Edge Detection using Modification Prewitt Operators

Suhad A.H.Al-Ani*

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Abstract

In this paper, we adopted ways for detecting edges locally. Classical Prewitt operators and modification it are adopted to perform the edge detection and comparing them with Sobel operators. The study shows that using a prewitt operator with multiplying it with factor give a good quality comparison with standard prewitt operators. Sobel operators are more powerful and useful than of classical and modification prewitt mask. Also we processed the image with classical prewitt mask (of any type) and then with the modificated prewitt mask a promising results will be obtained than the results we got from using the classical prewitt mask method. But Sobel operators still the accurate method.

Introduction

The edge and line detection operators presented here represent the various types of operators in use today. are implemented with Many convolution masks, and most are based approximations to discrete on differential operators. Differential operations measure the rate of change in a function, in this case, the image brightness function. A large change in image brightness over a short spatial distance indicates the presence of an edge. Some edge detection operators return orientation information timformation about the direction of the edzet, whereas others only return information about the existence of an edge at each point. Edge detection operators are based on the idea that edge information in an image is found by looking at the relationship a pixel has with its neighbors. If a pixel's gray-level value is similar to those around it, there is probably not an edge at that point. However, if a pixel has neighbors with widely varying gray levels, it may represent an edge point. In other words, an edge is defined by a discontinuity in gray-level values.

Ideally, an edge separates two distinct objects. In practice, apparent edges are caused by changes in color or texture or by the specific lighting conditions present during the image acquisition process [1].

Derivative Filters

Most edge detectors are based in some way on measuring the intensity gradient at a point in the image .The gradient operator ∇ is :

$$\nabla = \begin{bmatrix} \frac{\partial}{\partial x} \\ \\ \\ \frac{\partial}{\partial y} \end{bmatrix} \dots \dots (1)$$

when we apply this vector operator to a function, we get

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \dots \dots (2)$$

As with any vector, we can compute its magnitude $\|\nabla f\|$ and orientation $\Phi(\nabla f)$.

- The gradient magnitude gives the amount of the difference

^{*}Assistant Lecturer Physics department, College of Science - University of Baghdad, Jadriyah, Baghdad, Iraq

between pixels in the neighborhood (the strength of the edge).

- The gradient orientation gives the direction of the greatest change, which presumably is the direction across the edge (the edge normal) [2].

In general, gradient operators are classified into two groups:

First group

Belong the operators, which evaluate two orthogonal components of the gradient.

Second group

Is based on gradient detection by means of a set of templates or masks of different orientation [3][4].

In the <u>first group</u> two orthogonal components D_x and D_y of the gradient in each point are evaluated and then its magnitude is obtained by means of the relation :

$$D = \sqrt{D_x^2 + D_y^2} \dots (3)$$

and its direction is given by [5]

$$\Phi(\nabla f) = \tan^{-1} \frac{D_y}{D_x} \dots (4)$$

The two components D_x and D_y can be evaluated with several methods, by using different weights on a given number of values near the tested point. If we suppose that the point in examination has coordinates (i, j) and value f(i, j), the easiest way to obtain the two components D_x and D_y is given by the relations:

$$D_x = f(i, j+1) - f(i, j) \dots (5)$$

$$D_y = f(i, j) - f(i+1, j) \dots (6)$$

Thus the gradient in the point (i, j) can be evaluated by using the values in the points just on the right and below the considered point. This is the same as using the masks

$$D_x = \begin{bmatrix} -1 & 1 \\ 0 & 0 \end{bmatrix} \quad D_y = \begin{bmatrix} 1 & 0 \\ -1 & 0 \end{bmatrix}$$

and performing the addition of the products between the values of the masks and the underlaying values of the image. The evaluation of the gradient by considering matrices of 3×3 elements near the considered point (i, j) is more accurate. Several methods are known on this line with different weighting of the surrounding values. Often used mask are:

1- Smoothing gradient mask or **Prewitt gradient** mask $\begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$

$$D_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad D_{y} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

2- Sobel gradient masks
$$D_{x} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad D_{y} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The equations referring to the previous masks can be expressed in the form

$$D_{\mathbf{r}}(i,j) = f(i-1,j+1) + wf(i,j+1) + f(i+1,j+1) - f(i-1,j-1) - wf(i,j-1) - f(i+1,j+1)....(1)$$

$$D_{j}(i, j) = f(i-1, j-1) + wf(i-1, j) + f(i-1, j+1) - f(i+1, j-1) - wf(i+1, j) - f(i+1, j+1)....(8)$$

Where the weight w can assume the values 1,2 respectively for the two previous masks [6].

The second group of algorithms for the evaluation of the gradient and then for the identification of edges is based on gradient detection by means of a set of templates or masks of different orientation, searching sequentially at each point for the best match between image subarea and masks .Every mask of the set is superimposed on each sample of the image and the additions of products between the mask and the underlaying samples of the image are performed just as in the previous group of local operators . The gradient is assumed to be detected by the mask, which gives the greatest value of the addition of products and its direction is assigned to the direction of the mask. Each set of masks is composed by eight different 3×3 masks, each one of which is obtained from the previous

one by a *circular permutation* of its elements around the central one .Thus, if we assume that the first mask of a given set is

the second and third mask will be

H	
$G \rfloor$	
	$\left. \begin{array}{c} H \\ G \end{array} \right]$

and so on.

The sets of masks more frequently used are obtained through a permutation of the following masks :

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix}$$
2- Kirsch mask [7]
$$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

Numerical Implementations and Results

In this paper we study the effect of classical Prewitt filter (mask) and modification it, and comparing with classical Sobel filters. These modification filters differ from the classical filter in their coefficients. With these masks we are trying to find edges and aren't interested in the image itself. These masks posses the property that the sum of their coefficients is zero.

Satellite image was used to check the quality of edge detection using conventional and suggested methods as shown in figure (1a). Blurred image using Gaussian filter (with 5×5 size) and its histogram as shown in figure (1b). Figure (1c) display edge detection image and its histogram using Sobel operators. Figure (1d) show image from applying classical prewitt operators (obtained through a circular permutation) and its histogram. Those are more powerful and useful than those of prewitt (they weight the central differences more). We modified classical Prewitt mask (mask obtained through a circular permutation) by multiplying with factor (K) for increasing the brightness power, we selecting (K) randomly i.e.

$$H_{i} = (K) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix}$$

where $i = 1, 2, 3, 4, \dots$ let $K = -1, -2, 0.2, 0.3, 3$
masks that product are :

$$H_{1} = (-1) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 2 & -1 \\ 1 & 1 & 1 \end{bmatrix}$$
$$H_{2} = (-2) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} -2 & -2 & -2 \\ -2 & 4 & -2 \\ 2 & 2 & 2 \end{bmatrix}$$
$$H_{3} = (0.2) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 0.2 & 0.2 & 0.2 \\ 0.2 & -0.4 & 0.2 \\ -0.2 & -0.2 & -0.2 \end{bmatrix}$$

$$H_{4} = (0.3) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 0.3 & 0.3 & 0.3 \\ 0.3 & -0.6 & 0.3 \\ -0.3 & -0.3 & -0.3 \end{bmatrix}$$
$$H_{5} = (3) \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 3 & 3 & 3 \\ 3 & -6 & 3 \\ -3 & -3 & -3 \end{bmatrix}$$

Figure (2a),(2b),(2c),(2d), and (3a)demonstrate the effects of using masks H_1, H_2, H_3, H_4 , and H_5 and their histogram respectively on blurred image.

Another method to edge detection, we processed the image with classical prewitt mask (of any type) and then with the modified prewitt mask (such as H_1, H_2, H_3, H_4 , and H_5)a promising results will obtained as shown below :

Method $1 = D_y$ then H_1

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[1	1	1]	[-1	-1	-1]
method =	0	0	0 4	ien-1	2	-1
	-1	-1	-1	1	1	1
method2=	D, 1	then	H2	-		-
method2 =	[1	0 -	1]	[-2	-2	-2]
method =	1	0 -	-1 the	1-2	4	-2
	1	0 -	-1	2	2	2
method3						
then 112	÷.					
.	1	1	1]	[-2	-2	-2]
method =	1	-2	14	nen-2	• 4	-2
metho d =	-1	-1	-1	2	2	2
method4=	= D _v	the	n H ₂	-		
method4=	1	1	1]	∫ −2	-2	-2]
metho4 =	0	0	0 11	ich-2	4	-2
	-1	-1	-1	2	2	2
ł (3b),(3	3c),(3d),	and	(3e)	show
image	S	an	nd t	heir	histo	gram
obtain	ed 1	rom	appl	lying	meth	odl,
metho	d2,	met	hod3	, and	d met	thod4
respec	tive	ly (on b	lurred	ima	nge .
These	te	chni	que	are	done	e by
creatin	ng	an	edge	imag	e is	that
involv						
origin	al	gray	sca	le ir	nage	Into
gradie						mear
G(r	v):		(r v) * H	() 1	1
When	F	(x	v) G	(x v	Trep	resent
G(x, When the o	rigin	nal	and	outou	t gra	idient
image	S. 1	resp	ective	ly.	H(x,	(v) is
the li	near	OD	erator	s or	mask	and
* den	otes	two	o-dim	ensio	nal s	patial
convo	lutio	n	, af	ter c	onvo	lution
with a	all d	iffer	ence	opera	tors,	these
yield	li	ghtli	nes	on	a	dark
backg	rour	Id I	n dil	leren	ima	iges .
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table (1).

Table (1)
The statistical properties for different
modification filters and classical filter

Filters and Images	min	Max	mean	Stdv
Original	1	250	123.3448	43.132 8
Blurred ' image	0	255	129.868	56.800 5
Classical prewitt operators	0	255	17.305	350508
Sobel ⁴ operators	0	255	.139.489	138.8
Н,	0	255	16.840740	33.954 740
112	0	255	31.792130	59.323 569
11.	0	70	3.463846	7.1641
14	0	105	5.228225	10.752 868
11,	0	255	52.8893	83.871 8
Adl	0	143	6.7014	13.185 8
Ad2	0	255	47.557	79.876
Ad3	0	255	23.366	46.453
Ad4	0	255	27.1196	50.581

Conculsion

Depending on the previous results, we can conclude:

1- That using prewitt operator it with use when we multiplying it with

factor gives us better edge contrast comparing with standard prewitt

mask.

2- If we processed image with any type of classical prewitt mask then

with any modificated prewitt mask a good results will be

obtained than the classical prewitt.

3-Soble edge detection that is more powerful and useful than those

of classical and modification prewitt operators.

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Figure (1) a-Original Image and it's histogram. b- Blurred Image with Gaussian filter and it's histogram c- Sobel Operators and it's histogram d- Classical Prewitt Operators and it's histogram.



Figure (2) Edge detection (a) with H₁ mask and it's histogram (b) with H₂ mask and it's histogram (c) with H₃ mask and it's histogram (d) with H₄ mask and it's histogram Ç



Figure (3)

Edge detection (a) with H₅ mask and it's histogram (b) with method1 and it's histogram(c) with method2 and it's histogram (d) with method3 and it's histogram (e) with method4 and it's histogram

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تحديد الحواف باستخدام طريقة بروت المحورة

سهاد عبد الكريم حمدان*

*مدرس مساعد - جامعة بغداد - كلية العلوم - قسم الفيزياء

الذلاصة

يتضمن هذا البحث استخدام طريقة من طرق كشف الحواف وهي Prewitt Operators التقليدية واجرينا بعض التحويرات عليها وقررنت مع طريفة Sobel Operators ووجد ان Sobel Operators المحور الناتج من الضرب بمعامل معين يعطي نتائج افضل من Prewitt Operators التقليدي . Sobel Operators وعطي نتائج افضل من Prewitt Operators التقليدي . يعطي نتائج افضل من Prewitt التقليدي والمحور . وكذلك وجد عند معالجة الصورة بـ prewitt التقليدي ثم بالمحور يعطي نتائج مشجعة مقارنة بـ prewitt التقليدي فيما لو طبق منفرد . ولكن يبقى Sobel operators هو الطريقة الدقيقة . 2