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FUZZY APPROACH FOR ENHANCED EDGE DETECTION ALGORITHM BY ENTROPY OPTIMIZATION

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Fuzzy Approach for Enhanced Edge Detection Algorithm by Entropy Optimization

Gurpreet Kaur [α], Varun Raj [α]

Abstract - In this paper fuzzy based canny edge detection is explained. Global contrast intensification and local fuzzy edge detection are the two phases explained and is then merged with Canny operator for better results specially for noisy images and low contrast images. The resultant images are obtained using MATLAB which is the most convenient software and is efficient in terms of Image Processing as it is one of its toolbox. Although first-order linear filters constitute the algorithms most widely applied to edge detection in digital images but they don't allow good results to be obtained where the contrast varies a lot, due to non-uniform lighting, as it happens during acquisition of most part of natural images.

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I. Introduction

Edge detection is one of the fundamental issues of digital image which is a method of segmentation. Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. since edge detection is in the forefront of image processing for object detection, it is crucial to have good understanding of edge detection algorithms. Therefore, precise edge detection is required for numerous image analysis, evaluation and recognition techniques. In the past, a lot of research has been done in the area of image segmentation in various applications using edge detection.

The underlying idea of most edge detection techniques is by the computation of a local first or second derivative operator, followed by some regularization technique to reduce the effects of noise. Earlier edge detection methods, such as Sobel, Prewitt and Roberts' operator used local gradient method to detect edges along a specified direction.

The lack of noise control resulted in their poor performance on blurred or noisy images.

Canny [1] proposed a method to counter noise problems, wherein the image is convolved with the first order derivatives of Gaussian filter for smoothing in the local gradient direction followed by edge detection by thresholding. Marr and Hildreth [2] proposed an algorithm that finds edges at the zero-crossings of the image Laplacian. Non-linear filtering techniques for edge detection also saw much advancement through the SUSAN method [3], which works by associating a small area of neighboring pixels with similar brightness to each center pixel.

More recently, techniques have been proposed that characterize edge detection as a fuzzy reasoning problem.

Fuzzy logic by the local approach has been used in [4] for morphological edge extraction method. Ho *et al.* [5] used both global and local image information for fuzzy categorization and classification based on edges.

In this paper, we have proposed a fuzzy-Canny based approach to edge detection that uses both global and local image information. Firstly, we used a modified Gaussian membership function to represent each pixel in the fuzzy domain. After which, a global contrast intensification operator is used to enhance the image by adjusting its parameters. In this process, pixels having more edginess will be enhanced while that with the lesser will be decreased. The optimization of the entropy function by gradient descent function produces new optimized parameters of contrast enhancement. The second phase involves the edge detection process with local image information by a local fuzzy mask, similar to the one suggested in [4, 5]. Then simple thresholding method based on experimental observations and in the last step Canny edge detection is performed to link the edges obtained and results for very low contrast and noisy images are discussed in the paper.

II. Global Contrast Intensification

a) *Fuzzy image representation*

To represent an image in fuzzy domain from spatial domain, a gray tone image R of dimension M x N and L levels can be considered as an array of fuzzy singleton sets:

$$R = \{(\mu_{mn}, x_{mn}) \quad \text{where } m= 1,\ldots.M;\ n=1,\ldots.N;\} \qquad (1)$$

Here each pixel has some intensity value x_{mn} and its grade its membership grade $\mu_{mn}(0\leq \mu_{mn}\leq 1)$ relative to some brightness level in the range [0, L-1]

b) *Fuzzy membership function based on histogram*

Membership function is used for expressing the fuzzy property. Modified Gaussian membership function which is a simple transformation functions containing only one fuzzifier is given by

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$$\mu_{mn} = G(x_{mn}) = e^{\left[-\frac{(xmax\ -xmn\ )^2}{2fh^2}\right]} \qquad (2)$$

Here G (x_{mn}) is a Gaussian function, and x_{max}, x_{mn} are the minimum and (m, n) th gray values respectively. A fuzzy histogram is used to obtain the frequency of occurrence of membership functions of gray levels in the fuzzy image. Thus,

$$R = U\ \{\mu(x),\ p(x)\} = \{\mu_{mn}/x_{mn}\}\ ;\ m=1,\ldots,M;\ n=1,2,\ldots,N \qquad (3)$$

Where $\mu(x)$ is the membership of pixel with intensity value of x, and p(x) is the number of occurrences of the intensity value x, in the image R. The distribution of p(x) is normalized such that

$$\sum_{x=0}^{L-1} p(x) = 1 \qquad (4)$$

Membership function which is based on histogram by which pixels of spatial domain can be represented in fuzzy domain by histogrann fuzzification function as

$$\mu(k) = e^{[-(xmax\ -k)^2/2fh^2]} \qquad (5)$$

k is in the range [0, L-1] and the fuzzifier parameter, f_h can be determined as

$$f_h = \frac{\sum_{k=0}^{L-1}(xmax\ -k)^4 p(k)}{2\sum_{k=0}^{L-1}(xmax\ -k)^2 p(k)} \qquad (6)$$

p(k) stands for the frequency of occurrence of k in histogram R. In the fuzzy plane, a contrast –enhanced image is low perception (dark), μ € [0, 0.5] or high perception (bright) μ € [0.5, 1] values. The pixels near μ=0.5 which do not belong to any of the two classes describes the fuzzy boundary and hence they may contain edges.

c) Contrast intensification function

We first enhance the image using non linear new contrast intensification function as image degradation is non linear in nature. NINT [μ(k)] having 3 tunable parameters, that are intensification operator t, fuzzifier f_h and the crossover point x_c defined as

$$\mu'(k) = NINT[\mu(k)] = 1/(1+\exp[-t(\mu(k)-x_c)]) \qquad (7)$$

Here t controls the shape of the sigmoid function and the initial value of x_c is taken as 0.5. And other two parameters are adjusted through μ(k) while t will be fixed instead to control the level of contrast enhancement in the image.

d) Parameter x_C and f_h entropy optimization

To access the image quality different type of measures are reported which are difficult to be quantified. In the fuzzy based approach, entropy of the fuzzy set is a functional to measure the degree of fuzziness of a fuzzy set, giving the value of indefiniteness of an image. Entropy E can be defined in terms of Shannon's function S_e

$$E = \frac{1}{\ln 2} \sum_{k=0}^{L-1} Se\ p(k) \qquad (8)$$

Where

$$S_e(\mu'(k)) = -\ \mu'(k) \ln \mu'(k) - (1-\mu'(k)) \ln(1-\mu'(k)) \text{ and } \{0 \le \mu' \le 1\} \qquad (9)$$

Entropy optimization method with pre-set initial values of x_c and f_h. The derivatives of E w.r.to x_c and fh are

$$\frac{\partial E}{\partial xc} = \frac{\partial E}{\partial \mu'(k)} \frac{\partial \mu'(k)}{\partial xc} = \frac{1}{\ln 2} \sum_{k=0}^{L-1} [t^2(\mu(k) - xc) g(\mu')] p(k) \qquad (10)$$

$$\frac{\partial E}{\partial fh} = \frac{\partial E}{\partial \mu'(k)} \frac{\partial \mu'(k)}{\partial \mu(k)} \frac{\partial \mu(k)}{\partial fh} =$$

$$\frac{1}{ln 2} \sum_{k=0}^{L-1} \left[\frac{t^2 \mu(k)(\mu(k)-xc)(xmax\ -k)^2 g(\mu')}{fh^2}\right] p(k) \qquad (11)$$

Where g(μ') is defined by

$$g(\mu') = \mu'(k)(1-\mu'(k)) = \frac{e^{-t(\mu(k)-xc}}{[1+e^{-t(\mu(k)-xc)}]^{\wedge}2} \qquad (12)$$

Gradient descent technique is used for the recursive learning of the parameters x_c and f_h

$$x_{c,new} = x_{c,old} - \varepsilon_x \frac{\partial E}{\partial xc} \qquad (13)$$

$$f_{h,new} = f_{h,old} - \varepsilon_x \frac{\partial E}{\partial fh} \qquad (14)$$

Here ϵ_x and ϵ_f are learning factors or learning rates for parameters x_c and f_h. If these two diverge and converge too quickly, the value of ϵ_x and ϵ_f have to be altered respectively in order that the convergence of these values is ensured. We note that the optimization of x_c moves in both decreasing positive and negative search directions. The nearest optimization point of the both is taken as $x_{c,new}$.

III. Local Edge Detection

a) Local edge detector mask

Redefining contrast intensification function, NINT(.) in terms of (m,n)th pixel

$$\mu'(k) = NINT[\mu_{mn}] = 1/(1+\exp[-t(\mu_{mn}-x_c)]) \qquad (15)$$

A fuzzy parameter-based new Gaussian-type edge detector is proposed as

$$\dot\eta(m, n) = e^{\frac{-\sum_i \sum_j [\mu(m+i,n+j)]\alpha}{2(fh)\beta}} \qquad (16)$$

where i,j € [- (w-1) 2,(w-1) 2], and w x w is the size of the edge detector mask. $\mu'(m, n)$ is the

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membership value of central pixel of the mask at location (m, n) and $\dot{\eta}$(m, n) is the output edge pixel replacing the previous central pixel. The fuzzifier f_h is earlier optimized using equation.

Parameters α and β are adjustable and are pre-selected by experiments. As the mask is a generalized Gaussian function, different values of α and β would yield different functions, i.e. selecting $\alpha = \beta = 1$ would produce an exponential mask, while $\alpha = \beta = 2$ would yield a normal Gaussian mask. The operation performed by the mask is a nonlinear mapping process and the output pixel value $\dot{\eta}$(m,n) € [-∞,∞], though in general, the value of $\dot{\eta}$ (m, n) lies in [0,1].

b) Entropy optimization of parameters α and β

At the local window, optimization is also required to fine-tune parameters α and β, as the final edge output depends very much on the values of these two parameters. Taking into consideration that the edge mask is applied locally and does not involve the entire image, the entropy function is taken as

$$\mathrm{E}(\dot{\eta}\,(m,n)) = \dot{\eta}(m,n)1\mathrm{n}\,\dot{\eta}\,(m,n) + (1- \dot{\eta}\,(m,n))1\mathrm{n}- \dot{\eta}\,(m,n))] \tag{17}$$

Where the global membership value, $\mu(k)$ is now replaced by the local edge pixel $\dot{\eta}$ (m, n).The derivatives of E with respect to α and β are obtained as:

$$\frac{\partial E}{\partial \alpha} = \frac{\partial E}{\partial \dot{\eta}(\mathrm{m,n})}\,\frac{\partial \dot{\eta}(\mathrm{m,n})}{\partial \alpha} = \frac{n\sum_i \sum_j K\alpha\ In\ K}{2(fh)\beta}\ \mathrm{In}\left\{\frac{\dot{\eta}}{1-\dot{\eta}}\right. \tag{18}$$

$$\frac{\partial E}{\partial \beta} = \frac{\partial E}{\partial \dot{\eta}(\mathrm{m,n})}\,\frac{\partial \dot{\eta}(\mathrm{m,n})}{\partial \beta} = \frac{nIn\ fh\sum_i \sum_j K\alpha\ In\ K}{2(fh)\beta}\ \mathrm{In}\left\{\frac{\dot{\eta}}{1-\dot{\eta}}\right. \tag{19}$$

These derivatives are used in the learning of the parameters xc and fh recursively by the gradient descent technique:

$$\alpha_{\ new\ =}\ \alpha_{\ old} - \epsilon_{\alpha}\frac{\partial E}{\partial \alpha} \tag{20}$$

$$\beta_{\ new\ =}\ \beta_{\ old} - \epsilon_{\beta}\frac{\partial E}{\partial \beta} \tag{21}$$

Where ϵ_α and ϵ_β are learning factors for both parameters α and β respectively. Similarly, if α and β diverge or converge too quickly, the value of ϵ_α and ϵ_β have to be altered respectively to ensure stability.

Since the optimization formulae might be burdensome, we may not use all points (m, n) on the image. We proposed using only the maximum and minimum intensity points or a selection of points to represent different intensity ranges. Some conditions and assumptions are needed to monitor the convergence of these values and prevent optimization process from yielding local minima or maxima. The following are the selection criteria and feasible range of values for α and β

$$\alpha_{\ new} \geq 1\ and\ \alpha_{\ new} \geq \alpha_{\ old} + 0.2$$

$$\beta_{\ new} \geq \beta_{\ old}/2_{\ and}\ \beta_{\ new} \leq \alpha_{\ old}$$

If the value of α and β converges outside the above range of values, optimization can be discarded, and the old values, α old and β old, are used.

c) Removal of strong edges and noise

However, when strong edge and impulse noise are encountered, $\dot{\eta}$ (m, n) will have either very large values of $\dot{\eta}$ (m, n) > 1; or very small values of $\dot{\eta}$ (m, n) < 0

Thus, the AND operation is taken to avoid such situations, so that the membership is within [0, 1], that is

$$\dot{\eta}\,(m,n) = \min[\dot{\eta}\,(m,n)] \approx 1;\ when\ \dot{\eta}\,(m,n) > 1;\ AND$$

$$\dot{\eta}\,(m,n) = \max[\dot{\eta}\,(m,$$

$$n)] \approx 0;\ when\ \dot{\eta}\,(m,n) < 0;\ when\ \dot{\eta}\,(m,n) < 0\ ;$$

d) Edge image thresholding

After the edge image is produced through the edge detector, simple thresholding is required to binaries it according to a certain threshold level. An optimum threshold level λ is determined through experiments to be in the range of 0.7 to 0.9, where

$$\dot{\eta}\,(m,n) = \begin{cases} 1 & \lambda\ \geq 0.7 \rightarrow 0.9 \\ 0 & \lambda\ \geq 0.7 \rightarrow 0.9 \end{cases}$$

IV. Fuzzy-Canny Edge Detection

Now after fuzzifing the image we can simply apply canny operator to the resultant image. the simple algorithm for Canny edge detection is given below:

1. Minimum number of false negatives and false positives.
2. Good localization, report edge location at correct position.
3. Single response to single edge.

Solving an optimization problem using variational calculus and the criteria specified above he arrived at an optimal edge enhancing filter, the derivative of a Gaussian

$$\mathrm{G}\,(\mathrm{x},\mathrm{y}) = e^{-x^2+y^2/2\sigma^2} \tag{22}$$

$$\frac{\partial G}{\partial x} = -\frac{x}{\sigma^2}\mathrm{G} \tag{23}$$

$$\frac{\partial G}{\partial y} = -\frac{y}{\sigma^2}\mathrm{G} \tag{24}$$

Steps of Canny edge detection algorithm:

1. Convolve the image with the derivative of a Gaussian.
2. Apply non maxima suppression to the gradient magnitude image.
3. Use two thresholds $T_1 > T_2$:

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a) Class = {edge if magnitude > T1 Candidate if magnitude > T2}

b) Hysteresis: Any candidate which is a neighbor, in the gradient direction, of an edge is reclassified as an edge.

V. Results and Disscussions

Fig 5.1 : Original low contrast noisy image

Fig 5.2 : Detection of edges using Canny edge detection

Fig 5.3 : Detection of edges Using Fuzzy edge detector

Fig 5.4 : Detection of edges using Fuzzy-Canny edge detector

The Fuzzy-Canny detector algorithm is implemented on low contrast noisy image and prior to the application of this algorithm, no pre-processing was done on the image. As the algorithm has two phases – fuzzy based detection and then implementing Canny edge detector, we present the results of implementation on these images separately.

For noisy low contrast images Fussy is a good approach because it involves the enhancement of an image before filtering the edges in which Canny failed to provide acceptable results. This can be explained by the fig. 5.2 and 5.3 given above. The resultant image can be further improved by using Canny operator which will help in linking the edges and enhancing the edge pixels as given by fig. 5.4.

VI. Conclusion

The fuzzy –Canny edge detector presented in this paper uses both global (histogram of gray levels) and local(membership function in a window) information and finally edge linking which is one of the step of Canny. The local information is fuzzified using a modified Gaussian membership function. Using the contrast intensification operator, the image is enhanced to the required level of visual quality by the entropy optimization of parameters *fh* and *xc*. Then, the local edge detection operator is applied on the enhanced image using parameters α and β , which are again obtained from entropy optimization. Simple edge thresholding is applied and finally canny edge detection is performed. Results show that this edge detector is immensely suitable for applications such as face recognition and fingerprint identification, as it does not distort the shape and is able to retain the important edges and continuous edges unlike the Canny and fuzzy-Canny edge detector. Choice of some of the parameters t, α and β is crucial for the success of this algorithm.

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