УДК 004.93

V.G. Krasilenko[1], C. Sc.; A.A. Lazarev[1], C. Sc.; D.V. Nikitovich[1]
[1] *Vinnytsia National Technical University*

THE OPTICAL ARCHITECTURE WITH TIME INTEGRATION FOR CREATING OF MULTI-PORT NEURO-NETWORK HETERO-ASSOCIATIVE MEMORY AND ITS SIMULATION

Introduction. Neuro-models of associative memory are used in pattern recognition robotized systems, biometrical identification and neuro-physiological processes simulations. It is known a number of models and networks as Hopfield, bidirectional memory of Kosko, and others [1, 2]. Equivalence models of neuro-network autoassociative and heteroassociative memory (HAM) were offered in papers [3, 4]. Simulation results of such equivalence models (EM) [5, 6] have confirmed, that the EM has such advantages as substantial increase of memory capacity and possibility to keep highly correlated patterns. These researches of EM HAM have showed that these models allow to recognize patterns with considerable percents (to 25-30%) of damages, at the network capacity which in 4 -10 times exceeds the amount of neurons [4, 6]. Appearance of papers [7], the idea of which is based on work [3], where mul-tiport neuron networks and multiport auto-associative memory (MAM) were examined accordingly, stimulates the necessity of research of possibilities of EM application for creation of multiport hetero-associative memory (MHAM). The principles of construction realization of autoassociative memory (AM) on the base of EM with time-pulse integration is described in paper [7]. However, research results of such EM AAM/HAM were not shown.

Thus, the publications review and analysis allows defining as one of **important tasks, the further researches** of EMs, adjusted for realization of more general multiport hetero-associative memory (MHAM) architecture, and determination of its performance. Theoretical background and models of MHAM were considered in paper [8].

Presentation of the main material and research results. For organization of computations, necessity for realization of MHAM, it is desirable to use the high-performance specialized processors and architectures. **Optical realization of MHAM**. At considerable dimension of input patterns and considerable amount of them (this amount depends on the amount of input ports) the size of arrays which are processed can arrive to 1024×1024 pixels and more. At such dimensions of the processed images only optical and optoelectronic implementations will allow to provide the real-time processing and recognition-associating by such MHAM. Possible implementations of neuron networks (NN), NN AM and bidirectional associative memory (BAM) based on optical and optoelectronic realization with spatial and time integration are shown in papers [7, 9, 10]. In paper [9] it was shown that at processing of 2-D patterns, optical realizations, which are based on the use of spatial integration, have some fundamental limitations and does not allow providing the substantial increase of amount of memorized in AM patterns and increase of the processing performance. In papers [9, 10] it was shown that optoelectronic architecture with time integration could give substantial advantages. In addition, the picture type devices, described in papers [11 – 12], can be used as the macro-element basis for these architectures.

Therefore, we offer modifications of the known realization of AAM with time integration in case of realization of not one-port AAM, but MHAM. Differences between MAAM and MHAM at the use of time integration are unimportant. Actually on the same architecture it is possible to realize and MAAM and MHAM. The architecture of MHAM and the processed images at different places are shown in Fig. 1. It explains its principle of functioning. The use of polarization code, polarizer P1 and analyzers A1 and A2 allows to combine simultaneous implementation of memberwise operations of "equivalence" and "nonequivalence" (in essence the operation of XNOR and XOR of binary logic) above images, and also by spatial integration of images PPEQ1 and PPNQ1 by micro-lens arrays (MLA2, MLA1) to provide the calculation of normalized equivalence and normalized nonequivalence of every input character (letters by the dimension of 40×32 elements) operations from a set of QR (12 letters or 12 ports) with every stored and multiplied to 12 copies of the character from the learning set PRX1. Aggregate of QR input characters with noise or without is given either from a camera or from the corresponding block of feed-back to the first LCD1, and the multiplied images (the amount of copies equals the amount of ports) Q1, Q2, … Q12 of standard learning characters from the set PRX1 consistently are written to the LCD2. Signals at photodetectors matrix inputs PDA1 and PDA2 are proportional to signals of equivalence (PDA1) of every input port with one of stored characters and to the signals of nonequivalence (PDA2).

These signals are actually coefficients β in corresponding models. If the weighing of synapses is done only by this coefficient β, then as it is shown in papers [4, 7] needed nonlinear transformations are performed by increase of nonlinear factor. If an additional weighing of matrix/tensor of α coefficient (vectors of 1D data or matrix for 2D data) is used in accordance with formulas, then in the MHAM architecture it is necessary to set a corresponding shadow mask after the analyzers A1 and A2. This shadow mask is formed in accordance with the multiplied matrix of coefficients α, which in simplest case is formed as a binary matrix. Forming of such matrix from a set of learning characters and choice of a binarization threshold will be described in the next paragraph. Usage of two such identical shadow masks, which skip light only in some chosen part of pixels of every character at every port, allows to substantially reducing the degree of nonlinear transformation. It is better to execute such nonlinear transformation in corresponding electronic parallel processing circuits.

After nonlinear transformation of these signals by the arrays ENCA1 and ENCA2 of electronic nonlinear transformers, they are given to the laser diodes arrays (LDA1, LDA2). Optical signals from corresponding MLA3, MLA4 of different intensities, namely such, that a neuron-winner has most intensity after nonlinear treatment, and other neutral intensity (≈0.5 conventional unit), after passing of corresponding polarizers P2 and P3 and LCD3 with the analyzer A3, are given to the inputs of photo-detectors array PDA3 with time integration at every cycle with the record of new Q of the i-th set to LCD3. In the first cycle on the input of PDA3 the resultant image EE1 are formed from images E1V and E1W, which is the equivalence weighing of array Q2 (for MHAM) or array Q1 (for MAAM) by the matrix EN1 of signals which are formed after nonlinear transformation from the matrix of signals E1 at the inputs of photo-detectors. In the next cycle images EE2, EE3, which are formed analogically, are added to the resultant image EE1. The resulting image ES is formed at the end of processing and time integration. By threshold treatment of this image at output from PDA3, we get the array of image FV, which is given to the chart of feedback for the next processing iteration or to the output of the system. Estimate the possible parameters of such architecture. Amount of pixels, that is limited by possibilities of LCD will consider be not less than 1024×1024. If input character of every port will have a dimension of 32×32=1024 neurons, then an amount of such ports in MNNHAM will be no more 32×32. If to take into account losses of differentiation between the images at every port then really to consider this amount of ports even 20×20. Thus, such realization allows recognizing simultaneously about 400 characters with dimension 32×32. Amount of reference patterns, which are used for learning of such MHAM, can be more than amount of ports. It will result only in the increase of recognition time, as an amount of processing cycles is proportional to the amount of the interrelated associated pair of reference patterns from the learning selection (see Fig. 1 - "Set of teaching for MGAM"). Processing cycle can be really in a range of 0.5÷50μS if use modern fast-acting LCD, PDA and LDA. At the amount of reference patterns (cycles) 400, summary time of recognition of all input patterns will not exceed 0.2÷20mS. Taking into account, that the amount of neurons of every port is equal 1024, and for the MHAM it is needed to process 1024^2 connections, then at the 400 of ports productivity of processing can be appraised as 10^{10}-10^{12} connections per a second.

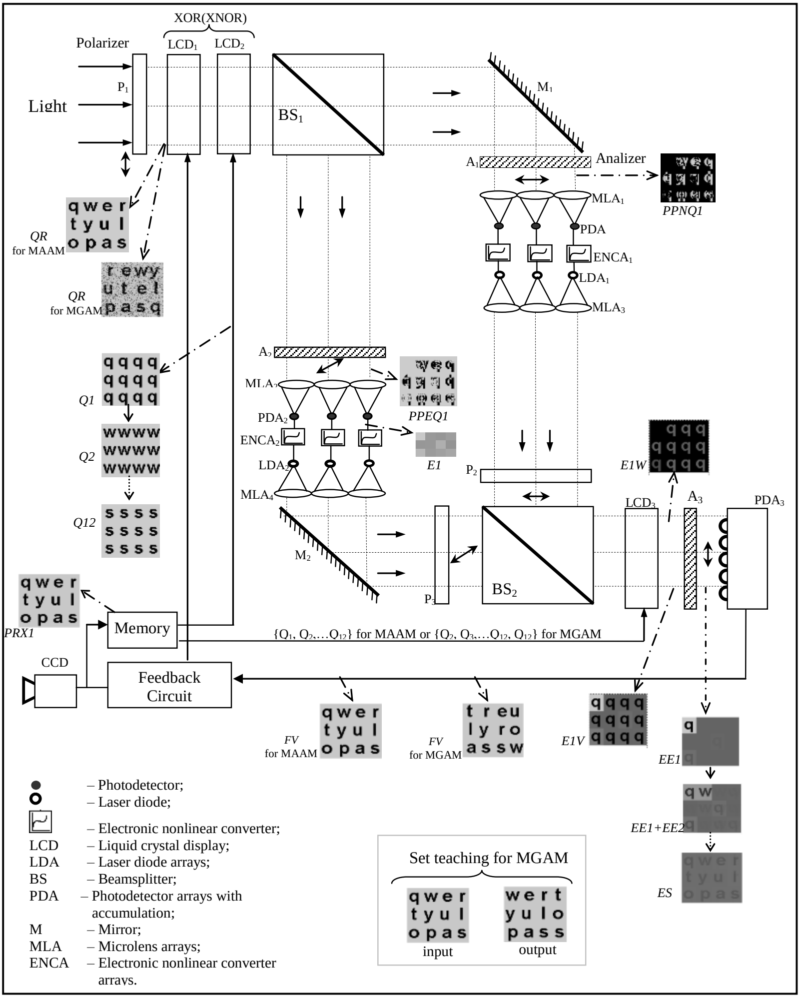

Fig. 1. The MNNHAM architecture with time integration

Forming shadow mask as a learning process of MHAM. Images of letters as a matrix by a dimension of 40×32 elements are used as input patterns for Mathcad MHAM simulation. Thus, the amount of inputs of each of 12 ports of MHAM equals 1280. Images of letters of the same dimension 40×32, which associated in pairs with input patterns, are used as output patterns. We used the next hetero-associated pair of letters : q - w, w - e, e - r, r - t, t - y, y - u, u - l, l - o, o - p, p - a, a - s, s - s. The learning set can be presented as two images which are shown in Fig. 1 and in Fig. 2a,b as corresponding binary matrices RPX1 and RPX1OUT (for the best displaying in Mathcad these matrices are self-weighted by a scalar coefficient 200).

Each of these matrices is the association of corresponding 12 matrices of every input or output image of letter. If an image, damaged by noise, is given to input of MHAM, for example matrix QR (Fig. 2c), which is the association of corresponding 12 (for the amounts of ports) input images of letters, then depending on an learning set to every letter the number of which is formed on a row, and then on a column, the corresponding letter associated with it must be at the output of MHAM. In every cycle of operation of such architecture with pulse-time integration multiplied images of input and output letters from a corresponding set which are the corresponding corteges of matrices Q_1, Q_2,… Q_{12} and Q_1, Q_2,…Q_{12} for MAAM or Q_1, Q_2,…Q_{12} and Q_2, Q_3,…Q_{12} for MHAM must be given to corresponding LCD2 and LCD3. They are represented in Fig. 1 and Fig. 2f. The corresponding images PPEQA1 and PPNQ1 (see Fig. 2g, h) turn out after the analyzers A1 and A2, if the images of QR and Q1 were given at the first cycle. Forming of shadow matrix is executed as follows. The corresponding multiplied images of every standard letter as matrices R1,... R12 are added and the mean-weighed image RMS is formed. Using the reference images M and MR (see "RM" in Fig. 2j), coefficient η=0.55 and formulas in Fig. 2m, a binary image of fragment AR is formed (Fig. 2k). The image is a shadow mask with dimension of 40×32 elements. Moreover, the resulting shadow mask from 12 reiterations of AR is formed as a matrix ARQ (Fig. 2l). **Simulation results of MHAM architecture.** After passing of such shadow masks which can be set after the analyzers A1 and A2, in accordance with formulas in Fig. 2n, the resulting images PPEQ1 and PPEQN1 (Fig.2o, p), in which the distinguished area is in accordance with the AR fragment, are formed from the images PPEQA1 (equivalence) and PPNQ1 (nonequivalence).

Integration and normalizing with micro-lens (including by coefficient k_0 (Fig.2m)), are equivalenced to mean value of sub-matrices $mean(submatrix(PPEQ1,0,39,0,31)$ and $mean(submatrix(PPEQN1,0,39,0,31)$ in the simulation for example.

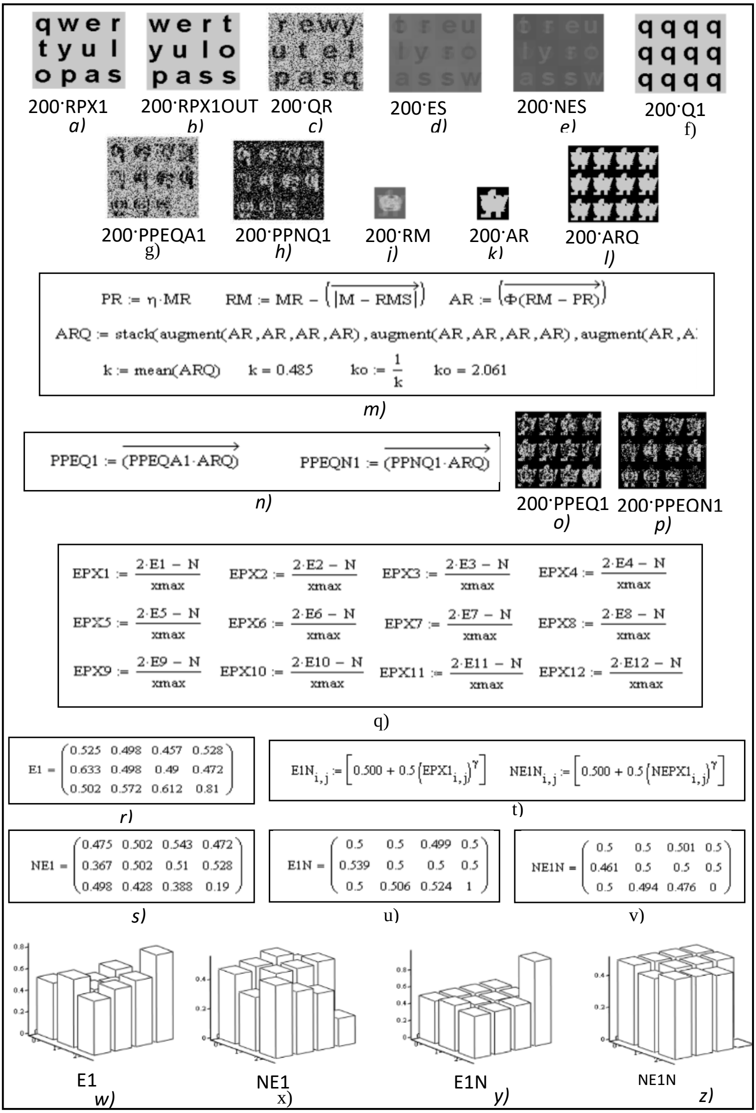

Fig. 2. Images of input and output letters and formulas in Matcad simulation of MHAM.

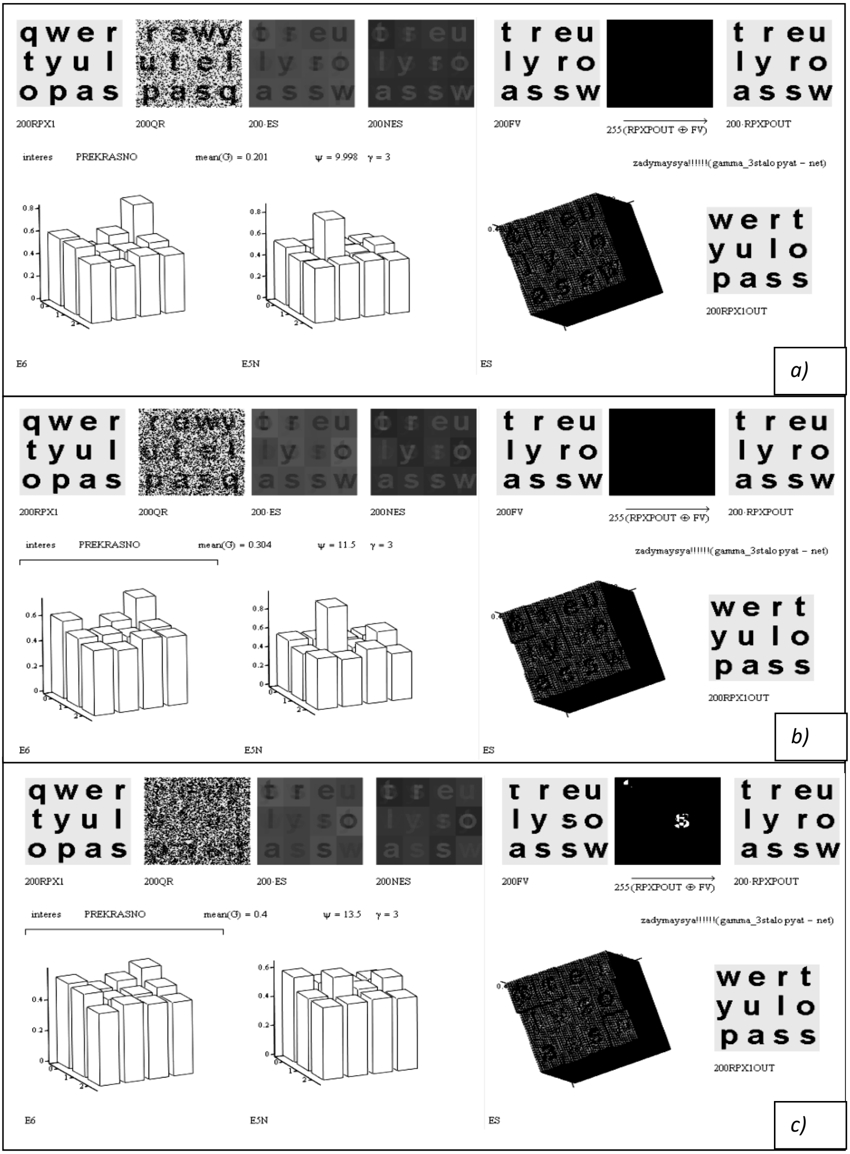

Fig. 3. Simulation result for different power of noise.

Therefore, there will be the formed matrices of optical signals at the input of corresponding matrices PDA2 and PDA1, that proportional and displayed by the matrices E1 and NE1 accordingly. Using formulas shown in Fig. 2q, where $x_{\max} = \max_i(\max(2\vec{E}_{i\in 1\div 12} - N)$ and formulas in Fig. 2t of nonlinear transformation of matrices EPX_i, actually from E1 and NE1 matrices E1N and NE1N are formed. They are shown in Fig. 2r, s, u, v and as 3D in Fig. 2w, x, y, z.

The analogical method is executed in every cycle. Fragments of MHAM simulation results for recognition of 12 noisy letters of input matrix QR with coefficient of non-linearity $\gamma=3$ and for different input sets of letters are shown in Fig. 3.

Simulation result for different power of noise 20.1% (a), 30.4% (b) and 40% (c) for recognition of all 12 noised letters from the first set. In all figures (a), (b), (c) the first: the reference patterns set; the second: the noisy input letters; the third and the fourth: time-pulse integrated signals before their threshold processing; the fifth: output recognized hetero-associated 12 letters; the sixth: etalon; the seventh: difference in the output and the etalon, which is a zero error; in the second rows: intensity of signals of hidden nonlinear neurons and integrated signals before threshold processing shown in 3D.

As evidently from presented results, the amount of damaged pixels (the power of noise), at which all letters are successfully recognized, can arrive to 20 % (Fig.3 a) or 30 % (Fig.3 b) and only at 40 % two letters from 12 remained unrecognized.

Conclusions. The architecture of MHAM based on modified equivalently models are offered with double adaptive -equivalently weighing (DAEW) for recognition of 2D-patterns (images). The MHAM simulation results on the concrete samples showed that have considerable capacity, productivity and make possible to recognize vectors with considerable percentage of the damaged components (up to 25-35 percent).

References

1. Kiselyov, B., Kulakov, N., Mikaelian, A., Shkitin, V. “Optical associative memory for high-order correlation patterns”, Opt. Eng., Vol. 31, № 4, pp. 764-767 (1995).

2. Rudenko O., Bodyansky E.V. Artificial neuron networks: Handbook: Kharkiv, "SMIT", 408 p. (2005).

3. Krasilenko, V. G., Magas, A. T., "Multiport optical associative memory based on matrix-matrix equivalentors", Proceedings of SPIE Vol. 3055 (SPIE, Bellingham, WA 1997) pp. 137-146. (1997).

4. Krasilenko V. Research and design of equivalence model of heteroasociative memory// V. Krasilenko, V. I. Yatskovsky, A. Yatskovska. the Scientific session of MIFI-2010.-Vol.2 M. :НИЯУ МИФИ, pp. 83-90 (2010).

5. Krasilenko, V. G., Saletsky, F. M., Yatskovsky, V. I., Konate, K., "Continuous logic equivalence models of Hamming neural network architectures with adaptive-correlated weighting", Proceedings of SPIE Vol. 3402, pp. 398-408 (1998).

6. Krasilenko, V.G., Nikolskyy, A.I. et al. "Some newest results and achievements of domestic neurocomputings", //MCTTP. Collection of scientific proceedings. 8 RTC, pp. 320-324, (2001).

7. Krasilenko, V. G., Nikolskyy, A. I., Yatskovskaya, R. A., Yatskovsky, V. I., "The concept models and implementations of multiport neural net associative memory for 2D patterns", Proceedings of SPIE Vol. 8055, 80550T (2011).

8. Krasilenko, V.G., Lazarev, A. A., Grabovlyak, S.K., Design and simulation of a multiport neural network heteroassociative memory for optical pattern recognitions, SPIE Vol. 8398, 83980N (2012).

9. Krasilenko, V. G., Nikolskyy, A. I., Flavitskaya, J. A., The Structures of Optical Neural Nets Based on New Matrix_Tensor Equivalently Models (MTEMs) and Results of Modeling, Optical Memory and Neural Networks (Information Optics), Vol. 19, No.1, pp. 31–38, Allerton Press (2010).

10. Krasilenko, V. G., Bogukhvalsky, A. K., Magas, A. T., "Designing and simulation of optoelectronic neural networks with the help of equivalence models and multivalued logics", Proceedings of SPIE Vol. 2824, pp. 135-146 (1996).

11. Krasilenko, V. G., Kolesnitsky, O. K., Bogukhvalsky, A. K., "Creation opportunities for optoelectronic continuous logic neural elements which are the universal circuitry macrobasis of optical neural networks", Proceedings of SPIE Vol. 2647, pp. 208-217 (1995).

12. Krasilenko, V. G., Nikolskyy, A. I., Lazarev, A. A., Design and Simulation of Time-Pulse Coded Optoelectronic Neural Elements and Devices, Optoelectronic Devices and Properties, Prof. Oleg Sergiyenko (Ed.), ISBN: 978-953-307-204-3, InTech, DOI: 10.5772/16175 (2011). Available from: http://www.intechopen.com/books/optoelectronic-devices-and-properties/design-and-simulation-of-time-pulse-coded-optoelectronic-neural-elements-and-devices.