Building and Studying a Model of the Human Cognitive Activity Dynamics

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Abstract

The paper describes the structure of the model of the dynamics of cognitive activity. The model is based on determining the characteristics of the trajectories of a two-dimensional projection of a multidimensional phase portrait on a plane formed by two leads of an EEG signal. The research technique of the obtained model is considered. The results of experiments illustrating the improvement of indicators of cognitive activity (reduction in computation time, reduction in the number of errors) after emotiogenic stimulation are presented.

Keywords

cognitive activity, emotiogenic stimulation, EEG

1. Introduction

The analysis of electroencephalographic signals is the basis for modern dynamic models that describe the thought processes in the human brain [1, 2, 3, 4, 5, 6, 7, 8]. We can consider an electroencephalogram as a multidimensional signal sample, considering the fact that these signals are recorded simultaneously from several sensors located at different points of the human head. When studying mental activity, the EEG signal analysis typically involves spectral methods, considering power spectra characteristics for individual leads [9, 10] or the coherence functions for a pair of interconnected leads [11].

We usually use the methods of nonlinear dynamics in our research. We reconstruct an attractor for a time series recorded from a separate EEG lead. Our experiments have shown that the properties of such attractors change with the changing current cognitive activity [12].

Nevertheless, these changes can vary significantly due to the EEG signal sensor location. Partial data integration takes place when building a phase portrait. It uses the lead axes (O1, O2, P3, P5, C3, C4, ...) that display the values of signal amplitudes from the corresponding EEG sensors. Each point in the phase space corresponds to the value of the brain electrical activity recorded at t_i moment in each lead.

The paper shows that the projection of the multidimensional phase portrait in several leads is sufficient for analyzing current cognitive activity.

The analysis involves nonlinear dynamics methods, as well as the phase portrait characteristics, which are used when comparing attractors reconstructed from physical signals.

During the experiments, we were evaluating the possibility of using these characteristics to build a cognitive activity dynamics model. We were using a specialized bioengineering system in the experiments [13]. The experiments had two main objectives: 1) to assess how the emotiogenic stimulation duration affects cognitive activity; 2) to select a limited number of EEG leads for building a cognitive activity dynamics model that will further simplify the process of interpreting simulation results.

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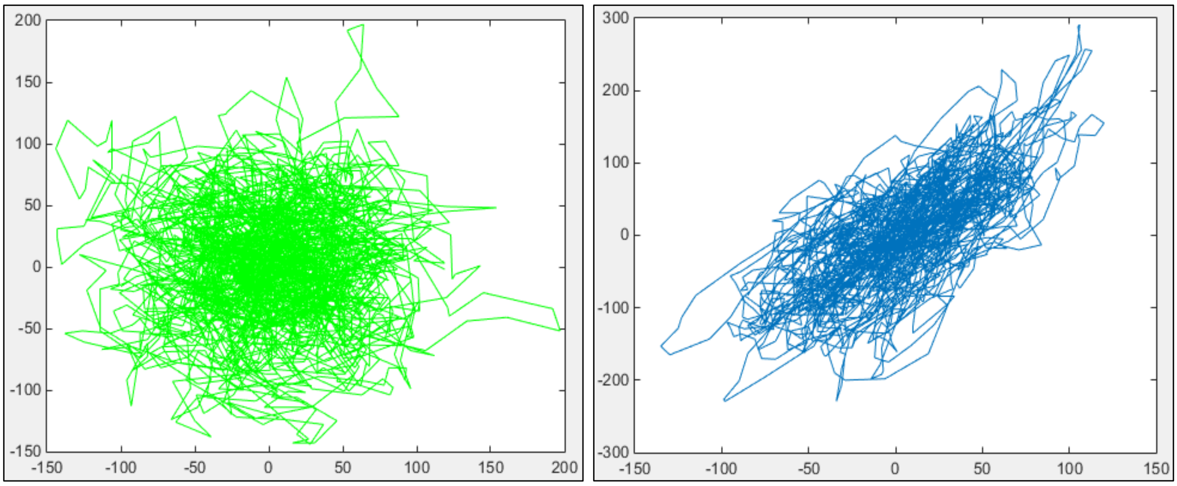
2. The multidimensional signal characteristics in the model

The main characteristics used in the model of cognitive activity dynamics are trajectory density estimates of a reconstructed attractor (Fig. 1a) or a multidimensional phase portrait (Fig. 1b) near the origin of coordinates.



(a) (b)

Figure 1: An attractor reconstructed on P4-A2 lead (a) and a phase portrait projection by P4-Pz leads (b)

They are defined as the sum of the trajectory points in the four central cells of the grid covering a two-dimensional projection of the attractor or a multidimensional phase portrait on the plane formed by two leads.

The experiments show that the trend in the central density of the attractor trajectories for the time series recorded in leads (C4-A2, Cz-A2) coincides with the trend in the central density of the trajectories of the multidimensional phase portrait on the plane formed by these leads (C4-Cz).

The graphs in fig. 2 show the density change when a testee performs calculating tasks before and after emotiogenic stimulation. On average, the density characteristic increases after stimulation, both when assessing it using attractors (according to C4-A2 and Cz-A2 leads) and when using the phase portrait projection (C4-Cz) reconstructed according to the indicated leads to estimate the density.

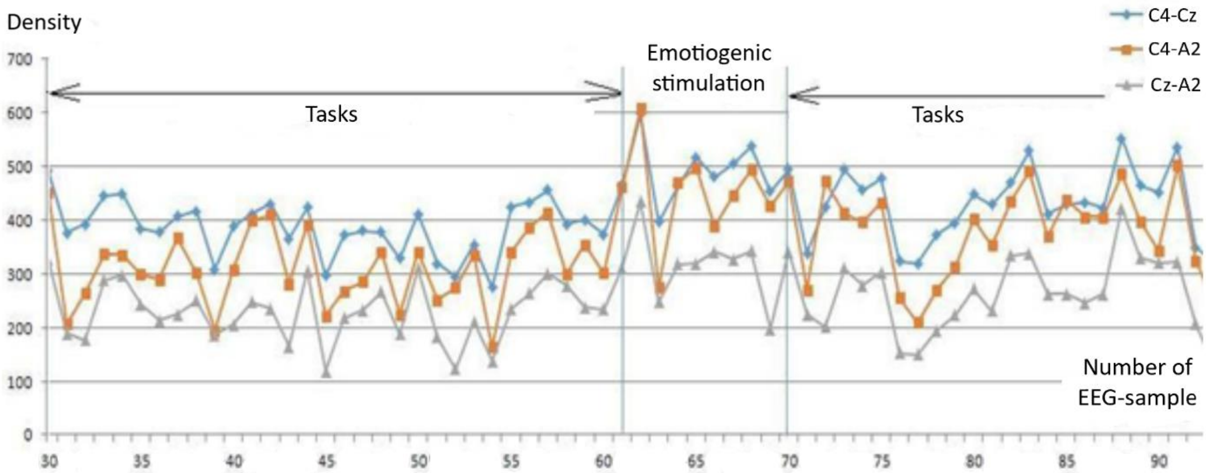


Figure 2: The density of attractor and phase portrait trajectories

Due to the similar trends in density estimates for attractors and for multidimensional phase portraits based on the same leads, the number of features in the model of the cognitive activity dynamics reduced.

3. Model components

The main characteristics of the multidimensional signal, which are included in the model of the cognitive activity dynamics, are related to the assessment of the density of phase portrait projection trajectories near the origin of coordinates. These characteristics changed most in 6 leads during cognitive activity. Therefore, the model includes the following components:

- f_1 – a central density of trajectories of the multidimensional phase portrait projection on the plane formed by Cz-A2 and C4-A2 leads,
- f_2 – a central density of trajectories of the multidimensional phase portrait projection on the plane formed by Pz-A1 and P3-A1 leads,
- $f_3, \ldots, f_6$ – a central density of trajectories of the multidimensional phase portrait projection on the plane formed by the leads (P4-A2 and P3-A1), (C3-A1 and C4-A2), (O1-A1 and O2-A2), (Pz-A1 and O1-A1).

In order to interpret the dynamics of these characteristics, there are two coefficients formed (*k1, k2*). Depending on their size and sign, we can characterize the direction and speed of the cognitive activity development.

The coefficient (*k1*) characterizes the course of changes in f_j characteristics:

$$k1 = \frac{del_{i+1}}{del_i}, \text{with } \ del_i = f(t_i)_j - f(t_{i-1})_j, \tag{1}$$

where: del_i characterizes the change in density during the transition from (t_{i-1})th measurement stage to the (t_i)th one, j is the number of the lead when measuring EEG signals (j = 1, 2, …, 6).

Depending on the second coefficient (*k2*) sign, it is possible to form an interpretation of the change in the cognitive activity rate during the transition from the (t_i)th measurement stage to the (t_{i+1})th stage (Table 1).

$$k2 = del_i * del_{i-1} \tag{2}$$

Previous studies show that it is advisable to use linguistic variables to interpret cognitive activity due to the variability of estimates of all model components reconstructed from EEG signals [14].

When constructing a model of the mental activity dynamics, we introduce linguistic variables were (y_j for j = 1, …, 6). There is a formed corresponding term-set for each y_j. It includes the estimates "small value", "average value", "big value". The attribute estimates are connected by the membership functions constructed by the base scale and the qualitative one. The membership functions are adjusted in accordance with the experimental results.

Table 1

N	|k1|	sign(k2)	Interpretation of model components
1	|k1| > 1	k2 > 0	Cognitive activity (CA) increases, the speed CA(t_{i+1}) > CA(t_i)
2	|k1| < 1	k2 > 0	CA increases, the speed CA(t_{i+1}) < CA(t_i)
3	|k1| = 0	k2 = 0	CA does not change
4	|k1| < 1	k2 < 0	CA changes direction, the speed CA(t_{i+1}) < CA(t_i)
5	|k1| > 1	k2 < 0	CA changes direction, the speed CA(t_{i+1}) > CA(t_i)

The model of the mental activity dynamics based on analyzing multidimensional signals takes the following final form:

$$\text{MMAD} = < \{y_j, \{TPr_j\}, \mu(TPr_i)\}, |k1|, \text{sign}(k2), j=1, 2, \ldots, 6 >, \tag{3}$$

where: $\{TPr_j\}$ is a term-set for estimating y_j attribute, $\mu(TPr_i)$ are membership functions of the corresponding fuzzy sets.

4. A model research procedure

Experimental procedures for monitoring cognitive activity differ depending on the type of cognitive load for a testee. The rules for recording answers and other testee's reactions may change depending on the type of tasks [1, 2, 15]. The methodological features of our experiments were partially described in earlier works [16, 17, 18].

In addition to the published procedure, we should note a consistent increase in the emotiogenic stimulation time with the increasing duration of the entire experiment. The cognitive load had the form of a set of slides with the same type of calculating tasks – multiplying a two-digit number by a single-digit number. The difficulty of the tasks was roughly the same. The tasks were presented in groups of 10.

All tasks were performed one after another, the transition to the next one was allowed only after the correct answer. It was forbidden to skip tasks, the time for solving the tasks was not limited.

The experiment has distinguished two types of stages that had different duration:

1. cognitive activity (performing calculating tasks),
2. emotiogenic stimulation.

Emotiogenic stimulation was carried out several times with a sequential increase in stage duration.

The report presents the results of an experiment with two stages of stimulation with weak negative video stimuli lasting 5 and 10 minutes. An electroencephalogram was recorded throughout the experiment.

The methodological support of the experiments was implemented within the framework of a special bioengineering system [15]. Its software allows processing the experimental results and obtaining interpretations for all components of the mental activity dynamics model of the form (3).

5. Experimental results

On average, the density characteristic increases after stimulation, both when assessing it using attractors (by P4-A2 and Pz-A2 leads) and when assessing it using the density of the projection of the phase portrait (P4-Pz) reconstructed according to the indicated pair of leads. Figure 3 shows a diagram of the density found from attractors. Similar diagrams are based on the results of the phase portrait analysis (Fig. 4).

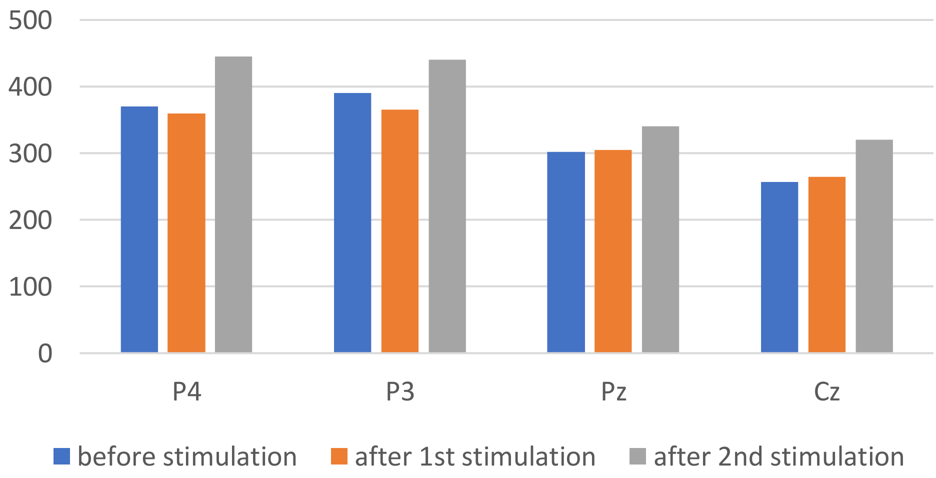


Figure 3: Average values of density for different attractors

The comparison of the diagrams shows that the relationship between the density before stimulation and then after 1st and 2nd stimulations completely coincides on a qualitative level for leads P3, P4 and the corresponding pairs (P3-P4, P4-Pz).

When comparing the results after the second (most effective) stimulation, we can see a complete coincidence of the conclusions from the diagram of attractors (Fig. 3) with the conclusions from the diagram in Fig. 4.

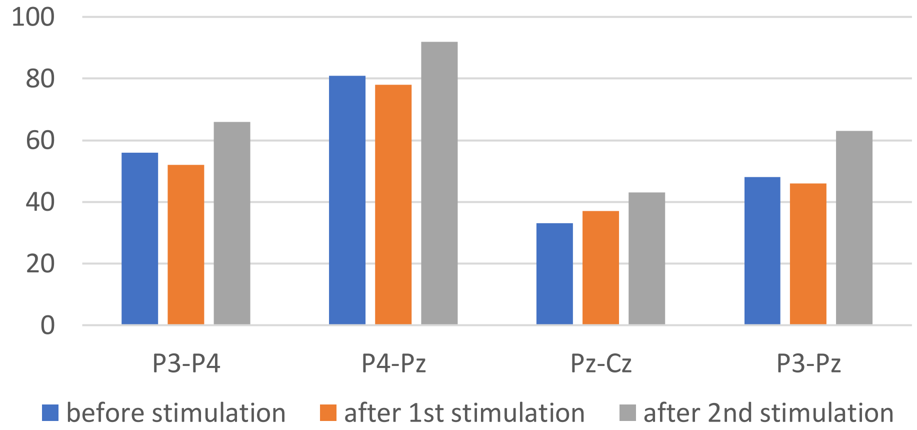


Figure 4: Average values of density for different phase portraits

Figure 5 shows the change in density during the transition from one experimental stage to another one. After analyzing these diagrams, we conclude that all pairs of electrodes are characterized by an increase in the average density at stimulation stages (stages "1st stimulation" and "2nd stimulation") in comparison with the working stages (stages "tasks 1", "tasks 2" and "tasks 3"). It should be noted that at the stage "tasks 3", the average density in all phase portraits is bigger than at stages "tasks 1" and "tasks 2". This is due to the fact that the second stimulation was twice as long as the first one. Thus, it confirms the thesis that an increase in the stimulation duration can increase the cognitive activity level.

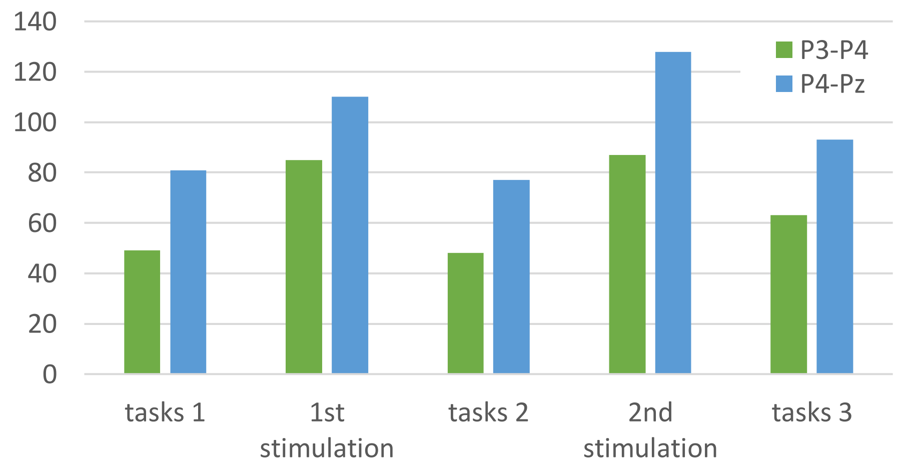


Figure 5: The change in the average density during the transition from one experimental stage to another one for different phase portraits

The analysis of the change in the average density at a separate experimental stage for the selected electrodes shows that the first stimulation does not cause a significant increase in cognitive activity. But the increase density characteristic of the (P4-Pz) phase portrait projection during the second stimulation leads to a significant increase in the average density (and average cognitive activity) in all leads.

The experiments have confirmed the effectiveness of the model tuning parameters. The results have shown that after emotiogenic stimulation the total time for completing cognitive tasks had decreased by almost 40%; the number of testee's mistakes has also decreased. Additionally, the rate of repeated errors has significantly decreased after emotiogenic stimulation. All these indicators improved with an increase in the stimulation duration (Fig. 6).

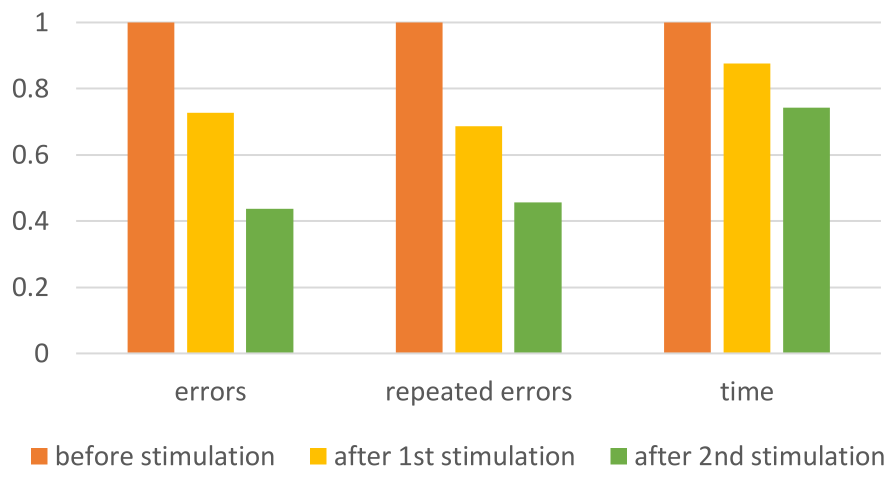


Figure 6: Results of performing computational tasks depending on the duration of emotiogenic stimulation

6. Conclusion

The experiments described in this paper have confirmed the assumption about monitoring cognitive activity by using the estimates of the central density of trajectories of the projection of the multidimensional phase portrait on the plane formed by a pair of leads. Previously, a similar characteristic was determined for a separate attractor reconstructed by one lead.

The constructed model expands the capabilities of the specialized bioengineering system focused on experimental studies of a student's mental activity.

The obtained results can become experimental evidence showing the possibility of implementing the scheme of emotiogenic stimulation of the cognitive activity of a person who uses computer systems.

7. Acknowledgements

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8. References

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