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Characterization of Memory Load in an Arithmetic Task using Non-Linear Analysis of EEG Signals

Pega Zarjam, *Student Member, IEEE,* Julien Epps, *Member, IEEE,* Nigel H. Lovell, *Fellow, IEEE* and Fang Chen

Abstract— **In this paper, we investigate non-linear analysis of electroencephalogram (EEG) signals to examine changes in working memory load during the performance of a cognitive task with varying difficulty levels. EEG signals were recorded during an arithmetic task while the induced load was varying in seven levels from very easy to extremely difficult. The EEG signals were analyzed using three different non-linear/dynamic measures; namely: correlation dimension, Hurst exponent and approximate entropy. Experimental results show that the values of the measures extracted from the delta frequency band of signals acquired from the frontal and occipital lobes of the brain vary in accordance with the task difficulty level induced. The values of the correlation dimension increased as the task difficulty increased, showing a rise in complexity of the EEG signals, while the values of the Hurst exponent and approximate entropy decreased as task difficulty increased, indicating more regularity and predictability in the signals.**

I. INTRODUCTION

A RELIABLE and noninvasive measurement of working memory load that can be made continuously while performing a cognitive task would be very helpful for assessing cognitive function, crucial for the prevention of decision-making errors, and the development of adaptive user interfaces [1]. Such a measurement could help to maintain the efficiency and productivity in task completion, work performance, and to avoid cognitive overload [1], especially in critical/high mental load workplaces such as air traffic control, military operations, and fire/rescue commands.

Electroencephalography (EEG) is a noninvasive neuro-imaging technique widely used for measuring cognitive workload, which offers high temporal resolution, ease of use, and a comparably low cost [2]. EEG contains useful information about various physiological states of the brain and can be very efficient for understanding the complex dynamical behavior of the brain, if interpreted correctly [3].

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P. Zarjam is with the School of EE&T, University of New South Wales, Sydney, Australia. She is also with ATP Research Laboratory, National ICT Australia (phone: +61 2 9385 4803; fax: +61 2 9385 5993; email: p.zarjam@student.unsw.edu.au).

J. Epps is with the School of EE&T, University of New South Wales, Sydney, Australia. He is also with ATP Research Laboratory, National ICT Australia (email: j.epps@unsw.edu.au).

Nigel Lovell is with the Graduate School of Biomedical Eng. University of New South Wales, Sydney, Australia (email: n.lovell@unsw.edu.au).

F. Chen is with ATP Research Laboratory, National ICT Australia (email: fang.chen@nicta.com.au).

Previously, a range of methods have been applied for measuring and classifying the memory load using EEG signal. These methods have used features such as power spectral density (PSD) or the averaged power and maximum/log power spectra [4-6], sub-band entropy [7-8], and autoregressive model [9]. The application of non-linear methods in classifying mental tasks is more recent, and measures like correlation dimension (CD) [10-12], Hurst exponent (HE), approximate entropy (ApEn) and largest Lyapunov exponent (LLE) [13-14] have been used to measure the complexity/irregularity of the underlying brain dynamics during the performance of some cognitive tasks compared with the rest condition. In [13], it was demonstrated that the CD and ApEn/HE values decrease/increase when the participants are subject to sound or reflexologic stimulation compared with the normal state, showing a lesser degree of cognitive activity. Stated differently, in these studies the brain activity states; such as normal/rest and stimulated have been differentiated [10, 13-14]. But to date, these measures have not been investigated in the analysis of the varying working memory load and the question whether these approaches could provide some information on the brain dynamics/behavior when performing a cognitive task with varying difficulty levels has not been addressed.

For this study, we designed a cognitive task, more specifically an arithmetic task with seven levels of difficulty. To our knowledge the largest number of mental task load levels reported to date is five levels [15-16]. Our earlier work with three levels on a reading task also showed very promising results in characterizing the memory load using linear features [17-18].

We hypothesize that non-linear measures change continuously according to the varying difficulty levels of the cognitive task induced and therefore they can be used to quantify changes in memory loads during the performance of a cognitive task.

II. NON-LINEAR MEASURES BACKGROUND

In this study, we analyze the EEG signals during the performance of an arithmetic task using CD, HE, and ApEn. The measures are briefly explained below. Full details of their computation and the selection of their parameters can be found in [11, 13, 19].

Correlation dimension (CD): this is a measure of the complexity of a time series. For a given EEG segment; $x[n], n = 1,2, \dots, N$, CD is a function of two parameters;

m and r, which represent the embedding dimension and radial space around each reference point, respectively. The CD is calculated using [11]:

$$CD = \lim_{r\to 0}\frac{\log C(m,r)}{\log(r)} \quad (1)$$

where $C(m,r)$ is a function showing the probability that two arbitrary points of $x[n]$ in an m-dimensional space on the orbit are closer together than r. Larger values of CD indicate more complexity in the signal.

Approximate entropy (ApEn): this is a non-linear entropy estimator showing regularity or predictability of a given time series. ApEn of a given $x[n]$; is calculated using the following formula [19]:

$$ApEn(m,r) = \Phi^{m}(r) - \Phi^{m+1}(r) \quad (2)$$

$$\text{where } \Phi^{m}(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\log\left(\frac{C_i{}^{m}(r)}{N-m+1}\right) \quad (3)$$

m: embedding dimension and r: radial space

Here, $C_i{}^{m}(r)$= (number of *X(j)* such that $d[X(i),X(j)] \leq r$. $d[X(i),X(j)]$ is the max distance between two given vectors of *X(i), X(j).* A vector is formed by parameter *m* such that $X(i) = [x(i), x(i+1), \ldots x(i+m-1)]$; $i = 1, \ldots, N-m+1$. Practically, ApEn quantifies the likelihood of vectors that remain close (within *r*) on the next incremental comparison [20]. Larger values of ApEn indicate unpredictability or irregularity in the signal.

Hurst exponent (HE): it is a measure of self-similarity and long-term dependence and its degrees in a time-series. It is defined by [13]:

$$HE = \log_T\left(\frac{R}{S}\right). \quad (4)$$

where $T = N * f_s$ is the duration of the sample data and $\frac{R}{S}$ the corresponding value of the rescaled range. If $H > 0.5$ the time-series covers more distance than a random walk. Larger values of HE represent increase of randomness in the signal.

III. Methods

A. Participants and Experiment Settings

We studied six male participants, between the ages of 24-30 years, engaged in postgraduate study. They were right-handed and had normal or corrected to normal eyesight and gave written informed consent, in accordance with human research ethics guidelines. We designed an addition task with seven levels of difficulty, starting from one digit addition (very low) to multi-digit addition (extremely difficult).

The task was displayed and controlled on a laptop PC with a viewing distance of 70 cm to the participant (subject). Each number was shown at the center of the screen in Arabic notation for three seconds. Subjects were asked to add the two presented numbers (shown sequentially), then were given two seconds (blank page) for retention followed by a multiple choice menu that presented the possible answers. The subjects were required to click on the correct answer using the mouse left button, with the minimum possible finger movement. There were 42 addition problems in total, across seven difficulty levels (6 per level), with each level lasting for two minutes. The difficulty level was manipulated by varying the *n*-digit numbers used and carries required to calculate the addition. The task detail is shown in Table I.

Table I.
Task difficulty level details.

Task level	Number of digits	Example
Very low (L1)	1&2 digit numbers	45+2
Low (L2)	1&2 digit numbers with 1 carry	54+9
Medium (L3)	2 digit numbers with 1 carry	67+42
Medium-High (L4)	2 digit numbers with 2 carries	39+65
High (L5)	2&3 digit numbers with 1 carry	377+32
Very high (L6)	2&3 digit numbers with 2 carries	76+347
Extremely high (L7)	3 digit numbers with 3 carries	983+748

The participants were asked to avoid any unnecessary physical movements to minimize the chance of muscle movement artifact (EMG) during the recording. Their hand was also placed in a fixed position, where they could still make finger movements in response to the correct answer on the mouse. Since the channels in the frontal lobes are sensitive to ocular artifact, participants were required to refrain from blinking as much as possible. The participants were given 30 second rests between each level, allowing them to relax, move or blink.

B. EEG Recording

The EEG signals were recorded from 32 channels mounted in an elastic cap, according to the extended international 10 - 20 system using an Active Two acquisition system. The experiment was conducted under controlled conditions in an electrically isolated laboratory, with a minimum distance of five meters from power sources to the experiment desk and under natural illumination. 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. Each recording was visually inspected to choose the epochs which contained minimal EMG artifact. As a result, 70 seconds (out of 90 seconds of each task level recording) for each subject was considered. However, the remaining portion of the recordings still included EOG and ECG artifacts.

IV. Analysis

A. EEG Source Localization

We used EEG source localization to estimate the localization and distribution of electrical events to select discriminatory channels, as in our previous work [21].

B. Sub-Band Filtering

We decomposed the EEG signals using the Discrete Wavelet Transform (DWT) into five levels (scales), according to the EEG frequency bands (0-4Hz delta, 4-8 Hz theta, 8-12 Hz alpha, 12-30 Hz beta, 30-100 Hz gamma). The selected mother wavelet was the Daubechies-4, which is localized and symmetric and has a smooth thresholding effect.

C. Non-Linear Measure Application

The EEG segments in a particular sub-band were denoted as

$x[n]; n = 1,2, \dots, N$ with the length of $T = 5$ seconds. Three non-linear measures; i.e. CD, ApEn, and HE were extracted from each EEG segment in different frequency sub-bands for each subject.

V. RESULTS

The source localization results showed that mainly the frontal and occipital regions of the brain were the most influenced regions, in all the task load levels across all six subjects. As the load level increased, not only were wider areas of these regions were affected, but also they were affected more deeply (shown by values closer to "1" in Fig. 1). The source maps of two load levels, the lowest (L1) and the most difficult levels (L7) for subject 1, are shown in Fig. 1. Therefore, for further analysis only EEG channels positioned in the frontal and occipital lobes were taken into account (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).

Fig. 2(a) shows the medians of the extracted CD measure from a frontal channel for subject 1 in the delta frequency band. As seen, the median of the CD increases regularly as the task load increases. Fig. 2(b) displays the median of the extracted ApEn measure from the same channel, subject and frequency band. Here, the median of the ApEn decreases consistently as the task load increases. The extracted HE values showed a similar trend to the ApEn. Therefore, their values tended to decline as the load level increases.

The results for the selected channels across all the six subjects in different sub-bands are summarized in Table II. The study of these measures by frequency sub-band indicated that the delta sub-band exhibited more channels that consistently vary with the load level induced. In terms of the brain regions investigated, the frontal lobe also showed the highest number of channels contributed to the load level distinction.

Due to the importance of the non-linear parameters' values in determining the outcome, we also examined their different values to find the optima for the purpose of memory load characterization in this study. Thus, we calculated the CD for $1 < m < 10$ and $\mathrm{r} > 10$. According to the results, the higher the dimension m, the more distinct the load levels were. But varying parameter r did not affect the results much. For the ApEn measure, we varied $0.1 * std < r < 0.9 * std$ and $m = 2$ or 3. The results showed that the lower the r value (closer to $0.1 * std$), the better the load levels were distanced but the choice of embedding dimension of 2 or 3 did not make any significant change.

We also used a Kruskal-Wallis test to statistically measure the effectiveness of the measures in distinguishing seven load levels. The channels which revealed a small p-value ($p < 0.01$) for each extracted measure, across six subjects are shown in bold in Table II.

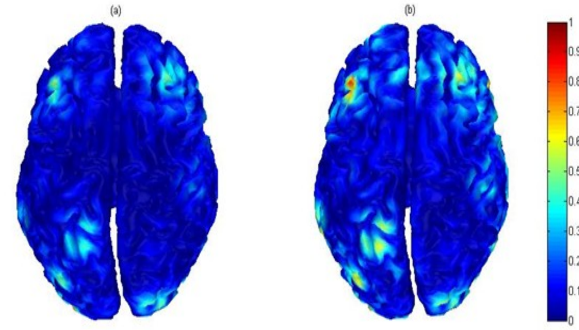

Fig. 1. The source maps of two load levels for subject 1; (a) the lowest load (L1), and (b) the most difficult load (L7). Both load levels influence the similar regions more or less but the degree of activation increased as the load level increased.

VI. DISCUSSION

In this study, we investigated the use of three non-linear measures for characterizing memory load in an arithmetic task with seven levels of difficulty. The source localization results assisted us in focusing on the brain regions/channels of interest which were the most influenced by the task load, namely the frontal and occipital lobes. When the more difficult task load was induced these regions were affected more deeply and widely. This is in line with previous findings that the increasing workload is reflected by activity mostly in the frontal lobe of the brain [15, 22].

The extracted non-linear measures from the selected channels were found to be successful in task load discrimination and representing the functional dynamics of the brain when performing a task with different difficulty levels. The CD values tended to increase as the task load increased; indicating the brain activity dimension/complexity increases with the increase of cognitive activity load. This can be supported by previous mental task studies showing lower dimension when the brain goes to a passive state or a state of relaxation [10, 13]. A decreased value of ApEn with increased task load implies higher predictability and less irregularity in the brain activity. The decline in HE values as the task load increased demonstrates that random behavior of the signal decreases as the task load increases. The last two measures may indicate the brain behaves in a more regular and focused manner when performing more difficult tasks.

The frequency sub-band analysis showed that the delta is the most contributing sub-band, including more channels for the three measures in the memory load characterization. This was statistically confirmed by low p-values.

As future work, this method should be validated on a larger database and in more realistic environments. This includes collection of EEG signals with increased subject numbers, running different cognitive tasks with a focus on cognitive overload, using a classification method for discriminating the task loads.

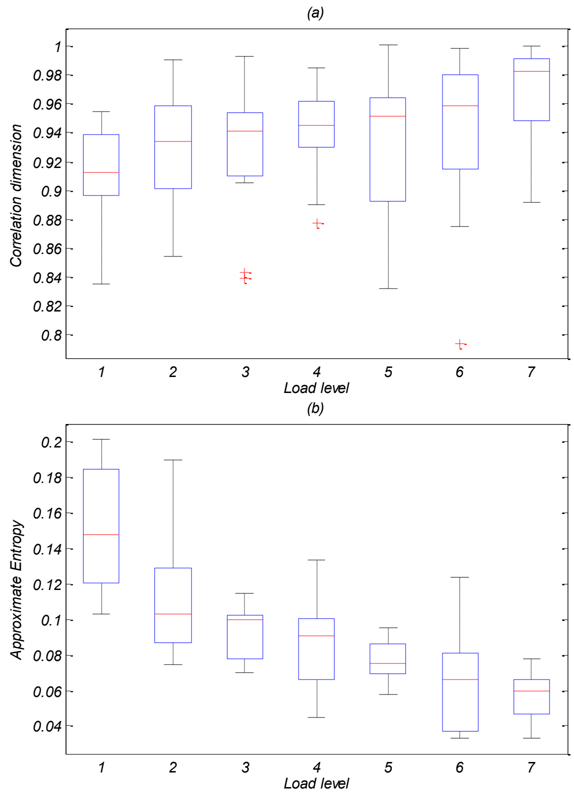

Fig. 2. (a) Medians of the CD ($m = 10, r = 20$) extracted from segmented EEG data in the delta band from a frontal channel (Fp1) of subject 1. (b) Medians of the ApEn ($m = 2, r = 0.2 * \text{std}$) extracted for the same channel, freq. band, and subject. On each box, the red mark is the median; the edges of the box are the 25th and the 75th percentiles.

TABLE II.
SELECTED CHANNELS FOR EACH EXTRACTED NON-LINEAR MEASURE WHOSE MEDIAN SHOWED A CONSISTENT TREND ACCORDING TO TASK LOAD VARIATION, IN DIFFERENT FREQUENCY SUB-BANDS, ACROSS ALL SIX SUBJECTS. CHANNELS IN BOLD DENOTE CASES WHERE A KRUSKAL-WALLIS TEST GAVE P<0.01 FOR ALL SIX SUBJECTS.

Freq. sub-band	Measure	Region of the brain/Channels
Delta	CD	Frontal: **Fp1**, AF3, FC1, F3, FC5, FC2, **F4**, **F8**, AF4, **Fp2** - Occipital: O1, **Oz**
	ApEn	Frontal: Fp1, **AF3**, **F7**, **F3**, FC5, **FC6**, FC2, F4, **F8**, **AF4**, Fp2 - Occipital: **O1**, Oz, **PO4**
	HE	Frontal: Fp1, AF3, FC1, **FC6**, F4, **F8**, AF4, Fp2 - Occipital: O1, **PO4**
Theta	CD	Frontal: **Fp1**, AF3, FC6, FC2 - Occipital: O1,Oz
	ApEn	Frontal: Fp1, AF3, FC1, F3, F8 - Occipital: O1, O2, PO4
	HE	Frontal: Fp1, AF3, FC1, FC2, F8 - Occipital: PO3,Oz, O2, PO4
Alpha	CD	-
	ApEn	Frontal: Fp1, AF3, F7, FC5, AF4, Fp2 - Occipital: PO3, O2
	HE	Frontal: FC1, FC6, F8 - Occipital: **Oz**
Beta	CD	-
	ApEn	Frontal: Fp1, AF3, FC6, Fp2 - Occipital: O1, Oz
	HE	Frontal: **Fp1**, **AF3**, FC2, Fp2 - Occipital: PO3

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