Экспериментальная психология
2020. Т. 13. № 2. С. 153—181
DOI: https://doi.org/10.17759/exppsy.2020130211
ISSN: 2072-7593
ISSN: 2311-7036 (online)

Experimental Psychology (Russia)
2020, vol. 13, no. 2, pp. 153—181
DOI: https://doi.org/10.17759/exppsy.2020130211
ISSN: 2072-7593
ISSN: 2311-7036 (online)

ASSESSING THE AIRCRAFT CREW ACTIONS WITH THE AID OF A HUMAN FACTOR RISK MODEL

LEV S. KURAVSKY
Moscow State University of Psychology and Education,
Moscow, Russia,
ORCID: http://orcid.org/0000-0002-3375-8446, e-mail: l.s.kuravsky@gmail.com

GRIGORY A. YURYEV
Moscow State University of Psychology and Education,
Moscow, Russia,
ORCID: https://orcid.org/0000-0002-2960-6562, e-mail: g.a.yuryev@gmail.com

VALENTIN I. ZLATOMREZHEV
State Research Institute of Aviation Systems (GosNIIAS),
Moscow, Russia,
ORCID: https://orcid.org/0000-0003-1776-6881, e-mail: vizlatomr@2100.gosniias.ru

NATALIYA E. YURYEVA
Moscow State University of Psychology and Education,
Moscow, Russia,
ORCID: https://orcid.org/0000-0003-1419-876X, e-mail: yurieva.ne@gmail.com

Presented is a human factor risk model when piloting an aircraft. This model is based on comparing representations of the evaluated crew actions with the comparable action representations of various types and performance quality, which form a representative sample and are contained in a pre-formed specialized database. The risk in question is represented by probabilistic estimates, which result from consistent applications of the Principal Component Analysis, Multidimensional Scaling, and Cluster Analysis to three types of characteristics, viz.: parameters of flights and states of aircraft systems, gaze movement trajectories and time series of oculomotor activity primary indexes. These steps form the clusters of flight fragments for various types and performance quality, including abnormal ones. The Discriminant Analysis provides calculating the probabilistic profile for belonging to certain target clusters, with a final conclusion being derived from this structure. Key elements of the approach presented are three new metrics used to compare crew actions and to ensure significant discrimination for flight fragments of various types and performance quality. Detailing flight parameters contributions in differences of the flight fragments in a given metric is carried out to provide meaningful analysis of the detected abnormality causes. With sufficient computational performance, the flight data analysis under consideration can be implemented in real time automatic mode.

Keywords: human factor risk model, Principal Component Analysis, Multidimensional Scaling, Cluster Analysis, oculomotor activity indexes.

Acknowledgements: This work was performed as a part of the "SAFEMODE" Project (Grant Agreement No 814961) with the financial support of the Ministry of Science and Higher Education of the Russian Federation (Project UID RFMEFI62819X0014).

For citation: Kuravsky L.S., Yuryev G.A., Zlatomrezhev V.I., Yuryeva N.E. Assessing the Aircraft Crew Actions with the Aid of a Human Factor Risk Model. *Eksperimental'naya psikhologiya = Experimental Psychology (Russia)*, 2020. Vol. 13, no. 2, pp. 153—181. DOI: https://doi.org/10.17759/exppsy.2020130211

ОЦЕНКА ДЕЙСТВИЙ ЭКИПАЖА ВОЗДУШНОГО СУДНА НА ОСНОВЕ МОДЕЛИ РИСКОВ ЧЕЛОВЕЧЕСКОГО ФАКТОРА

КУРАВСКИЙ Л.С.
Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация
ORCID: http://orcid.org/0000-0002-3375-8446, e-mail: l.s.kuravsky@gmail.com

ЮРЬЕВ Г.А.
Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация
ORCID: https://orcid.org/0000-0002-2960-6562, e-mail: g.a.yuryev@gmail.com

ЗЛАТОМРЕЖЕВ В.И.
Государственный научно-исследовательский институт авиационных систем (ФГУП «ГосНИИАС»), г. Москва, Российская Федерация
ORCID: https://orcid.org/0000-0003-1776-6881, e-mail: vizlatomr@2100.gosniias.ru

ЮРЬЕВА Н.Е.
Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация
ORCID: https://orcid.org/0000-0003-1419-876X, e-mail: yurieva.ne@gmail.com

В статье представлена модель рисков человеческого фактора при пилотировании воздушного судна. Эта модель построена на сравнениях представлений оцениваемых действий экипажей с сопоставимыми представлениями действий различных типов и качества исполнения, образующих репрезентативную выборку и содержащихся в заранее сформированной специализированной базе данных. Риск представляется вероятностными оценками, которые строятся в результате последовательного применения метода главных компонентов, многомерного шкалирования и кластерного анализа к трем типам характеристик: параметрам полета и состояния систем воздушного судна, траекториям движения глаз и временным рядам первичных показателей глазодвигательной активности, — что приводит к формированию кластеров фрагментов полетов различных типов и качества исполнения, включая аномальные. Дискриминантный анализ обеспечивает вычисление вероятностного профиля принадлежности к целевым кластерам, на основе которого строится итоговое заключение. Ключевым элементом представленного подхода являются три новые метрики, применяемые для сравнений действий экипажей и обеспечивающие значимую дискриминацию фрагментов полетов различных типов и качества исполнения. Выполняется детализация вкладов параметров полета и состояния систем воздушного судна в различия фрагментов полетов в заданной метрике, результаты которой используются при содержательном анализе причин выявляемой аномальности. При достаточной скорости вычислений рассмотренный анализ полетных данных в автоматическом режиме может быть выполнен в реальном времени.

Ключевые слова: модель рисков человеческого фактора, метод главных компонентов, многомерное шкалирование, кластерный анализ, показатели глазодвигательной активности.

Благодарности: Эта работа выполнена как часть проекта «SAFEMODE» (грант № 814961) при финансовой поддержке Министерства науки и высшего образования Российской Федерации (проект UID RFMEFI62819X0014).

Для цитаты: *Куравский Л.С., Юрьев Г.А., Златомрежев В.И., Юрьева Н.Е.* Оценка действий экипажа воздушного судна на основе модели рисков человеческого фактора // Экспериментальная психология. 2020. Том 13. № 2. С. 153—181. DOI: https://doi.org/10.17759/exppsy.2020130211

Introduction

An objective assessment of the piloting performance is important for assessing the risks associated with the Information Management Field (IMF) of the cockpit, optimizing IMF and training the crews. One of the critical issues in this regard is the development of evaluation criteria. Data based on the characteristics of crew actions can be used to objectively assess the effectiveness of training and the skills acquired as a result. Thus, it is relevant to develop methods of computerized diagnostics, which can be used during the selection of flight crews to assess the level of acquired knowledge, abilities and skills. These methods will help to improve objectivity, informativeness and accuracy of evaluations, as well as to ensure standardization and automation of measurements. Of particular importance are the development and analysis of new approaches that can be used to assess the level of training and the psychophysiological condition of pilots. The main direction is diagnostics on the results of work on modern *simulators and benches*, where it is possible to repeat the special conditions of pilots' work.

Risk is understood as a measure of the quantity of danger measured in the form of an expert value of a combination of two values — normalized frequency or a measure of the possibility of accidental occurrence of dangerous events and possible generalized damage from these events [14]. The classic approach to quantitative evaluation of piloting risks is based on the evaluation of the probability of crew errors, the value of which changes depending on different conditions and circumstances.

The analysis of the concepts and technologies used today to reduce the risks and severity of the consequences of aviation incidents shows a significant interest of the professional community in various aspects of flight safety. With the complication of aviation equipment and the increasing number of flights, it is possible to form accident prevention concepts based on mathematical and probabilistic models, using detailed information about both the parameters of aircraft piloting and the status of pilots, air traffic controllers and other crew members.

It is important to note that risk assessment approaches that require the use of multiple and difficultly identifiable parameters of aircraft and their systems have no prospect of practical application, as errors in the assessment of these parameters, as well as the generally uncertain sensitivity of the assessment result to variations in these parameters, make these approaches extremely unreliable. The structural stability of risk assessment models is usually not even discussed.

Big problems in practice create calculation models that require detailed risk assessment for aircraft subsystems. As at the decision of a problem it is necessary to consider a considerable quantity of interacting systems, it leads to search of numerous variants of behaviour of difficult technical system that unacceptably complicates the analysis.

Approaches based on statistical analysis of large samples, including data on the failure of individual systems, allow for the identification of trends, but do not allow for certain predictions in a particular practical situation, which significantly limits the possibility of application.

In addition, the transition from one aircraft type to another requires, for most of the approaches considered, an almost complete redesign of the entire calculation model.

Unfortunately, almost all previously developed methods have one or more of the listed disadvantages.

If to proceed from criteria of simplicity of practical application, absence of a binding of estimated model to the concrete type of an aircraft (universality) and absence of necessity to investigate in detail labor-consuming problems of sensitivity and structural stability of estimated models, it is expedient to build models of an estimation of risks of piloting on the direct analysis of measured parameters of flight and integral estimations of fragments of flight as a whole, without detailed elaboration on parameters (lacks of such detailed elaboration are considered in the subsequent article), as well as video oculography data to reliably assess the impact of the Cockpit IMF on piloting efficiency. One of variants of such approach is described in this work.

By now, a certain amount of results related to selection of abnormal exercise implementations has been accumulated [1—2; 5; 7—13; 15—16; 31—33; 37; 39—40]. The vast majorities of them consider aircraft trajectories only. Significant limitations that restrict the application of these results in practice are discussed in [28-30]. It should be noted that one of the principal weaknesses of the techniques in question is applying traditional metrics for comparing flight fragments since these metrics failed to solve the problem under study as well as related problems.

Since pilots are mentioned and because one of the most popular, but the least effective method for simple assessing the piloting quality is to check whether certain parameters are in the given critical value ranges for the specified flight modes, comments on this topic are unavoidable. Validity of such a technique is best clarified by the following analogy: it looks like an attempt to assess the quality of car driving via the number of collisions with a fence along the road, with all the other information about the car movement being ignored. It is obvious that the effectiveness and relevance of such evaluations do not hold water.

All the limitations presented above are overcome with the aid of the techniques [28—30]. The following is a way to assess skills using experimentally relevant data on piloting. As a result of their application, skill classes are determined using flight parameters identified during the exercises. *Flight parameters* are further defined as measured characteristics that determine the movement and condition of aircraft systems.

To analyze the data on piloting, a specialized database is needed, which collects *patterns* of their activities, characterizing the performance of exercises by pilots with different levels of training. A *pattern* is defined as the representation of a certain fragment of the analyzed activity, called an *exercise*, using a set of relevant parameters. These patterns correspond to one of the recognized levels of skill formation.

The data collected in the database should include exercise parameters as well as relevant comments containing expert evaluations from various sources, including different types of simulators and benches, virtual reality systems, and the results of real work. Expert comments should identify weaknesses in crew performance, covering typical errors in terms of activity parameters and advice to the instructor on how to correct these weaknesses.

The general assumption for the approaches under consideration is that the activities implemented in different styles and quality as well as exercises of different types can be discriminated in the multidimensional space formed with the aid of the wavelet coefficient metric or the likelihood metric of eigenvalue trajectories for activity parameters transforms. This statement is proved by computer experiments based on relevant empirical data. The general method that results from this conclusion is the pattern selection.

These approaches can be used to support pilot training, to generate instructor-led evaluations, and to provide automatic real-time evaluation of piloting quality. These analysis methods differ significantly from the probabilistic methods applied for system control, predictive diagnostics of technical failures, condition monitoring and activity support of pilot [18].

Human factor risk assessment in aircraft piloting

Since risk is understood as a measure of the quantity of danger, the human factor risk model in piloting an aircraft is actually a risk assessment model. The developed human factor risk assessment model related to the cockpit IMF is shown in Figure 1. This model is based on comparing the views of the evaluated actions of the crews with comparable views of actions of different types and quality of implementation, forming a representative sample and contained in a pre-formed specialized database.

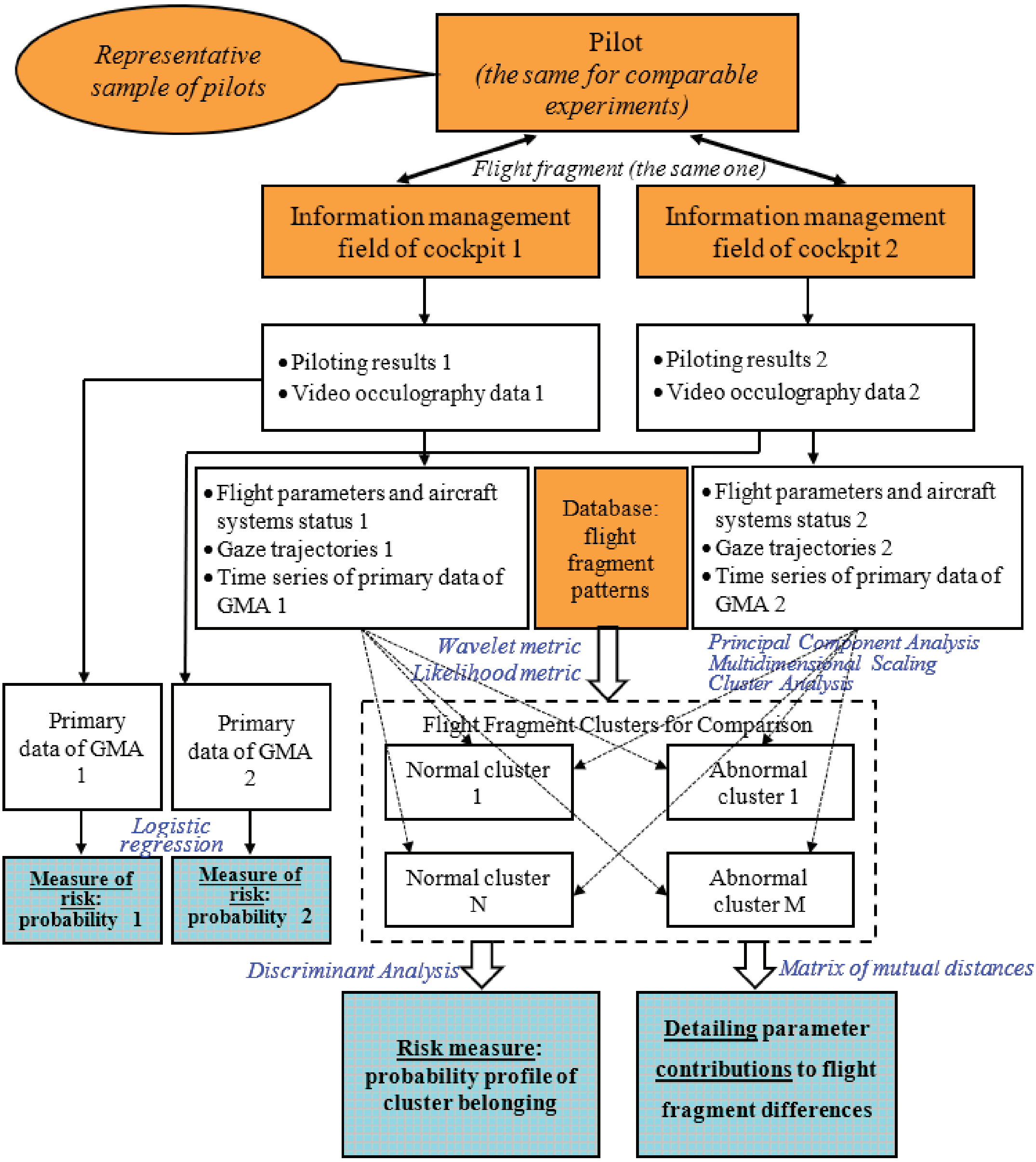

Fig. 1. A model for assessing the human factor risks associated with cockpit IMF in aircraft piloting

The risk is represented by probabilistic estimates which are constructed as a result of consecutive application of the Principal Component Analysis, Multidimensional Scaling and Cluster Analysis to three types of characteristics:

— Flight parameters and aircraft systems status,

— Gaze trajectories and

— Time series of primary data of gaze motor activity (GMA), which leads to the formation of clusters of flight fragments of various types and quality of performance, including abnormal.

The common discriminant analysis provides the calculation of the probability profile of belonging to the target clusters on the basis of which the final conclusion is built.

Key elements of the approach in use are three new metrics providing significant discrimination for flight fragments of different types and implementation quality, namely: the Euclidian metric and the Kohonen metric for wavelet representations of different crew activity variants, as well as the likelihood metric for eigenvalue trajectories of activity parameters transforms, without which the Multidimensional Scaling and Cluster Analysis would not give the acceptable result. Detailed contributions of flight parameters and the state of aircraft systems to the differences in flight fragments in a given metric are made, the results of which are used in a substantial analysis of the causes of the detected anomaly.

As a simplified alternative approach, risk probability can also be estimated from GMA primary data using *the logistic regression*.

Analysis of crew activity parameters represented by discrete wavelet transforms of their time series

It is assumed that a crew activity is represented by a set of time series describing the dynamics of technical system parameters as well as, if possible, the pilot's state. Both principal steps and connections of the analysis performed according to the proposed approach are presented in Figure 2.

Among the purposes of this analysis are:

— Support of the outcome grading for current activity by means of its comparing with the activity patterns collected beforehand in the corresponding record database;

— Recognition of abnormal activity and detection of the parameters characterizing pilot mistakes to reveal the sources of abnormality.

As preliminary processing, selections of time intervals for exercise comparison and data normalization are carried out.

The redundant information is eliminated using *Principal Component Analysis* [36; 41]. To do so, matrices of mutual correlations of time series values are computed, the algebraic problem of eigenvalues is solved and it is figured out to what extent it is possible to decrease the dimension of eigen subspace of the researched parameters so that this would contain a sufficiently representative part of variability of the observed parameters. For each of the selected eigendirections of this subspace (principal components), for one of the highest component loads *a representative is elected from registered parameters (transition to the basis of principal components is impractical due to uncertain substantial interpretation of principal components and, in a number of applied tasks, due to no precise synchronization of researched processes for different exercises in time)*. The purpose of this stage is to find out only relatively independent characteristics replacing groups of significantly dependent representatives with only one characteristic parameter to avoid distortions stipulating to combined effect of strongly dependent characteristics in the subsequent phases.

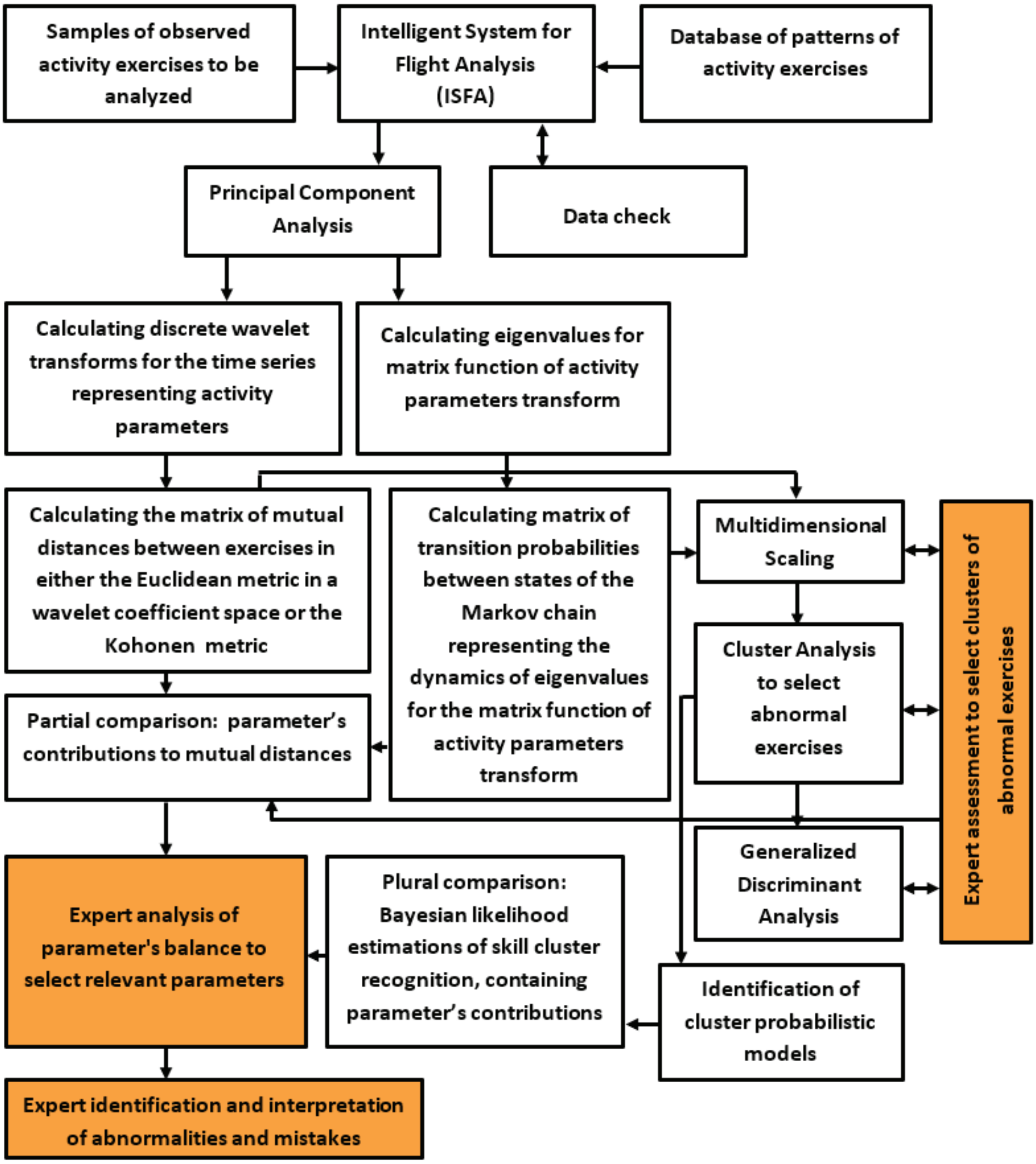

Fig. 2. The main steps of analysis and their connections (expert actions are painted over)

Time series representing the training processes under study are replaced with series of wavelet coefficients obtained as a result of *the Multiresolution Analysis* [35]. In this case, the original processes as functions of time are replaced with the integral characteristics of the time intervals, which are associated with these functions domain. In addition, significant saving (for about an order of magnitude) in the number of coefficients necessary for a correct representation of these process becomes available. *Due to the rules for assigning wavelet coefficients to time series fragments, which are in use in multiresolution analysis, problems associated with the need to precisely* *synchronize processes relating to various same-type training exercises in time have been cancelled since the most significant coefficients relating to relatively long time intervals are almost insensitive to moderate time shifts.*

For the exercises under study, one should either calculate a matrix of mutual distances between wavelet representations of different crew activity variants in the Euclidean and Kohonen metrics or apply the method where similar matrices associated with the observed activity fragments are calculated in the probability trajectories of eigenvalues. Matrices of mutual distances for all considered parameters are added to form the total matrix of mutual distances between the exercises under study. When analyzing the abnormally performed exercises, relative contributions of activity parameters to the elements of matrices of mutual distances are calculated, which makes it possible to determine the parameters characterizing pilot errors in order to identify the causes of the abnormality.

For the analysis of the mutual position of the exercises in the space of acceptable dimension, after calculating the matrix of mutual distances, a *multidimensional scaling* is performed [3,38]. The calculated distribution of the analyzed exercises in a constructed scaling space is further used to determine the distances between the exercises when drawing the diagnostic conclusions. The dimension of a scaling space is determined by the criterion of sufficient differentiation of the exercise samples related to different recognizable classes. The aim of this step is subsequent discrimination between the exercise types and normal/abnormal activity implementations in a scaling space.

The *Cluster Analysis* of patters in the obtained scaling space is performed to reveal clusters representing various types of exercises and operator skill classes. Obtained results provide possibility for creating certain classification rules to separate different scale levels of trial quality assessment in a scaling space. Wherein cluster differences for an exercise type can be explained by the exercise implementation resulted from individual skills.

Probabilistic models represented by Markov random processes with discrete states and continuous time for each pattern cluster are created using the identification procedure to represent probabilistic dynamics for each operator skill class to forecast probabilistic class behavior [6; 19—26; 34].

Computations of distances to pattern cluster centers or to the nearest patterns are based on results of performing a sequence of test exercises. If the pattern sample size is fairly large, distances are defined to centers of cluster patterns. These are computed based on the multidimensional scaling data obtained earlier. If pattern samples are small, the nearest pattern is defined, which definition may be done in two ways: either immediately through the computing of the pattern being nearest of wavelet representation or through the identifying of the pattern in the resulting scaling space, with such pattern being nearest.

So, three ways of skill class assessments are available:

— Direct comparison of current exercises with the activity database patterns in the wavelet representation metric associated with observed exercises, which is considered as a basic technique, as well as on

— Probabilistic assessment of skill class recognition via the Generalized Discriminant Analysis using sample distribution functions of exercise distances to cluster centers in a scaling space, which is considered as a supportive technique, and

— Bayesian likelihood estimation (selecting a skill class with the aid of probabilistic profile of staying in activity parameter ranges), which is also considered as a supportive technique.

Wherein, the actions, which an expert is responsible for, are:
— Assessment to select clusters of abnormal exercises;
— Analysis of parameter's balance to select relevant parameters to be under study;
— Identification and interpretation of abnormalities and mistakes.

The *Intelligent System for Flight Analysis (ISFA)* [27] implementing the developed techniques with the aid of the *LabVIEW* [4] graphical programming system provides the required calculations.

The Euclidian wavelet metric for various crew activities and the eigenvalue trajectory likelihood metric for activity parameter transforms are discussed in details in [28-30]. A description of the Kohonen metric developed after the publication of these papers is represented in the next section.

An example of the practical application of the approach under consideration, demonstrating the automatic real-time assessment of piloting risks, is represented in the Annex.

The Kohonen metric in a wavelet coefficient space

Calculating the Kohonen metric values in a wavelet coefficient space is performed with the aid of the Self-Organizing Maps (SOM), or Kohonen networks [10; 17]. Each parameter of the crew requires its own Kohonen Self-Organizing Map. The input layers of these structures receive wavelet coefficient representations of activity parameters. The output layers (topological maps) form rectangular matrices composed of elements on radial basis functions (Figure 3). When each element of a training sample is sequentially processed, the neuron closest to it in the Euclidean metric (or the "winning" neuron) is selected.

Then, taking the weighted sum of the former center of the selected radial element and the training sample element under consideration the parameters of the winning neuron and neurons from its vicinity are corrected so that they become more similar to the input, moreover, the implemented "shift" of the centers of neurons is made quite small. This vicinity is compressed to zero during the training process. As a result of a sequence of such corrections, certain parts of a topological map are "dragged" towards training sample elements and similar inputs activate sets of closely lying neurons of topological maps. Thus, a SOM learns to "understand" the structure of the input data. Those maps idea came by analogy with the associative properties of the human brain.

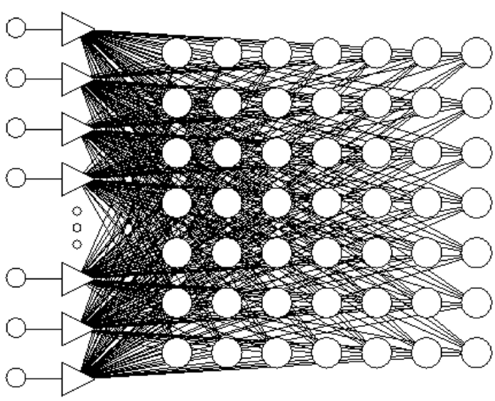

Fig. 3. The input and output layers of a Self-Organizing Map

A mutual distance between wavelet representations of a pair of source processes for different operator activities is determined as the mean for the two following differences:

— Between the SOM distance from the first process to its "winning" neuron and the SOM distance from the second process to the detected "winning" neuron of the first process and, vice versa,

— Between the SOM distance from the second process to its "winning" neuron and the SOM distance from the first process to the detected "winning" neuron of the second process.

The total mutual distance is the sum of corresponding distances for all crew activity parameters. Therefore, as for the Euclidean metric in a wavelet coefficient space, estimations of relative contributions of activity parameters in the elements of the mutual distances matrices are also available.

An example illustrating the effectiveness of using the three metrics under consideration when comparing flight fragments of different types is discussed in the next section.

Comparison of the metrics under consideration: a case study

To illustrate application efficiency of the metrics in question, presented hereinafter is a case study for 34 demonstration flight exercises belonging to five groups, which are conventionally called "Upset Recovery", "Wind Shear", "Single engine approach", "Engine fail", and "Flying around". These exercises were performed at the Aircraft Cockpit Universal Prototyping Bench of the State Research Institute of Aviation Systems (GosNIIAS) (Fig. 4). The matrices of mutual distances, which are calculated using the Euclidean and Kohonen metrics in a wavelet coefficient space, show definitely by sight substantial differences between the groups of exercises under study in all cases (Fig. 5 a, c). The matrices calculated via the likelihood metric also show these differences, however they are not so clearly expressed (Fig. 5b).

Fig. 4. The Aircraft Cockpit Universal Prototyping Bench of GosNIIAS

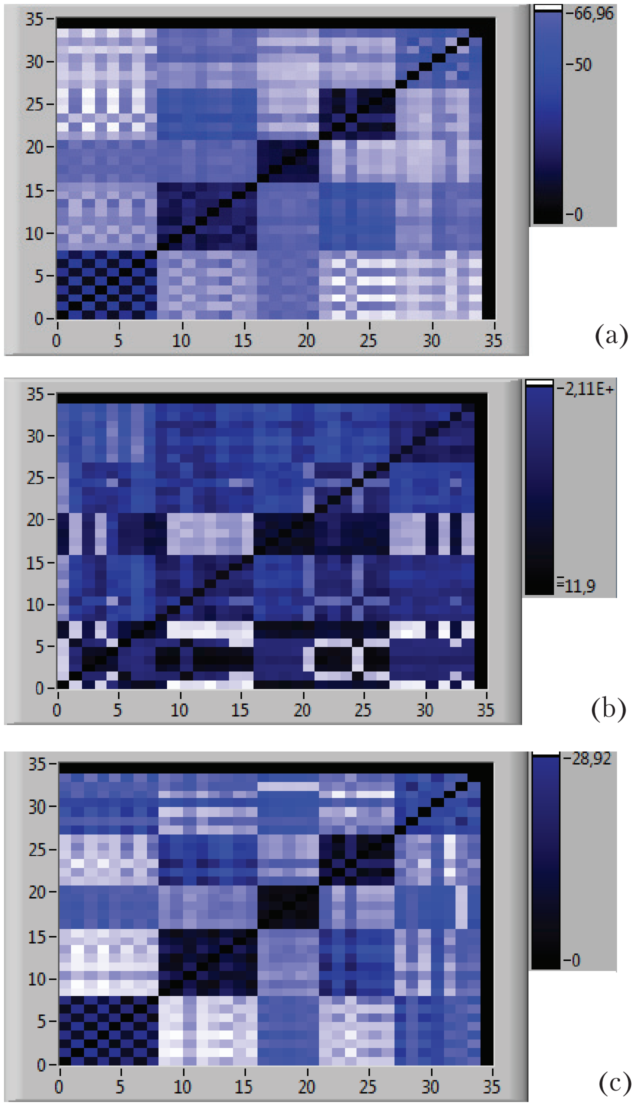

Fig. 5. Matrices of mutual distances for five groups of 34 demonstration flight exercises, which are obtained with the aid of: (a) the Euclidean metric in a wavelet coefficient space; (b) the likelihood metric; (c) the Kohonen metric in a wavelet coefficient space

Point representations of the flight exercises, which are resulted from the Multidimensional Scaling, are presented in Fig. 6. To evaluate quantitatively the quality of discrimination between the given groups of exercises, *the Wilks Lambda* (*L*) statistic can be applied to these point representations in the scaling spaces. Its values lie in interval [0;1], with the proximity to zero indicating good discrimination, and the proximity to one indicating poor discrimination. Since tables of the Wilks statistic distribution, which are available by now, are not accurate and complete enough, the more investigated the *F-ratio* (called *the associated F-statistic*), in which the Wilks statistic is recalculated, is used for testing the hypothesis of means equality for the groups under study.

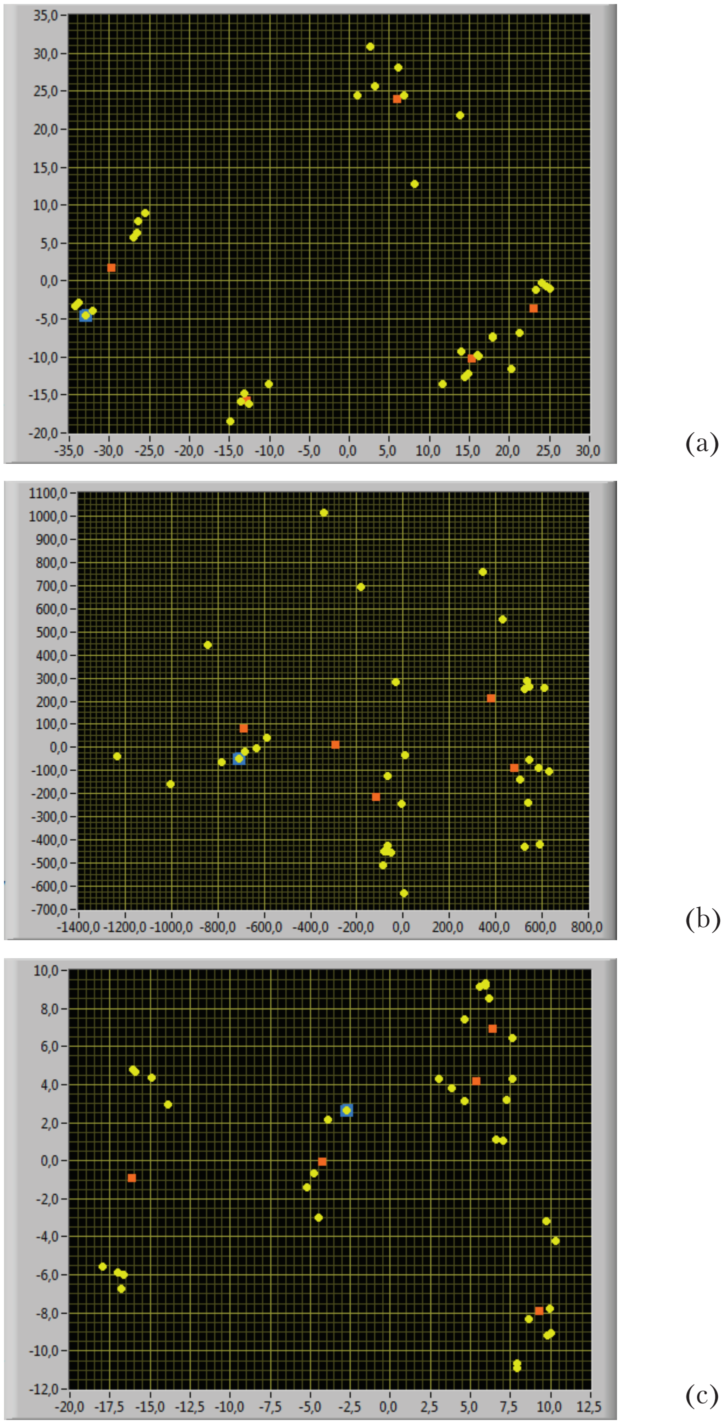

Fig. 6. Point representations for five groups of 34 demonstration flight exercises, which are resulted from the Multidimensional Scaling in case of: (a) the Euclidean metric in a wavelet coefficient space; (b) the likelihood metric; (c) the Kohonen metric in a wavelet coefficient space

Values of these statistics, which are shown in Table 1, confirm that the Euclidean and Kohonen metrics yield highly significant discrimination between exercises of different types for these case studies, whereas the likelihood metric results in sufficiently significant discrimination overall. The Fisher linear discriminant analysis shows slightly smaller number of wrong recognitions in case of the Kohonen metric (zero vs one). In total, the Euclidean and Kohonen metrics which are constructed in completely different ways look about the same at the given case studies.

Table 1

Evaluating the quality of discrimination between the given groups of exercises for the Euclidean, likelihood and Kohonen metrics: the Wilks Lambda and the associated F-statistic

	Euclidean metric in a wavelet coefficient space	**Likelihood metric**	**Kohonen metric in a wavelet coefficient space**
Wilks Lambda: 5 groups of 34 flight exercises	*0.0015*	*0.34*	*0.0016*
Associated *F*-statistic (F (*8,56*)): 5 groups of 34 flight exercises	*174.5* (*p<<0.0001*)	*5.07* (*p< 0.0001*)	*170.2* (*p<<0.0001*)

Despite these comparisons, taking into account the significantly different nature of metrics, it is reasonable not to choose one or two of them, but to use them in parallel, juxtaposing the results.

Simplified approach: assessing risk probability of making a wrong decision basing on primary GMA parameters using the logistic regression

Assessing risk probability of making a wrong decision is clearly associated with the probability of making the right decision leading to the elimination of a critical situation.

This index is estimated in two steps:

Identifying how this probability depends from a certain parameter that is available for estimations based on experimental data

Performing measurements to estimate the above specified parameter with the aid of a pilot gaze tracking system.

The duration of a correct response is further considered as such a specified characteristic.

Let us assume that $R = t_{r0} + t$ where R — duration of overcoming the critical flight situation, t_{r0}— duration of both reading and processing information from the cockpit indicators by a pilot, t — duration of the response.

Let us suppose that in case of sufficiently large time interval, the probability of a correct response can be expressed using the G. Rasch [25] model which is represented with the aid of the logistic function (Fig. 7):

$$p(\Delta) = \frac{e^{a\Delta}}{1 + e^{a\Delta}}$$

where $\Delta - C(t) - D$; $C(t)$ — ability of the correct response, which is represented in the *logit scale*; D — difficulty of a task (situation) , which is also represented in the logit scale; a — parameter (its real empirical value is *1.7*).

Both the ability to make the right decision and the difficulties of tasks (situations) are measured in a single dimensionless *logit scale*, which expresses the proportion of correct and incorrect actions during observations. The conversion into the logit scale is made by a formula:

$$L = ln\frac{r}{1-r}$$

where L — is the value in the logit scale, r — is the probability of correct exercise implementation. In case of evaluation of difficulty this parameter characterizes the possibility of performing a certain exercise for the whole variety of subjects, and in case of evaluation of abilities — the results of a certain subject for the whole variety of acceptable exercises. Statistical approximations of the given values are obtained after replacement in the given formula of probability r with its sampled estimations.

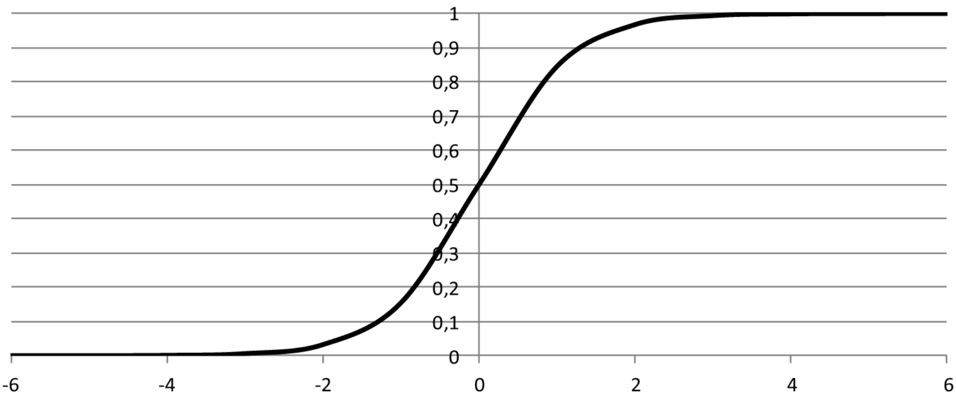

Fig. 7. The G. Rush model represented by the logistic function

A similar logistic function (Fig. 8) can be used to represent the dependence of the ability of the correct response $C(t)$ from the duration t of response deliberation:

$$C(t) = C_{max}\left(\frac{e^{f(t-t_{cr})}}{1+e^{f(t-t_{cr})}} - 0,5\right)$$

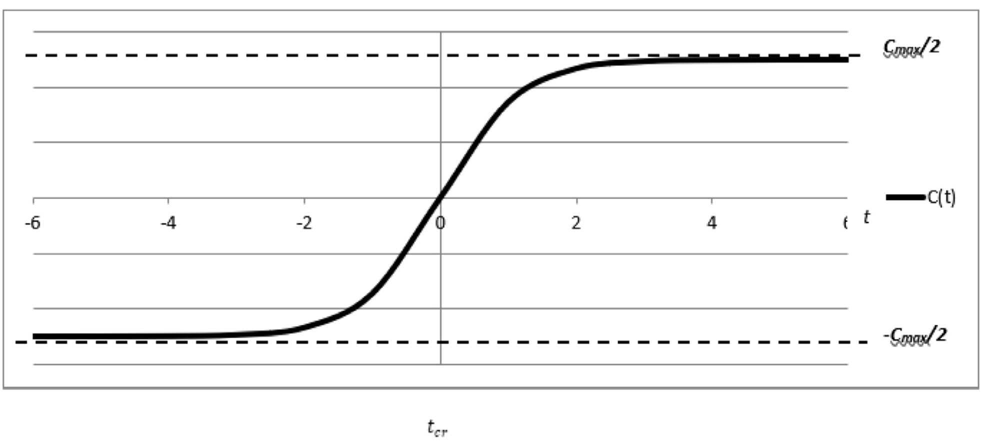

Fig. 8. Dependence of ability of the correct response from the duration of deliberation responses

The quantity t_{cr} represents individual pilot's characteristics.

Further, let us assume that the quantities t and t_{cr} are dimensionless and measured in the *logit scale*:

$$t = \ln\left(\frac{t_{dim}}{t_{cr,dim}}\right)$$

where t_{dim} — dimensional time, $t_{cr,dim}$ — dimensional critical time value.

In this case, $t_{cr} = 0$,

$C(t) = C_{max}\left(\frac{e^{ft}}{1+e^{ft}} - 0{,}5\right)$, C_{max} and f are the parameters to be identified.

The following representations of observation results are in use:

1) Matrix $\mathbf{M_1}$ of the response correctness at $t>>t_{cr}$;

2) Matrix $\mathbf{M_2}$ of the response correctness at t values having the order of magnitude of t_{cr} (it is assumed that the times of response t_{ij} are known for each pilot i and task j).

Matrices of the response correctness have form (one represents the correct decision, and 0 — the wrong one):

G_i — pilots,
T_i — training

	T_1	T_2	…	T_{n-1}	T_n
G_1	0 | 1	0 | 1	0 | 1	0 | 1	0 | 1
G_2	0 | 1	0 | 1	0 | 1	0 | 1	0 | 1
…	0 | 1	0 | 1	0 | 1	0 | 1	0 | 1
G_{m-1}	0 | 1	0 | 1	0 | 1	0 | 1	0 | 1
G_m	0 | 1	0 | 1	0 | 1	0 | 1	0 | 1

Let us consider the estimation of quantity a to be determined. Using matrix $\mathbf{M_1}$, the corresponding difficulty D_j is estimated for each task T_j via the frequency of correct responses. The ability $C_{max,i}$ is estimated for each pilot i by the maximum likelihood method (MLM) using the given known parameter a (one-parameter optimization).

Using matrix $\mathbf{M_2}$ and abilities $C_{max,i}$, which are found with the aid of matrix $\mathbf{M_1}$, one can use the f values from a specified range with the step that is equal to a specified accuracy to find the $t_{cr,i}$ values for each pilot i by MLM. Comparing the MLM-estimations (logarithms of the likelihood functions) of all pilots in the table for the considered f values, one is to obtain the maximum likelihood mean estimation of parameter f.

Let us assume that R — duration of a critical situation under study and $t_{r0} = q_0R$ — duration of reading information from indicators ($0 < q_0 < 1$) before training procedure. Let us suppose that duration of reading information has been changed in q times as a result of training: $t_r = qq_0R$ where $0 < q < 1$. Then the duration of response deliberation is to be changed in r times where

$$r = \frac{R - qq_0R}{R - q_0R} = \frac{1 - qq_0}{1 - q_0}$$

Let us denote the old duration of response deliberation as t and the new duration of response deliberation as $t^* = rt$. In this case

$$C(t) = C_{max}\,\frac{e^{f(t-t_{cr})}}{1+e^{f(t-t_{cr})}} = C_{max}\,\frac{e^{f(\frac{t^*}{r}-t_{cr})}}{1+e^{f(\frac{t^*}{r}-t_{cr})}} = C_{max}\,\frac{e^{\frac{f}{r}(t^*-rt_{cr})}}{1+e^{\frac{f}{r}(t^*-rt_{cr})}} = C(t^*).$$

Thus, at the transition to the new time scale after the training session, f is replaced by $\frac{f}{r}$, and t_c — by rt_{cr}. In the logit scale, the expression is even simpler:

$$C(t^*) = C_{max}\,\frac{e^{\frac{f}{r}t^*}}{1+e^{\frac{f}{r}t^*}}\,.$$

To simplify, one can assume that C_{max} is identified as a common parameter for all pilots.

Let the values of q and q_0 to be known and the parameters C_{max} and f to be identified with the aid of matrices $\mathbf{M}_1$ and $\mathbf{M}_2$. Assuming duration of response deliberation to be some free parameter, one can calculate values of the G. Rasch function

$$p(C(t) - D) = \frac{e^{a(C(t)-D}}{1+e^{a(C(t)-D}}$$

for various time values t and values of task difficulties D belonging to a certain reasonable range (for example $D \in [-3; 3]$) with a specified step in cases of old and new durations of reading information from indicators, with the results being presented in the form of two graphs of 3D-surfaces $p(t, D)$ to be compared.

Assuming the value $t - t_{cr}$ to be normally distributed with determined parameters (mean is equal to zero; standard deviation is estimated using the observed data, which determine t_{r0}, and the known R value), one can estimate mean values of $p(C(t,) - D)$ for each value of difficulty D in cases of the old and new durations of reading information and compare two obtained graphics $p_{mean}(D)$. This makes it possible to estimate how the probability of correct responses changes for various tasks (situations) after the training session due to both changes in the duration of reading information and improving ability of correct responses. This indicator can be used as a principal quantitative characteristic of training effectiveness. In addition, one can use the shift of mean *duration of response* t_{mean} for an available sample of pilots, which results from a training session, as an additional indicator. Statistical significance of this shift can be evaluated with the aid of parametric and nonparametric fit tests for the corresponding samples.

Results of the experiments based on the airplane TU-204 simulator revealed that keeping the aircraft at the desired trajectory in the approach mode yields the frequency of pilot's gaze transitions from one parameter under observation to another, which is equal to 130—150 movements per minute. Assuming that the mean time of gaze fixation is equal to *300 ms*, estimation of the q_0 value can be taken as

$$\frac{140 \times 300\ \text{мс}}{60 \times 1000\text{мс}} = 0{,}7\ .$$

in the first approximation. The q values can be checked in a reasonable range, selecting the level, for which a reasonable increase in the probability of correct responses for the given tasks (situations) is achieved.

The duration t_{r0} of both reading and processing the indicators information in the first approximation can be estimated as the sum of durations of the gaze fixations during a critical situation with the upper limit of *320 ms* (i.e. the fixations which duration exceeds *320 ms* are recorded as *320 ms* fixations). The experiments showed that individual characteristics of the pilots had rather weak influences on this feature.

An example of the logistic regression for risk assessment on one of the primary GMA parameters is shown in Fig. 9. The analyzed GMA parameter was the time spent on thinking over the situation, planning actions and making decisions, estimated by the duration of gaze fixation during the reading and interpretation of indicator data (when the gaze is directed at the devices, not at the cockpit window). The logistic regression parameters were identified using the *method of maximum likelihood*.

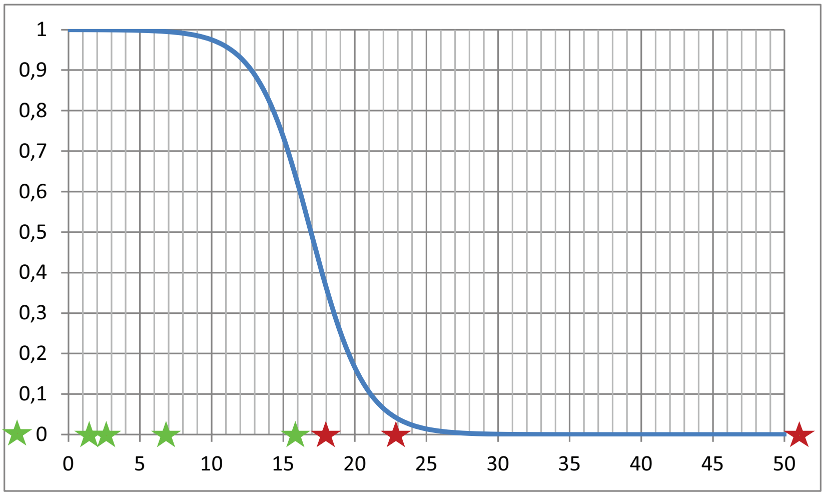

Fig. 9. The logistic regression to assess the probabilities of making the right decision basing on the duration of gaze fixation during the reading and interpretation of indicator readings (green stars correspond to successfully performed exercises and red stars correspond to unsuccessful attempts; on the abscissa axis the indicator under study is placed)

Principal results and conclusions

1. A human factor risk model has been developed for piloting an aircraft. This model is based on comparing the views of evaluated actions of crews with comparable views of actions of different types and implementation quality, forming a representative sampling and contained in a pre-formed specialized database. The risk is represented by probabilistic estimations which are built as a result of consistent application of the Principal Component Analysis, Multidimensional Scaling and Cluster Analysis to three types of characteristics: flight parameters and state of aircraft systems, eye trajectories and time series of primary indicators of gaze-tracking activity — which leads to formation of clusters of flight fragments of different types and quality of performance, including abnormal ones. The discriminant analysis provides the calculation of the probability profile of belonging to the target clusters, on the basis of which the final conclusion is built.

2. Key elements of the approach in use are three new metrics providing significant discrimination for flight fragments of different types and implementation quality, namely: the Euclidian metric and the Kohonen metric for wavelet representations of different crew activity variants, as well as the likelihood metric for eigenvalue trajectories of activity parameters transforms, without which the Multidimensional Scaling and Cluster Analysis would not give the acceptable re-

sult. Considering the different nature of the three applied metrics, it is reasonable to use them in parallel, comparing the results obtained.

3. Detailing contributions of flight parameters and state of aircraft systems to the differences of flight fragments in a given metrics is performed, which results are used for substantial analysis of the detected anomaly reasons.

4. As a simplified alternative approach, the risk probability is estimated from the primary indicators of pilot gaze tracking activity using the logistic regression.

5. The obtained results allow to create classification rules for division of different quality levels of exercises, as well as their types in a scaling space, with the differences between clusters of different variants of performing the same exercises explained by the fact that their implementation is determined by individual skills.

6. The evaluation of piloting risks comes down to determining the probabilities of belonging to target clusters related to the types of exercises and the quality of piloting.

7. With sufficient calculation speed, the considered analysis of flight data in automatic mode can be performed in real time.

Annex

Practical application example: automatic real-time assessment of piloting risks

The following are the stages of analysis of a given (performed) exercise in automatic mode, using a database of patterns containing five qualitatively different groups of flight fragments, consisting of 34 normally and abnormally performed flight exercises, performed at the Aircraft Cockpit Universal Prototyping Bench of the State Research Institute of Aviation Systems (GosNIIAS). Piloting risk assessment was performed in the process of performing a given flight exercise (32 seconds of flight), immediately after its completion (64 seconds of flight) and after a certain time after the completion of the exercise (128 seconds of flight). The analysis was automatically performed using a special version of Intelligent System for Flight Analysis (ISFA 2.1).

During the analysis of a given flight exercise, the following operations were performed:

- **32 seconds of flight:**

— Parameters representing principal components have been defined (Fig. 10);

— The matrices of mutual distances between the flight exercise implementations in the wavelet coefficients metric and the likelihood metric for eigenvalue trajectories of activity parameters transforms have been calculated (Fig. 11);

— The flight fragments from the database of patterns, which in the specified metrics are the closest to the given exercise, are defined, and the type of the exercise (“Upset recovery”) and its quality (“Wrong implementation” — abnormal) are defined according to the information corresponding them in this base (Fig. 12);

— As a result of consistent implementation of the Multidimensional scaling, Cluster Analysis and Discriminant Analysis, the distribution of flight exercises in a scaling space, the results of their clustering and assessment of the probabilities of belonging of a given exercise to each of the considered clusters, with the probability estimation for belonging to the “Upset recovery” type being equal to 0.89 (Fig. 13);

- **64 seconds of flight:**

— Parameters representing principal components have been defined;

— The matrices of mutual distances between the flight exercise implementation in the wavelet coefficients metric and the likelihood metric for eigenvalue trajectories of activity parameters transforms have been calculated (Fig. 14);

— The flight fragments from the database of patterns, which in the specified metrics are the closest to the given exercise, are defined, and the type of this exercise ("Upset recovery") and its quality ("Wrong Implementation" — abnormal) are confirmed according to the information corresponding them in this base (Fig. 15);

— In order to reveal the differences between the observed exercise and the master exercise of the type "Upset recovery" from the database of patterns, the relative contributions of flight parameters determined with the help of the Principal Component Analysis were evaluated, in the corresponding elements of the matrices of mutual distances calculated in the wavelet coefficients metric, which showed that the difference between the specified flight fragments is mainly determined by the parameters "Roll Euler Angle" and "Angle of Attack" (Fig. 15);

— As a result of consistent implementation of the Multidimensional Scaling, Cluster Analysis and Discriminant Analysis, the distribution of flight exercises in a scaling space, the results of their clustering and evaluation of the probabilities of belonging to a given exercise to each of the considered clusters, with the probability estimation for belonging to the "Upset recovery" type being equal to 0.71 (Fig. 16);

- **128 seconds of flight:**

— Parameters representing principal components have been defined (Fig. 17);

— The matrices of mutual distances between the flight exercise implementations in the wavelet coefficients metric and the likelihood metric for eigenvalue trajectories of activity parameters transforms have been calculated (Fig. 18);

— The flight fragments from the database of patterns, which in the specified metrics are the closest to the given exercise, are defined, and according to the information accompanying them in this base the type of this exercise ("Upset recovery") and its quality ("Wrong Implementation" — abnormal) are confirmed (Fig. 19);

— To confirm the reason for the differences between the observed exercise and the master exercise of the type "Upset recovery" from the database of patterns, a clarifying assessment of the relative contributions of flight parameters to the corresponding elements of the matrices of mutual distances was made, which, as before, showed that the difference between the specified flight fragments is mainly determined by the parameters "Roll Euler Angle" and "Angle of attack" (Fig. 20);

— As a result of consistent implementation of the Multidimensional Scaling, Cluster Analysis and Discriminant Analysis, the refined distribution of flight exercises in a scaling space, the results of their clustering and assessment of the probability of belonging of a given exercise to each of the considered clusters are calculated, with the probability estimation for belonging to the "Upset recovery" type being equal to 1.0 (Fig. 20);

— For the purpose of meaningful comparing dynamics of the parameters determining the differences between the observed and reference master exercise implementations, these parameters are presented in a form convenient for expert assessment (Fig. 21).

Obviously, with sufficient computational speed, the considered flight data analysis can be performed in the automatic mode in real time. The evaluation of piloting risks comes down to determining the probabilities of belonging to target clusters related to the types of exercises and the quality of piloting.

Fig. 10. Parameters representing principal components (32 seconds of flight)

Fig. 11. Calculation of matrices of mutual distances between the flight exercises in the given metrics (32 seconds of flight)

Fig. 12. Definition of flight fragments from the database of patterns that are closest to the given exercise, with the information associated with them in this base determining the type of this exercise («Upset recovery») and its quality («Wrong implementation» — abnormal) (32 seconds of flight)

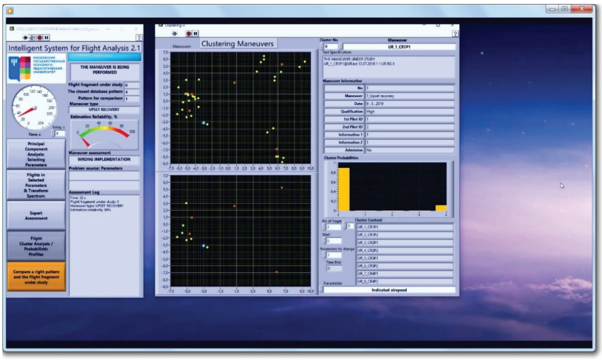

Fig. 13. As a result of consistent performing the Multidimensional Scaling, Cluster Analysis and Discriminant Analysis, the distribution of flight exercises in a scaling space is calculated. The results of their clustering and evaluation of probabilities of belonging of a given exercise to each of the considered clusters (32 seconds of flight) are presented

Fig. 14. Calculation of the matrix of mutual distances between the flight exercises in the Euclidean metric of wavelet coefficients and the likelihood metric for eigenvalue trajectories of activity parameters transforms (64 seconds of flight)

Fig. 15. Definition of flight fragments from the database of patterns that are closest to the given exercise, and the information associated with them in this database confirms the type of the exercise (“Upset recovery” and its quality “Wrong implementation” — abnormal). The evaluation of relative contributions of flight parameters to the corresponding elements of matrices of mutual distances showed that the difference between flight fragments is mainly determined by the parameters “Roll Euler Angle” and “Angle of attack” (64 seconds of flight)

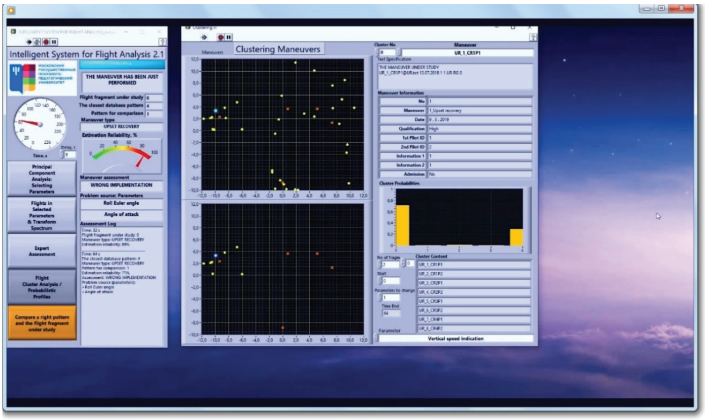

Fig. 16. As a result of consistent performing the Multidimensional Scaling, Cluster Analysis and Discriminant Analysis, the distribution of flight exercises in a scaling space is calculated. The results of their clustering and evaluation of probabilities of belonging of a given exercise to each of the considered clusters (64 seconds of flight) are presented

Fig. 17. Parameters representing principal components (128 seconds of flight)

Fig. 18. Calculation of the matrix of mutual distances between the implementation of flight exercises in the Euclidean metric of wavelet coefficients and the likelihood metric for eigenvalue trajectories of activity parameters transforms (128 seconds of flight)

Fig. 19. Identification of flight fragments from the database of patterns that are closest to the give exercise; the exercise type ("Upset recovery") and its quality ("Wrong Implementation" — abnormal) are confirmed by the information accompanying them in this database. The evaluation of relative contributions of flight parameters to the corresponding elements of matrices of mutual distances confirmed that the difference between flight fragments is mainly determined by the parameters "Roll Euler Angle" and "Angle of attack" (128 seconds of flight)

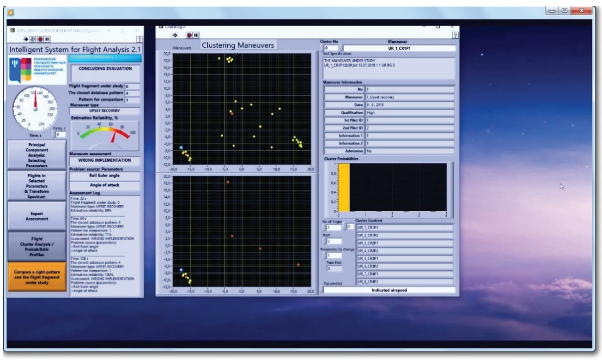

Fig. 20. As a result of consistent performing the Multidimensional Scaling, Cluster Analysis and Discriminant Analysis, the distribution of flight exercises in a scaling space is calculated. The results of clustering and evaluation of probabilities of belonging of a given exercise to each of the considered clusters are presented. (128 seconds of flight)

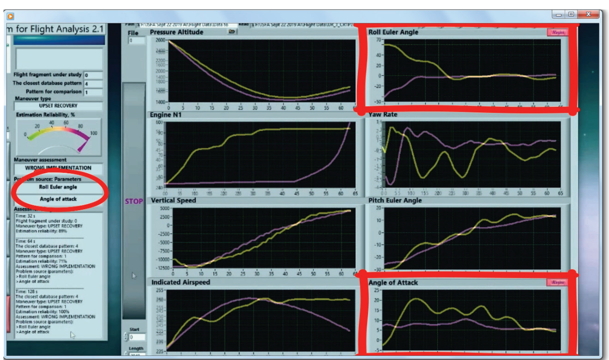

Fig. 21. For the purpose of meaningful comparing dynamics of the parameters determining the differences between the observed and reference master exercise implementations, these parameters are presented in a convenient form for expert assessment

References

1. Aaron M. Aircraft trajectory clustering techniques using circular statistics. Yellowstone Conference Center, Big Sky, Montana, 2016. IEEE.

2. Bastani V., Marcenaro L., Regazzoni C. Unsupervised trajectory pattern classification using hierarchical Dirichlet Process Mixture hidden Markov model. International Workshop on Machine Learning for Signal Processing (MLSP) / IEEE. 2014, pp. 1—6.

3. Borg, I., Groenen, P. J. F. Modern Multidimensional Scaling Theory and Applications. Springer, 2005. P. 140.

4. Bress, Thomas J. Effective LabVIEW Programming: NTS Press, 2013. ISBN 1-934891-08-8.

5. Cottrell M., Faure C., Lacaille J., Olteanu M. Anomaly Detection for Bivariate Signals. IWANN (1) 2019, pp. 162—173.

6. Cramer H. Mathematical Methods of Statistics. Princeton: Princeton University Press. 1999. P. 575.

7. Eerland W.J., Box S. Trajectory Clustering, Modelling and Selection with the focus on Airspace Protection. AIAA Infotech@ Aerospace. _ AIAA, 2016, pp. 1—14.

8. Enriquez M. Identifying temporally persistent flows in the terminal airspace via spectral clustering. Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013) / Federal Aviation Administration (FAA) and EUROCONTROL. Chicago, IL, USA: 2013. June 10—13.

9. Enriquez M., Kurcz C. A Simple and Robust Flow Detection Algorithm Based on Spectral Clustering. International Conference on Research in Air Transportation (ICRAT) / Federal Aviation Administration (FAA) and EUROCONTROL. Berkeley, CA, USA: 2012. May 22—25.

10. Faure C., Bardet J.M., Olteanu M., Lacaille J. Using Self-Organizing Maps for Clustering and Labelling Aircraft Engine Data Phases. In: WSOM 2017, pp. 96—103.

11. Gaffney S., Smyth P. Joint probabilistic curve clustering and alignment. In Advances in *Neural Information Processing Systems*. Vol. 17. Cambridge, MA: MIT Press, 2005, pp. 473—480.

12. Gaffney S., Smyth P. Trajectory clustering with mixtures of regression models. Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining. 1999, pp. 63—72.

13. Gariel M., Srivastava A., Feron E. Trajectory clustering and an application to airspace monitoring. *IEEE Transactions on Intelligent Transportation Systems*. 2011. Vol. 12, no. 4, pp. 1511—1524.

14. GOST R ISO/MEHK 31010 — 2011 Menedzhment riska. Metody otsenki riska. [Risk management. Risk assessment methods]. Moscow: Standartov Pub-l, 2011. P.71.

15. Grevtsov N. Synthesis of control algorithms for aircraft trajectories in time optimal climb and descent. *Journal of Computer and Systems Sciences International*. 2008. Vol. 47, no. 1, pp. 129—138.

16. Hung C., Peng W., Lee W. Clustering and aggregating clues of trajectories for mining trajectory patterns and routes. *The VLDB Journal — The International Journal on Very Large Data Bases*. 2015. Vol. 24, no. 2, pp. 169—192.

17. Kohonen T. Self-Organizing Maps. Springer, 3th Ed., 2001. P. 501.

18. Krasil'shchikov M.N., Evdokimenkov V.N., Bazlev D.A. Individual'no-adaptirovannye bortovye sistemy kontrolya tekhnicheskogo sostoyaniya samoleta i podderzhki upravlyayushchikh deistvii letchika [Individually adapted on-Board systems for monitoring the technical condition of the aircraft and supporting the pilot's control actions]. Moscow: MAI Pub-l, 2011. P. 438.

19. Kuravsky L.S., Artemenkov S.L., Yuriev G.A., Grigorenko E.L. New approach to computer-based adaptive testing. *Experimental Psychology*. 2017. Vol. 10. No. 3, pp. 33—45. doi:10.17759/exppsy.2017100303.

20. Kuravskii L.S., Margolis A.A., Marmalyuk P.A., Panfilova A.S., Yur'ev G.A. Matematicheskie aspekty kontseptsii adaptivnogo trenazhera [Mathematical aspects of the concept of the adaptive motion trainer]. *Psikhologicheskaya nauka i obrazovanie [Psychological Science and Education (Russia)]*, 2016, V. 21, № 2, pp. 84—95. (In Russ.; abstract in Engl.) doi: 10.17759/pse.2016210210
21. Kuravsky L.S., Margolis A.A., Marmalyuk P.A., Panfilova A.S., Yuryev G.A., Dumin P.N. A Probabilistic Model of Adaptive Training. Applied Mathematical Sciences, Vol. 10, 2016, no. 48, pp. 2369 — 2380. URL: http://dx.doi.org/10.12988/ams.2016.65168 (Accessed 15.03.2020).
22. Kuravskii L.S., Marmalyuk P.A., Yur'ev G.A. Diagnostika professional'nykh navykov na osnove veroyatnostnykh raspredelenii glazodvigatel'noi aktivnosti [Diagnostics of professional skills based on probabilistic distributions of oculomotor activity]. *Vestnik RFFI [Bulletin RFFI (Russia)]*, 2016, №3(91), pp. 72—82.
23. Kuravsky L.S., Marmalyuk P.A., Yuryev G.A. and Dumin P.N. A Numerical Technique for the Identification of Discrete-State Continuous-Time Markov Models. *Applied Mathematical Sciences*. Vol. 9, 2015, No. 8, pp. 379—391. URL: http://dx.doi.org/10.12988/ams. 2015.410882 (Accessed 15.03.2015).
24. Kuravsky L.S., Marmalyuk P.A., Yuryev G.A., Belyaeva O.B. and Prokopieva O.Yu. Mathematical Foundations of Flight Crew Diagnostics Based on Videooculography Data. *Applied Mathematical Sciences*, Vol. 10, 2016, no. 30, pp. 1449—1466. URL: http://dx.doi.org/10.12988/ams.2016.6122 (Accessed 15.03.2020).
25. Kuravsky L.S., Marmalyuk P.A., Yuryev G.A., Dumin P.N., Panfilova A.S. Probabilistic modeling of CM operator activity on the base of the Rasch model. *In: Proc. 12th International Conference on Condition Monitoring & Machinery Failure Prevention Technologies*, Oxford, UK, June 2015.
26. Kuravsky L.S., Yuriev G.A. Probabilistic method of filtering artefacts in adaptive testing. *Experimental Psychology*, Vol.5, No. 1, 2012, pp. 119—131.
27. Kuravskii L.S., Yur'ev G.A. Svidetel'stvo o gosudarstvennoi registratsii programmy dlya EHVM №2018660358 Intelligent System for Flight Analysis v1.0 (ISFA#1.0) / Pravoobladateli Kuravskii L.S., Yur'ev G.A. (Russia). — Zayavka №2018617617; Zayav. 18.07.2018; Zaregistr. 22.08.2018.—(ROSPATENT).
28. Kuravsky L.S., Yuryev G.A. Detecting abnormal activities of operators of complex technical systems and their causes basing on wavelet representations. *International Journal of Civil Engineering and Technology (IJCIET)*. Vol. 10(2). Issue 02, February 2019, pp. 724—742. URL: http://www.iaeme.com/MasterAdmin/UploadFolder/IJCIET_10_02_070/IJCIET_10_02_070.pdf (Accessed 17.09.2019).
29. Kuravsky L.S., Yuryev G.A. On the approaches to assessing the skills of operators of complex technical systems. *In: Proc. 15th International Conference on Condition Monitoring & Machinery Failure Prevention Technologies*, Nottingham, UK, September 2018. P. 25.
30. Kuravsky L.S., Yuryev G.A., Zlatomrezhev V.I. New approaches for assessing the activities of operators of complex technical systems. *Eksperimental'naya psikhologiya [Experimental psychology (Russia)]*, 2019, vol. 12, no. 4, pp. 27—49. (In Russ.; abstract in Engl.) doi:10.17759/exppsy.2019120403
31. Laxhammar R., Falkman G. Online learning and sequential anomaly detection in trajectories. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2014. Vol. 36, no. 6, pp. 1158—1173.
32. Li Z., et al. Incremental clustering for trajectories. Database Systems for Advanced Applications. *Lecture Notes in Computer Science*. 2010. Vol. 5982, pp. 32—46.
33. Liu H., Li J. Unsupervised multi-target trajectory detection, learning and analysis in complicated environments. 21st International Conference on Pattern Recognition (ICPR) / IEEE. 2012, pp. 3716—3720.

34. Markovskie modeli v zadachakh diagnostiki i prognozirovaniya [Markov models in the problems of diagnostics and forecasting]: Ucheb. posobie /Pod red. L.S. Kuravskogo. 2-e izd., dop. Moscow: MGPPU Pub-l, 2017. P. 197.
35. Neal P.G. Multiresolution Analysis for Adaptive Refinement of Multiphase Flow Computations. *University of Iowa*, 2010. P. 116.
36. René Vidal, Yi Ma, Shankar Sastry. Generalized Principal Component Analysis. *Springer-Verlag*: New York, 2016. URL: http://www.springer.com/ us/book/9780387878102 (Accessed 15.03.2020).
37. Rintoul M., Wilson A. Trajectory analysis via a geometric feature space approach. Statistical Analysis and Data Mining: *The ASA Data Science Journal*. 2015.
38. Trevor F. Cox, M.A.A. Cox. Multidimensional Scaling, Second Edition. *Chapman & Hall*. CRC, 2001. P. 299.
39. Wei J., et al. Design and Evaluation of a Dynamic Sectorization Algorithm for Terminal Airspace. Journal of Guidance, Control, and Dynamics. 2014. Vol. 37, no. 5, pp. 1539—1555.
40. Wilson A., Rintoul M., Valicka C. Exploratory Trajectory Clustering with Distance Geometry. International Conference on Augmented Cognition. *Springer*. 2016, pp. 263—274.
41. Xiangyu Kong, Changhua Hu, Zhansheng Duan. Principal Component Analysis Networks and Algorithms. *Springer*, 2017. P. 322. URL: http://www.springer.com/us/book/9789811029134 (Accessed 15.03.2020).

Литература

1. *Aaron M.* Aircraft trajectory clustering techniques using circular statistics. Yellowstone Conference Center, Big Sky, Montana, 2016. / IEEE.
2. *Bastani V., Marcenaro L., Regazzoni C.* Unsupervised trajectory pattern classification using hierarchical Dirichlet Process Mixture hidden Markov model // 2014 IEEE International Workshop on Machine Learning for Signal Processing (MLSP) / IEEE. 2014. P. 1—6.
3. *Borg I., Groenen, P.J.F.* Modern Multidimensional Scaling Theory and Applications. Springer, 2005. P.140.
4. *Bress Thomas J.* Effective LabVIEW Programming: NTS Press, 2013.
5. *Cottrell M., Faure C., Lacaille J., Olteanu M.* Anomaly Detection for Bivariate Signals. IWANN (1) 2019. P. 162—173.
6. *Cramer H.* Mathematical Methods of Statistics. Princeton: Princeton University Press, 1999. 575 p.
7. *Eerland W.J., Box S.* Trajectory Clustering, Modelling and Selection with the focus on Airspace Protection // AIAA Infotech@ Aerospace. AIAA, 2016. P. 1—14.
8. *Enriquez M.* Identifying temporally persistent flows in the terminal airspace via spectral clustering // Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013) / Federal Aviation Administration (FAA) and EUROCONTROL. Chicago, IL, USA, 2013. June. P. 10—13.
9. *Enriquez M., Kurcz C.* A Simple and Robust Flow Detection Algorithm Based on Spectral Clustering // International Conference on Research in Air Transportation (ICRAT) / Federal Aviation Administration (FAA) and EUROCONTROL. Berkeley, CA, USA, 2012. May. P. 22—25.
10. *Faure C., Bardet J.M., Olteanu M., Lacaille J.* Using Self-Organizing Maps for Clustering and Labelling Aircraft Engine Data Phases // WSOM. 2017. P. 96—103.
11. *Gaffney S., Smyth P.* Joint probabilistic curve clustering and alignment // Advances in Neural Information Processing Systems. 2005. Vol. 17. P. 473—480.
12. *Gaffney S., Smyth P.* Trajectory clustering with mixtures of regression models // Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining. 1999. P. 63—72.

13. *Gariel M., Srivastava A., Feron E.* Trajectory clustering and an application to airspace monitoring // IEEE Transactions on Intelligent Transportation Systems. 2011. Vol. 12. № 4. P. 1511—1524.
14. ГОСТ Р ИСО/МЭК 31010 — 2011. Менеджмент риска. Методы оценки риска. М.: Изд-во стандартов, 2011. 71 с.
15. *Grevtsov N.* Synthesis of control algorithms for aircraft trajectories in time optimal climb and descent // Journal of Computer and Systems Sciences International. 2008. Vol. 47. № 1. P. 129—138.
16. *Hung C., Peng W., Lee W.* Clustering and aggregating clues of trajectories for mining trajectory patterns and routes // The VLDB Journal — The International Journal on Very Large Data Bases. 2015. Vol. 24. № 2. P. 169—192.
17. *Kohonen T.* Self-Organizing Maps, Springer, 3th Ed., 2001. 501 pp.
18. *Красильщиков М.Н., Евдокименков В.Н., Базлев Д.А.* Индивидуально-адаптированные бортовые системы контроля технического состояния самолета и поддержки управляющих действий летчика. М.: Изд-во МАИ, 2011. 438 с.
19. *Kuravsky L.S., Artemenkov S.L., Yuriev G.A., Grigorenko E.L.* New approach to computer-based adaptive testing. Experimental Psychology. 2017. Vol. 10. № 3. P. 33—45. doi:10.17759/exppsy.2017100303
20. *Куравский Л.С., Марголис А.А., Мармалюк П.А., Панфилова А.С., Юрьев Г.А.* Математические аспекты концепции адаптивного тренажера. Психологическая наука и образование, 2016. Том. 21. № 2. С. 84—95. doi: 10.17759/pse.2016210210
21. *Kuravsky L.S., Margolis A.A., Marmalyuk P.A., Panfilova A.S., Yuryev G.A., Dumin P.N.* A Probabilistic Model of Adaptive Training [Электронный русурс] // Applied Mathematical Sciences. Vol. 10. 2016. № 48. P. 2369—2380. URL: http://dx.doi.org/10.12988/ams.2016.65168
22. *Куравский Л.С., Мармалюк П.А., Юрьев Г.А.* Диагностика профессиональных навыков на основе вероятностных распределений глазодвигательной активности // Вестник РФФИ. 2016. № 3(91). С. 72—82.
23. *Kuravsky L.S., Marmalyuk P.A., Yuryev G.A. and Dumin P.N.* A Numerical Technique for the Identification of Discrete-State Continuous-Time Markov Models [Электронный русурс] // Applied Mathematical Sciences. 2015. Vol. 9. № 8. P. 379—391. URL: http://dx.doi.org/10.12988/ams. 2015.410882
24. *Kuravsky L.S., Marmalyuk P.A., Yuryev G.A., Belyaeva O.B., Prokopieva O.Yu.* Mathematical Foundations of Flight Crew Diagnostics Based on Videooculography Data [Электронный русурс] // Applied Mathematical Sciences. 2016. Vol. 10. № 30. P. 1449—1466 URL: http://dx.doi.org/10.12988/ams.2016.6122
25. *Kuravsky L.S., Marmalyuk P.A., Yuryev G.A., Dumin P.N., Panfilova A.S.* Probabilistic modeling of CM operator activity on the base of the Rasch model // Proc. 12th International Conference on Condition Monitoring & Machinery Failure Prevention Technologies. Oxford: UK, June, 2015.
26. *Kuravsky L.S., Yuriev G.A.* Probabilistic method of filtering artefacts in adaptive testing. Experimental Psychology. 2012. Vol. 5. № 1. P. 119—131.
27. *Куравский Л.С., Юрьев Г.А.* Свидетельство о государственной регистрации программы для ЭВМ № 2018660358 Intelligent System for Flight Analysis v1.0 (ISFA#1.0) / Правообладатели Куравский Л.С., Юрьев Г.А. (Россия). Заявка № 2018617617; Заявка 18.07.2018; Зарегистр. 22.08.2018. (РОСПАТЕНТ).
28. *Kuravsky L.S., Yuryev G.A.* Detecting abnormal activities of operators of complex technical systems and their causes basing on wavelet representations [Электронный русурс] // International Journal of Civil Engineering and Technology (IJCIET). 2019. Vol. 10(2). Issue 02, February. P. 724—742. URL: http://www.iaeme.com/MasterAdmin/UploadFolder/IJCIET_10_02_070/IJCIET_10_02_070.pdf. (дата обращения: 17.09.2019).

29. *Kuravsky L.S., Yuryev G.A.* On the approaches to assessing the skills of operators of complex technical systems // Proc. 15th International Conference on Condition Monitoring & Machinery Failure Prevention Technologies. Nottingham, UK, September 2018. P. 25.
30. *Kuravsky L.S., Yuryev G.A., Zlatomrezhev V.I.* New approaches for assessing the activities of operators of complex technical systems // Eksperimental'naya psikhologiya = Experimental psychology. 2019. Vol. 12. № 4. P. 27—49. doi:10.17759/exppsy.2019120403
31. *Laxhammar R., Falkman G.* Online learning and sequential anomaly detection in trajectories // IEEE Transactions on Pattern Analysis and Machine Intelligence. 2014. Vol. 36. № 6. P. 1158—1173.
32. *Li Z., et al.* Incremental clustering for trajectories // Database Systems for Advanced Applications. Lecture Notes in Computer Science. 2010. Vol. 5982. P. 32—46.
33. *Liu H., Li J.* Unsupervised multi-target trajectory detection, learning and analysis in complicated environments // 2012 21st International Conference on Pattern Recognition (ICPR) / IEEE. 2012. P. 3716—3720.
34. Марковские модели в задачах диагностики и прогнозирования: Учеб. пособие 2-е изд., доп. / Под ред. Л.С. Куравского. М.: Изд-во МГППУ, 2017. 197 с.
35. *Neal P.G.* Multiresolution Analysis for Adaptive Refinement of Multiphase Flow Computations // University of Iowa. 2010. P. 116.
36. *René Vidal, Yi Ma, Shankar Sastry.* Generalized Principal Component Analysis [Электронный ресурс]. New York: Springer-Verlag, 2016. URL: http://www.springer.com/ us/book/9780387878102
37. *Rintoul M., Wilson A.* Trajectory analysis via a geometric feature space approach // Statistical Analysis and Data Mining: The ASA Data Science Journal. 2015.
38. *Trevor F. Cox, M.A.A. Cox.* Multidimensional Scaling, Second Edition. Chapman & Hall/CRC, 2001. P. 299.
39. *Wei J., et al.* Design and Evaluation of a Dynamic Sectorization Algorithm for Terminal Airspace // Journal of Guidance, Control, and Dynamics. 2014. Vol. 37. № 5. P. 1539—1555.
40. *Wilson A., Rintoul M., Valicka C.* Exploratory Trajectory Clustering with Distance Geometry // International Conference on Augmented Cognition / Springer. 2016. P. 263—274.
41. *Xiangyu Kong, Changhua Hu, Zhansheng Duan.* Principal Component Analysis Networks and Algorithms [Электронный русурс]. Springer, 2017. P. 322. URL: http://www.springer.com/us/book/9789811029134

Information about the authors
Lev S. Kuravsky, DSc (Engineering), Professor, Dean of Computer Science Faculty, Moscow State University of Psychology and Education, ORCID: http://orcid.org/0000-0002-3375-8446, e-mail: l.s.kuravsky@gmail.com

Grigory A. Yuryev, PhD (Physics and Mathematics), Associate Professor, Head of Scientific Laboratory, Moscow State University of Psychology and Education, ORCID: https://orcid.org/0000-0002-2960-6562, e-mail: g.a.yuryev@gmail.com

Valentin I. Zlatomrezhev, Head of Laboratory, State Research Institute of Aviation Systems (GosNIIAS), ORCID: https://orcid.org/0000-0003-1776-6881, e-mail: vizlatomr@2100.gosniias.ru

Nataliya E. Yuryeva, PhD (Engineering), Research fellow, Moscow State University of Psychology and Education, Research Associate, ORCID: https://orcid.org/0000-0003-1419-876X, e-mail: yurieva.ne@gmail.com

Информация об авторах
Куравский Лев Семенович, доктор технических наук, профессор, декан факультета информационных технологий, Московский государственный психолого-педагогический университет (ФГБОУ ВО

МГППУ), г. Москва, Российская Федерация, ORCID: http://orcid.org/0000-0002-3375-8446, e-mail: l.s.kuravsky@gmail.com

Юрьев Григорий Александрович, кандидат физико-математических наук, доцент, заведующий научной лабораторией, Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация, ORCID: https://orcid.org/0000-0002-2960-6562, e-mail: g.a.yuryev@gmail.com

Златомрежев Валентин Игоревич, заведующий лабораторией, Государственный научно-исследовательский институт авиационных систем (ФГУП «ГосНИИАС»), г. Москва, Российская Федерация, ORCID: https://orcid.org/0000-0003-1776-6881, e-mail: vizlatomr@2100.gosniias.ru

Юрьева Наталия Евгеньевна, кандидат технических наук, научный сотрудник, Московский государственный психолого-педагогический университет (ФГБОУ ВО МГППУ), г. Москва, Российская Федерация, ORCID: https://orcid.org/0000-0003-1419-876X, e-mail: yurieva.ne@gmail.com

Получена 09.03.2020
Принята в печать 20.04.2020

Received 09.03.2020
Accepted 20.04.2020