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RESEARCH THE POSSIBILITIES OF DIFFERENT FILTERS AND THEIR APPLICATION TO IMAGE RECOGNITION PROBLEMS

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Abstract. This article is devoted to the analysis from the viewpoint of accuracy allocation of contour points, and maintaining information about the distribution of non-derivative elements. In this article is researched the edge enhancement algorithms such as Prewitt, Sobel, Laplacian, Kirsch and evaluated their work, using some well-known performance measures. Also compared the efficacy of the researched algorithms, which was determined on the selected images with superimposed noise.

Key words: image analysis, contour points, filter, convolution mask

INTRODUCTION

The emergence of a huge number of tools shooting photos and video in the last decade strengthens the role of advanced vision systems and image recognition for processing images of various objects and paintings of the real world. Available collections of photos and video have significantly different technical parameters tools of shooting, storage formats and quality characteristics of images themselves. A variety of applied tasks analysis of static and dynamic images places high demands on the accuracy and speed of processing operations and recognition of visual information. To meet these requirements are need an informed choice of existing image processing methods based on their comprehensive comparison, as well as their modification and development of new methods.

THE ANALYSIS OF RECENT RESEARCHES AND PUBLICATIONS

One of the central problems in pattern recognition is the selection objects on image with a complex background and further interpretation properties and characteristics of these objects [1-5].

Recognition objects on images are one of the most important tasks. Its successful solution depends from many characteristics various objects and methods for their processing [6-10]. Most often we use the characteristic of contour information, which limiting recognizable objects. However, due to the large variability of the contour information, recognition methods don’t provide the necessary recognition results. So today on the forefront are coming the structural - linguistic methods, which besides the singular points (contour information) are used as characteristics of the distribution of non-derivative elements (filter response). In the simplest case, as non-derivative element we can use the brightness value and its distribution within the recognizable object can be it’s the characteristic.

Based on the foregoing, it becomes obvious that when we solving problem of recognition is necessary to use such filters which after the allocation contour information will not lost information about the distribution of non-derivative elements.

In this paper, we analysis filters in terms how exactly release special points, and how store information about the distribution of non-derivative elements.

A sharp change in brightness occurs for several reasons. First, such abrupt changes often occur at the boundaries of objects - it can be an image of the light object on a dark background or a dark object on a light background. Second, the abrupt changes in brightness are often the result of changes in reflectance on fairly typical structures. For sharp changes images brightness are also include abrupt changes of surface orientation.

Image points in which the brightness changes is particularly strong, often called edges, or edge (contour) points. Contour points in combination with other elements have been used successfully for image analysis and classification in the broad range of applications. Numerous applications and subjective approach to the definition of contour points led to the creation large number operators of their evaluation [11-14], the effectiveness of which depends essentially from the conditions of images formation and objects on the images.

OBJECTIVES

The aim of this work is the comparative study of the quality of set filter (allocation algorithms) contours of images of objects standard geometric forms in the absence and presence of noise with different parameters. Filter evaluation should be performed for each type of object using the known criteria of the quality of work. Furthermore, it is necessary take into consideration the connectivity contour points after performing the filtering of images of objects of each type.

MAIN RESULTS OF THE RESEARCH

To highlight the features of the raster images they are processed by sequential subdivision into groups associated neighboring pixels of two types: 1) a group of pixels arranged successively horizontally (or vertically) - univariate processing methods, 2) a group of pixels arranged successively horizontally in several vertical rows, - two-dimensional processing methods. Typically, the number of pixels in such groups is an odd number (the most commonly used 3 or 5), pixel, which processed at each step, is located at the center of the group.

In a previous work [15], the authors conducted a study of the work of one-dimensional filters for ideal, fuzzy and noise contour models. In this paper, we research a variety of edge enhancement algorithms, and assess their work, using well-known performance measures. As quantitative criteria typically used the following measures:

- percentage of contour points detected on the perfect image contour;
- number of detected contour points that do not coincide with the ideal;
- the ratio of the detected contour points that do not coincide with the ideal circuit to the number of detected points that coincide with the ideal;
- the average width of the detected contour - defined as the ratio of the total number of detected contour points to the number of ideal points of the contour;
- normalized deviation of actual contour points from the ideal points of the contour.

Nowadays we know a large number of papers about the effectiveness of filters for solving allocation contour information. Therefore, we have a question how such information is actually solves the problem of the recognition, in the case when an affine transformation for this object vary insignificantly, and relationship of contour components allow us to identify the object. Such cases are rare in practice. For example, changing the viewing angle is relative to the object which being analyzed, or a change in the lighting conditions which significantly change the description about the contour of objects, so the problem can be considered legitimate about what properties should filter has for the task.

At first, let's research the one-dimensional linear filters. Common form of these filters may be presented as characteristic of brightness $S_1(x,y)$ in pixel with coordinates (x,y) after filtering by next formulas:

$$S_1(x,y) = \sum_{i=-k}^{k} a(x,y) * g(x+i,y), \qquad (1)$$

where: $a(x,y)$ - value of brightness in pixel with coordinates (x,y) before filtering, $g(x+i,y)$ - weight of value in concrete pixel (set of these weights are determine concrete filter), $n = 2*k+1$ – quantity of picture's points, which are considering in concrete filter.

Notation (1) describes the discrete convolution of brightness values $a(x,y)$ with weights $g(x+i,y)$. A set of weights for the adjacent pixel values is called the convolution mask. Pixel is a member of an edge if the intensity of it is greater than that of the members of its surrounding pixels.

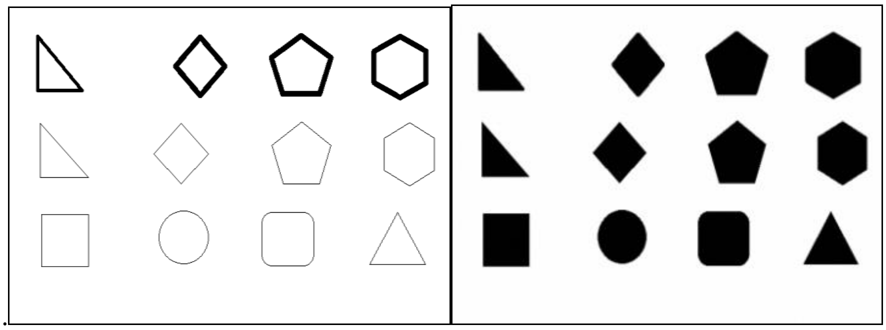
For example consider well-known masks (see Table 1).

Table 1. One-dimensional convolution mask

№	The name of the mask	Principal value of mask n	Values of convolution mask elements
1	Tone mask	3	1 2 1
2	Border mask	3	-1 0 1
3	Spot mask	3	-1 2 -1
4	Wave mask	5	-1 2 0 -2 1
5	Rippling mask	5	1 –4 6 -4 1
6	Vibration mask	7	-1 6 -15 20 -15 6 -1

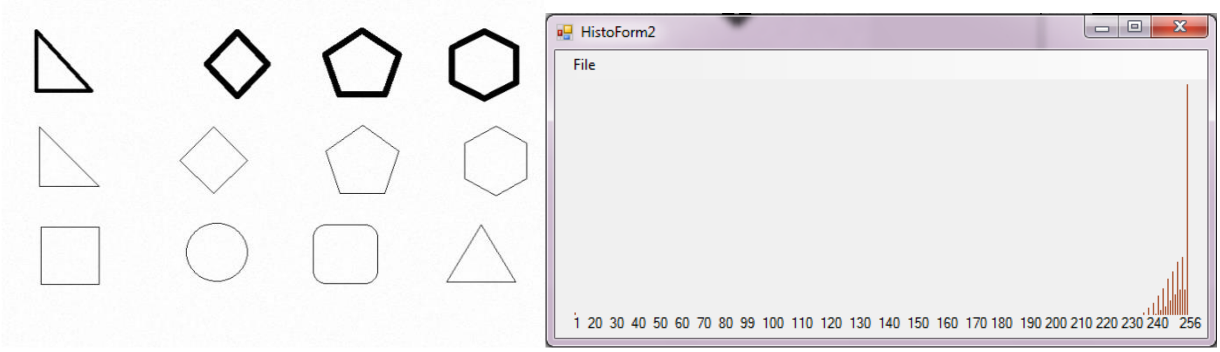
The research of these filters is shown that they can enhance the outline, but at the same time do not lose information about the distribution of brightness values within the object. For example, we can see it on a noisy picture with one from two standard deviation values: $\sigma_1 = 5$, $\sigma_2 = 10$.

After spending experiments and plotting the histograms, we can conclude that after the imposition noise $\sigma = 5$ and $\sigma = 10$ in Fig. 2-5 the difference is not noticeable, but the histogram allows you to track changes on the image.



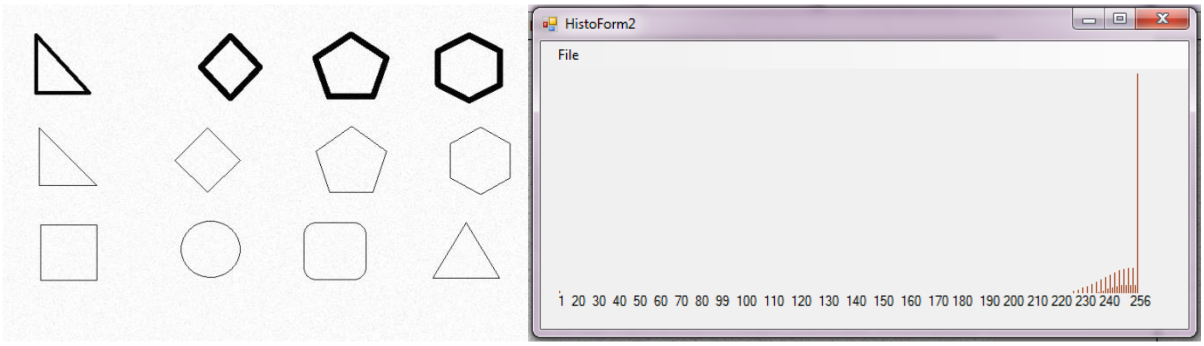
a) b)

Fig. 1. a) The template contour image, b) The template silhouette picture



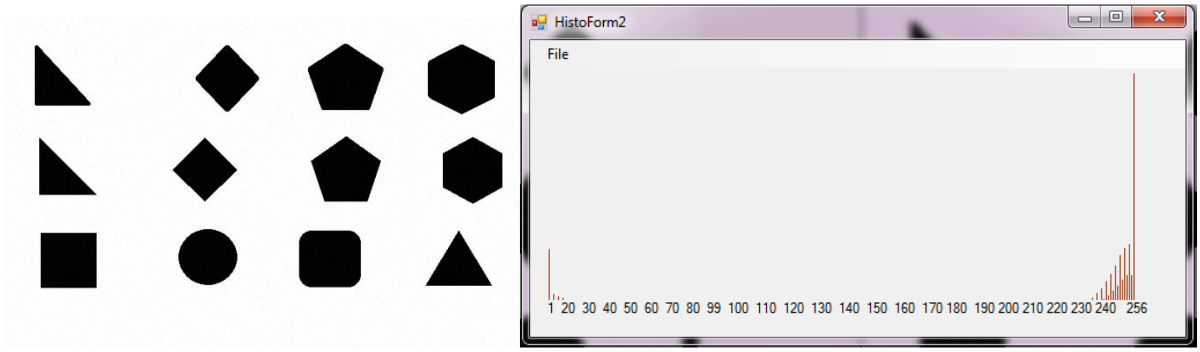
a) б)

Fig.2. Contour image with a gauss noise σ = 5. a) The template; b) A histogram of the template



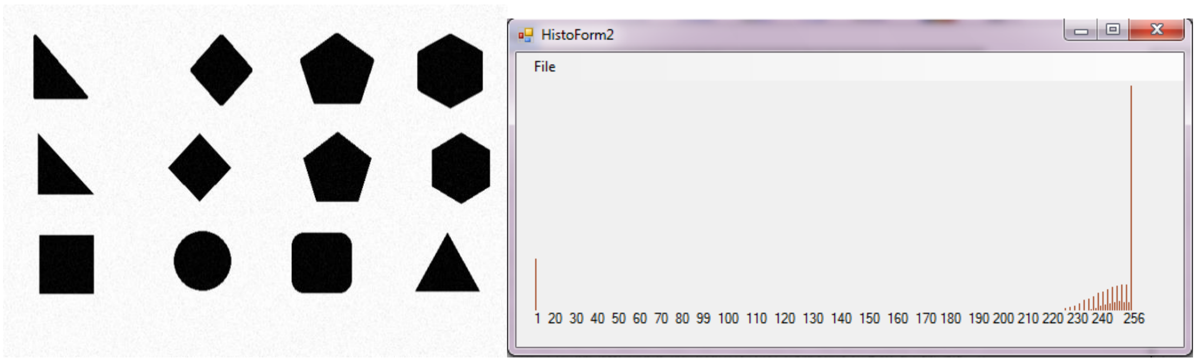
a) б)

Fig.3. Contour image with a gauss noise σ = 10. a) The template; b) A histogram of the template



a) б)

Fig.4. Silhouette image with a gauss noise σ = 5. a) The template; b) A histogram of the template



a) б)

Fig.5. Silhouette image with a gauss noise σ = 10. a) The template; b) A histogram of the template

The experimental results [15] suggest that the one-dimensional filters silhouette images do not allow to allocate contour of silhouette images, but let you receive the distribution of values within an image, and clearly fix Gaussian noise, which is good for the frequency and statistical processing methods.

Two-dimensional filters use different numerical methods to extract contours of objects using the next general formula:

$$S_{loc} = \sum_{i=-k}^{i=k} \sum_{j=-k}^{j=k} a(x, y) \cdot g_k(x+i, y+j), \quad (2)$$

where: x, y – the coordinates of the image plane; k – the dimension of the filter, as a rule $k = 3$ or $k = 5$.

Notation (2) describes the discrete convolution of brightness values $a(x, y)$ in pixel with coordinates (x, y) with weights $g(x+i, y+j)$, $i = \overline{1, k}$, $j = \overline{1, k}$.

There are several known filters, which are combined by the given general formula - filters Sobel, Prewitt, Kirsch, Laplace. For evaluation of the weights in the first three of them are used numerical first-order methods for calculating the gradient of the brightness change within the pixels covering the mask, in the last filter are used second-order method. At each point of the image gradient vector oriented in the direction of the greatest increase in brightness, and its length corresponds to the brightness change.

The components of the gradient vector are derivatives of image brightness on the horizontal and vertical directions:

$$grad(a(x, y)) = (da / dx, da / dy).$$

Sobel filter uses a 3x3 mask to calculate approximate values of derivatives with respect to horizontal and vertical.

Prewitt filter acts like a filter Sobel and considers separately two convolution kernels, but uses other values of the coefficients. The convolution is calculated for each mask separately. Response of the filter in each pixel is equal to the maximum of these two value convolutions.

Kirsch filter is a non-linear edge detector that takes a single kernel mask and rotates it in 45 degree increments through all 8 compass directions. The edge magnitude of the Kirsch operator is calculated as the maximum magnitude across all 8 directions.

Laplace filter uses as a mask Laplacian (the sum of the second order derivatives) in each pixel of the image. There are several mask of this filter.

Results of research with using a two-dimensional filters, such as Sobel, Kirsch, Prewitt, Laplace are presented in Tables 2 and 3. The values of error in these tables specifies the number of the detected contour points which do not coincide with the ideal image.

Table 2. Comparison of edge detection algorithms for contour images with superimposed noise

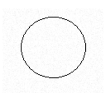
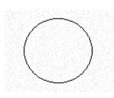
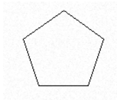
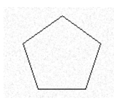
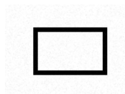
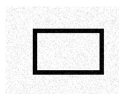
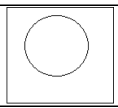
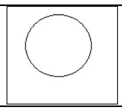
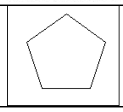
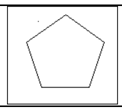
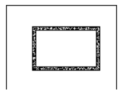
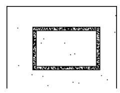
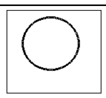
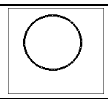
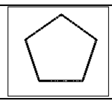
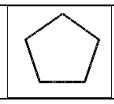
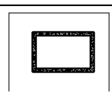
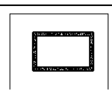
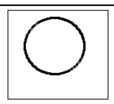
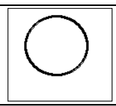
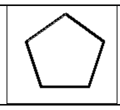
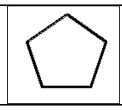
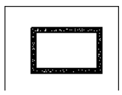
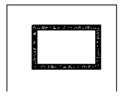
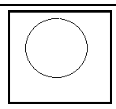
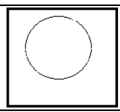
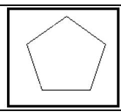
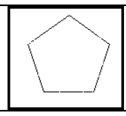
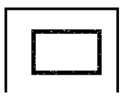
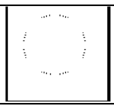
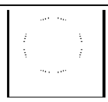
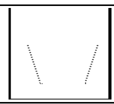
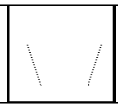
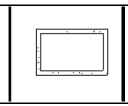
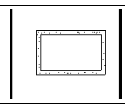
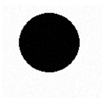
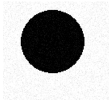
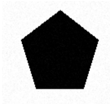
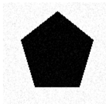
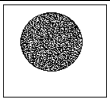
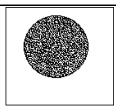
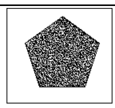
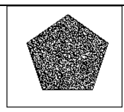
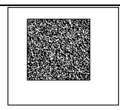
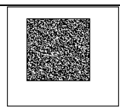
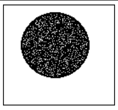
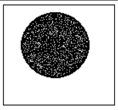
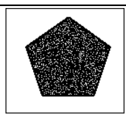
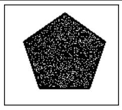
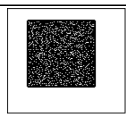
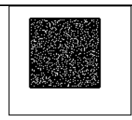
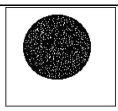
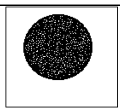
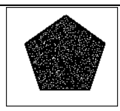
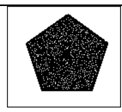
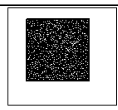
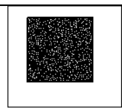
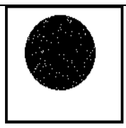
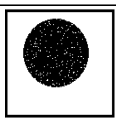
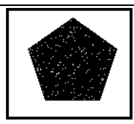
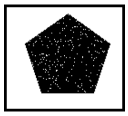
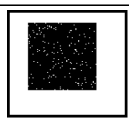
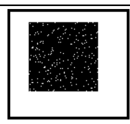
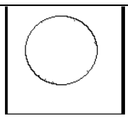
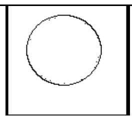
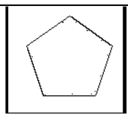
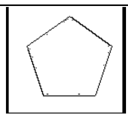
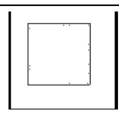
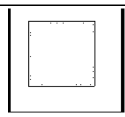
	Noise with a Gaussian distribution with standard deviation σ					
Filter	σ =5	σ =10	σ =5	σ =10	σ =5	σ =10
Original grayscale image						
Prewitt						
error	0	0	0	1	441	435
Sobel						
error	79	88	105	99	614	608
Kirsch						
error	0	0	0	0	647	626
Laplace						
error	1	12	2	12	283	299
Logic						
error	0	0	1001	1002	17	39

Table 3. Comparison of edge detection algorithms for silhouette images with superimposed noise

	Noise with a Gaussian distribution with standard deviation σ					
Filter	σ =5	σ =10	σ =5	σ =10	σ =5	σ =10
Original grayscale image						
Prewitt						
error	2685	2719	3317	3359	3240	3238
Sobel						
error	3609	3621	4471	4520	3382	4403
Kirsch						
error	3810	3817	4708	4734	4589	4629
Laplace						
error	4110	4034	5049	5014	4849	4806
Logic						
error	9	14	49	51	12	18

We can concluded that not all the algorithms are sufficiently effective when dealing with a silhouette image, and their effectiveness depends from the subject. The research has shown that with selected threshold locally adaptive algorithms for contour images such as Prewitt, Sobel, Laplace, Kirsch, Logical work well and allocate contour, but it does not consider the internal distribution. With increasing noise on the contour images the error increases too.

Table 2 shows, that Logical filter worse than all the other filters processes the contour images of circle and pentagon with noise. Image of circles after filtering has only a few unrelated points. Images of pentagon have not lines with small angles of inclination. For rectangles with wide lines, this filter detects two edges between the light and dark areas. Filtering of silhouette images this figures (see Table 3) shows another results.

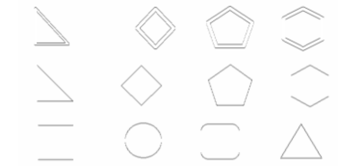
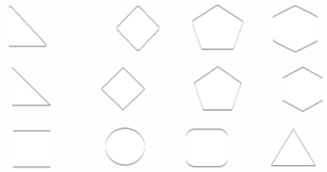
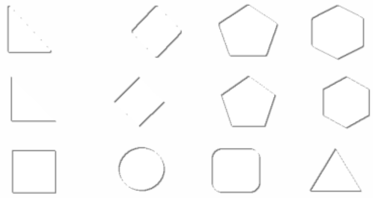
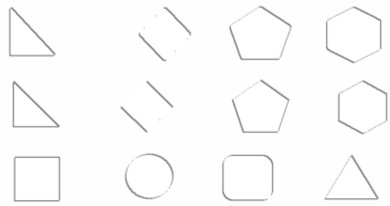
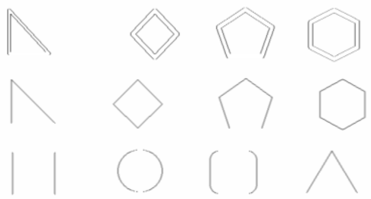
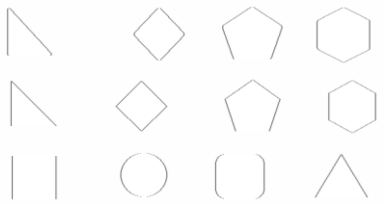
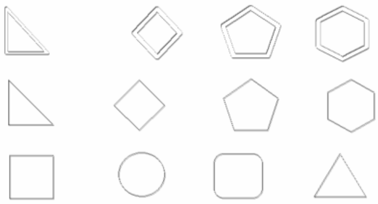
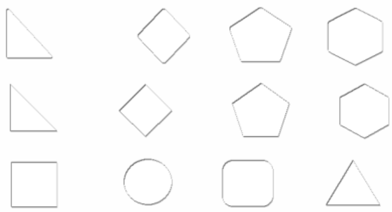
Results of research which using a two-dimensional filters has shown that they are well separated contour information, when properly choose threshold value, but using the threshold leads to losing information on the distribution of pixels brightness that constituting the object. The accuracy of the allocation contour information is largely determined by the accuracy of the selected threshold.

The experience of many studies show that for the edge detection of image elements, which have a complex geometrical shape, it is necessary to take into account the possible noise and use a combination of several filters. It is important to remember that different filters based on an approximation of the first derivative, have different sensitivity to noise. Significantly stronger in the presence of noise react the results of the filters that use the second derivative. In general, the higher the derivative, the more sensitive the operator. It is also useful to consider the results of applying the same filter with masks having larger number of pixels (e.g., 5*5 or 7*7).

This comparing the methods of image recognition and classification leads to the conclusion that for the method of structural recognition is important the accuracy of the allocation boundaries and information within these boundaries. For statistical methods is important to know the internal contours and mutual distribution of brightness values. For feature extraction methods (filters) should allocate contour components, which is typical for some existing methods, and obtain information about the distribution of structural elements outside the boundaries of objects. Losing any of these components, in principle, is not acceptable for decision a wide range of recognition problems.

The accuracy of allocated contour greatly depends by noise components. Even simple correlation methods give a big mistake. Losing the information about distribution inside the object, and its distortion after applying noise should be also used in pattern recognition.

Table 4. Application of two-dimensional filters to contour and silhouette images

Filter mask	The contour inverted image	The silhouette inverted image
$\begin{matrix} 0 & -1 & 0 \\ 0 & -1 & 0 \\ 0 & -1 & 0 \end{matrix}$		
$\begin{matrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{matrix}$		
$\begin{matrix} 0 & 0 & -1 \\ 0 & -1 & 0 \\ -1 & 0 & 0 \end{matrix}$		
$\begin{matrix} 0 & 0 & 0 \\ -1 & -1 & -1 \\ 0 & 0 & 0 \end{matrix}$		
$\begin{matrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & -1 & 0 \end{matrix}$		

This table shows that each of the above filters has drawbacks. The first filter is almost does not emit vertical borders; second - lines going from up to down as you move from left to right; the third - the lines going from the bottom-up as you move from left to right; fourth - horizontal border. In each case, these lines are perpendicular to the direction of recording of negative coefficients in the corresponding mask filter.

Last filter represents some combination of the first two. His results detects all directs of boundaries of all geometric shapes that has been processing. Disadvantages of the first two filters are shown much weaker - some of the boundaries are visible with less clarity.

Thus, we come to understand that we need a set of filters that would not lose the information about directions left-right, up-down, etc. We need to find a set of filters to identify each figure. The existence of these figures suggests that they can also be on the complex image, whereas the filter response, we will record the number of this filter. All of this allows us to build a diagram, which will display the number of filters and their sequence for detecting complex form of real image edges.

CONCLUSIONS

This comparing the methods of image recognition and classification leads to the conclusion that for the method of structural recognition is important the accuracy of the allocation boundaries and information within these boundaries. For statistical methods is important to know the internal contours and mutual distribution of brightness values. For feature extraction methods (filters) should allocate contour components, which is typical for some existing methods, and obtain information about the distribution of structural elements outside the boundaries of objects. Losing any of these components, in principle, is not acceptable for decision a wide range of recognition problems.

The accuracy of allocated contour greatly depends by noise components. Even simple correlation methods give a big mistake. Losing the information about distribution inside the object, and its distortion after applying noise should be also used in pattern recognition. Thus, it is necessary to develop rules for creating a set of filters, which can adjust the errors identified above depending on characteristics of the objects at the images.

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