Вісник Національного технічного університету "ХПІ", 2021, № 2 (6)
ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

UDC 681.5.015.52 DOI: 10.20998/2411-0558.2021.02.09

V. V. CHORI, Graduate student, ONPU (Odessa, Ukraine),
T. V. SHAMANINA, Graduate student, ONPU (Odessa, Ukraine),
V. D. PAVLENKO, DSc Eng, Professor Full, ONPU (Odessa, Ukraine)

BUILDING A CLASSIFIER IN THE PERSONALITY RECOGNITION SYSTEM BASED ON EYE TRACKING DATA

Identification systems that use biometric characteristics to solve the problem of access to information systems are becoming more common. The article proposes a new method of biometric identification of computer systems users, based on the determination of the integral Volterra model of the human oculo-motor system (OMS) according to experimental research "input-output" using innovative eye tracking technology. With the help of the Tobii Pro TX300 eye tracker, the data of OMC responses to test visual stimuli were obtained, displayed as bright dots on the computer screen at different distances from the start position in the "horizontal" direction. Based on the data obtained, the transition functions of the first, second and third orders of the OMS for two people were determined. To construct a personality classifier, the informativeness of the proposed heuristic features, determined on the basis of the transition functions in terms of the probability of correct recognition (PCR), is investigated. Pairs of features are established that are resistant to computational errors and have a high PCR value – in the range 0.92 – 0.97. Fig.: 8. Tabl.: 5. Refs.: 30 titles.

Keywords: biometric identification; personality recognition; Volterra model; oculo-motor system; eye tracking technology; informativeness of features; classification.

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 considered 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 many 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 – 22].

The article [23] proposes a new method of biometric identification of computer systems users, based on the Volterra integral model determination of the human oculomotor system (OMS) according to the experimental study "input-output" using innovative eye tracking technology. Computational instrumental and software tools for OMS identification have been developed, based on the use of test visual stimuli, which are displayed on a computer monitor. The responses to these stimuli are recorded by a special device – an eye tracker. In [24], based on experimental data obtained with the TOBII PRO TX300 eye tracker, a nonparametric OMS model was built in the form of transient functions of the first $h_1(m)$ and diagonal sections of the second $h_2(m,m)$ and third orders $h_3(m,m,m)$ orders. The resulting transition functions are used to construct the space of features that are used to classify two individuals [25].

The purpose of this study is to increase the reliability of personality recognition using nonparametric nonlinear dynamic models (Volterra models) of the human oculomotor system when constructing the space of features.

The object of the research is the process of biometric identification of a person based on eye tracking data. *The subject of the research* is the computational and software tools for the formation of the feature space and the construction of the classifier of individuals based on the results of OMS "input-output" identification based on the Volterra model using the eye tracking technology.

OMS model as multidimensional transient functions (MTF). The research uses an approximation identification method, which 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 [26 – 27].

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 $|a_j|\leq 1$ for $\forall j=1,2,...,N$; $x[m]$ is arbitrary

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

function). Then the linear combination of the OMS responses with the coefficients c_j is amount to the n-th partial component $\hat{y}_n[m]$ 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 $n > N$:

$$\hat{y}_n[m]=\hat{h}_n[m,...,m]=c_1^{(n)}y_{a_1}[m]+c_2^{(n)}y_{a_2}[m]+...+c_N^{(n)}y_{a_N}[m],\ n=1,2,...,N, \quad (1)$$

where $h_n[m,..., m]$ is a diagonal section of the discrete transient function of the n-th order

$$h_n[m,...,m]=\sum_{k_1,...k_n=0}^{m} w_n[m-k_1,...,m-k_n]; \quad (2)$$

in these parts $w_n[k_1,\dots,k_n]$ is a Volterra kernels of the n-th order; m is a discrete time variable; $y_{a_j}[m]=y(a_j\theta[m])$ – OMS response to a test signal with an amplitude a_j, $\theta[m]$ is a unit function (Heaviside step function); herewith, c_j is real coefficients such that

$$\mathrm{A}_N\,\mathrm{c}=\mathrm{b}, \quad (3)$$

where:

$$\mathrm{A}_N=\begin{bmatrix} a_1 & a_2 & \dots & a_N \\ a_1^2 & a_2^2 & \dots & a_N^2 \\ \dots & \dots & \dots & \dots \\ a_1^N & a_2^N & \dots & a_N^N \end{bmatrix},\quad \mathrm{c}=\begin{bmatrix} c_1 \\ c_2 \\ \dots \\ c_N \end{bmatrix},\quad \mathrm{b}=\begin{bmatrix} b_1 \\ b_2 \\ \dots \\ b_N \end{bmatrix}.$$

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

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 [28, 29].

According to the averaged data of OMS responses to visual stimuli (Fig. 1), the transient functions of OMS when using Volterra model of degree N = 3 were determined. Graphs of the first, second and third order transition functions for two persons are shown in Fig. 2, Fig. 3. and Fig. 4, respectively. As seen from Fig. 2 – Fig. 4, the obtained transition functions for two persons change significantly in values, therefore they can be effectively used as a

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

source of primary data when building a recognition system for individuals using machine learning.

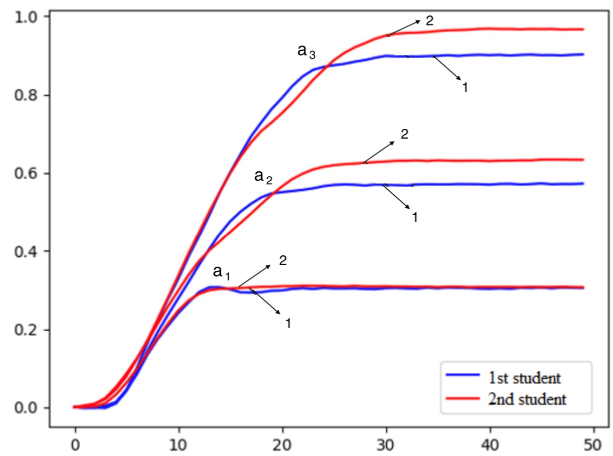

Fig. 1. Average responses of OMS of two individuals

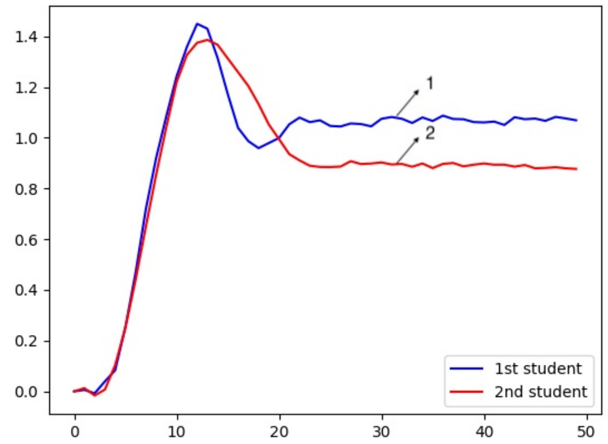

Fig. 2. Transient functions 1st orders of two individuals

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

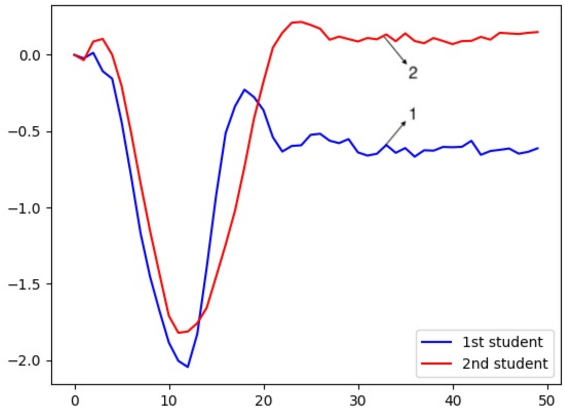

Fig 3. Transient functions 2nd orders of two individuals

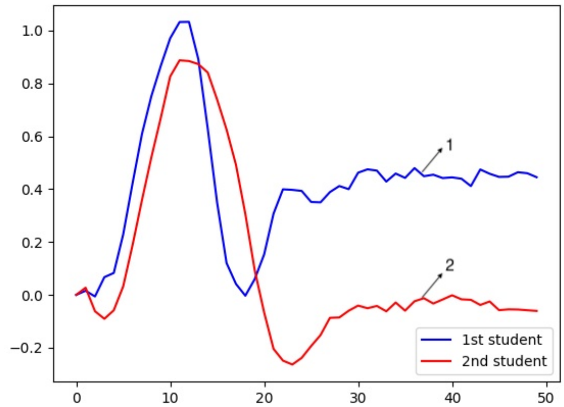

Fig. 4. Transient functions 3rd orders of two individuals

Formation of the features space based on MTF of the OMS. 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) of the Bayesian classifier is sequentially calculated based on training datasets for object classes Ω_1 (Individual #1 – 22 measuring), Ω_2 (Individual #2 – 16 measuring). To separate the two classes (dichotomy case) a discriminant function of the form is used:

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

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

where $x = (x_1, x_2, \ldots, x_n)'$ – features vector, n – features space dimensionality, m_i – mathematical expectation vector for a features of class i, $i = 1, 2$; $\mathrm{S}_i = \mathrm{M}[(\mathrm{x}-\mathrm{m}_i)(\mathrm{x}-\mathrm{m}_i)']$ – 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 (PCR) training sample objects.

The paper investigates the informativeness of the following feature space, formed on the basis of the transient functions of the first, second, and third orders of the third degree Volterra model ($N = 3$). A formal description of the features is described in Table 1 – Table 4.

Table 1

Investigated heuristic features – integral of the transient functions

#	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	$x_3 = \sum_{m=1}^{M} \lvert h_3(m,m,m) \rvert$

Table 2

Investigated heuristic features – the argument and value at maximum derivative of the transient functions

#	Features	Formal definition
1	x_4	$x_4 = \max_m h_1'(m)$
2	x_5	$x_5 = \arg\max_m h_1'(m)$
3	x_6	$x_6 = \max_m h_2'(m,m)$
4	x_7	$x_7 = \arg\max_m h_2'(m,m)$
5	x_8	$x_8 = \max_m h_3'(m,m,m)$
6	x_9	$x_9 = \arg\max_m h_3'(m,m,m)$

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

Table 3

Investigated heuristic features – the argument and value at minimum derivative of the transient functions

#	Features	Formal definition
1	x_{10}	$x_{10} = \min\limits_{m} h_1^{'}(m)$
2	x_{11}	$x_{11} = \arg\min\limits_{m} h_1^{'}(m)$
3	x_{12}	$x_{12} = \min\limits_{m} h_2^{'}(m,m)$
4	x_{13}	$x_{13} = \arg\min\limits_{m} h_2^{'}(m,m)$
5	x_{14}	$x_{14} = \min\limits_{m} h_3^{'}(m,m,m)$
6	x_{15}	$x_{15} = \arg\min\limits_{m} h_3^{'}(m,m,m)$

Table 4

Investigated heuristic features – the argument and value at the maximum transient response

#	Features	Formal definition
1	x_{16}	$x_{16} = \max\limits_{m} \lvert h_1(m) \rvert$
2	x_{17}	$x_{17} = \arg\max\limits_{m} \lvert h_1(m) \rvert$
3	x_{18}	$x_{18} = \max\limits_{m} \lvert h_2(m,m) \rvert$
4	x_{19}	$x_{19} = \arg\max\limits_{m} \lvert h_2(m,m) \rvert$
5	x_{20}	$x_{20} = \max\limits_{m} \lvert h_3(m,m,m) \rvert$
6	x_{21}	$x_{21} = \arg\max\limits_{m} \lvert h_3(m,m,m) \rvert$

Results of the research. Results of the informativeness studies of features from Tables 1 – 4 are presented below. The analysis of the reliability of personality recognition in the space of features calculated on the basis MTF consists in forming various combinations of features and evaluating their informativeness based on the classification results on the data sample under study using criterion PCR. Thus, all possible pairs of features were investigated by the exhaustive search method. For studies of the informativeness, the features presented in the tables 1 – 4 are used.

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

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:

$$\left(x_6 = \max_m h_2^{'}(m,m) \,\&\, x_{14} = \min_m h_3^{'}(m,m,m) \right)$$

or

$$\left(x_8 = \max_m h_3^{'}(m,m,m) \,\&\, x_{10} = \min_m h_1^{'}(m) \right),$$

or

$$\left(x_{10} = \min_m h_1^{'}(m) \,\&\, x_{16} = \max_m \left| h_1(m) \right| \right),$$

or

$$\left(x_{10} = \min_m h_1^{'}(m) \,\&\, x_{18} = \max_m \left| h_2(m,m) \right| \right),$$

or

$$\left(x_{10} = \min_m h_1^{'}(m) \,\&\, x_{20} = \max_m \left| h_3(m,m,m) \right| \right),$$

or

$$\left(x_{10} = \min_m h_1^{'}(m) \,\&\, x_{19} = \arg\max_m \left| h_2(m,m) \right| \right),$$

yields the PCR P=0.9211;

$$\left(x_6 = \max_m h_2^{'}(m,m) \,\&\, x_{10} = \min_m h_1^{'}(m) \right),$$

yields the PCR P=0.9474;

$$\left(x_{10} = \min_m h_1^{'}(m) \,\&\, x_{14} = \min_m h_3^{'}(m,m,m) \right),$$

yields the PCR P=0.9737.

For the task of analysing robustness of feature spaces informativeness, random samples from Gaussian distribution were created where the standard deviation of the distribution is equal to the product of the average of a feature vector and level noise (1 and 5 %). The results of robustness analysis are shown in Table 5 and Fig. 5.

Thus, these features provide robustness both at small and large noise rates.

The location of the objects of the training sample in the space of features yielding the best results is shown in Fig. 6 – Fig. 8.

Table 5

Values of PCR (%) for feature spaces at different noise level

Noise level, %	x_{10}, x_{14}	x_6, x_{10}	x_6, x_{14}	x_8, x_{10}	x_{10}, x_{16}	x_{10}, x_{18}	x_{10}, x_{20}	x_{10}, x_{19}
0	97.37	94.74	92.11	92.11	92.11	92.11	92.11	92.11
1	97.37	96.05	90.35	92.11	91.67	92.98	92.11	89.47
5	92.98	91.23	82.89	88.6	89.47	92.11	90.35	90.79

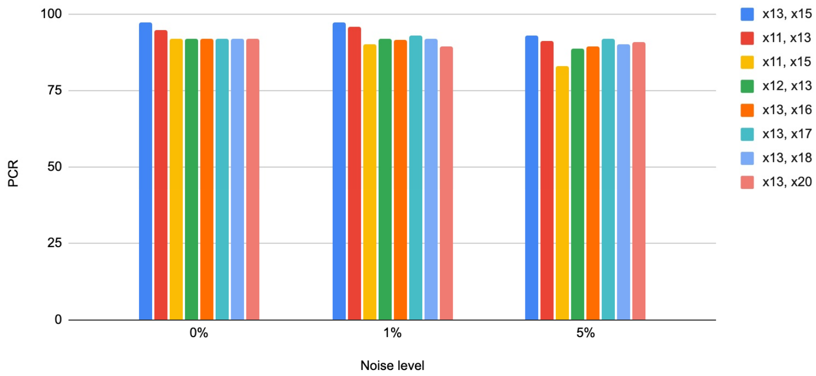

Fig. 5. Informativeness of features sets under the influence of different noise level

The most noise-robust feature spaces are as follows:

$$\left(x_{10} = \min_m h_1^{'}(m) \;\&\; x_{14} = \min_m h_3^{'}(m,m,m) \right),$$

$$\left(x_{10} = \min_m h_1^{'}(m) \;\&\; x_{18} = \max_m \left| h_2(m,m) \right| \right),$$

$$\left(x_{10} = \min_m h_1^{'}(m) \;\&\; x_{20} = \max_m \left| h_3(m,m,m) \right| \right).$$

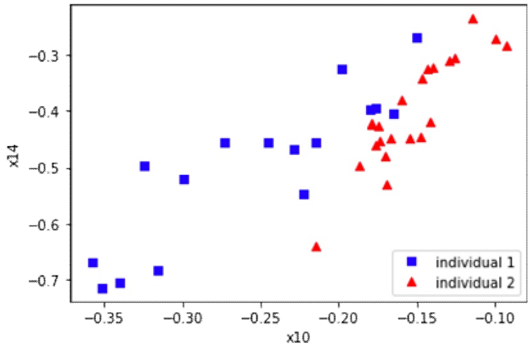

Fig. 6. The location of the objects of the training set in the space of features x_{10} and x_{14}

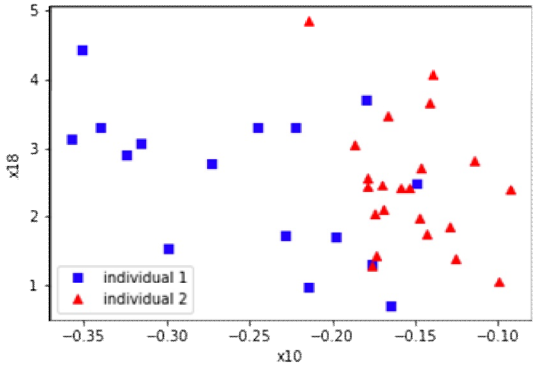

Fig. 7. The location of the objects of the training set in the space of features x_{10} and x_{18}

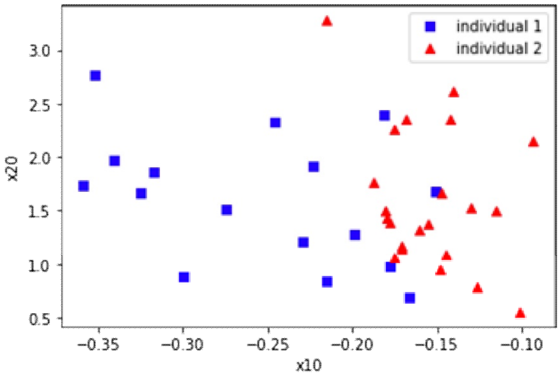

Fig. 8. The location of the objects of the training set in the space of features x_{10} and x_{20}

Conclusion. A new method of biometric identification is proposed formed on the determination of integrated Volterra models of the human OMS based upon experimental research "input-output" using innovative eye tracking technology. There is data of two respondents applied in experimental studies. More individuals' data will be involved in future study to expand the research base.

The first, second and third orders transition functions of the OMS were determined based on the data received using the Tobii Pro TX300 eye tracker [30]. Since there is a substantial difference between the diagonal intersections of the second and third order transition functions of two individuals, they can be used for feature space forming to build statistical classifiers for identity recognition. As a result, a pair of features was selected that are resistant to computational errors, which gives a high result of the probability of correct recognition.

References:

1. Resmi K.R., and Raju G. (2020), An empirical study and evaluation on automatic ear detection, *International Journal of Computing*, 19 (4), pp. 575-582.

2. Cherrat E.M., Alaoui R., and Bouzahir H. (2020), Score fusion of finger vein and face for human recognition based on convolutional neural network model, *International Journal of Computing*, 19 (1), pp. 11-19.

3. Sachenko Paliy, A., Kurylyak Y., Boumbarov O., and Sokolov S. (2009), Combined approach to face detection for biometric identification systems, *Proceedings of the 5th IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, IDAACS, pp. 425-429.

4. Labati R.D., Genovese A., Muñoz E., Piuri F., Scotti F., and Sforza G. (2016), Computational Intelligence for Biometric Applications: a Survey, *International Journal of Computing*, 15 (1), pp. 40-49.

5. Friedman L., Rigas I., Abdulin E., and Komogortsev O.V. (2018), A novel evaluation of two related and two independent algorithms for eye movement classification during reading Affiliations. *Behav Res Methods*, 50 (4).

6. Stuart S., Hickey A., Vitorio R., Welman K., Foo S., Keen D., and Godfre A. (2019), Eye-tracker algorithms to detect saccades during static and dynamic tasks: a structured review *Physiol Meas*. Feb. 26.

7. Lai M.-L., Tsai M.-J., Yang F.-Y., Hsu C.-Y., Liu T.-C., Lee S. W.-Y., Lee M.-H., Chiou G.-L., Liang J.-C., and Tsai C.-C. (2013), A review of using eye-tracking technology in exploring learning from 2000 to 2012, *Educational Research Review*, Vol. 10, pp. 90-115.

8. Brasil R.A., Andrade J.O., and Komati K.S. (2020), Eye Movements Biometrics: a Bibliometric Analysis from 2004 to 2019, *International Journal of Computer Applications*, Vol. 176, No.24, pp. 1-9.

9. Van Renswoude D. R, Raijmakers M. E J., Koornneef A., Johnson S. P., Hunnius S., and Visser I. (2018), Gazepath: An eye-tracking analysis tool that accounts for individual differences and data quality, *Behavior Research Methods*, Vol. 50 (2), pp. 834-852.

10. Wang D., Mulvey F. B., Pelz J. B. and K. Holmqvist. (2017), A study of artificial eyes for the measurement of precision in eye-trackers, *Behavior Research Methods*, Vol. 49 (3), pp. 947-959.

11. Quaia C., and Optican L.M. (2003), Dynamic Eye Plant Models and the Control of Eye Movements, *Strabismus*, Vol. 11, pp. 17-31.

ISSN 2079-0031 (Print) ISSN 2411-0558 (Online)

12. Kasprowski P., and Ober J. (2004), Eye Movements in Biometrics, *European Conference on Computer Vision*, Prague, Czech Republic, pp. 248-258.
13. Silver D.L., and Biggs A.J. (2006), Keystroke and EyeTracking Biometrics for User Identification, *International Conference on Artificial Intelligence (ICAI),* Las Vegas, NV, USA, pp. 344-348.
14. Cantoni V., Galdi C., Nappi M., Porta M., Riccio D. (2015), Gant: gaze analysis technique for human identification, *Pattern Recognition,* Vol. 48, pp. 1027-1038.
15. Sachenko A., Banasik A., and Kapczyński A. (2009), The concept of application of fuzzy logic in biometric authentication systems, *Advances in Soft Computing* , Vol. 53, pp. 274-279.
16. Yoon H.-J., Carmichael T.R., and Tourassi G. (2014), Gaze as a biometric, *SPIE Medical Imaging*, San Diego, California, United States.
17. Karpov A.V., and Komogortsev O.V. (2012), Aspects of matlab usage on computational cluster for solving of biometrics problems, *ISSN 2222-8896*, No. 1 (16), pp. 42-48
18. Komogortsev O.V., Holland C. D., Jayarathna S., and Karpov A. (2013), 2D linear oculomotor plant mathematical model: verification and biometric applications, *ACM Transactions on Applied Perception*, 10 (4), pp. 1-18.
19. Komogortsev O.V., Holland C.D., Karpov A., and Price L.R. (2015), Biometrics via Oculomotor Plant Characteristics: Impact of Parameters in Oculomotor Plant Model, *ACM Transactions on Applied Perception*, pp. 1-14.
20. Lohr D.J., Friedman L., and Komogortsev O.V. (2019), Evaluating the Data Quality of Eye Tracking Signals from a Virtual Reality System: Case Study using SMI's Eye-Tracking HTC Vive. arXiv e-prints, art. arXiv:1912.02083v1.
21. Griffith H.K., Katrychuk D., and Komogortsev O.V. (2019), Assessment of Shift-Invariant CNN Gaze Mappings for PS-OG Eye Movement Sensors, *IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*.
22. Pavlenko V., Salata D., Dombrovskyi M., and Maksymenko Y. (2017), Estimation of the multidimensional transient functions oculo-motor system of human, *Mathematical Methods and Computational Techniques in Science and Engineering*: AIP Conf. Proc. MMCTSE, UK, Cambridge, Vol. 1872, Melville, New York, pp. 110-117.
23. Shamanina T.V., Pavlenko V.D., and Chori V.V. (2021), Biometric Method of Personality Authentication based on the Eye Tracking Data, *Herald of the National Technical University "KhPI". Subject issue: Information Science and Modelling*, Kharkov: NTU "KhPI", No. 1 (5), pp. 142-152.
24. Pavlenko V.D., Shamanina T.V., and Chori V.V. (2021), Nonlinear Dynamics Identification of the Oculo-Motor System based on Eye Tracking Data, *International Journal of Circuits, Systems and Signal Processing*, Vol. 15, pp. 569-577. DOI: 10.46300/9106.2021.15.63.
25. Pavlenko V.D., Shamanina T.V., and Chori V.V. (2021), Identification of the oculo-motor system in the form Volterra model based on eye-tracking data, *EPJ Web of Conferences*, Vol. 248, 01009 (MNPS-2020), pp. 1-6.
26. Pavlenko V., Pavlenko S.. and Speranskyy V. (2014), *Identification of Systems using Volterra Model in Time and Frequency Domain*. In book V. Haasz and K. Madani (Eds.). Advanced Data Acquisition and Intelligent Data Processing, River Publishers, pp. 233-270.
27. Pavlenko V., Ivanov I., and Kravchenko E. (2017), Estimation of the Multidimensional Dynamical Characteristic Eye-Motor System, *Proceedings of the 9th IEEE Int. Conf. on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS'2017),* Bucharest, Romania, 2017, Vol. 2, pp. 645-650.
28. Pavlenko V.D., and Pavlenko S.V. (2018), Deterministic identification methods for nonlinear dynamical systems based on the Volterra model, *Applied Aspects of Information Technology*, No 01 (01), pp. 9-29.

29. Doyle F.J., Pearson R.K., and Ogunnaike B.A. (2002), *Identification and control using Volterra models*, Germany: Springer Publ, 314 p.
30. Pavlenko V., Milosz M., and Dzienkowski M. (2020), Identification of the oculo-motor system based on the Volterra model using eye tracking technology, *4th Int. Conf. on Applied Physics, Simulation and Computing (APSAC 2020)*, Rome, Italy. Journal of Physics: Conference Series, Vol. 1603. – IOP Publishing, 2020, pp. 1-8.

The article was presented by Dr. Tech. Sciences, prof. NTU "KhPI" A.A. Serkov.

Received 10.12.2021

Chori Vladyslav, Graduate student
Odessa National Polytechnical University
Ave. Shevchenko, 1, Odessa, Ukraine, 65044
Tel./phone: +3(8-096) 611-71-21, e-mail: vladyslav.chori@gmail.com
ORCID ID: 0000-0001-7823-8383

Shamanina Tatiana, Graduate student
Odessa National Polytechnical University
Ave. Shevchenko, 1, Odessa, Ukraine, 65044
tel./phone: +3(8-096) 959-65-65, e-mail: tatanatv8@gmail.com
ORCID ID: 0000-0002-3857-1867

Pavlenko Vitaliy, Dr.Sci.Tech, Professor
Odessa National Polytechnical University
Ave. Shevchenko, 1, Odessa, Ukraine, 65044
tel./phone: +3(8-048) 705-8-436, e-mail: pavlenko_vitalij@ukr.net
ORCID ID: 0000-0002-5655-4171

УДК 681.5.015.52

Побудова класифікатора в системі розпізнавання особистості на основі даних айтрекінга / Чорі В.В., Шаманіна Т.В., Павленко В.Д. // Вісник НТУ "ХПІ". Тематичний випуск: Інформатика і моделювання. – Харків: НТУ "ХПІ". – 2021. – № 2 (6). – С. 44– 58.

У статті пропонується новий метод біометричної ідентифікації користувачів комп'ютерних систем, що ґрунтується на визначенні інтегральної моделі Вольтерри окуло-моторної системи (ОМС) людини за даними експериментального дослідження "вхід-вихід" з використанням інноваційної технології айтрекінгу. За допомогою айтрекера Tobii Pro TX300 отримані дані відгуків ОМС на тестові візуальні стимули, що відображаються у вигляді яскравих точок на екрані монітора комп’ютера на різних відстанях від стартової позиції у напрямку "по горизонталі". На основі отриманих даних визначено перехідні функції першого, другого та третього порядків ОМС для двох осіб. Для побудови класифікатора особистостей досліджується інформативність запропонованих евристичних ознак, що визначаються на основі багатовимірних перехідних функцій, за показником вірогідності правильного розпізнавання (ВПР). Встановлено пари ознак, стійких до обчислювальних похибок, які мають високий показник ВПР – в інтервалі 0,92 - 0,97. Іл.: 8. Табл.: 5. Бібліогр.: 30 назв.

Ключові слова: біометрична ідентифікація; розпізнавання особистості; модель Вольтерри; окуло-моторна система; технологія айтрекінга; інформативність ознак; класифікація.

УДК 681.5.015.52

Построение классификатора в системе распознавания личности на основе данных айтрекинга / Чори В.В., Шаманина Т.В., Павленко В.Д. // Вестник НТУ "ХПИ". Тематический выпуск: Информатика и моделирование. – Харьков: НТУ "ХПИ". – 2021. – № 2 (6) . – С. 44 – 58.

В статье предлагается новый метод биометрической идентификации пользователей компьютерных систем, основанный на определении интегральной модели Вольтерры окуло-моторной системы (ОМС) человека по данным экспериментального исследования "вход-выход" с использованием инновационной технологии айтрекинга. С помощью айтрекера Tobii Pro TX300 получены данные откликов ОМС на тестовые визуальные стимулы, отображаемые в виде ярких точек на экране монитора компьютера на разных расстояниях от стартовой позиции в направлении "по горизонтали". На основе полученных данных определены переходные функции первого, второго и третьего порядков ОМС для двух человек. Для построения классификатора личностей исследуется информативность предложенных эвристических признаков, определяемых на основе переходных функций по показателю вероятности правильного распознавания (ВПР). Установлены пары признаков, устойчивых к вычислительным погрешностям и имеющим высокий показатель ВПР – в интервале 0,92 - 0,97. Ил.: 8. Табл.: 5. Библиогр.: 30 назв.

Ключевые слова: биометрическая идентификация; распознавание личности; модель Вольтерры; окуло-моторная система; технология айтрекинга; информативность признаков; классификация.

UDC 681.5.015.52

Building a classifier in the personality recognition system based on eye tracking data / Chori V.V., Shamanina T.V., Pavlenko V.D. // Herald of the National Technical University "KhPI". Subject issue: Information Science and Modelling. – Kharkov: NTU "KhPI". – 2021. – №. 2 (6). – P. 44 – 58.

The article proposes a new method of biometric identification of computer systems users, based on the determination of the integral Volterra model of the human oculo-motor system (OMS) according to experimental research "input-output" using innovative eye tracking technology. With the help of the Tobii Pro TX300 eye tracker, the data of OMC responses to test visual stimuli were obtained, displayed as bright dots on the computer screen at different distances from the start position in the "horizontal" direction. Based on the data obtained, the transition functions of the first, second and third orders of the OMS for two people were determined. To construct a personality classifier, the informativeness of the proposed heuristic features, determined on the basis of the transition functions in terms of the probability of correct recognition (PCR), is investigated. Pairs of features are established that are resistant to computational errors and have a high PCR value - in the range 0.92 - 0.97. Fig.: 8. Table: 5. Bibliography: 30 items.

Keywords: biometric identification; personality recognition; Volterra model; oculo-motor system; eye tracking technology; informativeness of features; classification.