MORPHOLOGIC EDGE DETECTION

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Abstract

Edge operators based on grayscale morphologic operations are introduced. These operators can be efficiently implemented in near real time machine vision systems which have special hardware support for grayscale morphologic operations. The simplest morphologic edge detectors are the dilation residue and erosion residue operators. The underlying motivation for these is discussed. Finally, the blur minimum morphologic edge operator is defined. Its inherent noise sensitivity is less than the dilation or the erosion residue operators.

Some experimental results are provided to show the validity of the blur minimum morphologic operator. When compared with the cubic facet second derivative zero-crossing edge operator, the results show that they have similar performance. The advantage of the blur minimum edge operator is that it is less computationally complex than the facet edge operator.

I. Introduction


This paper explores the capability of morphology to perform edge detection. As far as we can determine, the image processing literature does not discuss any grayscale morphological edge detector.

II. Basic Morphologic Operations

The dilation of a grayscale image \( f \) by a grayscale structuring element \( b \) is denoted by \( d \), and is defined by

\[
d(r, c) = \max_{i,j} (f(r-i, c-j) + b(i, j))
\]

Where the maximum is taken over all \((i, j)\) in the domain \(b\) such that \(r-i\) and \(c-j\) is the domain of \(f\). The domain of \(d\) is the dilation of the domain of \(f\) with the domain of \(b\). The erosion of a grayscale image \( f \) by a structuring element \( b \) is denoted by \( e \) and is defined by

\[
e(r, c) = \min_{i,j} (f(r+i, c+j) - b(i, j))
\]

where the minimum is taken over all \((i, j)\) in the domain of \(b\). The domain of \(e\) is the domain of \(f\) eroded by the domain of \(b\).

III. The Simple Morphological Edge Detectors

A simple method of performing gray scale edge detection in a morphology based vision system is to take the difference between an image and its erosion by a small structuring element. The difference image is the image of edge strength. We can then select an appropriate threshold value to threshold the edge strength image into a binary edge image.

We define rod as a grayscale structuring element which is flat on top and has disk like domain. As an example, the domain of the structuring element rod radius 1 is defined by the set

\[
D_{rod1} = \{(0, -1), (0, 1), (-1, 0), (1, 0)\}
\]

The \(D_{rod1}\) based erosion residue edge detector produce the edge strength image \( G_e \) defined by

\[
G_e(r, c) = f(r, c) - e(r, c)
\]

\[
e(r, c) = \min_{(i,j) \in D_{rod1}} f(r+i, c+j)
\]

\[
= \max_{(i,j) \in D_{rod1}} [ f(r, c) - f(r+i, c+j) ]
\]

Since \(D_{rod1}\) includes exactly the four connected neighbors of position \((0,0)\), the edge strength image we obtain is

\[
G_e(r, c) = \max_{(i,j) \in N_4(r,c)} [ f(r, c) - f(i, j) ]
\]

where \(N_4(r,c)\) is the set of four connected neighbors of position \((r,c)\).

It is possible to increase the neighborhood size of the morphologic edge operator. For example, by changing the structuring element to be flat on top and have domain...
$D_{8-connected} = \{(-1, -1), (0, -1), (1, -1),
(-1, 0), (0, 0), (1, 0), (-1, 1), (0, 1), (1, 1)\}$  

we can have an 8-connected neighborhood edge operator.

The erosion residue morphological edge detector is a nonlinear Laplacian-like operator which is noise sensitive, it cannot be a good edge detector for noisy images. The rule that increasing the neighborhood size of the operator will reduce the amount of noise fails with the erosion residue morphological edge detector. Consider, for example, the 8-connected based erosion residue morphological edge detector on the following image pattern

$$
\begin{array}{cccc}
F & F & F & F \\
F & F & F & F \\
F & F & 0 & F \\
F & F & F & F \\
0 & 0 & 0 & 0
\end{array}
$$

The pattern shown above is a flat area with pixel intensity $F$ and a noise spike at the center of this area with pixel intensity $0$. The response of the morphological edge operator is

$$
\begin{array}{cccc}
0 & 0 & 0 & 0 \\
0 & F & F & 0 \\
0 & F & 0 & F \\
0 & F & F & 0 \\
0 & 0 & 0 & 0
\end{array}
$$

which has the same value $F$ for all the 8-connected neighbors of the center point.

Similarly, we can define an edge operator as dilation residue

$$G_d(r, c) = d(r, c) - f(r, c) \tag{4}$$

IV. The Blur Minimum Morphologic Edge Detector

As mentioned in the previous section, the simple morphological edge operators are sensitive to noise. In this section we discuss the blur minimum morphological edge operator which can detect ideal step edges and are not noise sensitive.

The blur minimum morphological edge operator is defined by

$$I_{\text{edge-strength}} = \min\{I_1 - \text{Erosion}(I_1), \text{Dilation}(I_1) - I_1\} \tag{5}$$

where $I_1 = \text{Blur}(I_{\text{input}})$ and $\text{Blur}(I_{\text{input}})$ is the input image with a blurring operation. We use the same neighborhood size for the kernel of both blur and the structuring element of the dilation and erosion.

Consider the following one-dimensional step edge sequence as a motivation for this definition: The blur uses a neighborhood of width three and the erosion and dilation use a flat structuring element of domain $\{-1, 0, 1\}$.

The advantage of this operator, as illustrated below, is that it will not detect single noise point.

The reason why we need the small amount of blurring is that this operator only assigns a pixel to be an edge pixel if it has a value in the middle between two grayscale extremes of the neighborhood centered at the given pixel. Thus, there must be significant differences in grayscale value between the pixel and both its nearby grayscale maximum and nearby grayscale minimum pixel. The edge pixels for are the two pixels on either side of the jump. For the ideal step edge, these pixels are a local maximum and minimum. Hence, this operator can not detect the ideal step edges unless we blur the ideal step edge before applying this operator.

In order to have a better understanding of this edge operator, we give a derivation which explains this operator as an easily understandable local neighborhood non-linear operator. Let $K$ be the neighborhood size of the kernel of the blur and the domain of the structuring element. Without loss of generality we assume that $K$ is an odd number. Let $L = K - 1$, and $b_i = \text{Blur}(a_i)$, $e_i = b_i - \text{Erosion}(a_i)$, $d_i = \text{Dilation}(a_i) - b_i$, then

$$b_i = \frac{\sum_{p=i-L}^{i+L} a_p}{K}$$

$$e_i = \max_{q \in \{0, \ldots, K-1\}} \{b_i - b_{i+L-q}\}$$

$$\frac{1}{K} \max_{q \in \{0, \ldots, L\}} \left( \sum_{p=1}^{q} a_{i+L+p} - \sum_{p=1}^{q} a_{i-L+1+p} \right) - \left( \sum_{p=1}^{q} a_{i+L+1-p} - \sum_{p=1}^{q} a_{i-L+p} \right), 0 \right) \right)$$

and
\[ d_{i} = \max_{q \in \{0, \ldots, K-1\}} \{ b_{i-L-q} - b_{i} \} \]

\[ = \frac{1}{K} \max_{q \in \{1, \ldots, L\}} \left\{ \left( \sum_{p=1}^{q} a_{i-L-1-p} - \sum_{p=1}^{q} a_{i+L+1-p} \right) \right\} \]

For example, let \( K = 3 \), we define one-dimensional five point masks

\[ A_1 = \frac{1}{5} \begin{bmatrix} 1 & -1 & 0 & 0 & 1 \end{bmatrix} \]
\[ A_2 = \frac{1}{5} \begin{bmatrix} 0 & 1 & 0 & 0 & -1 \end{bmatrix} \]
\[ A_3 = \frac{1}{5} \begin{bmatrix} 1 & 0 & 0 & -1 & 0 \end{bmatrix} \]
\[ A_4 = \frac{1}{5} \begin{bmatrix} 0 & -1 & 0 & 0 & 1 \end{bmatrix} \]

And the edge detector outputs

\[ \min \{ \max \{ A_1 \ast f, A_2 \ast f \}, \max \{ A_3 \ast f, A_4 \ast f \} \} \]

where \( f \) is the input data and \( \ast \) is the convolution operation.

In the case that \( K = 5 \), we define one-dimensional nine point masks

\[ A_1 = \frac{1}{9} \begin{bmatrix} 1 & -1 & 0 & 0 & -1 & 0 & 1 & 0 & 1 \end{bmatrix} \]
\[ A_2 = \frac{1}{9} \begin{bmatrix} -1 & -1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix} \]
\[ A_3 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \end{bmatrix} \]
\[ A_4 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & -1 & -1 & 0 \end{bmatrix} \]
\[ A_5 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \end{bmatrix} \]
\[ A_6 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & -1 & -1 & 0 \end{bmatrix} \]
\[ A_7 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \]
\[ A_8 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 0 & -1 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \]
\[ A_9 = \frac{1}{9} \begin{bmatrix} 0 & 0 & 0 & -1 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \]

And the edge detector outputs

\[ \min \{ \max \{ A_1 \ast f, A_2 \ast f, A_3 \ast f, A_4 \ast f, A_5 \ast f, A_6 \ast f, A_7 \ast f, A_8 \ast f, A_9 \ast f \} \} \]

It is found that this operator finds the difference between each side of a given point. Instead of considering only the difference of the average pixel intensity on both sides of a pixel it considers differences of variety of local structures and combine the result of each difference by maximizations and a minimization operation. Thus, by increasing the neighborhood size of the blur operator and the neighborhood size of the morphologic operation this operator can reduce the noise effect and yet not blur too much the edges.

V. Experimental Results

To understand the performance of the morphologic edge operators, we examine the behavior of the morphologic edge operators on a simulated images and compare the results of the morphologic edge operators with the cubic facet second derivative edge operator (Haralick, 1984).

Figure 2 plots the probability results of these edge operators. The results show that the second derivative zero-crossing edge operator and the blur-minimum morphologic edge operator have similar performance. When the SNR is large, the blur-minimum edge operator of 5 X 5 neighborhood size and the cubic facet zero-crossing edge operator perform best. As the SNR becomes small, the blur-minimum edge operator having a 9 X 9 neighborhood size and the cubic facet zero-crossing edge operator perform best.

Finally, we illustrate an example of the morphologic edge detectors applied on a real image. The image is a figure for sand casting (see Figure 3(a)). We apply the blur minimum morphologic edge detector with 9 by 9 support, a difference of Gaussian operator with circular support of diameter 40 and 24 pixels (Marr, et al., 1980), and cubic facet second derivative zero-crossing of window size 9 by 9 on this image. The resulting edge images are shown in Figure 3(b)-3(d). A visual evaluation leaves the impression that the cubic facet edge operator and the blur-minimum morphologic edge detector have best performance. The difference of Gaussian operator produces thick edge lines and the edge connectivity is not as good as the blur-minimum edge operator.
VI. Conclusions

We have introduced some edge operators based on grayscale morphologic operations. These operators can be efficiently implemented in the machine vision systems which have special hardware support for morphologic operations. The simplest edge detectors are dilation residue and erosion residue operators. A combination called the blur minimum morphologic edge operator of these two simple operators has been introduced and justified.

Experimental results show the validity of the blur minimum morphologic edge operator. Upon comparing the performance of the morphologic edge detectors with the cubic facet second derivative zero-crossing edge operator, we found that the blur-minimum morphologic edge operator has performance comparable with the second derivative zero-crossing edge operator and it is less computational expensive. Thus it provides a less expensive way to find good edges from noisy images.

REFERENCES


Fig. 1. The perfect checkboard image and its noisy images. From left to right top to bottom are perfect, SNR = 6.67, SNR = 3.33, and SNR = 1.67, respectively. The image size is 100 X 100 pixels. The check size is 20 X 20 pixels. The edge contrast is 50 and the added noise is zero mean Gaussian noise.
Fig. 2. The performance probabilities of different edge operators applied on the noisy checkerboard images. curve 1: blur-minimum morphologic edge operator of 9 by 9 equivalent support; curve 2: second derivative zero-crossing edge operator of 9 by 9 support; curve 3: blur-minimum morphologic edge operator of 5 by 5 equivalent support; curve 4: second derivative zero-crossing edge operator of 5 X 5 support;

Fig. 3. The sand casting mold image (a) and its edge images; (b) Edge image of 9 by 9 blur-minimum morphologic edge operator; (c) Edge image of difference of Gaussian edge operator; (d) Edge image of the 9 X 9 cubic facet edge operator.