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METHODS OF INTELLIGENT ELECTROENCEPHALOGRAM DATA ANALYSIS FOR CLASSIFYING HUMAN EMOTIONAL STATES

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Abstract. *The paper presents a method for classifying human psycho-emotional states (positive and negative) based on the intelligent analysis of electroencephalogram (EEG) data. The proposed approach is an extension of the k-nearest neighbors method and is based on calculating the geometric distance from the analyzed signal to the barycenters of the formed clusters. Unlike direct comparison with individual reference samples, the use of barycenters mitigates the impact of random outliers and artifacts within the training set, ensuring the signal is compared against the most typical "integral portrait" of the emotion. Input EEG data are pre-processed to convert the dynamic amplitude series into stationary integral metrics over a time interval of 1000–3000 ms to filter out reaction noise. It has been experimentally confirmed that the method demonstrated 100% classification accuracy within the constructed test sample.*

Keywords: *artificial intelligence, data analysis, knowledge bases, clustering, EEG.*

Introduction

The rapid development of Brain-Computer Interfaces (BCI) and artificial intelligence systems underscores the critical need for objective instrumental monitoring of human emotional states. One of the main obstacles to creating reliable classifiers is the nature of emotional responses, which is characterized by fuzzy logic, signal non-stationarity, and high noise levels in electroencephalogram (EEG) recordings [1-2].

Classical frequency analysis methods, such as the Fast Fourier Transform (FFT), often prove ineffective for isolating the useful signal from the superposition of electromagnetic oscillations, as they do not allow for the classification of harmonics according to their origin. In previous studies, the authors proposed an approach for transitioning from dynamic parameters to stationary statistical data by calculating integral metrics of brain activity. However, classification using the classical nearest neighbor method can be susceptible to isolated anomalies or specific artifacts retained in the training set.

This study proposes an improved classification method that accounts for the integral contribution of reference patterns. The essence of the method lies in introducing the concept of a cluster barycenter—a point in the multidimensional lead space for which the total distance to all other points in the cluster is minimal. The barycenter serves as a generalized signature or "center of gravity" for a specific emotional state, allowing for abstraction from the individual variations of separate recordings.

The objective of this work is to formalize the algorithm for calculating barycenters for positive and negative emotional clusters, to describe the classification procedure based on minimizing Euclidean distances to these centers, and to verify the method's effectiveness as part of a complex majority decision-making model.

Main text

In this method, the barycenter is calculated for each reference cluster—a point in the multidimensional lead space characterized by the minimum total distance to all other points of the given cluster.

Unlike the classical arithmetic mean, the barycenter is defined as the point minimizing the sum of Euclidean distances to all cluster elements. This approach makes the model significantly more robust to outliers and asymmetry in the experimental data distribution [3-4].

The implementation of the mathematical function BC for calculating the barycenter within the Mathcad environment is presented in Fig. 1

To visualize the method's operation, a set of metrics for 20 cluster points along a single lead (u=10), as well as the average metric value and the calculated barycenter, are examined (Fig. 2).

Figure 3 presents the results of calculating averaged barycenters for negative and positive state clusters and visualizes their spatial distribution across EEG leads.

$$
BC(a1) := \left|
\begin{array}{l}
mins \leftarrow sort(a1)_0 \\
maxs \leftarrow sort(a1)_{19} \\
bcc \leftarrow mins \\
step \leftarrow \dfrac{maxs - mins}{100} \\
j \leftarrow 0 \\
\text{while } j \le 100 \\
\quad \left|
\begin{array}{l}
sd_{j,0} \leftarrow \displaystyle\sum_{i=0}^{19} \left(\left| bcc + j \cdot step - a1_i \right| \right) \\
sd_{j,1} \leftarrow bcc + j \cdot step \\
j \leftarrow j + 1
\end{array}
\right. \\
csort(sd, 0)_{0,1}
\end{array}
\right.
$$

Figure 1 – Implementation of the barycenter calculation function within the Mathcad environment

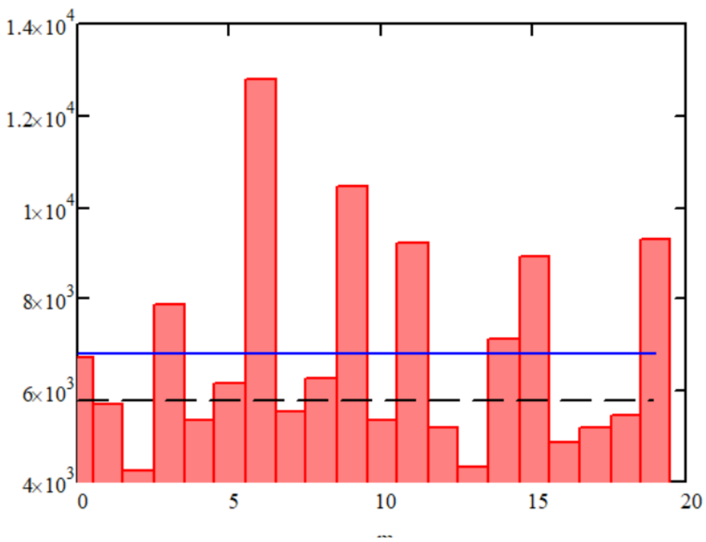

Figure 2 – Example of the distribution of cluster metrics for each lead

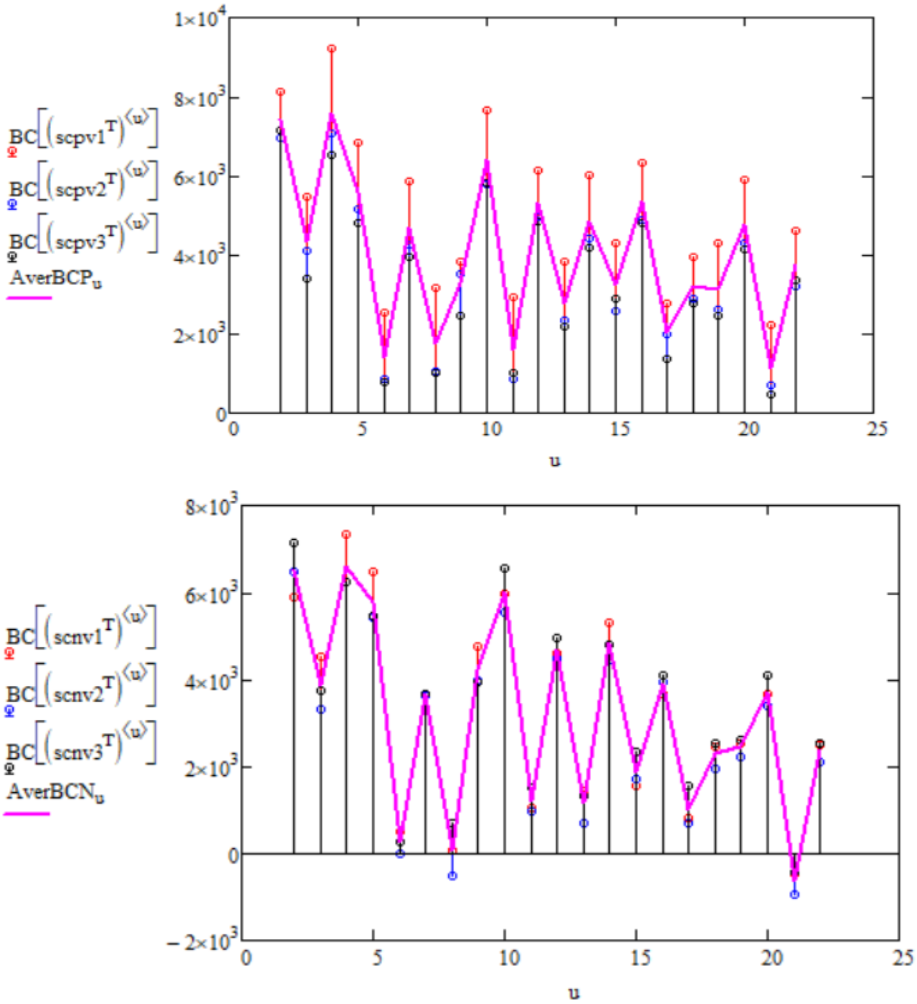

Figure 3 – Comparison of spatial distributions of averaged barycenters for positive and negative state clusters across leads

The upper part of the figure shows the mathematical framework for data aggregation. For each of the recorded leads (u = 2..22), the arithmetic mean of the barycenters of three base clusters is calculated:

- AverBCP - the averaged barycenter for positive states based on clusters scpv1, scpv2, scpv3;
- AverBCN - the averaged barycenter for negative states based on clusters scnv1, scnv2, scnv3.

The graphical section demonstrates the distribution of integral values across channels:

- Red, blue, and black point markers reflect the positions of the barycenters for individual clusters included in the training set.

- A solid pink line connects the calculated AverBC values, forming a single stable portrait of the emotional state.

The analysis of the obtained graphs demonstrates a distinct difference between the spatial configurations of the barycenters corresponding to positive and negative emotional states.

The classification logic is implemented as follows: if the cumulative Euclidean distance from the metric vector of the test EEG to the barycenter of the positive cluster is less than the distance to the barycenter of the negative cluster, the signal is classified as positive, and vice versa.

Figure 4 presents an example of calculating the differential difference in distances between the test electroencephalogram and the averaged barycenters of positive and negative states for each lead.

A positive deviation on the graph indicates the proximity of the test EEG to the negative cluster, while a negative deviation indicates proximity to the positive cluster.

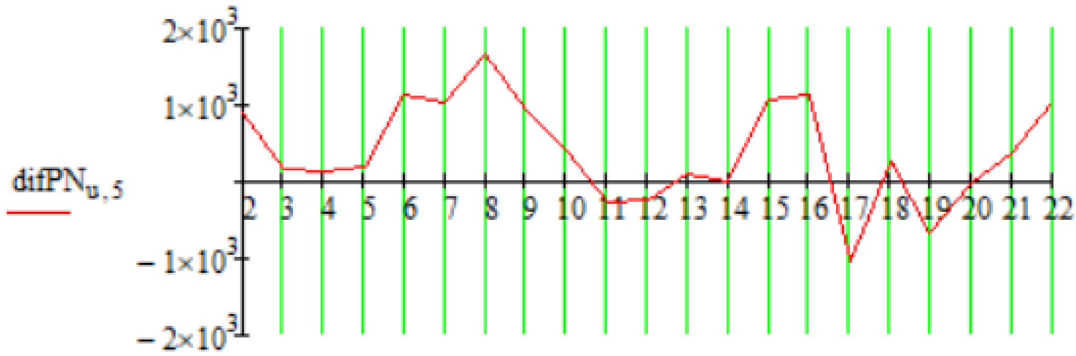

Figure 4 – Diagram of distance calculations between the test electroencephalogram and reference barycenters

The graph displays the difference Dpos - Dneg, where D represents the distance to the respective cluster. The interpretation of the results is as follows:

- Positive deviation (>0): Indicates that the distance to the positive reference is greater than to the negative one. Consequently, the signal is classified as being closer to the negative cluster.

- Negative deviation (<0): Indicates that the distance to the positive reference cluster is smaller. This signifies the proximity of the test EEG to the positive cluster.

Summary and conclusions.

To verify the developed model, a test sample of 20 EEG recordings (10 positive and 10 negative states) was formed; these were not used during the training phase. Data processing parameters:

- Integration start – 1000 ms, end – 3000 ms;
- Decimation factor kr = 50.

Testing results: All 10 test negative and positive control samples were correctly identified and assigned to the corresponding clusters. Within the constructed test sample, the method demonstrated 100% classification accuracy.

Detailed classification results for the negative emotion group are presented in Table 1. As seen in the table, all samples received negative cluster indices (-1, -2, -3), which corresponds to the correct recognition of the negative state.

Table 1 – Classification results of negative electroencephalograms

	0	1
0	15591	-1
1	11489	-1
2	9828	-2
3	17605	-2
4	7729	-2
5	9078	-3
6	20033	-2
7	13277	-1
8	11647	-2
9	17669	-2

The obtained results confirm the hypothesis that using integral metrics effectively mitigates the non-stationarity of psycho-emotional states.

The proposed method successfully isolates stable, reproducible patterns of brain electromagnetic activity, ensuring reliable separation of positive and negative emotional responses even in the presence of significant noise components.

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DEVELOPMENT OF ORBITAL AND INTERORBITAL UAV WITH NUCLEAR CHARGE

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Abstract. *The subject of this study is orbital and interorbital unmanned aerial vehicles (UAVs) and their design peculiarities. The work aims to find universal multipurpose UAV configurations for orbital defensive, environmental, and research purposes. The results of an analysis and comparison of various design layouts for orbital and interorbital UAVs are presented. Various design peculiarities and layouts are considered. Based on the existing UAV layout with a shrapnel-trinitrotoluene ordnance, a layout with a nuclear ordnance is proposed. It is noted that the launch of such an orbital and interorbital UAV is accomplished through the use of the Falcon Heavy launch vehicle. The scientific novelty lies in the developed layout of combat UAVs (UCAVs) with a nuclear ordnance, which allows for kinetic strikes from both sides of an asteroid's deepest central craters.*

Keywords: *UAV, nuclear, UCAV, asteroid, launch vehicle, satellite, environmental safety*

Introduction

Today, the World's most technologically advanced countries are constantly creating new universal space transport technologies and improving the existing ones in order to protect Earth from comets, asteroids and other Near-Earth Objects (NEO), which, when falling on our planet, can cause a series of huge tsunamis, a shift of tectonic plates, fire tornadoes the size of a continent, an impact winter or even several such apocalyptic events at once [1] – so it may be resulted not only in environmental damage and destruction of properties, but also in mass human deaths. According to previous studies by NASA scientists, a collision of an asteroid of 10 kilometers in size with the Earth will cause irreparable damage to the biosphere, which in turn will