Study and comparison of various image edge detection techniques used in quality inspection and evaluation of agricultural and food products by computer vision

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Abstract: Edges characterize boundaries and are therefore a problem of fundamental importance in quality assessment of agricultural and food products. Since edge detection is in the forefront of computer vision system for detection of vegetables, fruits and food grains needs to quality inspection and evaluation, it is crucial to have a good understanding of edge detection algorithms. In this paper the comparative analysis of various Image Edge Detection techniques is presented. The software is developed using MATLAB 7.6. It has been shown that the Canny's edge detection algorithm performs better than all operators (i.e. LoG, Robert, Prewitt and Sobel) under almost all scenarios.

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1 Introduction

Edge detection refers to the process of identifying and locating sharp discontinuities in an image's like vegetables, fruits and food grains. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in an image. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. This is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. Variables involved in the selection of an edge detection operator include:

1) Edge orientation: The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges.

2) Noise environment: Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Reducing the noise will result in blurred and distorted edges. Operators used in noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges.

3) Edge structure: Not all edges involve a step change in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The operator needs to be chosen to be responsive to such a gradual change in those cases. Newer wavelet-based techniques actually characterize the nature of the transition for each edge in order to distinguish, for example, edges associated with hair from edges associated with a face.

There are many ways to perform edge detection. However, the majority of different methods may be

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grouped into two categories: Gradient and Laplacian[1-6].

The primary objective is first we analyzed the various edge detection techniques (i.e. LoG, Robert, Prewitt, Zero-cross, canny and Sobel) and shown the visual comparisons of various edge detection techniques.

The visual comparison of the most commonly used Gradient and Laplacian based Edge Detection techniques was analyzed and performed. In Section 2 the problem definition with the Gradient and Laplacian working methods is presented. In Section 3 the various edge detection techniques have been studied and analyzed. In Section 4 the visual comparisons of various edge detection techniques have been done by developing software in MATLAB 7.6. Section 5 discusses the advantages and disadvantages of various edge detection techniques. Section 6 discusses the conclusion reached by analysis and visual comparison of various edge detection techniques developed using MATLAB 7.6.

2 Problem definition

There are problems of false edge detection, missing true edges, producing thin or thick lines and problems due to noise etc. We analyzed and performed the visual comparison of the most commonly used Gradient and Laplacian based edge detection techniques for problems of inaccurate edge detection, missing true edges, producing thin or thick lines and problems due to noise etc. The software is developed using MATLAB 7.6.

The methods of most commonly used Gradient and Laplacian based edge detection techniques are as follows.

2.1 Gradient

The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

2.2 Laplacian

The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location. Suppose we have the following signal, with an edge shown by the jump in intensity (Figure 1)[2,6].

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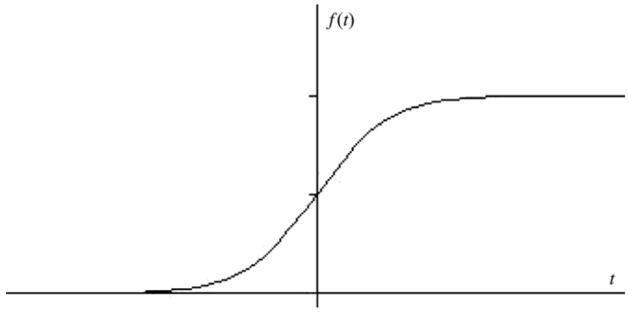


Figure 1 Following signal applied to the edge detector

If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to *t*) we get the following (shown in Figure 2).

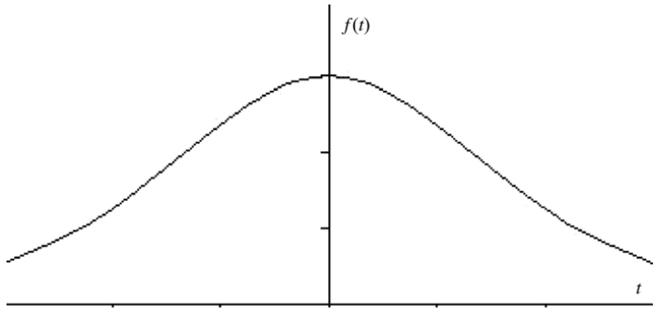


Figure 2 Gradient first derivative signal

Clearly, the derivative shows (Figure 2) a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the “gradient filter” family of edge detection filters and includes the Sobel method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As mentioned before, edges will have higher pixel intensity values than those surrounding it. So once a threshold is set, you can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded[6-7].

Furthermore, when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to find the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is shown in Figure 3[6-7].

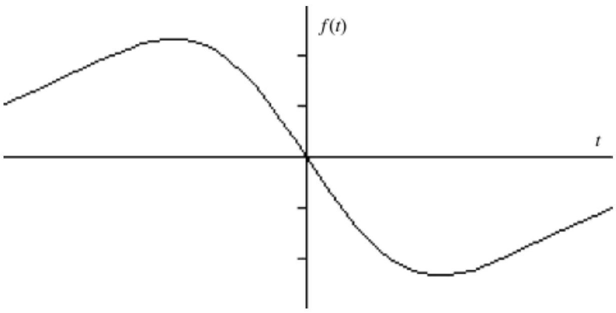


Figure 3 Gradient second derivative signal

3 Edge detection techniques

3.1 Sobel operator

The operator consists of a pair of 3×3 convolution kernels as shown in Figure 4. One kernel is simple, the other rotated by 90°.

-1	0	+1
-2	0	+2
-1	0	+1

a. *Gx*

+1	+2	+1
0	0	0
-1	-2	-1

b. *Gy*

Figure 4 Masks used by Sobel operator

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these *Gx* and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient[6,8]. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2} \quad (1)$$

Typically, an approximate magnitude is computed using:

$$|G| = |Gx| + |Gy| \quad (2)$$

Which is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$\theta = \arctan(Gy / Gx) \quad (3)$$

3.2 Robert's cross operator

The Roberts Cross operator performs a simple and quick computing, 2-D spatial gradient measurement on an image. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. The operator consists of a pair of 2×2 convolution kernels as shown in Figure 5. One kernel is simply the other rotated by 90°[6,9]. This is very similar to the Sobel operator.

+1	0
0	-1

a. *Gx*

0	+1
-1	0

b. *Gy*

Figure 5 Masks used for Robert operator.

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these *Gx* and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by Equation (1). Although typically, an approximate magnitude is computed using Equation (2), which is much faster to compute.

The angle of orientation of the edge giving rise to the spatial gradient (relative to the pixel grid orientation) is given by

$$\theta = \arctan(Gy \mid Gx) - 3\pi / 4 \quad (4)$$

3.3 Prewitt's

Prewitt operator[2] is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

-1	0	+1
-1	0	+1
-1	0	+1

a. *Gx*

+1	+1	+1
0	0	0
-1	-1	-1

b. *Gy*

Figure 6 Masks for the Prewitt gradient edge detector

3.4 Laplacian of Gaussian

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian Smoothing filter in order to reduce its sensitivity to noise. The operator normally takes a single gray level image as input and produces another gray level image as output. The Laplacian $L(x,y)$ of an image with pixel intensity values $I(x,y)$ is given by:

$$L(X,Y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (5)$$

Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian[2]. Three commonly used small kernels are shown in Figure 7.

1	1	1
1	-8	1
1	1	1

0	1	0
1	-4	1
0	1	0

-1	2	-1
2	-4	2
-1	2	-1

Figure 7 Three commonly used discrete approximations to the Laplacian filter

Because these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise. To counter this, the image is often Gaussian Smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components prior to the differentiation step.

In fact, since the convolution operation is associative, we can convolve the Gaussian smoothing filter with the Laplacian filter first of all, and then convolve this hybrid filter with the image to achieve the required result. Doing things this way has two advantages: Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations.

The *LoG* ('Laplacian of Gaussian')[10] kernel can be pre-calculated in advance so only one convolution needs to be performed at run-time on the image. The 2-D LoG function[6,11] centered on zero and with Gaussian standard deviation σ has the form:

$$LoG(x,y) = -1/\pi\sigma^4 \left[1 - \left(\frac{x^2+y^2}{2\sigma^2}\right)\right] e^{\frac{x^2+y^2}{2\sigma^2}} \quad (6)$$

and shown

0	1	0
1	-4	1
0	1	0

in Figure 8.

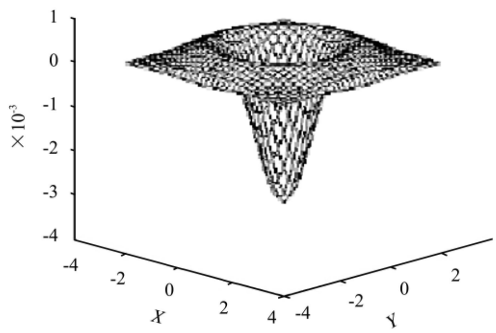


Figure 8 2-D Laplacian of Gaussian (*LoG*) function. The *x* and *y* axes are marked in standard deviations (*σ*)

A discrete kernel that approximates this function (for a Gaussian $\sigma = 1.4$) is shown in Figure 9.

0	1	1	2	2	2	1	1	0
1	2	4	5	5	5	4	2	1
1	4	5	3	0	3	5	4	1
2	5	3	-12	-24	-12	3	5	2
2	5	0	-24	-40	-24	0	5	2
2	5	3	-12	-24	-12	3	5	2
1	4	5	3	0	3	5	4	1
1	2	4	5	5	5	4	2	1
0	1	1	2	2	2	1	1	0

Figure 9 Discrete approximation to *LoG* function with Gaussian = 1.4

Note that as the Gaussian is made increasingly narrow, the *LoG* kernel becomes the same as the simple Laplacian kernels shown in Figure 7. This is because smoothing with a very narrow Gaussian ($\sigma < 0.5$ pixels) on a discrete grid has no effect. Hence on a discrete grid, the simple

Laplacian can be seen as a limiting case of the *LoG* for narrow Gaussians[6,12-14].

3.5 Canny edge detection algorithm

The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. He was very successful in achieving his goal and his ideas and methods can be found in his paper, "A Computational Approach to Edge Detection"[6,15]. In his paper, he followed a list of criteria to improve current methods of edge detection. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed and that there be no responses to non-edges. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum. A third criterion is to have only one response to a single edge. This was implemented because the first two were not substantial enough to completely eliminate the possibility of multiple responses to an edge.

This is a multi-step edge detection procedure by Canny[15]. The purpose of the following two methods is to detect edges with noise suppressed at the same time.

1) Smooth the image with a Gaussian filter to reduce noise and unwanted details and textures.

$$g(m,n) = G\sigma(m,n) * f(m,n) \tag{7}$$

Where,

$$G\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{m^2+n^2}{2\sigma^2}\right] \tag{8}$$

Compute gradient of $g(m,n)$ by using any of the gradient operators (Sobel, Prewitt, etc) to get:

$$M(m,n) = \sqrt{g^2 m(m,n) + g^2 n(m,n)} \tag{9}$$

and

$$\theta = \tan^{-1}\left[\frac{gn(m,n)}{gm(m,n)}\right] \tag{10}$$

2) Threshold *M*:

$$M_T(m,n) = \begin{cases} M(m,n) \\ 0 \end{cases} \text{ if } M(m,n) > T \text{ otherwise } 0 \tag{11}$$

Where *T* is so chosen that all edge elements are kept while most of the noise is suppressed.

3) Suppress non-maxima pixels in the edges in M_T obtained above to thin the edge ridges (as the edges might have been broadened in step 1). To do so, check to see whether each non-zero $M_T(m, n)$ is greater than its two neighbors along the gradient direction $\theta(m, n)$. If so, keep $M_T(m, n)$ unchanged, otherwise, set it to 0.

4) Threshold the previous result by two different thresholds *T*1 and *T*2 (where *T*1< *T*2) to obtain two binary images *T*1 and *T*2. Note that compared to *T*1, *T*2 has less noise and fewer false edges but larger gaps between edge segments.

5) Link edges segments in *T*2 to form continuous edges. To do so, trace each segment in *T*2 to its end and then search its neighbors in *T*1 to find any edge segment in *T*1 to bridge the gap until reaching another edge segment in *T*2.

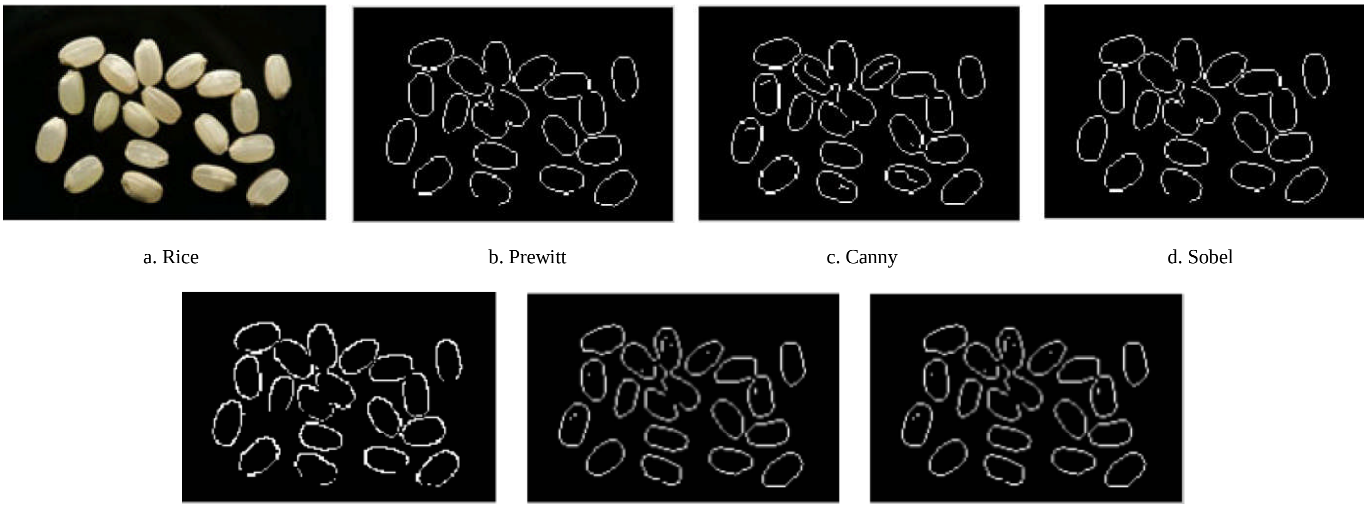
4 Visual comparison of various edge detection algorithms

4.1 Fruits

a. Apples b. Prewitt c. Canny d. Sobel e. Roberts f. LoG g. Zero Crossing

Figure 10 Canny is the best among results of fruits edge detection

4.2 Grains

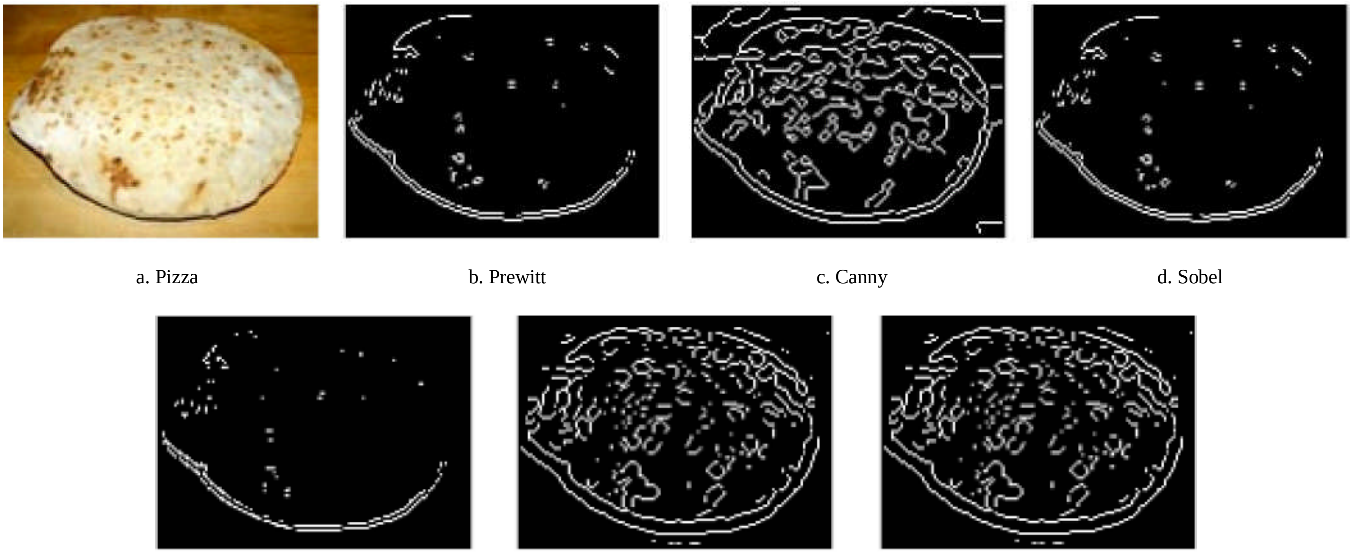


a. Rice b. Prewitt c. Canny d. Sobel

e. Roberts f. LoG g. Zero Crossing

Figure 11 Canny is the best among results of fruits edge detection

4.3 Bakery food product



a. Pizza b. Prewitt c. Canny d. Sobel

e. Roberts f. LoG g. Zero Crossing

Figure 12 Canny is the best among results of fruits edge detection

Edge detection of all four types was performed on above Figures 10a, 11a and 12a[16]. Canny yielded the best results. This was expected as Canny edge detection accounts for regions in an image. Canny yields thin lines for its edges by using non-maximal suppression. Canny also utilizes hysteresis with thresholding.

5 Advantages and disadvantages of edge detector

As edge detection is a fundamental step in computer vision, it is necessary to point out the true edges to get the best results from the matching process. That is why it is important to choose edge detectors that fit best to the application. In this respect, we first present some advantages and disadvantages of edge detection techniques[3-6, 16-21] within the context of our classification in Table 1.

Table 1 Some advantages and disadvantages of edge detectors

Operator	Advantages	Disadvantages
Classical (Sobel, prewitt, Kirsch,…)	Simplicity, Detection of edges and their orientations	Sensitivity to noise, Inaccurate
Zero Crossing(Laplacian, Second directional derivative)	Detection of edges and their orientations. Having fixed characteristics in all directions	Responding to some of the existing edges, Sensitivity to noise
Laplacian of Gaussian(LoG) (Marr-Hildreth)	Finding the correct places of edges, Testing wider area around the pixel	Malfunctioning at the corners, curves and where the gray level intensity function varies. Not finding the orientation of edge because of using the Laplacian filter
Gaussian (Canny, Shen-Castan)	Using probability for finding error rate, Localization and response. Improving signal to noise ratio, Better detection specially in noise conditions	Complex Computations, False zero crossing, Time consuming

6 Conclusions

Since edge detection is the initial step in object recognition, it is important to know the differences between edge detection techniques. In this paper we studied the most commonly used edge detection techniques of Gradient-based and Laplacian based edge detection. The software is developed using MATLAB 7.6.

Gradient-based algorithms such as the Prewitt filter have a major drawback of being very sensitive to noise. The size of the kernel filter and coefficients are fixed and cannot be adapted to a given image. An adaptive edge-detection algorithm is necessary to provide a robust solution that is adaptable to the varying noise levels of these images to help distinguish valid image contents from visual artifacts introduced by noise.

The performance of the Canny algorithm depends heavily on the adjustable parameters, σ, which is the standard deviation for the Gaussian filter, and the threshold values, '$T1$' and '$T2$'. σ also controls the size of the Gaussian filter. The bigger the value for σ, the larger the size of the Gaussian filter becomes. This implies more blurring, necessary for noisy images, as well as detecting larger edges. As expected, however, the larger the scale of the Gaussian, the less accurate is the localization of the edge. Smaller values of σ imply a smaller Gaussian filter which limits the amount of blurring, maintaining finer edges in the image. The user can tailor the algorithm by adjusting these parameters to adapt to different environments.

Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator. However, the Canny's edge detection algorithm performs better than all these operators under almost all scenarios. Evaluation of the images showed that under noisy conditions, Canny, LoG, Sobel, Prewitt, Roberts's exhibit better performance, respectively.

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