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SIMULATION OF SELF-LEARNING CLUSTERING METHODS FOR SELECTING AND GROUPING SIMILAR PATCHES, USING TWO-DIMENSIONAL NONLINEAR SPACE-INVARIANT MODELS AND FUNCTIONS OF NORMALIZED "EQUIVALENCE"

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The results of modeling combined with self-training clustering method of image fragments. For isolation, selection and use of cluster grouping of fragments of structural and topological features and two-dimensional spatial equivalence nonlinear functions. The simulation results showed that the method has good convergence. The method is fast, as the number of iterative steps self-training clustering was equal to between 5 and 17 for the experiments. The method is easily displayed on the matrix-matrix procedures.

Key words: Clustering fragments of images, adaptive learning, equivalence models, nonlinear function, spatially invariant model, matrix-matrix procedure, structural and topological feature.

Introduction. For images and objects clustering neural models are widely used. The latter are also widely used for modeling of associative memory, for pattern recognitions, biometrical identification and managing with robotized devices [1]. Equivalence models (EM) of autoassociative memory (AAM) and heteroassociative memory (HAM) were offered in papers [2, 3]. Simulation results of such models [4, 5, 6] have confirmed that the EM has such advantages as substantial increase of memory capacity and possibility to keep highly correlated patterns of considerable dimension. These researches of EM HAM have showed that these models allow to recognize vectors with 1024 components and considerable percent (to 25-30%) of damages, at the capacity of network which in 3 - 4 times exceeds the amount of neurons [3, 5]. Only one-port HAM and their simulations on a few number of real correlated images by a dimension of 128×128 and 64×64 pixels was conducted in these papers. In papers [6, 7] on the basic idea from paper [2] models of multiport AAM (MAAM) and multiport heteroassociative memory (MHAM) for associative storage and recognition of images are proposed and simulated. Mathematical models and implement of AM based on EM initiated in paper [2], and described in detail in papers [6] and their modification - in paper [7]. For of analysis and recognition should be solved the problem of clustering of different objects. This previous clustering allows organizing proper automated grouping processed data, to cluster analysis, to evaluate on the basis of many signs each cluster, put a class label and improve subsequent learning procedures and classification in intelligent systems. At the same time, knowing the significant advantages of EM when creating on their basis improved neural networks [3-7] and MAAM and MHAM [6,7], there was a suggestion about the possibility of modifying EM and MHAM for parallel cluster image analysis [8]. Hardware implementations of these models are based on structures, including matrix-tensor multipliers, equivalentors with spatial and tine integration [9]. But in papers [8, 9] models and their implementation for recognition and clustering of images without spatial displacements, i.e. spatially non-invariant models were considered. In paper [10] space-invariant models for image recognition, but not their clustering are examined. Therefore review allowed us to determine the purpose of this paper, which is to modify models of MAM based on EM and architectures with spatially invariant models for parallel cluster image analysis, modeling processes of such modified image clusterization, assessing performance and quality of these processes and the study of possible ways of learning and self-learning in such implementations.

The adaptation of MHAM equivalence models for cluster analysis. Since HAM is more common, so consider theoretical models of MHAM. Let for learning of MHAM M pair of mutually dependent N-element binary vectors is used: $\overrightarrow{SX}^m = \{0,1\}_m^N$, (input) and $\overrightarrow{SY}^m = \{0,1\}_m^N$ (output). If to designate a vector $\vec{\beta}^p = \{\beta_1^p, ..., \beta_m^p, \beta_M^p\}$ normalized equivalences of the input p-th vector with all M stored patterns, and to present the set of input vectors by a matrix $\mathbf{S}_{inp} = \bigcup_{p=1}^{P} \vec{S}_{inp}$, the set of output – by a matrix $\mathbf{S}_{out} = \bigcup_{p=1}^{P} \vec{S}_{out}$, then functioning of MHAM is described by the next model:

$$\mathbf{S}_{out}(t+1) = \Phi\left[\frac{1}{M}\left\{\gamma\left\{\frac{1}{N}\left(S_{inp}^{\alpha}(t) \overset{\dot{\sim}}{\times} TX_M\right)\right\} \overset{\dot{\sim}}{\times} TY_M\right\} - \left(\frac{1}{M}\left\{\gamma\left\{\frac{1}{N}\left(S_{inp}^{\alpha}(t) \overset{\dot{\not\sim}}{\times} TX_M\right)\right\} \overset{\dot{\sim}}{\times} TY_M\right\}\right)\right], \quad (1)$$

where $\left(\overset{\dot{\sim}}{\times}\right)$ and $\left(\overset{\dot{\not\sim}}{\times}\right)$ are the operations of equivalence and nonequivalence multiplication of vector $\vec{S}^p$ by a matrix TX_M or TY_M, and matrix TX_M is the set of vectors $\overrightarrow{SX}^m$ and matrix TY_M is the set of vectors $\overrightarrow{SY}^m$, and $\beta_n^{mp} = \gamma\left(\beta^{mp}\right) = 0,5(1+(2\beta^{mp}-1)^k)$ there is a nonlinear coefficient of weighing, which depends on the chosen parameter k and initial β^{mp} coefficient of the normalized equivalence of the p-th input and the m-th learning vectors, and every input vector of the input matrix $\mathbf{S}_{inp}$ is weighed by a vector $\vec{\alpha}$, what gives the self-weighted matrix $\mathbf{S}_{inp}^{\alpha} = \bigcup_{p=1}^{P} \vec{S}X_{inp}^{\alpha} = \bigcup_{p=1}^{P}\left(\vec{S}X_{inp} \dot{\sim} \vec{\alpha}\right)$. Implementation of the most generalized model of MHAM, described by the equation (1) and in paper [6], requires matrix-matrix procedures (MMP) in which the operation of multiplication is replaced by equivalence realized by so-called matrix-matrix equivalentors (MME). In papers [7, 9] it has been shown that the implementation of the MME is possible on the basis of two matrix-matrix multipliers (MMM). Consider the idea of clustering, that is based on the use of MAM, which can be used to simultaneously calculate the corresponding distances between all cluster neurons and all learning vectors [11], see also Fig.1. It is a multi-port approach allows the use of MMP in parallel computing the distances between the cluster and the learning neurons and to identify and mark all the winners which corresponds to each learning clustering vector (CV). We use as the metrics the generalized normalized functions of equivalence of vectors. This method gives a good convergence and high speed. In paper [11] shown a model based on the MMP with equivalence and functions of activation $\mathbf{F_{non}}$ performing element wise operations of matrices processing. It demonstrates an iterative learning process, which consists in calculating the optimal set of weight vectors for the cluster of neurons using a learning **TX** matrix. For the nomination labels and CVs represented by the matrix **TX**, **TX** is multiplied by the calculated an array of optimal learning CVs, which is matrix $\mathbf{W_{opt}}$. In such a MME - operations normalizing of vectors and non-linear processing in the form of a threshold transformation is calculated (Eq.1).

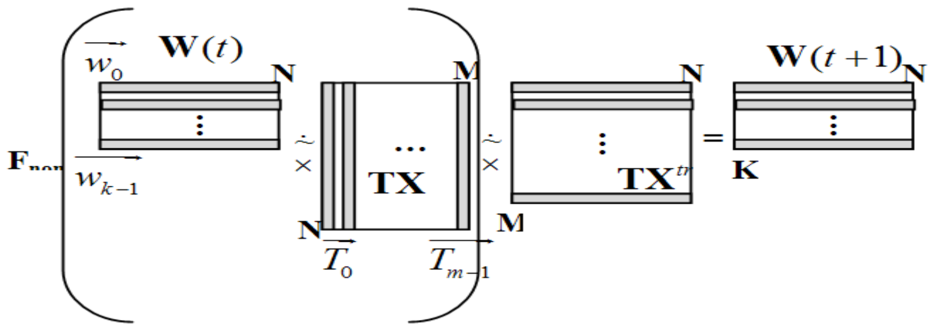


Figure 1. Figure explains the principles of learning NN model based on the MHAM to find CVs, model of iterative calculation of weights cluster vectors using MMP with nonlinear item processing $\mathbf{F_{non}}$ to index vectors winners.

To adapt architecture based on EM for the task of clustering take into account the following changes. Number of objects to be clustered equals the number of ports *P*. Number of cluster neural elements (CNE) equals *M*. Then the matrix $\mathbf{S}_{inp}$ is a set of vectors $\vec{S}^p$ for clustering. Matrix TX_M is a set of vectors $\overrightarrow{SX^m}$ synaptic connections to m-th CNE. Then the matrix $TY_M(p)$ is a set of *M* identical *p*-th *N*-dimension vectors $\vec{S}^p$, (multiplied *M* times), and will depend on *p* index. Moreover, this index means that for each *p*-th vector $\vec{S}^p$ *p*-th corresponding matrix $TY_M(p)$ is formed. With this substitution and such notations first equivalence multiplication in Eq. (1) corresponds to and describes the process of signals at the outputs of all *M* CNE. A second equivalence multiplication in Eq. (1), i.e. multiplication of CNE array signals by matrix $TY_M(p)$ corresponds to and describes the process of output images in accordance with grouped in clusters of objects from the input sample. At each *p*-th processing cycle corresponding input image will be displayed in the spatial. Moreover, accumulating directly or with the appropriate weighting such images, can be formed a matrix, which is a set of weight coefficients for all CNE. Since for determining the winner of all CNE, i.e. cluster number, when applying a specific input image in such model and corresponding architecture it is necessary to conduct a comparative analysis of the signals at the output of CNE (hidden layer), so to known from paper [7] architecture should also introduce some changes. Therefore, we consider this known architecture taking into account such changes. In paper [9] it was shown that the architecture with time integration [6, 7] can provide significant benefits and performance 10^9 - 10^{10} connections per second and they can be used to realize and MHAM. The principle of the operation is described in details in paper [9].

Simulation of self-learning clustering method of images based on space-invariant models. Above we considered the entire image clustering methods, but their pieces, especially with regard to their spatial displacement. Therefore, in this section we consider a parallel method and explore clustering features from images are combined via adaptive learning-forming of array of centered symbols. In paper [10] the space-invariant matrix-tensor non-linear EMs for 2D image recognition are shown. It is performed by means of input of spatially dependent function of normalized equivalence - (named as equivalental spatial function), determined below:

$$\tilde{e}(A,B) = \frac{\tilde{E}(A,B)(\varsigma,\eta)}{I \times J} = \frac{A \tilde{*} B}{I \times J} = \frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} (a_{\varsigma+i,\eta+j} \sim b_{ij}),$$

where

$$A = [a_{nm}] \in \{0,1\}^{N \times M}\ B = [b_{ij}] \in \{0,1\}^{I \times J}\ N > I, M > J, and\ \tilde{e} = [e_{\varsigma,n}] \in [0,1]^{(N-I+1)\times(M-J+1)},$$

symbol $(\tilde{*})$ meaning correlation with operation of "equivalence".

Therefore interpretation method for spatially invariant case requires the calculation of spatial features convolution-type $\mathbf{E}^m = \mathbf{W}^m \overset{t}{\tilde{\otimes}} \mathbf{A}$, where $E^m_{k,l} = 1 - mean\left(\left|\overline{submatrix(\mathbf{A}, k, k+r_0-1, l, l+r_0-1) - \mathbf{W}^m}\right|\right)$, nonlinear processing by the expression $EN^m_{k,l} = G\left(E^m_{k,l}\right) = 0,5\left[1 + \left(2E^m_{k,l} - 1\right)^a\right]$ and comparing each other to determine the winners for indexing expressions: $MAX_{k,l} = \underset{індекс\ m}{max}\left(EN^{m=0}_{k,l}, EN^{m=1}_{k,l} ... EN^{M-1}_{k,l}\right)$ and $EV^m_{k,l} = f^{акт}_{нел}\left(EN^m_{k,l}, MAX_{k,l}\right)$. The first algorithmic step defines all matrices M $\mathbf{EV}^m = \mathbf{F}\left(\mathbf{F}_{нел}\left(\mathbf{W}^m \overset{t}{\tilde{\otimes}} \mathbf{A}\right)\right)$ and considering the second step (convolution of the latter with the matrix A) model proposed method will look like: $\mathbf{W}^m(t+1) = \mathbf{F}\left(\mathbf{F}\left(\mathbf{F}\left(\mathbf{F}\left(\mathbf{W}^m_{(t)} \overset{t}{\tilde{\otimes}} \mathbf{A}\right)\right) \overset{t}{\tilde{\otimes}} \mathbf{A}\right)\right)$. Note, that for convenience and compliance to matrix type recording, here we are in contrast to [10], use the symbol **E**, not a symbol **e** for describe the spatial normalized «equivalence» function of the two images. Consider the results of the first experiment to divide the characters into 4 clusters. Fig. 2 shows a matrix **B** (In the above formulas, it plays the role of the matrix **A** !) with a set of 16 training images, which have dimension 64x64, stacked with each other and is a learning 2D picture with centered objects. Two of these fragments are shown as matrices **SB** (2, 1) and **SB** (0, 0). For the clusterization of input objects (represented by a matrix **A** in the figure and in the simulation, but not in the formulas !) and that is a set of 16 images but smaller in size (32x32 element) and with other locations, their division into 4 clusters was performed. To form the optimal weight matrices 4 image with size 32x32 shown by matrices **Wa**, **Ws, Wz, Wh,** were used to start and the next iterations. Here they are shown for the third iteration. On the right side of Fig.2 is a view of the original equivalence function and Fig. 3 shows its appearance after nonlinear and threshold processing.

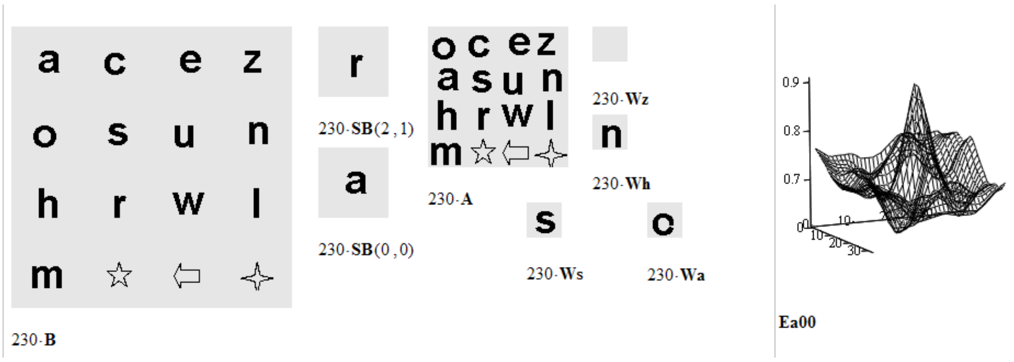


Figure 2. Images of matrices for space-invariant clustering, «equivalence» function.

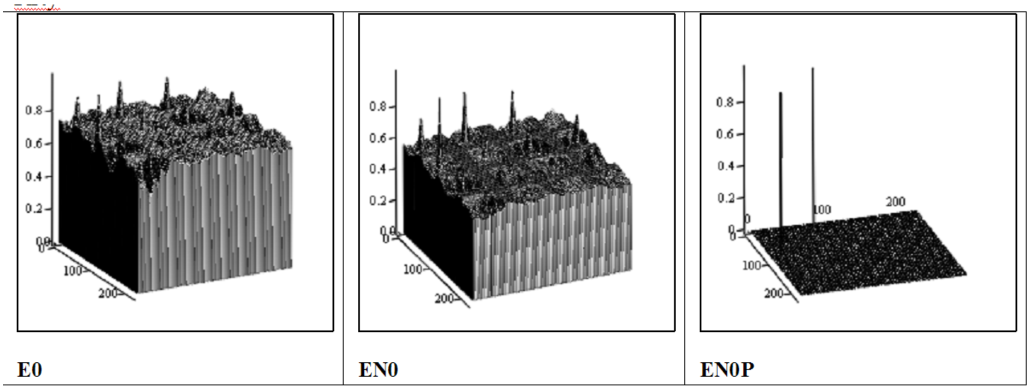


Figure 3. Original, after nonlinear and threshold processing equivalence functions.

Fig. 4 shows four two-gradation images **EPa**, **EPs**, **EPz**, **EPh**, indicating belonging to one of the four clusters and the location of the image with the spatial displacement. The combined merging image is shown as a matrix **EP**. Each of the 16 images **EP00** - **EP33** equivalence nonlinear function displays of all four images of the cluster fragments with one of 16 training images after threshold processing these functions. Clustered objects are marked by light dots in these images.

Fig. 5 shows that as a result of several learning iterative steps we formed four halftone images **EWaS**, **EWsS**, **EWzS**, **EWhS**, which appropriate to averaged images for clusters. After threshold processing these images are converted to images **EWaP**, **EWsP**, **EWzP**, **EWhP**, which are optimal cluster weight matrices. The latter is used to determine the equivalence 2D functions over the matrices with a set of images **B**. The clustering results are shown at the right: the first cluster - the letters o, c, e; the second cluster - s, the third cluster - h, n, m, the fourth - all others, including the background. Using the criterion that is equal to the maximum amount of normalized equivalence centroid image fragment with those who are in the cluster, you can judge the quality of learning and clustering, including the convergence of the learning process. By choosing the threshold for binarization of images and parameters of nonlinear transformations in the calculation of 2D equivalence function, you can improve the quality of clustering. These experiments confirm that the model allows to determining the affiliation of the input images, regardless of their spatial offset, to one of the clusters. To achieve space-invariant clustering images using the proposed models multi-channel image equivalentor is required [9, 10]. And it may consist of two correlators. For each cluster, you must 2 equivalentors or 4 correlators [9, 10, 12]. Multi-channel correlators are described in many articles, in particular, in [13].

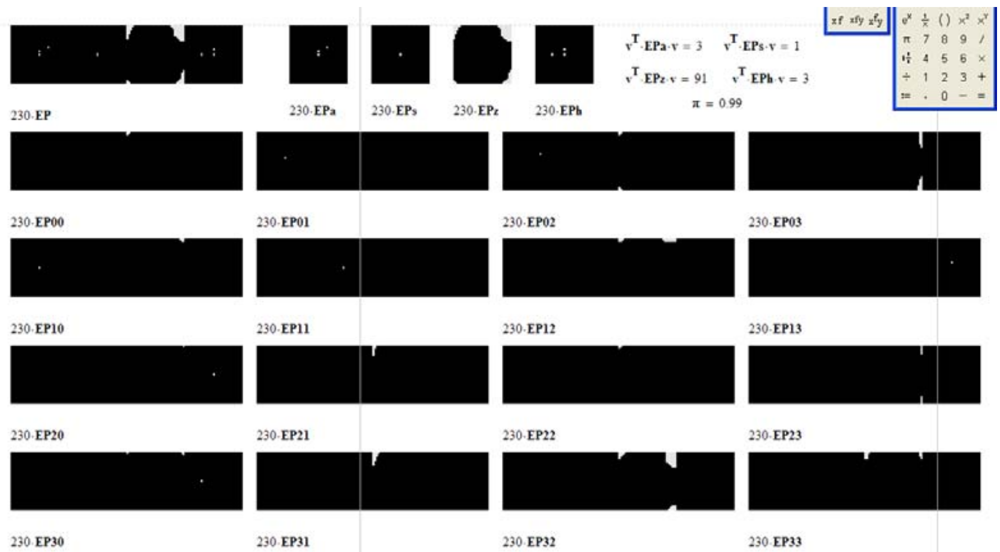


Figure 4. Images which meet the pointers of clusters, calculated as a spatially dependent equivalence functions over corresponding set of images.

Consider the results of the second experiment to divide the characters into 8 clusters. The essential difference of this experiment from the first was that carried no separate calculation of the spatially dependent equivalence functions for each character from a set of training, and the calculation of a generalized function for the entire set at once. The modelling results of spatially-invariant images clustering are shown in Fig.6, 7, 8, 9, 10. Fig. 7 shows a process of intermediate nonlinear processing of spatially dependent equivalence functions Fig. 6 shows images of clusters and clustering results: Image matrices (64x64x4x4) for space-invariant clustering, equivalence function, marked points of the cluster symbols. Images by appropriate signs belonging to clusters, calculated as a function of the spatial dependence of equivalence to appropriate image fragments, symbol. The results of clustering: a first cluster - the letters o, c;

second cluster - w, a third cluster – r, l, fourth – z, 5 – a, 6 –u, 7 – n, h, m, 8 – star and the rest, are shown. From Fig. 8 shows that the result of several iterative steps of learning we formed 8 halftone image New0 –New7, to appropriate the averaged image clusters. After the threshold processing, these images are converted to optimal weighted images W0t –W7t of clusters. Dynamics of changes in the weighting cluster images characterize the differenced image WR0 – WR7, in the number of pixels in them. Using the criterion that is equal to the maximum amount of equivalences CV with those who are in the cluster, you can judge quality and convergence of learning and clustering. Fig. 9 confirms the convergence process in just 5 iterations with the correct choice of the parameters of the intermediate processing of functions. Fragment of the Interface Mathcad window with the results of clustering are shown in Fig.10. Different color patches, that match the color of initial training clustering vectors, denoted character positions belonging to these clusters. These experiments confirm that the model allows to attributing similar input patterns irrespective of their spatial displacement to the same cluster.

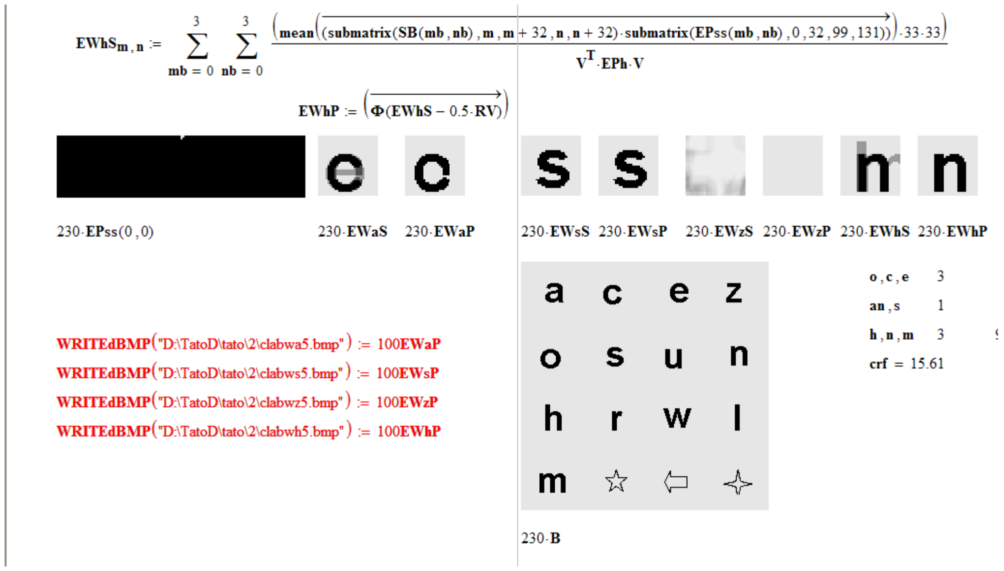


Figure 5. Images of cluster vectors and simulation results.

Very interesting, in our opinion, have the following simulation result, shown in figure11. By changing a little kind of non-linear processing equivalence functions, at each intermediate step of iteration, can determine the winner among the cluster vectors is not for the local neighborhood, and for each pixel. This makes it possible to allocate to a separate cluster all empty (without patterns!) fragments. A zone where there are fragments with patterns, referred to as the zone of competition between the CB. In these areas, winning SV displays a different color. The locations of these zones correspond exactly to the location of character images on the general image.

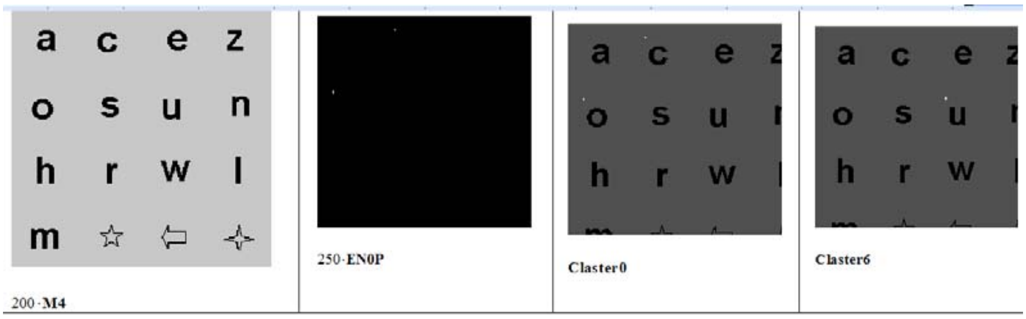


Figure 6. Simulation results: Images of matrices (64x64x4x4) for space-invariant clustering, equivalence function, marked points of the cluster symbols.

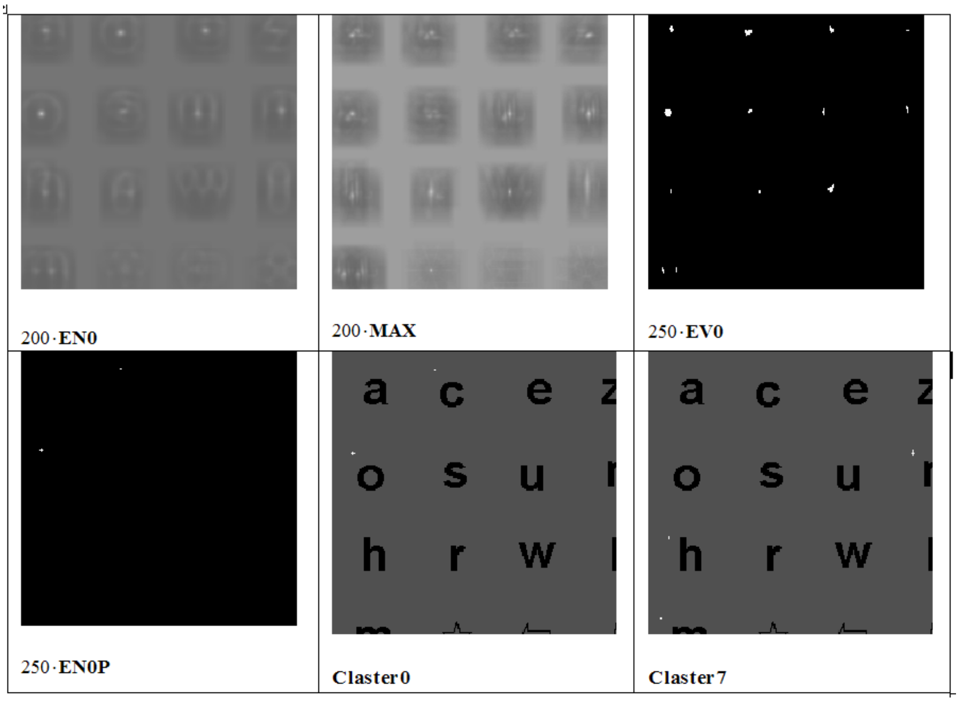
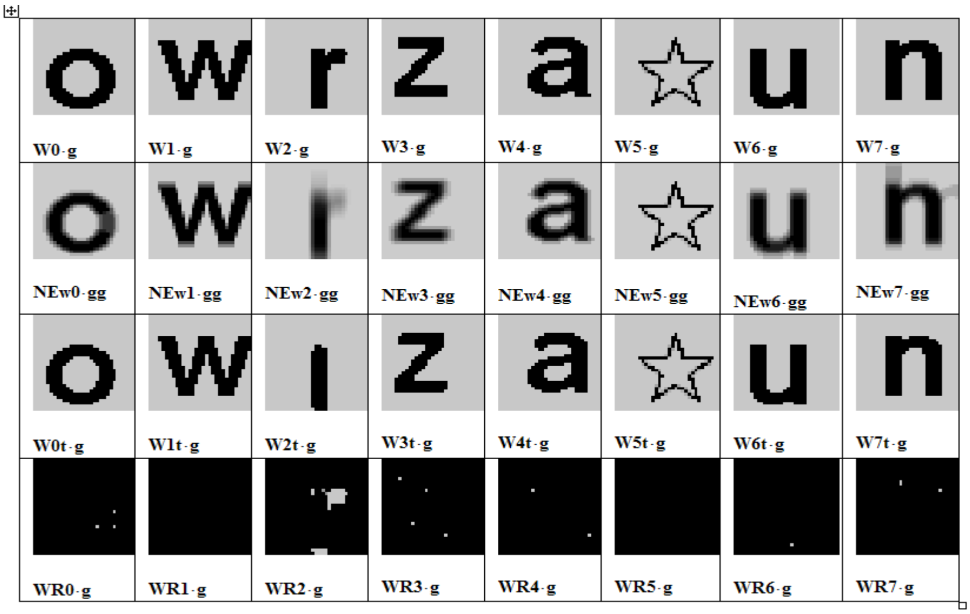


Figure 7. Nonlinear (**EN0** for first CV (**W0**)), max (**MAX**), index before (**EV0**) and after threshold processing (**EN0P**) equivalence functions, marked points of the cluster symbols.



3 0 40 4 2 0 1 3

Figure 8. Simulation of the formation of CV (centers) for dimension of images 32 * 32 and 8 of clasters (1 iteration).

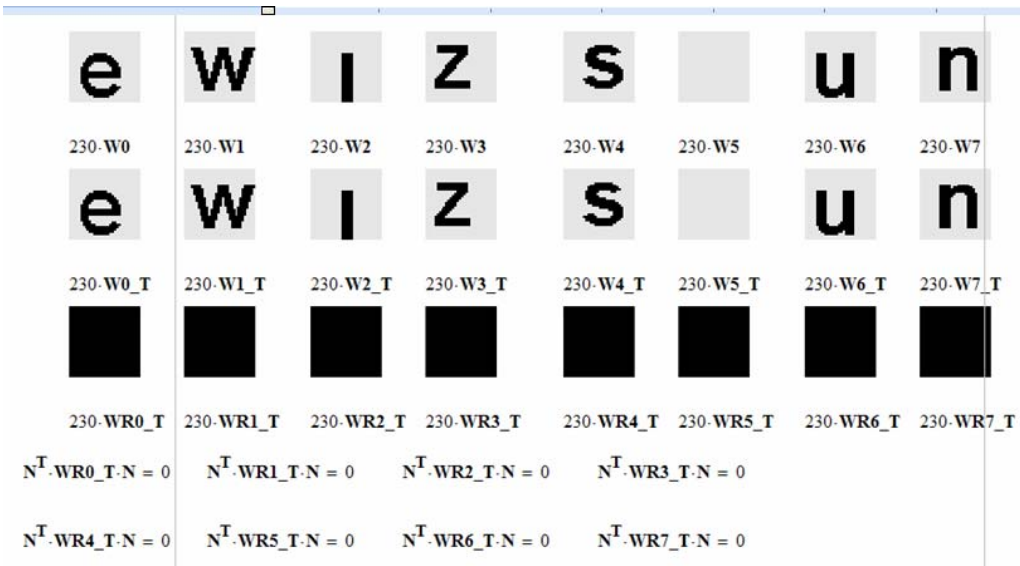


Figure 9. Simulation of the formation of CV (centers) for dimension of images 32 * 32 and 8 of clusters (latest 5 iteration).

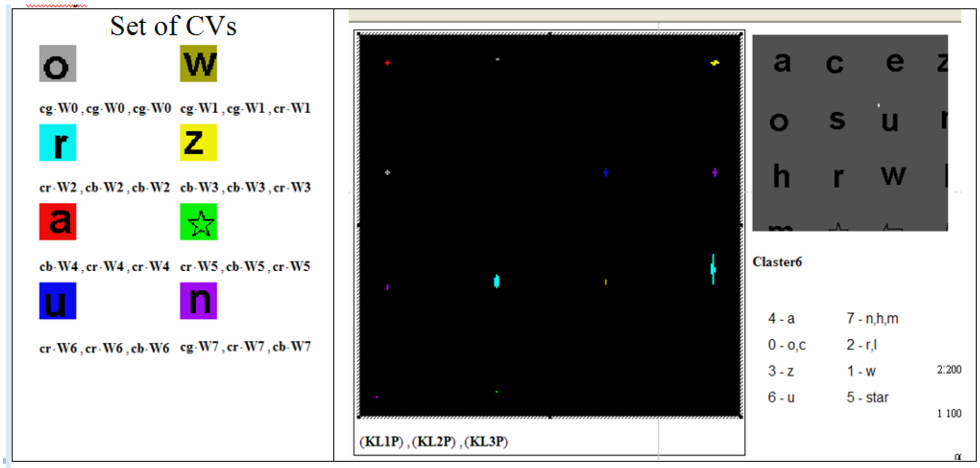


Figure 10. Fragment of the Interface Mathcad window with the results of clustering.

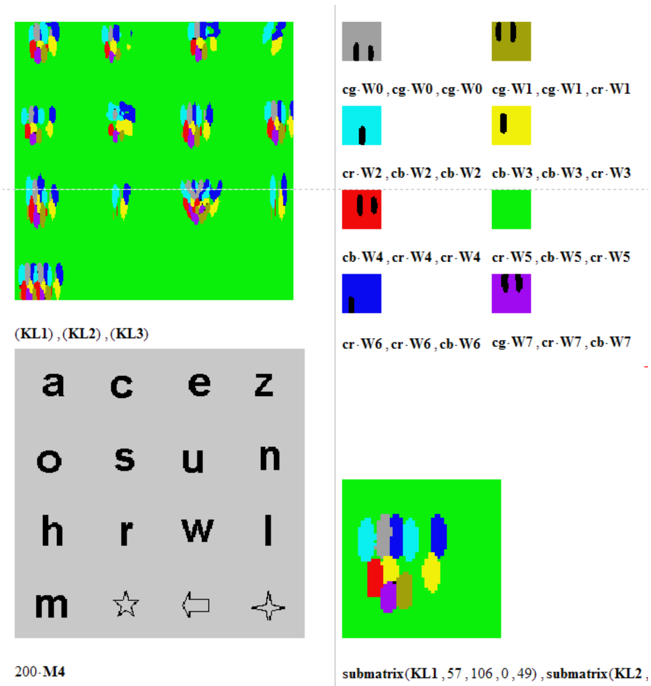


Figure 11. Fragment of the Interface Mathcad window with the results of clustering for another transformation. In the competition areas, winning SVs displays a different color.

Thus, to understand the mechanisms clusterization, accompanying her to the competitive processes in neurons, and the principles of recognition with the use of self-learning cluster patterns is very important there is the algorithm and the principles of non-linear processing of two-dimensional spatial functions of images comparison.

In Fig. 12 and Fig.13 shows the results of fission fragments of the same image (610*340) into 8 clusters, but fragments of dimension equal to 7*7 and 11*11. The learning process is similar. After the seventh iteration of the difference matrix is zero, it becomes clear that only 7 iterations ending learning process and the required forming CV. The experimental results confirms, that the proposed clustering fragments methods, using their structural and topological features, can be applied not only for binary but also for multi-level gray images. Therefore, in such cases it is necessary to increase the number of CVs. In addition, you should expect an increase in the number of iterations for the final formation of self-learning CVs. In addition, you should expect an increase in the number of iterations for the final formation of self- learning CVs. Class of problems for which it is possible, to apply our method, is very significant and demonstrates its versatility. This requires additional studies for each specific application method, and is subject to the limitations, here we do not consider them, and plan to cover them in future work.

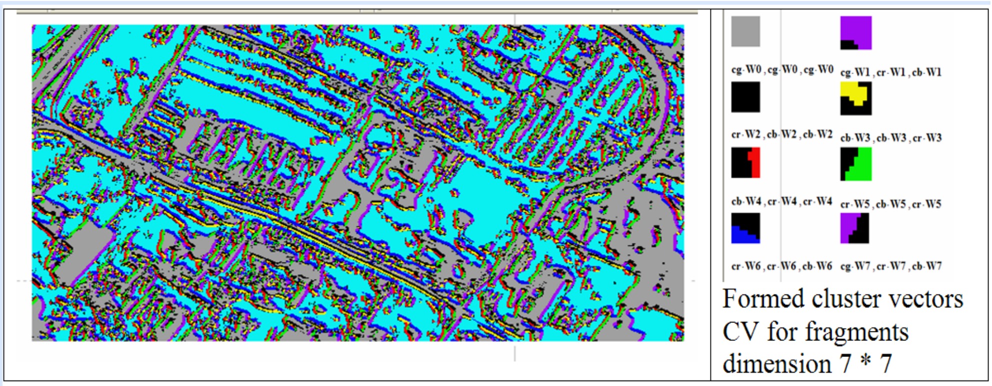


Figure 12. Results of cluster separation image (610*340) similar to fragments (7*7),
the Interface Mathcad window.

Summary. The proposed clustering of fragments method for their structural features of not only binary, but also color images combined with self-learning and the formation of cluster vectors. Its model is constructed and designed on the basis of the algorithm implementation. The experimental results confirmed, that larger images (610x340) and binary vectors with several thousands elements may be clustered. For the first time the possibility of generalization of these models for space invariant case is shown. The experiment for an image with dimension of 256x256 (a reference array) and fragments with dimension of 32x32 for clustering is carried out. The experiments, using the software environment Mathcad, showed that the proposed method is universal, has a significant convergence, the small number of iterations is easily, displayed on the matrix structure, and confirmed its prospects. Thus, to understand the mechanisms clusterization, accompanying her to the competitive processes in neurons, and the principles of recognition with the use of self-learning cluster patterns is very important there is the algorithm and the principles of non-linear processing of two-dimensional spatial functions of images comparison.

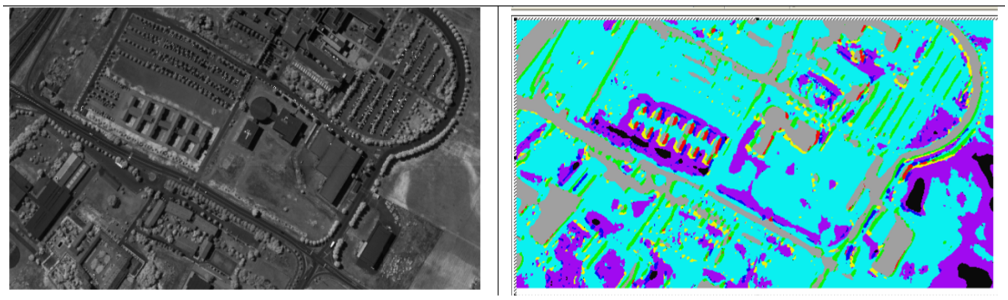


Figure 13. Results of cluster separation image (610*340) similar to fragments (11*11):
Input and clustered images.

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МОДЕЛЮВАННЯ СУМІЩЕННОГО З САМОНАВЧАННЯМ МЕТОДА КЛАСТЕРИЗАЦІЇ ДЛЯ СЕЛЕКЦІЇ ТА ГРУПУВАННЯ СХОЖИХ ФРАГМЕНТІВ З ВИКОРИСТАННЯМ ДВОВИМІРНИХ НЕЛІНІЙНИХ ПРОСТОРОВО-ІНВАРІАНТНИХ МОДЕЛЕЙ ТА ФУНКЦІЙ НОРМАЛІЗОВАНОЇ ЕКВІВАЛЕНТНОСТІ

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Розглядаються результати моделювання запропонованого суміщеного з самонавчанням метода кластеризації фрагментів зображень. Для виділення, селекції та поділу фрагментів на угрупування використовуються їх структурно-топологічні ознаки та двовимірні просторові еквівалентністні нелінійні функції. Результати моделювання показали, що метод має збіжність. Метод є швидкодіючим, оскільки кількість ітераційних кроків самонавчання становить для проведених експериментів від 5 до 17. Він легко відображається на матрично-матричні процедури та засоби.

Ключові слова: кластеризація фрагментів зображень, адаптивне самонавчання, двовимірна просторова еквівалентністна нелінійна функція, просторово-інваріантна модель, матрично-матрична процедура, структурна ознака.