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Recognition algorithms of multilevel images of multicharacter identification objects based on nonlinear equivalent metrices and analysis of experimental data

Предложены эквивалентностные пространственно-инвариантные алгоритмы распознавания полутоновых изображений идентификационных объектов, представленные набором символов, и результаты экспериментальных исследований. Показаны интерфейсы программы и результаты ее тестирования, подтверждающие высокое быстродействие и низкий процент нераспознанных символов.

Ecvivalently space-invariant pattern recognition algorithms halftone identification of objects and the results of experimental studies are proposed. Interface of this software are shown. Results of its tests confirmed the high performance and low part unrecognized characters, less than 0,01%.

Запропоновано еквівалентнісні просторово-інваріантні алгоритми розпізнавання напівтонових зображень ідентифікаційних об'єктів, що представлені набором символів, та результати експериментальних досліджень. Показано інтерфейси програми та результати її тестування, що підтвердили високу швидкодію і низький відсоток нерозпізнаних символів.

Introduction. The main perspective tendency of development of information-computating systems and computer technologies is making them intellectual and similar to human thinking and perception. As the models of intellectual systems in the field of neurophisiology, artificial intelligence the following models of auto-processing nets are mainly used: connection models, neural nets models, models with parallel distributed processing. Basic researches reveal a number of important general principles besides spontaneous intellectual qualities. Among those features we can mention the principle of parallel processing of information on all the levels of its processing (global system behaviour, considered as "intellectual") and the concept of active and not passive memory. The great interest to neural model forces to revalue the fundamental theses in many fields of knowledge, including computer techniques. Neural models of brain activity and cognitive processes, most probably will cause perspective results in neurophysiology, neurology, the advent of the systems with increased computing resources and intelligent qualities for solving problems of medical informatics and diagnostics. Many failures on the way of improving of artificial intelligence have appeared in recent years as firstly of all, the chosen computing techniques were not adequate to solve the important and complicated problems, and secondly, simple and not perfect neural models and nets were applied. Today, rapid progress in mathematical logic, especially matrix (multivalued, continuous, fuzzy, neural) [1–6], accumulation of data regarding continual (analog) and obviously nonlinear functions of neurons [7–9], elaboration of the neural net theory, neurobiology and neurocybernetic, and adequate algebrologic instruments for mathematical description and modeling [6, 10–15], development of optical technologies have created conditions for construction of technical systems, adequate almost to any problem of artificial intelligence. The works [10, 16], and especially [11–14] solve the problem of increase of capacity in artificial neural networks (ANN) and associate memory (AM), even in cased storing of greatly correlated images, and the problem of convergence of methods and training rules, using multilevel representation of signals. The use of operations of neural logic operations – equivalence and nonequivalence for construction of ANN and AM models is common for works [11–14]. In this connection such models and the theory were called "equivalental".

They showed, and described negative and inhibitting weights along with exciting ones at unipolar and bipolar coding. Neural biologic (NBL) [1, 3, 10–12] is integration (gnoseologically development loped and specified) of known logic: multivalued, hybrid, continuous, fuzzy etc. At the same time, the integrated operations in fuzzy logic are: operation of fuzzy negation, t-norms and *s*-norms, and they have the relation of dualism according to general form of De Morgan principle. The example of *t*-norms are: logical multiplication ($\min(a, b)$), algebraic multiplication ($a \cdot b$), limited multiplication etc. The example of s-norms are: logical sum ($\max(a, b)$), algebraic sum$(a+b-a \cdot b)$, limited sum $(1 \wedge (a+b))$, contract sum etc [15, 17]. The basic operations of NBL, used in equivalental models NNAM [10–13], are binary operations of equivalence and nonequivalence, which have a few variants [12]. The variants of these equivalence operations on a carrier set $^{\wedge}C_u = [0,1]$ are shown on fig. 1 (*a*,*b*,*c*) respectively for:

$$eq^1 = a \approx b = \max\{\min(a,b), \min(\bar{a}, \bar{b})\};$$
$$eq^2 = a \dot{\sim} b = a \cdot b + \bar{a} \cdot \bar{b};$$
$$eq^3 = a \overset{+}{\sim} b = 1 - |a - b| \qquad (1)$$

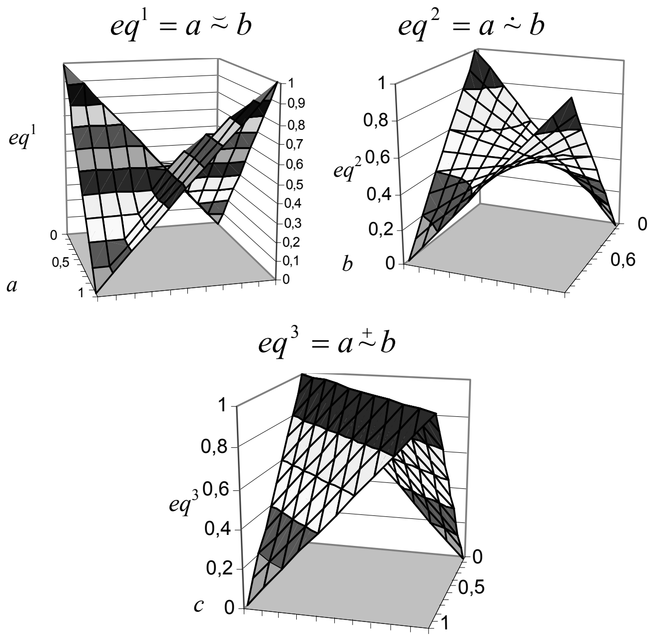


Fig. 1. Operations of equivalence

Their negations are first, second and third nonequivalence respectively. Relation of these operations when unipolar and bipolar coding is similar to relation of the signals and expressed as: $a_u \overset{(\sim)}{\not\sim} b_u = (D + (a_b \overset{(\sim)}{\not\sim} b_b))/2$, where $\overset{(\sim)}{\not\sim}$ is meaning valid for any of these operation variables, being: $a_u, b_u \in {}^{\wedge}C_u = [0, D]$, $a_b, b_b \in {}^{\wedge}C_b = [-D, D]$. In general case for scalar variables $a, b \in {}^{\wedge}C = [A, B]$ – continuous line segment, signals themselves and their functions and segment $^{\wedge}C$ can be brought to segments $[-D, D]$ (or [–1, 1]) in bipolar coding and $[0, D]$ (or [0, 1]) in unipolar coding. When shifting on interval, corresponding to $^{\wedge}C = [A, B]$, et at the value $\pm\varepsilon$ (i.e. when $^{\wedge}C = [A \pm \pm\varepsilon, B \pm \varepsilon]$)) set is chosen) the above mentioned equivalence and nonequivalence operations over variables $a_\varepsilon = a \pm \varepsilon, b_\varepsilon = b \pm \varepsilon \in {}^{\wedge}C^{\varepsilon}$ are expressed over the simple addition to equivalences and nonequivalences from non-shifted variables the shift $\pm\varepsilon$, namely: $a_\varepsilon \approx b_\varepsilon = (a \approx b) \pm \varepsilon$; $a_\varepsilon \overset{+}{\sim} b_\varepsilon = (a \overset{+}{\sim} b) \pm \varepsilon$.

Besides: for $k > 0$, $k \cdot (a \overset{(\sim)}{\not\sim} b) = (k \cdot a \overset{(\sim)}{\not\sim} k \cdot b)$.

Thus, equivalence (nonequivalence) of signals doesn't depend on constant shift (analogy to constant component), on scale factor *k*, on bipolar or unipolar coding. These operations are the generalization of *XNOR* and *XOR* operations of binary logic and allow logical comparison of continuous-level (analog) and multilevel signals with unipolar and bipolar representation, including scalar, vector and matrix. For that purpose normalized equivalence and nonequivalence of vectors and matrices are used [11, 12, 14], which for these two matrices $\mathbf{A} = \{a_{ij}\}_{I \times J}$, $\mathbf{B} = \{b_{ij}\}_{I \times J} \in [0,1]^{I \times J}$ are determined in the following way:

$$\mathbf{A} \underset{\mathrm{n}}{\sim} \mathbf{B} = \frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(a_{ij} \sim \mathrm{b}_{\mathrm{ij}}\right); \qquad (2)$$

$$\mathbf{A} \underset{\mathrm{n}}{\not\sim} \mathbf{B} = \frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(a_{ij} \not\sim \mathrm{b}_{\mathrm{ij}}\right). \qquad (3)$$

Normalized equivalence $\underset{\mathrm{n}}{\sim}$ and nonequivalence $\underset{\mathrm{n}}{\not\sim}$ – are more general new complementary metrics in metrical space R. In particular, $\overset{+}{\not\sim}_{n}$ is a normalized distance $d_1(\mathbf{A},\mathbf{B})/I\times J$ between matrices and for $\mathbf{A},\mathbf{B}\in\{0,1\}^N$ it turns into normalized distance $d_H(\mathbf{A},\mathbf{B})/N$ of Hamming. As it can be seen from expressions (2) and (3), component and component operation of NBL ($\sim$) or ($\not\sim$) is generalized for matrix case, and NBL logic becomes matrix NBL (MNBL). The variants of operations ($\sim$),($\not\sim$) depend on different types of t-norms and s-norms operations used in them and integrated fuzzy-operations of union and intersection [17]. Depending on the type or variants of equivalent algebra (EA) [11, 12] we can offer new algebro-logical instruments for creation of equivalental theory on the basis of MNBL. In works [11, 12] new notions of equivalental unidimension (1-D) and twodimension (2-D) functions were introduced:

$$\widetilde{E}(\xi) = f(\vec{a},\vec{b}_{\xi}) = \frac{1}{N}\sum_{i=1}^{N}(a_i \sim b_{i-\xi});$$

$$\begin{aligned}\widetilde{E}(\xi,\eta) &= \widetilde{f}(\mathbf{A},\mathbf{B}) = \mathbf{A}\tilde{*}\mathbf{B} = \\ &= \sum_{n=1}^{N}\sum_{m=1}^{M}(a_{n.m} \sim b_{\xi+n,\eta+n}).\end{aligned} \tag{4}$$

In this equation symbol ($\tilde{*}$) denotes the convolution (correlation) with operation of "equivalence".

Normalized space-dependent equivalence and nonequivalence functions were introduced in the work [14]

$$\tilde{\mathbf{e}} = \left(\mathbf{A}\,\tilde{*}\,\mathbf{B}\right)/I\times J \text{ and}$$

$$\begin{aligned}\mathbf{e}^{/\sim} &= \left(\mathbf{A}\overset{/\sim}{*}\mathbf{B}\right)/I\times J = [\mathbf{1}] - \tilde{\mathbf{e}} = \\ &= \left[ne_{\xi,\eta}\right]\in[0,1]^{(N-I+1)(M-J+1)}.\end{aligned}$$

These functions $\tilde{\mathbf{e}}$ and $\mathbf{e}^{\not\sim}$ reflect the measure of equivalence and nonequivalence of two images depending on their mutual spatial shifting. The connection of functions $\widetilde{E}(\xi,\eta)$ with correlation functions (linear LCF and nonlinear NCF) was demonstrated [11, 14]:

$$\begin{aligned}\dot{\tilde{\mathbf{e}}} &= \left(\mathbf{A}*\mathbf{B}\right)/I\times J + \left(\overline{\mathbf{A}}*\overline{\mathbf{B}}\right)/I\times J = \\ &= LCF_n(\mathbf{A},\mathbf{B}) + LCF_n(\overline{\mathbf{A}},\overline{\mathbf{B}});\end{aligned} \tag{5}$$

$$\dot{\mathbf{e}}^{\not\sim} = LCF_n(\mathbf{A},\overline{\mathbf{B}}) + LCF_n(\overline{\mathbf{A}},\mathbf{B}); \tag{6}$$

$$\begin{aligned}\overset{+}{\tilde{\mathbf{e}}} &= \left(\mathbf{A}\overset{+}{\tilde{*}}\mathbf{B}\right)/(I\times J) = \\ &= (\mathbf{A}\overset{\min}{*}\mathbf{B} + \overline{\mathbf{A}}\overset{\min}{*}\overline{\mathbf{B}})/(I\times J) = \\ &= N\hat{C}F_n(\mathbf{A},\mathbf{B}) + N\hat{C}F_n(\overline{\mathbf{A}},\overline{\mathbf{B}}).\end{aligned} \tag{7}$$

On the basis of these functions more generalized modified matrix-tensor neurological equivalental models ($MTNLEM_s$) for space-invariant recognition of 2-D images were synthesized [14].

Making use of formulae transformation for calculation of linear and nonlinear correlative functions and criterial functions of mean absolute error (MAE) and mean square error (MSE), authors show in work [18] that these formulae can be reduced to two groups of mathematical constructions. These constructions determine two groups of architectures of parallel action: high-speed correlators with nonlinear and image morphological processing. In practice there often appears the problem dealing with recognition of multilevel images of the objects being identified; on special seals, on engineering objects designed for various applications, documents etc. That is why, taking into account the above mentioned facts and possibilities of equivalent functions applications shown earlier, we will suggest in the given work the recognition algorithms based on nonlinear equivalent metrics and will show the results of investigation of these algorithms.

The algorithms of recognition without preliminary segmenting of input image (the algorithms of group I)

The idea of *NLEAs* is concluded in segmenting (on the base of a priori information) into fragments, corresponding to separate symbols, source image of multicharacter object or reference image, composed of a set of alphabet of symbols, subjected to recognition. For each i^{th} segment of source image nonlinear equivalence functions with general reference image for the first group of *NLEAs* realization variants are calculated. For the second group of *NLEA* realization variants *NLEFs* for each i[th] reference image segment with the general input multicharacter image are calculated. Inside of each *NLEA* group we apply several modifications of *NLEFs*, depending both on the type of "equivalence" ("nonequivalence") being used and on parameters, determining the type of nonlinearity and a number of autoequivalence transformations. Moreover the latter can be applied both to separate components of images being compared and to integrate *NLEF*-evaluations and normalized *NLEF* as a whole. Let dimensions (in the number of pixels) K (in vertical position) and L (in horizontal position) in rectangular fragment P of the image be chosen in such a way, that each of possible Q reference images of $\mathbf{S}_{q\in(0\div Q-1)}$ symbols from selected alphabet could be paced in fragment region (most closely and with minimal dimensions of rear plan). Then multi level image $\mathbf{A}=[a_{ij}]_{I\times J}$ to be recognized of multisymbol (R-symbol) identification object O with horizontal row wise accommodation of symbols will include all R of $\mathbf{P}_{r\in(0\div R-1)}$ fragments, each of which can be the image of one $\mathbf{S}_q$. of symbols. Total dimensions I, J of the image $\mathbf{A}$ must be greater than values K and $R{\cdot}L$ accordingly and meet the requirements: $I = K + d_1$; $J = R{\cdot}L + d_2$, where d_1 and d_2 – total amounts of pixels in vertical and horizontal positions accordingly complementing the interfragmental space till dimensions $\mathbf{A}$. Fig. 2,*a* shown initial multilevel (256 levels $a_{ij}\in(0\div 255)$) image $\mathbf{A} = \{0,255\}^{I\mathrm{x}J}$, to be recognized, images of arranged set (alphabet) of symbols $\mathbf{S}_q=[S_{k,l}]\in\{0,1...255\}^{K\times L}$ (see fig. 2,*b*). In this case, criterial function (space-dependent) $\mathbf{B}^q(\xi,\eta)\in[b_{\xi,\eta}]_q^{(I-K+1)\times(J-L+1)}$ can be determined for each $\mathbf{S}_q$ reference, as it is shown in fig. 2,*c*. Knowledge algorithms regarding the number of R symbols in identification object (number of fragments in the image $\mathbf{A}$) and possible deviations of symbols positions taking into account the gaps permit to divide the image of two-dimensional criterial function into R regions. In each R-th region there is an extremum (min or max) of criterial function $\mathbf{B}^q$ namely ${}^r\mathbf{B}^q_{\max(\min)}$ and its coordinates. Comparing all $\mathbf{B}^q_{\max(\min)}$ within r-th region, we can find index q' (number of symbol reference), which gives us the greatest (the least) value of criterial function in this region. Thus we determine (recognize) symbol-reference in each *r-th* region, and using the coordinate $x_{r,q'},(y_{r,q'})$ of the extremum of the best equivalence (similarity) or nonequivalence (nonsimilarity) the position of recognized reference symbol in the object is determined, and coordinates of the following region (sign location) are being searched.

For the analysis of NLEF functions obtained after the first step, both of integral signs and for decision taking based on their collection, we perform transformation of 2-D *NLEFs* into 1-D *NLEFs*, carrying out by component operations of minimum (maximum) over vector arrays, corresponding columns (or lines) of initial 2-D *NLEFs*. Thus we select local spatial extremums of *NLEF*. Such compression of information is possible and reasonable and permits to simplify considerably further analysis of recognition. On the following step by the result of comparisons of 1-D transformed *NLEF* local extremums (lighting countings out) (number of which corresponds to a number of reference recognized symbols), we come to a conclusion on the presence or absence (the most probable) of one of the reference symbols and on its coordinate location in initial image being recognized. The modification of the given algorithms is the algorithms, when criterial functions are calculated only in R'-th local regions ($\Omega_{R'}\subseteq\Omega_R$)in the proximity of arising determined possible position of the extremum. It considerably decreases temporal expenses needed for its realization.

Formula for calculation of maximorum (minimorum) of criterial function (q-th) in R region is the following:

$$ {}^rB^q_{\underset{(\min)}{\max}}(x_r)=\underset{(\min)}{\max}({}^rb^q_{x_r,y_0},{}^rb^q_{x_r,y_1},\dots,{}^rb^q_{x_r,y_{I-K+1}}). $$

Formula for q' selection is the following:

$$ q'=q\text{, if }\underset{(\min)}{\max}({}^rb^{q=0}_{x_r},{}^rb^{q=1}_{x_r},\dots\dots{}^rb^{q=Q-1}_{x_r})={}^rB^{q'}_{x_r}. \quad (8) $$

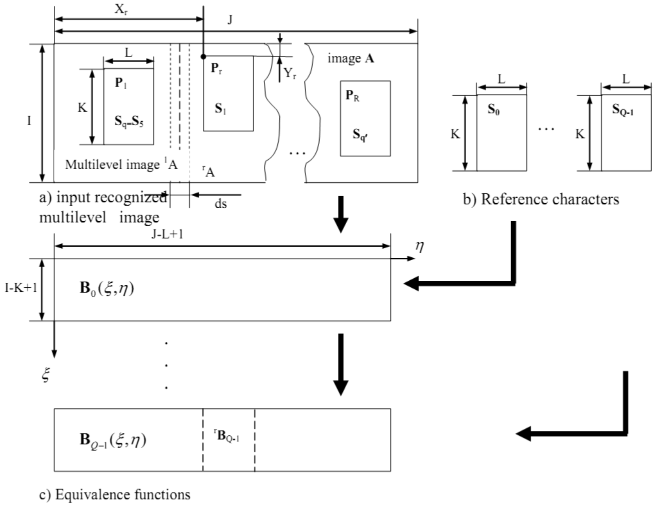


Fig. 2. Formation process of criterial functions

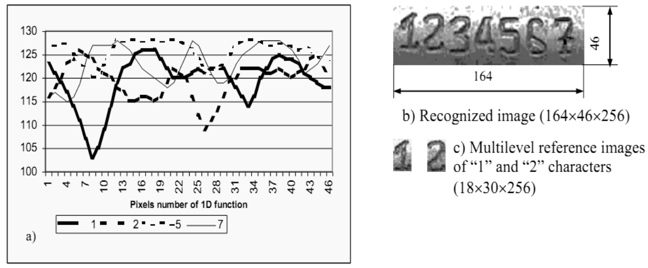
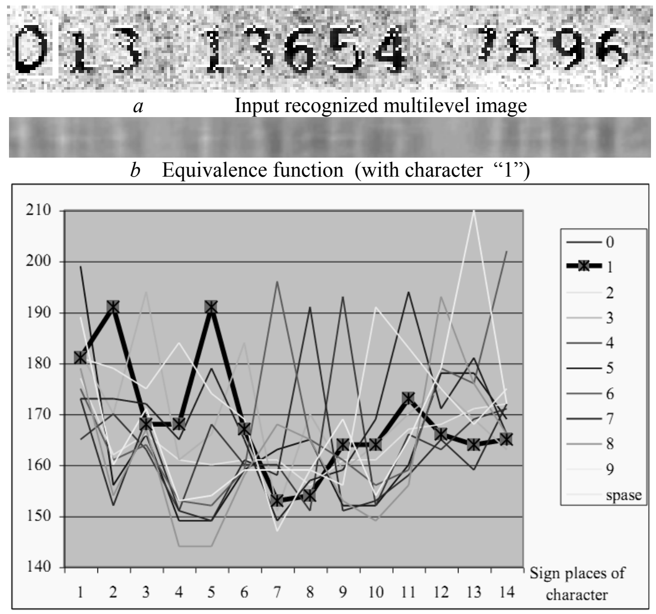


Fig. 3. Part of l*D NLEF* function ${}^{r\in 1,2}_{b}B^{q\in 1,2,5,7}_{\max}(\eta)$ ($X_{r=1}$= 8, $X_{r=2}$= 26)



a Input recognized multilevel image

b Equivalence function (with character "1")

c Dependency of function ${}^{r}_{c}B^{q}_{\max}(X_r)$

Fig. 4. Character «1» recognition processes are shown

Recognition algorithms applying the method of preliminary segmentation of input image (algorithms of group II)

First step: Image $\mathbf{P}_0$ is formed as arranged set of all reference symbols:

$$\mathbf{P}_0 = \bigcup_{i=1}^{Q} \mathbf{P}_i = \bigcup_{q=0}^{Q-1} \mathbf{S}_q = \left[P_{0,i,j}\right]^{(K+d_1)(LQ+d_2)}. \quad (9)$$

Second step: The image to be recognized $\mathbf{A} \in \{0{,}255\}^{I\times J}$ is segmented into R sections, regions (sign places of symbols) having the dimensions of $I \times J$ pixels taking into account a priori information-regarding the location of symbols and possible deviations.

Third step: Criterial functions $\mathbf{B}(\xi,\eta) = F({}^{r}\mathbf{A},\mathbf{P}_0)$ for each r$^{\text{th}}$ segment of input image **A** and $\mathbf{P}_0$ (as the set of references) or criterial functions $F({}^{r}\mathbf{A},{}^{q}\mathbf{P}_0)$ are calculated for each r^{th} segment ${}^{r}\mathbf{A}$ and arranged set q^{th} conventional region $\mathbf{P}_0$, namely ${}^{q}\mathbf{P}_0$.

Fourth step: For each segment ${}^{r}\mathbf{A}$ (its serial number) the number q' of conventional region of reference arranged set $\boldsymbol{P}_0$, is determined, this number gives the greatest (the least) value of criterial function for the best special mutual shift. By this number q' the recognition of r^{th} segment of identification object image is carried out (computer code or reference symbol is put on the position, coordinate of r^{th} segment).

Criterial functions

For all possible 3 groups of algorithms we apply the following criterial functions from two images $\mathbf{A} \in [a_{ij}]^{M\times N}$ and $\mathbf{P} \in [p_{kl}]^{K\times L}$, where a_{ij}, $p_{kl} \in \{0,$ $1,\ldots, 255\}$, $M > K$, $N > L$:

a)
$${}_{a}\mathbf{B}(_{\xi,\eta}) = \frac{1}{K\times L}\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\left(\frac{a_{\xi+k,\eta+l}\cdot p_{k,l} + (255 - a_{\xi+k,\eta+l})(255 - p_{k,l})}{255}\right), \quad (10)$$

moreover

$$\xi = 0 \div (M-K);\ \eta = 0 \div (N-L);$$

b)
$$\begin{aligned}{}_{b}\mathbf{B}(_{\xi,\eta}) &= \frac{1}{K\times L}\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\left(\left|a_{\xi+k,\eta+l} - p_{k,l}\right|\right) = \\ &= \frac{1}{K\times L}\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\left(\max(a_{\xi+k,\eta+l}, p_{k,l}) - \min(a_{\xi+k,\eta+l}, p_{k,l})\right) = \quad (11) \\ &= \frac{1}{K\times L}\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\left(255 - \min(a_{\xi+k,\eta+l}, p_{k,l}) - \right. \\ &\qquad \left. - \min(255 - a_{\xi+k,\eta+l}, 255 - p_{k,l})\right),\end{aligned}$$

c) $$_{c}\mathbf{B}(_{\xi,\eta}) = [f_n(_{a}b_{\xi,\eta})], \qquad (12)$$

d) $$_{d}\mathbf{B}(_{\xi,\eta}) = [f_n(_{b}b_{\xi,\eta})], \qquad (13)$$

where f_n – nonlinear function used in work [14] and named “autoequivalence”

$$f_n(a,\alpha) = a^{\alpha} =$$

$$= \begin{cases} \underbrace{a \dot{\sim} \ldots \dot{\sim} a}_{a\ times}, & for\ a > 0{,}5; \\ \underbrace{a \dot{\not+} \ldots \dot{\not+} a}_{a\ times}, & for\ a < 0{,}5; \end{cases} \qquad (14)$$

e) $$_{e}\mathbf{B}(_{\xi,\eta}) = [f_n(ap_{\xi,\eta,k,l}]. \qquad (15)$$

In criterial function $_{e}\mathbf{B}(\xi,\eta)$ nonlinear transformation is performed over the whole set of samples, obtained before addition over the region of indices k, l change.

Formation of reference images of symbols

Unlike the recognition algorithms suggested before, which are based on equivalence models of neuronets [14], input images being recognized and images of reference symbols (while teaching and input) are not converted into the set of two-grading images, but are processed in the initial gray scale format. In order to form reference symbols, mathematical expectations are determined from the sets of representatives for each q^{th} symbol. Averaged on several realizations fragments of separate symbols, were used for shaping of reference base and reference general image. Taking into account slight possible shifts the indistinct (blurring) representation of each q^{th} symbol is formed.

Computer modeling and the results

For the selection of the best optimal criterial function, taking into account the influence of various noises and interference, distorting the image being recognized, selection of the needed algorithm from the group of algorithms, we have developed the program aimed at modeling of suggested recognition algorithms. The suggest program permitted to establish the needed, form, algorithm type, criterial function, display the results (final and intermediate) in graphic interface (see fig. 5), suitable for researcher. Image, being recognized, in particular, of 164×46 pixels of dimensionality were coded by 256 gradation levels, presenting 7 symbol identification number of the object. Other images were also used, for instance, 14-symbol object with spaces etc. In the first case dimensionality of reference image was 30×18 pixels.

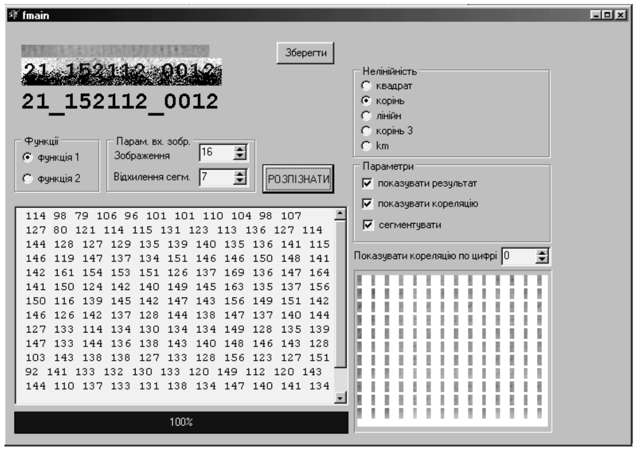


Fig. 5. Graphical interface of research program for recognition algorithms simulation

Deviation from forecasted distance between symbols at segmenting and processing we choose ±10 pixels. On image being recognized we superimposed a noise with different parameters and for each value of parameter and each type of *NLEFs* 1*D*-transformed *NLEFs* were computed, corresponding to all possible references. Fig. 3, 4 showed 2*D* and 1*D NLEFs*. When increasing a parameter, characterizing the degree of nonlinearity in 2*D NLEFs*, type of the latter can be controled. *NLEA* allow recognize under noising up to 50% (normal law). Correlation of peaks to lateral petals can be increased, selecting the type of function. Noised multilevel images and recognition results are shown by fig. 6. Consider the possible hardware implementation. For calculation of criterial functions equivalentors of images, introduced in [11, 12] can be used. They are correlators (convolution operation systems) realizing linear LCF and nonlinear NCF space-dependent functions from source and additional images (see (5)÷(7)). The realization of such devices is described in [14, 18] For calculation of nonequivalent functions the same devices are used, but while writing in LCTV two images are written (one original image and the second – complementary image) in accordance with formula (6). The important problem is the development of parallel operating real-time high per-

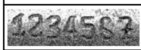
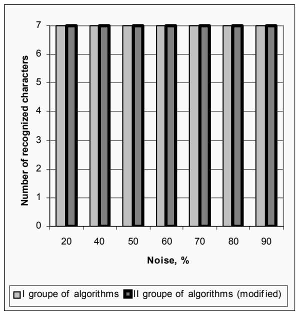
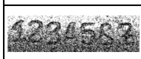
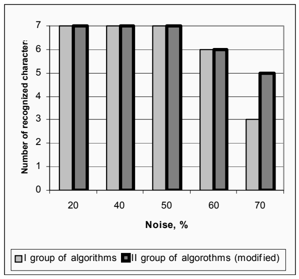
Input images	*Noise,* %	*Number of recognized characters*		*Diagrams*
		I *group of algorithms*	II *group of algorithms*	
For ${}_bB(\xi,\eta)$, *noise – normal*				
	20	7	7	
	40	7	7	
	50	7	7	
	60	7	7	
	70	7	7	
	80	7	7	
	90	7	7	
For ${}_bB(\xi,\eta)$, *noise – by Gause*				
	20	7	7	
	40	7	7	
	50	7	7	
	60	6	6	
	70	3	5	

Fig. 6. Noised multilevel images and recognition results

formance digital convolvers and correlators, functioning in signal region. This problem will be reported in further publications. To test the proposed approach has been developed a real program for the rapid identification numbers on buildings locking sealing devices. The program production tested at the state enterprise "Vinnitsatransprilad" South-Western Railway. The system has a number of advantages: 1) Enters the 20 images on the bodies of locking sealing devices with a matrix that is installed on the scanner; 2) Recognize the images invariant to shift and turn on the bodies of locking and sealing devices, and not sensitive to shift and rotation of the buildings themselves locking sealing devices in the matrix; 3) Signals of images to recognize bad and does not recognize at all; 4) Recognize the 7 digits on the image and exports them to bill submitted machine codes; 5) Refer recognized numbers of locking sealing devices with numbers already in a database; 6) Recognize the image of a seven-digit one set of 20 images of locking sealing device in 100-200 seconds; 7) Resistant to very noisy images of locking sealing devices and lighting glare on the surface.

Graphical interface of the experimental manufacturing program for recognition algorithms simulation are shown on fig. 7. Results of computer modeling and laboratory studies, conducted on real objects have confirmed advantages of such algorithms. Additional entering of correlation factors in recognition models improves the quality and validity of *NLE*-recognition algoritms. As our research shows, *NLEA* possess higher discriminant properties than correlation and other conventional algorithms.

When adding background component in the image being recognized in reasonable measues the character and quality of recognition doesn't change applying *NLEA*. As a result of modeling the hypothesis that the preliminary processing of images, containing considerable level of noise, in particular, seperation of sidebars does not improve but worsens the quality of recognition.

Conclutions. The suggested nonlinear-equivalent recognition algorithms of multilevel images of identification objects possess good recognition quality, especially if the objects to be recognized are in noisy environment, if background noises have been added. *NLE*-algorithms permit to recognize, as it has been proved by lab tests, in such noise conditions when traditional (correla-

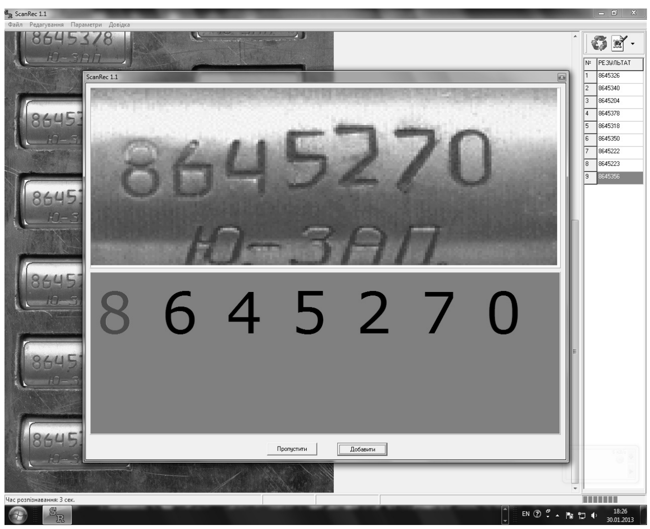


Fig. 7. Graphical interface of testing program for recognition algorithms simulation

tion) algorithms fail. The experiments have shown that preliminary processing of images being recognized, in particular those, whose outlining, when they are saturated with noise and decreased levels number, does not lead to increase of recognition quality. The results of theoretical research are implemented in a software product designed for the rapid identification numbers on the sealing devices. The software product was tested on production enterprise "Vinnitsatranspribor" South-Western Railway. Interface of this software are shown. Results of its tests confirmed the high performance and low part unrecognized characters, less than 0,01%.

1. *Krasilenko V.G.*, *Kolesnitsky O.K.*, *Bogukhvalsky A.K.* Creation Opportunities of Optoelectronic Continuous Logic Neural Elements, Which are Universal Circuitry Macrobasis of Optical Neural Networks // Proc. SPIE. – 1995. – **2647**. – P. 208–217.
2. *Levin V.I.* Continuous Logic, Its Generalization and Application // Automatica and Telemechanica. – 1990. – N 8. – P. 3–22.
3. *Krasilenko V.G.*, *Kolesnitsky O.K.*, *Mikhalnichenko N.N.* Lines of Optoelectronic Neural Elements with Optical Inputs/Outputs Based on BISPIN-devices for Optical Neural Networks // Proc. SPIE. – 1995. – **2647**. – P. 264–272.
4. *Krasilenko V.G.*, *Magas A.T.* Fundamentals of Design of Multifunctional Devices of Matrix Multilevel Logic with Fast Programmed Adjusting // Measuring and Computer Technique in Technological Processes. – 1999. – N 4. – P. 113–121.
5. *Awwal A.S. Abdul*., *Khan M. Iftekharuddin.* Computer Arithmetic for Optical Computing. Special Section // Optical Eng. – 1999. – **38**, N 3. – P. 400–402.
6. *Volgin L.N.* Complementary Algebra and Relative Models of Neural Structures with Coding of Channel Numbers // Electrical Modeling. – 1994. – **16**, N 3. – P. 15–25.
7. *Sokolov E.N.*, *Vaytkyavichus G.G.* Neurointelligence: from Neuron to Neurocomputer. – M.: Nauka, 1989. – 238 p.
8. *Pozin N.V.* Modeling of Neural Structures. – M.: Nauka, 1970. – 264 p.
9. *Antomonov Yu.G.* Principles of Neurodynamics. –Kiev.: Nauk. dumka, 1974. – 200 p.
10. *Krasilenko V.G.*, *Bogukhvalskiy A.K.*, *Magas A.T.* Equivalental Models of Neural Networks and Their Effective Optoelectronic Implementations Based on Matrix Multivalued Elements // Proc. SPIE. – 1996. – **3055**. – P. 127–136.
11. *Krasilenko V.G.*, *Kolesnitsky O.K.*, *Bogukhvalsky A.K.* Applications of Nonlinear Correlation Functions and Equivalence Models in Advanced Neuronets // Proc. SPIE. – 1997. – **3317**. – P. 211–222.
12. *Continuous* Logic Equivalental Models of Hamming Network Architectures with Adaptive-Correlated Weighting / V.G. Krasilenko, F.M. Saletsky, V.I. Yatskovsky et al. // Proc. SPIE. – 1997. – **3402**. – P. 398–408.
13. *Demonstration* of neural-network efficiency models with adaptive equivalentaly weightings and interconnection matrixes adjustment / V.G. Krasilenko, A. I. Nikolsky, V. M. Voloshin et al. // Measuring and Comp. Techn. in Technol. Processes. – 2000. – N 4. – P. 119–122.
14. *Optical* pattern recognition algorithms on neural-logic equivalental models and demonstration of their prospectivaness and possible implementations / V.G. Krasilenko, A.I. Nikolskyy, A.V. Zaitsev et al. // Proc. SPIE. – 2001. – **4387**. – P. 247–260.
15. *Gnoseological* Approach to Search of Most General Functional Model of Neuron / V. Krasilenko, A. Nikolskyy, V. Boyko et al. // Measuring and Comp. Techn. in Technol. Processes. – 2000. – N 7. – P. 23–27.
16. *Krasilenko V.G.*, *Nikolsky A.I.*, *Pavlov S.N.* The associative 2D-memories based on matrix-tensor equivalental models // Radio Electronics, Comp. Sci., Control. – 2002. – N 2 – P. 45–53.
17. *Kuzmin V.B.*, *Travkin S.I.* The theory of fuzzy signals in control tasks and construction principles of fuzzy processors. Survey of foreign literature // Automatic and telemechanica. – 1992. – N 11. – P. 3–36.
18. *Krasilenko V.*, *Motygin V.*, *Pastushenko A.* The architecture of high-speed correlators with non-linear and morphological image processing // Proc. SPIE. – 1994. – **2321**. – P. 538–541.

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