Recognition Algorithms of Images of Multi-character Identification Objects Based on Nonlinear Equivalent Metrics and Analysis of Experimental Data Using Designed Software.

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Abstract

The given paper suggested recognition algorithms of multilevel images of multi-character identification objects. These algorithms are based on application of linear (nonlinear) equivalent (nonequivalent) space-dependent similarity means of normalized matrix data as criterial (discriminant) functions. The results of modeling and experimental results have shown that such nonlinear-equivalent algorithms process higher discriminant properties and operating characteristics, especially in case of considerable (up to 40 %) noise level content of images.

1. Introduction

Today, rapid progress in mathematical logic, especially matrix (multivalued, continuous, fuzzy, neural, accumulation of data regarding continual (analog) and obviously nonlinear functions of neurons, elaboration of the neural net theory, neurobiology and neural-cybernetic, and adequate algebra-logic instruments for mathematical description and modeling [1-5], development of optical technologies have created conditions for construction of technical systems, adequate almost to any problem of artificial intelligence. The works [1,6], and especially [2-5] 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 [2-5]. In this connection such models and the theory were called “equivalental”. They showed, and described negative and inhibiting weights along with exciting ones at unipolar and bipolar coding. The basic operations of NBL, used in equivalental models NNAM [1-4], are binary operations of equivalence and nonequivalence, which have a few variants [3] on a carrier set $^\wedge C_u = [0,1]$:

$$eq^1 = a \approx b = \max\{\min(a,b), \min(\bar{a},\bar{b})\} \quad ;$$

$$eq^2 = a \dot{\sim} b = a \cdot b + \bar{a} \cdot \bar{b}$$

$$eq^3 = a \overset{+}{\sim} b = 1 - |a - b| \; .$$

The 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 [2,3,5], which for these two matrices **A**= $\{a_{ij}\}_{I \times J}$, **B**= $\{b_{ij}\}_{I \times J} \in [0,1]^{I \times J}$ are determined in the following way:

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

$$\mathbf{A} \underset{n}{\not\sim} \mathbf{B} = \frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(a_{ij} \not\sim \mathrm{b}_{ij}\right) \qquad (2).$$

Normalized equivalence $\underset{n}{\sim}$ and nonequivalence $\underset{n}{\not\sim}$ are more general new complementary metrics in metrical space R. In particular, $\overset{+}{\underset{n}{\not\sim}}$ is a normalized matrix distance $d_1(A,B)/I \times J$, and for $A,B \in \{0,1\}^N$ it turns into normalized Hamming distance $d_H(A,B)/N$. As it can be seen from expressions (1) and (2), component and component operation of NBL (~) or ($\not\sim$) is generalized for matrix case, and NBL logic becomes matrix NBL (MNBL). The variants of operations (~), ($\not\sim$) depend on different types of t-norms and s-norms operations used in them and integrated fuzzy-operations of union and intersection [7]. Depending from the type, variants of equivalent algebra (EA) [2, 3], as a new algebra-logical instrument for creation of equivalental theory on their basis proposed. In works [2,3] new notions of equivalental one-dimension (1-D) and two-dimension (2-D) functions were introduced:

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

$$\widetilde{E}(\xi,\eta) = \widetilde{f}(A,B) = A\tilde{*}B = \sum_{n=1}^{N}\sum_{m=1}^{M}(a_{n.m} \sim b_{\xi+n,\eta+n}) \quad (3),$$

symbol ($\tilde{*}$) meaning convolution (correlation) with operation of "equivalence". Normalized space-dependent equivalence and nonequivalence functions were introduced in the work [5]

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

$$\overset{/\sim}{\mathbf{e}} = \left(\mathbf{A}\overset{/\sim}{*}\mathbf{B}\right)/ I \times J = [\mathbf{1}] - \widetilde{\mathbf{e}} = \left[ne_{\xi,\eta}\right] \in [0,1]^{(N-I+1)(M-J+1)} \qquad (4).$$

These functions $\widetilde{\mathbf{e}}$ and $\overset{/\sim}{\mathbf{e}}$ reflect the measure of equivalence and nonequivalence of two images depending on their mutual spatial shifting.

Making use of formulae transformation for calculation of linear and nonlinear correlative and equivalent functions and criterial functions of mean absolute error (MAE) and mean square error (MSE), in work [8] authors showed 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.

2. The algorithms of recognition without segmenting of input image (group 1)

The idea of nonlinear equivalence algorithms (NLEAs) is concluded in segmenting (on the base of a priori information) into fragments, corresponding to separate symbols, source image of multi-character 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 (NLEFs) 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 multi-character 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 auto-equivalence 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 multi-symbol (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 of symbols $\mathbf{S}_q$.

Total dimensions I, J of the image **A** must be greater than values K and R·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 inter-fragmental space till dimensions **A**. Fig. 1a shown initial multilevel (256 levels $a_{ij} \in (0 \div 255)$) image $\mathbf{A} = \{0,255\}^{IxJ}$, 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. 1b). 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. 1c.

Knowledge algorithms regarding the number of R symbols in identification object (number of fragments in the image **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. Comparing all $\mathbf{B}^q_{\max(\min)}$ within q-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.

Recognition algorithms applying the method of preliminary segmentation of input image (group 2).

First step: Image $\mathbf{P_0}$ is formed as arranged set of all reference symbols:

$$\mathbf{P}_0 = \bigcup_{i=1}^{Q}\mathbf{P}_i = \bigcup_{q=0}^{Q-1}\mathbf{S}_q = \left[P_{0,i,j}\right]^{(K+d_1)(LQ+d_2)} . \qquad (5)$$

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×J pixels taking into account 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^{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 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).

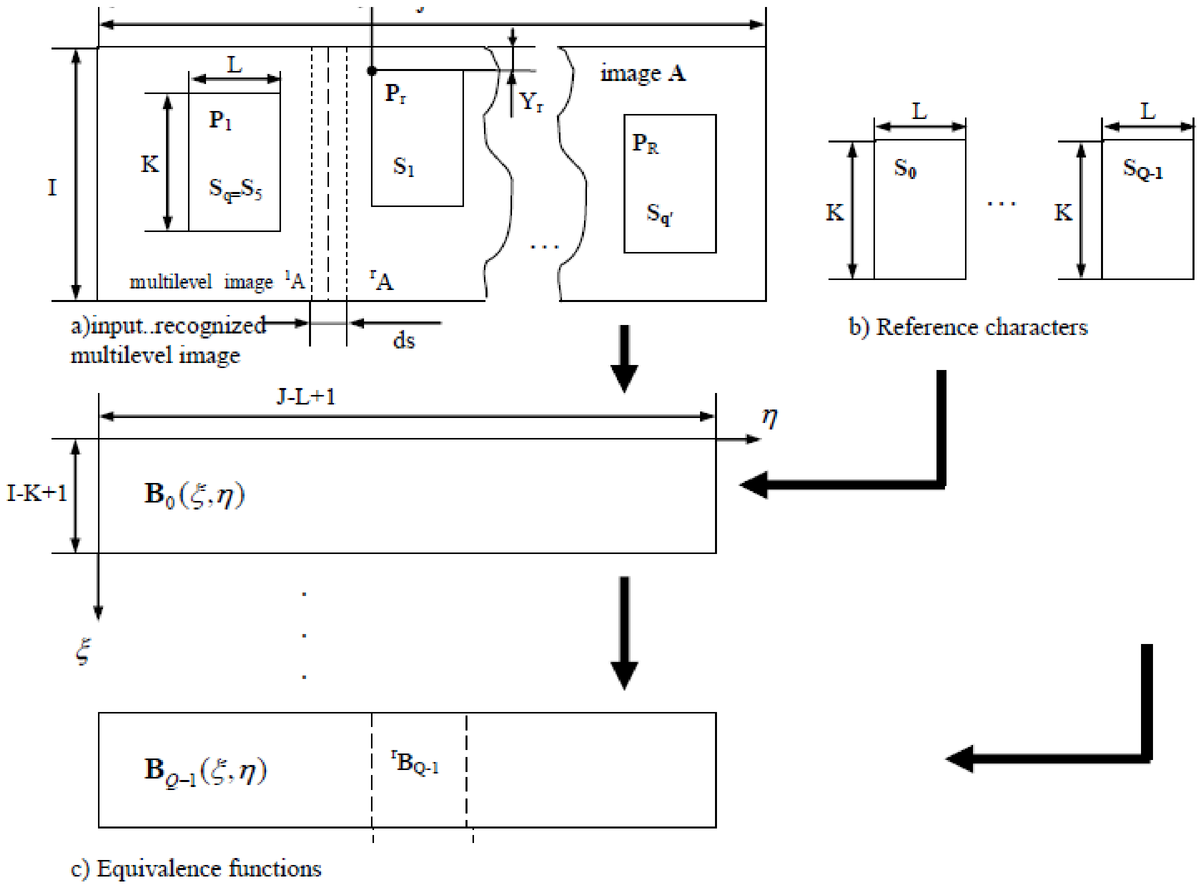


Figure 1: Formation process of criterial functions.

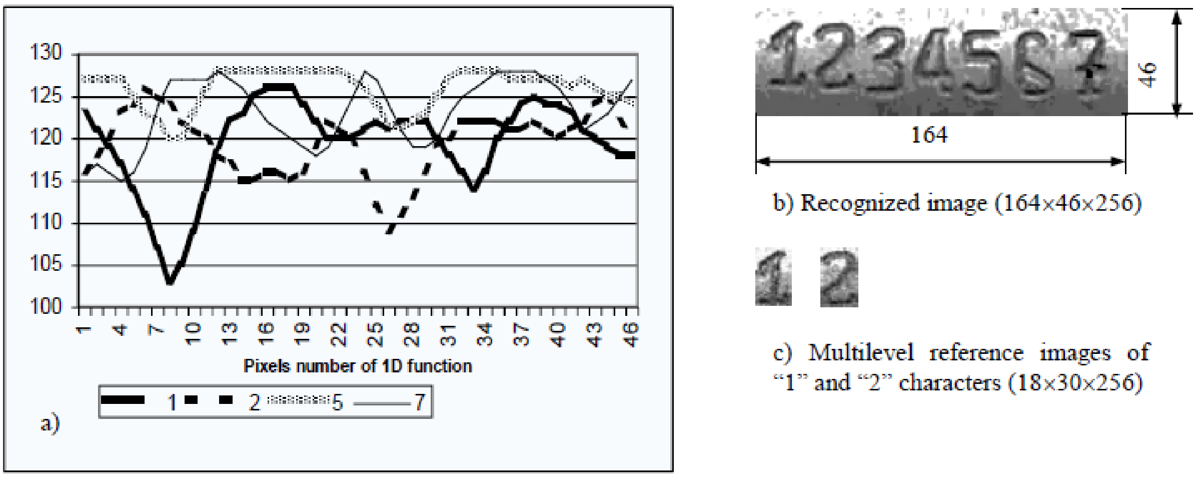


Figure 2: Part of 1D NLEF function ${}^{r\in 1,2}_{\ \ b}B^{q\in 1,2,5,7}_{\max}(\eta)$ ($X_{r=1}=8$, $X_{r=2}=26$)

3. The results of modeling and implementation using designed software

The 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. 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. 3), suitable for researcher.

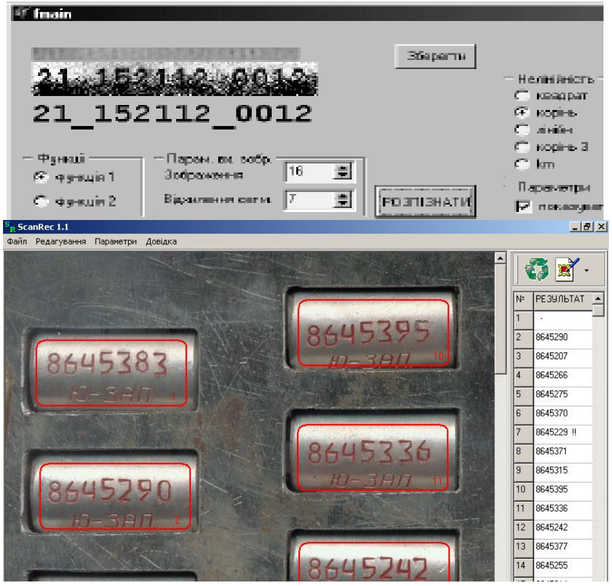


Figure 3: Graphical interface of the program for recognition algorithms simulation

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. Deviation from forecasted distance between symbols at segmenting and processing we choose ±10 pixels. Correlation of peaks to lateral petals can be increased, selecting the type of function. The noised multilevel images and recognition results showed on Fig. 4. Results of computer modeling and laboratory studies, conducted on real objects have confirmed advantages of such algorithms. As our research shows, NLEA possess higher discriminant properties than correlation and other conventional algorithms.

4. Conclusions

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 (correlation) algorithms fail. The developed program permits not only modeling of suggested NLE-algorithms, but it is used for recognition of given real objects.

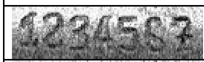
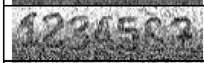
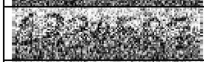
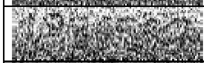
Input images	No-ise, %	Number of recognized characters	
		I group of algorithms	II group of algorithms
For $_b B(\xi,\eta)$, noise – normal			
	20	7	7
	40	7	7
	50	7	7
	60	7	7
	70	7	7
	80	7	7
	90	7	7

Figure 4: Noised multilevel images and recognition results

5. References

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