Training Kora-Type Algorithms[1]

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Abstract—The dependence of the quality of recognizing noisy objects by a Kora-type algorithm on the composition of the training sample is examined. The algorithm is considered in an example of recognition of noisy black-and-white images and compared with the morphological recognition algorithm.

INTRODUCTION

In this paper, we consider the influence of the "contents" of the training sample on the quality of recognizing noisy objects by a learning classification algorithm of the Kora type [1–4].

The algorithm is considered in an example of recognizing black-and-white images and compared with the morphological recognition algorithm, which is close to the ultimately exact recognition method as applied to this problem [5–8].

1. THE KORA-TYPE LEARNING RECOGNITION ALGORITHM

To describe a Kora-type algorithm, we have to define the notion of initial data and determine rules for evaluating the "similarity" between objects to be compared and the "closeness" of an object under examination to a certain class.

Suppose that a set M of objects Q and its partitioning $M = \bigcup_{l=1}^{m} K_l$ into finitely many subsets (classes) are given; the partitioning of M is defined incompletely. Each object $Q \in M$ is represented by a set of values of the features from a system $\{x_j\}_{j=1}^{n}$; the feature values belong to the domain X of admissible values (Fig. 1.1). Each class $K_l = \bigcup_{r=1}^{r_l} Q_r^l$ includes r_l objects for $l = 1, \ldots, m$.

We assume that the set of features is fixed. A set of values of the features $\{x_j\}_{j=1}^{n}$ determines a description $A(Q) = \{a_1, \ldots, a_n\}$ of an object Q, where a_j is the value of the feature x_j for each $j = 1, \ldots, n$. The *recognition problem* consists in relating an object Q to one of the classes K_l, $l = 1, \ldots, m$, on the basis of training data $A_0(K_1, \ldots, K_m)$ about the classes and of the description $A(Q)$ of the object.

To recognize an object means to make a decision to what class this object is to be related.

Suppose that W_s^n, $s \le n$, is the set of all s-tuples of indices of the form $(j_1, \ldots, j_s)$, where $j_t \in \{1, 2, \ldots, n\}$, $t = 1, 2, \ldots, s$, and $j_1 < \ldots < j_s$. Let us specify a rule for estimating the similarity between objects from M according to the subset of features determined by an s-tuple $\omega = (j_1, \ldots, j_s) \in W_s^n$.

We say that objects Q_i and Q_r are similar if they satisfy the inequality

$$|a_{ij}^l - a_{rj}^l| \le \varepsilon_j, \quad j = 1, \ldots, n;$$
$$i, r = 1, \ldots, r_l, \quad i \ne r, \quad l = 1, \ldots, m.$$

Let us take integers $q_1 \ge 1$ and $0 \le q_2 < q_1$ and say that a subset $w \subset W_s^n$ is a representative set from a class K_l if no less than q_1 objects in the class K_l and no more than q_2 objects in all the other classes together are similar. The number of the representative sets depends on q_1 and q_2.

To each jth feature, where $j = 1, 2, \ldots, n$, we assign a weight p_j, and to each object Q_k^l, where $k = 1, \ldots, r_l$ and $l = 1, \ldots, m$, we assign a weight γ_k^l. The weights characterize the importance of features and objects. A representative set generated by an object of some class K_l, $l = 1, \ldots, m$, allows us to distinguish this object from all objects not belonging to the class K_l.

For $\omega = (j_1, \ldots, j_s) \in W_s^n$, as a measure of closeness between objects Q and Q_r^l, we take the value

$$B_w(Q, Q_r^l) = \begin{cases} p_{j_1} + \ldots + p_{j_s} & \text{if } |a_{rj_t} - a_{j_t}| \le \varepsilon_{j_t} \\ & \text{for all } t \in \{1, \ldots, s\} \\ 0 & \text{otherwise.} \end{cases}$$

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Objects	$x_1, x_2, \ldots,$	x_j	x_n	Classes
Q_1^1	a_{11}^1	a_{1j}^1	a_{1n}^1	
.				
.				K_1
	.	.	.	
$Q_{r_1}^1$	$a_{r_1 1}^1$	$a_{r_1 j}^1$	$a_{r_1 n}^1$	
……	……			……
Q_1^m	a_{11}^m	a_{1j}^m	a_{1n}^m	
.				
.				K_m
	.	.	.	
$Q_{r_m}^m$	$a_{r_m 1}^m$	$a_{r_m j}^m$	$a_{r_m n}^m$	

Fig. 1.1.

Let $\Omega_r^{(l)}$, where $r = 1, \ldots, r_l$, be the family of all representative sets generated by the object Q_r^l of class K_l. Then the closeness of an unknown object Q to a description from the class K_l is estimated as

$$D_l(Q) = \frac{1}{\theta_l} \sum_{r=1}^{r_l} \sum_{w \in \Omega_r^{(l)}} \gamma_r^l B_w(Q, Q_r),$$

where

$$\theta_l = \sum_{r=1}^{r_l} \left|\Omega_r^{(l)}\right|.$$

An unknown object Q belongs to the class K_l, where $l = 1, \ldots, m$, if

$$D_l(Q) = \max_{1 \le t \le m} D_t(Q)$$
$$\text{and} \quad D_t(Q) \ne D_l(Q) \quad \text{for} \quad t \ne l.$$

No decision about the class containing the object Q is made if

$$D_{l1} = D_{l2} = \max_{1 \le t \le m} D_t(Q) \quad \text{for} \quad l1 \ne l2.$$

Varying the parameters q_1 and q_2, we can vary the family of representative sets [3, 4]. It is natural to consider representative those fragments of descriptions of training objects that are frequently encountered in one class and rarely in others. Since the closeness of the object to be tested to the description of the class K_l, where $l = 1, \ldots, m$, is estimated exclusively by the representative sets for this class, the most important part of the algorithm is the construction of these representative sets [1, 2]. After they are constructed, it seems possible to solve the problem stated above.

2. THE METHOD OF MORPHOLOGICAL RECOGNITION

Suppose that an image f is given. We treat it as a real-valued function defined on a subset X (field of view) of the plane R_2. The value $f(x, y)$ of the function determines the brightness of the image at the point (x, y) of the view field X. All images are elements of the Hilbert function space $L_2(X) = \left\{ f, \int_X f^2(x, y)dxdy < \infty \right\}$ with scalar product

$$(f, g) = \int_X f(x, y)g(x, y)dxdy,$$

and distance

$$\|f - g\| = \left(\int_X (f(x, y) - g(x, y))^2 dxdy \right)^{1/2}.$$

Let us introduce the operation of comparing images according to shape [6, 7]. We say that the shape of an image g is no more complex than the shape of f and write $f \prec g$ if there exists a function $F(\bullet)$ of one variable transforming the brightness of the image f in such a way that $g(x, y) = F(f(x, y))$ for $(x, y) \in X$. Let F_f be a class of functions $F(\bullet)$ such that $f \in L_2(X) \longrightarrow F(f) \in L_2(X)$; suppose that this class contains the composition $F_1(F_2(\bullet))$ whenever it contains functions $F_1(\bullet)$ and $F_2(\bullet)$. We define *the shape of an image* f to be the set

$$V(f) = \{g = F(f), F \in F_f\} \equiv \{g \in L_2(X), g \prec f\}.$$

Hereafter, we assume that the class F_f is such that $V(f)$ is convex and closed in $L_2(X)$ [5]. If $f \prec g$ and $g \prec f$, we say that the images f and g are isomorphic and write $f \sim g$. The operation $\sim$ of comparing images according to their shape is transitive, symmetric, and reflexive, which allows us to regard all images that are isomorphic to each other as an equivalence class [6].

Suppose that $A = \{A_1, \ldots, A_N\}$ is a measurable partitioning of the view field X into domains $A_1, \ldots, A_N$ (where $A_i \bigcap A_j = \varnothing$ for $i \ne j$, $i, j = 1, \ldots, N$, and $X = \bigcup_{i=1}^{N} A_i$) of positive areas $\mu(A_i) = \int_{A_i} dxdy > 0$, where $i = 1, \ldots, N$ [8]. Consider the image $f = \sum_{i=1}^{N} f_i \chi_{A_i}$ of constant brightness f_i over each domain A_i, $i = 1, \ldots, N$; we assume that all f_i, where $i = 1, \dots, N$, are pairwise different. Here, χ_{A_i} is the indicator function of the ith domain, i.e.,

$$\chi_{A_i}(x, y) = \begin{cases} 1, & (x, y) \in A_i \\ 0, & (x, y) \notin A_i. \end{cases}$$

On this domain, the brightness of the image f is constant and equals f_i, $i = 1, \dots, N$. The shape $V(f)$ of the image f is specified in the form of the set of images

$$V(f) = \left\{ \phi(x, y) = \sum_{i=1}^{N} c_i \chi_{A_i}(x, y), \right. \qquad (1)$$
$$\left. (x, y) \in X, -\infty < c_i < +\infty, \; i = 1, \dots, N \right\}.$$

Consider the problem of best approximation of an image g by images of the form $\sum_{i=1}^{N} c_i \chi_{A_i}(x, y)$, where $(x, y) \in X$; the partitioning of X into measurable domains A_i of positive areas ($i = 1, \dots, N$) is assumed given. It is required to determine the brightness c_i of best approximation over each A_i with $i = 1, \dots, N$.

According to [6], if F_f is the class of all functions on R_1, then the shape $V(f)$ given by Eq. (1) can be interpreted as an N-dimensional plane in the space $L_2(X)$; the indicator functions χ_{A_i}, $i = 1, \dots, N$, are vector-images determining the arrangement of this plane in $L_2(X)$. Every image whose shape is no more complex than $V(f)$ is represented by a vector entirely lying in this plane. For an arbitrary image $g \in L_2(X)$, the notion of its projection on $V(f)$ can be introduced. The projection is defined as a point in $V(f)$ at which the minimum distance between $g \in L_2(X)$ and $V(f)$ is attained. The minimum always exists and is attained at a unique vector from $V(f)$. We denote the projection of an image g on the set $V(f)$ by $P_f(g)$. Here, P_f denotes the rule assigning the image $\phi = P_f g$, where $\phi \in V(f)$, to each image $g \in L_2(X)$. The rule P_f is called *the orthogonal projector* onto the set $V(f)$. The projection $P_f g$ of a vector g on the plane $V(f)$ is defined by

$$P_f g(x, y) = \sum_{i=1}^{N} c_i^* \chi_{A_i}(x, y), \qquad (2)$$

where

$$c_i^* = (\chi_{A_i}, g)/\|\chi_{A_i}\|^2, \quad i = 1, \dots, N.$$

Here, the brightness values c_i^* of the domains A_i ($i = 1, \dots, N$) of the image $P_f g$ are defined so that the image $\sum_{i=1}^{N} c_i^* \chi_{A_i}(x, y)$ would be as close to the image g in $L_2(X)$ as possible. The image g belongs to the image shape $V(f)$ (i.e., the projection of g on $V(f)$ coincides with g) if the equality

$$P_f g = g,$$

which is equivalent to the relation $f \prec g$, holds.

Since the indicator function $\chi_{A_i}(x, y)$, where $(x, y) \in X$, of the domain A_i of constant brightness vanishes outside A_i and equals 1 at the points of A_i, the scalar product (χ_{A_i}, g) is the integral of the image g over the domain A_i, i.e.,

$$(\chi_{A_i}, g) = \int_X \chi_{A_i}(x, y) g(x, y) dx dy = \int_{A_i} f(x, y) dx dy,$$

and the squared norm $\|\chi_{A_i}\|^2 = \int_{A_i} dx dy$ is the area of A_i for $i = 1, \dots, N$. We can say that projection (2) of an image g on the set $V(f)$ is obtained by averaging g over each domain of constant brightness of the image f. The projector P_f plays a key role in morphological image analysis and is also called *the image shape* [6].

A number of morphological problems involve additional constraints on the brightness of the image f. For example, the brightness values on the domains $A_1, \dots, A_N$ may be ordered as $c_1 \le \dots \le c_N$. Then, the shape $V(f)$ of an image f is defined by the relation

$$V(f) = \left\{ f(x, y) = \sum_{i=1}^{N} c_i \chi_i(x, y), \right. \qquad (3)$$
$$\left. (x, y) \in X, -\infty < c_1 \le c_2 \le \dots \le c_N < \infty \right\}.$$

The set $V(f)$ is a convex closed cone in the space $L_2(X)$, and P_f is the projector onto $V(f)$ [6].

Consider the shapes of images of digits (say, 0 and 1) when it is known that the brightness of the symbol cannot be less than that of the background. The shape of the image of 1 is the image set

$$V(f^1) = \left\{ \sum_{i=1}^{2} c_i \chi_i^1(x, y), (x, y) \in X, -\infty < c_1 \le c_2 < \infty \right\}$$
$$= \{ F(\tilde{c}_1 \chi_1^1(x, y) + \tilde{c}_2 \chi_2^1(x, y)), (x, y) \in X, F \in F_f \},$$

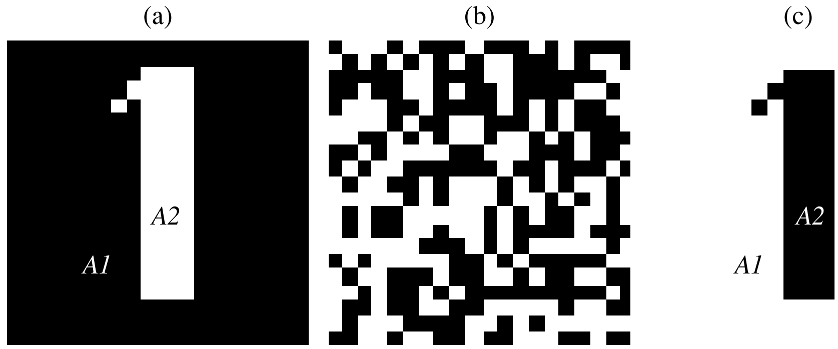


Fig. 3.1. (a) A noise-free image of 1; (b) image of 1 with 50% noise; and (c) image of 1 with 100% noise.

where $\tilde{c}_1 < \tilde{c}_2$; χ_1^1 and χ_2^1 are the indicator functions of the background and digit image domains, respectively; and F_f is the class of monotonically nondecreasing functions. The set $V(f^1)$ is a two-dimensional cone in the space $L_2(X)$. According to [5], there exists a unique projector $P_f^1 g$ onto the set $V(f^1)$, namely,

$$P_f^1 g(x, y) = c_1^* \chi_1^1(x, y) + c_2^* \chi_2^1(x, y), \quad (x, y) \in X,$$

where the brightness values c_1^* and c_2^* are defined as

$$c_1^* = \begin{cases} (\chi_1^1, g)/\|\chi_1^1\|^2 \\ \quad \text{if } (\chi_1^1, g)/\|\chi_1^1\|^2 \le (\chi_2^1, g)/\|\chi_2^1\|^2, \\ (\chi_1^1 + \chi_2^1, g)/\|\chi_1^1 + \chi_2^1\|^2 \\ \quad \text{if } (\chi_1^1, g)/\|\chi_1^1\|^2 > (\chi_2^1, g)/\|\chi_2^1\|^2 \end{cases}$$

and

$$c_2^* = \begin{cases} (\chi_2^1, g)/\|\chi_2^1\|^2 \\ \quad \text{if } (\chi_1^1, g)/\|\chi_1^1\|^2 \le (\chi_2^1, g)/\|\chi_2^1\|^2, \\ (\chi_1^1 + \chi_2^1, g)/\|\chi_1^1 + \chi_2^1\|^2 \\ \quad \text{if } (\chi_1^1, g)/\|\chi_1^1\|^2 > (\chi_2^1, g)/\|\chi_2^1\|^2. \end{cases}$$

The shape of the image of any other digit is defined similarly.

Suppose that, in a recognition problem, n reference images $f_1, \ldots, f_n$ are given and it is required to recognize an image g. Then, if $P_{f_1}, \ldots, P_{f_n}$ are the projectors determining the shapes of the images $f_1, \ldots, f_n$ and $P_{f_1} g, \ldots, P_{f_n} g$ are the projections of the image g on the shapes of $f_1, \ldots, f_n$, then, according to the simplest morphological recognition rule, the image g is related to the ith class if

$$i = \underset{1 \le j \le n}{\arg(\min)} \|P_{f_j} g - g\|^2.$$

3. ANALYSIS OF THE RESULTS

Initial data for testing a Kora-type algorithm were black-and-white 20 × 20-pixel images of digits (see, e.g., Fig. 3.1a). The images with 0% noise are considered pure and the images with 100% noise, inverted. A random number generator generates integers in the interval [0, 100]. An integer in the interval [0, 100] is called a *level*. Every pixel of the image is scanned, and the number generated by the random number generator at the current step is analyzed. If this number falls within the interval [0, the *level*], then the pixel is inverted. Thus, if the noise level is 50%, then 50% of image pixels are inverted (Fig. 3.1b), and if the noise level is 100%, then the image is entirely inverted (Fig. 3.1c).

Here, on the background domain *A1* and on the digit image domain *A2*, the indicator functions χ_1^1 and χ_2^1, respectively, take value 1.

In training the Kora-type algorithm, the following question was examined: Should training involve only pure (noise-free) images of digits, or both noisy and noise-free images should be used? For this reason, at the training stage, the following types of images were used:

- only noise-free images of digits;
- both pure and noisy images;
- only noisy images.

For training, ten classes of images were formed, one class for each digit from 0 through 9. Every class comprised ten different (in the level of noise) images, depending on the version of training. Recognition was performed for images both free of noise and distorted by noise of a level up to 50%.

The algorithm trained with the use of only pure (noise-free) images gave a low percentage of correctly recognized images (Fig. 3.2, curve *a*). In Fig. 3.2, curve *a* shows that the percentage of correct decisions was no lower than 80 only for test images with a level of noise up to 20%.

Including noisy images in the training class improved the results of recognition; thus, on adding images with a 25% level of noise, the percentage of correct decisions was no lower than 80 for test images with up to a 26% level of noise (Fig. 3.2, curve *b*). In the training classes, the level of noise increased uniformly from image to image (0, 3, 6, …, 21, 23, 25%) for ten images in each training class with the noise level of 25% maximum.

Increasing the noise level in the training classes to 35% gave the best recognition results in the case of training with the use of both pure and noisy images of digits (Fig. 3.2, curve *c*). Then, the percentage of correct decisions was no lower than 80 for a noise level in test images of up to 42%. With further increasing the noise level in the training sample, the recognition results sharply deteriorate.

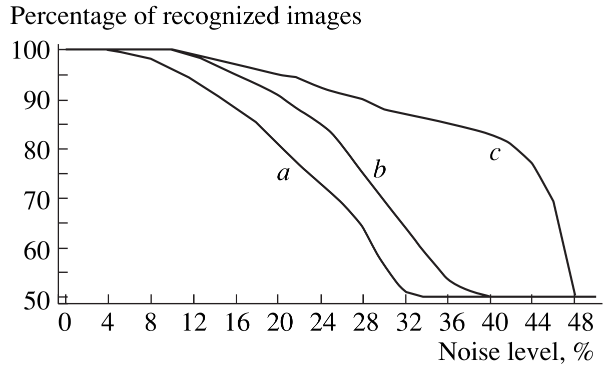


Fig. 3.2. The results of recognition by a Kora-type algorithm trained on (*a*) pure images of digits; (*b*) pure images and images with a noise level up to 25%; and (*c*) pure images and images with a noise level up to 32%.

The question arises, what happens if all pure images of digits are removed from the training classes, and only noisy images are used in training. For an algorithm trained on images of digits with 10% of noise and used for recognizing images with a noise level under 50%, the dependence shown in Fig. 3.3, curve *b*, was observed. In this case, the percentage of correct decisions was no lower than 80 for test images with 25% of noise, which is better than the result given by an algorithm trained on solely pure images of digits.

In Fig. 3.3, curve *b* shows that the percentage of correctly recognized images of digits with the same noise level as that in the training class is no lower than 90. Increasing the noise level in the training class up to 32% gave the results shown in Fig. 3.3, curve *c*, which are the best in the case where training only uses images with a certain noise level. Here, the percentage of correct decisions is no lower than 80 for test images of digits with 32% of noise. With enhancing the noise level over 32%, the number of recognition errors increases. For comparison, curve *a* in Fig. 3.3 represents the result of training with the use of solely pure images of digits.

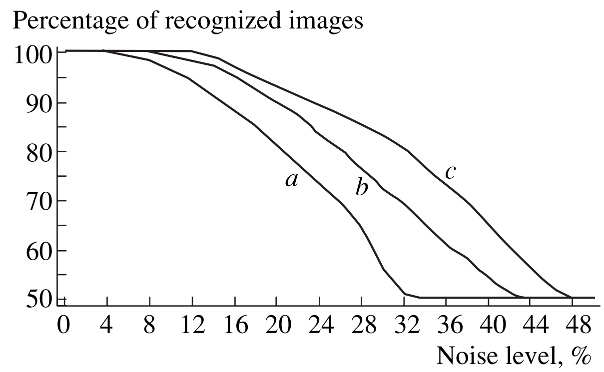


Fig. 3.3. The results of recognition by a Kora-type algorithm trained solely on (*a*) images of digits with 10% of noise; (*b*) images with 25% of noise; and (*c*) images with 32% of noise.

Let us summarize the results of all performed tests. If a Kora-type algorithm is used for recognizing noise-free images, then there is no need to train the algorithm on noisy images. It is sufficient to train it only on pure images. Otherwise, if a Kora-type algorithm is used to recognize noisy images, training should involve both pure and noisy images. An algorithm trained on images under a variable noise level (from 0 through 35%) gives significantly better recognition results than an algorithm trained only on images under a certain noise level (e.g., 32% as in Fig. 3.4).

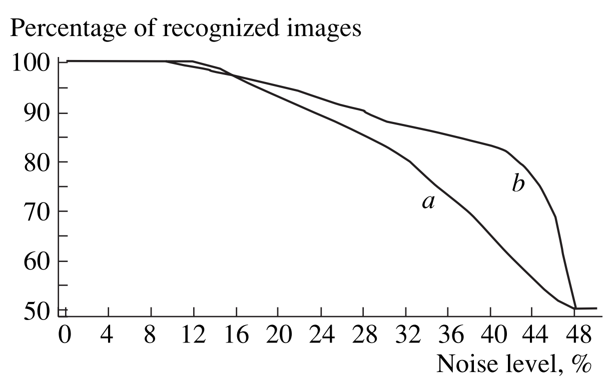


Fig. 3.4. The results of recognition by a Kora-type algorithm trained (*a*) solely on images of digits with 32% of noise and (*b*) on pure images and images with a noise level of up to 32%.

In Fig. 3.4, curve *a* represents the results of recognition by an algorithm trained solely on images with 32% of noise, and curve *b*, by an algorithm trained on images with uniformly distributed noise from 0 through 35% (the best recognition results were achieved when training involved both pure and noisy images of digits). The recognition results for these two series are close up to the 32% noise level in the tested images. For the noise level of 32%, the best recognition results were achieved when training involved images with a certain level of noise (Fig. 3.4, curve *a*). Some of the tested

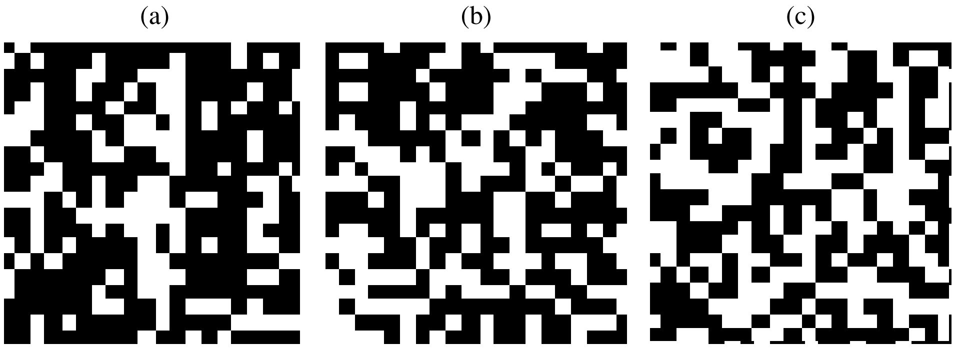


Fig. 3.5. (a) Image of 1 with 32% noise; (b) image of 1 with 42% noise; (c) image of 1 with 49% noise.

images (e.g., of digit 1) with the noise level of 32 and 42% are shown in Figs. 3.5a and 3.5b, respectively.

To recognize images by the morphological method, the same images of digits were used. The morphological method can recognize images under a noise level in the range between 0 and 49%. The percentage of correct decisions made by this method for test images with 49% of noise is no lower than 80 (Fig. 3.6, curve *c*).

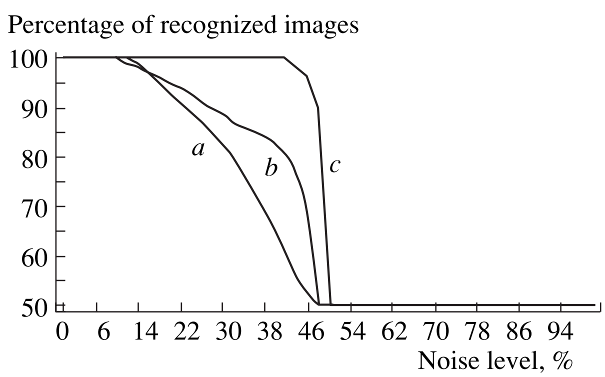


Fig. 3.6. Comparative results of recognition by a Kora-type algorithm trained solely on images of digits with 32% of noise (*a*) and on pure images and images with a noise level of up to 32% (*b*) and by the morphological method trained on pure images (*c*).

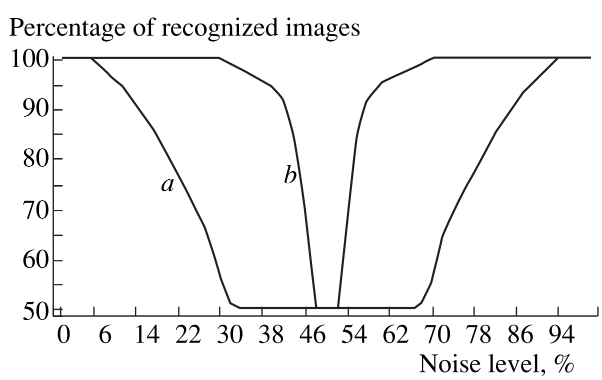


Fig. 3.7. Comparative results of recognition of "negative" images by a Kora-type algorithm trained on pure images (*a*) and by the morphological method trained on pure images (*b*).

Here, curves (*a*) and (*b*) correspond to the best results of image recognition by the Kora-type algorithm. Figure 3.5c represents one of the tested images where the morphological method still works. It is the image of digit 1 with 49% of noise.

The main difference of the morphological method from the Kora-type algorithms is that the former method does not require training on noisy images for recognizing both noisy and noise-free images; training on only pure images is sufficient. This is because the morphological method is based on shapes of images [4].

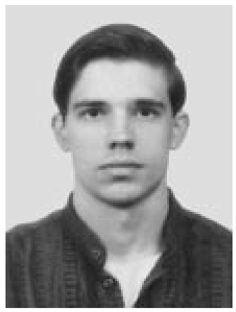
This also answers the question, what happens if the image to be recognized is the "negative" of a training image. If no additional constraints on brightness are imposed, the morphological method can recognize images with a noise level from 55 through 100% (Fig. 3.7, curve *b*). The recognition results given by a Kora-type algorithm trained on both training images and their "negatives" are shown in Fig. 3.7, curve *a*. Under additional constraints on brightness, such as the requirement that the brightness of the background should not exceed the brightness of the digit, the morphological method cannot recognize the "negative" of a training object image (Fig. 3.6, curve *c*).

REFERENCES

1. Djukova, E.V., *Ob odnoi parametricheskoi modeli algoritmov raspoznavaniya tipa Kora* (On One Parametric Model of Kora-Type Recognition Algorithms), *Soobshcheniya po prikladnoi matematike* (Commun. in Applied Mathematics), Moscow: Vychislitel'nyi Tsentr, Akad. Nauk SSSR, 1988.
2. Djukova, E.V., On the Complexity of Implementation of Some Recognition Procedures, *Zh. Vych. Mat. Mat. Fiz.*, 1987, vol. 21, no. 1, pp. 144–227.
3. Djukova, E.V., On One Algorithm for Constructing Irredundant Tests for Binary Tables, in *Sbornik rabot po diskretnoi matematike* (Collection of Works on Discrete Mathematics), Moscow: Vychislitel'nyi Tsentr, Akad. Nauk SSSR, 1976, issue 1, pp. 167–185.
4. Djukova, E.V., Asymptotically Optimal Test Algorithms in Recognition Problems, *Problemy kibernetiki* (Prob-

lems of Cybernetics), Moscow: Nauka, 1982, issue 39, pp. 165–199.

5. Pyt'ev, Yu.P., Morphological Image Analysis: Cybernetics, and Regulation Theory, *Dokl. Akad. Nauk SSSR*, 1983, vol. 269, no. 5, pp. 1061–1065.
6. Pyt'ev, Yu.P., Morphological Image Analysis, *Pattern Recogn. Image Anal.*, 1993, vol. 3, no. 1, pp. 19–28.
7. Pyt'ev, Yu.P. and Chulichkov, A.I., *EVM analiziruet formu izobrazheniya* (A Computer Analyzes the Shape of an Image), Ser.: Matematika, kibernetika (Mathematics, Cybernetics), Moscow: Znanie, 1988.
8. Stepanov, A.A., Zheltov, S.Yu., and Visilter, Yu.V., Shape Analysis Using Pytiyev Morphological Paradigm and Its Using in Machine Vision, *Proc. of SPIE Conf.*, 1994, vol. 2350 (Videometrics III), pp. 163–167.



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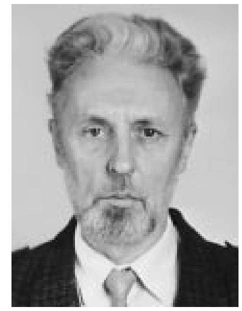

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