A Method of Soft Evaluation of the Dynamics of the Trainee Thinking Activity

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Abstract

The paper considers the issues of the dynamics of the cognitive activity changing process after emotiogenic stimulation, as well as the duration of the increased level of mental activity established after emotiogenic stimulation. Theку is the experimental prove of stimulation duration influence on the cognitive activity level. The average estimates of the central density of attractors reconstructed from EEG signals in the leads Cz, P4, P3, C4, C3, Pz were used as signs reflecting the cognitive activity level. When analyzing the experimental results, these characteristics are expressed using fuzzy numbers and make it possible to find approximate estimates for two new coefficients that reflect the direction of the spacecraft's rate of change. The paper presents the rules that determine whether the description of EEG signal patterns belongs to the human cognitive activity classes, as well as the dynamics of its change during the transition from the current observation stage to the next one.

Keywords cognitive activity, emotional stimulation, EEG signal, fuzzy sets, fuzzy inference.

1. Introduction

Nowadays, there is great interest in works related to the indirect control of a trainee's mental activity by artificial stimulating of emotional reactions during a certain period of time.

Since learning is remote or independent and involves electronic means, the issues of increasing the efficiency of the processes related to trainee's cognitive activity are of great importance [1-4]. It is possible to affect these processes without involving medication by changing trainee's emotional state. Techniques for stimulating emotions using external information stimuli are well developed. However, the problems of the process dynamics of cognitive activity changes after emotiogenic stimulation, as well as the duration of the increased level of mental activity established after emotiogenic stimulation, remain unclear. We want to answer these questions in this paper. Since the tastee's reaction to an emotiogenic stimulus at each moment of time may be different, and there are too many factors affecting this process, we have chosen the theory of linguistic variables and fuzzy sets as a mathematical apparatus for describing the cognitive activity dynamics model. This makes it possible to create models and algorithms for controlling mental activity with individual settings[5-6].

2. Experimental technique

The experiment involved using the multichannel bioengineering system "EEG-Speech+" [7]. An electroencephalograph "Encephalan-131-03" recorded an EEG signal in 19 leads according to the 10-20 system with a sampling rate of 250 Hz. The entire experiment had a history record: the timestamps of events and all testee's responses were recorded. The experiments involved men aged 20-25 years. All tests were carried out during the day in a comfortable environment in a quiet room. Before the starting the experiment, a testee underwent a short briefing. The further scenario of the experiment assumed that the testee performed blocks of cognitive tasks of constant volume and complexity, which were divided by emotiogenic stimuli of varying duration (Figure. 1). The cognitive tasks we homogeneous calculating operation – multiplying a two-digit number by a single-digit number.

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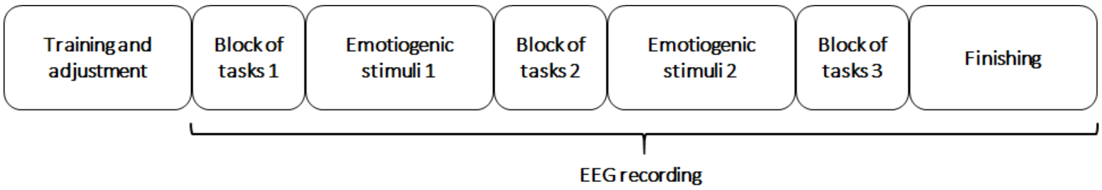

Figure 1: The experiment scenario

At the preliminary stage of the experiment called "Training and adjustment", a testee got used to work, got acquainted with the tasks, and chose the execution strategy. This stage involved the installation of electrodes, monitoring skin impedance, and the general adjustment of the EEG channel for recording. The stages with the tasks 1, 2 and 3 were the same in volume (100 tasks each). The tasks were displayed on the screen in groups of 10. The testee solved them sequentially and announced the answer aloud. It was allowed to proceed to the next task after the correct answer. Skipping the tasks was prohibited, the time and a number of attempts was not limited. During the execution of the task blocks, the experiment protocol recorded time closing, as well as the correctness of the testee's answers [8]. The emotional stimulation was performed twice during the experiment between blocks of tasks. Each stimulus was one video without sound, which was presented to the testee on the screen instead of tasks. The first emotional stimulation lasted 5 minutes, the second one lasted 10 minutes. During the experiment planning, the testee was interviewed and the stimuli were prepared according to the interview results: the subject of the stimuli was chosen so as to evoke weak negative emotions in the testee. At the final stage of the experiment involved EEG recording in a state of calm wakefulness with open and closed eyes. After the experiment, the testee underwent a survey: he assessed his level of fatigue throughout the experiment and confirmed an emotional reaction to stimuli. From each EEG recording, we obtained 100 artifact-free fragments of 4 seconds duration. In each stage of the experiment, we selected from 3 to 30 fragments (depending on the stage duration).

3. Interpretation of the cognitive activity dynamics after emotiogenic stimulation

The analysis of the results of EEG signal monitoring when the testee performed the above blocks of calculating tasks (as well as when perceiving video fragments that cause emotional reactions) made it possible to determine leads with the most powerful reactions to these stimuli. We formed the groups combining the electrodes of the frontal, central and parietal leads. When choosing the electrodes, we also took into account the information on the electrode localization points in the works with the tDCS technology devoted to the memory stimulation. Considering the large number of artifacts in the EEG signals recorded in the frontal leads, the most informative electrodes that illustrate the cognitive activity dynamics are C4-O2, C3-O1, Cz-O2 (central) and P4-O2, P3-O1, Pz-O2 (parietal). As we pointed out in earlier works [6, 7], the illustration of changes in EEG signals is possible through spectral characteristics, as well as the characteristics of attractors reconstructed from signals in each lead. The use of a set of indicators from these groups leads to a non-uniform basis in the EEG analysis problem [10]. On the one hand, this complicates the analysis procedure, and on the other hand, it increases the time spent on evaluating EEG characteristics. When analyzing the dynamics of cognitive processes related to performing the same type of calculating operations, we used a homogeneous basis to form a vector of evaluations of EEG characteristics. The density of attractor points in the vicinity of the origin [7] is used as a basic characteristic. To evaluate this property, the attractor projection was covered with a grid with a fixed cell size. We determined the number of attractor points hitting each cell of the grid. To estimate the degree of attractor point concentration, we calculated the sum of points in four central grid cells. This indicator that determines the density (ν) of the attractor trajectories near the coordinate origin was calculated for each EEG signal fragment. The duration of all fragments is the same and is equal to 1000 counts. Figure 2 shows a diagram of this characteristic changes for P4-O2 and C4-O2 leads during the entire experiment.

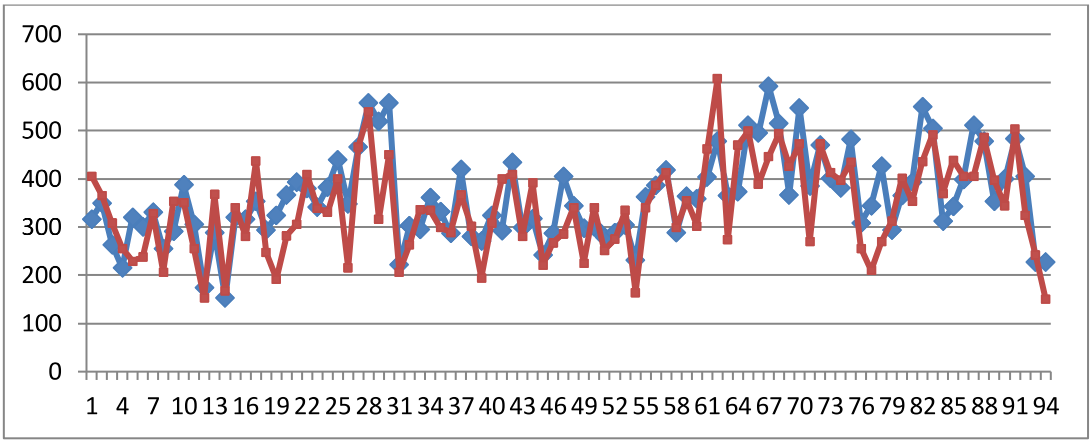

Figure 2: Density changes in the attractor reconstructed from EEG signals in P4-O2 and C4-O2 leads

The sliding calculating window made it possible to smoothen the time series $\{\nu\}$ for the selected leads:

$$\nu_{ij} = (\nu_{i-1,j} + \nu_{ij} + \nu_{i+1,j}) / m, \qquad i = \overline{1, p}, \qquad j = \overline{1, m} \qquad (1)$$

Where: p is the number of fragments in the experimental sample for the considered lead; m is the number of averaged leads. We combined leads similar in the level of EEG signals according to (1): $m=3$, $j=1$ for the P4-O2 lead, $j=2$ for the C4-O2 lead and $j=3$ for the Cz-O2 lead, i.e. leads close to the occipital ones[11]. This made it possible to illustrate the trend of these characteristics more clearly. Fig. 3 shows a graph of the density change (ν) for the P4-O2 lead throughout the experiment. The average values of this characteristic (ν) were calculated for all stages of the experiment[12].

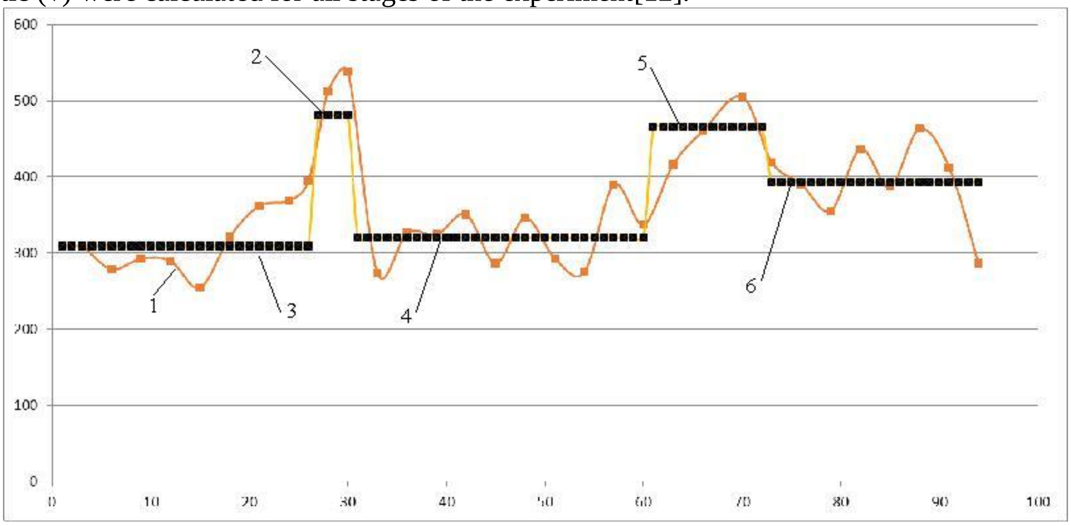

Figure 3: Changes in the central density of the attractor reconstructed from EEG signals in P4-O2 lead; 3 – the area before stimulation, 2 – the first stimulation, 4 – the area after the first stimulation, 5 – the second stimulation, 6 – the area after the second stimulation

When analyzing the experimental results, we used fuzzy numbers to estimate the values of the attractor characteristics (point density in the projection center). The transition to this apparatus is related to the accuracy of EEG signal registration, as well as with errors and rounding of calculated values when forming a phase portrait and a density matrix. Further, the estimate (ν_{ij}) will be considered as a normal convex fuzzy number[9-10]. Then the graph of the attractor central density changes for each lead will take the form of a strip with the upper and lower boundaries of these numbers (Fig. 4). The given diagrams (Fig. 3, Fig. 4) clearly illustrate the effect of the stimulation duration on the level (ν) and, therefore, on the cognitive activity level. The average density at the last (6) stage, and, consequently, the cognitive activity is 23% higher than this estimate after the first stimulation (stage 4), the duration of which is 40% less than the second one[11].

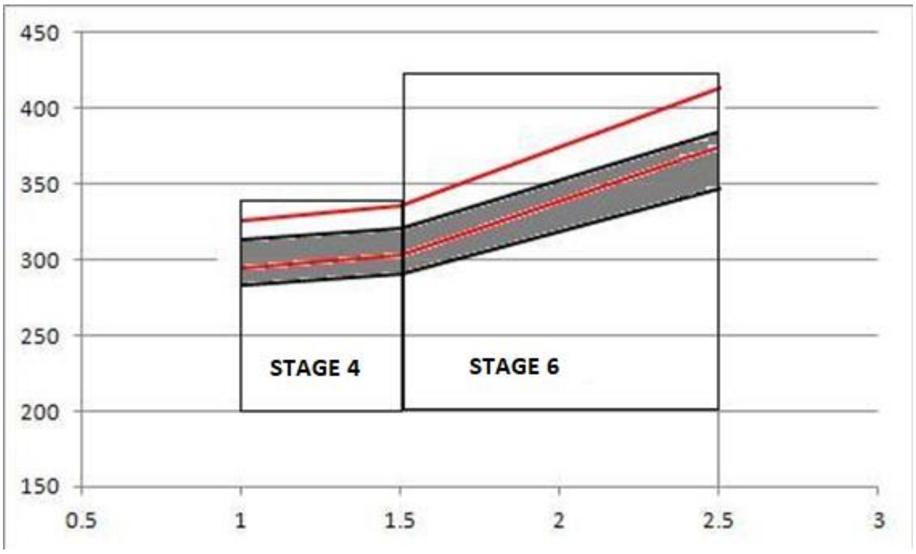

Figure 4: Changes in the attractor central density after the first stimulation (stage 4) and after the second stimulation (stage 6): red lines are for P4 lead, black lines are for C4 lead

4. Using fuzzy sets to describe the cognitive activity dynamics model

As shown in [12], to display the dynamics of a certain cognitive activity type, we can use a certain set of EEG signal characteristics (X(t)):

$$\bigcup_{j=1}^{m} X_j(t) \Rightarrow \bigcup_{i=1}^{r} \Phi_i(t) \Rightarrow K(A) \qquad (2)$$

Where: r is the number of characteristics, m is the number of EEG signal fragments. The characteristic $F_i(t)$ is included in the model if it changes in the same direction with the cognitive activity changes. Considering the electroencephalogram dimension, 6 groups of characteristics should be used to construct the vector $F(t)$. Then, to build a model illustrating the cognitive activity dynamics, and using a homogeneous basis we obtain ноу following:

- f_1 is the central density of the attractor reconstructed from an EEG signal in Cz lead,

- f_2 is the central density of the attractor reconstructed from an EEG signal in P4 lead,

- f_3, f_4, f_5, f_6 etc. is the central density of the attractor reconstructed from an EEG signal in P3, C4, C3, Pz leads respectively.

Comparison of these characteristics at all experimental stages illustrates similar values in individual groups.To build a dynamics model, we average the characteristics found for P4-O2, C4-O2, Cz-O2 leads, since estimates (f_i) are represented by fuzzy numbers, we use formulas for operations with fuzzy numbers[15].

For each feature (f_i), there is a corresponding linguistic variable ($ЛП_i$) formed and fuzzy sets of possible values determined.

[y1 :: LV1] – a linguistic variable “the center density of the attractor reconstructed from the EEG signal in Pz lead”,

[y2 :: LV2] – a linguistic variable “the center density of the attractor reconstructed from the EEG signal in P4 lead»,

[y3, y4, y5, y6 :: LV3, LV, LV 5, LV6] – similar linguistic variables “ the center density of the attractor reconstructed from the EEG signal in P3, Cz, C4, C3 leads.

The relationship between the values of the basic variables (f_i) and the corresponding values of linguistic variables (LV_i) is performed using specially constructed membership functions (FR) reflecting the experts’ opinions and research results (Fig. 5).

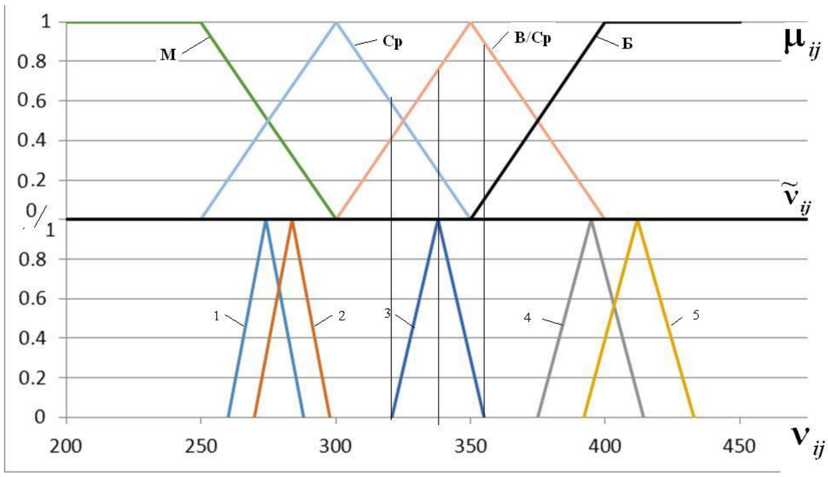

Figure 5: Average values ($\tilde{v}_{ij}$) for individual stages: 1 is before the first stimulation, 2 is after the first stimulation, 3 is after the second stimulation, 4 and 5 are the first and second stimulation.

Figure 5 shows the transition from the calculated feature estimates (ν_{ij}) to the corresponding fuzzy numbers ($\tilde{v}_{ij}$), and then to the linguistic variable values. To construct a cognitive activity model it was proposed in [13] to use linguistic variables that describe individual characteristics of attractors reconstructed from EEG signals:

$$CAM = <\{y_i, \{TPr1\_j\}, \mu(TPri), i=1,..,6\}>, \quad (6)$$

where {TPri_j} is a term set for evaluating y_i feature ("small" y_1, "average" y_2, "above average" y_3, "big" y_4); j = 1÷4; μ(TPri) are membership functions of fuzzy subsets of the universal set of estimates Pri. The model (6) is tuned to samples of arbitrary duration using the restrictions on the universal set of assessments of the feature that characterizes the central density of the attractor reconstructed from the EEG signal[13]. To describe dynamic changes, the model (6) is supplemented with two new features that characterize the changes in cognitive activity over time. To assess these properties, there are two coefficients introduced $(\tilde{k}1, \tilde{k}2)$. The coefficient $(\tilde{k}1)$ characterizes the change direction of the characteristic ($\tilde{v}(t)$), the coefficient $(\tilde{k}2)$ characterizes the rate of density change. Coefficient estimates are determined by the following formulas:

$$\tilde{k}1 = \frac{\tilde{del}_{i+1}}{\tilde{del}_i}, \qquad \tilde{del}_i = \tilde{v}_{i,j} - \tilde{v}_{i-1,j} \quad (7)$$

$$\tilde{k}2 = \tilde{del}_i * \tilde{del}_{i+1} \quad (8)$$

Where: $\tilde{del}_i$ characterizes the density change during the transition from the (*i-1*)th measurement stage to the (*i*)th one, *j* is the number of the lead when measuring EEG signals. The introduced rules make it possible to determine the membership of the EEG signal pattern descriptions to the classes of human cognitive activity: "low activity" (L1), "average activity" (L2) and "activity above average" (L3), "high activity" (L4) [13], as well as the dynamics of cognitive activity changes during the transition from the current observation stage to the next one (Table 1). The rules are formed according to the following pattern: If "pre_conditions", then (t_r: linguistic statement that interprets the situation"

Table 1.
Starting conditions of the rules

IF (starting conditions),				Then
$\tilde{del}_{i-1}$	$\tilde{del}_i$	$\tilde{k}1$	$\tilde{k}2$	t_r
… > 0	… > 0	… > 1	… > 0	t_1
… < 0	… < 0	… > 1	… > 0	t_2
… > 0	… < 0	… < -1	… < 0	t_3
… > 0	… < 0	… < 1	… > 0	t_4

Table 2 presents a fragment of the set of statements {t_r} used as a conclusion in the rules for interpreting cognitive activity.

Table 2.
Conclusions of the rules

t_r	Situation interpretation
t_1	Cognitive activity (CA) at adjacent monitoring intervals changes in one direction – increases
t_2	Cognitive activity (КА) at adjacent monitoring intervals changes in one direction – decreases
t_3	Cognitive activity (КА) at adjacent monitoring intervals changes in different directions: increases at the (*i-1*)-th interval, decreases at the (*i*)-th interval
t_4	Cognitive activity (КА) at adjacent monitoring intervals changes in one direction – increases, but at the *i*-th interval the rate of increase is less than on the (*i-1*)-th interval

5. Conclusion

The algorithms created on the basis of the considered ratios make it possible to process a sequence of EEG signal patterns recorded with a time shift (($t2$-$t1$)>0) and to form verbal conclusions about the most important characteristics of cognitive activity[17, 18]. A further line of research is related to adapting the obtained models for use in distance learning environments.

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