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Development of Statistical Edge Detector in Noisy Images and Implementation on the Web*

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Abstract

We describe a new edge detector based on the robust rank-order (RRO) test which is a useful alternative to Wilcoxon test, using $r \times r$ window for detecting edges of all possible orientations in noisy images.

Some experiments of statistical edge detectors based on the Wilcoxon test and T test with our RRO detector are carried out on synthetic and real images corrupted by both Gaussian and impulse noise. We also implement these edge detectors using Java on the Web

Key Words : Statistical edge detector; Robust rank-order detector, Wilcoxon detector; Noisy images; Web.

1. Introduction

Edge detection is a critical element in image processing, since edges contain a major fraction of image information. The function of edge detection is to identify the boundaries of homogeneous regions in an image based on properties such as intensity and texture.

Many edge detection operators have been developed based on computation of the intensity gradient vector, which, in general, is sensitive to noise in the image. Examples of these types of operators are Sobel operator, Roberts operator and Laplacian operator (Gonzalez and Woods(1992)). Alternatively, edge detection has been dealt with in the framework of statistics by some authors, e.g., Bovik et al. (1986), Huang and Tseng (1988), Lim and Jang (2002), and Hou and Koh(2003).

In this paper we describe a new edge detector based on the robust rank-order (RRO) test which is a useful alternative to Wilcoxon test, using $r \times r$ window for detecting edges of all

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possible orientations in noisy images. Our method is based on testing whether a $r\times r$ window is partitioned into two subregions having significant differences in local gray-level value between neighborhoods of a given pixel, using an edge-height model to extract edges of some sufficient height from images corrupted with noises.

The paper is organized as follows. In Section 2, we formulate a RRO test using an edge-height model for application to the edge detection problem. In Section 3, some experimental comparisons of statistical edge detectors such as the Wilcoxon test (Bovik et al. (1986), Lim and Jang (2002)) and T test (Lim and Jang (2002)) with our RRO detector are performed on both noisy image and noise-free images.

2. Edge Detection Based on Robust Rank-Order Test

It can be understood from Figure 1 that if an edge exists in the window, at least one of the partitions is matched with the direction of the edge. Here we only describe the detection algorithm for the diagonal edge oriented in the 135^o direction in Figure 1(a), as the final edge decision is simply taken to be the "OR" of each directional decision.

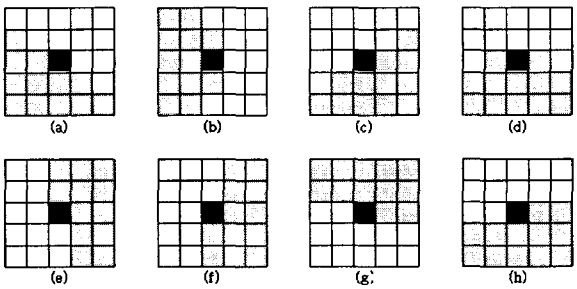


Figure 1. Partitioning the window in eight different ways where medium dark areas represent $\boldsymbol{X}$ partition and white areas represent $\boldsymbol{Y}$ partition.

We consider a set of $N=m+n$ independent observations excluding the center pixel which are divided into $\boldsymbol{X}=(X_1,\dots,X_m)$ and $\boldsymbol{Y}=(Y_1,\dots,Y_n)$, where the first samples come from continuous distribution $F(x-\mu_x)$, and the second samples from $G(y-\mu_y)$with shift parameter μ_x and μ_y.

Now consider the edge model with an edge-height parameter δ defined as follows:

$$A_i=\begin{cases} X_i+\delta & ;X_i\in\boldsymbol{X} \\ X_i & ;X_i\in\boldsymbol{Y}\end{cases} \text{ and } B_i=\begin{cases} X_i-\delta & ;X_i\in\boldsymbol{X} \\ X_i & ;X_i\in\boldsymbol{Y}\end{cases}.$$

Then we are interested in testing

$$H_0^{\uparrow} : \mu_x + \delta \geq \mu_y \quad versus \quad H_1^{\uparrow} : \mu_x + \delta < \mu_y$$

and

$$H_0^{\downarrow} : \mu_x - \delta \leq \mu_y \quad versus \quad H_1^{\downarrow} : \mu_x + \delta > \mu_y.$$

First, the RRO statistic for testing $H_0^{\uparrow}$ against $H_1^{\uparrow}$ on the $\{A_i\}$ is obtained as follows: For each $X_i + \delta$, $X_i \in X$ we count the number of lower-valued observations Y_i's in Y. This number represents the placement of the $X_i + \delta$ and will be denoted by $U(Y, X_{i+\delta})$. We then find the mean of the $U(Y, X_{i+\delta})$ by $U(Y, X+\delta) = \sum_{i=1}^{m} U(Y, X_{i+\delta})/m$. Similarly, we find the placement of each Y_i, $Y_i \in Y$. That is, we find $U(X+\delta, Y_i)$, the number of observations $X_i + \delta$, $X_i \in X$ which precede each Y_i. We then find the mean of the $U(X+\delta, Y_i)$ by $U(X+\delta, Y) = \sum_{i=1}^{n} U(X+\delta, Y_i)/n$. Next, let us define an index of variability of $U(Y, X_i +$ delta) and $U(X+\delta, Y_i)$ to be where $V_{x+\delta} = \sum_{i=1}^{m}[U(Y, X_i+\delta) - U(Y, X+\delta)]^2$ and $V_{y+\delta} = \sum_{i=1}^{n}[U(X+\delta, Y_i) - U(X+\delta, Y)]^2$.

The test statistic is thus given by

$$U_A = \frac{m \cdot U(Y, X+\delta) - n \cdot U(X+\delta, Y)}{2\sqrt{V_{x+\delta} + V_{y+\delta} + U(Y, X+\delta) \cdot U(X+\delta, Y)}}.$$

Then, the RRO statistic for testing $H_0^{\downarrow}$ against $H_1^{\downarrow}$ on the $\{B_i\}$ is given by

$$U_B = \frac{m \cdot U(Y, X-\delta) - n \cdot U(X-\delta, Y)}{2\sqrt{V_{x-\delta} + V_{y-\delta} + U(Y, X-\delta) \cdot U(X-\delta, Y)}}.$$

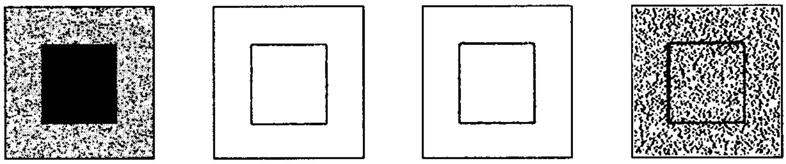
We reject $H_0^{\uparrow}$ (or $H_0^{\downarrow}$) for large values of

$$U^* = \max(U_A, U_B).$$

An edge is then detected if $U^* > u_\alpha$, for a specified threshold u_α at a significance level α. Fligner and Pollicello (1981) and Feltovich (2003) present critical values of U^* for small sample sizes up to 12.

3. Experimental Results

In this study we compare our RRO detector with two statistical detectors such as the Wilcoxon and T detectors for edge detection. Figure 2 shows the one of synthetic images used in this experiment and the results of applying the three statistical detectors to the synthetic image.



(a) (b) (c) (d)

Figure 2. (a) synthetic image corrupted by impulse noise I0.1, (b) edge map obtained by RRO detector (c) edge map obtained by Wilcoxon detector (d) edge map obtained by T detector

Figure 3 shows the one of natural images used in this experiment and the results of applying the three statistical detectors to the natural image.

(a) (b) (c) (d)

Figure 3. (a) Lenna image corrupted by Gaussian noise G25 (b) edge map obtained by RRO detector (b) edge maps obtained by Wilcoxon detector (c) edge map obtained by T detector

The RRO detector performs slightly better than the Wilcoxon detector in both Gaussian and impulse noise. For Gaussian noise, the T detector produces thicker edges; however, there is considerable noise speckling in impulse noise, as shown in Figure 2(d). Figure 4 shows the online Java image processing which is an applet/cation developed by 100% pure Java. It can perform many interesting image processing functions including edge detectors.

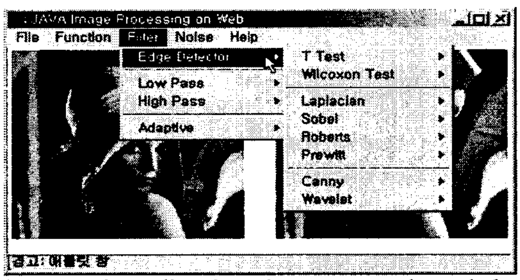


Figure 4. the online Java image processing window

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