of memory load. However, in our previous studies, the relationship between the signals' order/regularity and its complexity was not explicitly investigated. In this study, we investigate not only a recently proposed feature set; based on wavelet-complexity measures [14-16], for discriminating the memory load, but also the signals' changing complexity and order relationship with varying memory load imposed, and their implication on the neural activations towards a better understanding of the brain dynamics when dealing with higher loads.

2 Materials and Methods

2.1 Experiment and Dataset

EEG signals were acquired from twelve healthy male subjects; postgraduate students aged between 24-30 years. In the experiment, the participants were asked to do an arithmetic task (an addition task with varying difficulty level).

Each time, the numbers to be added were displayed sequentially and in Arabic notation, on a laptop PC with a viewing distance of 70 cm to the subject. The difficulty level was manipulated by varying the n-digit numbers used and carries required to calculate the addition, as follows: in very low level (L1); 1&2 digit numbers with no carry, in low level (L2); carry is introduced to L1, in medium level (L3); 2 digit numbers with one carry, in medium-high level (L4); 2 digit numbers with two carries, in high level (L5); 2&3 digit numbers with one carry, in very high level (L6); 2&3 digit numbers with two carries, in extremely high level (L7); 3 digit numbers with three carries. The subjects were required to click on the correct answer using the mouse left button, using the minimum possible finger movement. In the baseline/rest condition, conducted after the experiment, the participants were asked to sit relaxed and keep their eyes closed. To minimize any muscle movement artifact (EMG) during the recording, the subjects were asked to avoid any unnecessary physical movements and their hand was placed in a fixed position.

The subjects' EEG signals were recorded using an Active Two system. Each recording contained 32 EEG channels mounted in an elastic cap, according to the extended international 10 - 20 system. A linked earlobe reference was used and impedance was kept under 5 kÙ. The EEG signals were passed through a band-pass filter with cut-off frequencies of $0.1 - 100$ Hz and were recorded at a $f_s = 256$ Hz sampling rate. To select the epochs which contained minimal EMG artifact, each recording was judged by visual inspection. As a result, 70 seconds (out of 90 seconds of each task level recording) for each subject was considered. This portion of the recordings included EOG and ECG artifacts, which were not removed.

2.2 EEG Source Localization

Source localization can be used to estimate the localization and distribution of electrical events in brain disorders [17]. We used this technique to narrow down the number of channels under study and select discriminatory channels, as described in our previous work [12].

2.3 Wavelet-Based Complexity Measures

In studying EEG signals, entropy is a measure of order and more specifically, a degree of synchrony of the cell groups contributed in different neural responses [18]. If this entropy is considered with the system's likely state/architecture, one can define system complexity as a form of statistical complexity measure [16].

General form of wavelet statistical complexity measures can be found in [16], which uses different entropy types and distance measures. In this study, we use the complexity measure of $C_q^{(k)}[P]$ given in (1), which is based on the Kullback/q-Kullback distance measure [16], as below:

$$C_q^{(k)}[P] = (1 - H_q^{(k)}[P]).H_q^{(k)}[P]; k = 1,2,3,4 \tag{1}$$

In (1), P is the probability distribution of the Discrete Wavelet Transform (DWT) of parameter under study, q is the entropic index $(0 \leq q \leq 1)$ and k refers to the entropy types used as follows [18]:

$$\text{Shannon: } H_1^{(1)}[P] = H_{SH} = -\sum_{i=1}^{N} p_i \ln(p_i) \tag{2}$$

$$\text{Tsallis: } H_q^{(2)}[P] = H_{TS} = \frac{1}{q-1}\sum_{i=1}^{N}[(p_i - (p_i)^q] \tag{3}$$

$$\text{Escort-Tsallis: } H_q^{(3)}[P] = H_{ETS} = \frac{1}{q-1}\left(1 - \left[\sum_{i=1}^{N}(p_i)^{1/q}\right]^{-q}\right) \tag{4}$$

$$\text{Renyi: } H_q^{(4)}[P] = H_{RE} = \frac{1}{1-q}\ln\left[\sum_{i=1}^{N}(p_i)^q\right] \tag{5}$$

where p_i is the distribution of the DWT parameter of the under study EEG segment (i^{th}) and $q = 1$ for Shannon entropy and $0 \leq q < 1$ for other entropies.

3 Experimental Results

Our earlier source localization results demonstrated that mainly the frontal and occipital regions of the brain were the most influenced regions, in all the task load levels across all twelve subjects ([12, 13]). Therefore, only EEG channels located in these two regions (i.e. the frontal channels Fp1, AF3, F7, F3, FC1, FC5 FC6, FC2, F4, F8, AF4, Fp2 and the occipital channels PO3, O1, Oz, O2, PO4) were considered for further analysis.

We decomposed the EEG signals of length $T = 5$ seconds (non-overlapping), into five levels (scales) using Daubechies-4 mother wavelet. We denote the under study wavelet parameter here are wavelet coefficients. For instance, in case of approximate coefficients at the 5th level (which corresponds to the delta frequency band) we have:

$$\mathrm{a}_5 = [\mathrm{a}_{51}\ \mathrm{a}_{52} \dots \mathrm{a}_{5\mathrm{N}}] \tag{6}$$

where $N = 40$ is the number of approximate coefficients at the 5th level; ($N = \frac{Tfs}{2^5} = 40$). P in equations (2)-(5) is therefore defined as:

$$\mathrm{P} = \frac{\mathrm{a}_5}{\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{a}_{5\mathrm{i}}} \tag{7}$$

Then, we calculated four entropic features; H_{SH}, H_{TS}, H_{ETS} and H_{RE} using equations (2)-(5) for each EEG segment. The index q in H_{TS}, H_{ETS} and $H_{RE}$was varied to find its optimal value for the purpose of the load discrimination. The feature values showed a decreasing trend as the task load increased in many channels of interest. For instance, the extracted H_{RE} values for channel Fp1 of subject 1 for three load levels are L1=871.77, L4= 865.61, and L7= 859.68, while for the rest condition=877.70.

For illustration purposes, Fig. 1 shows the median of the extracted H_{RE} from the frontal channels in scale 5, for channel F7 of subject 1, for two extreme values of q; (a) $q = 0.9$, (b) $q = 0.1$, in the delta frequency band. As shown, the median of the extracted H_{RE} are able to distinguish the seven task loads better with q closer to 1, as it consistently reveals a decreasing median with increasing task load.

Following preliminary analysis, those features and frequency bands which show a consistent decreasing trend with increasing load across all twelve subjects, are summarized as follows: for the frontal lobe; channels Fp1, F7, F3, FC5, FC6, FC2, and AF4 in the delta band, channels FC5, AF4 in the alpha band; for the occipital lobe; channels PO3, O1, and O2, in the delta band. For illustration purposes, Fig. 2(a) shows the median of the extracted H_{RE} from the frontal channels in scale 5, across all subjects. We then calculated the complexity values for each entropic feature, using (1). The results showed that the complexity values increases as the task load increases, in the above selected channels. For illustration purposes, the complexity values corresponding to Fig. 1(a) for channel F7 of subject 1, using H_{RE} entropy is shown in Fig. 2(b). This demonstrates that the signal complexity increases with increasing task load, while the corresponding signal entropy/disorder decreases in Fig. 1(a).

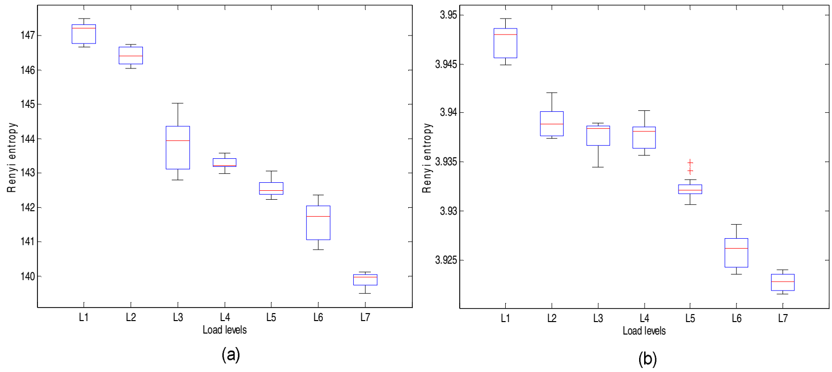

Fig. 1. The Renyi entropy variations for (a) $q = 0.9$, (b) $q = 0.1$ with the load levels, for channel F7 of subject 1. On each box, the red mark is the median; the edges of the box are the 25th and the 75th percentiles.

In order to study the performance of the entropic features in classifying different load levels, we applied the four extracted features from the EEG segments acquired from the selected channels into an Artificial Neural Network (ANN) classifier. Based on experimental results, we chose a multi-layer perceptron ANN, with a first hidden layer of 20 neurons, a second hidden layer of 14 neurons and an output layer of 7 neurons corresponding to 7 load levels. 75% of the data (for each task level for twelve subjects) were used for training and the remainder for testing, in a subject-dependent arrangement. Since the delta band contained more selected channels for all the extracted features across all the subjects, we considered the classification accuracy of the features only in this frequency band. The classification results are summarized in Table 1.

Table 1. Classification accuracy of the four entropic measures ($q = 1$ for Shannon and $q = 0.9$, for the remaining entropies) extracted from the delta band from channels in the two identified regions of interest

Channels	Feature	Accuracy %
Frontal: Fp1, F7, F3, FC5, FC6, FC2, and AF4	H_{SH}	96.83
	H_{TS}	94.18
	H_{ETS}	82.10
	H_{RE}	89.42
Occipital: PO3, O1, and O2	H_{SH}	85.71
	H_{TS}	88.36
	H_{ETS}	51.32
	H_{RE}	83.60

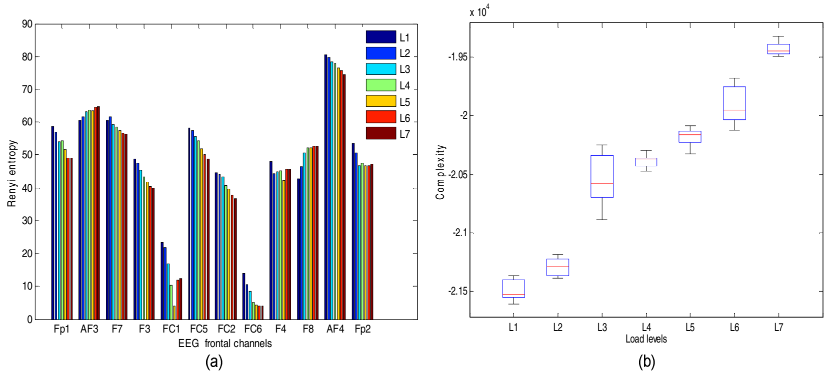

Fig. 2. (a) Medians of the Renyi entropy extracted from segmented EEG data in the delta band, from the frontal lobe, across twelve subjects. (b) The complexity variations with the load level increase from L1 to L7 for channel F7, using extracted H_{RE}, for subject 1.

4 Discussion

In this study, we investigated the use of four entropic measures in different wavelet levels (wavelet-complexity features) for discriminating working memory load in a cognitive task with seven load levels. The extracted measures from the selected channels; picked up by source localization from the frontal and occipital lobes of the brain, were found to be successful in memory load discrimination. The decline in the median values of the entropy features as the task load increased demonstrates that the degree of the disorder decreases as the task load/working memory load imposed increases.

The complexity values measured by each entropic measure showed an increasing trend as the task load increased. This indicates that with increasing memory load, not only the disorder of the signals declines but also the complexity grows. This can demonstrate a more organized manner of the brain characterized by more order and maximal complexity at the same time, when dealing with higher load levels. Practically, more order implicates higher degree of synchrony of the cell groups contributed in neural responses [18] and more complexity indicates higher activation of the neurons. This can confirm the changing dynamics of the brain when performing a task with different load/difficulty levels. This is supported by [8], in which the complexity of EEG signals (shown by correlation dimension) increases as more difficult cognitive tasks are performed and it indicates the level of vigilance and mental activity. This is also confirmed by previous studies that the increasing workload is reflected by more activity and mostly in the frontal lobe of the brain [19, 20]. On the other hand, our classification results revealed that the extracted features show a significantly higher accuracy for the selected frontal channels compared with the selected occipital channels.

We also examined different values of entropic index of q to find the optimal value for the purpose of task load discrimination in this study. The results showed the larger the value of q (closer to 1) the better the different load levels were distinguished, for the three measures of Tsallis, Escort-Tsallis and Renyi. This reason could be that as q increases the three entropic measures become closer to Shannon entropy, for which the classification rate outperformed the rest of the features in the frontal channels. Its classification accuracy is closely followed by Tsallis entropy which is a generalisation of Shannon entropy.

Since the used complexity formula is based on entropy, one may criticise that it could carry the same information as entropy. But in [21], it is demonstrated that this simple entropy-based measure is really an indicator of complexity in many systems.

The frequency band analysis showed that the delta is the most promising band for task load discrimination, including more selected channels for the four measures in our study. This is while, only two channels in the alpha band and no channel in the theta band, showed significant discrimination among all seven load levels. This was confirmed by classification results, as well. This is in line with previous studies showing that the delta activity could be an indicator of attention during some mental tasks, so that by increasing task demand, participant's attention to the task and also the delta band activity increases [22].

Comparison of the rest condition signals, recorded after task accomplishment, with the task condition signals showed that the entropy value of the highest load level is lower than the rest condition in all the subjects. This can indicate that the brain is in a less disordered (more ordered/focused) state when conducting a cognitive task.

The entropic features not only add to the collection of suitable feature sets for characterizing working memory load previously applied by the authors, but also proved to be computationally more efficient than using non-linear dynamical features such as correlation dimension, approximate entropy and Hurst exponent. Furthermore, the entropic features are relatively free of parameter tuning which is critical and highly application-dependent for non-linear dynamical features.

For future work, this method could be validated on a larger database and in more realistic environments and conducting other cognitive tasks with a focus on cognitive overload.

Acknowledgements. This research was supported by the Asian Office of Aerospace Research & Development, Grant No. FA2386-12-1-4049.

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