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ANALYSIS OF SPATIO-TEMPORAL EEG STRUCTURES FOR APPLICATION IN TECHNOLOGY BRAIN-COMPUTER INTERFACES (BCI)

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Abstract:
Brain-computer interfaces (BCIs) enable direct communication between the brain and information technologies, translating brain activity recorded intracranially into commands. Recent advances in BCIs have utilised multimodal approaches, such as electroencephalography (EEG)-based systems in combination with other biosignals, as well as deep learning to improve the efficiency and reliability of such technologies. Due to the inherent uncertainty of the data of electroencephalogram (EEG) patterns, traditional EEG diagnostic methods often face difficulties. Specifically, in multiple neurological disorders, the main motivation is to overcome the limitations of existing methods that are unable to cope with the complex and overlapping nature of EEG signals. In this paper, the use of Karhunen-Loève decomposition functions for the analysis of spatiotemporal EEG signals in a state of calm mental load in healthy persons and patients with nervous disorders is considered. Approaches in the time, frequency, and time-frequency domains are considered. The results in this study show the relationship between EEG modulation during a cognitive task involving healthy people of the control group and the pathological mental state of patients, according to the results of Karhunen-Loève decomposition in pre-selected EEG frequency ranges. The results given in this paper improve the quality and speed of recognising emotional states of patients with emotional expression disorders from the EEG signal, and also develop brain-computer interface (BCI) technologies, including for the application of artificial intelligence.

Key words: brain-computer interfaces, innovative technology, EEG analysis, neural networks, nonlinear dynamics, bifurcation, neurological disorders

INTRODUCTION

Human-computer interaction (HCI) focuses on developing effective and intuitive interactions between humans and computer systems [1]. Collective intelligence technologies (TCMs) are “technologies that facilitate and/or enable the creation of networks of two or more individuals who perceive, think, and/or make decisions collaboratively in real time” [2, 3, 4]. These include brain-computer interfaces (BCIs) and brain-brain interfaces (BBIs), as well as alternative combinations of brain and computer interfaces that can be called brain-computer-brain interfaces (BCBIs) [5], where a computer component such as artificial intelligence (AI) [6] essentially functions as a collaborator. Brain-computer interface has attracted considerable attention in recent years [7]. This new technology facilitates communication between the brain and the computer. Brain-computer interface (BCI) technology provides a realistic path toward human-computer fusion [8]. It is an interdisciplinary field related to biology, neurology, engineering, computer science and applied mathematics, among others [3, 9]. Meanwhile, the broad application prospects of BCI include medicine, education, industrial management, and other fields [10, 11]. Opportunities for the application of BCI are showing rapid growth [2, 8, 12].
BCI interface receives and records brain signals, decodes them using algorithms and decoders, and converts them into different representations of actions that can be used for control. BCI technology uses electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) [13] to “read” brain signals. EEG-based recording of brain signals using an array of electrodes placed on the scalp is considered more advanced [14, 15], which can provide

more accurate results [16, 17]. Standardised protocols [14, 18] can ensure effective interaction and interoperability between different BCI devices. Recognition of electroencephalography (EEG) signals is crucial for human-computer interaction, but currently many challenges need to be solved, such as designing more convenient electrodes, improving the accuracy and efficiency of decoding, developing more applicable systems for target patients, etc., before this new technology is mature enough to benefit clinical users [19]. EEG is a complex, multi-channel and non-linear signal with noise, which makes identification difficult. Current research is exploring the combination of EEG signals with other modalities. The growth of research and applications of brain-computer interfaces (BCIs) has generated a great deal of discussion [20, 21]. However, most existing studies have mainly addressed ethical issues related to BCI from a general perspective, paying little attention to the specific functions of BCI technology. By providing detailed descriptions of the functions and technical approaches of both writeable and readable BCIs, ethical management of BCI should follow the principle of precise management, which contributes to the improvement of management strategies for different functional types of BCIs. The least studied aspect of quantitative EEG assessment is the use of nonlinear analysis methods [22]. One of the key properties of the brain is the ability to spontaneously form and develop complex ordered neurodynamic structures in the process of adaptation, i.e. self-organization [23].

Adaptive processes in the brain allow the body to function in completely new conditions unknown to it. In any ambiguous or new situation, the brain, thanks to its ability to self-organise, generates patterns of new activity (new forms of behaviour). There is a mechanism that prepares sensory and motor systems for reactions to new environmental influences due to the chaotic interruption of patterns of "old" habitual activity and the deterministic formation of a new "acceptor of action results" [24]. Complex brain systems consist of many components, subsystems, and elements [25]. Some of them require explanation. The brain system has nodes (brain structures), the activity of which is described by a set of variables [26, 26, 27, 28].

The purpose of this research is to obtain some spatio-temporal EEG structures (EEG patterns). As a result of the research, it is necessary to find out whether these structures are built from simpler structures, by analyzing the dynamics that can be understood, which is the basis of the transformation of one spatio-temporal structure into another, and to what extent this process depends on the mental health of the person being tested.

The study was based on the assumption that the human brain, in a state of calm wakefulness, with elementary mental (countdown in the mind) and physiological loads, functions near the points of loss of stability. Therefore, it should be expected that the space-time EEG signal will be a superposition of a small number of fundamental spatial structures - modes with time-dependent amplitudes.

LITERATURE REVIEW

Research [29, 30, 31, 32, 33] in the field of ABCI is focused on the coordination of emotional states, modelling of emotional processes, synthesis of emotional expression and behaviour, and improved interactions between people and machines based on emotional background. Among the various non-invasive methods, the electroencephalogram [34, 35, 36] appears to be a widely used method that provides valuable information about brain patterns. The signs of abnormal brain activity, which are associated with neurological illnesses, are important to watch out for in EEG readings. In most studies [37, 38, 39, 40], BCI electrical brain activity, separated from the additional EEG or ECOG, is amplified, digitally recorded and calculated.

An analysis of the research results [41] showed that most BCI interfaces share the type of data they process, as well as their clock and spatial accuracy. Systems for recognizing emotions based on electroencephalography at the BCI interface have the potential to help enrich human-computer interactions with implicit information, although they may make it possible to understand the cognitive and emotional activities of people. Therefore, these systems have become an important topic of research today. The work shows that one way to study neural dynamics in the resting state is to measure brain signal variability [42]. In other words, brain dynamics are controlled by a small number of order parameters. The state of the brain system in time is described by the state vector. The state vector according to Haken H. [43] is determined by several factors: 1) the current state of the system, 2) connections between components, 3) control parameters, and 4) random events. The role of controlling parameters in the brain can be played, for example, by the concentration of neurotransmitters, the concentration of taken drugs, and the concentration of hormones. Random events that occur in our brain can include, for example, the spontaneous opening of bubbles in neurons, the random excitation of neurons.

Although the variability of the signal was defined as neural noise, recent studies [42] began to emphasise the importance of these temporary oscillations of brain activity, mainly in the ability to process information and functional integrity. Such variability is the most important characteristic for complex neural interactions, effective and optimal functioning of the brain, and flexible response to internal and external stimuli [34]. At the cellular level, populations of neurons with more diverse patterns of activation to the same stimulus (local noise) can code and generate representations more efficiently and adaptively (probabilistic population code [18]), and they can also detect weaker signals [12]. On a more global level, large-scale networks with more dynamic functional connectivity and temporally fluctuating patterns of activation demonstrate greater information processing capacity and integration, so they can support optimal learning, adaptation to the environment, and flexibility in neural processing [43]. As shown by the results of [40], in general, a more complex neural system in a state of rest can model the external environment in a more detailed and efficient way, therefore, it is more adaptive.

Since the current level of knowledge leaves microscopic processes in the brain unclear, the main idea of synergetics is to search for qualitative changes in macroscopic phenomena. There are phenomena in which qualitative changes in the macroscopic states of complex systems are observed. Of particular interest for subsequent analysis is the amplitude of the growing configuration, since it determines the macroscopic structures (patterns of brain activity) evolving. When the structures are just beginning to form, the amplitudes are very small. The amplitudes of growing configurations are called order parameters. They describe the macroscopic order and, more generally, the macroscopic structure of the system. It follows from the central theorem of synergetics that the order parameters uniquely determine the behaviour of growing and decaying configurations [12]. As a consequence, the general spatio-temporal evolution of the state satisfies the order parameters (or obeys the order parameters). This is the principle of subordination.

The state of the system can be described as a superposition of all, i.e. on melting and decaying configurations. If the number of system components is large, then the number of individual configurations is correspondingly large. This means that the information needed to describe the behaviour of the system is not reduced to its decomposition into configurations. The principle of subordination makes it possible to achieve a sharp reduction in the number of degrees of freedom. The number of order parameters is much smaller than the number of system components, so information is compressed. As a result of our research, we obtained some spatio-temporal EEG structures (EEG patterns). It is necessary to find out whether these structures are built from simpler structures, analysing the dynamics that can be understood, which is the basis of the transformation of one spatio-temporal structure into another, and to what extent this process depends on the mental health of the person being tested.

A promising research method is adaptive cognitive training, in which the difficulty of the task is adjusted according to the level of performance of the participants to improve learning and potential transfer effects. Measurement of intrinsic brain activity is suitable for detecting possible distributed effects of training, since the dynamics of the resting state are related to the functional flexibility of the brain and the efficiency of various cognitive processes.

A random process can be represented as a series expansion [44], which includes a complete set of deterministic functions with corresponding random coefficients. Several such series expansions are widely used. A common one is the Fourier series, in which the coefficients are real numbers and the basis of the expansion consists of sinusoidal functions. Zhang and Ellingwood (1994) [34] proposed another orthogonal series expansion, using Legendre polynomials as the deterministic basis function. However, the random coefficients in the expansion are correlated random variables. Other polynomials have also been used by Lee and Der-Kiureghian (1993) [33]. The use of the Karhunen-Loève decomposition with orthogonal deterministic basis functions and uncorrelated random coefficients has attracted interest due to its biorthogonal property, i.e. both the deterministic basis functions and the corresponding random coefficients are orthogonal. This allows for an optimal encapsulation of the information contained in a random process into a set of discrete uncorrelated random variables by Ganem and Spanos (1991) [34].

Thus, one of the effective analysis methods in this situation is the Karhunen-Loève decomposition method (or principal component analysis method).

RESEARCH METHODOLOGY

The essence of the Karhunen-Loève decomposition method is to decompose the spatio-temporal EEG signal into a sum of mutually orthogonal spatial structures - Karhunen-Loève modes, ordered according to the principle of minimizing the average decomposition error. Let us denote $\bar{h} = \bar{h}(t)$ as the vector of the spatio-temporal EEG signal, the components of which are the signals of individual EEG channels, and represent it as a sum:

$$\bar{h}(t) = \sum_{i=1}^{N} \xi_1(t) \cdot \bar{v}_i, \quad (1)$$

where:

N is the dimension of the vector $\bar{h}(t)$ (in our case N = 24), time-independent $\bar{v}_i$ are the Karhunen-Loève mode vectors, orthonormalized, i.e.

$$(\bar{v}_i, \bar{v}_k) = \delta_{ik}, \quad (2)$$

where:

δ_{ik} is the Kronecker symbol, selected and ordered according to the principle of minimizing the average decomposition error

$$E_k = \frac{1}{T} \cdot \int_0^T \left(\bar{h}(t) - \sum_{i=1}^{K} \xi_1(t) \cdot \bar{v}_i\right) \cdot dt, \quad (3)$$

where:

T is the time interval of measurements.

The problem of determining the Karhunen-Loève modes is reduced to the problem of finding the eigenvalues and eigenvectors of the matrix

$$R_{i,j} = \frac{\int_0^T \bar{h}_i(t) \cdot \bar{h}_j(t) dt}{\int_0^T \sum_{k=1}^{N} \bar{h}_k^2(t) dt}, i, j = 1, \ldots, N, \quad (4)$$

It turns out [1, 2] that the eigenvectors of this symmetric matrix coincide with the Karhunen-Loève modes, and the eigenvalues ($\lambda_i,\ i = 1, \ldots, N$) allow us to represent the average decomposition error in the form

$$E_k = 1 - \sum_{i=1}^{K} \lambda_i,\ \ K = 1, \ldots, N, \quad (5)$$

Thus, the magnitude of the corresponding eigenvalue determines the contribution of the Karhunen-Loève mode to the decomposition of the vector $\bar{h}(t)$ is spatio-temporal EEG signal (obviously, $\sum_{i=1}^{N} \lambda_i = \sum_{i=1}^{N} R_{i,j} = 1$). It turns out that when analyzing the spatiotemporal EEG signal, as a rule, it is sufficient to limit to considering the first few Karhunen-Loève modes – i.e., the spatiotemporal EEG signal can indeed be considered as a superposition of a small number of spatial structures with time-dependent amplitudes. The Karhunen-Loève expansion, as is known, characterizes the number of order parameters - the main EEG patterns - and allows us to determine the frequency of their occurrence (but, admittedly, not the dynamics of the order parameters), since in the general case there is no guarantee that the amplitudes in the Karhunen-Loève expansion are identical to the order parameters or the amplitudes of the subordinate modes. Two groups were examined: Group I - control, practically healthy males, 20–23 years old. Group II - patients diagnosed with nervous disorder. EEG recording was performed using a 24-channel encephalograph "BrainTest-24" by "DX Systems". A sampling frequency of 400 Hz and a 16-bit ADC were used. The electrodes were applied according to the international 10-20 system [Nuwer]. EEG examination was conducted according to the standard clinical protocol - the duration of each event was 120 s. Reverse mental counting for 120 s was used as an intellectual functional test. Clinical, correlation, spectral-coherent, multidimensional linear and multidimensional nonlinear EEG analysis was performed using the Neuro-Researcher®'2003 computer EEG (cEEG) system [45]. Artifact-free EEG sections lasting 30-35 s were used to perform the nonlinear analysis.

RESULTS

Let us consider some aspects of the application of the Karhunen-Loève decomposition for the analysis of the "background", i.e., taken in a state of calm wakefulness in the absence of external stimuli, spatiotemporal EEG signal and the analysis of the EEG signal corresponding to the performance of an elementary mental load - "mental counting backwards". There is reason to believe that the nature of the decomposition - the number of significant spatial Karhunen-Loève modes and their frequencies- will be different for a healthy and mentally ill (schizophrenic) person. The spectral analysis of the distribution of the average power of the spatiotemporal EEG signal by frequency in healthy subjects and mentally ill patients that we conducted revealed significant differences. Therefore, we considered it appropriate to apply the Karhunen-Loève decomposition not to the entire frequency range of the EEG signal, but to standard frequency ranges ($\delta-, \theta-, \alpha-, \beta_1-, \beta_2-$ ranges) selected using mathematical filters, believing that the redistribution of the EEG signal power can blur the observed picture.

Table 1

The values of the contributions of the first modes for the entire frequency range of the EEG signal and for the $-, \theta-, \alpha-, \beta_1-, \beta_2-$ ranges

Channel / Amplitude	Control group				Nervous disorder			
	Person 1		Person 2		Patient 1		Patient 2	
	field	count	field	count	field	count	field	count
	0.68	0.60	0.58	0.58	0.40	0.61	0.47	0.42
	0.09	0.11	0.15	0.14	0.16	0.13	0.15	0.16
Native EEG	0.06	0.09	0.10	0.10	0.10	0.05	0.09	0.09
	0.04	0.06	0.05	0.06	0.08	0.05	0.06	0.07
	0.04	0.05	0.03	0.04	0.07	0.04	0.06	0.06
δ-amplitude	0.27	0.44	0.33	0.35	0.51	0.75	0.69	0.63
	0.51	0.58	0.45	0.39	0.40	0.84	0.59	0.52
	0.21	0.18	0.17	0.34	0.30	0.07	0.19	0.25
δ-range	0.09	0.08	0.13	0.08	0.09	0.05	0.06	0.06
	0.07	0.06	0.09	0.07	0.06	0.01	0.04	0.05
	0.05	0.04	0.04	0.04	0.04	0.01	0.03	0.04
θ-amplitude	0.40	0.31	0.26	0.21	0.42	0.42	0.42	0.41
	0.40	0.41	0.45	0.38	0.37	0.51	0.45	0.35
	0.19	0.20	0.17	0.19	0.17	0.23	0.14	0.21
θ-range	0.16	0.15	0.13	0.15	0.15	0.08	0.13	0.13
	0.10	0.10	0.09	0.07	0.08	0.05	0.08	0.08
	0.04	0.05	0.04	0.06	0.07	0.04	0.06	0.06
α-amplitude	0.94	0.75	0.84	0.83	0.60	0.44	0.40	0.42
	0.84	0.79	0.76	0.72	0.50	0.37	0.46	0.51
	0.07	0.09	0.13	0.15	0.18	0.25	0.13	0.15
α-range	0.04	0.05	0.07	0.08	0.11	0.13	0.12	0.10
	0.02	0.02	0.02	0.02	0.06	0.07	0.08	0.06
	0.01	0.02	0.01	0.01	0.04	0.05	0.06	0.04
β_1-amplitude	0.30	0.28	0.27	0.31	0.35	0.25	0.32	0.33
	0.39	0.42	0.45	0.47	0.37	0.52	0.37	0.39
	0.21	0.21	0.17	0.18	0.17	0.14	0.17	0.16
β_1- range	0.13	0.11	0.13	0.16	0.12	0.12	0.12	0.13
	0.10	0.09	0.09	0.09	0.09	0.06	0.09	0.09
	0.05	0.04	0.04	0.03	0.07	0.05	0.07	0.07
β_2-amplitude	0.19	0.22	0.22	0.17	0.25	0.18	0.26	0.27
	0.40	0.37	0.39	0.36	0.51	0.36	0.36	0.39
	0.17	0.17	0.21	0.20	0.11	0.26	0.17	0.18
β_2-range	0.11	0.11	0.11	0.12	0.09	0.15	0.14	0.13
	0.09	0.07	0.09	0.10	0.07	0.06	0.10	0.09
	0.05	0.06	0.06	0.05	0.05	0.04	0.08	0.08

Table 1 shows the values of the contributions of the first 5 Karhunen-Loève modes for the entire frequency range and for the $\delta-, \theta-, \alpha-, \beta_1-, \beta_2-$ ranges of the "background" spatio-temporal EEG signal and the EEG signal recorded during the performance of the "mental counting" task.

As can be seen, the "background" spatiotemporal EEG signal of a healthy person, compared to the "background" spatiotemporal EEG signal of a patient (schizophrenia), is characterized by the prevailing influence of the first (main) mode and a more rapid decrease in the contributions of higher-order modes. In a healthy person, the first three Karhunen-Loève modes cover more than 83% of the EEG signal, while in a patient, they cover no more than 71%. A similar picture is observed for the spatiotemporal EEG signal during "mental counting", but it is somewhat more blurred (see Patient_2 – "mental counting"). This means that the dynamics of the total "background" spatiotemporal EEG signal of a healthy person is characterised by a smaller number of order parameters compared to the dynamics of the "background" spatiotemporal EEG signal of a patient with schizophrenia.

Additional order parameters in the EEG signal of a schizophrenic arise due to the presence of spontaneous internal pathological synchronous excitations of certain areas of the brain, higher-order modes. However, when performing the "mental counting backwards" task, these spontaneous internal pathological foci of synchronous excitations can either be partially suppressed or masked by the additional foci of synchronous excitations that arise.

Figure 1 shows the distribution of the amplitudes of the "background" spatio-temporal EEG signal and the EEG signal when performing the "mental counting backwards" task in healthy subjects and patients with schizophrenia for the δ-, θ-, α-, β_1-, β_2- ranges.

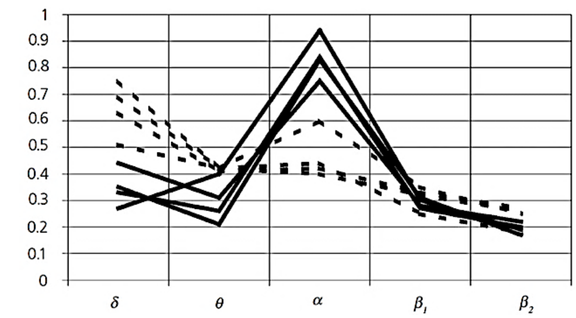

Fig. 1 Distribution of EEG signal amplitudes by frequency ranges. Solid line is control group, dotted line is schizophrenic patients

As can be seen from Figure 1, the most characteristic is the α_range - the relative amplitude of the spatio-temporal EEG signal of a healthy person in this range significantly exceeds the relative amplitude of the spatio-temporal EEG signal of patients with schizophrenia (in all cases, the relative amplitude of the spatio-temporal EEG signal of a healthy subject in the α_range was greater than 80% of the average amplitude of the total spatio-temporal EEG signal, while for a schizophrenic the corresponding amplitude did not exceed 60% of the average amplitude of the total spatio-temporal EEG signal.

Figures 2 and 3 present the distribution of the contribution of the first modes of the "background" spatiotemporal EEG signal and the EEG signal during the "mental counting" task for healthy subjects and schizophrenic patients, respectively, for the α- and δ- ranges.

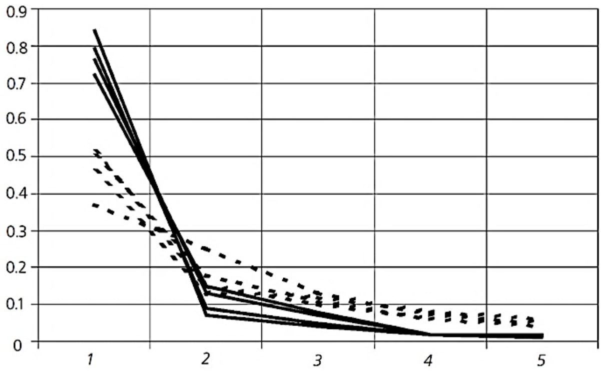

Fig. 2 Distribution of the contribution of the first modes to the signal for the α is range. Solid line is control group, dotted line is schizophrenic patients

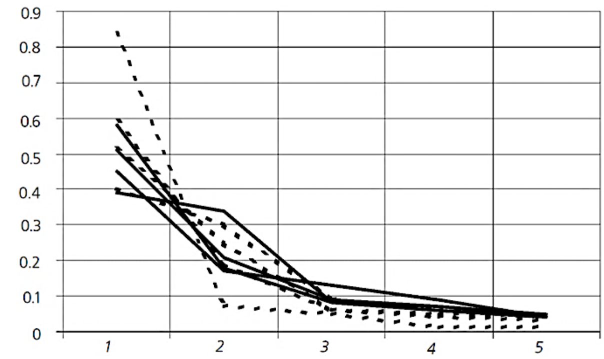

Fig. 3 Distribution of the contribution of the first modes to the signal for the δ is range. The solid line is the control group, the dotted line is schizophrenic patients

In the α range, the "background" spatiotemporal EEG signal of a healthy subject, compared to that of a schizophrenic patient, is characterised by the prevailing influence of the first (main) mode and a faster decrease in the contributions of higher-order modes. Thus, the first two Karhunen-Loève modes of a healthy subject cover up to 90% of the total signal (with the main Karhunen-Loève mode covering at least 76% of the signal), while in a schizophrenic subject, the first two Karhunen-Loève modes cover no more than 70% of the signal (with the main Karhunen-Loève mode covering no more than 51% of the signal). The picture is generally the same as in the study of the spatiotemporal EEG signal in the entire frequency range, but much clearer, which indicates the presence in this situation in patients with schizophrenia of pathological foci of synchronous excitations of certain areas of the brain active precisely at frequencies in the α-range.

During the "mental counting task" in the α-range, the spatio-temporal EEG signal of a healthy person, compared to that of a schizophrenic, is also characterized by the prevailing influence of the first (main) mode and a more rapid decrease in the contributions of higher-order modes (note that this picture was blurred when examining the EEG signal in the entire frequency range). Thus, the first

two Karhunen-Loève modes for a healthy person cover up to 87% of the total signal (with the main Karhunen-Loève mode covering at least 72% of the signal), while in a schizophrenic the first two Karhunen-Loève modes cover no more than 70% of the signal (with the main Karhunen-Loève mode covering no more than 51% of the signal). This indicates the presence of pathological foci of synchronous excitations of brain areas active at frequencies in the α-range in mentally ill people and when performing the "mental counting task". Table 2 shows the components of the first (main) Karhunen-Loève mode for the α_ range of the spatio-temporal EEG signal during the recording of the background EEG and the performance of the “mental counting” task for healthy subjects and patients with schizophrenia.
It follows from Table 2 that channels C3, P3 and O2 are characteristic.

Table 2
Components of the first mode for the α-range

Channel	Control group				Nervous disorder			
	Person 1		Person 2		Patient 1		Patient 2	
	field	count	field	count	field	count	field	count
Fp1	0.19	0.19	0.19	0.19	0.18	0.16	0.26	0.36
Fpz	0.20	0.20	0.21	0.20	0.20	0.18	0.26	0.15
Fp2	0.19	0.20	0.20	0.20	0.20	0.20	0.34	0.44
F7	0.20	0.19	0.16	0.15	0.16	0.12	0.06	0.11
F3	0.20	0.19	0.20	0.19	0.25	0.21	0.20	0.21
Fz	0.19	0.19	0.22	0.21	0.21	0.20	0.21	0.19
F4	0.17	0.17	0.17	0.17	0.22	0.20	0.19	0.18
F8	0.16	0.17	0.14	0.13	0.16	0.14	0.13	0.11
T3	0.03	0.03	0.00	0.01	0.04	0.05	0.00	0.00
C3	0.10	0.09	0.06	0.07	_0.01	_0.00	_0.03	0.04
Cz	0.13	0.12	0.15	0.15	0.04	0.13	0.05	0.18
C4	0.07	0.08	0.09	0.10	_0.02	0.15	0.06	0.07
T4	0.05	0.06	0.04	0.04	0.06	0.09	0.03	0.02
T5	-0.11	-0.10	-0.19	-0.18	-0.26	-0.16	-0.18	-0.27
P3	_0.26	_0.25	_0.22	_0.18	-0.39	_0.42	_0.34	_0.36
Pz	_0.16	_0.15	_0.07	_0.06	_0.22	_0.27	_0.25	_0.11
P4	_0.34	_0.33	_0.22	_0.20	_0.32	_0.38	_0.37	_0.20
T6	-0.20	-0.18	-0.22	-0.23	-0.15	-0.20	-0.20	-0.15
O1	_0.31	_0.31	_0.45	_0.47	_0.30	_0.27	_0.26	_0.29
Oz	_0.32	_0.33	_0.27	_0.29	_0.28	_0.27	_0.26	_0.24
O2	-0.43	-0.44	-0.41	-0.43	-0.23	-0.22	-0.24	-0.21
ECG	0.00	_0.01	0.00	0.00	0.03	0.01	0.05	0.02

On channels C3 and O2, the amplitude of the first Karhunen-Loève mode for a healthy person is noticeably higher than for a sick person, while on channel P3, the situation is the opposite. On channel Cz, the amplitude of the first Karhunen-Loève mode of the background signal for a healthy person is higher than the background signal for a sick person, while when performing the task "backwards counting in the mind", these amplitudes are equalised. Curiously, there are no obvious differences in the amplitudes of the components of the second (and higher) Karhunen-Loève modes for a healthy and sick person α these modes can be noticeably different from each other for different people. This is connected with the fact that the higher Karhunen-Loève modes for a healthy person in the α-range are not significant - their contribution is small, but in a patient with schizophrenia these modes are connected with the presence of pathological foci of synchronous excitations of brain areas active at frequencies in the α-range and, therefore, are different for different people and change depending on the circumstances.
It is evident from Table 1 that the second characteristic ranges are the δ- and θ-ranges. The relative amplitude of the spatio-temporal EEG signal of a healthy person in these ranges (in contrast to the α-range) is smaller (especially in the δ-range) than the relative amplitude of the spatio-temporal EEG signal of patients with schizophrenia. It is precisely because of the increased amplitude in these ranges of the spatio-temporal EEG signal in patients with schizophrenia (see Patient 2 – "mental counting") that the picture obtained when analysing the spatio-temporal EEG signal in the entire time range is blurred. Interestingly, in the δ-range, there is an increased influence of the higher modes (3-5) of Karhunen-Loève in healthy people, while the first Karhunen-Loève modes do not reveal such a pattern. This is due to the more complex dynamic nature of the functioning of the brain of a healthy person in the δ range, while in patients, the dynamics of the brain in the δ range are determined mainly by the emergence of foci of pathological brain activity.

CONCLUSIONS

Brain-computer interfaces may offer an alternative form of interaction between humans and technological systems. Noninvasive technological approaches include electroencephalography, functional near-infrared spectroscopy, and now even magnetoencephalography. While noninvasive devices have an established market for brain monitoring, their potential for brain-computer interaction has not yet been realized. However, as technology continues to improve, data processing methods are improving [46-49]. It is also important to ensure the physical and mental integrity of the BCI user is protected from the perspective of device safety.
Mental disorders disrupt cognitive abilities, emotions, and behavior of various patients and can reduce their quality of life and even cause death. Despite significant progress in the diagnosis and treatment of mental disorders, challenges remain in achieving objective understanding, accurate assessment, and timely intervention for personalized conditions. Our results open new opportunities for the field of neural interfaces, with potential for various applications, including assistive technologies and cognitive enhancement, to further improve human-machine interaction [50, 51]. The application of nonlinear dynamics in neuroscience has provided significant knowledge about the functioning of the brain, shedding light on its complex behavior and functions.
It is possible to conclude that the analysis of relative amplitudes of the spatio-temporal EEG signal in different frequency ranges (the most important in this sense are the δ-, θ-, α- ranges), as well as the analysis of the main Karhunen-Loève modes of the spatio-temporal EEG signal conducted in these frequency ranges (the most important is the α-range) allows to obtain additional, essential

information about the nature of the formation of spatial EEG patterns and frequencies of their occurrence. Apparently, this relatively simple procedure, in which all EEG channels are involved, can be successfully used for preliminary diagnosis of pathological brain conditions. A more in-depth diagnosis naturally involves a detailed analysis of the differences in the structure of the Karhunen-Loève modes and their dynamics in a healthy and diseased brain. This study highlights the potential of complexity measurements in combination with portable EEG devices to monitor changes in consciousness, especially when combined with low-density configurations, opening the way for better understanding BCI.

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