Practical Application of the Data Preprocessing Method for Kohonen Neural Networks in Pattern Recognition Tasks

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***Abstract* — Self-Organizing Map (SOM) is a very effective solution for solving pattern recognition problems. However, some ambiguities appear during learning process with the existence of linear patterns in the learning data, in this case, the learning process lasts for a long time and the network produces irrelevant results. The work provides the resolution of the detected problem and the application of the SOM for the pattern recognition. To achieve our objective and minimize the learning time, a SOM improved model has been developed. This model uses a special block able to filter the input data and reduce the size of the learning multitude. The presented experimental test results in this work show that the improved model exceeds the standard model in terms of the recognition results accuracy and the learning time. The results obtained in this work encouraged us to think about using the improved model to develop a smart approach (SmartMaps) of Geographic Information Systems (GIS).**

Keywords- Pattern recognitions; Artificial Neural Network; self-organizing map; preliminary processing of input vectors; Data visualising; principal component analysis; power iteration algorithm.

I. INTRODUCTION

The new information technologies offer great opportunities for human activity in different areas. However, the important element of their evolution is not only the extent increase of computer technology's capacity, but also its intellectualization by the creation of new intelligent systems in the form of software or hardware models. These systems must be equipped with intellectual abilities comparable to those of humans. Their use is to solve very complex problems for classical information systems, such as the recognition, diagnosis and prediction. Recently systems based on Artificial Neural Networks (ANN) are widely used to create these systems [1]-[3]. The essential advantage of ANN is a functional similarity to biological neural networks and the universality for solving a wide range of tasks. There are a variety of architecture and learning methods for different ANN models. Currently the models based in competitive learning algorithms, like Self-Organizing Maps (SOM) and counter-propagation network are widely used in pattern recognition tasks [4]-[8]. An important and useful feature of SOM is the ability to visualize multi-parameter objects in a one-dimensional or two-dimensional space [10].

However, tests show that the use of SOM as it stands, does not give relevant results, as the learning algorithm requires normalizing input data. The consequence of this operation is the loss of some information about the initial lengths of objects, and the ratio between the absolute values of input object components. In this case and with the existence of linear patterns, the learning process takes a long time and SOM produce irrelevant results [11]. In this work, we realized a new model of the SOM which provides the introduction of a preprocessing block and data optimization. Pre-treatment process is based on a method that combines two well-known and approved algorithms: Analysis Principal Components and Iterated Power. The both map models (standard and improved) are applied to solve a task of pattern recognition; the task objective is to visualize geographical information for the African continent countries. In this work we present also the results of this practical application, and the detailed analysis of their comparison.

The article consists of five sections. In the introduction, we show the importance of intelligent systems, their application area and new means for their development. We also describe the purpose of the work, the solved problem and the future perspective. The second section comprises the description of the pattern recognition task, citing the classical and modern methods used to solve this problem. So we give details of the learning algorithm of the SOM, and the principles of its application in this domain, including the ambiguities detected in this model of ANN and possible solutions. In the third section we present the algorithm of preliminary data processing and optimization, with argument and explanation of different steps of its implementation and the benefits obtained from its application with SOM. The fourth part provides the practical application of the two

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models for the recognition of the African continent countries. In this section we described: the approach we have followed to solve this task, the means and tools provided by the application developed for its use, as well as the results obtained and details of their analysis. As a conclusion, we mention the important moments concerning the problems encountered during the SOM applications in pattern recognition, the contribution of the proposed solution and our perceptive.

II. THE APPLICATION FEATURES OF NEURAL NETWORKS IN PATTERN RECOGNITION TASKS

The task of pattern recognition can be considered as a combination of two related subtasks: classification and clustering. The classification task is to determine the belonging of the input pattern to one of predefined classes [11]. This classification type is used for the recognition of handwritten texts, the lyrics and ECG signals. During clustering, the learning algorithm is based only on the input data without desired output. In this case, the learning process will try to identify the similarity between patterns, and similar objects will be brought to the same category (cluster); the proximity is often understood in the sense of the Euclidean metric [12] [13]. This problem occurs during the extraction of data, the study of their properties and compression. Therefore, two paradigms are identified in the problems of pattern recognition: recognition supervised based on the classification technique and unsupervised recognition where we use the clustering technique.

The classical model is based on supervised recognition methods; these are the probabilistic methods, in particular, the method based on Bayes formula, adapted for manual calculations [14]. The solution rules can be derived as probabilistic identification parameters of belonging of an object to a particular class (Bayesian method), or as a simple analytical function (discriminate analysis method). These methods have certain limitations, such as absence of reliability, because they are based only on the linear rules [15].

The modern recognition methods as neural networks cannot be used without computers. These systems are able to elaborate the classification and clustering rules, and to be used to develop intelligent systems for a wide use.

A. *The pattern recognition process with the self-organizing map of Kohonen*

Artificial neural networks are widely used for pattern recognition; these systems use specific algorithms for classification and clustering of multi-parameter objects (events, situations, processes). Currently, there are several ANN paradigms that are used in this task. However, the models which are mainly used are the ones using competitive learning methods. In particular, we can cite the SOM [6] and the counter propagation network [7].

The Kohonen network model uses the competitive learning method. This process brings together similar objects in same cluster by reserving the topological relationships in input data [16] [17]. During learning, the neurons compete, and for each group of similar objects, a single winner neuron is defined. The fixed neurons represent the centers of clusters. The metric used in this operation is the Euclidean distance between the synaptic weights vectors, and the input objects vectors.

The learning procedure begins with the normalization of input data and synaptic weights to reduce the learning time [11]. This operation is based on the following algebraic formula:

$$x_i = x_i / \sqrt{\sum_{j=0}^{n-1} x_j^2} \tag{1}$$

Where: x_i – the input object component or the vector of synaptic weights;

n – The number of variables in the vector x.

The main learning algorithm passes successively through a series of iterations, and it relies only on the input data. During the learning process, it attempts to define for each group of similar objects a specific neuron qualified as winner. At the end of this procedure the topologically adjacent neurons, respond to similar input vectors.

To fix the winner's neurons, we use the metric of the Euclidean distance [5] see formula below:

$$k : \|\mathrm{w}_k - \mathrm{x}\| \le \|\mathrm{w}_o - \mathrm{x}\| \quad \forall o \tag{2}$$

Subsequently the algorithm performs a correction of synaptic weights to gradually minimize the distance between the winning neurons and the input objects. For this correction we use the following formula [6]:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha_i(t) h(d,t) \cdot \left[y_i - w_{ij}(t)\right] \tag{3}$$

where: $\boldsymbol{y_i}$ - the value of the output neuron i;

w_{ij} (t) and w_{ij} (t +1): the synaptic weights during *t* and (*t + 1*) iterations.

$\boldsymbol{\alpha_i}$(t): learning rate, this coefficient can have a value between *0* and *1*, and it is calculated using the following equation:

$$\alpha_i = \alpha_0 e_t^i \tag{4}$$

where: ***i*** is the iteration number;

t is the iteration rate.

h(d, t) : neighborhood function, it is written according to the formula below:

$$h(d,t) = \begin{cases} 0, d \ge \delta(t) \\ e^{(-\frac{d}{2\delta(t)})}, d < \delta(t) \end{cases} \tag{5}$$

$$\delta(t) = \delta_0 e^{(-\frac{t}{\mu})} \tag{6}$$

where: d is the distance between the winner neuron and an x neuron.

$$\mu = \frac{n}{\log_{10}(\delta_0)} \tag{7}$$

where: $\boldsymbol{\delta_0}$ is Constant.
$\boldsymbol{n}$ is Iteration rate.

The learning process will be continued until the stabilization of the SOM, and the results will be presented as a grid of neurons in a two dimensional space.

However, the application of the SOM can give irrelevant results due to the problem of linear dependence [12]. To avoid these constraints we offer the use of an enhanced map model that can well classify data even with the presence of linear patterns. The new model included a pretreatment method and data optimization.

III. THE DATA PRETREATMENT METHODS BASED ON A GEOMETRIC APPROACH

The idea of the proposed method is to use a specific block of data preprocessing. The processing operation uses an algorithm based on two typical methods of data analysis: Principal Component Analysis (PCA) and Iterated Power (IP) [24] [32]. This combination allows filtering data to reduce the dimension of the data table and saving the most informative parameters in each multitude vectors. The new contribution of this block is the elimination of regularity between the vectors components and disappearance of the linear dependence problem, which could prevent this type of ANN to provide accurate and relevant results.

Initially, we assume that the learning data table is composed of $\boldsymbol{n}$ rows and $\boldsymbol{p}$ columns; see Figure 1.

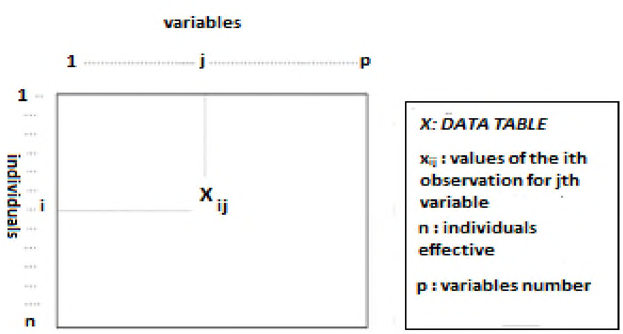

Figure 1. Learning data table

In the first step, the algorithm calculates the vector of main point $\boldsymbol{g}$. This point is the center of the points cloud in a space $\boldsymbol{F}$. See the formula below:

$$g^t = (\overline{x}^1, \ldots, \overline{x}^p) \tag{8}$$

$$\overline{x}^j = \frac{1}{n}\sum_{i=1}^{n} x_i^j \tag{9}$$

At the base of the vector $\boldsymbol{g}$ is calculated the data centered matrix, which is written in terms of $\boldsymbol{X}$ as the following way:

$$Y = X - 1g^t \tag{10}$$

where: g^t is the transposed of g, and the term centered signifies that the means of the variables $\overline{y}^j$ are zero.

The centered data matrix $\boldsymbol{Y}$ is used in this step for calculating the variance-covariance matrix $\boldsymbol{V}$, which is written as a function of Y as follows:

$$V = \frac{1}{n} Y^t Y \tag{11}$$

where: Y^t is the transposed of $\boldsymbol{Y}$.

The V matrix is presented as follows:

$$V = \begin{pmatrix} S_1 & . & . & S_{1p} \\ S_{21} & . & . & . \\ . & . & . & . \\ S_{p1} & . & . & S_p \end{pmatrix}$$

where: $\boldsymbol{S_{KL}}$ is the covariance of the variables k and l, and $\boldsymbol{S_k}$ is the variance of the variable k.

In the last step, in order to develop the correlation matrix $\boldsymbol{R}$ we must calculate the two diagonal matrices $\boldsymbol{D_{1/s^2}}$ and $\boldsymbol{D_{1/s}}$ as a function of $\boldsymbol{V}$ as follows:

$$D_{1/S^2} = \frac{1}{Diag(V)} \tag{12}$$

$$D_{1/S} = \frac{1}{Diag(D_{1/S^2})} \tag{13}$$

The matrix $\boldsymbol{R}$ is composed of linear correlation coefficients between the variables p. It summarizes and shows the structure of linear dependencies between these variables. The matrix is symmetric, and the component values of its diagonal equal $\boldsymbol{1}$. $\boldsymbol{R}$ calculates as a function of $\boldsymbol{V}$ as follows:

$$R = D_{1/S} V D_{1/S} \tag{14}$$

where: $D_{1/s}$ is a diagonal matrix, its diagonal is composed by the values $\frac{1}{s_1}, \ldots \ldots \ldots, \frac{1}{s_p}$.

Now it is the time to apply the iterative power method to search the eigenvectors [32]. These vectors are the rows of the final matrix of input objects $\boldsymbol{M}$.

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$$M = \begin{bmatrix} x_{11} & . & . & x_{1l} \\ . & . & . & . \\ . & . & . & . \\ x_{n1} & . & . & x_{nl} \end{bmatrix}$$

The figure below presents the proposed algorithm flowchart.

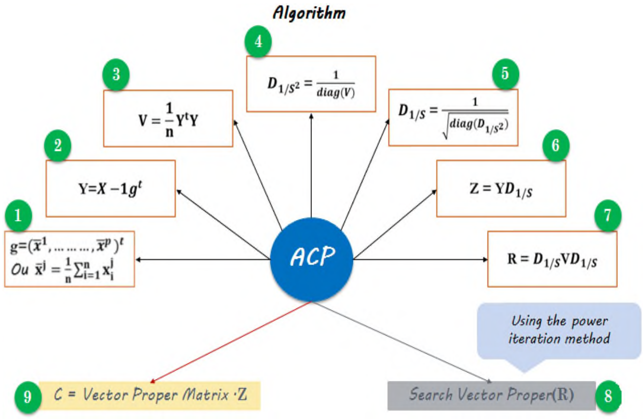

Figure 2. The proposed algorithm flowchart

In this algorithm, the first seven steps allows to calculate the correlation matrix ***R*** using the ACP method. This matrix will be used by the iterated power method to search the eigenvalues and the eigenvectors. The last two steps allows to develop the reduced final matrix based on the IP algorithm.

The new matrix calculated by using the proposed method will present the data source for learning the SOM. The results are displayed and interpreted using grids of neurons in two-dimensional space. The functional structure of the proposed model is shown below in Figure 3.

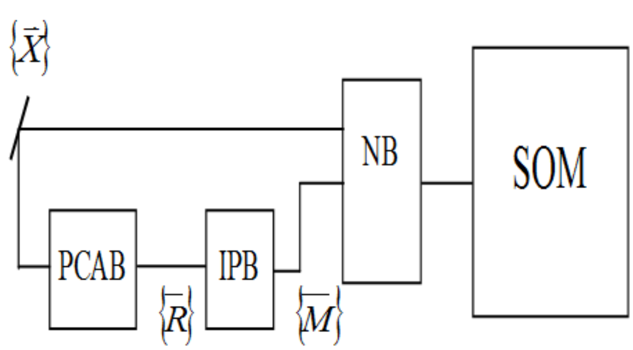

Figure 3. The functional structure of the proposed SOM model

According to the proposed algorithm diagram, and the functional structure schema of the proposed model, we can summarize the learning process of this neural network system in the following steps:

- The treatment of the initial data by the principal component analysis blocks PCAB, to obtain the correlation matrix R.
- At the base of the correlation matrix, the block of the iterated power IP seeks for eigenvectors that constitute the rows of the resulting matrix M of input objects.
- The NB blocks perform the normalization of data matrix M.
- The last step provides the phase of the network learning based on the pattern data calculated in the precedents steps.

IV. Objective and Research Base

The objective of research is to establish the advantages and disadvantages of the preprocessing method of realizations based on the geometric approach in practical pattern recognition problems. The research base is the software model of the SOM developed by us using the VP.net programming platform. The application includes both learning algorithms: standard and improved, and it is able to visualize the results as neural grids in a two-dimensional space. The interpretation of learning outcomes is based on the distribution of winner neurons on the map, and the definition of the cluster which they belong.

A. Application tests and results

To study and analyze the proposed method of preliminary data processing for the SOM, we use a typical problem of pattern recognition: the Recognition of the African Continent Countries [33]. The objective of this task is to test the implementation of two SOM models (standard and modified). The recognition will be performed using the SOM instruments and tools, including the possibility of classification and clustering, as well as to view the data on the neurons grid in a two-dimensional space. The application begins with the learning step to prepare the knowledge base necessary for its operation; this database should generate relevant results. For this typical neural network, the learning results evaluation is done by using the maps which visualize the classes and clusters objects (Country). After correct learning, the SOM can be used to build an intelligent Atlas map that is able to give the necessary information about the continent countries. The learning set is composed on 52 vectors, where each one corresponds to a country. Each vector is characterized by 20 parameters (geographic location, language, area, religion, color and flags elements, etc); see Table I.

The developed software works in two modes, and supports both models: standard and improved. The learning results are interpreted by using the two maps (Class map and Clusters map) and textual data. The maps are drawn as rectangles grids, of dimension (N × N), corresponding to the number of output layer neurons. The top left rectangle presents the first neuron. For a better interpretation of the learning results, we use a coloring system where the colored rectangles represent the winner neurons. By click on every

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rectangle the application displays the related information. The same principle is used with the map clusters; see Figure 4.

TABLE I. THE DESCRIPTIVE DATA OF THE AFRICAN CONTINENT COUNTRIES

Nº	The Country	The Parameters																			
1	Algeria	1	2388	20	8	2	2	0	3	1	1	0	0	1	0	4	1	1	0	3	1
2	Angola	2	1247	7	10	5	0	2	3	1	0	0	1	0	1	4	1	0	1	4	5
3	Benin	1	113	3	3	5	0	0	2	1	1	0	0	0	0	3	1	0	0	3	3
4	Botswana	2	600	1	10	5	0	5	3	0	0	1	0	1	1	6	0	0	0	5	5
5	Burkina	4	274	7	3	5	0	2	3	1	1	0	1	0	0	4	1	0	0	4	3
6	Burundi	2	28	4	10	5	0	0	3	1	1	0	0	1	0	4	3	0	0	1	1
7	Cameroon	1	274	8	3	1	3	0	3	1	1	0	1	0	0	2	1	0	0	3	2
8	Cape Verde Islands	4	4	0	6	0	1	2	5	1	1	0	1	0	1	2	1	0	0	4	3
9	Central African Republic	1	623	2	10	5	1	0	5	1	1	1	1	1	0	2	1	0	0	6	2
10	Chad	1	1284	4	3	5	3	0	3	1	0	1	1	0	0	2	0	0	0	6	4
11	Comoros Islands	2	2	0	3	2	0	0	2	0	1	0	0	1	0	3	4	1	0	3	3
12	Congo	2	342	2	10	5	0	0	3	1	1	0	1	0	0	4	1	0	1	4	4
13	Djibouti	1	22	0	3	2	0	0	4	1	1	1	0	1	0	6	1	0	0	1	3
14	Egypt	1	1001	47	8	2	0	3	4	1	0	0	1	1	1	5	0	0	0	4	5
15	Equatorial Guinea	1	28	0	10	5	0	3	4	1	1	1	0	1	0	3	0	0	0	3	4
16	Ethiopia	1	1222	31	10	1	0	3	3	1	1	0	1	0	0	3	0	0	0	3	4
17	Gabon	2	268	1	10	5	0	3	3	0	1	1	1	0	0	3	0	0	0	3	6
18	Gambia	4	10	1	1	5	0	5	4	1	1	1	0	1	0	4	0	0	0	4	3
19	Ghana	4	239	14	1	5	0	3	4	1	1	0	1	0	1	4	1	0	0	4	3
20	Guinea	4	246	6	3	2	3	0	3	1	1	0	1	0	0	2	0	0	0	4	3
21	Guinea Bissau	4	36	1	6	5	1	2	4	1	1	0	1	0	1	2	1	0	0	4	3
22	Ivory Coast	4	323	7	3	5	3	0	3	1	1	0	0	1	0	1	0	0	0	4	3
23	Kenya	1	583	17	10	5	0	5	4	1	1	0	0	1	1	4	0	0	1	5	3
24	Lesotho	2	30	1	10	5	2	0	4	1	1	1	0	1	0	6	0	0	1	3	6
25	Liberia	4	111	1	10	5	0	11	3	1	0	1	0	1	0	4	1	0	0	6	4
26	Libya	1	1760	3	8	2	0	0	1	0	1	0	0	0	0	3	0	0	0	3	3
27	Malagasy	2	587	9	10	1	1	2	3	1	1	0	0	1	0	4	0	0	0	1	3
28	Malawi	2	118	6	10	5	0	3	3	1	1	0	0	0	1	4	1	0	0	5	3
29	Mali	4	1240	7	3	2	3	0	3	1	1	0	1	0	0	2	0	0	0	3	4
30	Mauritania	4	1031	2	8	2	0	0	2	0	1	0	1	0	0	3	1	1	0	3	3
31	Mauritius	2	2	1	1	4	0	4	4	1	1	1	1	0	0	4	0	0	0	4	3
32	Morocco	4	447	20	8	2	0	0	2	1	1	0	0	0	0	4	1	0	0	4	4

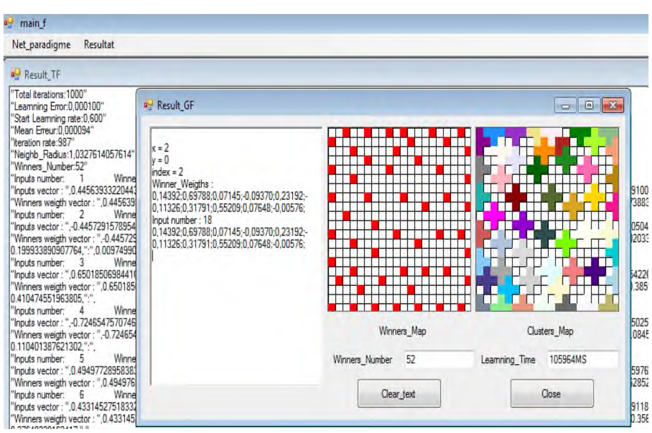

Figure 4. Graphic software interface

B. *Test results analysis*

In this section, we will try to interpret and analyze the learning results, in order to reveal the advantages and disadvantages of each model over the other. We use two specific metrics to compare the studied models: The first one is the percentage of recognition which defines a relationship between the number of winner neurons and the total number of input learning vectors. The second metric represents the learning time.

The research results presented in Figures 5 and 6 show that the standard model has defined 49 winner neurons for the 52 input objects, that present a recognition percentage equivalent to 94.23%, and a learning time that reaches 204660 MS. But the improved model has defined 52 winner neurons for the 52 individuals that present a recognition percentage reaches 100%, and a learning time not exceeding 105964 MS.

These results affirm that the new model exceeds the standard model at the level of the recognition relevance and the learning time. So we can say that with the proposed method of data pretreatment, the map possess new opportunities and able to give good results even with the existence of linear dependency in the learning data.

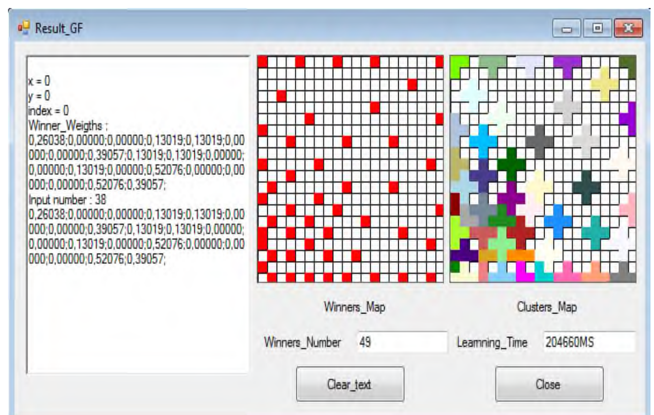

Figure 5. Learning Result recognition of African countries (modified model)

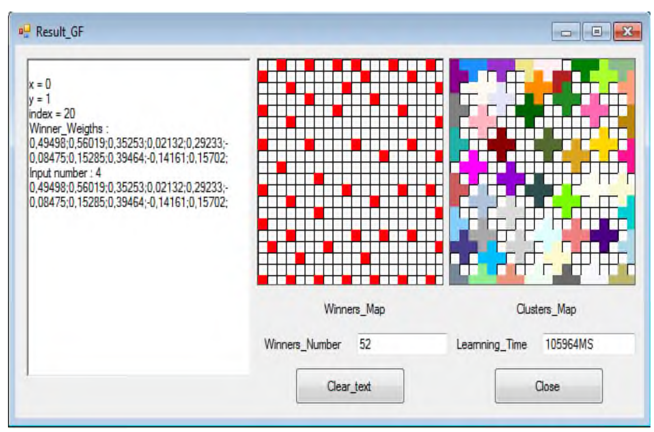

Figure 6. Learning result recognition of African countries (modified model)

The visual analysis of maps shows that for standard model the most of the winner neurons and their clusters are concentrated in the lower left half of the maps, but for the improved model these elements are well dispersed over the map surface. This improvement in the topological presentation of the results for both types of maps (winners and Clusters) is explained by the change in the learning data structure, including the relationship between objects. This modification is performed by using data pretreatment process.

To show the impact of the input data size on the learning time, and the contribution of the method used in the improved model, the data set has been distributed to groups containing different numbers of individuals going from 5 until 52; see Table 2.

The data in Table II shows that the data pretreatment method has reduced the individual lengths, from 20 to 10 components for each individual. This decrease has allowed to the improved model reduce the learning time compared to the standard model.

TABLE II. LEARNING RESULTS FOR ALL INDIVIDUAL GROUPS

Individual numbers	**Standard model**				**Improved model**			
	Component numbers	*winner numbers*	*Iteration rate*	*Learning time in MS*	*Component numbers*	*Winner numbers*	*iteration rate*	*Learning time in MS*
5	100	5	487	8076	50	5	495	5384
10	200	10	612	21446	100	10	633	13880
15	300	15	675	37671	150	15	720	24283
20	400	20	787	52239	200	20	774	32367
25	500	25	784	65214	250	25	767	43168
30	600	30	832	66254	300	30	816	56204
35	700	35	861	106513	350	35	890	68892
40	800	40	877	112596	400	40	900	84489
45	900	45	977	148312	450	45	908	92963
52	1040	49	1000	204660	520	52	987	105964

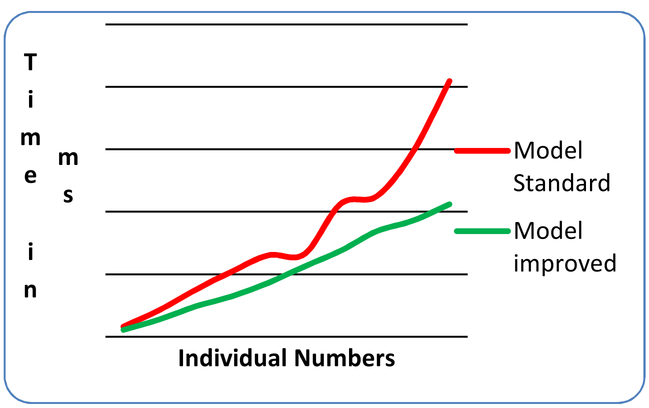

Figure 7. The graphical presentation of the learning results for both SOM models.

The graph in Figure 7 above shows the relationship between the learning time spent by both models, and the number of individuals employed. The graph curves show that the learning time for both models is increasing in parallel with the augmentation of the learning multitude size. Thus, it is observed that the learning process takes less time for the improved model than the standard model. And the difference of learning time between both models is enlarged with growth of the pattern multitudes size.

To sum up, the improved model exceeds the standard by three parameters: The relevance of the results of the recognition, learning speed and the dispersion the winner neurons on the map. The first parameter is justified by the recognition percentage, which reached 100% for the improved model, but only 94.23% for the standard. The second parameter is justified by the learning time that decreases twice using the improved model compared to the standard model. And the latter parameter is justified by equitable dispersion of winner neurons and the clusters on maps (classes and Clusters). So, the results show that the improved model has solved this task better than the standard model.

V. CONCLUSION AND FUTURE WORK

In this work we have tried to improve and implement a type of neural networks in a task of object recognition, called the Self-Organizing Map (SOM). In this work we have justified the choice of the used paradigm, and demonstrated that its direct application does not provide good results. So our objectives were determining the ambiguities and the means of their eliminations. For the first objective, via a theoretical study and experimental tests we have defined the problem that prevents the correct learning of network. To achieve the second objective, we proposed and approved a data pretreatment method, at the basis of which we have developed a new functional structure for the improved model of SOM. The results of the tests show that: The SOM is a reliable and intelligent tool for solving the recognition problems, and the method of preliminary processing of the input data enriches the SOM with new competences. Finally, the improved model exceeds the standard model in the accuracy of the results and the learning time. The obtained results encourage us to improve and apply the ANN in the various domains of human activities. In future work, firstly we will apply the new SOM model on the GIS, and then, the proposed method will be used in order to improve another ANN paradigm.

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