Biometric Identification via Oculomotor System Based on the Volterra Model

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Biometric Identification via Oculomotor System Based on the Volterra Model

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***Abstract*—In recent years, there has been an increase in interest in biometrics research involving the use of brain characteristics commonly known as behavioral traits. Human eyes contain a rich source of idiosyncratic information which may be used for the recognition of an individual's identity. This article implements an innovative experiment and a new approach to processing human eye movements, ultimately aimed at biometric identification of individuals. In our experiment, the subjects observe special test visual stimuli, which are generated on the computer monitor screen. The eye movements are tracked in dynamics providing information for constructing a nonparametric nonlinear dynamic model (Volterra model) of a human's oculomotor system (OMS) in the form of multivariate transient functions.**

The implemented method treats eye trajectories as 2-D distributions of points on the "Coordinate-Time" plane. The efficiency of dynamic characteristics for personality identification is confirmed by examples of models built on the basis of data from real experiments. The resulting OMS models are a source of information for the selection of informative features, in the space of which the decisive rule of optimal identification of individuals is determined using machine learning methods. Promising results at the task of identification according to behavioral characteristics of an individual have been obtained - recognition accuracy is higher than 97%.

Keywords—computer information protection, biometric identification, human oculomotor system, Volterra model, multidimensional transient functions, test visual stimuli, eye tracking technology

INTRODUCTION

Identification systems that use biometric characteristics of a person to solve the problem of access to information systems are becoming more widespread. By and large, there are several biometric traits that can be used for the recognition of the individuals: physiological, behavioral and soft biometric traits [1]. In practice, the following biometric methods are used: the fingerprint recognition, a human image, the iris, the retina - those features that are typical for the body of the individual - physiological traits. Biometric technology is very reliable and user-friendly. But most often only some of the biometric characteristics used to identify the user are taken into account such as ear detection [2], finger vein and face recognition [3]–[5]. Fingerprint, iris - all of this may not be enough for reliable protection. Moreover, these identification approaches can be technically violated by creating a model of a finger or retina using holographic methods.Therefore, a biometric technology was proposed that identifies a person by individual eye movements [6]–[8] - behavioral traits. This form of identification is particularly resistant to counterfeiting due to the complex eye movement patterns produced by the brain.

Research development trends show that the use of the eye-tracking technology has proliferated recently. Eye-trackers are a popular tool for studying cognitive, emotional, and attentional processes in different populations and participants of all ages, ranging from infants to the elderly [9], [10]. One of the themes eye movement measures are applied to is individual differences [11]. Anatomical biometric recognition is widely used in a large number of civilian and government applications, within well-tested biometric parameters [12], [13]. When tracking eye movements, it is suggested to spot two characteristics of the eye. The first is to fix the eye at a certain point on the display. The second is the moment of eye movement when moving the gaze from one point to another. The computer evaluates the data obtained and determines the unique characteristics for each case, i.e. for each person, including the work of the muscles of the eyeball [14]–[21].

The *aim* of the research is to increase the efficiency (reliability) of information protection on the computer through the development of hardware and software identification of the human oculo-motor system (OMS) based on a nonlinear dynamic model and data of experimental input-output research using innovative eye tracking technology. The Volterra model in the form of multidimensional transient functions (MTF) is used for identification [22]– [23].

The object of research is the process of biometric identification of a computer user on the basis of eye tracking data in dynamics – responses to given test visual stimuli (the eye tracking process).

The subject of research is software tools for constructing the Volterra model – evaluation of multidimensional transient functions of OMS according to the data eye tracking, determination based on transient functions of informative features and construction of defining rules of optimal classification.

I. The Volterra Model

Volterra model and the method of the identification OMS. The "input-output" ratio for a nonlinear dynamical system (NDS) with an unknown structure (such as a "black box") with a single input and a single output can be represented by a discrete Volterra series in the form [24]:

$$y[m]=\sum_{n=1}^{\infty}y_n[m]=\sum_{k_1=0}^{m}w_1[k_1]x[m-k_1]+$$
$$+\sum_{k_1=0}^{m}\sum_{k_2=0}^{m}w_2[k_1,k_2]x[m-k_1]x[m-k_2]+ \qquad (1)$$
$$+\sum_{k_1=0}^{m}\sum_{k_2=0}^{m}\sum_{k_3=0}^{m}w_3[k_1,k_2,k_3]x[m-k_1]x[m-k_2]x[m-k_3]+....$$

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.

The Volterra series is replaced by a polynomial and is usually limited to the first few terms of the series in practice. In this study we limited ourselves to the first three terms of the series (we chose the degree of the Volterra polynomial model $N = 3$).

The block diagram of the discrete polynomial Volterra model of the third degree is shown in Fig. 1.

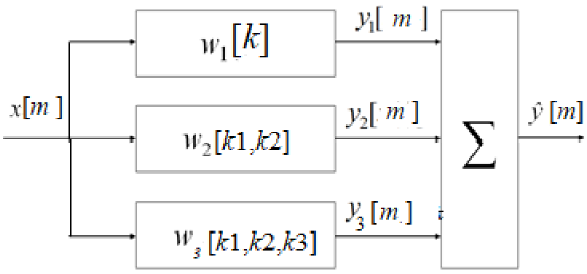

Figure 1. Block diagram of the discrete Volterra model

The problem of identification is to choose test signals $x[m]$ and develop an algorithm that allows to identify partial components $y_n[m]$, (n=1,2,3) based on the responses received $y[m]$ and determine on their multidimensional Volterra kernels: $w_1[k_1]$, $w_2[k_1,k_2]$, $w_3[k_1,k_2,k_3]$.

Taking into account the specifics of the studied OMS, test step signals are used for identification. If the test signal $x[m]$ = $\theta[m]$, where $\theta[m]$ is the unit function (Heaviside function), then the partial components of the response $y_1[m]$, $y_2[m]$, $y_3[m]$ are the first order transient function and diagonal sections of the second and third order transient functions, respectively:

$$y_1[m]=h_1[m]=\sum_{k_1=0}^{m}w_1[m-k_1],$$
$$y_2[m]=h_2[m,m]=\sum_{k_1,k_2=0}^{m}w_2[m-k_1,m-k_2], \qquad (2)$$
$$y_3[m]=h_3[m,m,m]=\sum_{k_1,k_2,k_3=0}^{m}w_3[m-k_1,m-k_2,m-k_3].$$

In this case, the responses of the Volterra model of the OMS are calculated based on the expression:

$$\tilde{y}_i[m]=a_i\hat{y}_1[m]+a_i^2\hat{y}_2[m]+a_i^3\hat{y}_3[m],\quad i=\overline{1,N}, \qquad (3)$$

where

$\hat{y}_1[m]=\hat{h}_1[m]$, $\hat{y}_2[m]=\hat{h}_2[m,m]$, $\hat{y}_3[m]=\hat{h}_3[m,m,m]$ are obtained estimates of the partial components of the model (MTF).

II. The Method Identification of the OMS

The research uses an approximation identification method. The approximation method of identification in domain time is based on the allocation of the n-th partial component in the OMS response by constructing linear combinations of responses to test signals with different amplitudes.

Let at system input test signals are given successively $a_1x[m]$, $a_2x[m],\ldots,a_Nx[m]$ (N is approximation model order, a_1, $a_2,\ldots,a_N$ are different real numbers, which satisfy the term $|a_j|\le 1$ for $\forall j=1,2,...,N$; $x[m]$ is arbitrary function). Then the linear combination of the OMS responses with the coefficients c_j is amount to the n-th partial component of the OMS response to the input signal $x[m]$. In this case, a methodical error arises in the selection of the n-th partial component, due to the partial components of the OMS response of higher orders $n>N$:

$$\sum_{j=1}^{N}c_j y(a_j x[m])=y_n(x[m])+\sum_{j=1}^{N}c_j\sum_{n=N+1}^{\infty}y_n(a_j x[m]), \qquad (4)$$

where

$$y_n(x[m]) = y_n[m];$$
$$y(a_j x[m])=\sum_{n=1}^{\infty}a_j^n\sum_{k_1=0}^{m}\ldots\sum_{k_n=0}^{m}w_n[k_1,\ldots,k_n]\prod_{i=1}^{n}x[m-k_i];$$

if c_j is real coefficients such that

$$A_N\,c=b, \qquad (5)$$

where

$$A_N=\begin{bmatrix}a_1 & a_2 & \ldots & a_N\\ a_1^2 & a_2^2 & \ldots & a_N^2\\ \ldots & \ldots & \ldots & \ldots\\ a_1^N & a_2^N & \ldots & a_N^N\end{bmatrix},\quad c=\begin{bmatrix}c_1\\ c_2\\ \ldots\\ c_N\end{bmatrix},\quad b=\begin{bmatrix}b_1\\ b_2\\ \ldots\\ b_N\end{bmatrix},$$

and $b_l=1$ at $l=n$ and $b_l=0$ at $l\ne n$, $\forall l\in\{1,2,\ldots,N\}$.

The evaluation of transient functions can be set in general as follows:

$$\hat{h}_n[m,...,m] = \hat{y}_n[m] = \sum_{j=1}^{N} c_j^{(n)} y(a_j\theta[m]) =$$

$$= c_1^{(n)} y_{a_1}[m] + c_2^{(n)} y_{a_2}[m] + ... + c_N^{(n)} y_{a_N}[m], \qquad (6)$$

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

where $y_{a_j}[m] = y(a_j\theta[m])$ – OMS response to a test signal with an amplitude a_j.

III. Results

To identify the OMS in the form of MTF according to the data eye tracking program Signal Manager was created to generate test visual stimuli on the computer monitor screen. The obtained physiological features of the OMS, in experiments on eye movement tracking, step signals (bright dots) with different distances a_j (j = 1,2,…,N; N is number of experiments) from the starting position are used. Thus, visual stimuli can be considered as functions $x_j[m]= a_j\theta[m]$, where $\theta[m]$ is a unit function of Havicide. With the help of an eye tracker, the responses of the OMS are recorded, which are used to determine the MTF [22].

In the studies of each respondent, three experiments were performed sequentially for the three amplitudes a_1, a_2, a_3 (N=3) of the test signals in the horizontal direction. The distance between the starting position and the test stimuli is: (1/3)lx, (2/3)lx and (1.0)lx, where lx is the length of the monitor screen. Coordinates of the starting position (x=0, y= (1/2)ly), where ly is the width of the monitor screen. Experimental studies of OMS were conducted using high-tech equipment – eye trecker TOBII PRO TX300 (300 Hz) [25].

The obtained results of measurements of the OMS responses at N=3 obtained in one study cycle ("Horizontally") are shown in Fig. 2. Transient process in the OMS response to the test signal a_1 = 0.33 are illustrated on Fig. 3 [25].

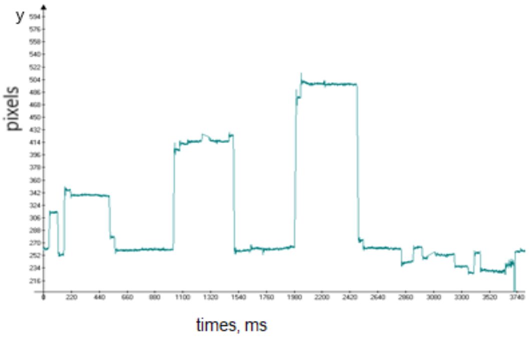

Figure 2. OMS responses at L=3 obtained using the TOBII PRO TX300 eye tracker

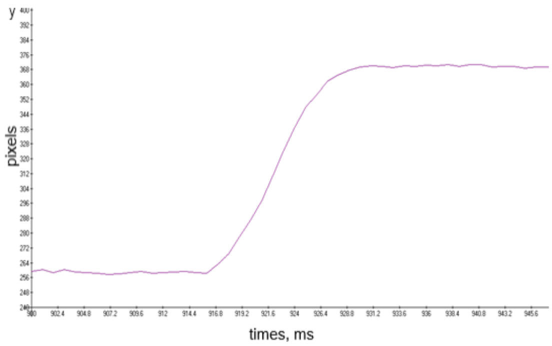

Figure 3. Transition process in the OMS response to the test signal: a_1 = 0.33

Most modern video eye trackers deliver binocular data. Many researchers take the average of the left and right eye signals to decrease the variable error. However, the systematic error of a single eye signal is lower than that of the average of the left and right eye signals at the cost of a higher variable error [26]. In our research, to minimize the variable error, we used data produced by the one eye.

In Fig. 4 and Fig. 5 OMS responses to test visual stimuli with amplitudes a_1, a_2 and a_3. in two individuals are shown that were obtained on different days and at different times of the day.

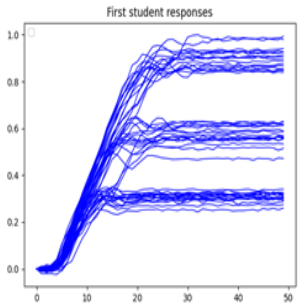

Figure 4. 1st student's OMS responses to visual stimuli with amplitudes a_1, a_2, a_3

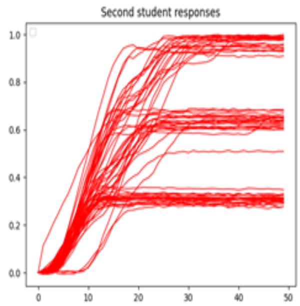

Figure 5. 2nd student's OMS responses to visual stimuli with amplitudes a_1, a_2, a_3

According to the averaged data of OMS responses to visual stimuli (Fig. 6), the transient functions of OMS when using Volterra models of different degree N (N=1,2,3) were determined. Graphs of transient functions for two individuals based on the model at N=1 are presented in Fig. 7, at N=2 – in Fig. 8 and at N=3 – in Fig. 9. As it can be seen from Fig. 7 – Fig. 9, the obtained transient functions of the 1st order almost coincide for two individuals. However, the diagonal sections of the transient functions of the 2nd (Fig. 8) and third (Fig. 9) orders in two individuals change significantly in values, therefore, can be effectively used as a source of primary data in building a system of recognition of individuals with application of machine learning.

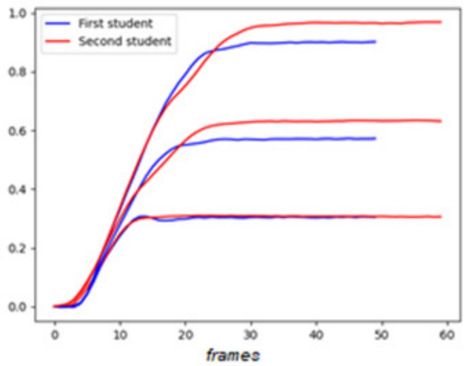

Figure 6. Average responses of OMS of two students

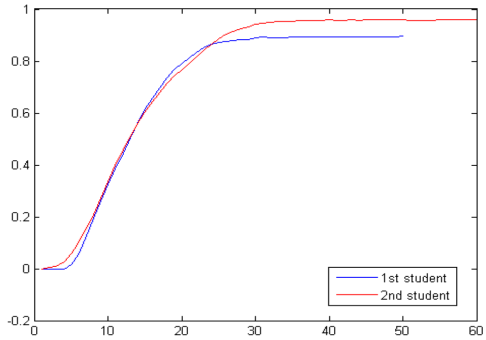

Figure 7. Transient functions 1st orders of two individuals

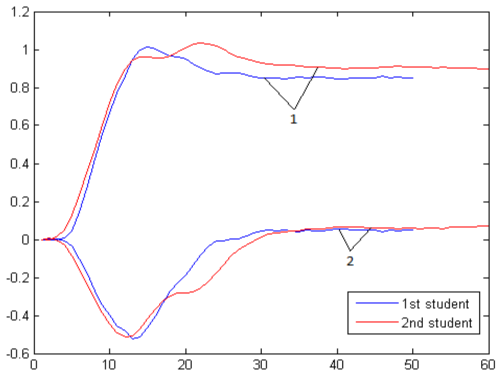

Figure 8. Transient functions: 1 – 1st; 2 – 2nd orders of two individuals

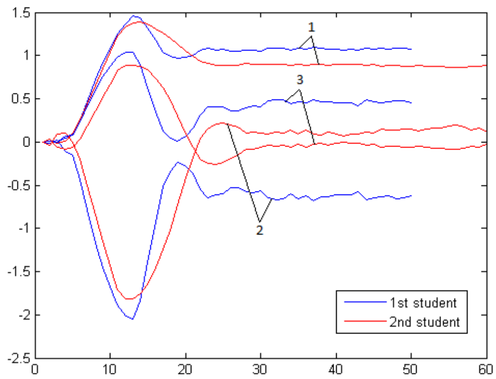

Figure 9. Transient functions: *1* – 1st; *2* – 2nd; *3* – 3rd orders of two individuals

A. The Analysis of the MTF variability

The variability (deviation) of transient functions of different orders n (n=1,2,…,N) of OMS models for N=1, 2, 3 of two individuals – the respondent #1 $\hat{h}_{1n}^{(N)}[m]$ and the respondent #2 $\hat{h}_{2n}^{(N)}[m]$ is quantified using indicators:

σ_{nN} is maximum deviation

$$\sigma_{nN} = \max_{m\in[0,M]} \left|\hat{h}_{1n}^{(N)}[m] - \hat{h}_{2n}^{(N)}[m]\right|, \tag{7}$$

ε_{nN} is standard deviation

$$\varepsilon_{nN} = \left(\frac{1}{M}\sum_{m=0}^{M}\left(\hat{h}_{1n}^{(N)}[m]-\hat{h}_{2n}^{(N)}[m]\right)^2\right)^{1/2}, \tag{8}$$

where M is the number of measurements.

Indicators of deviations of transient functions of different orders of n models of OMS of respondents #1 and #2 for N = 1, 2, 3 are given in Table 1.

TABLE I. THE DEVIATION INDICATORS OF MTF

N	ε_1	σ_1	ε_2	σ_2	ε_3	σ_3
1	0.025	0.056	-	-	-	-
2	0.066	0.118	0.489	0.264	-	-
3	0.158	0.22	0.83	0.808	1.182	0.66

B. Building a classifier of the individuals

For identity recognition of the individuals based on the OMS nonlinear dynamical model conducted researche:

- Building a feature space for designing classifier of the individe with using machine learning.
- Classifiers construction with using statistical methods of learning the pattern recognition based on the data obtained using eye tracking technology.

The discriminant function d(x) is sequentially calculated on the basis of training datasets for object classes **A** (Individual #1, 22 measuring), **B** (Individual #2, 16 measuring). To separate the two classes (dichotomy case) a discriminant function of the form is used:

$$d(\mathrm{x}) = \frac{1}{2}\mathrm{x}'(\mathrm{S}_2^{-1} - \mathrm{S}_1^{-1})\mathrm{x} + (\mathrm{S}_1^{-1}\mathrm{m}_1 - \mathrm{S}_2^{-1}\mathrm{m}_2)'\mathrm{x} + \\ + \frac{1}{2}(\mathrm{m}_1'\mathrm{S}_1^{-1}\mathrm{m}_1 - \mathrm{m}_2'\mathrm{S}_2^{-1}\mathrm{m}_2 + \ln\frac{|\mathrm{S}_2|}{|\mathrm{S}_1|}) + \lambda_{\max} \tag{9}$$

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

The analysis of the reliability of personality recognition in the space of features calculated on the basis of the MTF (Appendix) consists in forming various combinations of features and evaluating their informativeness based on the classification results on the data sample under study using criteria for the probability of correct recognition (PCR).

Bayesian classifier. Bayesian classifier of individuals in two-dimensional features space is provided of the maximum recognition reliability (P) at the combinations by the following of the features:

Volterra model at N=2:

$$\left(x_8 = \arg\min_m h_2^{'}(m,m) \ \& \ x_{13} = \min_m h_1^{'}(m) \right)$$

or

$$\left(x_{13} = \min_m h_1^{'}(m) \ \& \ x_{16} = \max_m \left|h_1(m)\right| \right)$$

yields the PCR P=0.9737;

$$\left(x_1 = \sum_{m=1}^{M} \left|h_1(m)\right| \ \& \ x_{11} = \max_m h_2^{'}(m,m) \right)$$

yields the PCR P=0.9474;

Volterra model at N=3:

$$\left(x_{13} = \min_m h_1^{'}(m) \ \& \ x_{15} = \min_m h_3^{'}(m,m,m) \right)$$

yields the PCR P=0.9737.

Support Vector Machine classifier. Close results were obtained by means of Support Vector Machine (SVM) [27]:

Volterra model at N=2:

$$\left(x_8 = \arg\min_m h_2^{'}(m,m) \ \& \ x_{13} = \min_m h_1^{'}(m) \right)$$

or

$$\left(x_{13} = \min_m h_1^{'}(m) \ \& \ x_{16} = \max_m \left|h_1(m)\right| \right)$$

yields the PCR P=0.9474;

$$\left(x_1 = \sum_{m=1}^{M} \left|h_1(m)\right| \ \& \ x_{11} = \max_m h_2^{'}(m,m) \right)$$

yields the PCR P=0.9211

Volterra model at N=3:

$$\left(x_{13} = \min_m h_1^{'}(m) \ \& \ x_{15} = \min_m h_3^{'}(m,m,m) \right)$$

yields the PCR P=0.9737.

The classifier is built using a 2nd order polynomial kernel:

$$K(\mathrm{x},\mathrm{x}') = (\langle \mathrm{x},\mathrm{x}' \rangle + 1)^d \qquad (10)$$

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

Scikit-learn library was used (class sklearn.svm.SVC) to apply SVM. The location of the objects of the training sample in the space of features is shown in Fig. 10–13 accordingly.

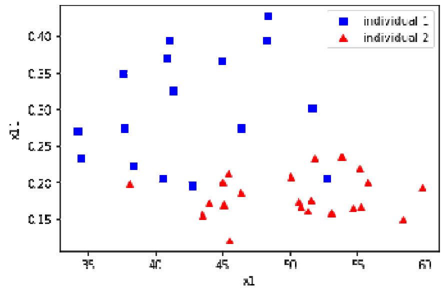

Figure 10. The location of the objects of the training set in the space of features x_1 and x_{11}

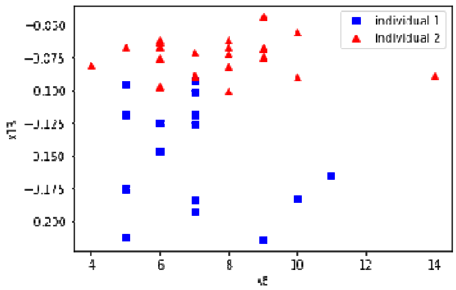

Figure 11. The location of the objects of the training set in the space of features x_8 and x_{13}

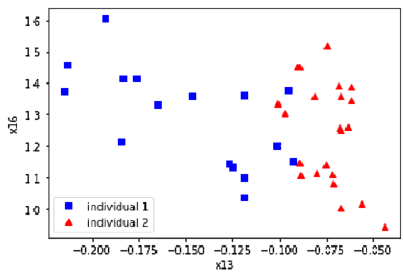

Figure 12. The location of the objects of the training set in the space of features x_{13} and x_{16}

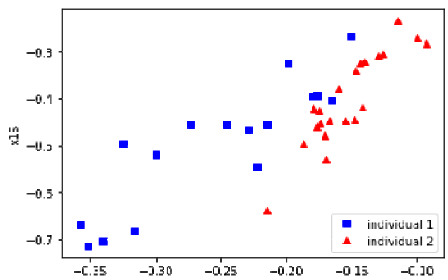

Figure 13. The location of the objects of the training set in the space of features x_{13} and x_{15}

CONCLUSION

Managing and delineating access to computer systems and their resources is an important aspect of information security. It can be implemented through user identification. Recently, identification systems that use human biometric characteristics in solving the problem of access to information systems are becoming more common. The paper proposes a new method of biometric identification of users of computer systems based on the definition of integrated Volterra models of the OMS human according to experimental research "input-output" using innovative technology of eyetracking. Developed in the Python IDLE programming environment software to identify OMS.

Experimental studies of OMS have been carried out in two people. Based on the data obtained using the TOBII PRO TX300 eye tracker, the transition functions of the first, second and third orders of the OMS are determined. There is a significant difference between the diagonal intersections of the second and third order transition functions of two individuals. That is why thay can be used to form a space of informative features and build statistical face classifiers using machine learning.

APPENDIX. INVESTIGATED HEURISTIC FEATURES

#	Features	Formal definition
1	x_1	$x_1 = \sum_{m=1}^{M} \lvert h_1(m) \rvert$
2	x_2	$x_2 = \sum_{m=1}^{M} \lvert h_2(m,m) \rvert$
3	x_3	$x_3 = \sum_{m=1}^{M} \lvert h_3(m,m,m) \rvert$
4	x_4	$x_4 = \arg\max_m h_1^{'}(m)$
5	x_5	$x_5 = \arg\max_m h_2^{'}(m,m)$
6	x_6	$x_6 = \arg\max_m h_3^{'}(m,m,m)$
7	x_7	$x_7 = \arg\min_m h_1^{'}(m)$
8	x_8	$x_8 = \arg\min_m h_2^{'}(m,m)$
9	x_9	$x_9 = \arg\min_m h_3^{'}(m,m,m)$
10	x_{10}	$x_{10} = \max_m h_1^{'}(m)$
11	x_{11}	$x_{11} = \max_m h_2^{'}(m,m)$
12	x_{12}	$x_{12} = \max_m h_3^{'}(m,m,m)$
13	x_{13}	$x_{13} = \min_m h_1^{'}(m)$
14	x_{14}	$x_{14} = \min_m h_2^{'}(m,m)$
15	x_{15}	$x_{15} = \min_m h_3^{'}(m,m,m)$
16	x_{16}	$x_{16} = \max_m \lvert h_1(m) \rvert$
17	x_{17}	$x_{17} = \max_m \lvert h_2(m,m) \rvert$
18	x_{18}	$x_{18} = \max_m \lvert h_3(m,m,m) \rvert$
19	x_{19}	$x_{19} = \arg\max_m \lvert h_1(m) \rvert$
20	x_{20}	$x_{20} = \arg\max_m \lvert h_2(m,m) \rvert$
21	x_{21}	$x_{21} = \arg\max_m \lvert h_3(m,m,m) \rvert$

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