Image Edge Detection using Extended Epanechnicov Function and Non maxima Repression

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ABSTRACT
In this paper proposed an edge detection technique for gray level images, and which can overcome the limitations of gradient based edge detection methods. The 3 x 3 mask in the image is measured and two pixels S0 and S1 in the mask are used to define an objective function. The objective function value consistent of four directions determines the edge intensity and edge pixel in the mask. The edge map and direction map are generated, and then apply an extended Epanechnicov function as a fuzzy set membership function for each class where class assigned to each pixel is one with the greatest fuzzy truth about membership. This classification is done then used to the non-maxima repression method to extract the edge points. The proposed technique can detect the edge successfully, while double edges, thick edges, speckles edges can be avoided.

Key Words:
Image processing, Edge detection, Fuzzy classifier, Non-maxima repression

1. INTRODUCTION

The edge detection [1] plays an important role in image processing [2] of image analysis. Edges are the most basic feature of images. If the edges in an image are identified accurately, some basic properties such as area, perimeter and shape can be measured. An important property of the edge detection [3] method is its ability to extract the accurate edge line with better orientation in the consider image. There are many edge detectors proposed during the past two decades. Among all the existing technique [4] the gradient based detectors [5] are such as the Sobel edge operator [6], the Prewitt edge operator, the Robert edge operator, Laplacian and Canny [7], but some common problems of these are a large volume of computation, sensitivity to noise, anisotropy and thick lines. The image based on the abrupt change of gray level. But in the region with smooth gray level variation, the detected edge is always thicker. The digital image is applied such as areas of research and technology such as geographical information systems and astronomy as well as daily life like satellite television, magnetic resonance imaging.
The process of proposed edge detection algorithm which is optimized for extracting edge maps from image processing. The proposed edge detection system is based on the variations in the image gradient. The remainder of this paper is organized as follows. In section 2, the proposed approach is presented. Section 3 proposes a non-maxima repression edge detection method. The results are displayed in section 4. Financially, section 5 present conclusions.

2. METHODOLOGY

2.1 Image Classification

Edge detection does not matter the format of the image, it's essential to read the data information that compares the original image. It is assumed all image data are made by a data matrix of size M x N. There are different types of operations in image processing which operation will be performed will be performed the M x N matrix image. M x N matrix divided image into numbers of rows and numbers of columns.

$$f(i,j)=\begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,N-1) \\ f(1,0) & f(1,1) & \dots & f(1,N-1) \\ & & & \\ f(M-1,0) & f(M-1,1) & & f(M-1,N-1) \end{bmatrix}$$

As shown in fig.1.1 neighbors of central pixel P5 can be computed from the absolute intensity difference between neighbor pixels, its neighbors pixel is P1, P2….. P8. The bi-directional summed magnitude differences calculated in Competitive Fuzzy Edge Detection [8] may be inaccurate because only two neighbor pixels in each edge direction are taken into account. So improve it as bellow.
In the edge pattern of direction-1, nine pixels can be divided into two sets, S0 and S1 as S0 = {P1, P2, P3, P4, P5, P6} and S1 = {P7, P8, P9} or S0 = {P1, P2, P3} and S1 = {P4, P5, P6, P7, P8, P9}. The bi-directional summed magnitude differences in gray level between *S*0 and *S*1 are designated by *d*1, *d*2, *d*3 and *d*4 for directions 1, 2, 3 and 4, respectively, are calculated by

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$$d1 = \frac{1}{12}|(P1 + P2 + P3 + P4 + P5 + P6) - 2 * (P7 + P8 + P9)| + \frac{1}{12}|(P4 + P5 + P6 + P7 + P8 + P9) - 2 * (P1 + P2 + P3)| \quad (1)$$

$$d2 = \frac{1}{12}|(P1 + P2 + P3 + P5 + P6 + P9) - 2 * (P4 + P7 + P8)| + \frac{1}{12}|(P1 + P4 + P5 + P7 + P8 + P9) - 2 * (P2 + P3 + P6)| \quad (2)$$

$$d3 = \frac{1}{12}|(P1 + P2 + P4 + P5 + P7 + P8) - 2 * (P3 + P6 + P9)| + \frac{1}{12}|(P2 + P3 + P5 + P6 + P8 + P9) - 2 * (P1 + P4 + P7)| \quad (3)$$

$$d4 = \frac{1}{12}|(P1 + P2 + P3 + P4 + P5 + P7) - 2 * (P6 + P8 + P9)| + \frac{1}{12}|(P3 + P5 + P6 + P7 + P8 + P9) - 2 * (P1 + P2 + P4)| \quad (4)$$

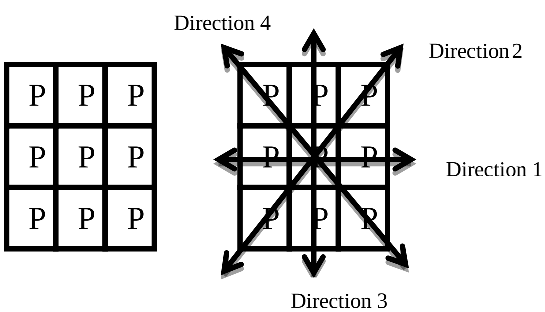

Figure 1: pixel and directions in 3 x 3 neighbourhoods

The gradient magnitude of traditional gradient based edge detection method is usually calculated as follows

$$\sqrt{d_1^2 + d_2^2 + d_3^2 + d_4^2} \quad (5)$$

However, this method neglects the relationship between each directional magnitude difference. For example, the gradient magnitude of some detailed region calculated by equation (5) may be very small because of interference or poor contrast. So it is difficult to extract these edges through an appropriate threshold. However, these edges can be detected through the following criterion: whether one directional magnitude difference is smaller than three other's. This thesis is just proposed based on this principle; the concrete process is described as follows. First, four-dimensional feature vector is defined as $X = (d1, d2, d3, d3)$ where *lo* and *hi* represent low and high summed magnitude differences in the directions indicated. The feature vector can approximately be expressed as *c* = (*lo*, *lo*, *lo*, *lo*) when four directional magnitude differences are small. Thus pixels can be divided into five classes according to the value.

In this step image is divided input image pixels into classes. The classes are defined in a background class, four classes for the edges and a class for speckles edge. The vectors will contain 'lo', 'mi' and 'hi' attributes. These attributes correspond to the amplitude in the four directions. The attributes lo and hi will be defined by the user depending on the degree of sensitivity needed in the application. The six vectors are given below:

Pixel Classes	Pixel Properties	Features Vectors
Class 0	Background	$C_0 = (l_0\ l_0\ l_0\ l_0)$
Class 1	Edge	$C_1 = (l_0\ h_i\ h_i\ h_i)$
Class 2	Edge	$C_2 = (h_i\ l_o\ h_i\ h_i)$
Class 3	Edge	$C_3 = (h_i\ h_i\ l_o\ h_i)$
Class 4	Edge	$C_4 = (h_i\ h_i\ h_i\ l_o)$
Class 5	Speckle edge	$C_5 = (h_i\ h_i\ h_i\ h_i)$

The six sets of membership function corresponding to six classes. The membership functions are represented by symmetrical triangular functions and determined by the central vector and a parameter, w, with which you can change the base of the surface. The parameter w is set by the user. After reading the input image, each pixel must be classified as belonging to one class, otherwise it will be considered as belonging to the background, and its color will be changed to black.

2.2 Extended Epanechnicov Function

A fuzzy set can be described by an infinite number of membership functions at the same time a weakness and strength: uniqueness is sacrificed at the advantage of flexibility, thus making the "adjustment" of a fuzzy model possible. On the four-dimensional feature space it define the fuzzy set membership functions for the six classes as extended Epanechnikov [9] functions by

Equation's. (6)– (11) for any input feature vector $\boldsymbol{x}$. The extended Epanechnikov functions are shown here with small diameters for clarity. In practice, they overlap so that each input feature vector falls into one or more of the fuzzy set membership functions. Such functions are dome shaped.

$$u_0\,(x) = max\left\{o, 1 - \frac{\|x-c_0\|}{w}\right\} \quad for\ class\ 0$$
(7)

$$u_0\,(x) = max\left\{o, 1 - \frac{\|x-c_2\|}{w}\right\} \quad for\ class\ 2$$
(8)

$$u_0\,(x) = max\left\{o, 1 - \frac{\|x-c_3\|}{w}\right\} \quad for\ class\ 3$$
(9)

$$u_0\,(x) = max\left\{o, 1 - \frac{\|x-c_4\|}{w}\right\} \quad for\ class\ 4$$
(10)

$$u_0\,(x) = max\left\{o, 1 - \frac{\|x-c_5\|}{w}\right\} \quad for\ class\ 5$$
(11)

2.3 The Non Maxima Repression Method

The concept of the local non-maxima of the magnitude of the gradient of image intensity in the direction of this gradient [10] also called NMR. Apply NMR to the direction maps and extract the edge points in the image, only the pixel whose edge intensity is the largest along the direction perpendicular to its edge direction can be regarded as an edge point. Therefore, the width of almost any edge line detected in the image is only one pixel. This avoids the occurring of the speckles and the double edges which are caused by the neighbor edge points closing the center edge point in the mask. NMR consists of:

1. Let a point (i; j), where i and j are integers and I (i; j) the intensity of the pixel (i; j).
2. The gradient calculates of image intensity and its magnitude in (i; j).
3. Estimate the magnitude of the gradient along the direction of the gradient in some neighborhood around (i; j).
4. If (i; j) is not a local maximum of the magnitude of the gradient along the direction of the gradient then it is not an edge point.

$I\,(i, j) = 1$ and $d\,(i, j) > d\,(i, j-1)$ and $d\,(i, j) > d\,(i, j+1)$.
$I\,(i, j) = 2$ and $d\,(i, j) > d\,(i-1, j)$ and $d\,(i, j) > d\,(i+1, j)$.
$I\,(i, j) = 3$ and $d\,(i, j) > d\,(i-1, j+1)$ and $d\,(i, j) > d\,(i+1, j-1)$.
$I\,(i, j) = 4$ and $d\,(i, j) > d\,(i-1, j-1)$ and $d\,(i, j) > d\,(i+1, j+1)$.

Usually for step 4 the neighborhood is taken to be 3X3 and the values of the magnitude are linearly interpolated between the closest points in the neighborhood,

2.4 Double Thresholding

Later the non-maximum repression step, the edge pixels are still marked with their strength pixel-by-pixel. These may be several real edges of the image, but some might be caused by noise or color variations for instance due to the rough surface. In instruction to get rid of such unpleasant state, it can apply thresholding so that only edges stronger than a certain value would be preserved. It has used double thresholding [11] in implementation. Edge pixels which are stronger than the high threshold are marked as strong; edge pixels which are weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak. Potential edges are determined by thresholding. It has kept the provision to tune this high threshold and low threshold parameter value if required.

3. RESULTS

The better result is achieved from our algorithm as compare to other edge detectors. The digital image as input is given and edges of that image are produced. The results are shown as below:

Figure: 2.1 (a) Original Image

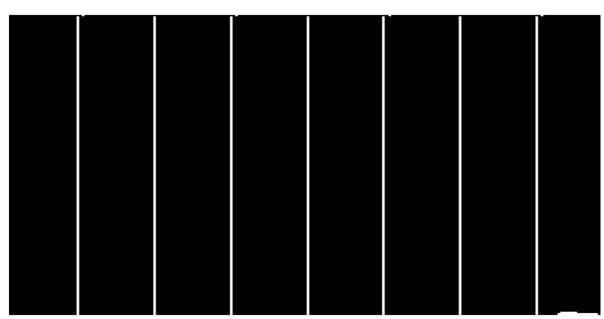

Figure: 2.2 (b) Output Image

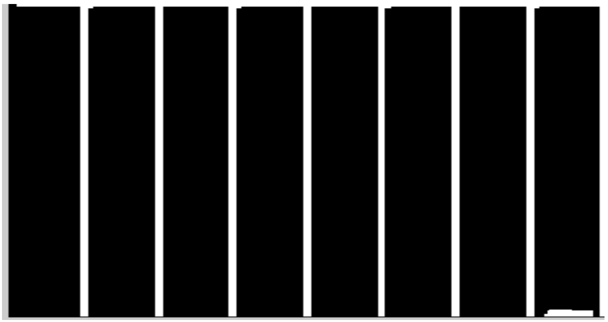

Figure: 2.3 (c) Output Image

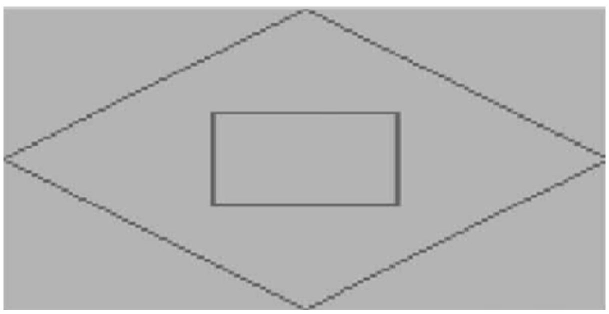

Figure: 3.1 (a) Original Image

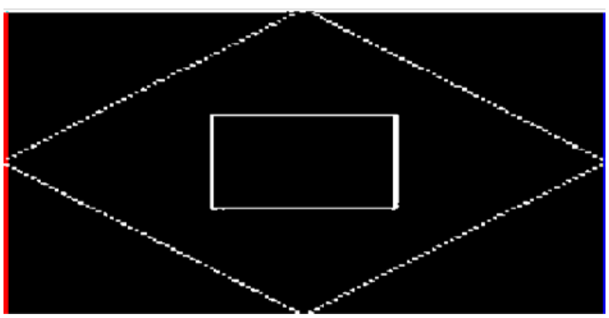

Figure: 3.2 (b) Output Image

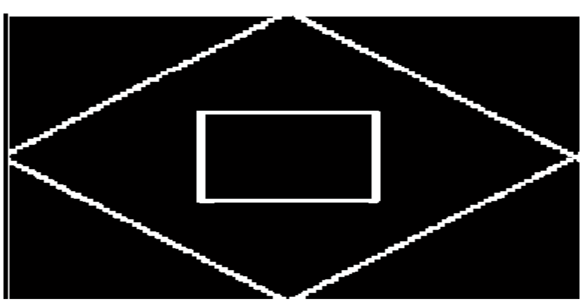

Figure3.3 (c) Output Image

4. CONCLUSIONS

This paper has provided a method to detect the edge in both monochrome and gray level images, based on the extended epanechnicov function, non-maxima repression and the double thresholding. The proposed method not only measures the intensity of the edge but also detects its direction so it can obtain edge maps and direction map. By applying maxima concept, the largest edge in the local image is extracted. It has used double thresholding; edge pixels which are stronger than the high threshold are obvious as strong; edge pixels which are weaker than low thresholds are suppressed and edge pixels between two thresholds are marked as weak. Clearly, the proposed method provides a better edge detection results and the proposed method does not have the drawback of thick edges and speckles edges.

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