Improvements to Canny's Edge Detection Algorithm

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CERTIFICATE

*This is to certify that the work contained in this thesis entitled "**Improvements to Canny's Edge Detection Algorithm**" is a bonafide work of **Arpan Indora** (**Roll No. 140101011**), carried out in the Department of Computer Science and Engineering, Indian Institute of Technology Guwahati under my supervision and that it has not been submitted elsewhere for a degree.*

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Chapter 1

Introduction

Edges represent important features in an image, and are also important attributes in early stages of recognition in the human eye. They are the significant local changes of intensity in an image and can be described as areas of discontinuity within an object or changes in illumination and color. Edges typically occur between boundaries of two different regions which exhibit some local uniformity among themselves.

1.1 Edge Detection

Edge detection is usually the first step in recovering information from an image. The main purpose of edge detection is to significantly reduce the image size and filter out information which may be regarded as irrelevant, and also preserve structural properties of the image for further processing. Often, edges occur at locations in an image which represent object boundaries, so edge detection is extensively used in image segmentation when the images are divided into areas corresponding to different objects.

1.2 Edge Detection Algorithms

Edges are usually associated with discontinuity in image intensity or first derivative of the image intensity. Their are several algorithms, which use the first and the second order derivatives to give information about this intensity change. Although first order differential operator methods like Robert, Sobel, Prewitt and second order differential operator methods like Laplacian and Marr-Hilderth's edge detection method which uses zero crossing of Laplacian of Gaussian of an image[5], are simple and computationally less intensive, but are often sensitive to noise, and therefore not applicable for engineering applications. Among the existing edge detection methods, John F. Canny's edge detection algorithm is the most widely used and optimized approach to problem, which is owed to its evaluation criterion based on good detection, localization, and minimal response to an edge. This report focuses on this algorithm presented by John F. Canny in 1986[3].

1.3 Canny's Edge Detection Approach

The success of Canny's approach can be attributed to its comprehensive set of precise goals, enough to produce the desired behaviour of the algorithm while making minimal assumptions about the solution. Basically, his approach was to develop an algorithm whose performance relies on following criteria:

- **Good Detection:** The probability of detecting non edge points should be minimized and the probability of marking true edge point should be maximized. Both of these probabilities are functions of Signal to Noise Ratio(SNR), and the objective corresponds to maximizing this SNR.

- **Good Localization:** Detected edges should be as close as possible to the real edges in the image.

- **Minimum Response:** There should be only one response for an edge, that is, the noise should not lead to false edges. This is implicit by the first criteria but this criteria was intentionally added because first criteria's mathematical formulation could not capture this criteria.

Canny's edge detection algorithm can be summarized in following steps:

1. Apply Gaussian filter to smooth out the image, removing noise and other unwanted features.

$$f_s(x,y) = \sum_{i=-1}^{1}\sum_{j=-1}^{1} G(i,j) * f(x+i, y+j) \quad \text{,where } G(x,y) = \frac{1}{\sqrt{2\pi}\sigma} exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1.1}$$

2. Find the gradient of the image using 2x2 vertical and horizontal gradient operators, and then obtain gradient magnitude M and direction θ.

$$M(x,y) = \sqrt{\frac{\partial f_s}{\partial x}^2 + \frac{\partial f_s}{\partial y}^2}, \quad \theta(x,y) = tan^{-1}\left(\frac{\partial f_s/\partial y}{\partial f_s/\partial x}\right) \tag{1.2}$$

3. To obtain a single response for each edge, apply Non Maximum Suppression. Mark a point only if the gradient magnitude $M(x,y)$ of that point is higher than the neighbours in the gradient direction $\theta(x,y)$.
4. Using Double Threshold T_h and T_l, where $T_h > T_l$, reject the points whose gradient value is less than T_l, and if the gradient magnitude is greater than T_h mark those points as strong edges and output them. For points with gradient value between T_h and T_l, mark them as weak edges. Then finally add weaker edges to the output, if they are connected to the strong edges, directly or indirectly.

1.4 Otsu's Segmentation method

This section is an introduction Otsu's segmentation[4] method which will be later used in chapter 3. In this method, we try to divide a set of values into two clusters by separating them at a threshold, and we want this threshold such that it keeps the two resulting clusters closely tight while maximizing the separation between them. This objective corresponds to minimizing (within)intra-class variance or maximizing of (between)inter-class variance of the two clusters. If two classes A and B are separated by threshold t, then their within class variance is defined as

$$\sigma_w^2 = p_A \sigma_A^2(t) + p_B \sigma_B^2(t) \tag{1.3}$$

where σ_A^2, σ_B^2 are variances of two classes, and p_A, p_B are the probabilities that the two classes are divided by threshold t. Minimizing this within class variance σ_w^2 is equivalent to maximizing the between class variance σ_b^2, defined as

$$\sigma_b^2 = \sigma^2 - \sigma_w^2 \;=\; p_A(t)[\mu - \mu_A]^2 + p_B(t)[\mu - \mu_B]^2 \tag{1.4}$$

Here μ and σ^2 are the global mean and global variance respectively. So, by going through all the possible values of threshold t we can find a value that maximizes this between class variance σ_b^2 and minimizes within class variance σ_w^2.

Chapter 2

Literature Review

2.1 Issues with Canny's edge detection algorithm

Although Canny's method is still widely used at present, there are few aspects of the algorithm which can be improved and made more adaptive to different images with varying properties like noise and edge information.

1. The Gaussian filter applied to remove noise in the image, also smooths out the real edges, which increases the probability of missing out a real weak edge.
2. Canny's traditional algorithm uses 2x2 operator to compute the image gradient, which is more sensitive noise and because of not joining 45^o and 135^o directions, it can easily loose the real edge information[1].
3. Double threshold T_h and T_l are found by trail method, as there is no standard method to choose these values because of the varying properties of different images. This report provides an insight as to how they can be estimated for selection.

2.2 Existing Solutions

By using a 3x3 gradient operator more edge information can be preserved. Experimental observations have shown that larger masks provide better edge detection results. And also, edge detection method using gravitation field intensity operator works better than both Sobel and Prewitt gradient operators, as it retains more useful information about an edge and has good inhibition effect on the noise present in image[1]. Using the following gravitational field intensity formula, we define operators G_x and G_y,

$$\overrightarrow{E} = \frac{Gm}{|\overrightarrow{r}|^2}.\frac{\overrightarrow{r}}{|\overrightarrow{r}|} \tag{2.1}$$

Here m is a pixel's grey value. The resulting gravitational field intensity $\overrightarrow{E}_{total}$ on a point is superposition of the gravitational field intensity due to all the neighbouring pixels. Taking $G = 1$ the resulting 3x3 operator can be written as,

$$G_x = \begin{bmatrix} -\sqrt{2}/4 & 0 & \sqrt{2}/4 \\ -1 & 0 & 1 \\ -\sqrt{2}/4 & 0 & \sqrt{2}/4 \end{bmatrix} \quad G_y = \begin{bmatrix} \sqrt{2}/4 & 1 & \sqrt{2}/4 \\ 0 & 0 & 0 \\ -\sqrt{2}/4 & -1 & -\sqrt{2}/4 \end{bmatrix} \tag{2.2}$$

and,

$$M'(x, y) = \sqrt{{E_x}^2 + {E_y}^2}, \quad \theta' = tan^{-1}(E_y/E_x) \tag{2.3}$$

Further, selection of double threshold can be done by analysing the image gradient histogram. The mean of gradient represents the center location of the gradient magnitude distribution and standard deviation of gradient is the dispersion of the gradient values in the image. And the threshold values have a close relationship with the mean and the standard deviation of gradient magnitude[2]. For images with less edge information, the majority of gradient values are located in a small range. So the threshold values can be chosen as:

$$T_h = \mu + k.\sigma \quad \text{, where } k \ \epsilon \ (1.2, 1.8) \qquad T_l = T_h/2 \tag{2.4}$$

The above thresholds T_h and T_l work well when there is low edge information in the image but fail when there is high edge information present in an image. Since for an image with high edge information, the standard deviation is also quite large, which leads to omission of strong edges due to resulting high upper threshold.

2.3 Conclusion

This chapter provided details of existing method for solving the problem of edge information loss due to gradient operator and a double threshold estimation method. In next chapter, we discuss adaptive filtering and a selection method for double threshold using Otsu's segmentation, and how it can be used in Canny's edge detection algorithm.

Chapter 3

Improvements

3.1 Adaptive Filtering

To apply the image filtering without loosing any edge information, we need to increase the smoothing effect on noise and reduce its effect on weak edges present in the image. To accomplish this goal we use an adaptive filter on the image. This filter will evaluate the discontinuity in pixel intensity at each point. The lower the discontinuity, higher will be the smoothing at that point and vice versa. This process can be applied recursively till the correlation between the noise and smoothed image is minimized. Objective is,

$$Min\left\{\frac{cov(I_o - I_s, I_s)}{\sqrt{var(I_o - I_s)}\sqrt{var(I_s)}}\right\}, \quad \text{where } I_s \rightarrow \text{smoothed image and } I_o \rightarrow \text{original image}$$

Implementation of this process can be summarized as follows for n iterations,

Step 1: Calculate the $G_x^{(i)}(x,y)$,$G_y^{(i)}(x,y)$ gradient values using any gradient operator.

Step 2: Calculate weights,

$$W^{(i)}(x,y) = exp\left(-\frac{\sqrt{\left[G_x^{(i)}(x,y)\right]^2 + \left[G_y^{(i)}(x,y)\right]^2}}{2d^2}\right)$$

Step 3: Apply filter,

$$f_s^{(i)}(x,y) = \frac{1}{D}\sum_{i=-1}^{1}\sum_{j=-1}^{1} f_s^{(i-1)}(x+i,y+j).W^{(i)}(x+i,y+j)$$

where $D = \sum_{i=-1}^{1}\sum_{j=-1}^{1} W(x+i,y+j)$.

Step 4: If $i = n$ stop, else go to step 1.

3.2 Automated Double Threshold Selection

Using Ostu's segmentation method we find a threshold using gradient magnitude histogram of the image that separates the low and high gradients, then use this threshold to find the low and high threshold for the step of double thresholding. Steps to find the double threshold using gradient histogram of the image are as follows,

- Find the threshold t that minimizes intraclass variance or maximizes interclass variance of gradient value classes formed by threshold t, this can be done by using equation 1.3 and 1.4 respectively.

- Suppose the two cluster formed by threshold t are, A and B, where A has edge points that have higher gradient values and B has non edge points with lower gradient values. Find their mean μ_A, μ_B, and standard deviations σ_A,σ_B.

- Now further, we can assume that the non edge pixels lie in the range $\mu_B \pm \sigma_B$. So the high threshold T_h must not lie in this range, because if T_h lies in that range then non edge points will result as false edges. This implies that T_h should be greater than $\mu_B + \sigma_B$.

- Cluster B can be further divided for low threshold T_l into weak edge and non edge points by again using Otsu's Segmentation. The other choice is to simply choose $T_l = \mu_B$.

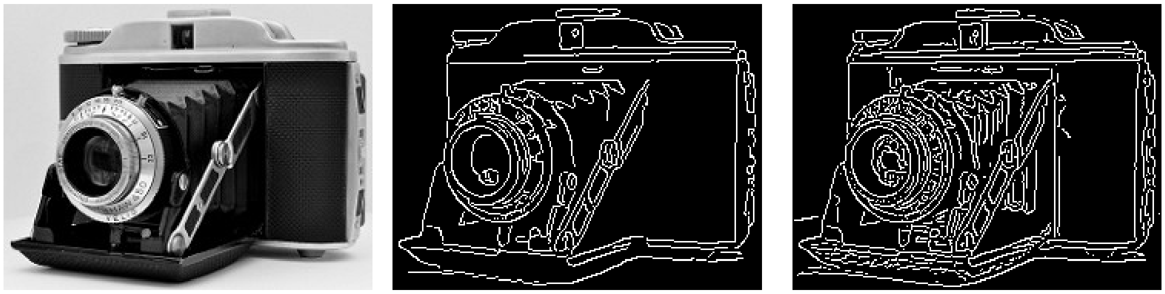
Chapter 4

Results and Comparison

The results of Canny's modified algorithm using adaptive filtering, automatic double threshold selection method using Otsu's segmentation presented in chapter 3, and the gradient operator defined using gravitational field intensity presented in chapter 2 are compared with the traditional implementation of canny edge detection of algorithm using the previous double threshold selection method mentioned in chapter 2.

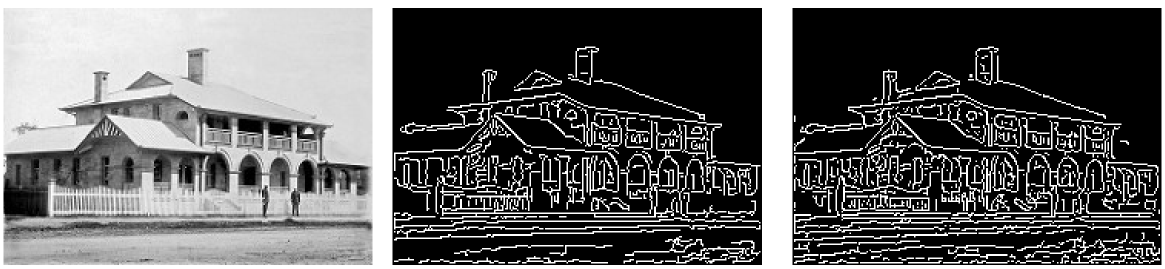
The algorithms were implemented using numpy and scipy python packages. The Figure 4.1 displays comparison of an image of a camera which holds moderate edge information. Figure 4.2 is an image of a house which has high edge information in it whereas Figure 4.3 has low edge information.

The performance of the presented method is better than previous method in cases when the edge information present in the image is high or moderate as can be seen in Figures 4.1 and 4.2. Whereas when presence of edge information in the image is on the lower side like in the flower image, both the methods exhibit similar performance, as seen in Figure 4.3.



(a) Original (b) Previous Method (c) Presented Method

Fig. 4.1: Camera Image



(a) Original (b) Previous Method (c) Presented Method

Fig. 4.2: House Image

(a) Original (b) Previous Method (c) Presented Method

Fig. 4.3: Flower Image

Chapter 5

Conclusion and Future Works

5.1 Conclusion

In this report, some modifications to the traditional implementation approach of canny's edge detection algorithm were presented. The first modification presented was to use adaptive filter instead of Gaussian filter to preserve the weak edges present in the image. Next modification was to use a new gradient operator, which was formulated using the idea of gravitational field intensity, in order to preserve more edge information. Then an automated method of selecting high and low thresholds using Otsu's segmentation method for the step of double thresholding in Canny's algorithm was given, which was compared to a previous threshold selection method.

5.2 Future Works

In the images which have high edge information and the edge intensity is not evenly distributed, that is, edges are dense in some regions whereas sparse in others. In those cases, performance of canny edge detection algorithm will go down, due to the reason that a global threshold will not be able to accommodate for all the different regions of the image as they will have varying number, intensity and contrast of edges. So selecting a fixed threshold will then result in loss of edge information in some regions. In those cases it would be better to divide an image into sub-images and then apply the edge detection algorithm separately on those sub-images, which will be computationally expensive. So a better solution to this problem is still needed to be found. The results of this report need to be evaluated properly with a bigger dataset and analysis of those results is still needed to be done, which will be continued in the next semester.

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