# Nonlinear Dynamic Model of a Oculo-Motor System Human based on Volterra Kernels 

VITALIY PAVLENKO, DMYTRO SALATA<br>Institute of Computer Systems<br>Odessa National Polytechnic University<br>Shevchenko Av. 1, Odessa, 65044<br>UKRAINE<br>pavlenko_vitalij@mail.ru, isalatik.dmitry@gmail.com<br>YURI MAKSYMENKO<br>Military Academy (Odessa)<br>Fontanskaya Road 10, Odessa, 65009<br>UKRAINE<br>max75-08@ukr.net


#### Abstract

The paper is devoted to the development of information technology for the construction nonparametric dynamic model instrumental means of oculomotor system (OMS) based on the data video recording of experimental studies "input-output" (Eye-tracking technology). A mathematical apparatus of the Volterra series is used, which enables taking into account nonlinear and dynamic properties of research objects. Based on the experimental data with the use of test step signals, a nonparametric dynamic model of human eyemovement apparatus was constructed in the form of transitive functions of the 1st, 2nd and 3rd order.


Key-Words: - Oculo-motor system, modeling, identification, nonlinear dynamic model, Volterra kernels, multidimensional transient functions, Eye-tracking technology.

## 1 Introduction

The innovative technology of Eye-tracking which is rapidly developing nowadays - is the process of determination of the point where look being sent to or the determination of eye movements relatively to the head [1] - [3]. 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 [4] - [5]. Using nonlinear dynamic model of Wiener and Volterra-Laguerre [6] and their identification is based on a random effects test [7], which requires the application of methods of correlation analysis and generate a large amount of experimental data (long-term experimental studies).

In order to build a model of Volterra [8] 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) [9], which simplifies the computational algorithm to identify and significantly reduce the time of processing of experimental data. There is a method and computer algorithms identifying deterministic
nonlinear dynamical systems in the form of Volterra models using multi-test signals [10].

## 2 The Purpose and Research Problems

The purpose of work is development method for constructing nonparametric dynamic model of oculo-motor system, taking into account its inertial and nonlinear properties, based on experimental studies of "input-output" and also computational tools and software for the information technology processing experimental data. To achieve this goal were set this following tasks:

- Development methods for constructing nonlinear dynamic model of OMS as a Volterra kernels which characterizing both nonlinear and inertial properties of the nature objects;
- Development information technology of obtaining experimental data for identification OMS based on pupil's movement tracking using video registration;
- Development computational methods of identification multidimensional dynamic (transient) characteristics OMS using test inputs as a Heaviside functions of different amplitudes;
- Verification constructed model OMS.


## 3 The Volterra Model and Identification OMS

Basis for creation of mathematical (informational) model of investigated object are the results of measurements of its input and output variables, and the solution of the problem associated with the identification of the experimental data and process them with the noise measurements.

To describe the objects of unknown structure appropriate to use the most universal nonlinear nonparametric dynamic models - Volterra model [8]. The nonlinear and dynamic properties investigated object is uniquely described by a sequence of invariant with respect to the type of input signal is of multidimensional weight functions - Volterra kernels.

For continuous nonlinear dynamical system connection between the input $x(t)$ and output $y(t)$ signals with zero initial conditions can be represented by Volterra series

$$
\begin{align*}
& y(t)=\sum_{n=1}^{\infty} y_{n}(t)=\int_{0}^{t} w_{1}(\tau) x(t-\tau) d \tau+ \\
& +\int_{0}^{t} \int_{0}^{t} w_{2}\left(\tau_{1}, \tau_{2}\right) x\left(t-\tau_{1}\right) x\left(t-\tau_{2}\right) d \tau_{1} d \tau_{2}+  \tag{1}\\
& +\int_{0}^{t} \int_{0}^{t} \int_{0}^{t} w_{3}\left(\tau_{1}, \tau_{2}, \tau_{3}\right) x\left(t-\tau_{1}\right) x\left(t-\tau_{2}\right) \times \\
& \quad \times x\left(t-\tau_{3}\right) d \tau_{1} d \tau_{2} d \tau_{3}+\ldots,
\end{align*}
$$

where $w_{n}\left(\tau_{1}, \ldots, \tau_{n}\right)$ - Volterra kernel $n$-th order, function is symmetric with respect to real variables $\tau_{1}, \ldots, \tau_{n} ; y_{n}(t)$ - the $n$-th partial component of response system ( $n$-dimensional convolution integral); $t$ - current time.

For nonlinear dynamical system multiple-input and multiple-output used multivariate Volterra series, which has the form:

$$
\begin{align*}
& y_{j}(t)=\sum_{i_{1}=1}^{v} \int_{0}^{t} w_{i_{1}}^{j}(\tau) x_{i_{1}}(t-\tau) d \tau+ \\
& +\sum_{i_{1}=1 i_{2}=1}^{\nu} \int_{0}^{t} \int_{0}^{t} w_{i_{i-2}}^{j}\left(\tau_{1}, \tau_{2}\right) x_{i_{1}}\left(t-\tau_{1}\right) x_{i_{2}}\left(t-\tau_{2}\right) d \tau_{1} d \tau_{2}+  \tag{2}\\
& +\sum_{i_{1}=1 i_{2}=1 i_{j}}^{v} \sum_{i_{3}=1}^{v} \int_{0}^{t} \int_{0}^{t} \int_{0}^{t} w_{i i_{2} i_{3}}^{j}\left(\tau_{1}, \tau_{2}, \tau_{3}\right) X_{i_{1}}\left(t-\tau_{1}\right) X_{i_{2}} \times \\
& \times\left(t-\tau_{2}\right) x_{i_{3}}\left(t-\tau_{3}\right) d \tau_{1} d \tau_{2} d \tau_{3}+\ldots,
\end{align*}
$$

where $w_{i_{1} i_{2} \ldots i_{n}}^{j}\left(\tau_{1}, \ldots, \tau_{n}\right)-$ Volterra kernel $n$-th order in $i_{1}, i_{2}, \ldots, i_{n}$ inputs and $j$-th output $(j=1,2, \ldots, \mu)$, the functions symmetric with respect to real variables $\tau_{1}, \ldots, \tau_{n} ; y_{j}(t)$ - system response for the $j$-th output at the current time $t$ for zero initial conditions;
$x_{1}(t), \ldots, x_{\nu}(t)$ - input signals; $v, \mu-$ quantity of inputs and outputs, respectively.

In the context the problem stated above identification OMS - need to use the model (2) for the mathematical description of the object [8]: two pair rectus muscles (input object) provide eye movement up and down, left and right, and various combinations Fig. 1; measured responses - the coordinates $u(t)$ and $v(t)$ current position the pupil relative to the initial position $u_{0}$ and $v_{0}$ (the outputs of the object). In this case in model (2) adopting $v=2$ and $\mu=2$.


Fig. 1. Direct eye muscles
In this paper to simplify the experiment and data identification, problem solved for the case horizontal pupil's movement ( $v=1$ and $\mu=1$ ), i.e. based on the model (1).

Problem identification (model constructing) as (1) or (2) consist to determine the Volterra kernels based on experimental data "inputoutput" OMS. Construction of the model is the selection of test actions $x(t)$ and development of algorithm, which enables for the measured response $y(t)$ allocate partial components $y_{n}(t)$ and determined on the basis of their Volterra kernels $w_{n}\left(\tau_{1}, \ldots, \tau_{n}\right), n=1,2, \ldots$ [9].

### 3.1 Computing Method of Multidimensional Transient Functions for Identification OMS

Taking into account specificity investigated object to identification used test multistage signals. If test signal $x(t)$ represents an identity function (Heaviside function) - $\theta(t)$, the result of identification the transition function of the first order and the diagonal section $n$-th order.

To determine the sections subdiagonal transition functions $n$-th order ( $n \geq 2$ ) OMS tested using the $n$ step test signal with given amplitude and different intervals between signals. With appropriate
processing responses get subdiagonal section $n$ dimensional transition functions $h_{n}\left(t-\tau_{1}, \ldots, t-\tau_{n}\right)$, which represent $n$-dimensional integral of Volterra kernel $n$-order $w_{n}\left(\tau_{1}, \ldots, \tau_{n}\right)$ :

$$
\begin{align*}
& h_{n}\left(t-\tau_{1}, \ldots, t-\tau_{n}\right)= \\
& =\int_{0}^{\infty} \ldots \int_{0}^{\infty} w_{n}\left(t-\tau_{1}-\lambda_{1}, \ldots, t-\tau_{n}-\lambda_{n}\right) d \lambda_{1} \ldots d \lambda_{n} . \tag{3}
\end{align*}
$$

Method for determination sections of $n$ dimensional transition functions based on the statement, proof of which is similar to that given in [10].

### 3.2 The Method of Constructing Approximate Model of Volterra Nonlinear Dynamical System

Is developing a method of constructing approximate Volterra model of the OMS. Method identification is based on the approximation $y(t)$ at an arbitrary deterministic signal $x(t)$ in the form of integral power of the polynomial Volterra $N$-th order ( $N$ order approximation model)

$$
\begin{align*}
& \tilde{y}_{N}(t)=\sum_{n=1}^{N} \hat{y}_{n}(t)= \\
& =\sum_{n=1}^{N} \int_{0}^{t} \ldots \int_{\text {times }}^{t} w_{n}\left(\tau_{1}, \ldots, \tau_{n}\right) \prod_{i=1}^{n} x\left(t-\tau_{i}\right) d \tau_{i} . \tag{4}
\end{align*}
$$

Let the input test signals OMS are fed alternately $a_{1} x(t), a_{2} x(t), \ldots, a_{L} X(t) ; a_{1}, a_{2}, \ldots, a_{L}$ - distinct real numbers satisfying the condition $\left|a_{j}\right| \leq 1$ for $\forall j=1$, $2, \ldots, L$; then

$$
\begin{align*}
& \tilde{y}_{N}\left[a_{j} x(t)\right]=\sum_{n=1}^{N} \hat{y}_{n}\left[a_{j} x(t)\right]= \\
& =\sum_{n=1}^{N} a_{j}^{n} \int_{0}^{t} \ldots \int_{0 \text { times } 0}^{t} w_{n}\left(\tau_{1}, \ldots, \tau_{n}\right) \prod_{i=1}^{n} x\left(t-\tau_{i}\right) d \tau_{i}=  \tag{5}\\
& =\sum_{n=1}^{N} a_{j}^{n} \hat{y}_{n}(t)
\end{align*}
$$

The partial components in the approximation model are found using the least square method (LSM). This makes it possible to obtain such evaluation in which the sum of squared deviations of responses identified the nonlinear dynamical system $y\left[a_{j} x(t)\right]$ on the model $\tilde{y}_{N}\left[a_{j} x(t)\right]$ response is minimal, i.e., OMS provides a minimum criterion

$$
\begin{align*}
& J_{N}=\sum_{j=1}^{L}\left(y\left[a_{j} x(t)\right]-\tilde{y}_{N}\left[a_{j} x(t)\right]\right)^{2}=  \tag{6}\\
& =\sum_{j=1}^{L}\left(y_{j}(t)-\sum_{n=1}^{N} a_{j}^{n} \hat{y}_{n}(t)\right)^{2} \rightarrow \mathrm{~min},
\end{align*}
$$

where $y_{j}(t)=y\left[a_{j} x(t)\right]$. Minimization of the criterion (6) is reduced to solving the system of normal equations of Gauss, which in vector-matrix form can be written as

$$
\begin{equation*}
\mathbf{A}^{\prime} \mathbf{A} \hat{\mathbf{y}}=\mathbf{A}^{\prime} \mathbf{y} \tag{7}
\end{equation*}
$$

where
$\mathbf{A}=\left[\begin{array}{cccc}a_{1} & a_{1}^{2} & \cdots & a_{1}^{N} \\ a_{2} & a_{2}^{2} & \cdots & a_{2}^{N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{L} & a_{L}^{2} & \cdots & a_{L}^{N}\end{array}\right], \mathbf{y}=\left[\begin{array}{c}y_{1}(t) \\ y_{2}(t) \\ \cdots \\ y_{L}(t)\end{array}\right], \hat{\mathbf{y}}=\left[\begin{array}{c}\hat{y}_{1}(t) \\ \hat{y}_{2}(t) \\ \cdots \\ \hat{y}_{N}(t)\end{array}\right]$.
From (7) we obtain

$$
\begin{equation*}
\hat{\mathbf{y}}=\left(\mathrm{A}^{\prime} \mathbf{A}\right)^{-1} \mathrm{~A}^{\prime} \mathbf{y} \tag{8}
\end{equation*}
$$

In (8), matrix operations, we obtain

$$
\begin{align*}
& {\left[\begin{array}{c}
\hat{y}_{1}(t) \\
\hat{y}_{2}(t) \\
\ldots \\
\hat{y}_{N}(t)
\end{array}\right]=\left[\begin{array}{llll}
\sum_{j=1}^{L} a_{j}^{2} & \sum_{j=1}^{L} a_{j}^{3} & \cdots & \sum_{j=1}^{L} a_{j}^{N+1} \\
\sum_{j=1}^{L} a_{j}^{3} & \sum_{j=1}^{L} a_{j}^{4} & \cdots & \sum_{j=1}^{L} a_{j}^{N+2} \\
\cdots & \ldots & \ldots & \cdots \\
\sum_{j=1}^{L} a_{j}^{N+1} & \sum_{j=1}^{L} a_{j}^{N+2} & \cdots & \sum_{j=1}^{L} a_{j}^{N}
\end{array}\right]^{-1} \times }  \tag{9}\\
& \times\left[\begin{array}{ll}
\sum_{j=1}^{L} a_{j} y_{j}(t) \\
\sum_{j=1}^{L} a_{j}^{2} y_{j}(t) \\
\cdots \\
\sum_{j=1}^{L} a_{j}^{N} y_{j}(t)
\end{array}\right] .
\end{align*}
$$

## 4 The Results of the Research

For successful implementation of the technology of experimental determination of the dynamic characteristics of OMS and human diagnostics in technical and medical applications, it's necessary to have data sets - the coordinates of the position of the pupil on plane, namely, the values of the horizontal and vertical eye rotation angles with respect to the initial position.

Software tools that perform automatic site of interest location (pupil) in the sequence of frames of a video recording and coordinate calculation were developed. The most important feature of this software is the fact that it is easily scalable and is non-demanding in terms of hardware. The experiment can be easily performed with any device with a camera with at least 5 Mpx of resolution and a sample rate of at least 30 frames per second. Calculations can be performed on any device with appropriate adjustments in software code.

Technology stack used during development of the software: Library algorithms, computer vision, image processing and numerical algorithms from general purpose Open Source - library OpenCV (Open Source Computer Vision Library), which is easily deployed under most of the existing operating systems (Android, Windows, Linux, iOS); Python programming language with appropriate libraries; gradient algorithm.

The experiment was implemented with the help of the proposed system for tracking the behaviour of the pupil based on video recording is performed in the following sequence.

1. Head of the observed person is located in front of the recording device (camera) at the known distance.
2. On fixed intervals, the display shows a graphic test signal in the form of a bright spot (light spot). At the same time the recording of the eye movement from the initial position to a position determined by the light spot (test signal) starts.
3. After passing a series test signals an experiment is terminated. File with video recording of pupil's movement is stored .in memory of the measuring system.
4. After finishing experiment, start the application, that realizing intelligent object detection algorithm (pupil) in the captured video. The graph of the changing in the position of the pupil with a test signal input ("input-output" experiment) is then plotted.
5. Obtained data is stored in the database and displayed.

For experimental studies of the OMS, Olympus PEN E-PL1 $14-42 \mathrm{~mm}$ camera with a $4 / 3$ matrix of 12 Mpx is used. The length of a sample is 408,17 ms (50 photo frames). An article [11] describes a method of calibrating a digital camera in order to determine distances by a photographic method. It shows the solution to the problem and its geometrical interpretation. The accuracy of the estimation of the coordinates can reach up to $\pm 2$ pixels. The distance from the test subject to the light disturbance source (in this case, a computer monitor) equals 300 mm .

The study of the oculomotor apparatus of a person involves the analysis of eye movement data. To obtain this data, the test signals to which the eye responds must be reproduced. To generate test signals, an application is developed that runs on the Windows operating system. In the application it is possible to create lists of test signals - coordinates of bright points on the monitor screen or generate signals by random law. The lists of test signals are saved in files when you exit the application. To save
the test signal lists, you use the serialization of lists in an XML file. When the application is launched, the XML file is deserialized into the test signal lists.

To create the application, .Net technology and the C\# programming language were used. Using the template WinForms allows you to use the graphical capabilities of the .Net. Framework to play test signals on the monitor screen. An example of displaying test signals on a computer monitor using the developed application is shown in Fig. 2.


Fig. 2. Displaying test signals on the monitor screen
Multi-stage approach to eye center detection was used in order to acquire coordinates of the eye centre. The first stage of detection consists of acquiring regions of interests in the form of eye regions by using artificial neural networks, in this case - a Haar cascade classifier [12]. We then applied gradient algorithm of eye center location to the regions of interest, which allowed us to acquire precise location of eye centers.

The main advantage to using Haar cascade classifier is its speed, which in turn makes it easy to process videos. Haar cascade classifier is implemented in OpenCV library [13], which also provides easy and stable tools for training it. The training consists of computing characteristic values based on positive and negative images [12] and saving them in a XML file. The file is then used with an implementation of Viola-Jones method in OpenCV.

The algorithm used is based on [14], with modifications added to it. The optimal centre $\mathbf{c}^{*}$ of a circular object in an image with pixel positions $\mathbf{x}_{i}$, $i \in\{1,2, \ldots, M\}$, where $M$ is the size of the image, is given by:

$$
\begin{align*}
& \mathbf{c}^{*}=\underset{c}{\arg \max }\left\{\frac{1}{M} \sum_{i=1}^{M}\left(\mathbf{d}_{i}^{T} \mathbf{g}_{i}\right)^{2}\right\},  \tag{10}\\
& \mathbf{d}_{i}=\frac{\mathbf{x}_{i}-\mathbf{c}}{\left\|\mathbf{x}_{i}-\mathbf{c}\right\|_{2}}, \forall i:\left\|\mathbf{g}_{i}\right\|_{2}=1, \tag{11}
\end{align*}
$$

here, $\mathbf{d}_{i}$ - a normalized displacement vector of the possible center $\mathbf{c}, \mathbf{g}_{i}$ - a gradient vector at position $\mathbf{x}_{i}$. The gradient vector is calculated by means of partial derivatives in this case, but any method can be used without affecting the complexity of the software implementation.

The geometrical solution to the problem essentially comes down to checking, whether the displacement vector and gradient vector have same orientations, and if so, the center in question c is the optimal center of the dark object (Fig. 3).


Fig. 3. A geometrical solution to the problem
The first modification addresses the threshold of dark and light centers. Since the pupil is usually dark compared to sclera and skin, we apply a weight wc for each possible centre c such that dark centers are more likely than bright centers.

Integrating this into the objective function leads to:

$$
\begin{equation*}
\mathbf{c}^{*}=\underset{\mathbf{c}}{\arg \max }\left\{\frac{1}{M} \sum_{i=1}^{M} w_{\mathbf{c}}\left(\mathbf{d}_{i}^{T} \mathbf{g}_{i}\right)^{2}\right\} \tag{12}
\end{equation*}
$$

where $w_{\mathrm{c}}=\mathrm{I}^{*}\left(c_{x}, c_{y}\right)$ is the grey value at $\left(c_{x}, c_{y}\right)$ of the smoothed and inverted input image $I$. The image needs to be smoothed, e.g. by a Gaussian filter, in order to avoid problems that arise due to bright outliers such as reflections of glasses.

Testing of the tracking technology of the pupil's behavior based on video registration is performed on the task of analysis of work of the OMS along the horizontal axis. Result eye image analysis shown on Fig. 4.


In mm: $x=31,9, y=27,4$
In pixels: $x=90, y=78$

n mm: $x=36,0, y=27,5$


In mm: $x=33,9, y=27,4$
In pixels: $x=94, y=77$


In mm: $x=37,9, y=26,9$

In pixels $x=99, y=77 \quad$ In pixels: $x=107, y=76$
Fig. 4. Result eye image analysis
Measured response of the eye $y_{1}(t), y_{2}(t), y_{3}(t)$ to the input test signals $(L=3)$ for values of the test signal amplitudes $a_{1}=0,33, a_{2}=0,66$ and $a_{3}=1$ shown in Fig. 5.


Fig. 5. Respofnses OMS $y_{1}(t), y_{2}(t)$ and $y_{3}(t)$
Obtained graphs of OMS transient functions first and second shown in Fig. 6, Fig. 7, respectively.

The model response is calculated on the basis of estimates of the transient functions and

$$
\begin{equation*}
\tilde{y}(t, a)=a \hat{h}_{1}(t)+a^{2} \hat{h}_{2}(t, t) . \tag{13}
\end{equation*}
$$



Fig. 6. Transient functions $\hat{h}_{1}(t)$


Fig. 7. Transient functions $\widehat{h}_{2}(t, t)$
Comparison of the response of the constructed model with the response of the identified OMS (with experimental data) $y(t, a)$ shown in Fig. 8.

The verification of adequacy of the mathematical model in relation to the experiment data is calculated by Mean Square Error (MSE) criteria:

$$
\begin{equation*}
\varepsilon=\sqrt{\frac{1}{m} \sum_{i=1}^{m}\left[y\left(t_{i}, a_{1}\right)-\tilde{y}\left(t_{i}, a_{1}\right)\right]^{2}} \tag{14}
\end{equation*}
$$

and Percentage-Normalized Mean Square Error (PNMSE) criteria:

$$
\begin{equation*}
\sigma=100 \sqrt{\frac{\sum_{i=1}^{m}\left[y\left(t_{i}, a_{1}\right)-\tilde{y}\left(t_{i}, a_{1}\right)\right]^{2}}{\sum_{i=1}^{m} y^{2}\left(t_{i}, a_{1}\right)}} \tag{15}
\end{equation*}
$$



Fig. 8. Responses OMS $y(t)$ and model
$\tilde{y}\left(t, a_{1}\right), \hat{y}_{1}\left(t, a_{1}\right), \hat{y}_{2}\left(t, a_{1}\right)$
Provided graphs are practically the same (standard deviation $\varepsilon=0,0011, \sigma=3,3 \%$ ) which confirms effectiveness computational algorithm of identification and adequacy of the constructed model based on experimental data "input-output".

Obtained graphs of OMS transient functions first $\hat{h}_{1}(t)$, second $\widehat{h}_{2}(t, t)$ and third order $\widehat{h}_{3}(t, t, t)$ shown in Fig. 9 respectively.


Fig. 9. Transient functions $\hat{h}_{1}(t), \widehat{h}_{2}(t, t)$ and $\widehat{h}_{3}(t, t, t)$
The model response is calculated on the basis of estimates of the transient functions $\widehat{h}_{1}(t)$,

$$
\begin{align*}
& \hat{h}_{2}(t, t) \text { and } \hat{h}_{3}(t, t, t) \\
& \qquad \tilde{y}(t, a)=a \hat{h}_{1}(t)+a^{2} \hat{h}_{2}(t, t)++a^{3} \hat{h}_{3}(t, t, t) . \tag{16}
\end{align*}
$$

Comparison of the response of the constructed model $\tilde{y}(t, a)$ with the response of the identified OMS (with experimental data) $y(t, a)$ shown in Fig. 10.


Fig. 10. Responses EMS $y(t)$ and model $\tilde{y}(t)$, $\hat{y}_{1}\left(t, a_{1}\right), \hat{y}_{2}\left(t, a_{1}\right), \hat{y}_{3}\left(t, a_{1}\right)$ at an amplitude $a_{1}=0.33$

Provided graphs are practically the same which confirms effectiveness computational algorithm of identification and adequacy of the constructed model based on experimental data "input-output".

## 5 Conclusion

Instrumental algorithmic and software tools for constructing a nonparametric dynamic model of human oculomotor apparatus 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 Volterra's model.

An application for the automation of experimental human Oms studies is developed - a program for testing test signals, the main features of which are ease of use, small size of the application, high speed, clear interface, many settings for conducting various experiments.

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 transitive function and transitive functions of the 2nd and 3rd orders is constructed. Verification of the constructed model showed the adequacy of its investigated object - practical coincidence (within the acceptable error) of the object and model feedback for the same test effect.

The application of the method of OMS identification based on the Volterra model in the form of multidimensional transitive functions using the test signals - Heaviside functions of different amplitudes is substantiated.

The information technology for obtaining experimental data for identification of OMS based on tracking the pupil's rotational angle with the help of video registration is developed.

The computational algorithms of OMS identification in the form of multidimensional transitive functions with the help of stepped functions are developed.

The method of carrying out an experiment on pupil eye tracking on the basis of Eye-tracking technology has been developed. Software for automation of experimental research for the identification of OMS has been created.

## References:

[1] J. Kepler and U. Linz, Biomechanical Modelling of the Human Eye, Netz Werk für Forschung, Lehre und Praxis, Linz, 2004.
[2] E. D. Guestrin and M. Eizenman, General Theory of Remote Gaze Estimation Using the Pupil Center and Corneal Reflections, IEEE Trans. Biomed. Eng., 53 (6), 2006, pp. 11241133. DOI:10.1109/tbme.2005. 863952.
[3] O. V. Komogortsev and A. Karpov, Automated Classification and Scoring of Smooth Pursuit Eye Movements in Presence of Fixations and Saccades, Journal of Behavioral Research Methods, 45 (1), 2013, pp. 1-13.
[4] D. Jansson and A. Medvedev, Volterra Modeling of the Smooth Pursuit System with Application to Motor Symptoms

Characterization in Parkinson's Disease, European Control Conference (ECC),2014, pp. 1856-1861. DOI:10.1109/ecc.2014.6862207
[5] D. Jansson, Stochastic Anomaly Detection in Eye-Tracking Data for Quantification of Motor Symptoms in Parkinson's Disease, Advances in Experimental Medicine and Biology,823, 2015, pp. 63-82. DOI:10.1007/978-3-319-10984-8_4
[6] D. Jansson and A. Medvedev, System identification of Wiener systems via VolterraLaguerre models: Application to human smooth pursuit analysis, European Control Conference (ECC), 2015, pp. 2700-2705. DOI: 10.1109 /ECC. 2015.7330946
[7] P. Z. Marmarelis and V. Z. Marmarelis, Analysis of Physiological Systems. The White Noise Approach, Plenum Press, New York, 1978.
[8] F. J. Doyle, R. K. Pearson and B. A Ogunnaike, Identification and Control using Volterra Models, Published Springer Technology \& Industrial Arts, 2001.
[9] A. Fomin, M. Masri, V. Pavlenko and A. Fedorova, Method and information technology for constructing a nonparametric dynamic model of the oculomotor system, Eastern European Journal of Enterprise Technologies, 2/9 (74), 2005, pp. 64-69. DOI: 10.15587/1729-4061.2015.41448
[10] V. D. Pavlenko, O. O. Fomin, A. N. Fedorova and M. M. Dombrovskyi, Identification of Human Eye-Motor System Base on Volterra Model, Herald of the National Technical University "KhPI". Subject issue: Information Science and Modelling, Kharkov, NTU "KhPI", 21 (1193), 2016, pp. 74-85.
[11] G. A. Shekhovtsov, R. P. Shekhovtsova, E. V. Popov and Yu. N. Raskatkin, Calibration of a Digital Photocamera to Measure Distances, Privolzhsky Scientific Journal, 4 (36), 2015, pp.131-140.
[12] P. Viola and M. Jones, Robust Real-Time Object Detection, Second International Workshop On Statistical and Computational Theories of Vision - Modeling, Learning, Computing and Sampling, Vancouver, Canada, July13, 2001, pp. 1-25.
[13] S. V. Viraktamath, M. Katti, A. Khatawkar and P. Kulkarni, Face Detection and Tracking using OpenCV, The SIJ Transactions on Computer Networks \& Communication Engineering (CNCE), Vol. 1, No. 3, July-August, 2013, pp. 45-50.
[14] F. Timm and E. Barth, Accurate Eye Centre Localisation by means of Gradients, Proceedings of the Int. Conference on Computer Theory and Applications (VISAPP), 1, INSTICC, Algarve, Portugal, 2011, pp. 125130.

