Information & Communication Technologies

Investigation of edge detection methods using the example of wave field pattern image

Alexander Yakimenko
Department of Computer Engineering, Laboratory of Geophysical Informatics
Novosibirsk State Technical University, Institute of Computational Mathematics and Mathematical Geophysics SB RAS
Novosibirsk, Russia
yakimenko@corp.nstu.ru

Ann Makfuzova
Department of Computer Engineering
Novosibirsk State Technical University
Novosibirsk, Russia
anya-makfuzova@mail.ru

***Abstract*— This article explores the methods of detecting boundaries in images of wave field patterns. As a result, an application for image processing was developed using Sobel, Prewitt, Roberts, Gabor and Canny filters and experiments were carried out to detect the edge on images of wave field patterns. In conclusion, the quantitative and qualitative characteristics of the filters were presented, and a conclusion was made on the selection of the boundary detection filter. The results of this study will be used in the study of the neural network neocognitron for the recognition of geological and physical models of environments (GPME). This work was supported by the Russian Science Foundation (project No. 19-71-00011).**

Keywords—boundary detection, neocognitron, image recognition, Sobel, Prewitt, Roberts, Gabor, Canny.

I. Introduction

The search for a solution to the inverse problem of geophysics is currently the current direction. The inverse problem is to find the characteristics of the medium according to the physical parameters of the field, that is, the determination of the parameters of the medium from the existing pattern of propagation of the wave field [1]. Existing approaches to solving the inverse problem require a large amount of time for modeling proportional to the accuracy of the model.

The restore the GPME from the wave propagation pattern, it is proposed to use neural networks [2], which have already proven themselves in the field of image recognition. One example of a neural network for image recognition is the neocognitron network developed by K. Fukushima [3]. One of the features of the network is its insensitivity to shifts, resizing of the model or other distortions. The structure of the neocognitron contains a layer responsible for the selection of contrast, which will be modified to apply to this task.

This article examines the filters Sobel, Prewitt. Roberts, Gabor and Kanni's method for detecting the boundaries of images of wave field patterns by qualitative (visual) and quantitative (confusion matrix) characteristics.

II. Problem Definition

It is necessary to consider the theory of detecting the boundaries of images in pictures, using error matrices (confusion matrix) and qualitative characteristics (visually).

III. Theory

Border detection filters are well designed for halftone images. A halftone image of a wave field pattern will be considered as a function of two variables (x, y). The boundaries of the regions correspond to the maxima of the gradient of this function, and for their search we will use the filters Sobel, Prewitt, Roberts, Gabor and the Canny method, because they are one of the frequently used for solving such problems.

A. Filter Sobel

The Sobel filter is used in image processing, especially in edge detection tasks.

Filter Sobel calculates the direction of the greatest increase in the brightness of the image at each point [4]. The Sobel filter is built on the calculation of the convolutions of the original image with the G_X and G_Y cores, which provide the calculation of the first derivatives in the directions:

$$G_X = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \times A \qquad (1)$$

$$G_Y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \times A \qquad (2)$$

where is $\times$ – dimensional convolution operation;

A – the origin image.

The use of the operator G_X allows to determine the approximate value of the first partial derivative of the intensity change in the horizontal direction, G_Y - in the vertical direction.

Two-dimensional operation of convolution is carried out according to the formula (3).

$$B(x,y) = \sum_i \sum_y F(i,j) \times A(x+i, y+i), \qquad (3)$$

where is $F(i,j)$ – core filter Sobel.

An important role in detecting outlines is played by the magnitude of the gradient in each pixel of the image, which is determined by the formula:

$$G = \sqrt{G_X^2 + G_Y^2} \qquad (4)$$

Therefore, the Sobel filter is a discrete differential operator that calculates an approximate value of the brightness gradient at each point in the image. This filter is simple to implement with the least expenditure of resources,

978-1-7281-2896-2/19/$31.00 ©2019 IEEE

however, in problems of detecting thin and smooth edges, the filter is inaccurate.

B. Filter Prewitt

The Prewitt Filter is similar in how it works with the Sobel filter. It is an appropriate method for estimating the size and orientation of the boundary [5]. The Prewitt filter gives direction straight from the kernel with the maximum result. The method of detecting segments with its help along the boundary of the object localization:

$$G_X = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \times A, G_Y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \times A \quad (5)$$

The result of the Prewitt filter is:

$$\max\{P,Q\} \quad (6)$$

where is P и Q – kernel responses G_X and G_Y.

The advantages of the Prewitt filter are similar to the Sobel filter, but the appearance of noise in the circuit and the appearance of corner elements are several times higher than that of the Sobel filter.

C. Filter Roberts

The Roberts Filter is a non-linear contrasting method using two-dimensional discrete differentiation operations [6]. The method of detecting segments with its help examines two different convolution kernels:

$$G_X = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \times A, G_Y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \times A \quad (7)$$

In the Roberts filter, a total vector of two diagonal differential vectors is used, which shows the largest value of the differential between the four covered points.

The transformation of each pixel by the Roberts cross filter can show the derivative of the image along a non-zero diagonal, and the combination of these transformed images can also be viewed as a gradient from the two upper pixels to the lower two. The response of this filter is determined by the formula:

$$S = \sqrt{P^2 + Q^2} \quad (8)$$

These core sizes do not have a clearly defined central element, which will significantly affect the segmentation process, but this filter is one of the fastest in the image processing task.

D. Method Canny

The method Canny consists of five steps [7]:

- Smoothing. It is used to suppress noise using a Gaussian image blur:

$$G(r) = \frac{1}{(2\pi\sigma^2)^{N/2}} e^{-r^2/(2\sigma^2)}, \quad (9)$$

where is r – blur radius;

N – number of measurements;

σ – standard deviation of the Gaussian distribution.

- Search for gradients. At this stage, the Sobel filter is used, which is described in A.
- Suppression of non-maxima: pixels are declared as edges pixels in which a local gradient maximum is reached in the direction of the gradient vector.
- Dual threshold filtering. If the value of the gradient in some place on the fragment being viewed exceeds the upper threshold, then this element also remains the acceptable limit in those places where the value of the gradient considers two different convolution kernels;
- Trace ambiguity. Total boundaries are determined by suppressing all edges that are not bound to strong boundaries.

This method has a smoothing effect to remove noise when detecting boundaries, however, the thickness of the boundary appears, which must be eliminated by suppressing non-maximum points in the gradient direction. As a result, when borders are detected on the image, an effect such as "re-segmentation" may occur.

E. Filter Gabor

The core of the Gabor filter is the product of a Gaussian and harmonic function, and filters the signal based on the preferred spatial frequency parameter λ^{-1} [8]:

$$g(k,l) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(\frac{2\pi x'}{\lambda} + \psi\right), \quad (10)$$

where is x', y' - transition to polar coordinates;

k, l - position of the light pulse in the receptive area;

λ - the number of parallel excitatory and inhibitory zones in the receptive field;

σ - size of receptive field;

ψ - symmetry of excitatory and inhibitory zones;

γ - degree of ellipticity of receptive field.

Based on [9], the optimal value of the preferred spatial frequency can be calculated from the relation:

$$\frac{\sigma}{\lambda} = 0,56 \quad (11)$$

Gaussian serves to determine the receptive inhibitory and excitatory zones, the shape and dimensions of which determine the parameters σ, γ. The harmonic function generates a signal, when coinciding with a grayscale signal, the signal is amplified, or its complete attenuation otherwise. The Gabor filter due to the use of Gaussian and harmonic functions contrasts the borders of the images while removing noise in it, however, representing the border as a set of directions can cause blurred filter response in various curls and distortions in the image.

IV. Experiments

For experiments, an application was developed in C # to detect the boundaries of the image of a wave field pattern. The appearance of the application is shown in Figure 1.

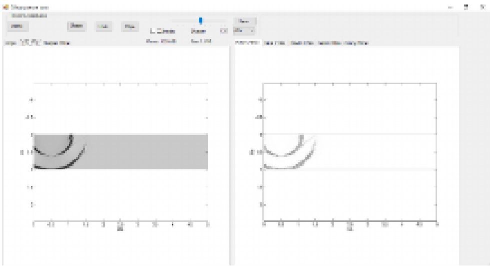


Fig 1. Edge Detection Application

This application visually consists of two zones: processing the original image (Origin tab) into a halftone image (Gray tab), sharpening the image (Sharpen tab), and processing the original image with Roberts, Sobel, Prewitt, Gabor filters and Kanni to choose from.

It also provides for the binarization of the original image to improve the quality of border detection, and adjust the image sharpness (slider "Sharpen".

The image of the wave field pattern is dynamic, namely, the original images are made at equal intervals of time (Fig. 2). Thus, experiments should be carried out not with one image, but with several.

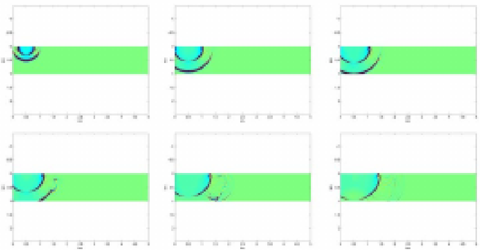


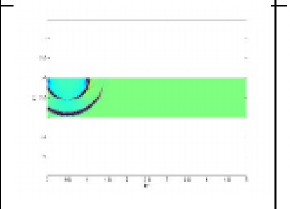
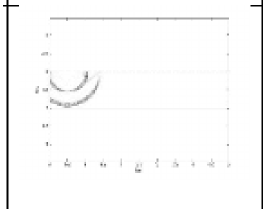
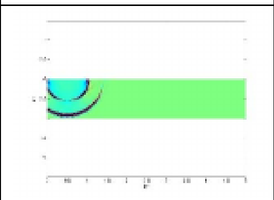
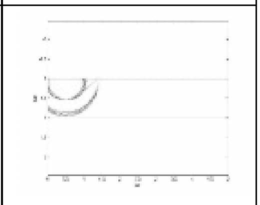
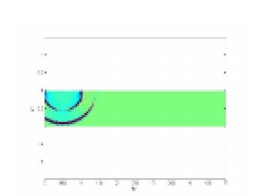
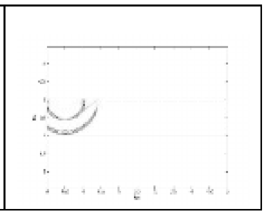
Fig 2. Original images of the wave field pattern

In Figure 2, the initial data are synthetic, and they were obtained from the already existing GFME. For each model, 16 images of wave field patterns are presented. A total of 100 GFME with different positions in space and geometric characteristics.

A. Edge detection using a Roberts filter

The results of edge detection using the Roberts filter for various values of sharpness are presented in Table I.

TABLE I. EDGE DETECTION WITH FILTER ROBERTS

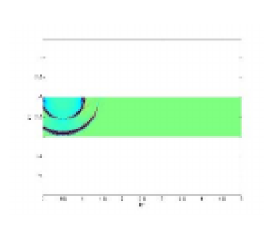
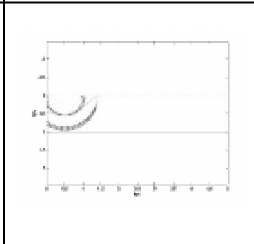
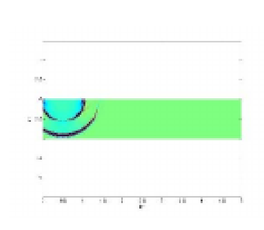
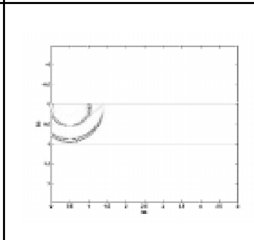
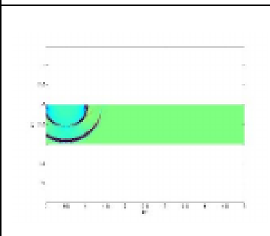
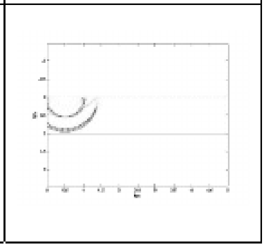
Sharpness	Original image	The resulting image
30		
100		
180		

Based on the results, the recommended sharpness value for the Roberts filter is 45

B. Edge detection using a Sobel filter

The results of edge detection using the Sobel filter for various values of sharpness are presented in Table II.

TABLE II. EDGE DETECTION WITH FILTER SOBEL

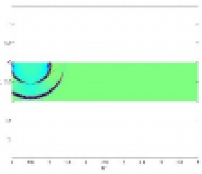
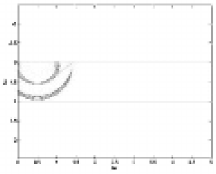
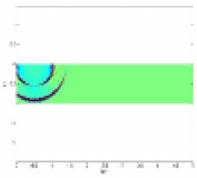
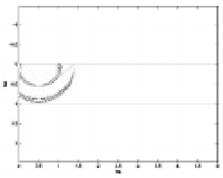
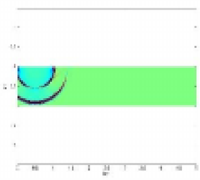
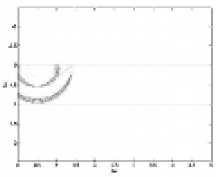
Sharpness	Original image	The resulting image
30		
100		
180		

Based on the results, the recommended sharpness value for the Sobel filter is 55.

C. Edge detection using a Prewitt filter

The results of edge detection using the Sobel filter for various values of sharpness are presented in Table III.

TABLE III. EDGE DETECTION WITH FILTER PREWITT

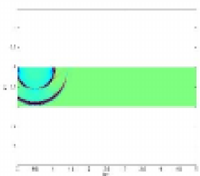
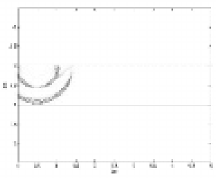
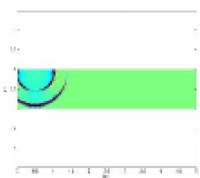
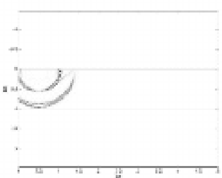
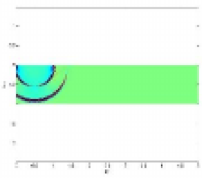
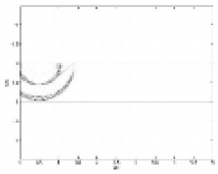
Sharpness	Original image	The resulting image
30		
100		
180		

Based on the results, the recommended sharpness value for the Prewitt filter is 87.

D. *Edge detection using a method Canny*

The results of edge detection using the Sobel filter for various values of sharpness are presented in Table IV.

TABLE IV. EDGE DETECTION WITH METHOD CANNY

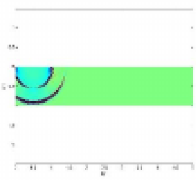
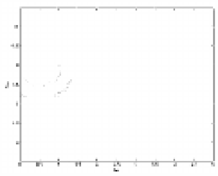
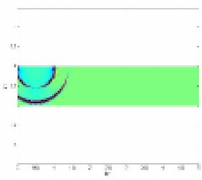
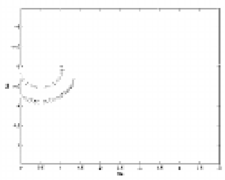
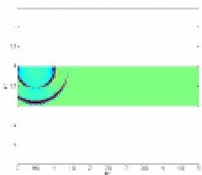
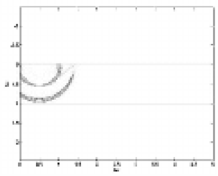
Sharpness	Original image	The resulting image
30		
100		
180		

Based on the results, the recommended sharpness value for the method Canny is 32.

E. *Edge detection using a Gabor filter*

The results of edge detection using the Sobel filter for various values of sharpness are presented in Table V.

TABLE V. EDGE DETECTION WITH FILTER GABOR

Sharpness	Original image	The resulting image
30		
100		
180		

Based on the results, the recommended sharpness value for the Gabor filter is 100.

V. CHOICE OF FILTER

A. *Qualitative characteristics*

Based on Chapter IV, it can be concluded that the detection of boundaries is affected by: the depth of field of the image, the filter parameters, and the binarization of the image. In consequence of this, for each filter, the parameters are selected separately, based on theoretical aspects. Thus, in experiments, the parameters of the filters did not change, but the amount of sharpness was varied. For the Roberts filter, the amount of sharpness is 45 based on qualitative analysis, 55 for the Sobel filter, 87 for the Prewitt filter, 32 for the Canny method, 100 for the Gabor filter.

B. Quantitative characteristics

To assess the quality and comparison of the above filters we will use metrics. But in order to go to metrics, it is necessary to introduce a concept to describe these metrics in terms of classification errors - confusion matrix [10].

Suppose that there are 2 classes and an algorithm that predicts that each object belongs to one of the classes, then the error matrix will look like this (Table VI).

TABLE VI. CONFUSION MATRIX

	y=1	y=0
$y^*=1$	True Positive (TP)	False Positive (FP)
$y^*=0$	False Negative (FN)	True Negative (TN)

where is y^* the response of the algorithm at the facility; y is the true class label on this object. Thus, classification errors are of two types: FN and FP.

- Metric accuracy

A basic metric that measures the number of correctly classified objects relative to the total number of all objects.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (12)$$

- Metric precision

The accuracy metric determines how many of all objects that are classified as positive are indeed positive, relative to the total number of positive labels received from the model.

$$precision = \frac{TP}{TP+FP} \qquad (13)$$

- Metric recall

The completeness metric determines how many objects our model was able to correctly classify with a positive label from among a multitude of positive ones.

$$recall = \frac{TP}{TP+FN} \qquad (14)$$

To select a filter for detecting borders on images of a wave field pattern, we use the accuracy metric, since the number of correctly detected borders on the image relative to the total number is important for us.

The calculation of the selected metric was carried out on the basis of the TensorFlow framework using the Keras library, where this metric is already included.

The results of the calculation are presented in table VII.

TABLE VII. QUANTITATIVE CHARACTERISTICS

	Sobel	Prewitt	Roberts	Gabor	Canny
accuracy, %	72	68	40	89	76

Thus, the Gabor filter showed the best result for the selected metric, and therefore, it is advisable to use it to detect boundaries in images of wave field patterns.

VI. CONCLUSION

Experiments have shown that the Gabor filter is recommended to use as a detector for detecting boundaries in images of wave field patterns. This was confirmed by calculated quantitative and qualitative characteristics. During the study, a program was created to detect borders on the image, in which the parameters of the image can vary. This program can be implemented not only to solve the problem, but also for other experiments.

REFERENCES

[1] Mikhailenko, B.G. and Fatyanov, A.G., A Semi-Analytical Method to Calculate Nonstationary Wave Fields for Layered-Inhomogeneous Media Models inMatematicheskiemetody resheniya pryamykh i obratnykh zadach geofiziki (Mathematical Methods of Solving Direct and Inverse Problems of Geophysics), Novosibirsk: Computing Center, Sib. Branch, USSR Acad. Sci., 1981, pp. 92–104. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2] Yakimenko A. A. Practical aspects of using a neural network to solve inverse geophysical problems / A. A. Yakimenko, A. E. Morozov, D. A. Karavaev // Journal of Physics: Conference Series. - 2018. - Vol. 1015 : International conference information technologies in business and industry, Tomsk, 2018. – Art. 032148 (6 p.). - DOI: 10.1088/1742-6596/1015/3/032148.

[3] K. Fukushima: "Neocognitron for handwritten digit recognition", Neurocomputing, 51, pp. 161-180 (2003).

[4] I. Sobel and G. Feldman, "A 3x3 isotropic gradient operator for image processing," presented at the Stanford Artificial Intelligence Project (SAIL), 1968.

[5] R. Gonzalez and R. Woods, Digital image processing (3rd Edition). Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 2006.

[6] Z. Guo, W. Xu, and Z. Chai, "Image edge detection based on FPGA," in Distributed Computing and Applications to Business Engineering and Science (DCABES), 2010 Ninth International Symposium on Distributed Computing and Applications to Business, Engineering and Science, pp. 169-171. IEEE, 2010.

[7] J. Canny, "A computational approach to edge detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. 6, pp. 679-698, 1986.

[8] Huang, L.-L. &. Shimizu, A. &. Kobatake and Hidefumi, "Classification-Based Face Detection Using Gabor Filter Features," in Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2014.

[9] R. L. DeValois, D. G. Albrecht, and L. G. Thorell, "Spatial frequency selectivity of cells in macaque visual cortex," Vis. Res., vol. 22, pp. 545–559, 1982.

[10] N. Gordienko, P. Gang, Yu. Gordienko, W. Zeng, O. Alienin, O. Rokovyi, and S. Stirenko, "Open Source Dataset and Machine Learning Techniques for Automatic Recognition of Historical Graffiti", In Proc. 25th International Conference on Neural Information Processing (Siem Reap, Cambodia), December 14 - 16, 2018; arXiv preprint arXiv:1808.10862 (2018).