Information Technology of the Diagnostics of Neuro-Physiological States of Personality based on the Eye-Tracking Data

Valeriy Makarov, Dmitro Broska, Volodymyr Chorniy, Vitaliy Pavlenko

Abstract. Instrumental algorithmic and software tools for constructing a nonparametric dynamic model of the human oculo-motor system (OMS) based on its inertial and nonlinear properties are developed in the paper on the basis of the experimental studies data of «input-output» in the form of the Volterra model. Taking into account the specificity of the object investigated, test multistage signals (visual stimulus) were used for identification. Based on the experimental data obtained using the developed computational algorithms and data processing software, a nonparametric dynamic model of OMS in the form of a transient function and transient functions of the 2nd and 3rd orders is constructed. Verification of the constructed model showed its adequacy to the object investigated – a practical coincidence (within the acceptable error) responses of the object and model for the same test signal. Experimental studies of the OMS made of the same subject before and after the working day. Based on the data using the eye-tracker, multidimensional transient functions of the OMS has obtained. The revealed variability of the transient functions of the 2nd and 3rd orders for different neurophysiological states of the respondent (level of fatigue) has observed. Thus, they can be used in diagnostic studies in the field of the neuroscience and psychology.

Keywords: Eye-tracking technology, identification, oculo-motor system, neurophysiological states, Volterra model.

I. Introduction

Innovative technology of eye tracking which is rapidly developing nowadays is the process of determination of the view or of eye movements. This high-tech innovation has been further developed and effectively used in the construction of a mathematical model of process of tracking eye movement to detect anomalies in data tracking to quantify the motor symptoms of Parkinson's disease [1–4]. Using nonlinear dynamic Wiener and Volterra-Laguerre model for identification of OMS is based on a random effects test, which requires the application of methods of correlation analysis and generates a large amount of experimental data (long-term experimental studies).

In order to build the Volterra model of the human OMS, a person is encouraged to use the test deterministic effects; for example, step signals (the most appropriate for the study of the dynamics of OMS), which simplifies the computational algorithm to identify and significantly reduce the time of processing of experimental data [5–9]. There is a method and computer algorithms identifying deterministic nonlinear dynamical systems in the form of Volterra models using multi-step test signals [10].

The purpose of the work is the development of the method for constructing of the nonparametric dynamic model of OMS in the form of Volterra series based on experimental studies of "input-output" and also computational tools and software for the information technology processing experimental data.

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II. Literature Analysis

The developed software enables support of the following tasks:

1) The relationship study of mental states and cognitive processes in educational activities, a post-traumatic stress disorder, the diagnosis of the Parkinson's and Alzheimer's disease stage, checking the psychophysiological state of pilots and drivers, the professional suitability, the fatigue syndrome [1], [11], [12].
2) The interaction of mental states and cognitive processes during the educational activities of students and schoolchildren, an objective assessment of their cognitive development level, assessment of the effectiveness of training to improve mental processes (ie. thinking processes) and for psychological correction of personality [11–13].
3) Extension of the individual's creative life due to the early diagnosis of degenerative processes of cognitive functions of the brain. Identification of a gifted personality (building a psychological model of the personality) and evaluation of its abilities. Professional selection (the identification and education of leaders) [14–16].
4) The assimilation of scientific knowledge and their respective skills serves as the main goal and the main result of educational activities. The process of mastering knowledge is the central part of the learning process. Managing this process implies the existence of effective objective indicators for assessing an individual's intellectual abilities [17–21].

The methods of psychophysiological identification of a person proposed in the project, based on obtaining experimental data using eye-tracking technology and computing means for their processing, will allow monitoring and diagnosing the state of cognitive processes in during the educational activities of students and schoolchildren.

III. Object, Subject, And Methods Of Research

Object of research: the process of identification of human OMS on the basis of a nonlinear dynamic model of Volterra according to the eye-tracking data using special test visual stimuli.

Subject of research: algorithms and software to support information technologys of the diagnostics of neurophysiological states of personality based on eye-tracking data.

A. Intelligent IT of Diagnostics Neuronal Processes

An intelligent information technology for diagnosing the states of neural processes based on nonparametric identification of OMS in the form of nonlinear dynamic Volterra models is proposed. The technology involves a consistent solution of the following tasks:

1) *Identification of OMS.* The goal is to construct an information model of OMS in the form of multidimensional transient functions (MTF) – integral transformations of Volterra kernels. Stages of the implementation: submission of test signals with different amplitude to the inputs of OMS (horizontal, vertical, diagonal); measurement of OMS responses to test signals using an eye tracker; calculation of MTF based on the data of the experiment «input-output» type.

2) *Construction of diagnostic model of OMS.* The goal – formation of the feature space. Stages of the implementation: compression of MTF; determination of the diagnostic features; selection of optimum system features (reduction of the diagnostic model).

3) *Construction of the classifier of the individual's psychophysiological state on the basis of the OMS model*. The goal is to build a family of decision rules for optimal classification. Stages of the implementation: construction of decision rules based on the results of OMS identification (training); assessment of classification reliability (examination); optimization of diagnostic model.

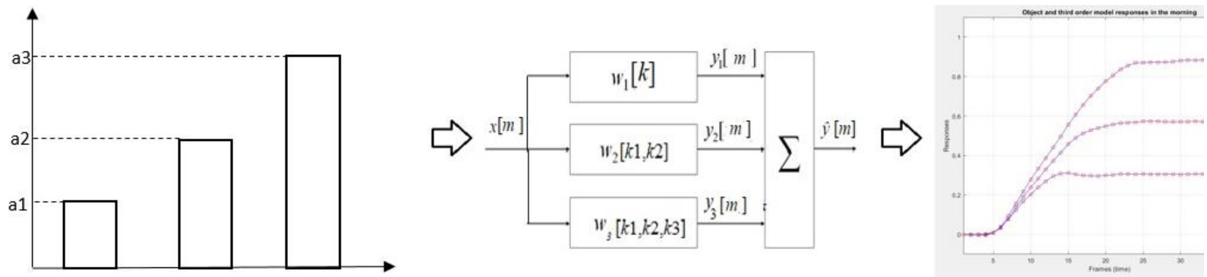
4) *Diagnosis of neural processes.* The goal is to assess the state of the individual. Stages of the implementation: identification of OMS; evaluation of diagnostic features; classification -classification of the individual under study to a certain class.

B. Eye Tracking for Identification of OMS

Text Information technology of the constructing a nonparametric dynamic model of the human OMS taking into account its inertial and nonlinear properties based on the data of experimental studies "input-output" was developed. As a basic OMS model - the Volterra model is used in the form of multidimensional transient functions.

Methods and tools for the identification of OMS have been developed using the help of eye tracking technology, and building a features space and optimal classification human states using machine learning. In the Laboratory of Motion Analysis and Interface Ergonomics at the Lublin University of Technology (Lublin, Poland), joint studies of the human OMS were performed to obtain diagnostic information for solving urgent problems in the neuro informatics and the computational neuroscience. Experimental research was carried out using eye tracking technology with the use of the video based Tobii TX300 (300 Hz sampling rate) eye tracker and appropriate software.

Taking into account the specificity of the object investigated, test multistep signals were used for identification. If a $x(t)$ test signal represents a unit function (the Heaviside function) – $\theta(t)$, it will result in identification of the transient function of the first order and the diagonal sections of the transient functions n-th order. This show on Fig. 1.



Test signals — Volterra Model — Responses OMS and model on test signals with different amplitudes

Fig. 1. Test signals and responses of OMS and its Volterra model

To determine the sections of subdiagonal transient of functions of the n-th order ($n \geq 2$) OMS was tested using the n step test signal with the specified amplitude and different intervals between signals. With appropriate processing responses get a subdiagonal section of n-dimensional transient functions $h_n(t_1,...,t_n)$, which represent the n-dimensional integral of the Volterra kernel n-order $w_n(t_1,...,t_n)$ [5], [10], [22]:

$$h_n(t_1,...,t_n) = \int_0^\infty \dots \int_0^\infty w_n(t_1-\lambda_1,...,t_n-\lambda_n)d\lambda_1 \dots d\lambda_n. \qquad (1)$$

Based on the experimental data obtained using the developed computational algorithms and data processing software, a nonparametric dynamic model of the human-eye apparatus in the form of a transient function and transient functions of the 2nd and 3rd orders is constructed [9].

The method for constructing an approximate Volterra model of the OMS is developped. The method of identification is based on the $y(t)$ approximation at an arbitrary $x(t)$ deterministic signal in the form of the Volterra polynomial of the N-th order (N – the order of the approximation model) [5], [23]:

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

where $\hat{y}_n(t)$ – the partial components in the human OMS approximation model.

Let the input test signals of OMS be fed alternately: $a_1x(t)$, $a_2x(t)$,…, $a_Lx(t)$; a_1, a_2,…,a_L – distinct real numbers satisfying the condition $|a_j| \leq 1$ for $\forall j=1,2,...,L$; then minimization of the criterion:

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

is reduced to solving the system of normal equations of Gauss, which in the vector-matrix form can be written as:

$$\mathrm{A}'\mathrm{A}\hat{\mathrm{y}} = \mathrm{A}'\,\mathrm{y}, \tag{4}$$

where:

$$\mathrm{A} = \begin{bmatrix} a_1 & a_1^2 & \cdots & a_1^N \\ a_2 & a_2^2 & \cdots & a_2^N \\ \cdots & \cdots & \cdots & \cdots \\ a_L & a_L^2 & \cdots & a_L^N \end{bmatrix}, \mathrm{y} = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \cdots \\ y_L(t) \end{bmatrix}, \quad \hat{\mathrm{y}} = \begin{bmatrix} \hat{y}_1(t) \\ \hat{y}_2(t) \\ \cdots \\ \hat{y}_N(t) \end{bmatrix}.$$

From (4) we obtain:

$$\hat{\mathrm{y}} = (\mathrm{A}'\,\mathrm{A})^{-1}\mathrm{A}'\,\bar{\mathrm{y}}\,. \tag{5}$$

In expanded form, equation (5) has the form:

$$\begin{bmatrix} \hat{y}_1(t) \\ \hat{y}_2(t) \\ \cdots \\ \hat{y}_N(t) \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{L} a_j^2 & \sum_{j=1}^{L} a_j^3 & \cdots & \sum_{j=1}^{L} a_j^{N+1} \\ \sum_{j=1}^{L} a_j^3 & \sum_{j=1}^{L} a_j^4 & \cdots & \sum_{j=1}^{L} a_j^{N+2} \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{j=1}^{L} a_j^{N+1} & \sum_{j=1}^{L} a_j^{N+2} & \cdots & \sum_{j=1}^{L} a_j^{2N} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \sum_{j=1}^{L} a_j y_j(t) \\ \sum_{j=1}^{L} a_j^2 y_j(t) \\ \cdots \\ \sum_{j=1}^{L} a_j^N y_j(t) \end{bmatrix}. \tag{6}$$

C. Software tools

The following instrumental algorithmic and software tools are developed to achieve the goal of the research:

1) Formation of test signals in the form of bright dots on the computer monitor screen at different distances from the initial position horizontally, vertically and diagonally.

2) Preprocessing (bringing the OMS responses to a common start and rationing to one) and analyzing the data obtained from the eye tracker.

3) Constructing an identification model of OMS in the form of multidimensional transient functions (integral transformations of Volterra kernels).

4) Visualization of data and processing results of experimental research.

5) Constructing a feature space for designing the status classifier of a human using machine learning.

6) Classifiers construction using deterministic and statistical methods of learning the pattern recognition based on the data obtained using eye tracking technology.

D. Organization and methodology of experimental research using eye tracking technology

When conducting experimental studies, such actions are carried out:

1) The subject is placed in front of the computer so that his eyes are at the center of the monitor at a distance of 40-50 cm from him.
2) The subject's head is fixed in order to prevent its movements during the study and to ensure the same experimental conditions.
3) On the subject's readiness, the Signal Manager of the test visual stimulus program is launched (Fig. 2).
4) A red circle appears in the center (or from its edge) – of the screen in the starting position (Fig. 2, *a*).
5) After a short pause (2-3 sec.), the circle in the starting position disappears and a circle of a different color appears at the point with the specified coordinates (Fig.2, *b*) – a visual stimulus (test signal), which is displayed in this position for a specified duration (1-2 sec.) – the action makes the eye move in the direction of the visual stimulus.
6) Then this stimulus circle disappears and a red circle appears in the starting position – this makes the eye move in the opposite direction to the starting position, after these actions the experiment ends.
7) Using the eye tracker, the coordinates of the pupil of the eye are determined during its movement (reaction to the visual stimulus) in the period between the starting positions and the coordinate values are stored in the xls file.

a) *b*)

Fig 2. Test visual incentives:*a*) starting position; *b*) position of the stimulus

In the studies of each respondent, three experiments were successively implemented for three amplitudes of test signals in the horizontal direction. The distance between the starting position and the test incentives is equal to: 0.33 l_x, 0.66 l_x, 1.0 l_x, where l_x is the length of the monitor screen. Coordinates of the starting position ($x = 0$, $y = 0.5\ l_y$), l_y – mean the width of the monitor screen. The obtained results of measurements of the OMS responses at L=3 obtained with using the Tobii TX300 eye tracker in one study cycle ("Horizontally") are shown in Fig. 3. Transient process in the OMS response to the test signal $a_1 = 0.33$ are illustrated on Fig. 4.

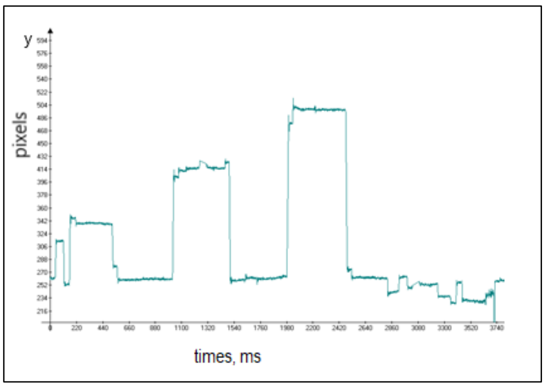


Fig. 3. The OMS responses at L=3 obtained using the Tobii TX300 eye tracker

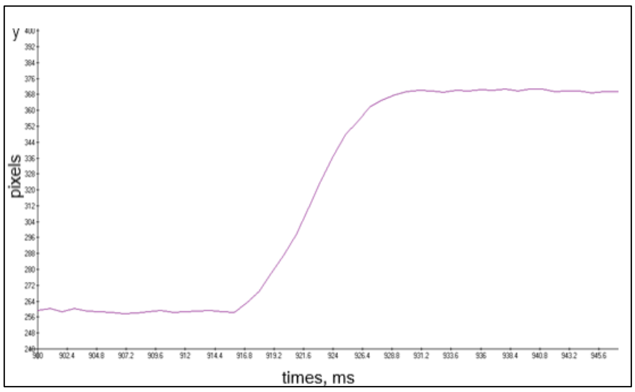


Fig. 4. The transient process in the OMS response to the test signal: $a_1 = 0.33$

IV. Research Results

In order to conduct experiments with eye-traking technology, special software has been developed.

A. Signal Manager for generating test signals

A software product called "Signal Manager" was created to generate, store and process input data. It was developed using WinForms technology and the C# programming language on the Microsoft .NET Framework. The program uses a Microsoft Access database file to store data.

The structure of the database (Figure 5) file includes two tables: first named "point_lists" includes the information about the lists of points: ID, name of the list of points and the name of generation algorithm; the second table "points" includes the points themselves: ID, id of list the point belongs to, horizontal coordinates x and vertical y, width and height of the point, information about the shape of the point, timing, information about the type of the point, grouped data (direction and etc.).

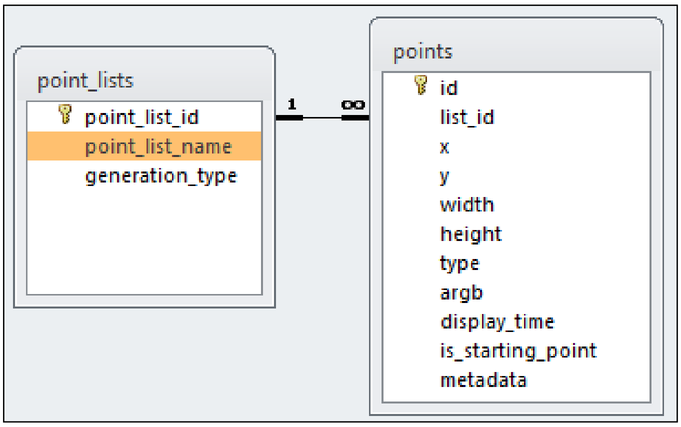
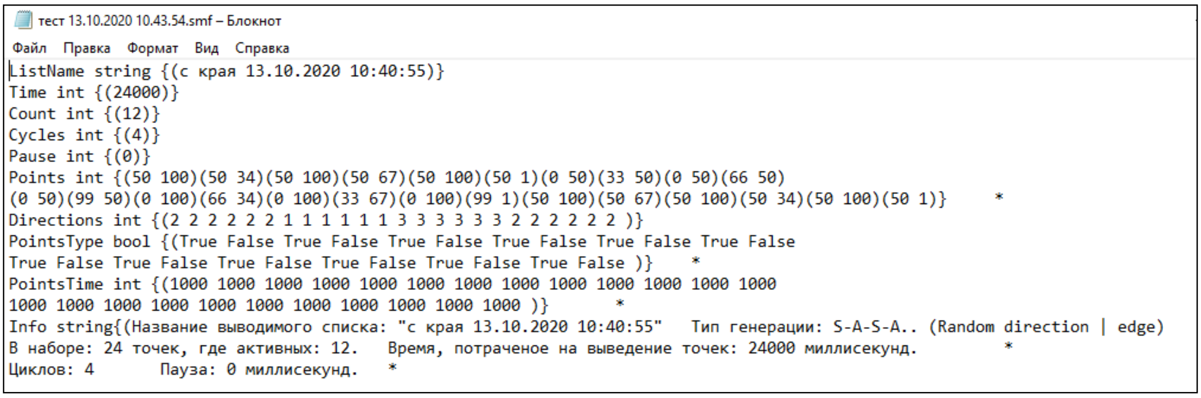


Fig. 5. Database structure

At the start of the experiment, the eSmart program begins to read the reactions to the excitation, and Signal Manager forms the protocol of the experiment shown in Fig. 6.



```
тест 13.10.2020 10.43.54.smf – Блокнот
Файл  Правка  Формат  Вид  Справка
ListName string {(с края 13.10.2020 10:40:55)}
Time int {(24000)}
Count int {(12)}
Cycles int {(4)}
Pause int {(0)}
Points int {(50 100)(50 34)(50 100)(50 67)(50 100)(50 1)(0 50)(33 50)(0 50)(66 50)
(0 50)(99 50)(0 100)(66 34)(0 100)(33 67)(0 100)(99 1)(50 100)(50 67)(50 100)(50 34)(50 100)(50 1)}     *
Directions int {(2 2 2 2 2 2 1 1 1 1 1 1 3 3 3 3 3 3 2 2 2 2 2 2 )}
PointsType bool {(True False True False True False True False True False True False
True False True False True False True False True False True False )}    *
PointsTime int {(1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 1000
1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 )}      *
Info string{(Название выводимого списка: "с края 13.10.2020 10:40:55"   Тип генерации: S-A-S-A.. (Random direction | edge)
В наборе: 24 точек, где активных: 12.   Время, потраченое на выведение точек: 24000 миллисекунд.        *
Циклов: 4       Пауза: 0 миллисекунд.   *
```

Fig. 6. Experiment protocol

This file stores information about the name of the set of points: ListName – data of string type; contains the name of the point set; Time – numerical data, contains the number of milliseconds taken to display; Count – numerical data; contains the number of active points (L); Cycles – numeric data, contains the number of cycles; Pause – numerical data, contains the number of milliseconds spent on the pause between displaying points; Points – numeric data; horizontal (x_k) and vertical (y_k) coordinates (in %) of all K points (k = 1,2,…, K) displayed on the display screen: (x_1 y_1)… (x_K y_K); Directions – numerical data, contains the index of the direction of each point; PointsType – boolean data, contains information about whether the point is the starting point; PointsTime – numerical data, contains the display time of each point in milliseconds; Info – data of string type, contains the information described above in words, as well as the name of the used generation algorithm.

After receiving a set of data - responses of the oculomotor system to test stimuli, for further data processing, it is necessary to organize the data by coordinates in each direction. To do this, after the experiment, you need to create the data sorting file using the "sort data" button in the program settings.

Data sorting file file shown in Fig. 7 is a file that stores information for restoring a sequence of experimental response data, which is necessary for further processing - the implementation of an algorithm for nonlinear dynamic identification of OMC. This file stores data about the number of points, coordinates in the desired order, directions of points, the type of each point.

```
*sorted.smf – Блокнот
Файл  Правка  Формат  Вид  Справка
Count int {(24)}
Points int {(0 50)(33 50)(50 100)(50 34)(50 100)(50 34)(0 100)(33 67)(0 50)(66 50)(50 100)(50 67)
(50 100)(50 67)(0 100)(66 34)(0 50)(99 50)(50 100)(50 1)(50 100)(50 1)(0 100)(99 1)}
Directions int {(1 1 2 2 2 2 3 3 1 1 2 2 2 2 3 3 1 1 2 2 2 2 3 3)}
PointsType bool {(True False True False True False True False True False True False True False
True False True False True False True False True False )}
```

Fig. 7. Sorting file

After the sort file was created, it is transmitted to the eSmart program over the network. It, in turn, sorts the experimental data.

The experiment currently uses 2 algorithms for generating stimuli:

1. With a gradual double randomness, where first randomly selected direction, and then randomly generating points in this direction. So we get the specified number of points in one direction.

2. With synchronous double randomness, where a random point is generated in a random direction. In this way, all points are generated in different directions. Their repetition is excluded.

B. eSmart program for reading OMS responses

Developed software for Android-smartphones that automatically recognize images of objects (face, eye, pupil) on the sequence of video recording frames and calculate the coordinates of the pupil in the dynamics of the eye movement. An important feature of this intelligent information technology is the undemanding to the hardware.

The technology of development of this application consists in use of the OpenCV library (Open Source Computer Vision Library) by means of which the algorithm of recognition of a pupil of an eye is realized and training of a cascade of Haar is carried out. Google's Realm IO Firebase cross-platform mobile database is used to store the results of the experiments. The FFMpeg library is used to work with video files. To save the coordinates of the pupil of the eye in CSV format and build graphs "Coordinate – Time", which is shown on figure 8, used graphics library with open source – MPAndroidChart. Implemented the function of smoothing coordinate arrays using a moving average algorithm with the selection of the desired level of smoothing for further processing of the data array.

To find an object in the image, the Viola-Jones method is used, which is based on an integrated representation of the image on the basis of Haar, the construction of a classifier based on an adaptive boosting algorithm and a method of combining classifiers into a cascade structure. This allows you to search for an object in the image in real time. ESmart technology software is implemented in Java.

Using the Signal Manager program, we conduct experiments and process the video using the ESmart program. Using the Edit Activity, we obtain the following graph number 9.

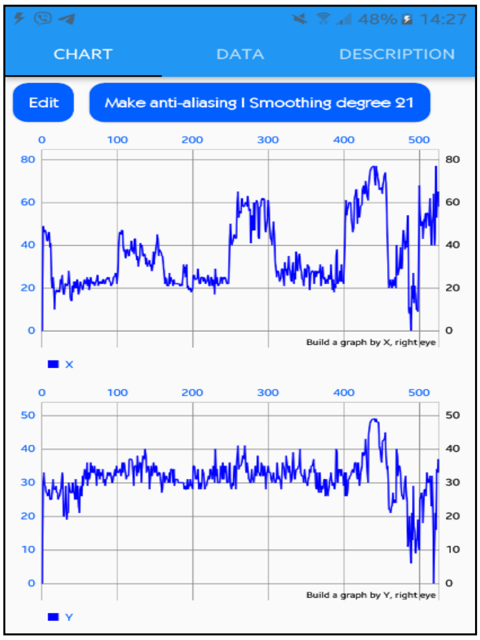


Fig. 8. Graphs of *x* and *y* coordinates

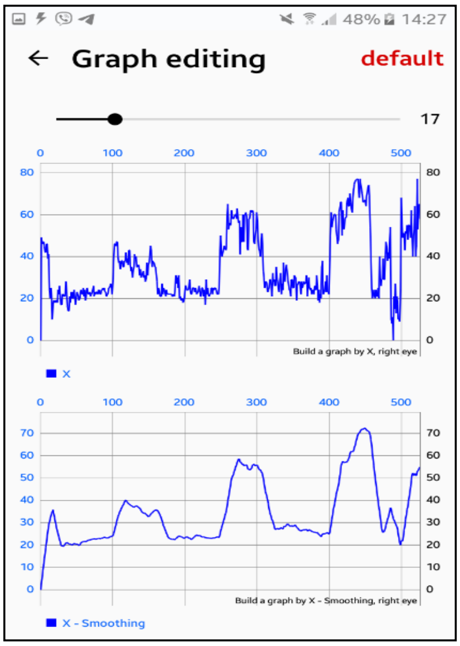


Fig. 9. Activities of editing data tracking

When processing video, ESmart breaks the video into frames and writes the coordinates of the pupil of the eye in a separate Excel file. In the second file, the program writes data vertically.

Using Photoshop, the center of the pupil of the eye is located. The data obtained in Photoshop is compared with the data obtained using the eSmart program. The error in determining the center of the pupil eye using eSmart is 1% on average.

C. Identification of the OMS

The experiments were organized in order to classify subjects by the state of fatigue. The data for constructing the model – the OMS responses to the same test signals, were obtained using the eSmart program at different times of the day: "In the Morning" (before work) and "In the Evening" (after work). The average values of the OMS responses obtained from the eye tracker at various amplitudes of the test signals "In the Morning" and "In the Evening" are shown in Fig. 10 and Fig. 11, respectively.

According to averaged data of OMS responses on visual stimuli with different distance from the start position (Fig. 12) on the basis of the formula (5) defined the transient functions of the OMS when used approximation models of various degrees N ($N = 1, 2, 3$). Graphs of the transient functions for the states of the respondent "In the Morning" and "In the Evening" based on the model (1) when $N = 1$ is shown in Fig.13, when $N = 2$ and in Fig. 14 and when $N = 3$ in Fig. 15. Identified responses with the help of calculations on models with different amplitudes of test signals for the same conditions when $N = 1, 2, 3$, graphs which are presented in comparison with similar responses OMS in Fig. 16, 17 and 18, respectively. In Fig. 19 shows graphs of the responses at different amplitudes of the test signals "In the Morning" and "In the Evening", calculated by the model with $N = 3$.

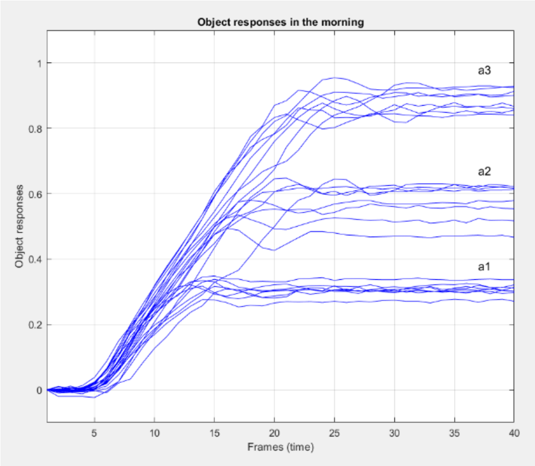


Fig. 10. The responses of the OMS at various test amplitudes signals: "In the Morning"

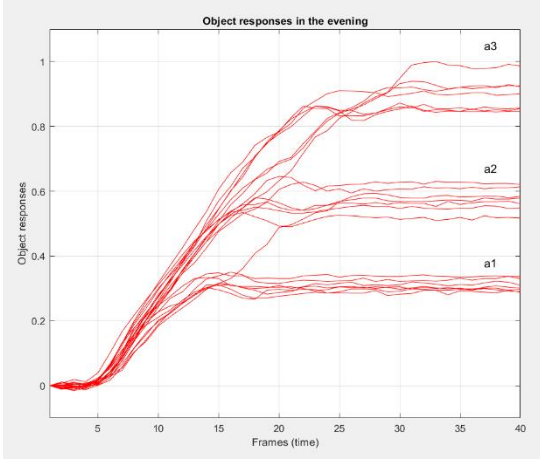


Fig. 11. The responses of the OMS at various test amplitudes signals: "In the Evening"

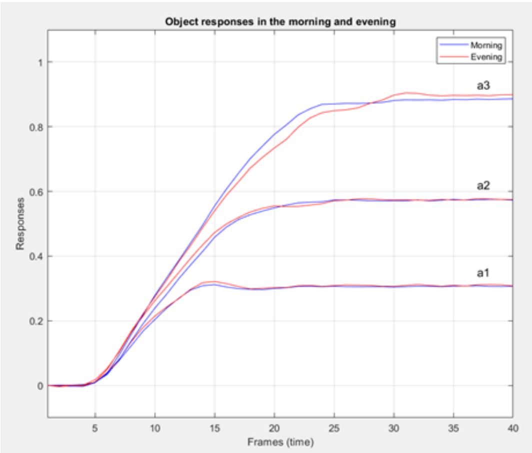


Fig. 12. The averaged OMS responses at various amplitudes of test signals “In the Morning” and “In the Evening”

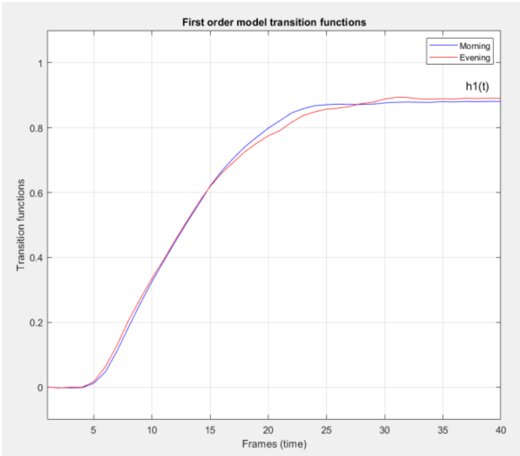


Fig. 13. The transient functions estimates at $N = 1$ "In the Morning" and "In the Evening"

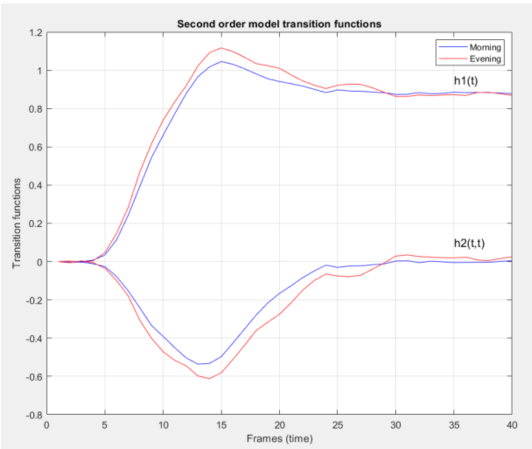


Fig. 14. The transient functions estimates at $N = 2$ "In the Morning" and "In the Evening"

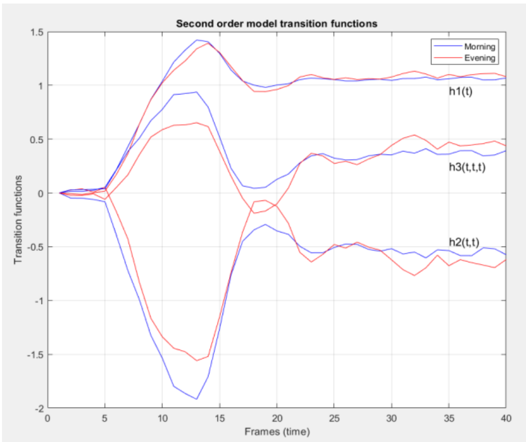


Fig. 15. The transient functions estimates at $N = 3$ "In the Morning" and "In the Evening"

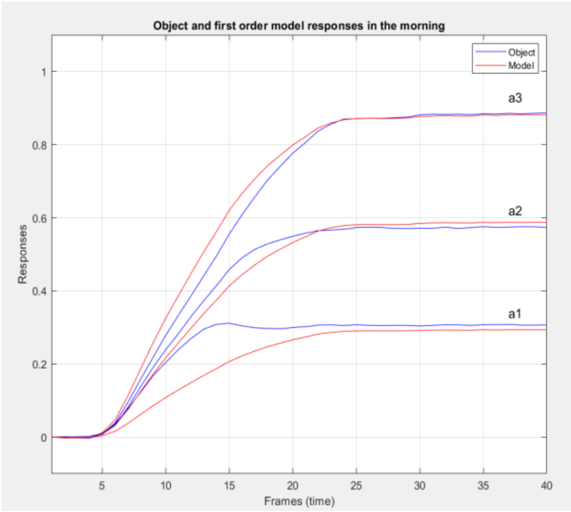


Fig. 16. The responses of the OMS and the model at N = 1 at various amplitudes of the test signals "In the Morning"

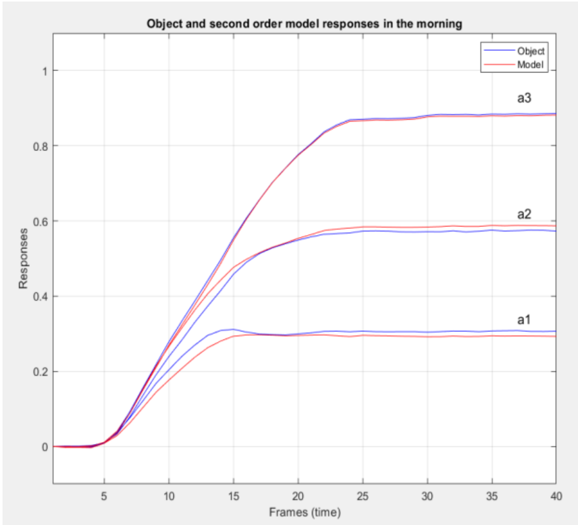


Fig. 17. The responses of the OMS and the model at N = 2 at various amplitudes of the test signals "In the Morning"

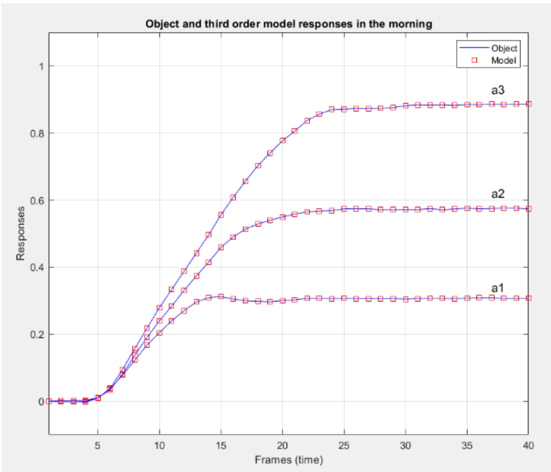


Fig. 18. The transient functions estimates at N =3 “In the Morning” and “In the Evening”

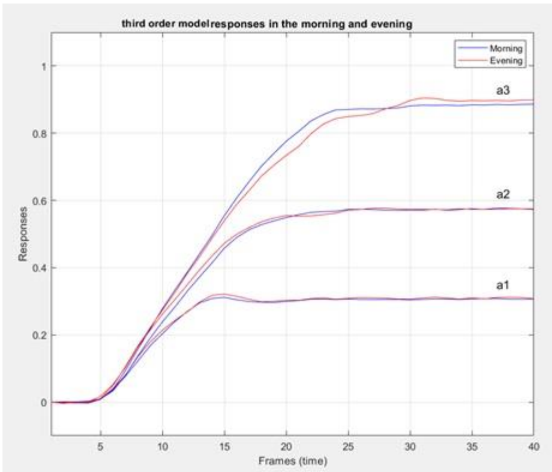


Fig. 19. The responses of the OMS and the model at N = 3 at various amplitudes of the test signals "In the Morning"

The analysis of the deviation of the averaged OMS responses for the respondent states "In the Morning" $\bar{y}_{\mathrm{m}}[m]$ and "In the Evening" $\bar{y}_{\mathrm{e}}[m]$ for various values of the amplitudes of the test signals a_1, a_2, and a_3 is based on the calculations of the following indicators:

$$\sigma = \max_{m\in[0,M]} \left|\bar{y}_{\mathrm{e}}[m] - \bar{y}_{\mathrm{m}}[m]\right|, \tag{7}$$

$$\varepsilon = \left(\frac{\sum_{m=0}^{M} \left(\bar{y}_{\mathrm{e}}[m] - \bar{y}_{\mathrm{m}}[m]\right)^2}{\sum_{m=0}^{M} \bar{y}_{\mathrm{m}}^2[m]} \right)^{1/2}, \tag{8}$$

where σ, ε – the maximum and normalized standard deviation (RMSD), of the OMS responses, respectively. The calculation results of these indicators are shown in Table 1.

Table 1. The indicator of the deviation of the average responses of the GDS for the states of the respondent "In the Morning" and "In the Evening"

The amplitudes of test signals	Maximum deviation, σ	RMSD, ε
a_1	0.013	0.019
a_2	0.027	0.025
a_3	0.045	0.027

The variability (deviation) of the multidimensional transient functions of various orders *n* of the approximation model of OMS for the states of the respondent "In the Morning" and "In the Evening" is quantified using the indicators:

σ_{nN} - maximum deviation:

$$\sigma_{nN} = \max_{m\in[0,M]} \left| \hat{y}_{ne}[m] - \hat{y}_{nm}[m] \right|, \tag{9}$$

ε_{nN} – normalized standard deviation:

$$\varepsilon_{nN} = \left(\frac{\sum_{m=0}^{M} \left(\hat{y}_{ne}[m] - \hat{y}_{nm}[m] \right)^2}{\sum_{m=0}^{M} (\hat{y}_{nm}[m])^2} \right)^{1/2}, \tag{10}$$

$n = 1, 2, \ldots, N.$

The deviation indicators of multidimensional transient functions of various orders of the OMS approximation model for respondent states "In the Morning" and "In the Evening" are given in Table 2 and are represented by diagrams in Fig. 14 and Fig. 15.

Table 2. The deviation indicators of multidimensional transient functions

N	ε_{1N}	σ_{1N}	ε_{2N}	σ_{2N}	ε_{3N}	σ_{3N}
1	0.019	0.03	–	–	–	–
2	0.051	0.078	0.232	0.109	–	–
3	0.04	0.1	0.199	0.387	0.322	0.291

The maximum deviations of the responses of the approximation model of different orders $\tilde{y}_N[m]$ from the response of the OMS $y[m]$ at different values of the amplitudes of the test signals a_1, a_2 and a_3 for the respondent's states "In the morning" and "In the evening" are given in Table 3. The corresponding estimates of RMSD are given in Table 4.

Table 3. The maximum deviation of the response of the approximating model of the order *N* from the response of the OMS at various amplitudes of test signals for the respondent states "In the Morning" and "In the Evening"

N	a_1		a_2		a_3	
	In the Morning	In the Evening	In the Morning	In the Evening	In the Morning	In the Evening
1	0.127	0.128	0.046	0.06	0.067	0.08
2	0.033	0.023	0.033	0.023	0.011	0.008
3	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13

Table 4. RMSD of the approximation model of different order *N* from the OMS response at different values of the amplitudes of the test signals a_1, a_2 and a_3 for the respondent's states "In the Morning" and "In the Evening"

N	a_1		a_2		a_3	
	In the Morning	In the Evening	In the Morning	In the Evening	In the Morning	In the Evening

1	0.198	0.209	0.043	0.063	0.042	0.054
2	0.057	0.05	0.033	0.028	0.007	0.007
3	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13	~1.0e-13

The maximum deviation of the responses of the OMS approximation models of the corresponding orders N "In the Morning" $\tilde{y}_{N\mathrm{m}}[m]$ and "In the Evening" $\tilde{y}_{N\mathrm{e}}[m]$ at different values of the amplitudes of test signals is given in Table 5.

Table 5. Maximum deviation of the responses of the OMS approximation models different orders N for the states of the respondent "In the Morning" and "In the Evening" for different values of the amplitudes of the test signals a_1, a_2 and a_3

N	a_1	a_2	a_3
1	0.01	0.02	0.03
2	0.018	0.022	0.043
3	0.013	0.027	0.045

The variability (deviation) of the MTF of different orders n of the approximation model of OMS for the states of the respondent "In the Morning" and "In the Evening" is quantified using the indicators of σ_{nN} – maximum deviation (9) and ε_{nN} – normalized standard deviation (10). The indicators deviation of the MTF of different orders n of the OMS approximation model for respondent states "In the Morning" and "In the Evening" are given in Table 1 and are represented by diagram in Fig. 20 and Fig. 21. As can be seen from Fig. 14 and Fig. 15 the obtained transient function of the first order for the "In the Morning" and "In the Evening" are virtually independent of the status of the subject. However, the diagonal cross section of the transient functions of the second and third order change significantly in magnitude and, therefore, can be effectively used as the primary data source when building models of classifiers of psychophysiological conditions of the person using machine learning.

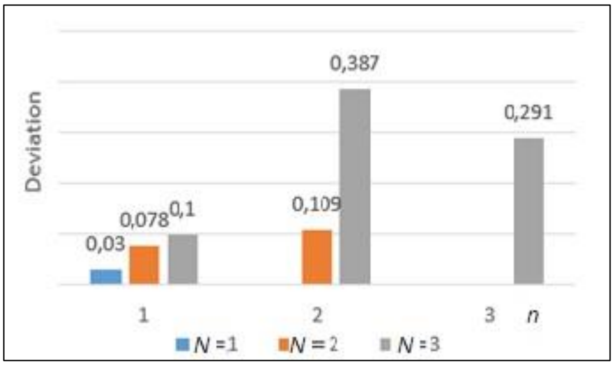


Fig. 20. The diagram of deviations indicators σ_{nN}

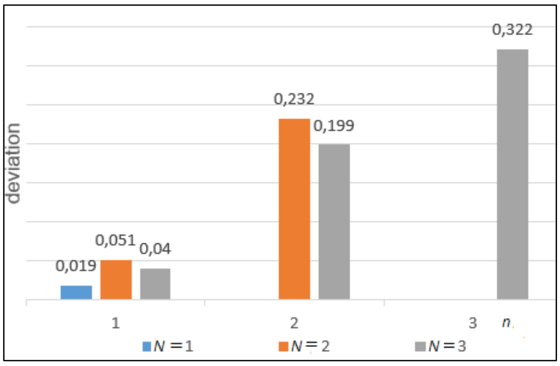


Fig.21. The diagram of deviations indicators ε_{nN}

D. Building a classifier of the fatigue

For estimate psycho-physiological state of the individual based on the OMS model conducted researchers:

1) Building a feature space for designing the status classifier of a human using machine learning.
2) Classifiers construction using deterministic and statistical methods of learning the pattern recognition based on the data obtained using eye tracking technology.

On base of training sets of data for an object's classes **A** ("In the Morning"), **B** ("In the Evening") there successively calculate discriminant function $d(\mathbf{x})$. To separate the two classes (dichotomy case) it uses discriminant function [24]–[26] of the form:

$$d(\mathbf{x}) = \frac{1}{2}\mathbf{x}'(\mathbf{S}_2^{-1} - \mathbf{S}_1^{-1})\mathbf{x} + (\mathbf{S}_1^{-1}\mathbf{m}_1 - \mathbf{S}_2^{-1}\mathbf{m}_2)'\mathbf{x} + \frac{1}{2}(\mathbf{m}_1'\mathbf{S}_1^{-1}\mathbf{m}_1 - \mathbf{m}_2'\mathbf{S}_2^{-1}\mathbf{m}_2 + \ln\frac{|\mathbf{S}_2|}{|\mathbf{S}_1|}) + \lambda_{\max}, \quad (11)$$

where $\mathbf{x}=(x_1,x_2,\ldots,x_n)'$ – features combination, n – features space dimensionality, $\mathbf{m}_i$ – mathematical expectation vector for a features of class i, i=1, 2; $\mathbf{S}_i=\mathrm{M}[(\mathbf{x}-\mathbf{m}_i)(\mathbf{x}-\mathbf{m}_i)']$ – covariance matrix for class i (M[] – mathematical expectation operation). $\mathbf{S}_i^{-1}$ – matrix inverse to $\mathbf{S}_i$, $|\mathbf{S}_i|$ – matrix determinant $\mathbf{S}_i$, $\lambda_{\max}$ – classification threshold that provides the highest criterion probability of the correct recognition of objects in the training sample.

V. Conclusions

Method and software have been developed for constructing a nonparametric dynamical model of the OMS human, taking into account its inertial and nonlinear properties, based on experimental input-output data using test visual stimuli and innovative eye-tracking technology. A nonlinear dynamic model in the form of a Volterra polynomial is used.

Test visual stimulus in the form of bright points that are consistently displayed at different distances from the starting position are used. This formally corresponds to the different amplitudes of the step test signals. The transient functions of the 1st, 2nd, and 3rd orders are determined using LS method.

The developed software tools for data processing of the eye-tracking are tested on real data from an experimental study of the OMS. Verification of the constructed model confirms the adequacy model of the investigated OMS – a practical coincidence (within an acceptable error) of the responses of the OMS and its model at the same test signal.

The revealed variability of the transient functions of the 2nd and 3rd orders for different psychophysiological states of the respondent (level of fatigue) has observed. Thus, they can be used in diagnostic studies in the field of the neuroscience and psychology.

The development of the topic in the future is aimed at constructing a space of diagnostic signs for the development of a classifier of a human state using machine learning [24]–[26]. Investigation of the efficiency of the classifier are created with statistical training methods for pattern recognition based on eye-tracking data [27].

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