Predicting Individual Cognitive Status Based on EEG Data Fit to Power Law Distribution

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1 Introduction

Effective application of information technologies and immersion of today's citizens into digital environment relies upon understanding of the users' cognitive abilities, in order to optimally design information perception and selection in a human-computer system. The same consideration applies to more advanced technologies generally associated with cyberspace, such as virtual and augmented reality, or brain-computer interfaces. Correspondingly, the new research direction of Cyberpsychology was forged, which studies neurocognitive, affective, and social aspects of interaction between people and digital devices and computer systems, as well as the effects of online and off-line usage of digital technologies [1–3]. Lack of consideration of a user's cognitive status when organizing a cyber-interaction might result in degraded user experience (UX) and even involve health hazards.

The problem of investigating the cognitive status of a person is considered from various positions (medicine, psychology, neurophysiology, etc.) by different authors. In medicine, most commonly, Montreal Mental State Scale (MMSE), mental status assessment scale, or a battery of frontal dysfunction tests are currently used to assess the cognitive status of patients [4]. These techniques make it possible to diagnose already noticeably impaired cognitive functions. Despite this, the MMSE scale is widely used as a predictor of progression of different forms of dementia, in longitudinal studies of the dynamics of cognitive impairment or for cognitive screening of patients' condition after stroke [5–7].

The popularity of this technique is determined by the simplicity of use and the ability to cover various areas of cognitive activity, including orientation in space, attention, memorization, object naming, etc. At the same time, registration of

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electrical activity of the brain with changing functional capabilities of the organism associated with aging and/or cardiovascular diseases using modern mathematical methods of processing and analysis of data allows performing more differentiated diagnosis of cognitive deficits [8].

Electroencephalography (EEG) allows quantitative analysis of the functional state of different regions of the cerebral cortex, which reflects the potential readiness of the nervous system to solve problems and the reaction to the effects of stimuli during various activities. Clinical studies more often consider the closed-eye resting state to elucidate the individual features of topographic distribution and the degree of synchronization/de-synchronization of neuronal (synaptic) activity depending on the state of the patients [9, 10]. EEG identifies several main rhythms related to selection and memorization of information, motivation, and emotional regulation. In particular, amplitude and peculiarities of spatial organization of theta rhythm (frequency 4–8 Hz) are considered as a marker of cognitive status disorders [11–14]. A study by Babiloni et al. [15] showed that theta rhythm in the parietal, occipital, temporal, and limbic regions was higher in a mild form of Alzheimer's disease compared to mild cognitive disorders and the normal group. In another study, the increase in theta-power was recognized as the most pronounced indicator of cognitive deficits in patients with dementia [13].

For the study of frequency characteristics of EEG, spectral analysis methods based on the Fourier transform are widely used. However, the use of spectral analysis methods alone may not be sufficient to characterize the causes and dynamics of events that underlie the features of the frequency-spatial organization of EEG associated with different cognitive functions. Therefore, the development of new methods of EEG analysis to assess cognitive status is an important task.

At the same time, it is well known that the EEG power spectrum follows a power-law function: $P \propto 1/f^{\beta}$, where P is power, f is frequency, and β is the "power-law exponent" parameter, which is associated with aperiodic brain activity (or "scale-free brain activity" in reference to its scale-invariant nature) [16]. Identifying diverse values of the power law parameters is of interest, since it characterizes the mechanisms of generating arrhythmic activity of the brain in different states.

Another promising approach to describe the structure of EEG is the application of graph theory [17, 18]. Visibility graph algorithms allow a time sequence to be characterized by a network topology: A periodic sequence can be transformed into a regular lattice, and a chaotic series corresponds to random graphs. This approach was successfully used to classify networks in Alzheimer's patients and control networks [18–20]. Moreover, the theta range of EEG bio potentials turned out to be the most informative for distinguishing between patients with Alzheimer's disease and minimal brain dysfunctions [20].

It has been shown that the electrical activity of the brain can be described with Benford's law. The algorithm based on this law was used to differentiate the awake and the anesthesia sleep states or to imitate artifacts in EEG recording [21]. In [22], the distribution analysis of EEG signal time derivatives for compliance with the Benford distribution law method was used to differentiate Alzheimer's patients from healthy individuals. The authors note that an additional advantage of the proposed method of data classification using half total error rates (HTER) is lack of influence of sample size.

In the current work, we apply similar approach to classify patients with coronary heart disease with different levels of cognitive status according to MMSE. To test the hypothesis that the distribution of the EEG signals corresponds to the power law, we consider the power of the theta rhythm in the parietal part of the right hemisphere of the brain. We select one of the leads in EEG registration and construct regression model that predicts MMSE with the goodness-of-fit to power law factor.

The rest of our chapter is organized as follows. In Sect. 2, we describe the methods used in our study: EEG recording, power law distribution, and Kolmogorov-Smirnov test for the goodness-of-fit. In Sect. 3, we perform correlation and regression analyses for the data extracted from the EEG signals. In conclusion, we summarize our results, note limitations of our current study, and outline further research directions.

2 Method

The dataset used in the study included EEG collected from 18 subjects who were patients of a clinic specializing on heart diseases. All of them were male, with the age ranging from 57 to 74 years (mean = 65.4, SD = 4.17). Their neurophysiologic examination was carried out during the preoperative period of coronary artery bypass surgery.

The indicators of the short mental status assessment scale (MMSE) of patients were in the range of 25–30 points (cognitive deficits are diagnosed at MMSE <26).

EEG registration was performed with 64 leads in accordance with the international system 10–10 (the arrangement of the electrodes is shown in Fig. 1). However, only the signal recorded from the TP8 temporal-parietal electrode of the right hemisphere was used to construct the model in our study. Basically, it was selected during several calculations for different leads as the lead that shows the most prominent effect.

During the EEG registration, the subjects were in relaxed state. The signal recording time was on average 10 min and the sampling frequency was 1000 Hz. Prior to the detailed analysis, artifacts were removed from the EEG records, in accordance with the standards implemented in the neuroscanner software.

Spectral analysis allows measuring the power of the analyzed frequency range and comparing the EEG rhythms intensity in different electrodes [23]. Using the fast Fourier transform, the periodogram was built and the spectral power of the signal in the parietal lead TP8 was determined. Then, the correspondence of the distribution of spectral power in the frequency range 4–8 (for theta-rhythm) to the power law distribution was determined.

Power functions are very different from the popular Gaussian distribution and are of fundamental importance in models of nonlinear dynamics and can be specified as follows [24]:

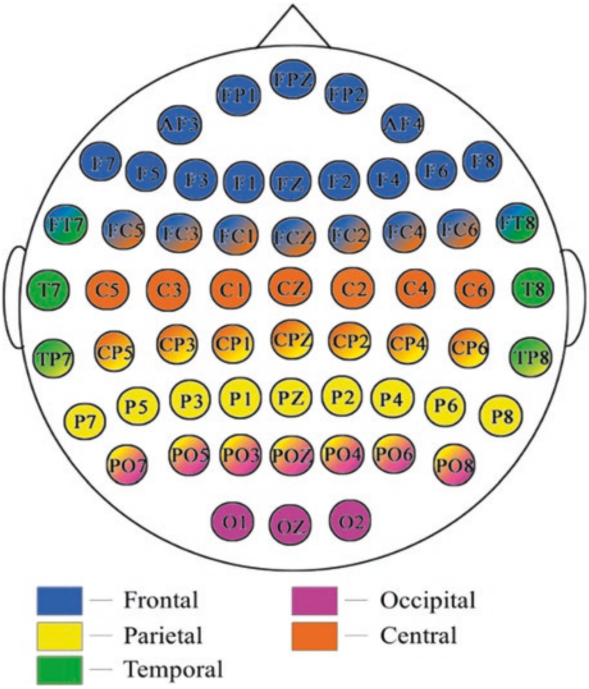

Fig. 1 Arrangement of the electrodes according to the 10–10 system

$$p(x) \propto x^{-a}, \tag{1}$$

More formally, the distribution has the form:

$$p(x) = Cx^{-a} = \frac{C}{x^{a}}, \tag{2}$$

where C is a normalization constant.

When testing the fit to power law, one needs to limit x, since the graph diverges at zero. The graph is usually normalized so that the area under the entire curve is equal to one, which leads to the expression:

$$p(x) = Cx^{-a} = \frac{a-1}{x_{\min}}\left(\frac{x}{x_{\min}}\right)^{-a}. \tag{3}$$

Power law distribution was found in studies of a wide variety of empirical phenomena, such as the frequency of words in the text (Zipf's law), the number of citations, the popularity of resources on the Internet, sales of books, earthquake magnitudes, etc. In some cases, the hypothesis of fit to power law had to be rejected, but the goodness-of-fit value would still be indicative of some phenomenon's characteristics. For instance, it was found that the goodness-of-fit can be used to predict the quality of crowdworkers' performance in image labeling [25]. Variations of power laws, particularly Benford's law, were successfully used for such diverse applications as financial fraud detection and Alzheimer's disease detection based on EEG signals [22].

Statistical testing of fit to power law is not straightforward, and the conventional least-squares fitting is misleading in many cases. In [24], it was convincingly demonstrated that Kolmogorov-Smirnov statistic in combination with maximum-likelihood is far more appropriate. Correspondingly, in our study, we rely on plpva software library provided in [24] to obtain the goodness-of-fit values. The cut-off parameter was set to the minimum due to the limited amount of data available in our case.

So, in our analysis, we check fit of the spectral power distribution to the power law and relate it to MMSE that we use as the dependent variable. EEG signal is used as the main independent variable, and we also control for the age of the subjects.

3 Results

Kendall's tau-b correlation between the subjects' MMSE scores (ordinal scale) and age was statistically significant ($\tau_{18} = 0.411$, $p = 0.028$) and, somehow unexpectedly, positive. Generally, studies report inverse relations between MMSE scores and age.

Figure 2 shows the graph of theta rhythm spectral power values arranged in descending order for the 18 subjects. The MMSE values for each subject are given in brackets in the legend, and the lines are displayed in green (MMSE = 29–30), orange (MMSE = 27–28), or red (MMSE = 25–26). Further, we calculated goodness-of-fit (GOF) values for each subject's EEG signal, based on the Kolmogorov-Smirnov test statistics implemented in plpva.m. The values for MMSE and the independent variables obtained in our study are presented in Table 1.

Pearson correlation between MMSE score and GOF was highly significant and positive ($r_{18} = 0.639$, $p = 0.004$).

The relationship between the MMSE score, goodness-of-fit to power law distribution (GOF), and age (Age) of the test subject was further investigated using regression analysis. The following linear regression model was obtained ($R^2 = 0.513$, $F_{2,15} = 7.91$, $p = 0.005$):

$$\text{MMSE} = 14.735 + 20.992 * \text{Gof} + 0.106 * \text{Age} \tag{4}$$

In the model, the GOF factor was significant ($p = 0.006$, Beta = 0.585), while Age was not ($p = 0.091$, Beta = 0.329). However, the Akaike Information Criterion value (AIC = 59.359) obtained for (4) was lower than the corresponding value (AIC = 60.892) for the model that only had the GOF factor. This suggests that the relative amount of information "lost" is lower in (4) and it should be preferred over the one-factor (GOF) regression model.

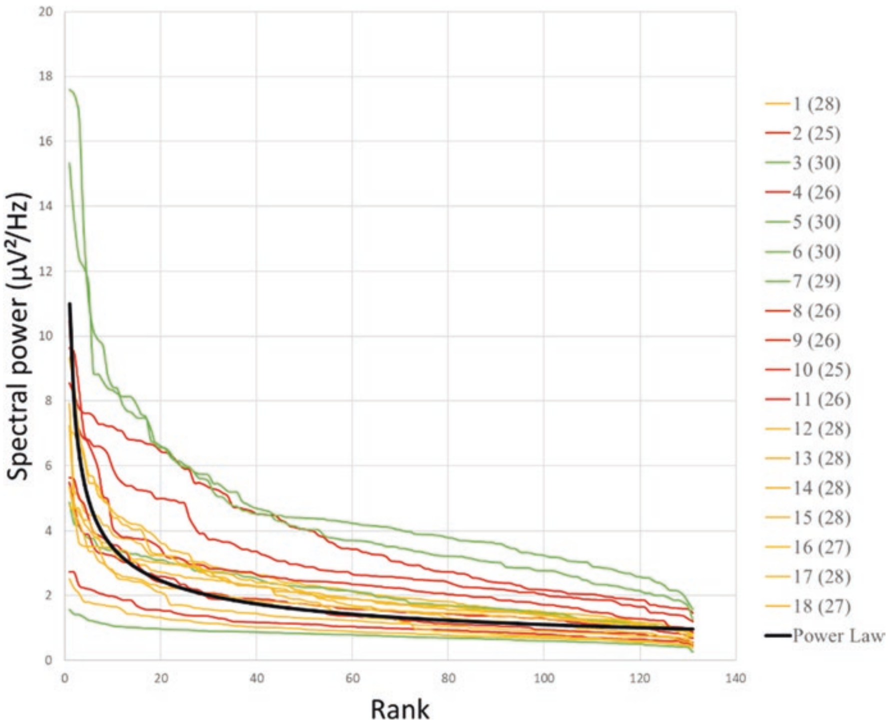

Fig. 2 Ordered spectral power values for the theta rhythm in the subjects EEG signals

The discovered correspondence of the theta rhythm to the power law indicates that the presented approach can be used to analyze both the distribution of spectral power in the other EEG frequency ranges and in other cortical sites reflecting the brain functional state.

4 Discussion and Conclusion

As individuals' immersion in high-tech information and cyber environments intensifies, the role of effective and affective interaction with various computers and gadgets becomes crucial for users of all ages and cognitive abilities.

This is particularly important for the currently advancing VR/AR technologies and brain-computer interfaces, which rely on fast and proper assessment of a user's cognitive status. Understandably, monitoring the cognitive status must not break the immersion, which is unavoidable in some currently used assessment methods that rely on surveys.

The results of the study of the application of power law to describe the distribution of the spectral power of the EEG, in particular, the amplitude of theta

Table 1 The values for the variables in the study

Subject number	Age	GOF	MMSE score
1	68	0.2579	28
2	59	0.1710	25
3	69	0.3014	30
4	64	0.2653	26
5	67	0.3936	30
6	68	0.2831	30
7	59	0.3118	29
8	62	0.2826	26
9	62	0.2810	26
10	60	0.2704	25
11	67	0.2639	26
12	68	0.2817	28
13	57	0.3146	28
14	76	0.2859	28
15	69	0.2588	28
16	66	0.2198	27
17	74	0.3029	28
18	63	0.2694	27

oscillations in the parietal region of the right hemisphere, suggest that it might be applicable for the classification of individuals with respect to their cognitive status. Statistically significant association of cognitive status indicator (MMSE) and goodness-of-fit calculated for distribution of spectral power in one of EEG leads (TP8) was revealed. The best regression model (4) constructed for MMSE included GOF and Age factors and was significant. Therefore, further studies of the application of power law for EEG analysis in order to classify the functional state of the brain can be considered promising.

Our findings regarding the significance of Benford's law with regard to the EEG signal features are consistent with the results reported in [21, 22]. In [21], however, the statistics they obtained from Kolmogorov-Smirnov test for Benford's law were similar for the different groups of EEG signals. Informal visual analysis of QQ-plots (which are advised against in [24]) was used to make conclusions, and no specific goodness-of-fit values were reported. We believe that our approach that involves a particular model for GOF and the concrete R^2 value might be more robust.

At the same time, we need to note that the $R^2 = 0.513$ obtained in our study implies rather moderate prediction quality. This might be explained by using regression and focusing on individuals, which implies more uncontrolled factors, instead of classification of EEG signals into several groups, as done in many related studies. For instance, in [26] the very best model for classification into two emotional states achieved accuracy of 0.623, while the ones for the four other considered models were at about 0.55. Also, whereas the currently mainstream method for EEG-based classification, artificial neural networks (see, e.g., in [27]), requires large datasets, our proposed approach does not need thousands of data records.

The construct validity of our study might be somehow affected by the usage of MMSE to operationalize cognitive status of the participants. This score is rather aimed towards assessing mild cognitive impairments [5], and even for that purpose it is known to be relatively crude, so that, for example, Montreal Cognitive Assessment (MoCA) is often recommended as an advantageous alternative [12]. One benefit of relying on MMSE was its easier availability, since it is widely collected in medical clinics during examination and monitoring of the patients. With regard to research applications, it has been noted though that it shows insufficient criterion validity [7]. At the same time, MMSE is still reported as a significant factor, whose importance is higher is the one of demographics and activity factors [6].

The weak influence of age, which is known to be negatively associated with MMSE values [6, 28], is probably due to the relatively narrow age range of the patients examined, since the most pronounced change in MMSE was found for the age between 84 and 105 years. Correspondingly, experiments with more subjects, whose number in our study was relatively small, should be done, and more factors explored, besides the Age parameter.

Another limitation of our study is the somehow arbitrary choice of the EEG lead for the analysis. TP8 has no reliable theoretical justification with respect to cognitive status, unlike, for instance, the Fz lead, for which we found no effect. At the same time, in [21] they found that the electrodes O1 and O2 were particular characteristic, while the occipital region of the brain is generally thought to be less affected by the changes resulting from Alzeihmer's disease. Correspondingly, we call for more studies to replicate or refute our findings.

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