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ASSESSMENT OF PSYCHOPHYSIOLOGICAL STATUS USING A CLOUD COMPUTING PLATFORM

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Abstract. *This paper presents a methodology for identifying the human eye movement system (EMS) using Volterra integral models expressed through first- and second-order transient characteristics. Experimental input-output data were collected with visual stimuli placed at varying distances from a reference point on the monitor, and ocular responses were recorded using the Tobii Pro TX300 eye tracker operating at 300 Hz. Model construction was performed using the least squares method. Two feature spaces were formed: one based on heuristic descriptors derived from transient responses, and another obtained from wavelet decomposition coefficients. To differentiate between normal and fatigued status, a support vector machine classifier with a Gaussian kernel was employed. Classification performance was evaluated using the probability of correct recognition (PCR). All computations were carried out on a cloud-based platform integrating PaaS and SaaS components, enabling both code-level development and GUI-based interaction. The results demonstrate a maximum PCR of 93.75% when wavelet-based features are applied, confirming the efficiency and practical applicability of the proposed methodology for intelligent diagnosis of the human psychophysiological status.*

Key words: *psychophysiological status, eye movement system, modeling, identification, eye-tracking, machine learning, cloud computing platform.*

Introduction.

The human eye movement system (EMS) is an important subject of research in neuroscience and medicine. Eye movement analysis provides valuable information about cognitive processes, psychophysiological status, and neurological disorders, which makes the development of mathematical models of the EMS highly relevant. In [1], eye movements were used for the early detection of cognitive impairment in Alzheimer's disease, and [2] proposed a model for autism detection based on real-time retinal image processing. Volterra polynomials are applied for the identification of the

EMS [3], and Volterra-Laguerre models are used for modeling smooth eye movements [4]. The theoretical foundations of identification based on Volterra models are presented in [5]. Practical applications of eye-tracking technology include the evaluation of team interaction in medical simulations [6], the analysis of pilots' attention and workload [7], and the study of dynamic visual acuity of astronauts under gravitational transitions [8].

The proposed methods for assessing the psychophysiological status based on eye-tracking data and nonlinear dynamic identification of the EMS enable monitoring and diagnostics of students' cognitive processes [4], [9].

For the integration of these technologies into research and educational processes, it is advisable to employ cloud technologies [10]. Currently, such software tools as Project Jupyter and Google Colab are used to support cloud computing. These tools are more interactive notebooks than platforms for conducting experiments and data processing. They mainly serve as editors and execution environments for a single programming language, without enabling work on project source code in multiple programming languages and without providing interaction with already implemented GUI interfaces for cloud computing in neurophysiological research.

There is a need for the development of software tools that will support cloud computing simultaneously under two concepts: PaaS and SaaS. This will allow effective work in both research and educational domains, with project code in programming languages such as Python and JavaScript for the development and improvement of computational tools, as well as with implemented identification methods in the form of GUI interfaces. Another important aspect is the social component, the improvement of which will facilitate data exchange among researchers and increase the productivity of scientific studies—an option that is lacking in existing solutions.

Problem Statement.

The aim of this work is the development of algorithmic and software tools for constructing a nonparametric dynamic model of the human EMS, taking into account its inertial and nonlinear properties, based on experimental "input-output" data obtained with the use of eye-tracking technology, and their integration into a cloud computing platform to increase the productivity of psychophysiological status research.

For EMS modeling, Volterra models are employed, which provide an explicit description of the relationship between the input (stimulus) $x(t)$ and the output (response) $y(t)$ signals of a nonlinear dynamic system. An approximation model of the EMS based on a Volterra polynomial of order N has the form [11]:

$$\hat{y}_N(t) = \sum_{n=1}^{N} \hat{y}_n(t), \tag{1}$$

where

$$\hat{y}_n(t) = \underbrace{\int_0^t \dots \int_0^t}_{n\ times} w_n(t-\tau_1,\dots,t-\tau_n)\prod_{i=1}^{n} x(\tau_i)d\tau_i, \tag{2}$$

$\hat{y}_N(t)$ is the output function of the model; $\hat{y}_n(t)$ is the n-th partial component of the output function (n-th order convolution integral); $w_n(t-\tau_1,\dots,t-\tau_n)$ is the Volterra kernel (weighting function) of order n of the EMS; t is current time.

The nonlinear and dynamic properties of the studied system are unambiguously described by a sequence of multidimensional weighting functions, invariant with respect to the form of the input signal. Identification of the EMS in the form of the polynomial model (1) consists in determining the Volterra kernels from experimental "input-output" data. The modeling process includes applying test signals $x(t)$ and computing the partial components $\hat{y}_n(t)$ from measured responses $y(t)$, which makes it possible to determine the corresponding weighting functions $w_n(\tau_1,\dots,\tau_n)$ [11].

Considering the specifics of the EMS, multistep signals are used for identification [9]. If the test signal is a unit function $x(t) = \theta(t)$ (where $\theta(t)$ is a Heaviside function), then for n=1:

$$\hat{y}_1(t) = \hat{h}_1(t), \tag{3}$$

where $\hat{h}_1(t)$ is the estimate of the first-order transient characteristic $h_1(t)$. For $2 \le n \le N$ we obtain:

$$\hat{y}_n(t) = \hat{h}_n(t,\dots,t), \tag{4}$$

where $\hat{h}_n(t,\dots,t)$ are the estimates of the diagonal sections of the n-th order transient characteristics $\hat{h}_n(t_1,\dots,t_n)$, which are n-dimensional integrals of the kernels $w_n(\tau_1,\dots,\tau_n)$:

$$h_n(t,...,t) = \int_0^\infty \dots \int_0^\infty w_n(t-\tau_1,...,t-\tau_n)\mathrm{d}\tau_1 \dots \mathrm{d}\tau_n \quad (5)$$

The responses of the Volterra polynomial model of the EMS of degree N to a step input with amplitude a are calculated by the formulas:

$$\tilde{y}(t) = a\hat{y}_1(t) + a^2\hat{y}_2(t) + ... + a^N\hat{y}_N(t), \quad (6)$$

or

$$\tilde{y}(t) = a_1 h_1(t) + a^2 h_2(t,t) + ... + a^N h_N(t,...,t). \quad (7)$$

The obtained transient characteristics of the EMS are used to construct a feature space of effective diagnostic features, within which, using the created dataset and machine learning methods, a classifier of the psychophysiological status is synthesized. The efficiency of this classifier is determined by the probability of correct recognition (PCR).

Cloud Platform Integration.

For the automation and optimization of research on the psychophysiological status of a human, web-oriented software tools have been developed that combine two approaches to user interaction with software: PaaS (Platform as a Service) and SaaS (Software as a Service). This combination provides researchers with extended capabilities for both the creation of new instrumental tools and the use of already implemented solutions.

Thanks to the built-in code editor, the user can directly program, modify, or extend the functionality of the tools, forming custom algorithmic approaches to data processing (PaaS). At the same time, there is the possibility to use built-in GUI-based interfaces of instrumental tools created via the integrated builder, which enables researchers to focus directly on conducting experiments and analyzing data without interacting with the code (SaaS). Such an approach makes it possible to combine programming flexibility with the convenience of ready-to-use solutions, scale developed tools according to research needs, and launch computations on a remote server in the cloud. The results of experiments thereby become directly available in the browser, simplifying access to computational resources and increasing the efficiency of scientific research.

In this way, the construction of EMS models, determination of transient characteristics, and implementation of algorithms for classification of the psychophysiological status are performed directly within the environment of the cloud platform. Figure 1 shows an example of the user interface of the developed system, which allows modifying model parameters and constructing an SVM classifier.

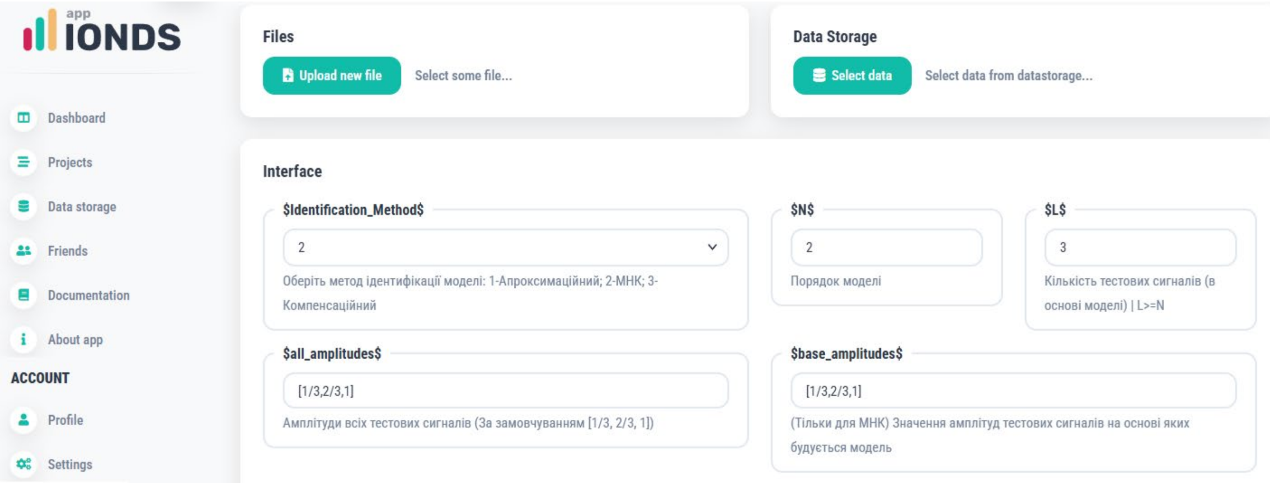

Figure 1 - User interface on the cloud computing platform of the research project

A source: Created by the authors

The developed software tools consist of separate modules and functional units, which are independent and interact with each other. The server-side contains all computational modules, data processing logic, and is responsible for executing computational processes. Each module operates autonomously and can be scaled independently of the others. The client-side is represented by a cross-platform web interface in the form of a SPA (Single Page Application), which provides user interaction with the system.

This allows for independent development and scaling of all software components, ensuring seamless integration of applications across different platforms (Windows, Linux, Android, macOS, iOS). Centralization of all logic and data processing on the server side also enables third-party applications to integrate the functionality of the developed software tools, providing additional scalability opportunities.

Thus, the developed cloud platform creates the conditions for the implementation of a full research cycle, which includes several stages. At the first stage, the identification of the EMS is performed in the form of multidimensional transient characteristics, based on experimental “input-output” data using innovative eye-tracking technology. At the second stage, a diagnostic feature space is formed by parameterizing the obtained characteristics and selecting the most informative and robust combinations. At the third stage, classifiers of the psychophysiological status are trained, reliability is evaluated, and decision rules are optimized. The final stage involves the direct recognition of individual status based on the constructed nonlinear dynamic models of the EMS.

Experimental Studies.

Considering the physiological features of the EMS, test visual stimuli were used for identification. These stimuli were displayed on a computer monitor as a bright dot at different distances a_i (i=1,2,…,L; L is a number of experiments) from the starting position “horizontally.” Formally, they can be considered step test signals with amplitudes a_i: $x(t)=a_i\theta(t)$ (where $\theta(t)$ is the Heaviside function). The EMS responses were recorded by an eye tracker and used to construct multidimensional transient characteristics $h_1(t)$, $h_2(t,t)$, $h_3(t,t,t)$. For identification, sets of responses to stimuli displayed on the monitor at different distances x_j (j = 1, 2, 3): x_1=(1/3)X, x_2=(2/3)X, x_3=X (where X is the screen width in pixels) were used. Empirical data were obtained from students using a Tobii Pro TX300 eye tracker at different times: "Morning" (before classes – “no fatigue”) and "Evening" (after classes – “fatigue status”), as well as on different days [9]. A full experimental cycle for one respondent consisted of three experiments with amplitudes a_1, a_2 and a_3, corresponding to the distances x_1, x_2 and x_3.

To implement the nonparametric identification algorithm, preliminary signal processing was performed: normalization, synchronization, and extraction of the leading edge [12]. As shown in [13], when constructing the quadratic model M2.2/3 using the least squares method, the use of three step signals reduces the identification error by half compared to the M2.2/2 model. This study investigates quadratic integral models of the EMS: M2.2/2 and M2.2/3, constructed on the basis of two and three test signals, respectively.

Figure 2 presents the first- and second-order transient characteristics of the M2.2/3 model for the "Morning" and "Evening" status.

a) *b*)

Figure 2 - First- and second-order transient characteristics of the M2.2/3 model for status: a) "Morning"; b) "Evening"

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The variability (deviation) of the averaged transient characteristics of different orders of EMS models M2.2/2 and M2.2/3 for the respondent status "Morning" $\hat{h}_{nN}^{(\mathrm{M})}(t_m)$ and "Evening" $\hat{h}_{nN}^{(\mathrm{E})}(t_m)$ is determined using the following indicators:

- maximum deviation σ_{nN};
- normalized root-mean-square deviation ε_{nN}:

$$\sigma_{nN} = \max_{m\in[0,M]}\left|\hat{h}_{nN}^{(\mathrm{M})}(t_m) - \hat{h}_{nN}^{(\mathrm{E})}(t_m)\right|; \tag{8}$$

$$\varepsilon_{nN} = \left(\frac{\sum_{m=0}^{M} \left(\hat{h}_{nN}^{(\mathrm{M})}(t_m) - \hat{h}_{nN}^{(\mathrm{E})}(t_m) \right)^2}{\sum_{m=0}^{M} \left(\hat{h}_{nN}^{(\mathrm{M})}(t_m) \right)^2} \right)^{1/2}, \qquad (9)$$

where n is the order of the transient characteristic, $n = 1, 2, \ldots, N$.

The obtained indicators for EMS models M2.2/2 and M2.2/3 are given in Table 1.

Table 1 - Variability indicators of the averaged transient characteristics of EMS models M2.2

Model	ε_{1N}	σ_{1N}	ε_{2N}	σ_{2N}
M2.2/2:a_1a_2	0.038	0.080	0.149	0.163
M2.2/2:a_1a_3	0.034	0.053	0.160	0.071
M2.2/2:a_2a_3	0.078	0.124	0.466	0.132
M2.2/3	0.045	0.071	0.244	0.080

A source: Calculated by the authors.

Reduction of Information Models of the EMS.

For the classification of the psychophysiological status, two feature spaces are used. Heuristic features are formed on the basis of the transient characteristics of the models (feature space E_0); the list of heuristic features defined on the basis of the M2.2 model is a subset of the features $e_k \in \mathrm{E}_0, k = \overline{1,21}$ studied in [12] (Table 2). Additionally, features are extracted on the basis of the discrete wavelet transform of transient characteristics (feature space W). Such a combination provides a multidimensional representation of the nonlinear and dynamic properties of the EMS for further classification.

To construct the feature space W, the discrete wavelet transform (DWT) [14] was applied, implemented using the PyWavelets library in the Python environment. As the basic wavelet, Coiflet 4 with a decomposition level of 2 was used.

Feature vectors $w_m \in \mathrm{W}, m = \overline{1,10}$ are formed from the approximation coefficients array *ca*: w_1=*ca*[1],…, w_5=*ca*[5]; and from the detail coefficients array *cd*: w_6 = *cd*[1],…, w_{10}=*cd* [5].

Here, $\hat{h}_1'(t_m)$, $\hat{h}_2'(t_m, t_m)$ denote the derivatives of the first- and second-order transient characteristics, respectively.

Table 2 - Heuristic features based on EMS models M2.2

Feature	Formal definition	Feature	Formal definition
e_1	$\sum_{m=0}^{M} \lvert \hat{h}_1(t_m) \rvert$	e_{11}	$\arg\min_{m\in[0,M]} \hat{h}_1^{'}(t_m)$
e_2	$\sum_{m=0}^{M} \lvert \hat{h}_2(t_m,t_m) \rvert$	e_{12}	$\min_{m\in[0,M]} \hat{h}_2^{'}(t_m,t_m)$
e_4	$\max_{m\in[0,M]} \hat{h}_1^{'}(t_m)$	e_{13}	$\arg\min_{m\in[0,M]} \hat{h}_2^{'}(t_m,t_m)$
e_5	$\arg\max_{m\in[0,M]} \hat{h}_1^{'}(t_m)$	e_{16}	$\max_{m\in[0,M]} \lvert \hat{h}_1(t_m) \rvert$
e_6	$\max_{m\in[0,M]} \hat{h}_2^{'}(t_m,t_m)$	e_{17}	$\arg\max_{m\in[0,M]} \lvert \hat{h}_1(t_m) \rvert$
e_7	$\arg\max_{m\in[0,M]} \hat{h}_2^{'}(t_m,t_m)$	e_{18}	$\max_{m\in[0,M]} \lvert \hat{h}_2(t_m,t_m) \rvert$
e_{10}	$\min_{m\in[0,M]} \hat{h}_1^{'}(t_m)$	e_{19}	$\arg\max_{m\in[0,M]} \lvert \hat{h}_2(t_m,t_m) \rvert$

A source: [12].

Construction of the SVM classifier.

A classifier was built based on datasets for the classes "Morning" and "Evening" in the feature spaces E_0 and W. To evaluate the informativeness of the features, a complete search over all possible pairs was performed, followed by the calculation of the probability of correct recognition (PCR) and their robustness. Classification was carried out using the Support Vector Machine (SVM) method with a Gaussian kernel [15] in the Python environment, employing the functions of the scikit-learn library and the built-in visualization tools of the platform.

As a result of training the SVM classifier in the feature space E_0, defined on the basis of EMS models M2.2, the highest PCR value of 87.5% was obtained for robust feature pairs:

•M2.2/2:a_1a_2 : e_{10}&e_{12} :

$$\left(e_{10} = \min_{m\in[0,M]} \hat{h}_1^{'}(t_m)\right) \& \left(e_{12} = \min_{m\in[0,M]} \hat{h}_2^{'}(t_m,t_m)\right); \tag{10}$$

•M2.2/2:a_2a_3 : e_2&e_5 :

$$\left(e_2 = \sum_{m=0}^{M} \lvert \hat{h}_2(t_m,t_m) \rvert\right) \& \left(e_5 = \arg\max_{m\in[0,M]} \hat{h}_1^{'}(t_m)\right); \tag{11}$$

•M2.2/3 : e_{10}&e_{12} :

$$\left(e_{10} = \min_{m\in[0,M]} \hat{h}_1^{'}(t_m) \right) \& \left(e_{12} = \min_{m\in[0,M]} \hat{h}_2^{'}(t_m, t_m) \right); \tag{12}$$

For the feature space E_0, constructed on the basis of the M2.2/3 model (12), the distribution of dataset objects in the e_{10}&e_{12} plane is shown in Figure 3.

SVM classifiers built in the W feature space reached a maximum PCR value of 93.75% based on the M2.2/2:a_2a_3 model for the following feature pairs: w_4&w_5; w_4&w_8; w_5&w_7; w_5&w_8; w_5&w_9; w_5&w_{10} and w_6&w_8.

For the feature space W, constructed on the basis of the M2.2/2:a_2a_3 model, the distribution of dataset objects in the w_4&w_5 plane is shown in Figure 4.

SVM classifiers in the W feature space also achieved a PCR value of 87.5% for the following robust feature sets derived from the models:

- M2.2/2:a_1a_3 : w_8&w_9 and w_8&w_{10};
- M2.2/3 : w_4&w_8 and w_6&w_8 .

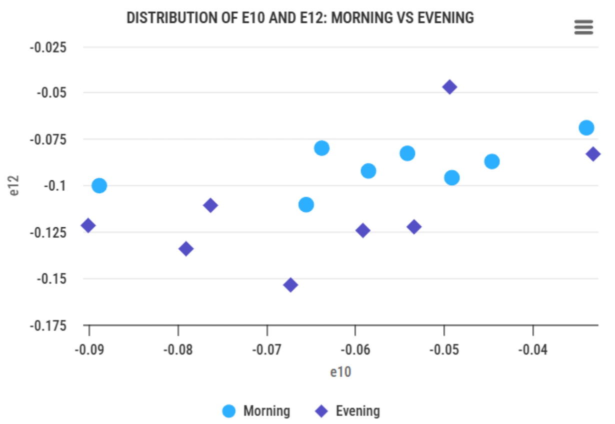

Figure 3 - Distribution of dataset objects e_{10}&e_{12}, constructed on the basis of the EMS model M2.2/3

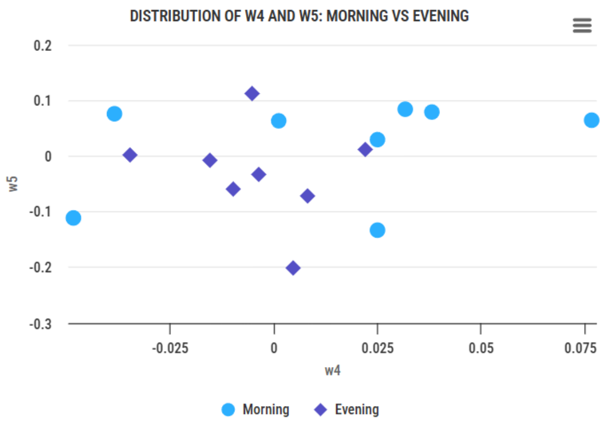

Figure 4 - Distribution of dataset objects w_4&w_5, constructed on the basis of the EMS model M2.2/2:a_2a_3

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Conclusions.

This study investigated the diagnostic potential of quadratic models of the eye movement system (EMS) represented as multidimensional transient characteristics that account for the nonlinear and dynamic properties of the studied system.

Feature spaces were constructed on the basis of experimental input-output transient characteristics. Two approaches were applied: extraction of heuristic features and formation of features based on wavelet decomposition coefficients. Feature selection involved the analysis of all possible pairs with an evaluation of their informativeness for the classification of psychophysiological status.

For the implementation of EMS identification procedures, feature construction, and classifier training, an innovative cloud computing platform was used, which significantly increased the efficiency of the research.

An important feature of the developed software tools is their minimal requirements for client hardware due to server-side computation. The modular structure provides flexible scalability, while the combination of PaaS and SaaS services makes the tools versatile. They also have advantages over solutions such as Project Jupyter and Google Colab, thanks to the ability to work with popular programming languages (Python and JavaScript), integration of validated software tools through specialized GUI interfaces, a higher level of abstraction, and extended social functionality. This increases the productivity of both scientific research and the educational process.

By means of machine learning methods, classification of the psychophysiological status of a person was performed in the constructed feature spaces using the Support Vector Machine (SVM) method. In the feature space formed on the basis of wavelet decomposition coefficients, the maximum probability of correct recognition (PCR) reached 93.75%, while in the heuristic feature space, lower accuracy was recorded, not exceeding 87.5%. Thus, the study conducted on the cloud computing platform confirms the effectiveness of quadratic integral models for the assessment of the psychophysiological status of a person.

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