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FUZZY KNOWLEDGE BASE SYNTHESIS OF THE EXPERIENCE LEVEL CLASSIFICATION OF AVIATION SECURITY SCREENERS USING SUB-TRACTIVE CLUSTERING AND ANFIS-TRAINING

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ABSTRACT

This paper describes a new approach to the estimate reliability improvement of the competence related to the visual searching for prohibited items by aviation security screeners consisting in the application of fuzzy knowledge bases and equipment-specific diagnostic techniques of the psychophysiological state. As equipment-specific methods it is suggested using the eye-tracking technology giving an opportunity to take into consideration visual searching strategies and the variational cardio-intervalometry method giving an opportunity to estimate the operator's psychophysiological strain. This paper considers the theoretical basis of the automatic synthesis of both Sugeno and Mamdani fuzzy knowledge bases. It is demonstrated that the identification of fuzzy knowledge bases using clustering algorithms consists of cluster forming in the dataspace and cluster transforming into fuzzy rules describing the certain part of the investigated system behavior. Experiments were carried out to test the suggested approach. The quality of the synthetized Sugeno fuzzy knowledge base was compared with the Mamdani knowledge base and with the linear regression model. Results showed that this model based on the subtractive clustering and the ANFIS-training with respect to the root-mean-square error does better apprise the investigated dependence than other models. The training sample accuracy was 0.0049. The test sample accuracy was 0.0275. The application of fuzzy knowledge bases will give an opportunity to create decision-making support systems to estimate the competence level of aviation security screeners in intellectual simulator complexes.

Key words: Aviation security, Aviation Security screener, Competence, Fuzzy Models, Subtractive Clustering, Eye-Tracking Technology and Heart Rate.

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1. INTRODUCTION

Despite of the constant improving of X-ray technologies and improving automation in inspection systems, the human factor in the form of operators' qualification and the responsibility is an essential component of the efficient process structuring of inspecting in airports. The primary goal of aviation security screeners is to decide whether there are any dangerous and prohibited items and matters at the aircraft using X-ray images of the baggage and carry-on. In connection therewith, today one of the most important and urgent tasks to be resolved by the aviation industry is to improve the quality of the professional training of this very category of the aviation personnel. The professional training system of aviation security screeners is based on the simulator training technology. Today the simulator training of operators is carried out using various simulators. X-ray Tutor (Halbherr et al. 2013; Michel et al. 2014) [7, 12] is the most common. Implementation of psychophysiological state monitoring mechanisms of trainees is one of promising trends in improving simulators for aviation security screeners. It is suggested using the eye-tracking technology for the visual searching strategy estimation and the variational cardio-intervalometry method for the psychophysiological strain estimation (the psychophysiological "price" of the executing task) as equipment-specific monitoring methods. Eye movement features investigation when performing professional tasks and training are being actively developed in various functional areas. Investigations has been significantly advanced when working with the oculomotor activity of medical experts, in particular: surgeons when working together in one team (Atkins et al. 2013; Causer et al. 2014) [2, 5]; radiologists when analyzing the X-ray image (Wood et al. 2013) [21]; cardiologists when reading the ECG tracing (Wood et al. 2014; Bond et al. 2014) [20,3]. The series of investigations (Vrzakova et al. 2012; Weibel et al. 2012) [17, 18] relate to using the eye-tracking technology for the estimation of vision perception parameters and pilot's attention allocation during the simulator training when resolving various tasks. During the professional training of sportsmen, the eye-tracking technology can be used as an instrument for resolving such tasks as molding of efficient strategies for the visual searching or comparing oculomotor patterns of trainees with various levels of training (Hancock et al. 2013; Witte et al. 2012; Button et al. 2010; Vickers, 2007) [8, 19, 4, 16]. In investigations (Swann et al. 2014; Swann et al. 2015) [14, 15] using the eye-tracking technology there is activity structure of aviation security screeners identified, including: visual searching, image evaluation, compatibility with the equipment interface, cooperation with other inspection staff, compatibility with the investigated object. Thus, the implementation of equipment-specific means for the psychophysiological monitoring will provide objective and comprehensive information about the process of the operators' simulator training. At the same time, taking into consideration the increase in the amount of the processed information, it is necessary to develop new approaches to support the decision-making in estimating the quality of the operators' simulator training of operators based on artificial intelligence systems. These systems include the fuzzy logics apparatus, artificial neural networks, genetic algorithms. Estimation of the results of the operators' simulator training often occurs under conditions of the uncertainty and the incompleteness of the initial data, therefore, in this paper it is proposed to apply fuzzy knowledge bases. In the work (Hayajneh et al. 2007) [10] the authors resolved the issue of identifying the nonlinear dependence in the well quality control task when drilling based on the fuzzy knowledge base. In the work (Hayajneh et al. 2010) [9] the authors used the fuzzy knowledge base as the basis of the system for monitoring tile defects when producing. In the work (Priyono et al. 2012) [13] the result of fuzzy knowledge base designing for the traffic manage-ment task is presented. The investigation (Aires et al. 2009) [1] reflects the results of fuzzy knowledge bases designing for identifying malfunctions in the oil refining industry.

The objective of this investigation is to substantiate the possibility of using fuzzy knowledge bases and equipment-specific diagnostic techniques of the psychophysiological state of operators during the simulator training.

1.1. Theoretical basis for designing fuzzy knowledge bases

Today, there are two main types of fuzzy knowledge bases: Mamdani and Sugeno. The difference between Mamdani and Sugeno fuzzy inferences is since in the first case conclusions of rules are represented by fuzzy terms as well as for input variables, and in the second case conclusions are a function of input variables. Mamdani knowledge base is described as follows (Mamdani and Assilian, 1975) [11]:

$$\text{If } (x_1 = a_{i1}\ u\ x_2 = a_{i2}\ u \ldots u\ x_n = a_{in}),\ \text{then } y = d_i, \text{weighted } w_i,\ i = \overline{1,N}, \tag{1}$$

Where:

a_{ij} is the fuzzy term used for the linguistic variable estimation of the factor x_j in the i-rule, $i = \overline{1,N},\ j = \overline{1,n}$;

N is the number of rules in the knowledge base;

d_i is the consequent of the i-rule in the form of the fuzzy term;

$w_i \in [0;1]$ is the weight of the i-rule representing the expert's certainty in its authenticity.

Zero-order Sugeno knowledge base is described as follows (Chiu, 1994) [6]:

$$\text{If } (x_1 = a_{i1}\ u\ x_2 = a_{i2}\ u \ldots u\ x_n = a_{in}),\ \text{then } d_j = b_{j0} + \sum_{i=\overline{1,n}} b_{ji} x_i, \tag{2}$$

Where:

$b_{j0}, b_{j1}, \ldots, b_{jm}$ are some real numbers.

Clustering methods, namely, the subtractive clustering algorithm or fuzzy c-means are often used for the synthesis of fuzzy knowledge bases. Structuring a Sugeno fuzzy knowledge base of experimental data consists of two main steps. The first is the identification of the knowledge base structure, which includes the formation of the initial set of rules in "IF-TO" statements using subtractive clustering. The second is the identification of parameters using the ANFIS-algorithm (ANFIS is Adaptive Network Based Fuzzy Inference System), which includes the setting of accession and weights of rules functional parameters. The use of clustering gives an opportunity to identify natural data groups from the overall set, thereby providing the identification and the brief presentation of the overall structure of the knowledge base. The advantage of the subtractive clustering algorithm is the lack of need to determine the initial number of clusters. The algorithm includes the following steps: consideration of data elements as potential candidates for cluster centers; probability calculation that the data element is the center of the cluster; selection of the point with the greatest potential as the center of the first cluster; calculation of potentials for the next cluster centers (deducting the contribution of the center of the cluster just found); implementation of an iterative recalculation procedure for potentials and separation of cluster centers until the maximum potential value exceeds the initially specified threshold (Yager and Filev, 1984)

[22]. Although the subtractive clustering algorithm is not fuzzy, it is often used for the task of the automatic generation of fuzzy rules from experimental data.

Thus, the identification of fuzzy knowledge bases using subtractive clustering involves forming of clusters in the data space and describing the certain part of the investigated system behavior. After projecting the membership degrees of clusters on the input space and the corresponding approximation, the membership functions of terms in the premises of fuzzy rules are determined. Conclusions of rules are determined by the least square method.

At the second stage, parameters of the synthesized knowledge base are configured using the ANFIS-algorithm. The representation of the fuzzy inference in the form of the neuro-fuzzy model gives an opportunity to the use neural network learning algorithms. The structure of the ANFIS-network is isomorphic to the fuzzy knowledge base and is a five-layer, forward-propagation neural network. Layers have the following assignments: the first layer is the term of input variables; the second layer is sending fuzzy rules; the third layer is the normalization of the compliance degree of rules; the fourth layer is the conclusion of rules; the fifth layer is the aggregation of the results obtained by various rules. Combination of the back-propagation of error algorithm and the least square method are often used as training procedures for these models.

The fuzzy *c*-means algorithm is used to design the Mamdani fuzzy knowledge base use. Clustering in this case can be formulated using the characteristic function. The characteristic function takes the value in the interval [0, 1] reflecting the degree of belonging of the element to the cluster. The description of the partitioning matrix of fuzzy clusters using a characteristic function is represented as $F=[\mu_{ki}]$, where $\mu_{ki}\in[0,1]$, $k=\overline{1,M}$, $i=\overline{1,c}$. In this case, the *k*-line characterizes the degree of belonging of the element $X_k=(x_{k1},x_{k2},...,x_{kn})$ to clusters $A_1,A_2,...,A_c$. The *F*-matrix must satisfy the following requirements (Mamdani and Assilian, 1975) [11]:

$$\begin{gathered}\sum_{i=\overline{1,c}}\mu_{ki}=1,\ k=\overline{1,M},\\ 0<\sum_{k=\overline{1,M}}\mu_{ki}<M,\ i=\overline{1,c}.\end{gathered}\qquad(3)$$

The idea of the fuzzy *c*-means algorithm is to iteratively recalculate the *F*-matrices and cluster centers. The scatter criterion is used as the target function, which must be minimized (Mamdani and Assilian, 1975) [11]:

$$\sum_{i=\overline{1,c}}\sum_{k=\overline{1,M}}(\mu_{ki})^m\left\|V_i-X_k\right\|^2\to\min,\qquad(4)$$

Where:

$V_i=\dfrac{\sum_{k=\overline{1,M}}(\mu_{ki})^m X_k}{\sum_{k=\overline{1,M}}(\mu_{ki})^m}$ are fuzzy cluster centers; $m\in(1,\infty)$ is the exponential weight.

In this case, the Euclidean distance is taken as the metric of the anomaly. Membership functions of output variable terms in conclusions of rules of the knowledge base are found as well as for input variables.

2. TASK SUBSTITUTION

Synthesizing the fuzzy knowledge base for resolving the issue related to the estimation of the competence level of aviation security screeners is to identify fuzzy rules relating input data (*x*) to the output (*y*):

$$(X_r, y_r),\ r=\overline{1,M}, \tag{5}$$

Where:

X_r is the input data vector related to r-line of the sample and y_r is the value of the output variable.

Setting up the fuzzy knowledge base is carried out by the criterion of the root-mean-square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{M}\sum_{r=\overline{1.M}}(y_r - F(P,W,X_r))}, \tag{6}$$

Where:

M is the number of experimental data pairs; P is the parameter vector of variable membership functions (x) and (y); W is the knowledge base weight coefficient vector; $F(P,W,X_r)$ is the result of the fuzzy knowledge base calculation.

As input data (x), it is proposed to use (3) the integral indicators characterizing the strategies of visual searching for prohibited items, and (4) the indicator characterizing the psychophysiological tension of the operator during the visual searching based on the heart rate estimation.

1. The first indicator (DT) is calculated using the formula (7):

$$DT = \sum_{i=1}^{k} \frac{\sum_{j=1}^{n} DT_{\mathrm{pro}} \cdot \frac{1}{FC_{\mathrm{pro}}}}{\sum_{l=1}^{m} DT_{\mathrm{nonpro}} \cdot \frac{1}{FC_{\mathrm{nonpro}}} + \sum_{j=1}^{n} DT_{\mathrm{pro}} \cdot \frac{1}{FC_{\mathrm{pro}}}}, \tag{7}$$

Where:

DT_{pro} is the average vision holding time of the test person in AOI (area of interest) with the prohibited item, ms;

DT_{nonpro} is the average vision holding time of the test person in AOI without the prohibited item, ms;

$1/FC_{\mathrm{pro}}$ is monitoring frequency of the j-prohibited item;

$1/FC_{\mathrm{nonpro}}$ is monitoring frequency of the l-nonprohibited item;

k is the number of test X-ray images, pcs;

n is the number of AOI with the prohibited item, pcs;

m is the number of AOI without the prohibited item, pcs.

2. The second indicator (SE) is calculated using the formula (8):

$$SE = \frac{\sum_{i=1}^{k} SE_{\mathrm{pro}}}{k}, \tag{8}$$

Where:

SE_{pro} is the index characterizing the concentration fixation scheme of the test person equal to 0 or 1. If the test person began the searching scheme from AOI with the dangerous and prohibited item or matter, the indicator will be equal to 1. Otherwise it will be equal to 0;

k is the number of test X-ray images, pcs.

3. The third indicator (ET) is calculated using the formula (9):

$$ET = \sum_{i=1}^{k}\left(\frac{\sum_{j=1}^{n} ET_{\text{pro}} \cdot S_{\text{pro}}}{\sum_{l=1}^{m} ET_{\text{nonpro}} \cdot S_{\text{nonpro}} + \sum_{j=1}^{n} ET_{\text{pro}} \cdot S_{\text{pro}}}\right), \quad (9)$$

Where:

ET_{pro} is the average time from the beginning of the experiment to the first fixation in AOI with the prohibited item, ms;

ET_{nonpro} is the average time from the beginning of the experiment to the first fixation in AOI without the prohibited item, ms;

S_{pro} is the part of the *j*-dangerous item area against the total area of the stimulus;

S_{nonpro} is the part of the *l*-not dangerous item area against the total area of the stimulus;

k is the number of test X-ray images, pcs;

n is the number of AOI with the prohibited item, pcs;

m is the number of AOI without the prohibited item, pcs.

4. The indicator (*HR*) is calculated as follows:

$$HR = \frac{Y_{\text{HR}}^{\text{Cur}}}{Y_{\text{HR}}^{\text{BG}}}, \quad (10)$$

Where:

Y_{HR}^{Cur} is the current value of the operator’s heart rate and Y_{HR}^{BG} is the background value of the heart rate.

Detection rate of prohibited items is used as the output variable (*DP*).

To test the proposed approach, experimental investigations were carried out using the mobile eye-tracker Eye Tracking Glasses 2.0 of Senso Motor Instruments. To assess the heart rate, a set of psychophysiological testing devices UPFT-1/30 “Psychophysiologist” was used. 35 cadets of the Ulyanovsk Civil Aviation Institute took part in these investigations. They were trained at the Aviation Training Center of the Institute under the 40-hour program “Retraining of cadets in the department of aviation security. Preflight and post-flight inspection”. The collection of experimental data included the following steps: block forming of test X-ray images of baggage and carry-on consisting of 20 images; preprocessing of test images using SMI BeGaze 3.7 software; experimental testing of test persons with the simultaneous removal of the oculomotor activity, heart rate and fixing the time and accuracy of the object identification (images were presented with the exposure of 10 seconds); processing and analyzing of the experimental data. The initial sample was divided into the training (30 cadets) and the testing sample (5 cadets).

3. RESULTS AND DISCUSSION

The robust estimation of the initial data matrix (their suitability for the subsequent analysis and the absence of outliers) was carried out using the Statistica program. Table 1 presents a window of descriptive statistics of the experimental data obtained.

Table 1 Results of the robust estimation of initial data

In dex	Mean	Trim med mean, 5,000 %	Win so- rized mean, 5,000 %	Grubbs Test Statistic	p-value	Mini-mum	Maxi-mum	Std. Dev.	Std. Er ror, %
DT	2.981	2.989	2.983	2.208	0.795	1.999	3.781	0.445	7.524
SE	0.106	0.100	0.106	2.006	1.000	0.000	0.300	0.097	1.637
ET	2.286	2.258	2.294	2.603	0.220	0.623	4.096	0.695	11.753
HR	0.953	0.958	0.955	3.037	0.039	0.805	1.000	0.049	0.823

The robust estimation in the Statistica program was carried out according to three indicators (Swann et al. 2014) [14]: the truncated mean (the average value after the removal of outliers); the winsorized mean (the average value after replacing outliers with the percentile, which made the truncation); the Grubbs criterion for outliers.

It can be seen from Table 1 that the arithmetic mean, the truncated mean and the winsorized mean have approximately equal values for each of the estimated parameters. The critical value of the Grubbs criterion for a significance level of 0.01 is 3.33. For the analyzed parameters, Grubbs criteria are 2.207525; 2.006237; 2.603334; 3.036886; 2.001045 and do not exceed the critical value; levels of significance equal to 0.795209; 1; 0.219935; 0.038577; 1 respectively exceed the selected level. Thus, the analysis performed allowed us to substantiate the absence of outliers in the initial data and their suitability for the subsequent analysis.

The factor analysis of the initial data matrix using the method of isolating the main components shows that all indicators used bear enough factor load and can be used to synthesize the fuzzy knowledge base (Table 2).

Table 2 Matrix of factor loads (the «varimax» method)

Index	Factor 1	Factor 2	Factor 3	Factor 4
DT	0.937	0.038	0.182	0.290
SE	0.160	0.182	0.967	-0.072
ET	-0.033	-0.953	-0.191	0.232
HR	-0.337	0.281	0.091	-0.894
Expl. Var.	1.021	1.022	1.014	0.943
Prp. Totl.	0.255	0.256	0.253	0.236

The Matlab Fuzzy Logic Toolbox package was chosen as the software environment for implementing the fuzzy knowledge base. The procedure for synthesizing the Sugeno fuzzy knowledge base is implemented in this package as the genfis2 function. Set the following parameters of the subtractive clustering algorithm: the cluster radius is 0.7 (the value is set from the range [0, 1]); the suppression ratio is 1.25; the adoption rate is 0.5; the rejection coefficient is 0.15. Figure 1 shows the scheme of the synthesized Sugeno fuzzy knowledge base.

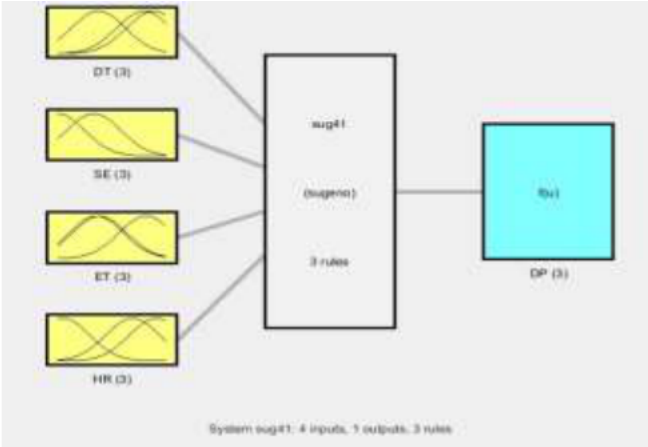


Figure 1. Scheme of the synthesized Sugeno fuzzy knowledge base

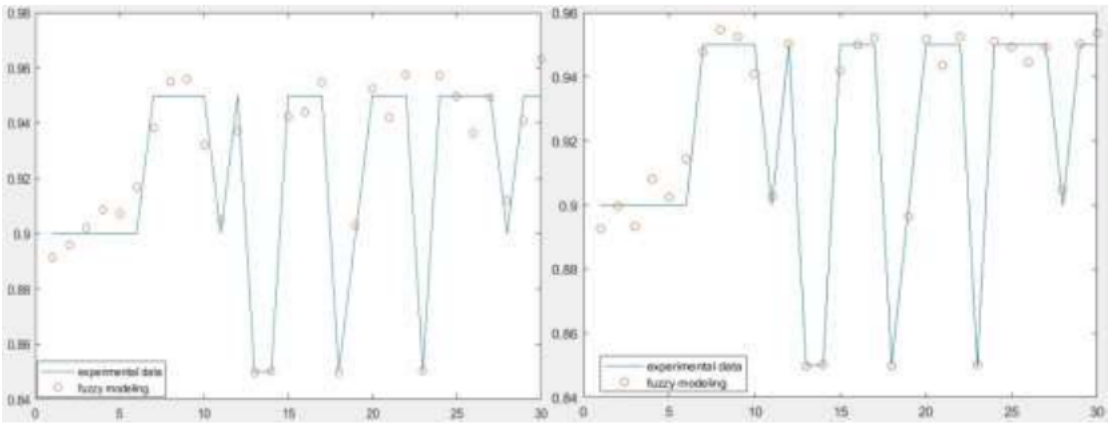
The resulting knowledge base includes 3 rules that correspond to three found clusters:

IF *DT*=in1cluster1 AND *SE*=in2cluster1 AND *ET*=in3cluster1 AND *HR*=in4cluster1, THEN *DP*=out1cluster1;

IF *DT*=in1cluster2 AND *SE*=in2cluster2 AND *ET*=in3cluster2 AND *HR*=in4cluster2, THEN *DP*=out1cluster2;

IF *DT*=in1cluster3 AND *SE*=in2cluster3 AND *ET*=in3cluster3 AND *HR*=in4cluster3, THEN *DP*=out1cluster3.

The error on the training sample is equal to trnRMSE1 = 0.0084. The error on the test sample (outside training points) is equal to chkRMSE1 = 0.0445. Figure 2a presents the results of comparing the value of the output variable from the experimental data and the simulation results.



a) b)

Figure 2. Testing results of the model

a) after the subtractive clustering; b) after the ANFIS-training

In some cases, there are discrepancies between the experimental data and the simulation results (Figure 2a). To improve the accuracy of the model, we will train it using the ANFIS-algorithm. Let us assign the value of learning iterations equal to 18. Based on the graph in Figure 2b, we can conclude that the quality of the simulation has increased. Figure 3 shows the dependence of modeling errors on the number of iterations of the ANFIS-algorithm.

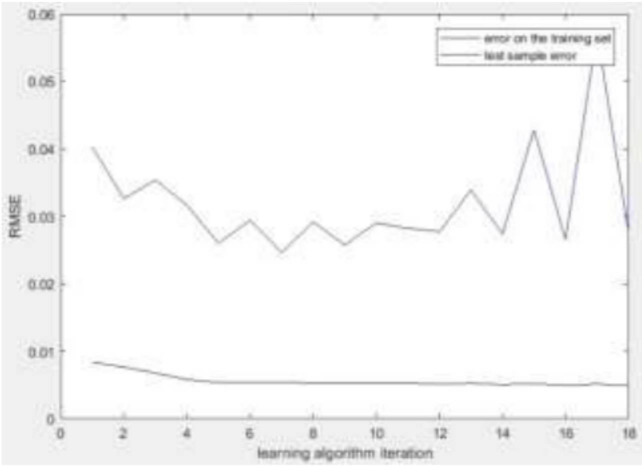


Figure 3. Dependence of modeling errors on the number of iterations of the ANFIS-algorithm

The errors after the ANFIS-training were equal to trnRMSE2 = 0.0049 and chkRMSE2 = 0.0275. Thus, even a small training allowed to increase the accuracy of the model. Analysis of the training dynamics (Figure 3) allows us to conclude that the error on the test sample reaches the lowest value at the 7^{th} iteration (chkRMSE = 0.0246). At the same time, the error on the training sample decreases throughout all 18 iterations.

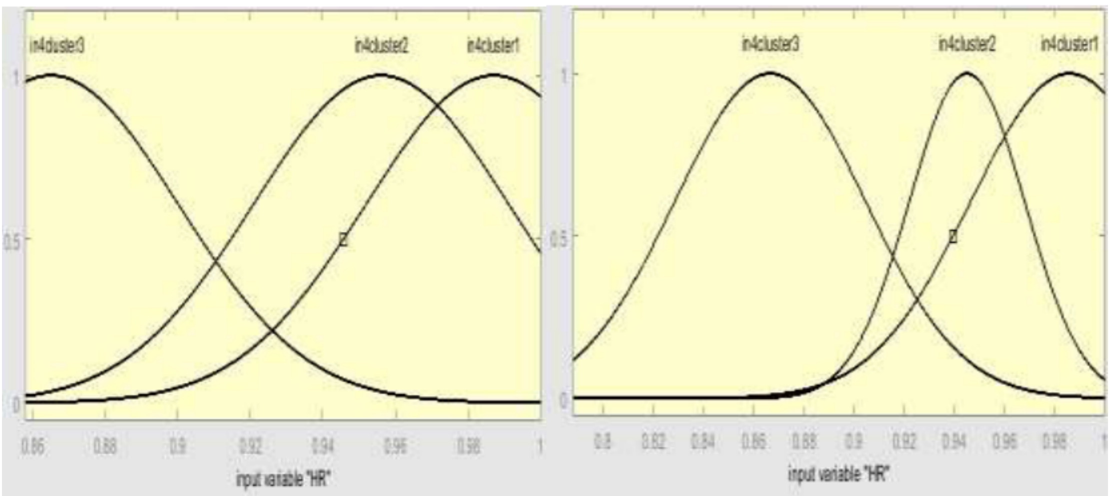
The membership functions in the hypothesis of rules are described by the following Gaussian function [17]:

$$\mu(x) = e^{-\frac{(x-b)^2}{2c^2}}, \tag{11}$$

Where:

b is the coordinate of the membership function maximum and c is the coefficient of the membership function concentration.

Example of the form of the membership function for the input variable *HR* of fuzzy clusters before the training by the ANFIS-algorithm and after it is shown in Figure 4.



a) b)

Figure 4. Membership functions for the input variable *HR* of fuzzy clusters
a) before training; b) after the ANFIS-training

Parameters of all membership functions are presented in Table 3.

Table 3 Parameters of membership functions of the Sugeno fuzzy knowledge base

Input variable	Cluster	Before training		After the ANFIS-training	
		b	***c***	***b'***	***c'***
DT	cluster1	2.668	0.441	2.671	0.443
	cluster2	3.413	0.441	3.413	0.444
	cluster3	3.573	0.441	3.572	0.441
SE	cluster1	0.1	0.074	0.077	0.066
	cluster2	0.1	0.074	0.126	0.070
	cluster3	0	0.074	0.0005	0.075
ET	cluster1	1.967	0.859	1.967	0.861
	cluster2	1.865	0.859	1.86	0.857
	cluster3	3.452	0.859	3.452	0.860
HR	cluster1	0.987	0.035	0.986	0.039
	cluster2	0.956	0.035	0.945	0.023
	cluster3	0.865	0.035	0.866	0.038

Reported values of conclusions of rights for the Sugeno knowledge base are presented in Table 4.

Table 4 Conclusions of the Sugeno knowledge base

Output variable (*DP*)		
Cluster	Before training	After the ANFIS-training
cluster1	$= 0.31+0.9432\cdot DT-0.2238\cdot SE-0.01595\cdot ET+0.4891\cdot HR$	$= 1.281+0.02203\cdot DT-0.01662\cdot SE-0.00039\cdot ET-0.3849\cdot HR$
cluster2	$= -0.005155+0.144\cdot DT+0.1199\cdot SE+0.001565\cdot ET+0.3977\cdot HR$	$= -0.154+0.1672\cdot DT+0.1938\cdot SE+0.003474\cdot ET+0.4531\cdot HR$
cluster3	$= 0.7259+0.003549\cdot DT-2.492\cdot SE+0.0007605\cdot ET+0.126\cdot HR$	$= 0.7096+0.00613\cdot DT+3.61\cdot SE+0.002314\cdot ET+0.1281\cdot HR$

Based on Table 3 and Table 4, it can be seen that because of the ANFIS-training, both parameters of the membership functions and parameters in conclusions of fuzzy inference rules were refined.

Let us compare the quality of the synthesized Sugeno model with the Mamdani fuzzy knowledge base and the linear regression. Synthesis of the Mamdani knowledge base is accomplished using the genfis3 function. Let us assign the following parameters of the fuzzy *c*-means algorithm: the number of clusters is 3; the exponential weight is 2; the value of the improvement of the objective function for one iteration is 0.00001; the number of iterations is 100. As a result, the fuzzy knowledge base, which also contains 3 fuzzy rules, is extracted from the experimental data. Error values are equal to trnRMSE3 = 0.0304 and chkRMSE3 = 0.0349.

The quality of the identified linear regression model according to the adjusted determination coefficient of was $R^2 = 0.83$. Coefficients of this model and its characteristics are presented in Table 5.

Table 5 Regression model

Variable	Coefficient	Standard error	Value of Student t-criterion	Test significance (p-value)
Constant	0.554	0.103	5.332	9.102E-06
DT	-0.025	0.007	-2.874	0.007
SE	0.095	0.034	2.873	0.008
ET	-0.005	0.005	-0.920	0.364
HR	0.467	0.084	5.595	4,339E-06

The model error values were trnRMSE4 = 0.0371 and chkRMSE4 = 0.0313.

To assess the splitting quality of the source data into 3 fuzzy clusters, we calculate the Xei-Beni index using the following formula (Yager and Filev, 1984) [22]:

$$\chi = \frac{\sum\limits_{i=1,c} \sum\limits_{k=1,M} (\mu_{ki})^m \left\| X_k - V_i \right\|^2}{M \min\limits_{i \neq j} (\left\| X_k - V_i \right\|^2)}. \tag{12}$$

The calculated value of the Xei-Beni index by the formula 8 was 0.5348. The optimal splitting into clusters meets the Xei-Beni criterion less than 1. Thus, we can conclude that a good result has been obtained for splitting into fuzzy clusters.

From Table 6 it can be seen that the Sugeno fuzzy knowledge base based on the subtractive clustering and the ANFIS-training do better approximate the dependence between the indicators of the operator's visual searching strategies, the indicator of psychophysiological tension and the detection efficiency of prohibited items than other models.

Table 6 Comparison results of obtained models

Model	RMSE on training sample	RMSE on test sample
Sugeno fuzzy model (without the ANFIS-training)	0.0084	0.0445
Sugeno fuzzy model (with the ANFIS-training)	**0.0049**	**0.0275**
Mamdani fuzzy model	0.0304	0.0349
Linear regression model	0.0371	0.0313

4. CONCLUSIONS

This paper proposes a new approach to estimating the competence level of aviation security screeners allowing to take into consideration parameters of the oculomotor activity and the heart rate variability of the test operators, which differs from the existing approaches using fuzzy classification models. According to the results of an experimental investigation, three different models were synthesized. Comparison results showed that the Sugeno model based on the subtractive clustering and the ANFIS-training is more accurate than the Mamdani model and regression models.

Monitoring mechanism integration of the psychophysiological state of operators into the process of the simulator training will give an opportunity to form the comprehensive conclusion about the degree of development of their professional competencies and readiness for real practical activities. The results of this monitoring can be used to improve the selection of the operator's training strategy based on not only training indicators, but also using the so-called psychophysiological "price" of the test person activity. The introduction of the additional feedback loop into adaptive training algorithms based on the use of eye-tracking technology will give an opportunity to instructors to track and to timely adjust the activity of the trained operator in real time. Application of fuzzy knowledge bases will give an opportunity to create decision-making sup-port systems for the estimation of the competence level of aviation security screeners in intelligent training complexes.

In addition to the noted, the proposed approach can be used to resolve the task of determining the risk level in the airport inspection system. In this case, physical and technological parameters of inspected objects and relevant characteristics of equipment-specific inspection methods can be considered as input parameters of the fuzzy logical inference. For example, physical indicators of the prohibited item can be density, mass, dimensions, volatility, etc. Characteristics of equipment-specific inspection methods can include detection probability, false alarm probability, throughput, reliability, etc. At the same time, this system is considered as an ergatic one. That is why the key role is assigned to the human factor, which is characterized by the reliability of the human operator. Probability of the fact that prohibited items and substances pass the inspection, can be considered as an integral risk indicator. Application of fuzzy knowledge bases will increase the interpretability of the risk model and identify those indicators which value has mostly affected the risk level. Eventually, this will reduce costs of the aviation security audit.

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