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INVESTIGATION OF CONVERGENCE AND DYNAMIC IN SELF-LEARNING EQUIVALENT-CONVOLUTIONAL NEURAL STRUCTURES FOR IMAGE CLUSTERING AND RECOGNITION

Introduction. For creation of biometric identification and machine vision systems necessary solve the problem of object recognition in images. The basis of most known methods is to compare two different images of object, or its fragments, one of which is a benchmark and the second image is a set of images that belong to different classes. Discriminant measure of the reference fragment with the current image fragment, the coordinate offset is often two-dimensional correlation function. In our work [1] it was shown that to improve accuracy and recognition qualities of distorted and correlated images, it is desirable to use methods based on mutual equivalently two-dimensional spatial functions, nonlinear transformations of adaptive-correlation weighting. For the recognition and clustering of images, for modeling associative memory, biometric identification and robotic devices equivalence models (EMs) of auto-associative memory (AAM) and hetero-associative memory (HAM) were proposed [2, 3]. The simulation results of such EMs [2-4] were showed and confirmed that the EM has advantages. These EM HAM studies have shown that models allow the recognition of large-size vectors and a significant percentage (up to 25-30%) of damage, at a network power that is 3 to 4 times higher than the number of neurons. At the same time, knowing the significant advantages of EM when creating on their basis improved NNs, multiport AAM and HAM [3, 4], there was a suggestion about the possibility of modifying EM, MHAM for parallel cluster image analysis [4, 5]. Hardware implementations of these EMs are based on structures, including multipliers, equivalentors with spatial, time integration [3]. In previous work [5], these questions were considered for bitmaps of multi-level images. Therefore, in report, we want to generalize and show that the self-learning concept works with directly multi-level images without processing the bitmaps. In addition, the previous works [6, 7] did not investigate the influence of the filters size on the convergence of the self-study method and no simulation was carried out for different types and sizes of the images.

Presentation of the main material. We consider the based on MHAM idea of clustering, which can be used to simultaneously calculate the corresponding distances between all cluster-neurons (CN) and all training vectors in our other report at the same conference. Therefore, in this paper, we focus our attention on the study of the convergence of the self-learning model we proposed and the dependence of the time of convergence on various factors. We specify the number of clusters and their size. A visualization of optimal templates is formed by the corresponding iterative procedure on the basis of the definition of regularities in fragments that are in the images from the set of trainees. The process of self-learning is combined with the recognition process. This process is repeated and after several steps, the optimal values of these filters are formed. Similarly, when all the RGB components are at the input in sequence, auto-coding and decoding are realized by using the same basic modules. Sometimes the number of filters can be adaptively chosen taking into account the errors in auto-decoding of images.

To model the base unit in the first experiment, we used a color image “eye” with a size of 360x362 elements and 8 filters of size 7x7, the elements of which were randomly selected for the first iteration. Weights are sampled randomly from a uniform distribution in the range [0, 255]. Simulation results of process combined with self-learning recognition for all spectral components are shown in report. Dynamics of the change of clusters of spectral R component of color image for 7x7 filters size are shown in Fig. 1. View of filters in digital and picture formats and their changes are shown. Other details of the process and its dynamics can be seen in the Fig. 1. With the help of self-learned filters, you can restore in a compressed form multilevel images, spectral components of a color image. The compression ratio, as shown by our experiments, varies from **5 to 30 times** for different types and dimensions of images. The type of concrete cluster maps obtained in the color and gray formats and their changes for different iteration steps and different filter sizes are shown in our other report. Experiments show that with some reconstruction methods and such cluster transformation with compression of multilevel images, errors always exist and there can be occasional significant deviations, but the mean deviation values always decrease. For clarity of the transformations and some intermediate results obtained, in order to study the effect of the filter sizes on the rate of convergence and the quality of the clustering and the compressed representation, we used the color image “cat” “eye”, “field”, in another sets of experiments, the simulation results with which are shown in Fig. 2, 3. The results of the experiments show that the convergence of the process is faster for larger-size filters, clustering and the corresponding segmentation occur more coarsely, and recovery errors on cluster maps are higher, but the trend leads to a decrease in the mean error over the entire field. This suggests that, most likely, in the bio-inspired structures of self-learning in the initial layers of SL_EC_NS, it is necessary to use filters of larger size with subsequent reduction. Fig. 4 shows the graphs of the dependence of changes in the values of the weights during the self-learning of the filters and the extraction of useful features from the images. Analysis shows that for all images chosen for modeling “cat”, “eye”, “field”, fast convergence of the process of self-learning is observed (the number of iterations for all selected sizes of the images does not exceed 15-20 to provide filters errors at the level of ± 1 level of 256 gray levels). The smaller the filter size, the more accurately the filter is set up and the errors are generally zero.

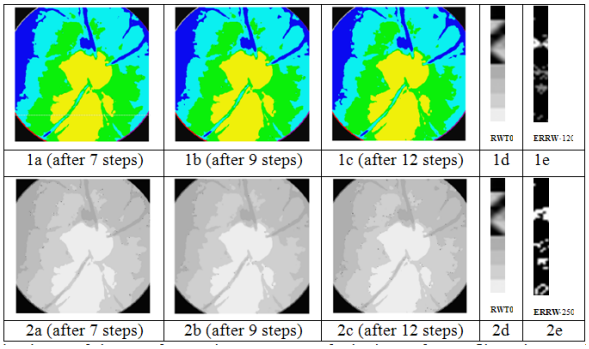

Fig. 1. Fragments of Mathcad windows: Dynamics of the change of clusters of R component of color image for 7x7 filters size: 1a, 1b, 1c – color clusters for R, 1d - set of filters after 8 steps, 1c - set of changes in filter values after 8 steps; 2a, 2b, 2c –gray clusters for R (the maximum value of the deviation of the intensity of pixels does not exceed 7), 2d - set of filters after 11 steps, 2e - set of changes in filter values after 11 steps

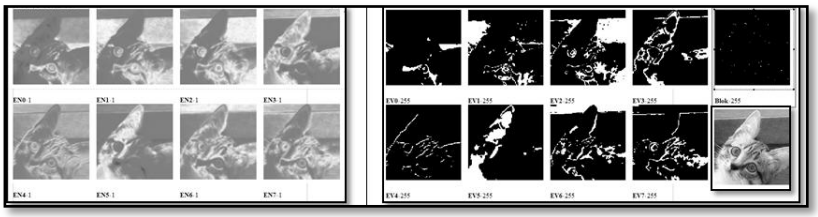

Fig. 2. Fragments of Mathcad windows: View of R components of the original color image "cat" (128x128 size), 8 normalized equivalence functions corresponding to the 8 filters (left), the Blok matrix and the eight cluster maps obtained after nonlinear processing, representing the disjoint sets of winning neurons for each cluster (right)

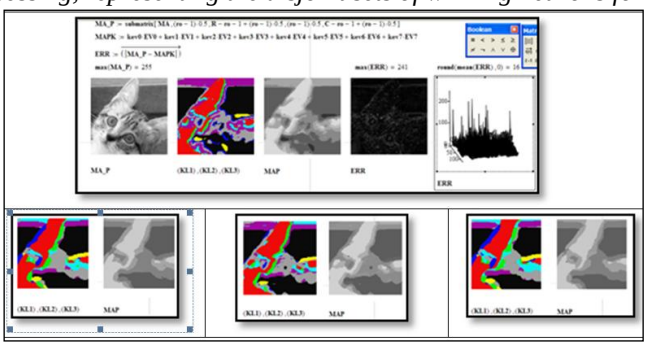

Fig. 3. Fragments of Mathcad windows: The results of clustering the R component of the color image "cat" into 8 clusters corresponding to 8 self-learning filters: a) for the filter size 7x7 pixels, where MA_P is the original image, KL1, KL2, KL3 is the image of 8 clusters in the color, MAP is the restored image, ERR is the recovery error; from left to right: for the size of filters 11x11 pixels; 15x15 pixels; 17x17 pixels after 8 iterative steps

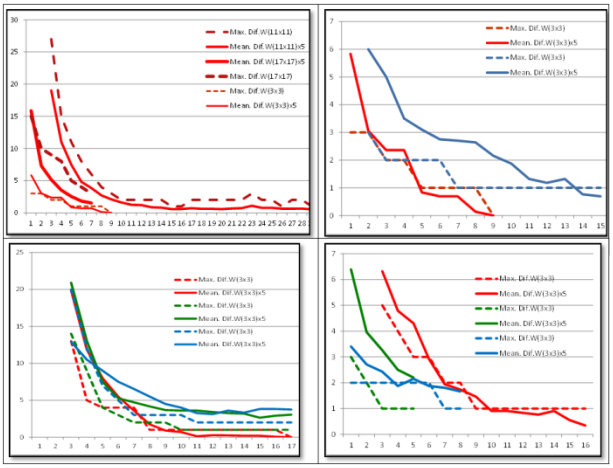

Fig. 4. Top left: Dependence of the maximum and average changes in the weights in the filter set from the iteration step number for filter sizes 11x11, 17x17, 3x3 for R of the image "cat". In the upper right: the same dependencies for the filter size 3x3 for the R and B components of image "cat". At the bottom left: the same dependencies for the size of the 3x3 filter for R, G, B of the image "eye". The lower right: the same dependencies for the size of the 3x3 filter for R, G, B components of the colored image "field" (dimension 800x533)

The conducted model experiments show great promise of the proposed methods and models of self-learning-recognition of multilevel and color images. But for their work in real time, taking into account the large requirements for

performance and the amount of calculations, it is necessary to have appropriate high-performance and energy-efficient arrays and image processors with parallel principles of operations and picture input-outputs. In Fig. 5 shows the part of the formulas from the interface window and the simulation results of the recognition-allocation process for the generated color cluster filters of one of the possible (8x8x8) color areas, such as blood vessels. The program module in Mathcad allows display the palette of all created 512 color clusters and, at the choice of one color filter, to recognize the corresponding areas. For this, weighted NEFs from each spectral component are used, the number of which can be significant for hyper-spectral images, and the weights can also be adjusted automatically. The results of modeling the process of clustering and recognition of the large-scale color image "field" (800 × 535) are shown in Fig. 6.

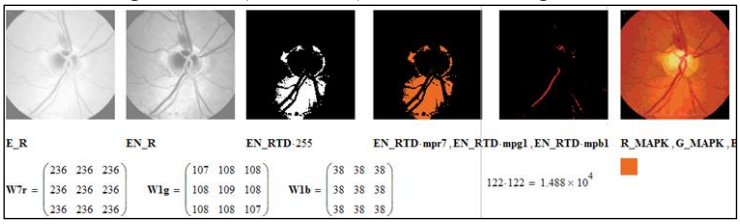

Fig. 5. The Mathcad windows on which the results of recognition of fragments on the color image are shown, which are closest to the selected color filter from the set of possible (8x8x8 = 512) self-learning filters

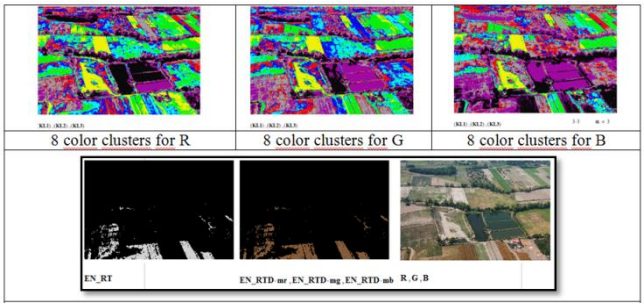

Fig. 6. The results of recognition of fragments of the field according to the color scale corresponding to one filter from the set formed after learning. In the upper from the left to the right: a map of the selected fragment by the color filter, the selected fragment in color, the original color image

Conclusions. The proposed clustering method of fragments with regard to their structural features is suitable not only for binary, but also color images and combines self-learning and the formation of weight clustered patterns. The experimental results confirmed that larger multilevel and color images and their fragments with a large numbers of elements may be clustered. For the first time the possibility of generalization of these models for space invariant case is shown. The experiments for images with dimension from 128x128 to 800x533 and fragments with dimensions of 3x3, 7x7, 11x11, 17x17 and others for clustering are 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.

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