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INTELLIGENT SYSTEM OF HELICOPTER PILOTS SIMULATOR TRAINING

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Abstract—*The construction of an intelligent training system for helicopter pilots is under consideration. In the article the structural scheme of the simulator is developed, which includes the intellectual part that implements the process of selection of pilots, the adaptation of training assignments to the individual characteristics of the pilots, with the calculation of optimal training times and the number of repetitions of tasks, with the goal of forming stable helicopter control skills and knowledge control. Creation of tasks is carried out based on the usage of knowledge bases. As intellectual elements, artificial neural networks are used, in particular, a multi-layer perseptron and a Kohonen networks. The learning algorithm for Kohonen networks is given. To calculate the optimal training time and the number of repetitions of individual skills, mathematical models of the learning process have been developed.*

Index Terms—Simulator training; intelligent system; artificial neural network; knowledge base.

I. INTRODUCTION

The training of helicopter pilots on an aircraft simulator is one of the most important elements for ensuring the safe operation of a helicopter. It allows minimizing the negative impact of the human factor, that is reduce the possibility of erroneous actions of the helicopter crew. Practice on the simulator is a specific stage in the training of future pilots. In general, the helicopter simulator is a specialized complex of technical facilities, modeling the process of piloting in terrestrial conditions with a high level of similarity. The simulator is a universal means of ground preparation of the flight crew and serves to solve the following tasks:

– familiarization with the activities of the controls of the aircraft and its systems;

– training skills performing in assessing the situation and making decisions in special cases and during performance of tactical tasks;

– the development of operational skills in special cases in flight;

– working out of actions by controls on elements of flight assignments;

– automated setting of tasks for the flight shift;

– pilots self-training;

– group control of readiness for the flight task;

– the individual analysis of flights and in the composition of the flight group [6].

Training of pilots on the simulator will allow in optimal terms:

– to improve the quality of skills mastering at the given time of training due to the optimal distribution of time between them;

– to reduce, at a given level of mastering the necessary skills, the total time of training by determining the sequence of mastering in step-by-step or parallel learning. As preliminary estimates show, the total training time can be reduced by 10 – 20%, and hence the cost of training [4].

Further increase in the effectiveness of simulator training can be achieved through the use of an intelligent system in its structure that ensures a qualitative preliminary selection of trainees, the adaptation of educational material to the individual characteristics of the pilot with the calculation of the optimal training time and the number of repetitions of individual operations for the formation of sustainable skills [5].

II. PROBLEM STATEMENT

The proposed intelligent system of a simulator consists of two bases of knowledge, three artificial neural networks (ANN), and of a database (Fig. 1).

At the beginning of preliminary selection a pilot performs initial set of tasks, formed by an instructor. His results send into ANN 2 for estimation and next task selecting from the knowledge base 2 and download into the database.

Preliminary selection results fill the database which is used for simulator training. The results form the level of the pilot. ANN 1 estimates the testing results from the database and forms the next tasks using the knowledge base 1 content. The results also send into database. ANN 3 performs the pilots estimation using the data from sensors of the simulator.

As an intelligent system of the simulator is proposed the use of an artificial neural network. It is necessary to select a suitable neuron network and train it.

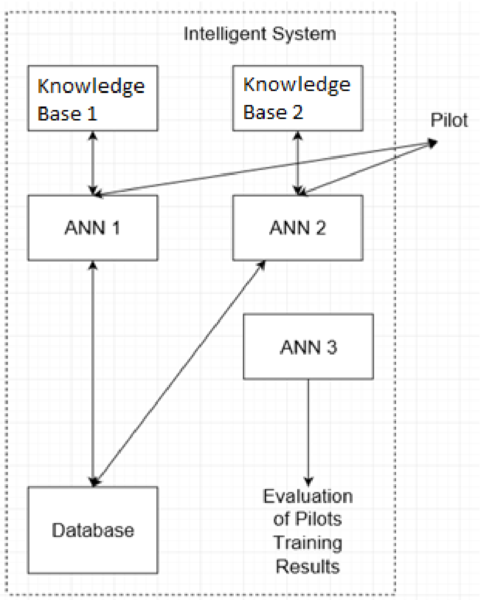

Fig. 1. Structural scheme of intelligent system of simulator

III. PROBLEM SOLUTION

One of the modern and flexible to learn is the neural network of Kohonen (Fig. 2). In its architecture, it is more suitable for processing the results of performing tasks on the simulator, since in such a network all objects are classified, and represented as a certain vector that feeds the input of the neural network [2]. In addition, Kohonen networks can be used to reduce the size of data with minimal loss of information. In the architecture under consideration, the signal propagates from the inputs to the outputs in the forward direction. The structure of the neural network contains a single layer of neurons (the Kohonen layer) without bias coefficients. The total number of weighting factors is calculated as the product:

$$N_w = MK.$$

The number of neurons is equal to the number of clusters, among which there is an initial distribution and subsequent redistribution of training examples. The number of input variables of the neural network is equal to the number of features that characterize the object of study and on the basis of which there is the assignment of it to one of the clusters. It is necessary to distinguish the self-learning and self-organization of the Kohonen neural network. In normal self-learning, the network has a strictly fixed structure, that is, the number of neurons that does not change throughout the life cycle. In self-organization, the network, on the other hand, does not have a constant structure. Depending on the distance found to the winner-neuron, either this neuron is used to cluster the example, or a new cluster with the corresponding weight coefficients is created for the example submitted to the inputs. In addition, in the process of self-organization of the Kohonen network structure, individual neurons can be excluded from it.

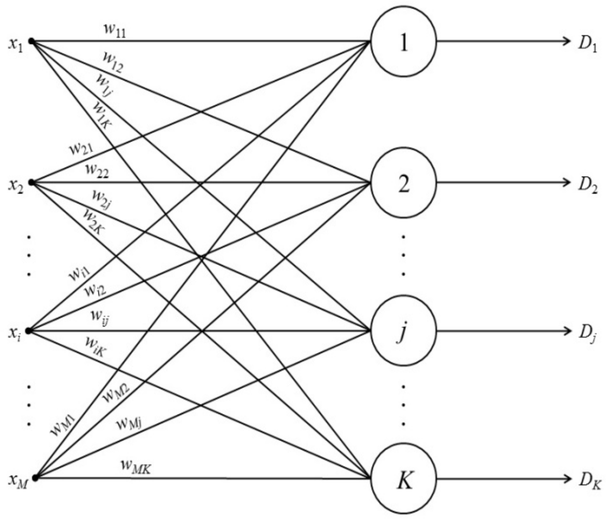

Fig. 2. General structure of the Kohonen neural network

Normalization of input variables is performed within [-1, 1] or [0, 1].

For the life cycle of neural networks of this architecture, three main stages of the life cycle are characteristic: training, cluster analysis and practical use [1].

The Kohonen network learning algorithm includes stages whose composition depends on the type of structure: a constant (self-learning network) or a variable (self-organizing network). For self-study, the following are consistently performed.

1) Specifying the network structure (the number of neurons in the Kohonen layer) (K).

2) Random initialization of weights by values satisfying one of the following restrictions:

– when the initial sample is normalized within [-1, 1]:

$$|w_{if}| \le \frac{1}{\sqrt{M}},$$

– when the initial sample is normalized within [0, 1]:

$$0.5-\frac{1}{\sqrt{M}}\leq w_{if}\leq 0.5+\frac{1}{\sqrt{M}},$$

where M is the number of input network variables – characteristic features of the object of investigation.

3) Submission of the random learning example of the current learning epoch to the network inputs and calculation of the Euclidean distances from the input vector to the centers of all clusters:

$$R_j=\sqrt{\sum_{i=1}^{M}(\tilde{x}_i-w_{if})^2}.$$

4) By the smallest of the values of R_j, the neuron-winner j, which is closest in values with the input vector, is chosen. For the selected neuron (and only for it), correction of the weight coefficients is performed:

$$w_{ij}^{(q+1)}=w_{ij}^{(q)}+v(\tilde{x}_i-w_{ij}^{(q)}),$$

where v is the coefficient of training speed.

5) The cycle is repeated from step 3 until one or more end conditions are fulfilled:

– exhausted the given limiting number of learning epochs;

– was no significant change in the weight coefficients within the specified accuracy during the last era of training;

– exhausted the given limiting physical time of training.

The rate of learning progress can be set constant from the limits (0, 1] or a variable value, gradually decreasing from epoch to epoch.

In the case of self-organization of the Kohonen network, the algorithm undergoes certain changes.

1) The critical distance R_{cd} is assigned, corresponding to the maximum allowable Euclidean distance between the inputs of the example and the weights of the winner neuron. The initial structure does not contain neurons. When the very first example of the training sample is applied to the network inputs, a first neuron with weight coefficients equal to the input values is created.

2) On the network inputs are supplied with a randomly selected new current epoch example training calculated Euclidean distances from Example center of each cluster of relation (3) is determined and the winning neuron with the lowest of them $R_{\min}$.

3) If condition $R_{\min}$ <= R_{cd}, the weighting coefficients of the corresponding winner neuron are corrected by the relation (4), otherwise a new neuron is added to the network structure, the weights of which are taken numerically equal to the input values of the given example.

4) The procedure is repeated from point 2. If during the last era of learning any clusters remain unoccupied, the corresponding neurons are excluded from the structure of the Kohonen network.

5) Calculations terminate if one of the conditions prescribed in the self-learning algorithm of a network of a fixed structure is met.

Another modification of the algorithms of self-learning and self-organization involves the correction of the weight coefficients of not only the neuron-winner, but also all other neurons. To do this, use the learning rate coefficient, which decreases with increasing distance to the center of the cluster R_j:

$$v_j=v_0\left(1-\frac{1}{1+e^{-\beta(R_j-R_{cd})}}\right),$$

where R_{cd} is the critical value of the distance: the smaller it is, the more significant will be the adjustments to the weights of the clusters closest to the training example and are practically insignificant – weights more or less remote from it; β is the parameter that sets the degree of influence of nonlinearity on the distance speed ratio; v_0 is the basic (maximum possible) value of the speed coefficient at the current learning epoch.

As a value R_{cd} you can calculate the average distance for each cluster at the current presentation of the training example. The parameter β is recommended to be chosen equal to 3.0 ± 0.5.

As a rule, in practice, using the self-organization of Kohonen's neural network, one has to deal with one more problem. On the one hand, some clusters may contain too few examples, which leads to difficulties in the subsequent generalization of information. On the other hand, some clusters may be too large, that is, contain many examples. In this case, in order to regulate the size of the cluster and solve the problem of its overflow, you can specify as an additional parameter the limiting number of examples that form the cluster (N_{cd}). If, at some point, it turns out that the new example should be assigned to a cluster that is already maximized, a decision is made to create another cluster, the center of which will be a vector of variables of one of the (N_{cd} + 1) examples of the cluster (including the new one) of the cluster most remote from the center [7].

A cluster analysis procedure is used for the trained neural network – a procedure for describing the properties of a cluster on the basis of an analysis of the quantitative and qualitative composition of the examples that formed it. It should be borne in mind that the description of clusters can be based not only on the values of the input variables of the training sample, but also on the values of variables that did not participate in the formation of clusters. In particular, the description can include data on the average values of such variables among all the examples that formed the cluster. In addition, it is advisable for each cluster to have data on the root-mean-square deviation or dispersion for each variable.

In practical use of the Kohonen neural network, a new example is submitted to its input and refers to one of the existing clusters, or it is concluded that such a reference is impossible (for a large distance to the center of the nearest cluster). If the selection of the cluster was completed, its description, obtained as a result of the cluster analysis, and the decisions corresponding to the cluster should be distributed including the submitted example [3].

The practical use of the Kohonen network is facilitated by visualizing the results of clustering. As a result of self-learning (self-organization) of the network, a set of clusters is obtained, each of which is characterized by its center (the values of the weight coefficients of the corresponding neuron) and the number of training examples that formed it. It is easy to determine the Euclidean distance between the centers of all possible pairs of clusters and graphically represent them on the so-called Kohonen map – a two-dimensional graphical structure that allows us to judge not only the size and position of each cluster, but also the proximity and mutual arrangement individual clusters.

The number of neurons in the input layer is determined by the number of components of this input vector, and the number of outputs is determined by the number of classes, but it is possible that several neurons belong to the same class. Weight coefficients are objects of the same type as the input data. Next, we introduce the distance function between objects of a given type, in our case, this is the Levenshtein distance. The Kohonen neural network is used in the classical form, but the calculation of the Levenshtein distance is modified to solve a specific problem [9].

IV. RESULTS

A result of work of Kohonen neural network is the classification of all trained pilots (20 pilots in our case) into 3 groups according to their training results.

The group of pilots with high academic performance have the following training results:

A Cluster number –1;
Cluster size – 5;
Average training effectiveness – 0.86;
Average probability of making an error – 0.05;
Average general rating – 0.9.

The group of pilots with intermediate academic performance have the following training results:

A cluster number –2;
Cluster size – 9;
Average training effectiveness – 0.71;
Average probability of making an error – 0.09;
Average general rating – 0.76.

The group of pilots with low academic performance have the following training results:

A cluster number –3;
Cluster size – 6;
Average training effectiveness – 0.64;
Average probability of making an error – 0.14;
Average general rating – 0.68.

V. CONCLUSION

In this article, a method for solving the problem of an intelligent system for the preliminary selection of helicopter-trained drills on a simulator is considered. Particular attention should be paid to the model of fuzzy estimation using neural networks, since the use of neural networks provides a fundamentally new approach to solving the problems of testing and controlling knowledge. By the way, the use of neural networks is suitable for analyzing the execution of tasks on the simulator. This can maximize the assessment of knowledge and skills by the intellectual system to the conclusions that the instructor makes when verifying the performance of a practical task.

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В. М. Синєглазов, В. О. Глухов. Інтелектуальна система навчання пілотів гелікоптерів на тренажері

Розглядається побудова інтелектуальної системи навчання пілотів гелікоптерів. В статті розроблена структурна схема тренажера, що включає інтелектуальну частину, яка реалізує процес відбору пілотів, адаптацію навчальних задач до індивідуальних особливостей пілотів з розрахунком оптимальних значень часу підготовки та кількості повторювань завдань, з метою формування стійких навичок керування гелікоптером, а також контролем знань. Формування завдань здійснюється на підставі використання бази знань. В якості інтелектуальних елементів використовуються штучні нейронні мережі, зокрема, багатошаровий персептрон і мережі Кохонена. Наведений алгоритм навчання мереж Кохонена. Для розрахунку оптимального часу навчання та кількості повторень окремих навичок, розроблені математичні моделі процесу навчання.

Ключові слова: навчання на тренажері; інтелектуальна система; штучна нейронна мережа; база знань.

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В. М. Синеглазов, В. О. Глухов. Интеллектуальная система обучения пилотов вертолетов на тренажере

Рассматривается построение интеллектуальной системы обучения пилотов вертолетов. В статье разработана структурная схема тренажера, включающего интеллектуальную часть, которая реализует процесс отбора пилотов, адаптацию учебных заданий к индивидуальным особенностям пилотов с рассчетом оптимальных значений времени подготовки и количества повторений заданий, с целью формирования устойчивых навыков управления вертолетом, а также контролем знаний. Формирование заданий осуществляется на основании использования баз знаний. В качестве интеллектуальных элементов используются искусственные нейронные сети, в частности, многослойный персептрон и сети Кохонена.

Приведен алгоритм обучения сетей Кохонена. Для рассчета оптимального времени обучения и количества повторений отдельных навыков, разработаны математические модели процесса обучения.
Ключевые слова: тренажерное обучение; интеллектуальная система; искусственная нейронная сеть; база знаний.

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