

Methods of Obtaining and Processing Information Reflecting the Electromagnetic Activity of the Brain

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ABSTRACT This paper presents methods for processing information obtained using an electroencephalograph to develop an effective human-machine interface based on mental control. The research focuses on clustering statistical data that reflects the brain's electrical activity and determining its correlation with a person's psycho-emotional state. A novel aspect of this approach is the classification of emotions into two primary types – acceptance (e.g., agreement, joy) and denial (e.g., rejection, grief) – with further gradation from slight to intense expression. The proposed method includes signal normalization, feature extraction, and the calculation of a barycenter for clustering EEG data. These techniques allow identifying emotional signatures corresponding to human perception at the time of EEG recording. The presented framework is designed for integration with artificial intelligence systems through machine learning algorithms. Its practical applications include medical diagnostics, cognitive training for professionals, and intelligent control systems. The approach enables real-time interpretation of emotional states, laying the groundwork for next-generation neural interfaces and adaptive control technologies.

KEYWORDS artificial intelligence, neural networks, diagnostics, data analysis, knowledge bases, clustering, Barycenter, electroencephalogram.

I. INTRODUCTION

Expanding the capabilities of data input into model environments and enabling efficient interaction between humans and machines remains a key objective in artificial intelligence system development. This, in turn, requires the creation and advancement of new interfaces and the improvement of machine learning methods. One means of communication may be an electroencephalograph.

As an objective control tool, the electroencephalograph allows for the monitoring of brain electromagnetic activity and obtaining highly encrypted information about a person's intellectual state, which includes a multi-level representation of psychological, emotional, and abstract logical activity.

Such multilayered information is valuable not only for medical diagnostics but also for adaptive control systems, where machines adjust their responses according to the detected mental state of the user.

When developing an interface based on an electroencephalograph, researchers face two major complex problems:

1. Electromagnetic noise interference occurs in sensors due to environmental influences and complex neural processes.

2. The multidimensional nature of the dynamic characteristics of electromagnetic oscillations, which arise when information is transmitted through the intricate structures of brain tissue.

These challenges explain why EEG analysis requires sophisticated preprocessing, artifact rejection, and statistical modeling techniques before meaningful features can be extracted.

Deciphering and identifying various psychological, logical, and abstract processes in the brain is extremely challenging. This task is comparable to trying to understand the mechanical structure of a steam locomotive just by analyzing the smoke coming from its chimney. It is far more complex than deciphering hieroglyphs using the Rosetta Stone.

Encephalogram curves cannot be considered a language that can be directly used for communication between humans and computers. However, the associative properties of any information obtained under certain conditions can be interpreted as an analogue representation of those conditions.

Human intellectual activity is multidimensional and can be conventionally divided into several layers. We are interested in the layer of abstract thinking, the layer of psycho-emotional perception, intuition and the subconscious, heuristic thinking.

Each of these layers leaves a distinct trace in EEG recordings, often revealed through specific frequency bands or synchronization across cortical regions.

The objective of this research is to define methods for interpreting encephalograms in terms of their correspondence to a person's psychological and emotional state.

At the initial stage of data processing, two fundamental states are identified:

1. Perception (agreement, pleasure, joy)
2. Denial (rejection, disgust, grief)

Acceptance is conventionally taken as one and negation as zero. Of course, there is a much wider range of psychological and emotional states of a person, but for now, for the sake of simplicity and efficiency of future machine learning of a neural network, we will accept these two states.

Thus, the development of an information model and experimental setup is aimed at creating a method for clustering and classifying EEG data, which can then be used in machine learning algorithms for artificial intelligence neural networks to identify typical human emotions through objective control methods. This will serve as a foundation for an artificial intelligence system to interpret human emotional states in real-time interaction.

This article presents preliminary research materials for a large-scale project aimed at developing software, hardware tools, and intelligent data analysis methods for creating a mental interface based on human emotional perception using objective EEG indicators. The provided algorithms and statistical processing methods serve as representative examples of typical patterns. In this way, the foundational classification approach is demonstrated prior to applying deep machine learning on larger datasets.

II. STATE OF THE ART

Electroencephalography (EEG) has become one of the most widely used methods for studying the electrical activity of the brain and its correlation with emotional and cognitive states. In recent years, a large body of research has focused on emotion recognition using EEG signals, feature extraction, and machine learning algorithms to enhance human-machine interaction (HMI).

A. EEG FEATURE EXTRACTION FOR EMOTION RECOGNITION

Traditional approaches to EEG-based emotion recognition heavily rely on features extracted from well-defined frequency bands. The most common method involves calculating the Power Spectral Density (PSD) to quantify the signal power in different rhythmic components: delta (δ , 0.5–4 Hz), theta (θ , 4–8 Hz), alpha (α , 8–13 Hz), and beta (β , 13–30 Hz). These spectral features are often supplemented with statistical descriptors such as mean, variance, standard deviation, and kurtosis of the signal in both time and frequency domains.

Singh and Krishnan (2023) [21, 27] provided a comprehensive summary of these feature extraction methods, demonstrating that frequency-based and wavelet-based features remain effective and interpretable tools for initial EEG analysis. However, a significant limitation of these traditional methods is their high sensitivity to noise and artifacts, limited adaptability to the non-stationary nature of EEG signals, and their inability to capture complex, non-linear dynamics that may be crucial for distinguishing subtle emotional states.

Alghamdi *et al.* (2025) [22] introduced a cross-subject contrastive learning framework to reduce inter-subject

variability and label noise, achieving robust performance across multiple public EEG datasets. This approach addresses one of the fundamental challenges in EEG analysis by learning subject-invariant representations through contrastive learning techniques.

B. MACHINE LEARNING AND DEEP LEARNING IN EEG ANALYSIS

The evolution of machine learning (ML) has profoundly impacted EEG-based emotion recognition, moving from methods reliant on manually engineered features to models capable of automated feature extraction. Conventional classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest have demonstrated robust performance in numerous studies, achieving acceptable accuracy by operating on pre-defined feature sets like power spectral density and statistical moments [21, 28]. However, their effectiveness is inherently bound by the quality and comprehensiveness of these hand-crafted features, which may not fully capture the complex, non-linear dynamics of emotional states in EEG signals [14].

This limitation has catalyzed a shift towards deep learning (DL) models, which can learn hierarchical representations directly from raw or minimally processed temporal or spectral EEG data, thereby reducing the need for domain-specific feature engineering. Convolutional Neural Networks (CNN) are extensively applied to treat EEG data as images (e.g., using spectrograms or topographical maps) to exploit spatial relationships between electrodes [19]. Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) networks, are effective at modeling the temporal dependencies inherent in brain signal sequences [20].

More recently, advanced architecture has been developed to address the unique challenges of EEG data. For instance, Xu *et al.* (2023) [14] proposed multimodal Graph Convolutional Networks (GCN) to explicitly model the functional connectivity between different brain regions, significantly enhancing the prediction of cognitive states by capturing intricate spatial dependencies. Alongside novel architecture, comprehensive reviews have emerged to synthesize the rapidly expanding field.

The systematic review Ganepola *et al.* (2024) [8] meticulously catalogues the application of various deep learning models for detecting confusion from EEG signals, highlighting a critical trend: while DL models often achieve superior accuracy, they frequently struggle with generalization across diverse subjects and datasets and operate as “black boxes,” lacking interpretability.

Despite their promise, DL models present challenges, including a high demand for large, annotated datasets and substantial computational resources, which can be prohibitive for real-time embedded systems. Furthermore, as noted in [8], the field continues to grapple with the problem of inter-subject variability, where models trained on one cohort of participants often experience a significant performance drop when applied to another, underscoring the need for more generalized and adaptable learning frameworks.

C. FEATURE SELECTION AND CLUSTERING TECHNIQUES

The high dimensionality and noise inherent in EEG data necessitate robust feature selection and optimization methods to improve classification accuracy and reduce computational load. Beyond conventional statistical features, meta-heuristic

optimization algorithms have emerged as powerful tools for identifying the most discriminative feature subsets.

Kumar et al. (2024) [23] demonstrated the efficacy of hybrid swarm intelligence techniques in selecting optimal EEG features for emotion recognition, reporting significant improvements in accuracy over traditional methods. Similarly, the application of evolutionary computation approaches was explored to navigate the vast feature space and mitigate the risk of overfitting [25].

Furthermore, clustering techniques serve not only for classification but also as a preprocessing step for feature refinement. Barycenter-based approaches, akin to the method proposed in this paper, have been suggested to enhance the stability of EEG pattern recognition under noisy conditions. These methods aim to find a central point (barycenter) that minimizes the distance to all points in a cluster, thus providing a more robust prototype for each emotional state compared to simple averaging [26]. This is particularly relevant for real-time applications where signal quality can vary.

D. MULTIMODAL LEARNING AND HUMAN MACHINE INTERFACES

Recent studies demonstrate that combining EEG with other modalities (e.g., speech, facial expressions, or text) can enhance emotion recognition accuracy. For instance, the Emotion Fusion-Transformer (2025) [24] integrates EEG and text modalities for improved emotional state detection in interactive systems. However, multimodal systems introduce additional complexity, while pure EEG-based methods remain attractive due to their non-invasive and real-time nature, especially in medical diagnostics and adaptive control applications.

E. IDENTIFIED RESEARCH GAPS

Despite the considerable progress outlined above, several persistent challenges hinder the widespread deployment of robust EEG-based emotion recognition systems:

1. **Generalization Across Subjects and Sessions:** The high variability in EEG signals between different individuals (inter-subject) and even across recording sessions for the same individual (intra-subject) remains a major obstacle. Models often overfit to the training data, failing to perform well on new, unseen subjects without extensive recalibration [22].
2. **Noise and Artefact Sensitivity:** EEG signals are notoriously susceptible to physiological (e.g., eye blinks, muscle movement) and environmental noise. Developing methods that are inherently robust to these artefacts, rather than relying on perfect preprocessing, is crucial for real-world applications.
3. **Interpretability and Explainability:** While deep learning models achieve high accuracy, they often function as “black boxes”. There is a growing need for models that not only perform well but also provide interpretable insights into which features, and brain rhythms are most indicative of specific emotional states.
4. **Real-Time Processing Efficiency:** Many state-of-the-art algorithms are computationally intensive, making them unsuitable for integration into low-power, real-time human-machine interface systems. Developing lightweight yet effective frameworks is an ongoing research focus.
5. **Limited Exploration of Geometric Clustering Methods:** Although clustering is used, advanced geometric concepts like the barycenter for defining robust cluster

prototypes in high-dimensional EEG feature space are not sufficiently explored. This represents a methodological gap that could lead to more stable emotion classifiers [26].

Our work addresses these gaps by proposing a barycenter-based clustering method for EEG data, combined with normalization and statistical feature extraction. This approach provides a more stable and interpretable framework for recognizing human emotional states and enables practical integration into adaptive HMI systems.

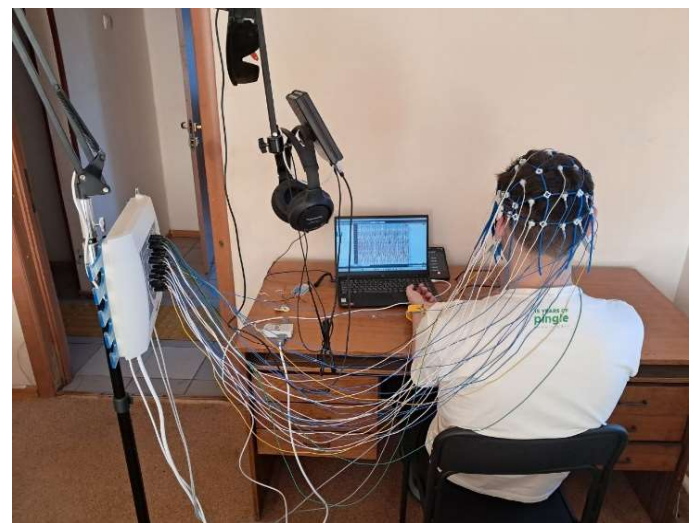
III. MATERIAL AND METHODS

A. EXPERIMENTAL AND MATHEMATICAL JUSTIFICATION FOR EEG INTERPRETATION

In experimental research, a standardized BRAINTEST 24-channel electroencephalograph was used for data acquisition. The study involved two healthy male participants aged 24 and 27, with no history of neurological disorders. All participants provided written informed consent prior to the experiment. The first two channels are used for the contour correlation of general signals. The 24th channel records an electrocardiogram (ECG) to correlate artefacts or other manifestations in individual sensors during EEG data acquisition. Figure 1 shows the encephalograph and the installation diagram for the 24-channel research system.



(a)



(b)

Figure 1. a – BRAINTEST Encephalograph 24 channel, b – installation diagram

The electroencephalograph is an extremely sensitive device. Conducting an EEG recording session requires precise calibration of each lead before the session begins. The calibration procedure followed manufacturer specifications, with impedance checks maintained below 5 k Ω for all electrodes to ensure optimal signal quality. Only 21 leads contain direct informational data. The first two leads serve as references for signal recording. The last lead (ECG) is used to correlate heartbeat artefacts that may interfere with EEG data interpretation.

The goal of the experiment is to identify those artefacts that are characteristic of phenomena corresponding to the sought-after registrations. The complete set of recorded data is structured into a signal table (see Figure 2).

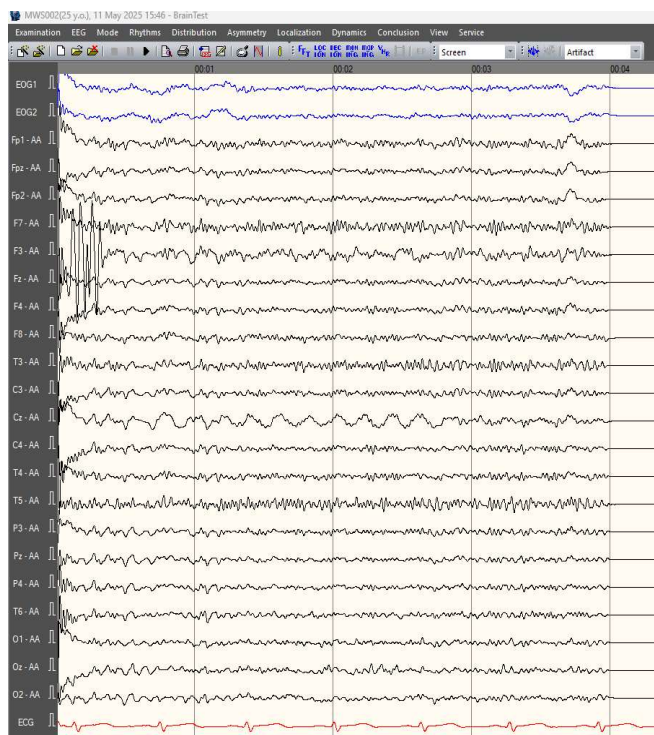


Figure 2. The main encephalogram data table

EEG recording was conducted in a specially equipped room with controlled noise and lighting conditions. Participants were seated in a comfortable position, and during the recording they were presented with visual stimuli of positive and negative emotional valence. Each stimulus lasted 4 seconds, followed by a 10 second interval to restore the baseline state.

EEG data were systematically recorded for two participants during both perception and denial emotional states. For each state, the recordings were organized into three distinct clusters, each corresponding to a separate EEG recording session. Each cluster included 20 electroencephalograms, resulting in a dataset of 120 EEG recordings per participant and 240 recordings for the entire experiment.

All experiments must be conducted while maintaining the same installation scheme and standard calibration settings for the leads. In some cases, it is recommended to apply the signal normalization procedure. In this case, the final signal is dimensionless and scaled to one. This can be achieved by dividing each time-fixed encephalogram value by its maximum recorded value. In this case, the absolute amplitude value of the signal remains within the range between zero and one, is dimensionless, and retains the overall relative characteristic of the signal shape over time. Such normalization does not distort the dynamic characteristics of the extracted patterns and can be

applied to encephalograms with various amplitude calibration settings.

Additionally, the software allows identifying certain stochastic characteristics and statistical indicators of the brain's electromagnetic activity. The feature extraction process included calculation of power spectral density in standard frequency bands (delta: 0.5-4 Hz, theta: 4-8 Hz, alpha: 8-13 Hz, beta: 13-30 Hz) along with statistical features (mean, variance, standard deviation, kurtosis) for each of the 21 data channels.

The statistics table in Figure 3 demonstrates a typical encephalogram of a patient in a resting state. This table contains processed data characterizing the manifestation of various brain bioelectric rhythms: δ , θ , α , β . In particular, the signal power and the corresponding rhythm frequency are recorded.

Statistics				
Power	Frequency	Dispersion		
...	δ	θ	α	β
Fp1	2838.420	2890.419	785.433	1467.986
Fpz	2496.836	2374.255	1652.447	1196.039
Fp2	7718.867	2804.228	1517.273	1942.498
F7	7444.301	7115.089	2183.560	2506.391
F3	1331.292	883.748	451.744	1008.829
Fz	4123.130	4925.735	3578.058	3801.853
F4	5608.317	2125.762	1358.728	1515.807
F8	4075.753	2920.763	1529.475	1341.613
T3	5029.992	2632.448	1088.879	1287.200
C3	3355.286	2346.212	1423.183	1426.372
Cz	4036.748	2616.777	362.841	575.528
C4	8981.411	6372.335	2296.585	1918.340
T4	1537.801	2727.796	1854.459	1543.709
T5	6832.660	3620.629	1940.840	2247.029
P3	4039.880	2155.337	1024.177	1767.155
Pz	5743.567	3799.399	2395.526	1813.478
P4	7092.104	3629.170	1975.142	2309.936
T6	2258.758	14622.958	7948.331	13773.455
O1	7010.016	4260.456	1774.078	2747.190
Oz	10083.892	3487.999	1738.273	1661.735
O2	8308.886	4463.490	2554.165	2493.598

Figure 3 The table of statistics

Such data, structured into a matrix for each lead and the corresponding rhythm type, can be interpreted as an independent signature of a typical brain state. This signature can be recorded and used in the formation of patterns that clearly correspond to specific states. As a result of the experiments, patterns of emotion acceptance and rejection of certain events in which the patient participates can be identified.

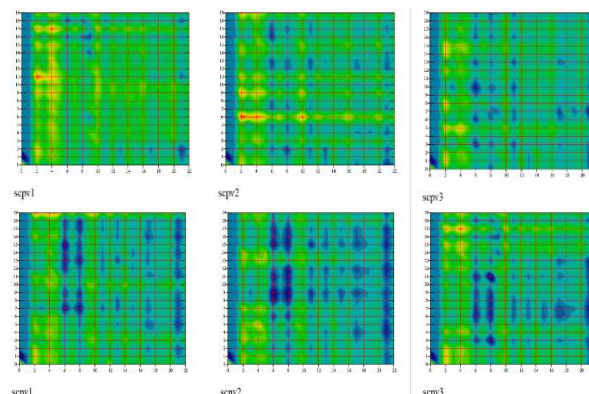


Figure 4. Heatmaps of statistical signatures representing clusters of positive and negative psycho-emotional states.

To visually represent these integral indicators, Figure 4 demonstrates the structural matrices for both emotional states. The horizontal axis represents the EEG channels, while the vertical axis corresponds to the number of the electroencephalogram within the corresponding cluster. The top row (scpv1, scpv2, scpv3) visualizes the three formed clusters associated with the positive emotional state (acceptance), whereas the bottom row (scnv1, scnv2, scnv3) displays the corresponding clusters for the negative state (denial). Scpv denotes the cumulative indicator of the acceptance signature for the corresponding cluster, while scnv represents the cumulative indicator of the negative (denial) cluster signature. These visual heatmaps clearly illustrate the distinct spatial and statistical distributions of the brain's electromagnetic activity, confirming the pronounced divergence in patterns between different psycho-emotional responses.

It is extremely important to accurately determine the patient's actual emotion. Incorrect interpretation can significantly distort the final classification of emotions. It is recommended to conduct multiple stochastic tests with at least 100 patterns for the overall statistical assessment of the identified emotion. The authors of this publication emphasize the necessity of processing information with a 95% confidence interval. This interval, for example, corresponds to the determination of Student's t-test in psychological experiments.

Typical encephalogram signals are shown in Figure 5. As seen in the figure, the amplitudes of each lead are approximately the same. At the beginning of the signal recording, a transient process is clearly present. It lasts about 30–50 milliseconds and has virtually no impact on the results when processing stochastic data. However, before processing statistical material, it is recommended to remove transient processes and artifacts from the averaging list, as they are not related to the states studied.

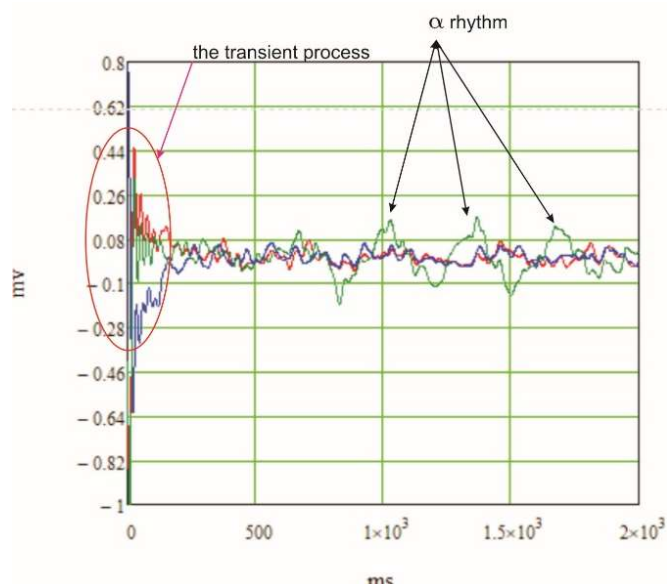


Figure 5. The signals by leads

To assess the robustness of the extracted features, repeated trials were performed, and the stability of feature distributions was evaluated using cross-validation. Reliability analysis ensured that identified patterns of acceptance and denial were

not random artefacts but reproducible across different epochs and sessions

The graphs of the average signal power per channel, for an example of four tests, are shown in Figure 6.

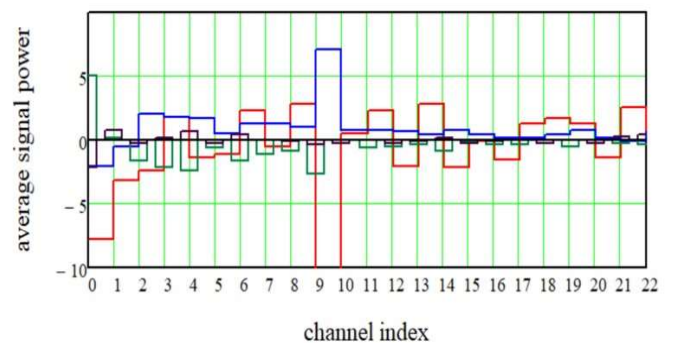


Figure 6. The average signal power in each channel

The average power by the channel is an element of the pattern for the selected state of the patient. For example, the encephalogram readings are taken from a sample (e.g., 50 records) for the same psychological state. In the case of the denial (zero state), averaging over each layer of the sample will give us a typical key to this state.

Similar processing of signals for deviations by channels gives us a second picture (pattern) for full clustering of the class of states (see Figure 6).

The graph in Figure 7 shows the average value of deviations from the average parameter of channel power for the comparative procedure of the first and last layers of the sample. Obviously, the magnitude of deviations for each channel differs insignificantly. This indicates that the stability of the deviation is preserved with the stability of the patient's state. The test for this example was carried out specifically in a state of complete rest of the patient, the absence of visual and sound stimuli and other external influences. The patient was warned that it was necessary to refrain, if possible, from significant memories that could influence his condition by deflecting him towards acceptance or non-perception of any stimuli. In this way, the necessary data was obtained for the calibration processes of the encephalograph. A slight discrepancy in the deviation readings by channels confirms that the calibration was successful.

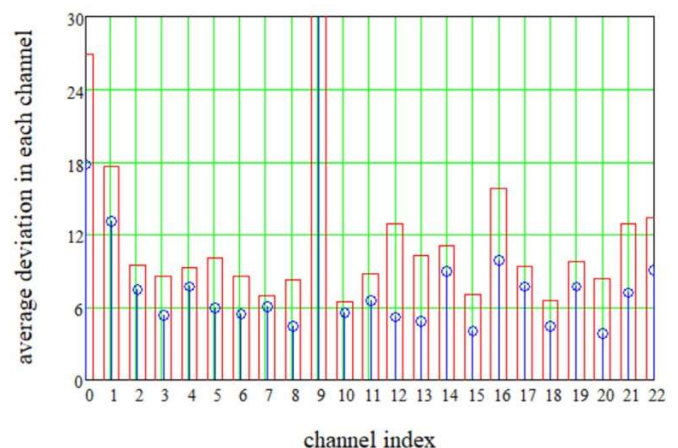


Figure 7. The average signal power in each channel

Thus, when processing encephalograms, we can obtain numerous points of scattered stochastic data for signal power

across channels and deviations across channels. This results in a set of points in a 23-dimensional encephalogram space. The authors then propose an improvement to the KNN (K-Nearest Neighbors) method by determining the Barycenter point, for which all stochastic points obtained based on a given parameter are at the minimal Euclidean distance from the set of sample points.

```

MinBC := | xt ← 0
          | ncl ← 0
          | while ncl ≤ 22
          |   | distN ← 1000000
          |   | k ← 0
          |   | while k ≤ j
          |   |   | x2_k ← AvNCM_k.ncl
          |   |   | k ← k + 1
          |   | xt ← min(x2^T)
          |   | while xt ≤ max(x2^T)
          |   |   | dist ← ∑_{h=0}^j √(x2_h - xt)^2
          |   |   | if dist ≤ distN
          |   |   |   | distN ← dist
          |   |   |   | xmin_ncl ← xt
          |   |   |   | xt ← xt + step
          |   | ncl ← ncl + 1
          | xmin

```

Figure 8. The algorithm for calculating the barycenter.

Figure 8 shows the current algorithm of the linear computational process of the coordinates of the 23-dimensional barycenter. Its essence lies in the search for a certain point in the space of the minimum and maximum readings of the clustering sample parameter, for which the total Euclidean distance to each of the cluster points is minimal.

It is important to note that the proposed approach is not a KNN method. The associativity with KNN methods is maintained solely in the shared general approach of calculating Euclidean distances of signatures across the EEG leads.

The presented linear computational programs demonstrate the application of these methods specifically for intelligent data analysis. The intelligent method within our approach refers to the clustering technique based on the similarity of the integral indicators of signatures.

B. METHODS OF EEG DATA PROCESSING. CLUSTERING OF STATISTICAL DATA

Figure 9 shows the coordinates of the barycenter for the selected cluster (blue bars) and the coordinates of a certain encephalogram layer (red segments). In this example, the deviation of the layer's coordinates from the barycenter's coordinates does not exceed 30%. This indicates that this layer

corresponds to the given cluster by approximately 70%. This is a relatively low value, but compared to other clusters, it is a defining characteristic.

Such deviations are typical for EEG studies, as neural responses are inherently variable and subject to numerous external and internal factors.

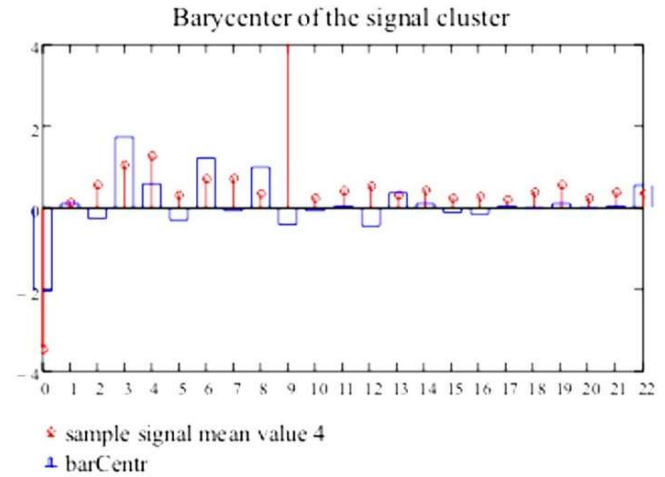


Figure 9. The barycenter of the averaged amplitude.

Figure 9 illustrates the application of the barycenter for average amplitudes across channels. It is evident that the more EEG layers are included in the barycenter calculations, the more accurate the processed cluster's readings will be. It is recommended to create a sample of 10 recordings, with 10 segments per recording, for signal processing. This results in a total of 100 layers.

This sampling strategy ensures statistical stability, as a single recording may contain random artifacts, while averaging across multiple layers increases the reliability of extracted features.

Figure 10 presents the barycenter data points of the cluster (blue segments) and the encephalogram signature data for deviations (red bars). In this example, the signature values deviate from the cluster barycenter by less than 5%, which, with a 95% confidence interval, confirms the signatures belonging to the given cluster.

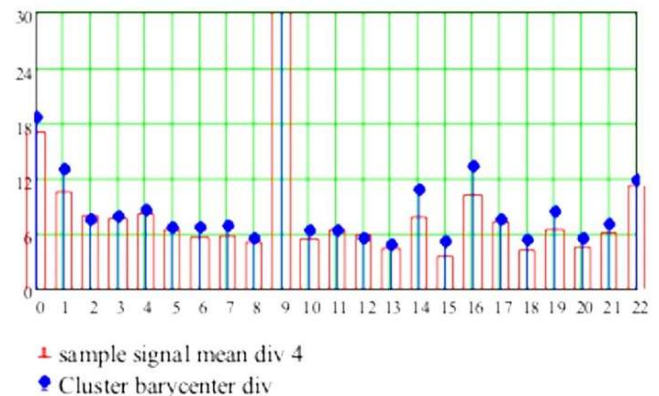


Figure 10. The barycenter of average deviations.

The small deviation (less than 5%) is a critical indicator for validating the homogeneity of the cluster. Such results suggest that EEG signals grouped in this way can be reliably attributed

to a specific psychological or cognitive state.

In cases where EEG data is processed to find correlations with certain phenomena of abstract human thinking, such as symbol recognition, specific patterns can be extracted from the overall signature across multiple channels that correspond to the perception of the studied symbols.

These correlations support the hypothesis that clustering can isolate cognitive processes related to memory, recognition, and decision-making.

Another component of the overall encephalogram signature is the statistical block of rhythm frequencies (see Figure 11). Statistical rhythm analysis represents an average harmonic analysis of the oscillations of electromagnetic indicators across channels and may contain unique characteristics corresponding to specific psychological or abstract states of a person.

...	δ	θ	α	β
Fp1	2,4	5,5	10,8	16,6
Fpz	2,5	5,5	10,4	15,8
Fp2	2,7	5,1	10,4	16,4
F7	2,7	5,3	10,6	16,7
F3	3,0	5,0	10,5	17,1
Fz	2,9	5,2	10,4	15,7
F4	2,6	5,5	10,5	16,1
F8	2,8	6,4	9,1	17,6
T3	2,6	5,5	10,9	16,6
C3	2,8	6,1	10,7	15,7
Cz	2,8	5,8	10,5	15,5
C4	2,6	5,4	10,6	16,0
T4	3,0	4,8	10,7	15,8
T5	2,8	5,9	10,6	16,6
P3	3,0	4,9	10,6	16,1
Pz	2,9	5,3	10,7	15,5
P4	2,7	6,0	10,6	16,7
T6	3,0	4,8	10,7	17,4
O1	2,6	5,7	10,7	15,5
Oz	2,7	6,1	10,6	18,0
O2	2,9	5,4	10,6	16,5

Figure 11. Rhythm processing statistics.

Rhythm statistics are particularly useful in differentiating between emotional states, since patterns in delta and theta rhythms often correspond to states of relaxation or drowsiness, while alpha and beta rhythms are associated with active attention and problem solving.

Thus, the overall signature contains averaged amplitude parameters, averaged deviation parameters, statistical data on signal power, and rhythm frequency statistics. These four components are sufficient for identifying and forming patterns for classifying a person's state.

IV. CONCLUSIONS

The article examines methods for obtaining and processing information about the brain's electromagnetic activity using an electroencephalograph as an objective tool for monitoring a person's emotional and abstract thinking state.

The present mathematical framework enables the use of specific data determinants to confirm or refute the classification of a person's psychophysiological state into various classes. This approach can be applied to interpret emotions or abstract images perceived by a person using a neural network. The extraction of relevant patterns for class formation can be utilized in machine learning through backpropagation error methods.

Given the optimal scope of this publication, this article focuses on the most representative examples of statistical data. This sample is entirely sufficient to visually demonstrate clear distinctions, effectively isolate the useful signal, and identify the target signatures for subsequent classification. We fully acknowledge that comprehensive neural network training in the future will require a significantly larger dataset of at least 200 signatures for each emotional state, comprising a minimum of 10 clusters. The current research aims to lay the foundational framework and determine the methodological directions for our subsequent, larger-scale development.

The proposed approach may be beneficial for developers of human-machine mental interfaces.

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