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Algorithm for automatic estimation of human brain activity features during mental task evaluation

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Introduction: *It is known that many types of human activity involve a generation of particular patterns in electroencephalographic recordings with common properties for different subjects. Among them one can highlight the brain response to the visual stimuli in occipital lobe or motor-related activity in motor cortex. At the same time, more complex human activity can induce different scenarios of the neural dynamics in brain, which depends on the human personal features. Personality is more pronounced during mental task processing. In particular, it is shown that human personality causes individual scenarios during decision-making and affects learning performance. We suppose that individual features of human personality, when we wish to define the ways of how a human processes mental tasks, affect neural network dynamics and therefore can be seen in electroencephalographic recordings.* ***Purpose:*** *Development of the algorithm for estimating the personal spatio-temporal and time-frequency features of electrical brain activity during mental task evaluation.* ***Results:*** *We propose algorithm, which allows to reveal individual features of the brain activity during completion of mental tasks based on multichannel electroencephalogram analysis. Algorithm is implemented in brain-computer system and tested during experimental session for the subjects who perform the Schulte table test. We show, that revealed individual features of brain activity can predict the properties of human attention.* ***Practical relevance:*** *We believe that the results are of the great interest for testing and diagnostics. It can be the starting point for development of automatic intelligent systems for estimation and control of human mental abilities.*

Keywords *— continuous wavelet transformation, electroencephalography, mental task evaluation.*

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Introduction

It is known, that many types of human activity involve a generation of particular patterns in electroencephalographic (EEG) recordings with common properties for different subjects. For instance, the perception of visual stimuli is known to induce an event-related response of the neuronal brain network, in particular, a decrease in alpha-wave (8–12 Hz) and an increase in beta-wave (15–30 Hz) activities [1–3]. Such a behavior reflects different cognitive functions, namely, the alpha-wave suppression is associated with visual [4] or auditory [5] attention, while the beta-wave activation relates to information processing [6] and an alerted state [7].

Different physiological and psychological states (e. g., sleep stages, arousal, etc.) are known to possess specific properties of neural activity. For instance, motor-related brain activity is manifested in the brain as a specific scenario of neural activity with well-defined frequency and spatial localization. Particularly, it is characterized by event related desynchronization (ERD) in alpha/mu- and beta-bands [8]. The same features are observed during motor imagery in specially trained subjects [9, 10]. However, different scenarios occur in untrained subjects, where EEG patterns can vary from subject to subject [11]. Such a variation is caused by the task complexity when each subject chooses his own strategy to process the task, that results in individual time-frequency and spatio-temporal EEG structures. Along with motor imagery, the personality is more pronounced during mental task processing. It was also shown that human personality causes individual scenarios during decision-making [12] and affects learning performance [13].

We suppose that individual features of human personality, when we wish to define the ways of how a human processes mental tasks, affect neural network dynamics and therefore can be seen in EEG recordings. Correlation between EEG and personal features provides possibility to estimate such human features as personality traits and mental abilities. It should be noted that this problem was attacked yet in 1973. By analyzing resting states, Edwards and Abbott [14] tried to reveal personality traits in EEG signals. However, their attempt was unsuccessful because personality is not manifested when a person is at rest. Until now, this problem remains open [15, 16]

In the present work, we propose algorithm, which allows to reveal individual features of the brain activity during completion of mental tasks based on multichannel EEG analysis. Algorithm is implemented in brain-computer system and tested during experimental session for the subjects who perform the Schulte table test.

Algorithm for EEG analysis

The proposed algorithm is schematically illustrated in Fig. 1. via a flowchart. One can see that it is evaluated in seven steps.

Step I: Acquisition of multichannel EEG with the help of non-invasive electrodes located on the surface of the head, according to the arrangement of 10–20. Electrical brain activity signals are recorded with a sampling frequency of 250 Hz. The recorded signals are processed by a bandpass filter.

Step II: EEG signals recorded in different parts of the cortex are divided into two equal groups. The first group contains the channels located in the left hemisphere (Fp1, F7, F3, T3, C3, P3, T5, O1), the second group contains the channels located in the right hemisphere (Fp2, F8, F4, T4, C4, P4, T6, O2). The channels located in the interhemispheric region (Fz, Cz, Pz) are excluded from consideration.

Step III: For each channel $X_n(t)$ (in the first and second group), wavelet transformation is performed. The wavelet energy spectrum $E^n(f,\ t) = \sqrt{W_n(f,\ t)^2}$ is calculated for each EEG channel in the frequency range 10–40 Hz. Here, $W_n(f, t)$ is the complex-valued wavelet coefficients calculated as [17]

$$W_n(f,\ t) = \sqrt{f} \int\limits_{t-4/f}^{t+4/f} X_n(t)\varphi^*(f,\ t)dt, \qquad (1)$$

where $n = 1,\ ...,\ N$ is the EEG channel number ($N = 19$) being the total number of channels used for the analysis) and "*" defines the complex conjugation. The mother wavelet function $\varphi(f, t)$ is the Morlet wavelet often used for the analysis of neurophysiological data, defined as

$$\varphi(f,\ t) = \sqrt{f}\pi^{1/4} e^{j\omega_0 f(t-t_0)} e^{f(t-t_0)^2/2}, \qquad (2)$$

where $w_0 = 2\pi$ is the central frequency of the mother Morlet wavelet.

Step IV: For each channel, the obtained wavelet energy spectrum is analyzed in several frequency ranges (in accordance with Table 1.)

For these bands the values of wavelet energy $E_\delta^n(t), E_\theta^n(t), E_\alpha^n(t), E_{\beta_1}^n, E_{\beta_1}^n, E_\gamma^n$ for each -th EEG channel are calculated as

$$E^n_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}(t) = \frac{1}{\Delta f} \int\limits_{f \in \delta,\theta,\alpha,\beta_1,\beta_2,\gamma} E^n(f,\ t)df. \qquad (3)$$

Based on Eq. (3) the percentages of the spectral energy distributed in the considered bands are estimated as

$$e^n_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}(t) = E^n_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}(t) \,/\, E_0^n(t)\,(\times 100\%), \qquad (4)$$

where is defined as the whole energy and calculated as

$$E_0^n(t) = \frac{1}{\Delta f} \int\limits_{1\text{Hz}}^{40\text{Hz}} E^n(f,\ t)df. \qquad (5)$$

Step V: In order to describe the ratio between high frequency and low frequency brain activity for each channel the coefficient ε^n is calculated via equation

$$\varepsilon^n = E^n_{\text{HF}} \,/\, E^n_{\text{LF}}, \qquad (6)$$

where

$$E^n_{\text{HF}}(t) = \frac{1}{\Delta f} \int\limits_{f > 10\text{Hz}} E^n(f,\ t)df, \qquad (7)$$

■ ***Table 1.*** Frequency bands of EEG signals

Name	Definition	Frequency range, Hz
Delta-band	δ	1–4
Theta-band	θ	4–8
Alpha-band	α	8–13
Beta1-band	b_1	13–23
Beta2-band	b_2	32–34
Gamma-band	γ	34–40

$$E^n_{\mathrm{LF}}(t) = \frac{1}{\Delta f} \int_{f<10\mathrm{Hz}} E^n(f, t)df. \quad (8)$$

Step VI: The coefficients ε^n are calculated for each EEG channel for both during the task evaluation (active phase) and during resting state (passive phase). The obtained values of ε^n are averaged over the channels belonging to the first and secon groups (see Step II for groups definition)

$$\varepsilon_{\mathrm{LH}} = \frac{1}{N_{\mathrm{LH}}} \sum_n \frac{E^n_{\mathrm{HF}}}{E^n_{\mathrm{LF}}}, \quad n = \{\mathrm{Fp1},\ \mathrm{F3},\ \mathrm{F7},\ \mathrm{C3},\ T3,\ P3,\ T5,\ O1\}, \quad N_{\mathrm{LH}} = 8. \quad (9)$$

$$\varepsilon_{\mathrm{RH}} = \frac{1}{N_{\mathrm{RH}}} \sum_n \frac{E^n_{\mathrm{HF}}}{E^n_{\mathrm{LF}}}, \quad n = \{\mathrm{Fp2},\ \mathrm{F4},\ \mathrm{F8},\ \mathrm{C4},\ T4,\ P4,\ T6,\ O2\}, \quad N_{\mathrm{RH}} = 8. \quad (10)$$

As the result, the values $\varepsilon^{active}_{\mathrm{LH}}$, $\varepsilon^{active}_{\mathrm{RH}}$, $\varepsilon^{passive}_{\mathrm{LH}}$, $\varepsilon^{passive}_{\mathrm{RH}}$ are obtained.

Step VII: Based on the obtained coefficients $\varepsilon^{active}_{\mathrm{LH}}$, $\varepsilon^{active}_{\mathrm{RH}}$, $\varepsilon^{passive}_{\mathrm{LH}}$, $\varepsilon^{passive}_{\mathrm{RH}}$ which characterize the activity of the left and right hemispheres, the lateralization coefficient for the active and passive phases $k^{active} = \varepsilon^{active}_{\mathrm{RH}} / \varepsilon^{active}_{\mathrm{LH}}$, $k^{passive} = \varepsilon^{passive}_{\mathrm{LH}} / \varepsilon^{passive}_{\mathrm{RH}}$ are calculated.

Mental ability evaluation

In order to compare the results of EEG analysis with the human mental abilities we used Schulte tables. Such method is frequently used as a psychodiagnostic test for studying properties of human attention. It allows to determine working effectiveness and ability, as well as resistance to external interference. It is known, that the time of the -th table completion can be used to evaluate personal criteria:

1. Work efficiency *WE* (the arithmetic mean of the values of table completion times)

$$WE = \frac{\tau_1 + \tau_2 + \ldots + \tau_R}{R}, \quad (11)$$

2. Warming-up work indicator *WU* (the ratio of the working time which subject spend for the first table to the value of work efficiency)

$$WU = \frac{\tau_1}{WE}, \quad (12)$$

3. Psychological stability *PS* (the human ability to sustain the operational activity for a long period of time).

$$PS = \frac{\tau_R - 1}{WE}. \quad (13)$$

The work efficiency is known to illustrate the attention consistency and performance. The resulted *WU* close to or lower than 1 indicates good warming-up, while 1 and higher means that the subject needs longer preparation time (warm-up) for the main work. The *PS* results close to 1 and less indicate a good psychological stability.

Data processing and main results

The results of the proposed algorithm evaluation are shown in Fig. 2. on the single subject example.

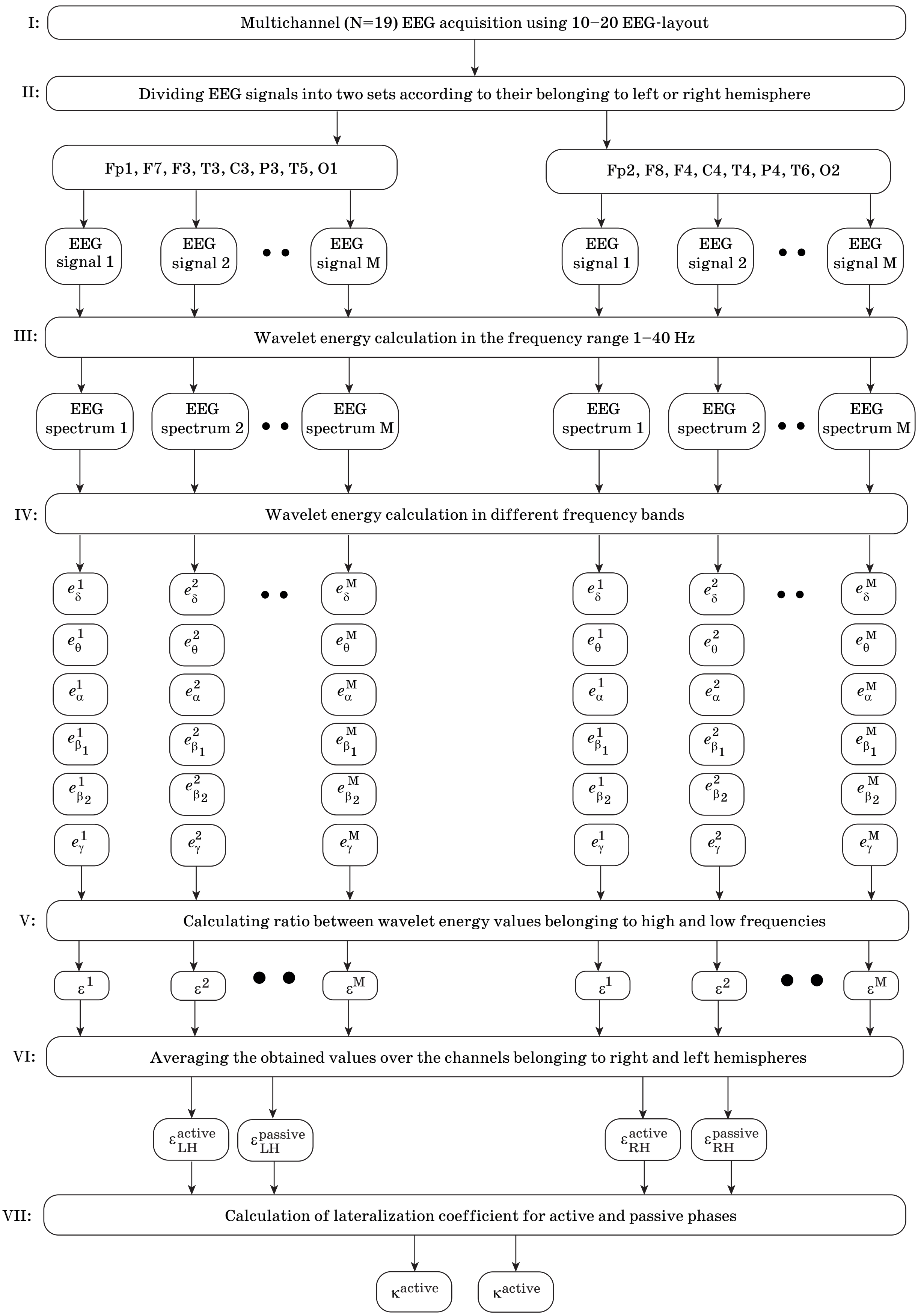
Fig. 2 (a) demonstrates the typical EEG recordings obtained in left and right hemispheres during the step I of the algorithm.

Fig. 2 (b) shows the values of $e^{\mathrm{F4}}_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}(t)$ calculated during for a single EEG trial recorded from the frontal lobe, specifically, from the F4 electrode. One can see, that when the active phase is replaced by the passive phase, the values of $e^{\mathrm{F4}}_{\delta,\theta}(t)$ calculated for low frequencies (namely, δ, and θ frequency bands) rapidly increase, while the values of $e^{\mathrm{F4}}_{\alpha,\beta_1,\beta_2,\gamma}(t)$, calculated for α, b_1, b_2, and γ frequency bands, pronouncedly decrease. Such a dynamical behavior repeats itself during subsequent completions of the Schulte tables.

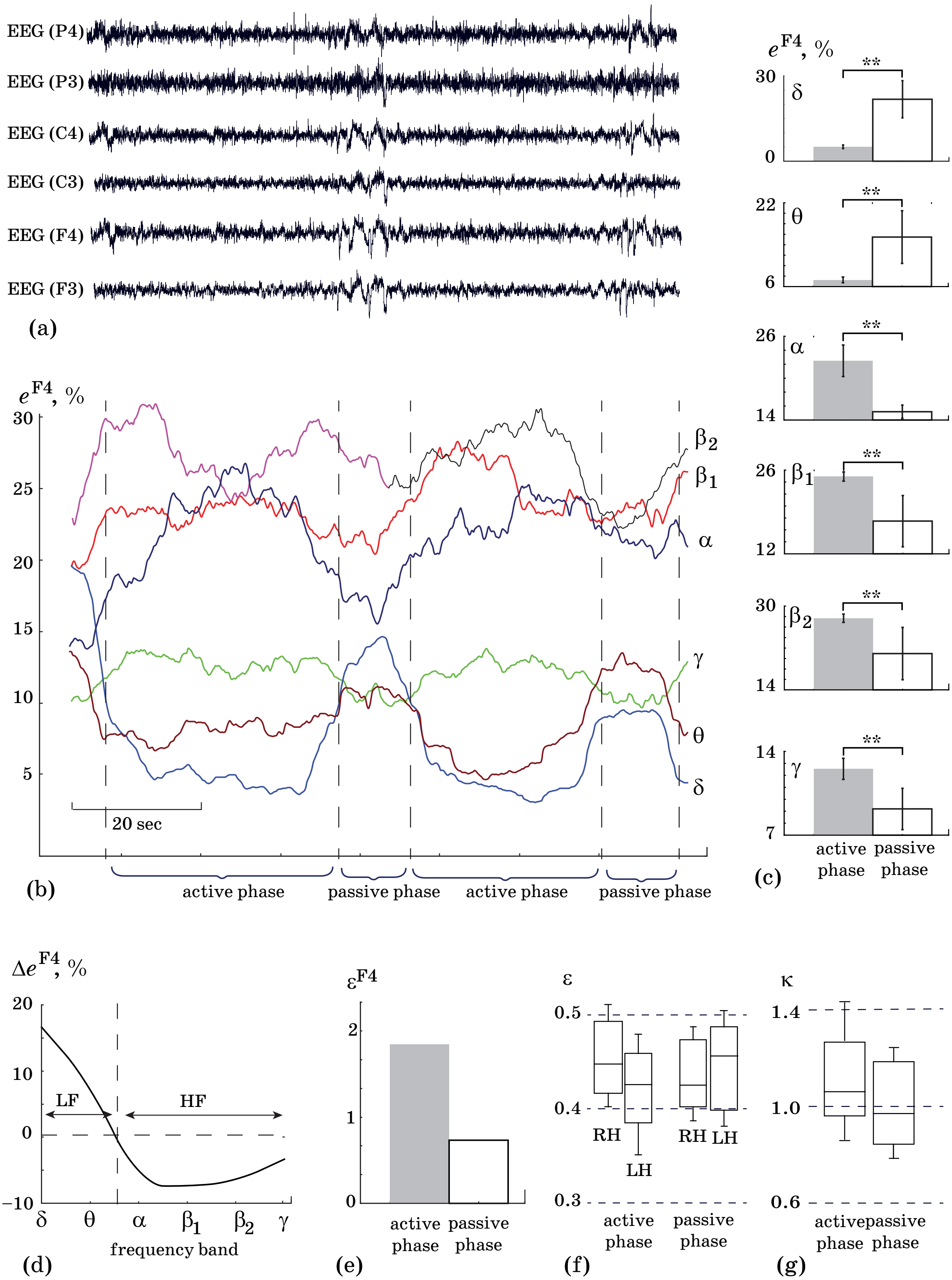
Fig. 2 (c) shows the results of statistical analysis of the values $e^{\mathrm{F4}}_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}$ calculated for the time intervals corresponding to $N = 5$ consecutive active and passive sessions. Data are shown as mean SD. Obtained results demonstrate the significant increase of $e^{\mathrm{F4}}_{\delta,\theta}$ and significant decrease of $e^{\mathrm{F4}}_{\alpha,\beta_1,\beta_2,\gamma}$ during the transition from passive to active phase (**$p < 0.01$ via nonparametric Whitney U-test).

Fig. 2 (d) demonstrates the distinctive features between the mean values $e^{\mathrm{F4}}_{\delta,\theta,\alpha,\beta_1,\beta_2,\gamma}$ obtained for the active and passive phases for each frequency band. One can see that in the low frequency range, which includes δ, and θ frequency bands, such difference is positive ($De^{\mathrm{F4}} > 0$), while in the high frequency range (α, b_1, b_2, and γ frequency bands) it is negative ($De^{\mathrm{F4}} < 0$).

According to this result, one can easily distinguish active and passive phases, based on the consideration of EEG properties, i. e., by comparing the energy of the spectral components belonging either to high (HF) or low (LF) frequency bands. For this purpose, it is convenient to use coefficient ε^n



■ ***Fig. 1.*** Flowchart of the algorithm for EEG analysis. Each step is marked as I...VII on the left-hand side



■ *Fig. 2.* The results of the proposed algorithm evaluation

(Eq. 6), which reflects the ratio between the values of spectral energy in the high and low frequency ranges. In particular, for the considered F4 electrode, the values of ε^{F4}, shown in Fig. 2 (e) are significantly lower during the passive phase than during the active phase.

Thus, the time frequency analysis performed for a single EEG recording demonstrates a pronounced change in the ratio between the energy of high and low spectral components. At the same time, along with the features of time-frequency structure revealed in a single EEG, the spatio-temporal features of electrical brain activity also play an important role. This is mostly reflected in hemispheric differences commonly observed in electrical activity of the brain associated with the completion of mental tasks [18–22].

The spatio-temporal features are taken into account in our algorithm by consideration of the values $\varepsilon_{\mathrm{LH}}^{active}$, $\varepsilon_{\mathrm{RH}}^{active}$, $\varepsilon_{\mathrm{LH}}^{passive}$, $\varepsilon_{\mathrm{RH}}^{passive}$ calculated during step VI by averaging over the channels, belonging to left and right hemispheres.

Fig. 2 (f) demonstrates the values $\varepsilon_{\mathrm{LH}}^{active}$, $\varepsilon_{\mathrm{RH}}^{active}$, $\varepsilon_{\mathrm{LH}}^{passive}$, $\varepsilon_{\mathrm{RH}}^{passive}$ calculated for group of 8 subjects during active and passive phases. Data are shown as median and 25–75 percentiles (box) and outlines (whiskers). One can see that there are differences in the electrical activity in the hemispheres during active and passive phases. Namely, during active phase subjects of the considered group exhibit increase of high-freauency activity in right hemisphere, while during the passive phase such increase is observed in left hemisphere. As the result, median value of lateralization coefficient becomes >1 for active pahse and <1 for passive phase. At the same time, such deviations in median lateralization coefficient are insignificant. It evidences the variability of this coefficient between subjects in the group.

It can be supposed, that such variability is connected with personal differences which affect the process of mental task accomplishing. According to this we have applied algorithm, described above for the group of 20 subjects and compared the behaviour of lateralization coefficient with the results of psychodiagnostic test. We have shown that the subjects, for which the lateralization coefficient is close to unity for both active and passive phases demonstrate the lowest value of work efficiency (WE > 40 seconds) and the lowest degree of psychological stability (PS~1.0). On the contrary, subjects, for which the lateralization coefficient $\kappa > 1.0$ for active phases and $\kappa < 1.0$ for passive phases demonstrate the value of work efficiency much higher (WE~30 seconds) as well as the higher degree of psychological stability ($PS < 0.9$).

Materials and methods

Twenty healthy men (33±7 years), participated at the experiment. All participants provided informed written consent before participating in the experiment. The experimental procedure was performed in accordance to the Helsinki's Declaration and approved by the local Ethics Committee of the Yuri Gagarin State Technical University of Saratov.

Experiments was carried out during the first half of the day. All participants performed a series of simple psycho-diagnostic tests using the Schulte tables to study their attention features. Shulte table is a simplified version of Zahlen-Verbindungs-Test (ZVT) [23, 24], widely used in Russia [25]. The Schulte table is a 5×5 matrix of random numbers from 1 to 25. The psychological task was to find all numbers in a reverse order. During these *active* experimental phases, each person had to complete $R = 5$ tables. For every i-th testing series, the completion time T_i was registered. Between the active phases, each volunteer had a short resting interval referred to as a *passive* experimental phase. Length of active phases was varied from 30 to 50 second depending on the speed of task completion. Length of passive phases was set as 10 seconds.

Electrical brain activity was recorded with multi-channel EEG-acquisition system — electroencephalograph-reorder Encephalan-EEGR-19/26 (Russia) with multiple EEG channels and the two-button input device. To study EEGs the monopolar registration method and the classical ten-twenty electrode system were used.

Conclusion

We propose the algorithm for the estimation of the spatio-temporal and time-frequency features of electrical brain activity during the mental task evaluation. Time-frequency features of the brain activity are estimated by analyzing EEG spectral energy in high- and low- frequency bands. Spatio-temporal features are estimated with the help of lateralization coefficient. Proposed algorithm is implemented in brain-computer interface and tested and tested during experimental session for the subjects who perform the Schulte table test. We demonstrate, that the dynamics of lateralization coefficient reflects the personal features of the brain activity, which correlates with the properties of human attention. In particular we show that that the subjects, for which the lateralization coefficient is close to unity for both active and passive phases demonstrate the lowest value of work efficiency and the lowest degree of psychological stability. On the contrary, subjects, for which the lateralization coefficient $\kappa > 1.0$ for active phases and $\kappa < 1.0$ for passive phases demonstrate the value of work efficiency much higher as well as the higher degree of psychological stability.

We believe that the results are of the great interest for testing and diagnostics. It can be the starting point for development of automatic intelligent systems for estimation and control of human mental abilities.

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Алгоритм для автоматического детектирования особенностей активности мозга во время выполнения когнитивных задач

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Введение: многие виды человеческой деятельности ассоциируются с возникновением характерных паттернов на электроэнцефалографических записях, которые обладают общими свойствами для разных испытуемых. Среди них можно выделить отклик мозга на визуальные стимулы, регистрируемый в затылочной области, или нейронную активность, связанную с двигательными функциями, регистрируемую в моторной коре. В то же время, более сложная деятельность человека может вызывать различные сценарии нейронной динамики в зависимости от индивидуальных особенностей человека. Наиболее значительно данный эффект проявляется при выполнении человеком когнитивных задач. В частности, показано, что индивидуальные особенности определяют сценарии нейронной активности при принятии решений и влияют на эффективность обучения. Можно предположить, что индивидуальные особенности человеческой личности определяют стратегию, которую человек использует при решении когнитивных задачи, что, в свою очередь, отражается на динамике нейронной сети мозга и может быть детектировано на электроэнцефалографических записях. **Цель:** разработка алгоритма оценки индивидуальных пространственно-временных и частотно-временных характеристик электрической активности головного мозга при решении когнитивных задачи. **Результаты:** предложен алгоритм, позволяющий выявить индивидуальные особенности функционирования нейронной сети мозга при выполнении когнитивных задач на основе анализа многоканальных электроэнцефалограмм. Алгоритм реализован в виде интерфейса мозг-компьютер и протестирован на группе испытуемых, которые выполняют тест Шульте. Показано, что выявленные индивидуальные особенности активности мозга могут ассоциироваться со свойствами человеческого внимания в процессе решения задач. **Практическая значимость:** полученные результаты представляют большой интерес для тестирования и диагностики. Они являются основой для разработки автоматических интеллектуальных систем для оценки и контроля умственных способностей человека.

Ключевые слова — вейвлетное преобразование, электроэнцефалография, решение когнитивной задачи.

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