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Estimation psychophysiological state via nonlinear dynamic integral models

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ABSTRACT

The method of experimental research "input-output" of the human oculo-motor system was developed and implemented using innovative eye-tracking technology for recording oculo-motor system responses to test visual stimuli. Stimuli are displayed on the monitor screen at different distances from the starting position. This formally corresponds to the action of step signals with different amplitudes at the input of the oculo-motor system. According to the empirical data of the "input-output" studies of the respondent's oculo-motor system obtained with the aid of the Tobii Pro TX300 eye tracker, the transient functions of the first and diagonal intersections of the transient functions of the second and third orders of the oculo-motor system were determined. Experimental studies of the respondent's oculo-motor system to identify the state of fatigue were carried out before the beginning (in the morning) and after the working day (in the evening). The obtained multidimensional transient functions are used as a source of primary data in the implementation of intelligent information technology for diagnosis and monitoring of the psychophysiological state of a person. Instrumental algorithmic and software tools for determining diagnostic features based on the identification data of the oculo-motor system in the form of multidimensional transient functions in the Python language have been developed. Training samples of data for two states of the respondent ("Normal" and "Fatigue") were formed on the basis of the proposed heuristic features, which are determined using integral and differential transformations of the obtained multidimensional transient functions of the oculo-motor system. Training samples of data are used to build classifiers of psychophysiological states of an individual using machine learning tools. The informativeness of individual features and all their possible combinations in pairs according to the indicator of the probability of correct recognition was studied using the method of complete search. The research results were obtained by evaluating the quality of recognition of states built by Bayesian classifiers in different spaces of the proposed features. An analysis of the stability of the correct recognition informativeness indicator of different feature spaces under the influence of different levels of additive noise on the features was carried out. Two-dimensional feature spaces with the maximum and most stable value of the correct recognition indicator were found when solving the scientific and practical task of assessing the psychophysiological state (fatigue) of a person (0.9375). Thus, it seems appropriate to use the multidimensional transient functions obtained from eye-tracking data in diagnostic studies in the fields of neuroscience and experimental psychology.

Keywords: Estimation of psychophysiological state; diagnosis; oculo-motor system; identification; Volterra model; multidimensional transient functions; test visual stimuli; eye-tracking technology

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1. INTRODUCTION

As a result of hostilities, natural disasters occurring today, a considerable number of people received psychological trauma of varying degrees, which often lead to Post-Traumatic Stress Disorder (PTSD) and require constant psychological support and assistance [1]. Because PTSD is a complex disorder that manifests itself simultaneously on psychological, biological, and social levels, treatment, depending on its depth, includes psychotherapy and sometimes the use of psychopharmacological drugs [2]. The oculo-motor system (OMS) model [3] proposed by us allows to determine the presence of PTSD syndrome, as well as to obtain a quantitative assessment of the depth of PTSD and, based on these studies, to choose the most effective treatment tactics.

Modern PTSD care protocols recommend two psychotherapeutic methods: Cognitive behavioral therapy (CBT) [4, 5], [6] and eye movement desensitization and reprocessing (EMDR) [7, 8], [9]. That is why it is important to diagnose the psychophysical condition of the person. Studies of human eye movements and the trajectory of their

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movement allow us to reveal the structure of the individual's relationship with the environment. Analysis of the relationship between oculo-motor and the central nervous system, with the content of mental processes, with various forms of activity (behavior, activity, communication), contributes to the study of the mechanisms of brain work and their disorders, the identification of the dynamics of psychophysiological states of a person, patterns of perception, thinking, ideas, differentiation personal intentions.

In recent years, the high-tech innovation of eye-tracking has received further development and effective application in the construction of a mathematical model of the process of continuous eye movement tracking in order to detect anomalies in the tracking data for the quantitative assessment of motor symptoms of Parkinson's disease [10, 11], [12]. At the same time, nonlinear dynamic models of Wiener and Volterra-Laguerre [13] are used, and the identification of the OMS is based on the use of test random effects, which requires the use of correlation analysis methods and obtaining a large amount of experimental data (long duration of experimental studies).

To build the Volterra model of the human OMS, deterministic test effects can be used, for example, step signals (most suitable for studying the dynamics of OMS) [14, 15], which will simplify the computational identification algorithm and significantly reduce the time of experimental data processing [3, 16], [17, 18], [19].

In work [20] a method of deterministic identification of OMS in the form of multidimensional transient functions (MTF) using step test signals was developed, similar to the compensatory method of identification of nonlinear dynamic systems using impulse test signals [14]. Although the method requires a minimum number of test signals to identify OMS, its accuracy is insufficient for constructing Volterra models of more than second order, which hinders its practical application.

The advantages of deterministic methods in comparison with methods of statistical identification are the comparative ease of processing experimental data and implementing test signals. However, the results of deterministic identification are significantly affected by measurement errors [21, 22]. The obtained estimates of the transient characteristics are unstable to the measurement errors of the OMS responses, which limits the application of the methods in the conditions of a real experiment [20].

The analysis of literary sources showed that, at the moment, no effective methods of building OMS models based on the Volterra polynomial based on experimental data obtained by eye-tracking have been developed. There is no proper instrumental, algorithmic and software tools to support methods of identification of OMS using eye-tracking technology.

There is a need to increase the accuracy and computational stability of the assessment of multidimensional transient functions of OMS, to develop hardware and software tools for controlling the identification process, as well as to create information technology and intelligent computing systems for classification in the space of features determined by the results of OMS identification based on eye-tracking data.

The purpose of this work is to implement methods and means of nonlinear dynamic identification "input-output" of the oculo-motor system based on eye-tracking data based on Volterra models in the form of multidimensional transient functions and their application in information systems for diagnosing the psychophysiological state of a person, which expand the diagnostic capabilities of tools state assessment information technology.

The following tasks must be solved:

- Implement computational methods for identification OMS in the form of MTF using test visual stimuli – Gaviside functions of different amplitudes.
- Determine the transient functions of the 1st, 2nd, and 3rd orders based on the data of oculographic studies.
- To develop instrumental algorithmic and software tools for determining diagnostic features based on the identification data of OMS in the form of MTF.
- To carry out a study of the informativeness of features using the estimation of the probability of correct recognition (PCR) and to build a classifier of the psychophysiological state of a person in the established space of the most informative diagnostic features.

The object of research is the process of diagnosing the psychophysiological state of an individual based on the innovative technology of eye-tracking.

The subject of the research is computational algorithms and software tools for determining diagnostic features based on the identification data of OMS in the form of MTF, Bayesian classifiers in the proposed space of features.

2. IDENTIFICATION OF OCULO-MOTOR SYSTEM BASED ON THE DISCRETE VOLTERRA POLYNOMIAL

The "input-output" ratio for a NDS with an unknown structure (like a "black box") with one input and one output can be represented by a discrete cubic Volterra polynomial in the form [23]:

$$y[m]=\sum_{n=1}^{N=3}\hat{y}_n[m]=\sum_{k_1=0}^{m}w_1[k_1]x[m-k_1]+$$
$$+\sum_{k_1=0}^{m}\sum_{k_2=0}^{m}w_2[k_1,k_2]x[m-k_1]x[m-k_2]+ \tag{1}$$
$$+\sum_{k_1=0}^{m}\sum_{k_2=0}^{m}\sum_{k_3=0}^{m}w_3[k_1,k_2,k_3]x[m-k_1]x[m-k_2]x[m-k_3],$$

where $w_1[k_1]$, $w_2[k_1,k_2]$, $w_3[k_1,k_2,k_3]$ are discrete weight functions (Volterra kernels) of the 1st, 2nd and 3rd orders; $x[m]$, $y[m]$ are input (stimulus) and output (response) function (signals) of the system, respectively; $y_n[m]$ is partial components of the response (convolution of n-th order sequences $w_n[k_1,\ldots,k_n]$ and $x[m]$); m is a discrete time variable, m=0,1,...,M.

$$\hat{y}_n[m]=\hat{h}_n[m,\ldots,m]=$$
$$=\sum_{k_1,\ldots,k_n=0}^{m}w_n[m-k_1,\ldots,m-k_n],\quad n=1,2,3. \tag{2}$$

Multi-step test signals with different amplitudes a_j (j=1,2,…,L; L is number of experiments, $L \ge N$) $x_j(t)=a_j\theta(t)$ are used for identification [14]. The responses of the OMS, which are measured at the same time, will be denoted as $y_1[m]$, $y_2[m]$,…, $y_L[m]$. If we determine the partial response components of the model $\hat{y}_1[m]$, $\hat{y}_2[m]$, $\hat{y}_3[m]$ then this will lead to the estimation of the transient functions of the first order $\hat{h}_1[m]$ and the diagonal intersections of the transient functions $\hat{h}_2[m,m]$, $\hat{h}_3[m,m,m]$ (2).

The responses of the Volterra polynomial model are equal

$$\tilde{y}_i[m]=a_i\hat{y}_1[m]+a_i^2\hat{y}_2[m]+a_i^3\hat{y}_3[m],\ i=1,2,\ldots,L. \tag{3}$$

To determine the transient functions $\hat{h}_1[m], \hat{h}_2[m,m], \hat{h}_3[m,m,m]$, the method of least squares (LSM) [16, 17] is used, which provides a minimum of the root mean square error of the deviation of the model responses from the OMS responses to the same stimulus:

$$J_N=\sum_{j=1}^{L}\left(y_j[m]-\sum_{n=1}^{N=3}a_j^n\hat{y}_n[m]\right)^2\to\min \tag{4}$$

The minimization of criterion (4) is reduced to the solution of the system of normal Gaussian equations, which in vector-matrix form can be written as

$$\mathrm{A}'\mathrm{A}\hat{\mathrm{y}}=\mathrm{A}'\,\mathrm{y}, \tag{5}$$

where

$$\mathrm{A}=\begin{bmatrix}a_1 & a_1^2 & a_1^3\\ a_2 & a_2^2 & a_2^3\\ \ldots & \ldots & \ldots\\ a_L & a_L^2 & a_L^3\end{bmatrix},\quad \mathrm{y}=\begin{bmatrix}y_1[m]\\ y_2[m]\\ \ldots\\ y_L[m]\end{bmatrix},\quad \hat{\mathrm{y}}=\begin{bmatrix}\hat{y}_1[m]\\ \hat{y}_2[m]\\ \hat{y}_3[m]\end{bmatrix}.$$

After solving the system of equations (5) with respect to $\hat{y}_1[m]$, $\hat{y}_2[m]$, $\hat{y}_3[m]$, we obtain estimates of the multidimensional transient functions $\hat{h}_1[m], \hat{h}_2[m,m], \hat{h}_3[m,m,m]$ в of the OMS at each moment of time m in the observation interval.

From equation (5), we get

$$\hat{\mathrm{y}}=(\mathrm{A}'\mathrm{A})^{-1}\mathrm{A}'\mathrm{y}. \tag{6}$$

After performing the matrix operations in (6), we get

$$\begin{bmatrix}\hat{h}_1^{(3)}[m]\\ \hat{h}_2^{(3)}[m,m]\\ \hat{h}_3^{(3)}[m,m,m]\end{bmatrix}=\begin{bmatrix}\hat{y}_1[m]\\ \hat{y}_2[m]\\ \hat{y}_3[m]\end{bmatrix}=$$
$$=\begin{bmatrix}\sum_{j=1}^{L}a_j^2 & \sum_{j=1}^{L}a_j^3 & \sum_{j=1}^{L}a_j^4\\ \sum_{j=1}^{L}a_j^3 & \sum_{j=1}^{L}a_j^4 & \sum_{j=1}^{L}a_j^5\\ \sum_{j=1}^{L}a_j^4 & \sum_{j=1}^{L}a_j^5 & \sum_{j=1}^{L}a_j^6\end{bmatrix}^{-1}\cdot\begin{bmatrix}\sum_{j=1}^{L}a_jy_j[m]\\ \sum_{j=1}^{L}a_j^2y_j[m]\\ \sum_{j=1}^{L}a_j^3y_j[m]\end{bmatrix}. \tag{7}$$

Thus, for the model based on the cubic Volterra polynomial for N=3 (1), we can estimate the transient functions of the first $\hat{h}_1^{(3)}[m]$, second $\hat{h}_2^{(3)}[m,m]$ and third $\hat{h}_3^{(3)}[m,m,m]$ orders (7).

Similarly, we obtain the formulas for evaluating the first-order transient functions $\hat{h}_1^{(1)}[m]$ – at N=1; of the first and second orders $\hat{h}_1^{(2)}[m]$, $\hat{h}_2^{(2)}[m,m]$ – at N=2:

$$\hat{h}_1^{(1)}[m]=\hat{y}_1^{(1)}[m]=\frac{\sum_{j=1}^{L}a_jy_j[m]}{\sum_{j=1}^{L}a_j^2} \tag{8}$$

$$\begin{bmatrix}\hat{h}_1^{(2)}[m]\\ \hat{h}_2^{(2)}[m,m]\end{bmatrix}=\begin{bmatrix}\hat{y}_1^{(2)}[m]\\ \hat{y}_2^{(2)}[m]\end{bmatrix}=$$
$$=\begin{bmatrix}\sum_{j=1}^{L}a_j^2 & \sum_{j=1}^{L}a_j^3\\ \sum_{j=1}^{L}a_j^3 & \sum_{j=1}^{L}a_j^4\end{bmatrix}^{-1}\cdot\begin{bmatrix}\sum_{j=1}^{L}a_jy_j[m]\\ \sum_{j=1}^{L}a_j^2y_j[m]\end{bmatrix}. \tag{9}$$

The system of normal Gaussian equations (6) gives good results for the approximation of functions if the number of measurements L is large enough (much greater than the degree of the approximating polynomial N) or the measurement errors are small. Otherwise, the determinant of the system turns out to be close to zero, and the system becomes indeterminate. In this case, large errors in the estimation of the parameters of the approximating polynomial are possible. To obtain a solution of SLAE (6) resistant to measurement errors, the regularization method of A.N. Tikhonov is used [15, 22].

3. EXPERIMENTAL STUDIES OF OCULO-MOTOR SYSTEM USING EYE-TRACKING AND CALCULATION OF THE MULTIDIMENSIONAL TRANSIENT FUNCTIONS

With the help of the developed software, a study of the psychophysiological states of a person was carried out. The experiments were organized in order to classify the subjects (informants) according to the state of fatigue.

Data for building OMS models – OMS responses to the same test visual stimuli with different distances x_j (j = 1, 2, 3) from the starting position, which formally corresponds to test signals with amplitudes a_1, a_2 and a_3, obtained using the Tobii Pro TX300 eye-tracker at different times of the day: “In the Morning” (before work) and “In the Evening” (after work) and on different days. One complete cycle of OMS research for one respondent consists of 3 experiments at different amplitudes of test signals a_1, a_2 and a_3 for the “In the Morning” state and for the “In the Evening” state. The graphs of OMS responses received in the “In the Morning” and “In the Evening” were brought to the common beginning (starting point) and shown in Fig. 1.

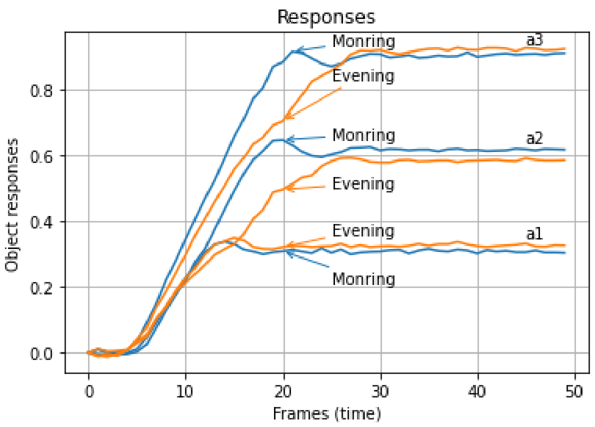


Fig. 1. **Oculomotor system responses at different amplitudes of test signals**
Source: **compiled by the authors**

According to the OMS responses based on calculations using formulas (7)-(9), the transient functions of the OMS “In the Morning” and “In the Evening” were determined when using approximation models of various degrees of N (N=1, 2, 3): with N=1 – $\hat{h}_1^{(1)}[m]$ (8); with N=2 – $\hat{h}_1^{(2)}[m]$ and $\hat{h}_2^{(2)}[m,m]$ (9); with N=3 – $\hat{h}_1^{(3)}[m]$, $\hat{h}_2^{(3)}[m,m]$ and $\hat{h}_3^{(3)}[m,m,m]$ (7).

The graphs of the transient functions of the OMS and the corresponding responses of the OMS based on the model at N=1 (3) at different amplitudes of the input signals for the state of the respondent “In the morning” and “In the evening” are shown in Fig. 2 and Fig. 3.

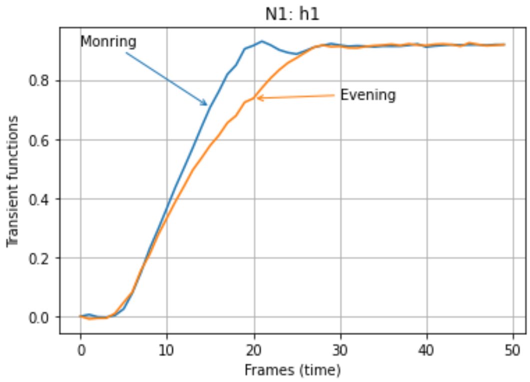


Fig. 2. **Transient functions of the oculo-motor system models at N=1 for the state of the respondent “In the Morning” and “In the Evening”**
Source: **compiled by the authors**

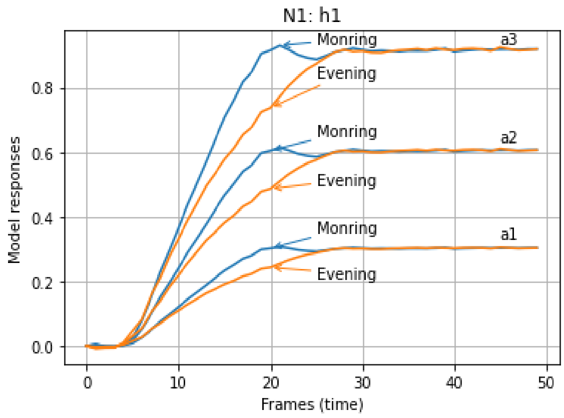


Fig. 3. **Responses of the oculomotor system models at N=1 for different amplitudes of test signals “In the Morning” and “In the Evening”**
Source: **compiled by the authors**

Similar results were obtained based on the model with N=2 and are shown in Fig. 4 and Fig. 5 – for the state of the respondent “In the Morning” and “In the Evening”, as well as based on the model with

N=3 and shown in Fig. 6 and Fig. 7 – for the state of the respondent "In the Morning" and "In the Evening".

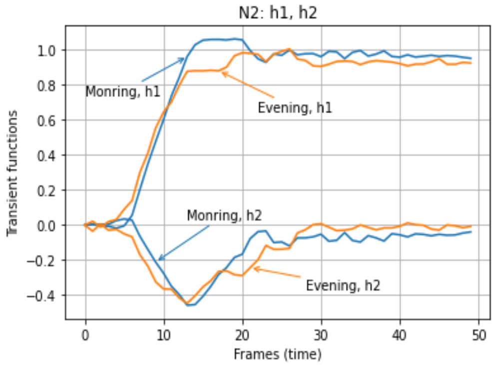


Fig. 4. **Transient functions of the oculo-motor system models at *N*=2 for the state of the respondent "In the Morning" and "In the Evening"**
***Source:* compiled by the authors**

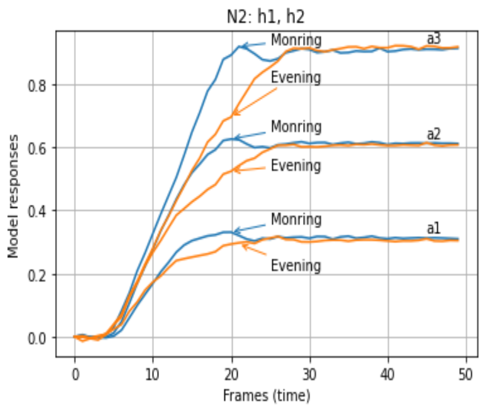


Fig. 5. **Responses of the oculomotor system models at *N*=2 for different amplitudes of test signals "In the Morning" and "In the Evening"**
***Source:* compiled by the authors**

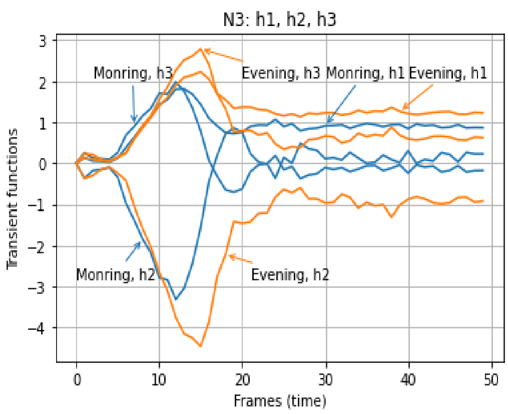


Fig. 6. **Transient functions of the oculomotor system models at *N*=3 for the state of the respondent "In the Morning" and "In the Evening"**
***Source:* compiled by the authors**

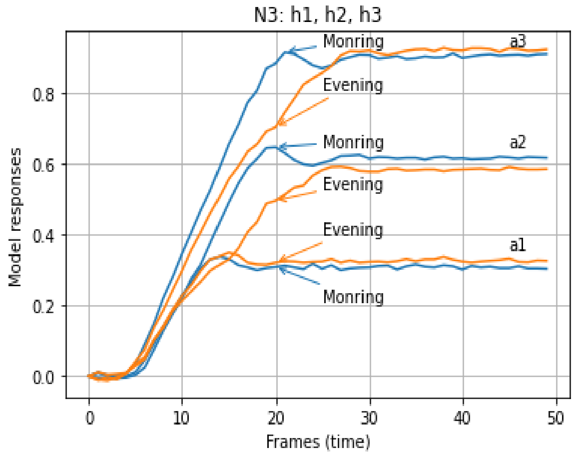


Fig. 7. **Responses of the oculomotor system models at *N*=3 for different amplitudes of test signals "In the Morning" and "In the Evening"**
***Source:* compiled by the authors**

The normalized root mean square errors (RMSE) of the OMS model at N=1 were calculated for different amplitudes of input signals a_1, a_2 and a_3 for the states of the respondent "In the Morning" and "In the Evening", which are given in the Table 1.

Table 1. **Root mean square errors of the oculo-motor system model at *N*=1**

The state of the respondent	Amplitudes of input signals			Mean error
	a_1	a_2	a_3	
In the Morning	0.047	0.019	0.019	0.028
In the Evening	0.067	0.022	0.016	0.035

***Source:* compiled by the authors**

Root mean square errors of the OMS model at N=2 for different amplitudes of input signals a_1, a_2 and a_3 for the states of the respondent "In the Morning" and "In the Evening", which are given in the Table 2.

Table 2. **Root mean square errors of the oculo-motor system model at *N*=2**

The state of the respondent	Amplitudes of input signals			Mean error
	a_1	a_2	a_3	
In the Morning	0.023	0.023	0.008	0.018
In the Evening	0.038	0.038	0.013	0.03

***Source:* compiled by the authors**

The responses of the OMS model at N=3 for different amplitudes of the input signals a_1, a_2 and a_3 for the respondent's states "Morning" and "Evening" practically coincide with the corresponding responses of the OMS.

4. CLASSIFIER FOR ASSESSING THE PSYCHOPHYSIOLOGICAL STATE OF A PERSON

Data for building OMS models – OMS responses to the same test visual stimuli with different distances x_j (j = 1, 2, 3) from the starting position, which formally corresponds to test signals with amplitudes a_1, a_2 and a_3, obtained using the Tobii Pro TX300 (300 Hz) eye-tracker at different times of the day: “In the Morning” (before work) and “In the Evening” (after work), and on different days. One full cycle of OMS research for one respondent consists of 3 experiments at different amplitudes of test signals a_1, a_2 and a_3, 8 complete research cycles were performed for the “In the Morning” state and 8 – for the “In the Evening” state. The graphs of OMS responses received in the “In the Morning” and “In the Evening” were brought to the common beginning (starting point) and shown in Fig. 8a and Fig. 8b, respectively.

To assess the psychophysiological state of an individual based on the OMS model in the form of first-order transient functions $h_1[m]$, and diagonal intersections of second – and third-order transient functions $h_2[m,m]$ and $h_3[m,m,m]$, training data samples were formed for the two states of the respondent using the proposed heuristic features [24] determined on the basis of the obtained MTF.

Training data samples are used to build classifiers of psychophysiological states of an individual using machine learning tools [25, 26]. A psychophysiological state classifier was built on the basis of training samples of data for objects of classes Ω_1 (“Morning”) and Ω_2 (“Evening”).

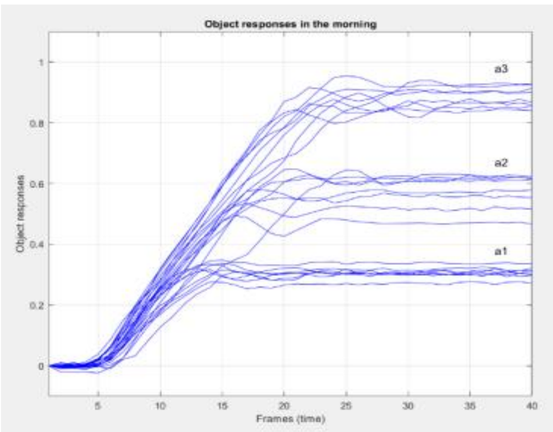
To recognize objects of two classes (the case of dichotomy), the shifted discriminant function of the Bayesian species classifier is used [25, 26]:

$$d(\mathrm{x}) = \frac{1}{2}\mathrm{x}'(\mathrm{S}_2^{-1} - \mathrm{S}_1^{-1})\mathrm{x} + (\mathrm{S}_1^{-1}\mathrm{m}_1 - \mathrm{S}_2^{-1}\mathrm{m}_2)'\mathrm{x} + \frac{1}{2}(\mathrm{m}_1'\mathrm{S}_1^{-1}\mathrm{m}_1 - \mathrm{m}_2'\mathrm{S}_2^{-1}\mathrm{m}_2 + \ln\frac{|\mathrm{S}_2|}{|\mathrm{S}_1|}) + \lambda_{\max}, \quad (10)$$

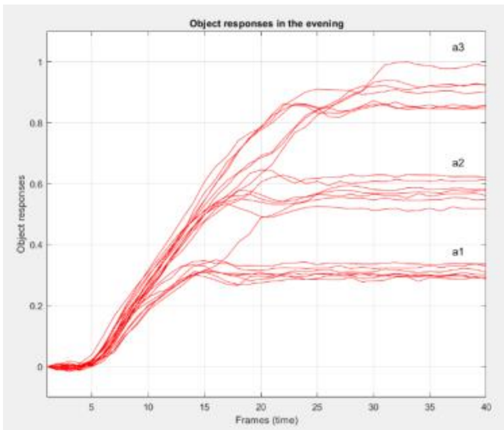
where $\mathrm{x}=(x_1,x_2,\ldots,x_n)'$ is a vector of features, n is the dimension of the space of features, m_i is a vector of mathematical expectations of features of class i, i=1,2; $\mathrm{S}_i=\mathrm{M}[(\mathrm{x}-\mathrm{m}_i)(\mathrm{x}-\mathrm{m}_i)']$ is the covariance matrix for class i (M – is a mathematical expectation operation); S_i^{-1} is the matrix inverted to S_i, $|\mathrm{S}_i|$ is the determinant of the S_i matrix, $\lambda_{\max}$ is the object classification threshold, which ensures the maximum value of the criterion of the probability of correct recognition (PCR).

The analysis of the reliability of the classification of psychophysiological states in the space of the proposed features [28] consists in the formation of all possible combinations of features and the assessment of their informativeness based on the results of the classification of the training sample of data using the PCR criterion [24, 28]. Thus, all possible pairs of features were investigated by the method of complete search. The diagnostic value of only all possible pairs of features is investigated, since we have a small amount of training sample.

Bayesian classifier of psychophysiological states in two-dimensional feature spaces, providing the maximum PCR P_{max} for combinations of features determined on the basis of the Volterra polynomials at N=1, 2 and 3.



a



b

Fig. 8. **Oculo-motor system responses at different amplitudes of test signals: a – “In the Morning”; b – “In the Evening”.**
Source: **compiled by the authors**

For the Volterra model with N=1, the following combinations of features were obtained:

$$\left(x_1 = \sum_{m=0}^{M} \left| h_1[m] \right| \,\&\, x_4 = \max_{m\in[0,M]} h_1^{'}[m] \right), \text{ or}$$

$$\left(x_5 = \arg\max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_{11} = \arg\min_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_4 = \max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{17} = \arg\max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_{10} = \min_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \,\&\, x_{17} = \arg\max_{m\in[0,M]} \left| h_1[m] \right| \right),$$

here $h_1^{'}[m]$ is the derivative of the transient function of the 1st order.

For individual features, we have the following values of the PCR criterion: x_{16} – P_{max} = 0.625; x_{10}, x_{11} – P_{max} = 0.688; x_4 , x_5 – P_{max} = 0.75; x_1, x_{17} – P_{max} = 0.876.

For the Volterra model with N=2, the following combinations of features were obtained:

$$\left(x_5 = \arg\max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_{13} = \arg\min_{m\in[0,M]} h_2^{'}[m,m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_4 = \max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{12} = \min_{m\in[0,M]} h_2^{'}[m,m] \right), \text{ or}$$

$$\left(x_4 = \max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{16} = \max_{m\in[0,M]} \left| h_1[m] \right| \right), \text{ or}$$

$$\left(x_{18} = \max_{m\in[0,M]} \left| h_2[m,m] \right| \,\&\, x_{17} = \arg\max_{m\in[0,M]} \left| h_1[m] \right| \right),$$

here $h_2^{'}[m,m]$ is the derivative of the transient function of the 2nd order.

For individual features, we have the following values of the PCR criterion: x_5 – P_{max} = 0.625; x_{12}, x_{13}, x_{17}, x_{18} – P_{max} = 0.75; x_4 – P_{max} = 0.813; x_{16} – P_{max} = 0.875.

For the Volterra model with N=3, the following combinations of features were obtained:

$$\left(x_3 = \sum_{m=0}^{M} \left| h_3[m,m,m] \right| \,\&\, x_{12} = \min_{m\in[0,M]} h_2^{'}[m,m] \right), \text{ or}$$

$$\left(x_3 = \sum_{m=0}^{M} \left| h_3[m,m,m] \right| \,\&\, x_{14} = \min_{m\in[0,M]} h_3^{'}[m,m,m] \right), \text{ or}$$

$$\left(x_5 = \arg\max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{11} = \arg\min_{m\in[0,M]} h_1^{'}[m] \right), \text{ or}$$

$$\left(x_5 = \arg\max_{m\in[0,M]} h_1^{'}[m] \,\&\, x_{15} = \arg\min_{m\in[0,M]} h_3^{'}[m,m,m] \right), \text{or}$$

$$\left(x_9 = \arg\max_{m\in[0,M]} h_3^{'}[m,m,m] \,\&\, x_6 = \max_{m\in[0,M]} h_2^{'}[m,m] \right), \text{or}$$

$$\left(x_9 = \arg\max_{m\in[0,M]} h_3^{'}[m,m,m] \,\&\, x_{10} = \min_{m\in[0,M]} h_1^{'}[m] \right), \text{or}$$

$$\left(x_{13} = \arg\min_{m\in[0,M]} h_2^{'}[m,m] \,\&\, x_6 = \max_{m\in[0,M]} h_2^{'}[m,m] \right), \text{or}$$

$$\left(x_{13} = \arg\min_{m\in[0,M]} h_2^{'}[m,m] \,\&\, x_{10} = \min_{m\in[0,M]} h_1^{'}[m] \right), \text{or}$$

$$\left(x_6 = \max_{m\in[0,M]} h_2^{'}[m,m] \,\&\, x_8 = \max_{m\in[0,M]} h_3^{'}[m,m,m] \right), \text{ or}$$

$$\left(x_{12} = \min_{m\in[0,M]} h_2^{'}[m,m] \,\&\, x_{14} = \min_{m\in[0,M]} h_3^{'}[m,m,m] \right),$$

here $h_3^{'}[m,m,m]$ is the derivative of the transient function of the 3rd order.

For individual features, we have the following values of the PCR criterion: x_9, x_{13} – P_{max} = 0.625; x_3 – P_{max} = 0.688; x_{12} – P_{max} = 0.75; x_6, x_{10}, x_{14} – P_{max} = 0.813.

An analysis of the stability of the indicators PCR in different feature spaces was carried out. For this, random samples with a Gaussian probability density distribution were created, where the standard deviation of the distribution is equal to the product of the mean value of the feature vector at the noise level (1 % and 5 %). The results of the PCR stability analysis are presented in Fig. 9 and in Table 3 for model at N=1; in Fig. 10 and in Table 4 for model at N=2; in Fig. 11 and in Table 5 for model at N=3.

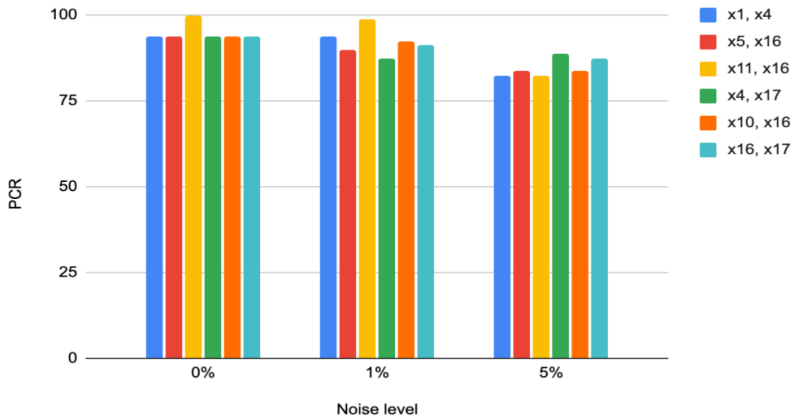


Fig. 9. **The maximum value of probability of correct recognition for classifiers in the spaces of the selected features obtained on the model-basis at N=1 when the features are affected by different levels of noise**
Source: **compiled by the authors**

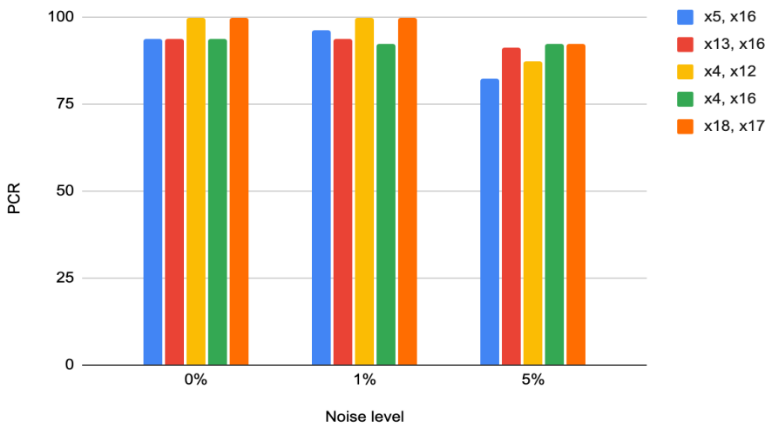


Fig. 10. **The maximum value of probability of correct recognition for classifiers in the spaces of the selected features obtained on the model-basis at *N*=2 when the features are affected by different levels of noise**
Source: **compiled by the authors**

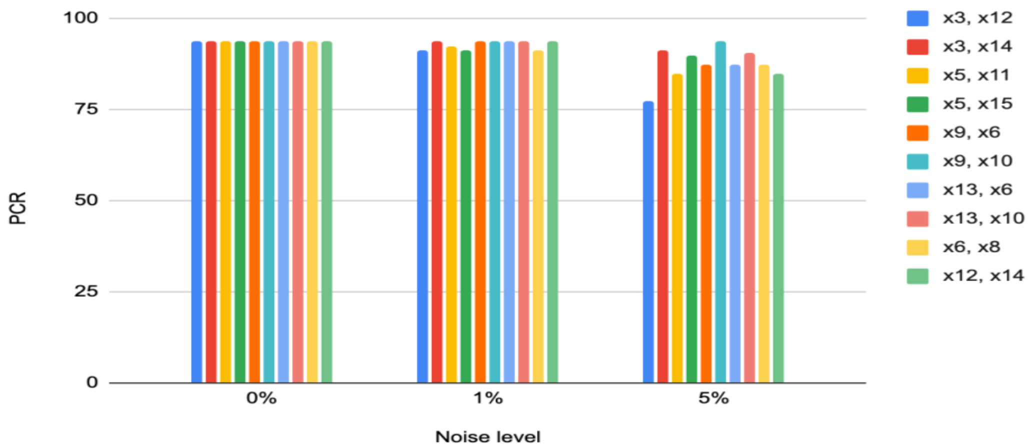


Fig. 11. **The maximum value of probability of correct recognition for classifiers in the spaces of the selected features obtained on the model-basis at *N*=3 when the features are affected by different levels of noise**
Source: **compiled by the authors**

Table 3. **Average values of probability of correct recognition (%) for classifiers in feature spaces at *N*=1 with different levels of additive noise**

Feature combinations	Noise level, %		
	0	1	5
x_1, x_4	93.75	93.75	82.50
x_5, x_{16}	93.75	90.00	83.75
x_{11}, x_{16}	100	98.75	82.50
x_4, x_{17}	93.75	87.50	88.75
x_{10}, x_{16}	93.75	92.50	83.75
x_{16}, x_{17}	93.75	91.25	87.50

Source: **compiled by the authors**

Table 4. **Average values of probability of correct recognition (%) for classifiers in feature spaces at *N*=2 with different levels of additive noise**

Feature combinations	Noise level, %		
	0	1	5
x_5, x_{16}	93.75	96.25	82.50
x_{13}, x_{16}	93.75	93.75	91.25
x_4, x_{12}	100	100	87.50
x_4, x_{16}	93.75	92.50	92.50
x_{18}, x_{17}	100	100	92.50

Source: **compiled by the authors**

Table 5. **Average values of probability of correct recognition (%) for classifiers in feature spaces at *N*=3 with different levels of additive noise**

Feature combinations	Noise level, %		
	0	1	5
x_3, x_{12}	93.75	91.25	77.50
x_3, x_{14}	93.75	93.75	91.25
x_5, x_{11}	93.75	92.19	85.00
x_5, x_{15}	93.75	91.25	90.00
x_9, x_6	93.75	93.75	87.50
x_9, x_{10}	93.75	93.75	93.75
x_{13}, x_6	93.75	93.75	87.50
x_{13}, x_{10}	93.75	93.75	90.63
x_6, x_8	93.75	91.25	87.50
x_{12}, x_{14}	93.75	93.75	85.00

Source: **compiled by the authors**

Analysis of the obtained results of studies of the stability of the PCR index for various combinations of features in different models shows that the most noise-resistant combinations of features are pairs of features for the model at *N*=3. At a noise level of 1%, these are the features: (x_3, x_{14}), (x_9, x_6), (x_{13}, x_6), (x_{13}, x_{10}), (x_{12}, x_{14}) (highlighted in Table 5); at a noise level of 5 % – (x_9, x_{10}). On Fig. 12 shows the location of the training sample objects in the feature space (x_9, x_{10}).

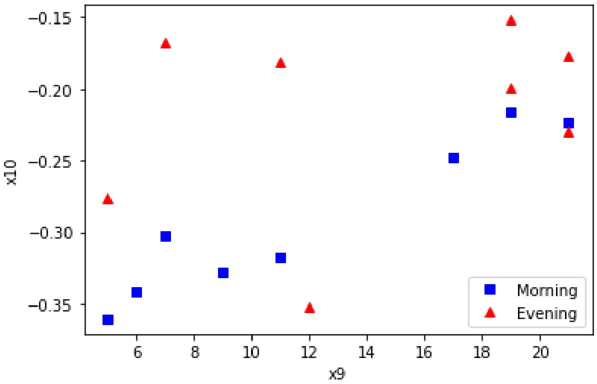


Fig. 12. **The location of objects of the training set in the feature space (x_9, x_{10})**
Source: **compiled by the authors**

Support vector machine (SVM) was also used to build the classifier [26, 27]. The best results of the evaluation of the efficiency of classifiers, built using SVM, were obtained in the feature spaces (x_5, x_{15}), (x_9, x_{10}), (x_{13}, x_{10}) and are shown in the Table 6. In this case, SVM using a second-order kernel is used:

$$K(x, x') = (\langle x, x' \rangle + 1)^d \,, \qquad (11)$$

where *d* is specified by parameter degree, *d*=2.

Calculation of indicators from the Table 6 [25] was obtained using the Scikit-learn library (sklearn.svm.SVC class) and functions of the sklearn.metrics module.

Table 6. **Metrics for evaluating the effectiveness of classifiers constructed in two-dimensional feature spaces using Support vector machine**

Metrics	x_5 & x_{15}	x_9 & x_{10}	x_{13} & x_{10}
Error Type I, α	1	2	2
Error Type II, β	1	1	1
PCR, $\frac{TP + TN}{TP + FP + FN + TN}$	0.875	0.813	0.813
Recall, $\frac{TP}{TP + FN}$	0.875	0.875	0.875
Precision, $\frac{TP}{TP + FP}$	0.875	0.778	0.778
F1- Score, $\frac{2 * \mathrm{Preision} * \mathrm{Recall}}{\mathrm{Preision} + \mathrm{Recall}}$	0.875	0.824	0.824

Source: **compiled by the authors**

CONCLUSIONS

The methodology of experimental studies of human OMS using innovative eye-tracking technology for registration of OMS responses to test visual stimuli was developed and implemented. The obtained empirical data of the "input-output" studies are used to identify the OMS based on Volterra polynomials. Experimental studies of the respondent's OMS were carried out before and after the working day. Based on the data obtained with the Tobii Pro TX300 eye-tracker, the transient functions of the first, second and third orders of the OMS were determined. The variability of second- and third-order transient functions for different psychophysiological states of the respondent (by level of fatigue) was revealed. Thus, it seems appropriate to use multidimensional transient functions in diagnostic studies in the fields of neuroscience and psychology.

The information technology of diagnosing human psychophysiological states has received further development due to the use as a source of primary data of OMS information models based on Volterra polynomials. This allows increasing the accuracy of OMS modeling and, as a result, to increase the reliability of diagnosis in the space of the proposed heuristic features.

A set of heuristic features are proposed, which are determined using integral and differential transformations of the MTF of the OMS. The informativeness of individual features and all their possible combinations in pairs according to the PCR indicator was studied. Two-dimensional feature spaces with the maximum value of the PCR indicator were found when solving problems of assessing the psychophysiological state (fatigue state) of a person (P_{max}=0.9375).

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Оцінка психофізіологічного стану за допомогою нелінійних динамічних інтегральних моделей

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АНОТАЦІЯ

Розроблено та реалізовано метод експериментального дослідження «вхід-вихід» окуло-моторної системи людини з використанням інноваційної технології айтрекінгу для реєстрації відгуків окуло-моторної системи на тестові візуальні стимули. Стимули відображаються на екрані монітора на різній відстані від початкового положення. Це формально відповідає дії ступінчастих сигналів з різною амплітудою на вході окуло-моторної системи. За емпіричними даними досліджень «вхід-вихід» окуло-моторної системи респондента, отриманих за допомогою айтрекера Tobii Pro TX300, визначені перехідні функції першого та діагональні перетини перехідних функцій другого і третього порядків окуло-моторної системи. Експериментальні дослідження окуло-моторної системи респондентів для виявлення стану втоми проводили до початку (вранці) та після робочого дня (увечері). Отримані багатовимірні перехідні функції використовуються як джерело первинних даних при реалізації інтелектуальної інформаційної технології діагностики та моніторингу психофізіологічного стану людини. Розроблено інструментальні алгоритмічні та програмні засоби визначення діагностичних ознак на основі ідентифікаційних даних окуло-моторної системи у вигляді багатовимірних перехідних функцій на мові Python. На основі запропонованих евристичних ознак сформовано навчальні вибірки даних для двох станів респондента («Норма» та «Втома»), які визначаються за допомогою інтегральних та диференціальних перетворень отриманих багатовимірних перехідних функцій окорухової системи. Навчальні вибірки даних використовуються для побудови класифікаторів психофізіологічних станів індивіда за допомогою засобів машинного навчання. Інформативність окремих ознак та всіх можливих їх комбінацій у парах за показником вірогідності правильного розпізнавання досліджувалась методом повного перебору. Результати дослідження отримано шляхом оцінки якості розпізнавання станів за допомогою побудованих байєсівськими класифікаторами в різних просторах запропонованих ознак. Проведено аналіз стабільності показника інформативності правильного розпізнавання різних просторів ознак під впливом на ознаки різних рівнів адитивного шуму. При вирішенні науково-практичної задачі оцінки психофізіологічного стану (втоми) людини виявлено двовимірні простори ознак з максимальним і найбільш стабільним значенням показника правильного розпізнавання (0.9375). Таким чином, видається доцільним використовувати багатовимірні перехідні функції, що отримані за даними айтрекінга, в діагностичних дослідженнях у галузях нейронаук та експериментальної психології.

Ключові слова: Оцінка психофізіологічного стану; діагностика; окуло-моторна система; ідентифікація; модель Вольтерра; багатовимірні перехідні функції; тестові візуальні стимули; технологія айтрекінга

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