SIMULATION OF ARRAY CELLS FOR IMAGE INTENSITY TRANSFORMATION USED IN MIXED IMAGE PROCESSORS AND NEURAL NETWORKS

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INTRODUCTION. For creation of biometric systems, machine vision systems are necessary to solve the problem of object recognition in images. Discriminant measure of the mutual alignment reference fragment with the current image, the coordinate offset is often a mutual 2D correlation function. In paper [1] it was shown that to improve accuracy and probability indicators with strong correlation obstacle-damaged image, it is desirable to use methods of combining images based on mutual equivalently 2D spatial functions and equivalence models (EMs), nonlinear transformations of adaptive-correlation weighting. For the recognition, clustering of images, various models of neural networks (NN), auto-associative memory (AAM) and hetero-associative memory (HAM) are also used [2,3]. The EM has such advantages as a significant increase in the memory capacity and the possibility of maintaining strongly correlated patterns of considerable dimensionality. Mathematical models and implement of HAM based on EMs and their modification described in papers [3,4]. For of analysis and recognition should be solved the problem of clustering of different objects [4]. Hardware implementations of these models are based on structures, including matrix-tensor multipliers, equivalentors [5]. And the latter are basic operations in the most promising paradigms of convolutional neural networks (CNN) with deep learning [6-8, 9]. Scientists create algorithms to identify previously unknown structures in data, including those whose complexity exceeds human understanding. In paper [10] we showed that the self-learning concept works with directly multi-level images without processing the bitmaps. But, as will be explained below, for all progressive models and concepts, nonlinear transformations of signals, image pixel intensities are necessary.

SUBSTANTIATION **of the need to design devices for parallel nonlinear image intensity transformations in self-learning equivalent-convolutional neural structures (SLECNS).** In papers [9, 10] we showed models for the recognition and clustering of images that combine the process of recognition with the learning process. For all known convolutional neural networks, as for our EMs, it is necessary to calculate the convolution of the current fragment of the image in each layer with a large number of templates that are used, which are a set of standards that are selected or formed during the learning process. But, as studies show, large images require a large number of filters to process images, and the size of the filters can also be large. Therefore, the problem of increasing the computing performance of hardware and software-hardware implementations of such CNNs is acute. Therefore, the last decade was marked by the activation of works aimed at the creation of specialized neural accelerators and we proposed a new structure [10, 11]. It consists of a micro-display dynamically displaying current fragments, an optical node in the form of a micro-lens array (MLA) with optical lenses (not shown!) and a 2D array of equivalentors **(Eqs**) with optical inputs. Simulation on 1.5μm CMOS in different modes has shown that the **Eq** and their base units can operate correctly in low-power modes and high-speed modes, their energy efficiency is estimated to be not less than 10^{12} an.op / sec per W the produced and can be increased by an order, especially considering FPAA. But much depends on the accuracy of the current mirrors and their characteristics. Thus, at the inputs of each **Eq** we have two arrays of currents representing the compared fragment and the corresponding filter, and the output of the **Eq** is an analog signal, nonlinearly transformed in accordance with the activation function. As will be shown work [10], non-linear component-wise transformations allow even without WTA network to allocate the most Eq with the greatest activity. From the above described it follows that for hardware implementations of all the advantages of SI EM, an important issue is the design of parallel nonlinear transformations, transformations of intensity levels. And, as will be shown below, the use of an array of cells that perform hardware, non-linear transformations adequate to auto-equivalence operations, allows the laborious computational process of searching for extremums in maps for clustering and learning not to be performed, but to automatically select these extremums using only several transformations steps. **Brief review of mathematical operators, which are implemented by neurons**. Almost all models of NN, CNN use mathematical models of neurons, which are reduced to the presence of two basic mathematical components-operators: the first component computes a function from two vectors and the second component corresponds to nonlinear transformation of the output value of the first component to the output signal. The input operator can be implemented as sum, maximal or minimum value, product of the self-weighted inputs. But in the above works, activation functions were not simulated and shown. A lot of work has been devoted to the design of hardware devices that realize the functions of activation of neurons, but they do not consider the design of exactly the auto-equivalent transformation functions for EMs and the most common arbitrary types and types of nonlinear transformations. Therefore, the goal of this paper is the design of cells for hardware parallel transformation of image intensity levels. In work [10], the question of the simplest approximations of auto-equivalence functions (three-piece approximation with a floating threshold) was partially solved. The basic cell of this approximation consisted of only 18 - 20 transistors and allowed to work with a conversion time of 1 to 2.5 μs. At the same time, the general theoretical approaches to the design of any nonlinear type of intensity transformation were not considered, and this is the object of the paper. We will note that on a current mirror more easily to execute these operations of addition or subtraction of currents. Therefore, we proposed a new structure [11]. **Mathematical models of nonlinear transformations of image intensities**. Consider a mathematical model for the piecewise approximation of a nonlinear transformation of the pixel intensity of an image. The input analog intensity of the pixel is denoted by x where $x \in [0, D]$, where D – the maximum intensity of the selected range, and denote the output analogized transformed intensity by y where $y \in [0, D]$. Then the operator of the nonlinear intensity transformation can be written in the form: $y = F_{trans}(x)$. As such functions can be threshold processing functions, exponential, sigmoid and many others, which, in particular, are used as activation functions in the construction, synthesis of neural elements and networks based on them. To form the required nonlinear intensity transformations, it is possible to use piecewise linear approximation of the chosen functions. For piecewise-linear approximation, break the range of input levels D into N equal sub-bands, width $p = \frac{D}{N}$. Using the function of bounded difference known from paper [1], defined as $a \dot{-} b = \begin{cases} a-b, & if\ a > b \\ 0, & if\ a \le b \end{cases}$. Form for the input signal x and each upper sub-band level $pD_i = i \cdot p$, where $i = 1 \div N$, the following signals: $s_i = (x \dot{-} (i-1)\cdot p) \dot{-} (x \dot{-} i \cdot p)$. For $i = 1$ we get $s_1 = x \dot{-} (x \dot{-} p)$, and this is the minimum $\min(x, p)$ and there is a step signal with height p. For $i = 2$ we get $s_1 = (x \dot{-} p) \dot{-} (x \dot{-} 2 \cdot p)$, which corresponds to a step in height p, but which begins at p. For $i =$ N we get $s_N = (x \dot{-} (N-1)\cdot p) \dot{-} (x \dot{-} N \cdot p) = (x \dot{-} (N-1)\cdot p)$, which corresponds to a step in height p, but which begins at $(N-1)\cdot p = D - p$. Summing with the weight coefficients k_i these steps, we can form a piecewise approximated intensity

$$y_a = \sum_{i=1}^{N} k_i \cdot s_i = \sum_{i=1}^{N} k_i \cdot [(x \dot{-} (i-1)\cdot p) \dot{-} 2 \cdot (x \dot{-} i \cdot p)] , \qquad (1)$$

for forming $y_a \in [0, D]$, that is, the normalized range of its levels, the weighting coefficients of the steps are selected from the condition: $\sum_{i=1}^{N} k_i = N$. Analysis of formula (1) shows that by changing the gain of the steps, we can form any required piecewise continuous intensity conversion function. If the coefficient k_i negative, it means that the corresponding step is subtracted. Thus, in order to implement the transformations, a set of nodes, realizable operations of bounded difference, weighting (multiplication), and simple summation are needed. If the input pixel intensity is set by the photocurrent, then having the current mirrors (CM), by which the operations of the limited difference and the summation of the photocurrents are easily realized, it is sufficient to have a plurality of limited difference schemes and the specified upper sub-band levels pD_i . By choosing the parameters of the current mirror transistors, operations of dividing or multiplying currents by the required fixed k_i. If it is necessary to dynamically change the view, the conversion function, i.e. the weight of the components, then you need the coded amplifiers. When working with currents and CM, a set of keys and a multiplying mirror with discrete weights (binary) perform the role of code-controlled amplifiers and are essentially DAC with the only difference that instead of a reference analog signal an analog signal s_i. After some transformations, formula (1) is transformed to this form:

$$y_a = \sum_{i=1}^{N} k_i \cdot [(x \dot{-} pD_{i-1}) \dot{-} (x \dot{-} pD_i)] = \sum_{i=1}^{N} k_i \cdot \min(x \dot{-} pD_{i-1}, p) \qquad (2)$$

Formula (2) indicates that for the implementation of the intensity conversion, it is necessary to have analogous minimum circuits, but it is realized in the form of two operations of bounded difference: $a \dot{-} (a \dot{-} b) = \min(a, b)$. In addition to the formulas (1) and (2) considered above, it is possible to realize the required function by means of triangular signals:

$$y_a = \sum_{i=1}^{N} k_i \cdot t_i = \sum_{i=1}^{N} k_i \cdot [(x \dot{-} (i-1)\cdot p) \dot{-} 2 \cdot (x \dot{-} i \cdot p)] \qquad (3)$$

For the formation of the constants s_i or t_i, the input signal x can be multiplied by N and then all components are simultaneously generated simultaneously in each sub-assembly. On the other hand, in each sub-assembly a signal $(x \dot{-} pD_{i-1})$, which is fed to the next in the pipeline sub-assembly for the formation of signals and components from it. This corresponds to a conveyor circuit that will have a large delay, but does not require the multiplication of the input signal. The choice of this or that scheme and element base depends on the requirements for the synthesized node.

SIMULATION **of image intensity transformation with Mathcad.**

Using both the basic components for the composition of the lambda function **fspΔs2** , shown in Fig. 1 and described by expression: $\mathbf{fsp\Delta s2(xs, p\Delta x, p\Delta, k) := k \cdot obs(obs(xs, p\Delta x), obs(xs, p\Delta) \cdot 2)}$, where **xs** - function argument, **pΔx**- parameter indicating the lower bound-level **xs** (beginning), **pΔ** - the second parameter indicating the level for the maximum, k - is the third parameter indicating the scalar gain multiplier; and obs (a,b)= $a \dot{-} b$ we proposed a function-composition **fspΔsS,** which is calculated by the expression:

$$\mathbf{fsp\Delta sS(xs, \Delta k, VK)} := \sum_{\mathbf{i}=1}^{\mathbf{\Delta k}} \mathbf{fsp\Delta s2}\left[\mathbf{xs}, \frac{255}{\mathbf{\Delta k}}\cdot(\mathbf{i}-1), \frac{255}{\mathbf{\Delta k}}\cdot(\mathbf{i}), \mathbf{VK_i}\right]$$

, where **Δk** - number of components (lambda functions), **xs** - argument of the function, VK-vector of gain factors. The result of constructing some types of transfer characteristics (TC) using these functions in the Mathcad environment is shown in Fig. 1. To approximate auto-equivalence, we also offer simpler (2-step) basic N-functions:

$$\mathbf{af(xs, xp)} := [\mathbf{obs(xs, obs(xs, xp)) + obs[xs, (DP - xp)]}] \cdot \left(\frac{\mathbf{DP}}{\mathbf{xp}\cdot 2}\right)$$

and triple their composition:

$$\mathbf{afS(xs, VaF, KaF)} := \sum_{\mathbf{iv}=0}^{2} \mathbf{af(xs, VaF_{iv})\cdot(KaF_{iv})}$$

. In general, the number of components in a composition can be arbitrary, but for modeling we used 8 and 16 component compositions and adjustment vectors. Examples of such functions and compositions for the synthesis of TC are shown in Fig. 2 (left). Another variety of functions is shown in Fig. 2 (right), and the results of using such TCs to prepare the original PIC image are shown in Fig. 3.

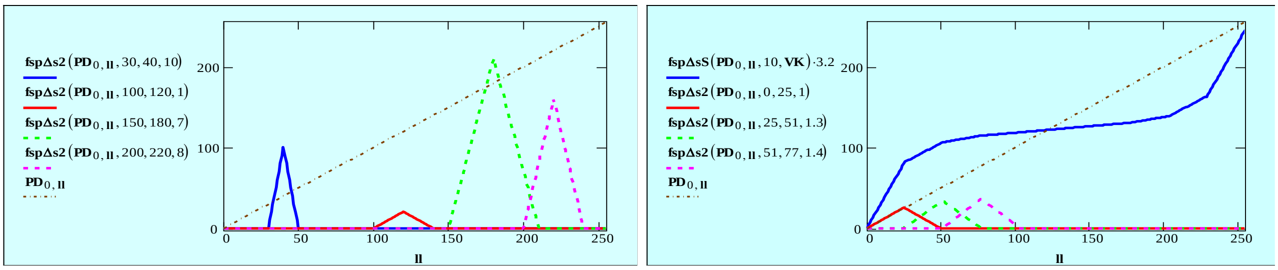

Fig. 1. Graphs of synthesized transformation functions

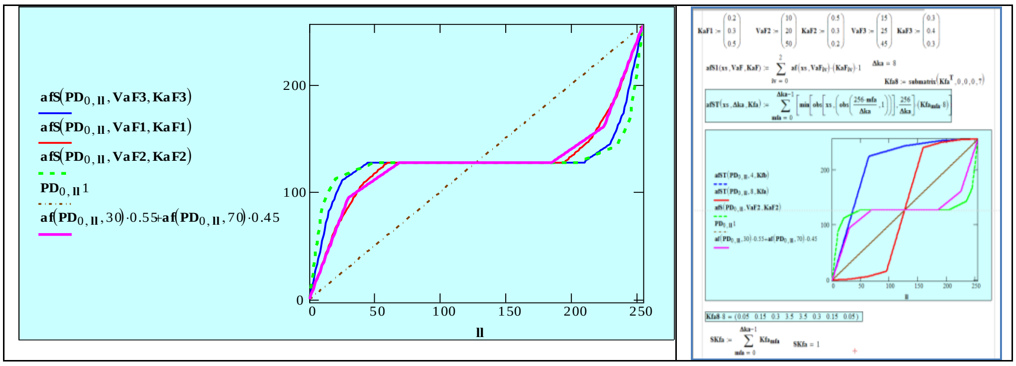

Fig. 2. Examples of synthesized transfer characteristics for auto-equivalence functions (left), Mathcad windows with the formulas and graphs of synthesized functions transformation (right).

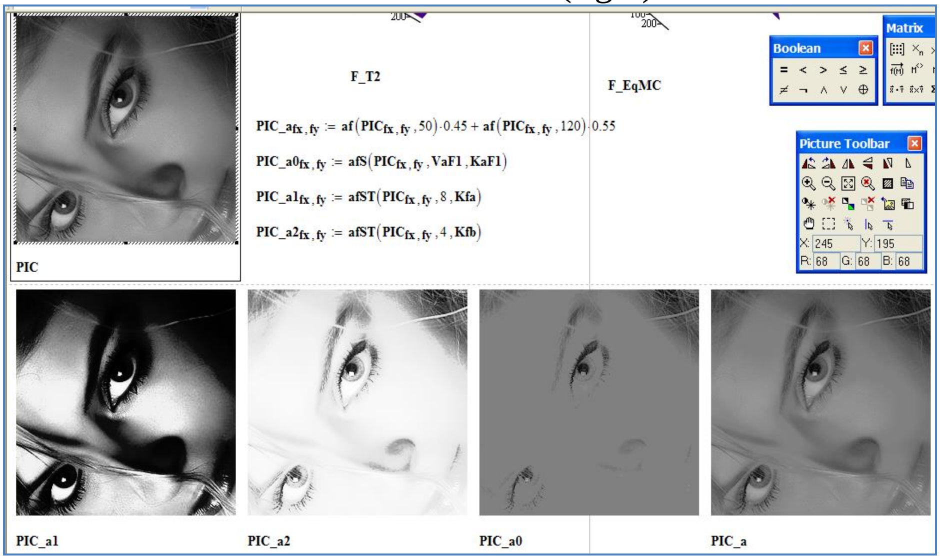

Fig. 3. Mathcad windows on which the formulas and results image intensity transformation are shown, where in 2D from left to right: input image PIC, the computed auto-equivalence functions, non-linear (after activation) output images (bottom row).

CONCLUSIONS. The paper proposes the mathematical foundations of design of continuously logical cells (CLC) based on current mirrors (CM) with functions of preliminary analogue processing for image intensity transformation for construction of mixed image processors (IP) and neural networks (NN). Several effective schemes have been developed and modeled of CLC and optoelectronic complement dual analog neuron-equivalentors as hardware accelerators SLECNS. The proposed **CLC** have a modular hierarchical construction principle and are easily scaled. Their main characteristics were measured. They have a processing-conversion time of 0.1-1μs, low supply voltages of 1.8-3.3V, minor relative computational errors (1-5%), small consumptions of no more than 1mW, can operate in low-power modes less than 100μW) and high-speed (1-2MHz) modes. The relative to the energy efficiency of CLC and **Eqs** is estimated at a value of not less than 10^{12} an.oper. / sec. per W and can be increased by an order. The obtained results confirm the correctness of the chosen concept and the possibility of creating neuron-equivalentors (**NEqs**) and MIMO structures on their basis. They can become the basis for the implementation self-learning biologically inspired devices, SLECNS and CNN with the number of such **NEqs** equal to 1000, to realize the parallel calculation.

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