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To cite this article: A A Yakimenko and A I Makfuzova 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1019** 012008

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

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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 RFBR grant No. 19-07-00170.

1. 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.

2. Problem definition

It is necessary to develop an algorithm for determining the shape and location of the boundaries of the density drop in the geological-physical model of the environment. Consider and analyze filters for the edge detection method based on the difference in brightness. To develop software for the implementation of an algorithm for determining the shape and location of the boundaries of the density drop in the geological-physical model of the environment. Conduct a series of experiments with synthetic data.



3. 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).

3.1. 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:

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

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

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 equation (3).

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

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

The magnitude of the gradient in each pixel of the image is determined by the equation:

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

Therefore, the Sobel filter is a discrete differential operator that calculates an approximate value of the brightness gradient at each point in the image.

3.2. 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 and Q – kernel responses G_X and G_Y .

3.3. 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 equation:

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

3.4. 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.

3.5. 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:

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

4. Experiments

Figure 1. Edge Detection Application.

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 (Figure 2). Thus, experiments should be carried out not with one image, but with several.

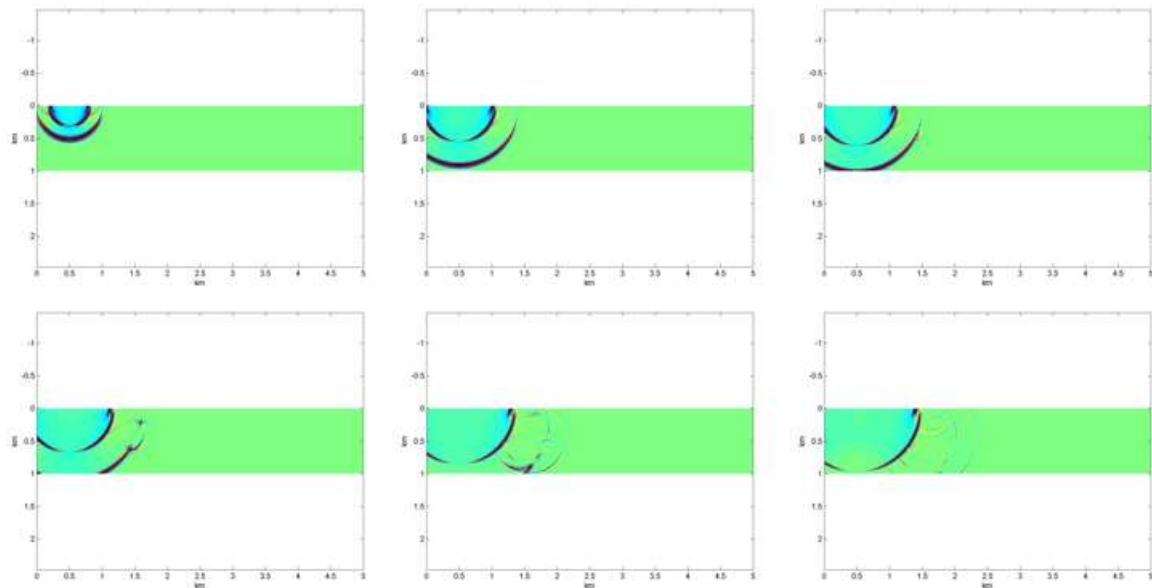


Figure 2. Original images of the wave field pattern.

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.

4.1. Edge detection using a Roberts filter

The results of edge detection using the Roberts filter for various values of sharpness are presented in table 1.

Table 1. Edge detection with filter roberts

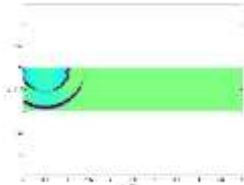
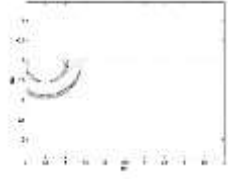
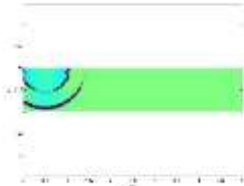
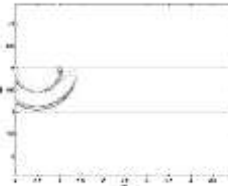
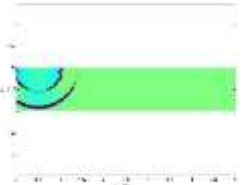
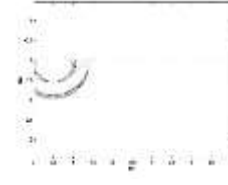
Sharpness	Original image	The resulting image
30		
100		
180		

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

4.2. Edge detection using a Sobel filter

The results of edge detection using the Sobel filter for various values of sharpness are presented in table 2.

Table 2. Edge detection with filter sobel

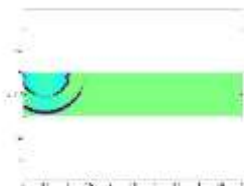
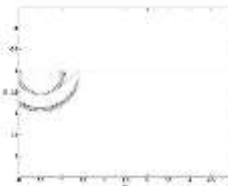
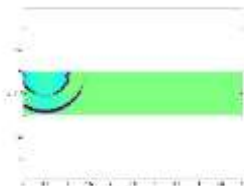
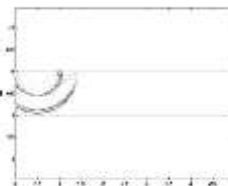
Sharpness	Original image	The resulting image
30		
100		
180		

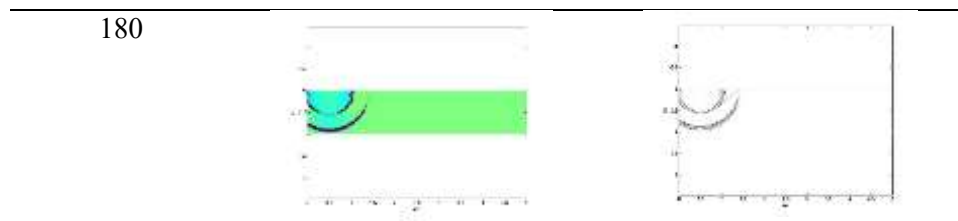
Based on the results, the recommended sharpness value for the Sobel filter is 55.

4.3. Edge detection using a Prewitt filter

The results of edge detection using the Sobel filter for various values of sharpness are presented in table 3.

Table 3. Edge detection with filter prewitt

Sharpness	Original image	The resulting image
30		
100		

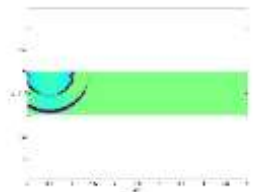
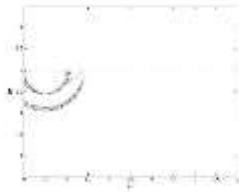
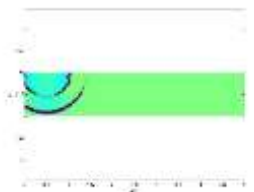
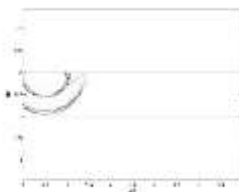
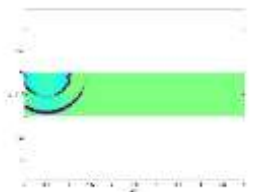
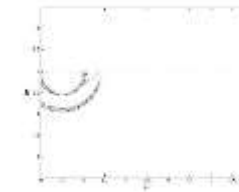


Based on the results, the recommended sharpness value for the Prewitt filter is 87.

4.4. Edge detection using a method Canny

The results of edge detection using the Sobel filter for various values of sharpness are presented in table 4.

Table 4. Edge detection with method canny

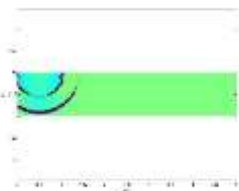
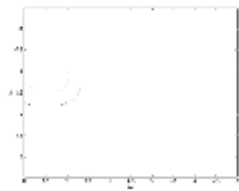
Sharpness	Original image	The resulting image
30		
100		
180		

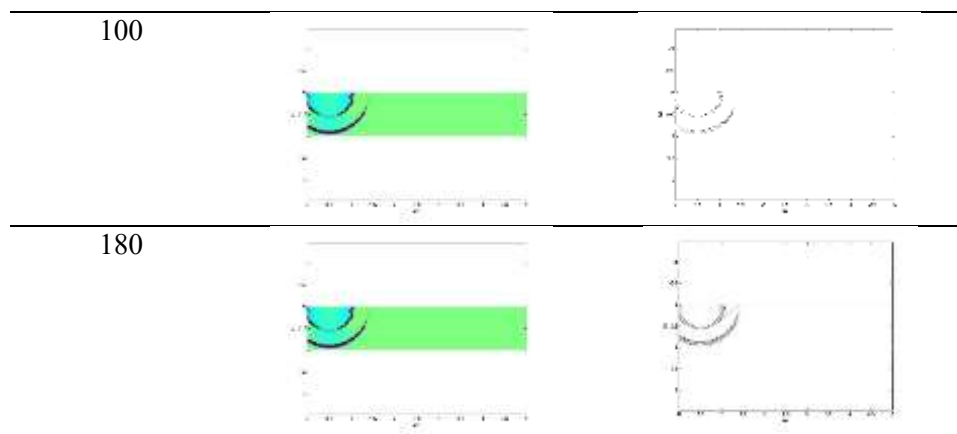
Based on the results, the recommended sharpness value for the method Canny is 32.

4.5. Edge detection using a Gabor filter

The results of edge detection using the Sobel filter for various values of sharpness are presented in table 5.

Table 5. Edge detection with filter gabor

Sharpness	Original image	The resulting image
30		



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

5. Choice of filter

5.1. 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.

5.2. 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 6).

Table 6. 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.

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

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

5.2.2. 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.

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

5.2.3. *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.

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

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 7.

Table 7. 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.

6. 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.

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