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Implementation of Magnified Edge Detection using Fuzzy-Canny Logic

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ABSTRACT

In this paper edge detection with fuzzy using canny is explained. Two basic phases of edge detection i.e. Global contrast intensification and local fuzzy edge detection are first explained and is then merged with Canny operator for better results specially for noisy images and low contrast images. The software used for the observation of edges in digital images is by using MATLAB software (ToolBox) because of its efficiency and convenience for handling images for Image Processing. Initially, 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.

KEYWORDS- Edge detector, fuzzy image processing, image enhancement, entropy, contrast intensification operator, fuzzifier, crossover point, Gaussian membership function

1. Introduction

Edge detection is one of the most critical and hot topic for digital images for segmenting images and to improve the quality of the images. As we know, about data abstraction, i.e. it focuses on some of its data but eliminates unwanted data. In the same way, Edge Detection is used to trim down and strain some amount of data and inadequate information, at the same time preserving the important structural(edges) properties in an image. As, edge detection is currently in its developing stage of processing the images for the detection of objects, so it is important to have good understanding of algorithms for edge detection. In past few years, a couple of researches have been done for improving the quality of images with various applications and methods using edge detection. The core proposal of most edge detection techniques is based on the local first or second derivative operator, which is used by some techniques to reduce the effects of noise in digital images. Some of the previously developed edge detection methods, such as Prewitt, Sobel and Robert's operators used local gradient method for detecting edges for some specified direction. But these were deficient in controlling noise, which resulted in their degraded performance for blurred or noisy images.

Based on the Gaussian filter Canny [1] proposed a method to answer noise problems, for the images involved with the first order derivatives for smoothing in the local gradient direction which was followed by edge detection by thresholding the images. Algorithms were also proposed by Marr and Hildreth [2] for finding edges at the zero-crossings in the image Laplacian. Some other algorithms like SUSAN[3] which were based on Non-linear filtering techniques for edge detection, which works by associating a small area of adjacent pixels with related brightness to each center pixel.

Also during recent years, techniques have been proposed that uses edge detection as a fuzzy problem. Some local and global approaches has used morphological edge [4] extraction method using Fuzzy logic. Ho *et al.* [5] used both global and local image information for fuzzy categorization and classification based on edges.

In this paper, we have projected an approach based on fuzzy-Canny for edge detection that works on both global and local image information. Initially, we would use an adapted Gaussian membership function for presenting each pixel in the fuzzy domain. After which, a universal contrariety intensification operator is used for improving image quality by adjusting its parameters. In this process, the pixels which are having more edginess will be enhanced and on the other hand the pixels with less edginess will be decreased. The entropy optimization function with gradient descent function gives new optimized parameters of contrast/pixel enhancement. In the second phase of edge detection which will involve the edge detection with local image information by a local fuzzy mask, similar to the one used with [4, 5]. Thereafter, simple thresholding method based on experimental observations using MATLAB which will be followed by the last step i.e. Canny edge detection, which will be used to link the edges obtained and results for very low contrast and noisy images as discussed in the paper.

2. Universal Contrast Intensification

2.1 Image representation using fuzzy logic

A gray tone image R of dimension M x N and L levels for representing any image in fuzzy domain from spatial domain, can be considered as an array of fuzzy singleton sets:

R = {(μ $_{mn}$, x_{mn}) where m= 1,….M; n=1,….N;} (1)

With this every pixel has its own intensity value x_{mn} and with the intensity membership grade $\mu_{mn}(0\le \mu_{mn}\le 1)$ relative to some brightness level in the range [0, L-1]

2.2 Membership function based on histogram using Fuzzy

For expressing the properties of fuzzy Membership function is used.The extended Gaussian membership function for simply transformation containing only one fuzzifier is given by

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

With G (x_{mn}) is a extended Gaussian function, and x_{max}, x_{mn} are the minimum and (m, n)th gray values resp. A histogram with fuzzy will be used to obtain the number of possible occurrences of gray levels in the fuzzy image. So,

R = U {μ(x), p(x)} = {μ_{mn}/x_{mn}} ; m=1,….,M; n=1,2,…..,N (3)

Where μ(x) is a function i.e. membership of pixel with intensity value of x, and p(x) is the function for the frequency of occurrences of the intensity value x, in the image R. The distribution of p(x) is normalized such that

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

Histogram based membership function with which pixels of spatial domain can be represented in fuzzy domain is given as

$$\mu(k) = e^{\left[-\frac{(xmax-k)^2}{2fh^2}\right]} \quad (5)$$

where k varies from 0 to L-1 and the fuzzifier parameter, f_h can be determined as

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

where p(k) specifies the probable occurrences of k in histogram R. In the fuzzy plane, an image with enhanced-contrast is in low perception i.e. will be dark, μ Є [0, 0.5] or high perception i.e. bright μ Є [0.5, 1] values. The pixels which approximates to μ=0.4 do not belong to any of the two classes (bright/dark) focuses on the fuzzy boundary and hence they may contain edges.

2.3 Non-Linear/Contrast intensification function

We will first enhance the image using non linear intensification function as image detection is non linear in nature. NINT [μ(k)] having 3 defined parameters, which are: crossover point $x_{c,}$ intensification operator t and the fuzzifier f_h which are used as

μ'(k)= NINT[μ(k)] = 1/(1+exp[-t(μ(k)-x_c)]) (7)

With t used to control the shape of the sigmoid function and x_c is initialized to the default value 0.5. Other parameters are adjusted through μ(k) while t will remain fixed to control the level of contrast enhancement in the image.

2.4 Entropy optimization parameters(x_C and $f_{h)}$

For accessing image quality in the fuzzy based approach, entropy of the set of parameters is used for measuring the degree of fuzziness of the given fuzzy set, giving the value of indefiniteness of an image. Shannon's function S_e can also be used to define entropy E in terms of

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

Where

$S_e(\mu'(k)) = - \mu'(k) \ln \mu'(k) – (1- \mu'(k)) \ln(1- \mu'(k))$ and $\{0\le\mu'\le1\}$ (9)

x_c and f_h uses entropy optimization method with some already initialized values . The derivatives of E with respect to x_c and fh are

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

$$\frac{\partial E}{\partial f\boldsymbol{h}} = \frac{\partial E}{\partial \mu'(k)}\frac{\partial \boldsymbol{\mu}'(k)}{\partial \boldsymbol{\mu}(k)}\frac{\partial \mu(k)}{\partial f\boldsymbol{h}} =$$

$$\frac{1}{ln2}\sum_{k=0}^{L-1}\left[\frac{t^{2}\mu(k)(\boldsymbol{\mu}(k)-xc)(xmax-k)^{2}g(\mu')}{f\boldsymbol{h}^{2}}\right]p(k) \quad (11)$$

Where g(μ') is defined by

$$g(\mu')= \mu'(k)(1-\mu'(k)) =$$

$$e^{\uparrow}(-t(\mu(k)-xc)/([1+e^{\uparrow}(-t(\mu(k)-xc)\ )]^{\uparrow}2) \quad (12)$$

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

$$x_{c,new} = x_{c,old} - \varepsilon_{x}\frac{\partial E}{\partial xc} \quad (13)$$

$$f_{h,new} = f_{h,old} - \varepsilon_{x}\frac{\partial E}{\partial f\boldsymbol{h}} \quad (14)$$

x_c and f_h. has ϵ_x and ϵ_f as learning factors. If these two divergence and convergence is too quick, then the value of ϵ_x and ϵ_f have to be altered respectively so that the convergence of these values is ensured. We note that the optimization of x_c is in both decreasing positive and negative search directions. The nearest optimization point of the both is taken as $x_{c,new}$.

3. Edge Detection in local edges

3.1 Mask edge detector in local edges

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

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

Fuzzy parameter-based new Gaussian-type edge detector is proposed as

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

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 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 α = β = 1 would produce an exponential mask, while α = β = 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].

3.2 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

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

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:

$$\frac{\partial E}{\partial \alpha} = \frac{\partial E}{\partial \dot{\eta}(\mathbf{m},\mathbf{n})}\frac{\partial \dot{\eta}(\mathbf{m},\mathbf{n})}{\partial \alpha} = \frac{n\sum_i\sum_j K\alpha\ In\ K}{2(f\boldsymbol{h})\beta}\ \text{In}\left\{\frac{\dot{\eta}}{1-\dot{\eta}}\right. \quad (18)$$

$$\frac{\partial E}{\partial \beta} = \frac{\partial E}{\partial \dot{\eta}(\mathbf{m},\mathbf{n})}\frac{\partial \dot{\eta}(\mathbf{m},\mathbf{n})}{\partial \beta} = \frac{nIn\ f\boldsymbol{h}\sum_i\sum_j K\alpha\ In\ K}{2(f\boldsymbol{h})\beta}\ \text{In}\left\{\frac{\dot{\eta}}{1-\dot{\eta}}\right. \quad (19)$$

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

$$\alpha_{new} = \alpha_{old} - \epsilon_{\alpha}\frac{\partial E}{\partial \alpha} \quad (20)$$

$$\beta_{new} = \beta_{old} - \epsilon_{\beta}\frac{\partial E}{\partial \beta} \quad (21)$$

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

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

$$\beta_{new} \geq \beta_{old} \frac{\square}{2} \text{ and } \beta_{new} \leq \quad \alpha_{old}$$

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.

3.3 Removal of strong edges and noise

However, when strong edge and impulse noise are encountered, ὴ (*m*, *n*) will have either very large values of ὴ (*m*, *n*) > 1; or very small values of ὴ (*m*, *n*) < 0

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

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

ὴ (*m*, *n*)= max[ὴ (*m*, *n*)]$\approx 0; when\ \dot{\eta}\ (m, n) < 0; when\ \dot{\eta}\ (m, n) < 0\ ;$

3.4 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

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

4. Canny-Fuzzy edge detection

After fuzzing our image canny operator can be applied for the resulting image. Simple algorithm for Canny edge detection consists of the following steps:

1. Initially find out the minimum number of false negatives and false positives.
2. There should be good localization, i.e. edge locations should be at the correct position.
3. There should be only response to every edge.

   To solve an optimization problem using variational calculus and the criteria specified above has arrived at an optimal edge enhancing filter, the derivative of a Gaussian;

$$G\,(x,\,y) = e^{-x^{2}+\frac{y^{2}}{2\sigma^{2}}} \qquad (22)$$

$$\frac{\partial G}{\partial x} = -\frac{x}{\sigma^{2}}\,G \qquad (23)$$

$$\frac{\partial G}{\partial y} = -\frac{y}{\sigma^{2}}\,G \qquad (24)$$

Steps of Canny edge detection algorithm:

1. Intervolve the image with the derivation of a Gaussian.
2. Then take the non-maxima suppression to the gradient magnitude image.
3. Use two thresholds $T_1 > T_2$:

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

   (b)Hysteresis: All the candidates which are acting as the neighbours in the gradient direction, of an edge is recalled as an edge.

5. Results

5.1 Basic gradient operators

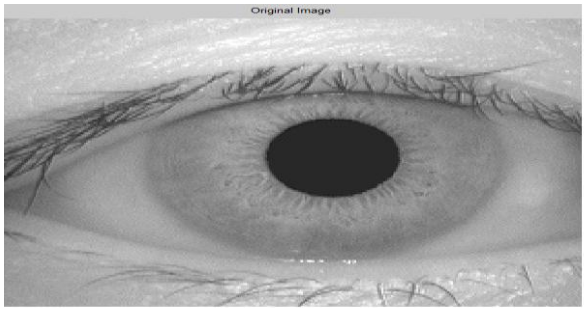

Fig.5.1 Original image of size 320 x 280 pixels with intensity values scaled to the range [0, 1].

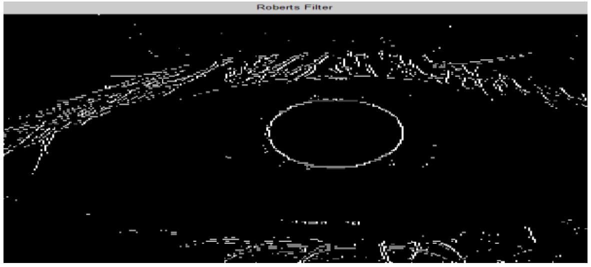

Fig.5.2 Detection of edges using Robert's masks.

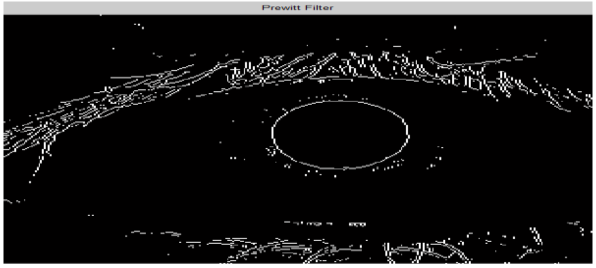

Fig.5.3 Detection of edges using Prewitt's mask.

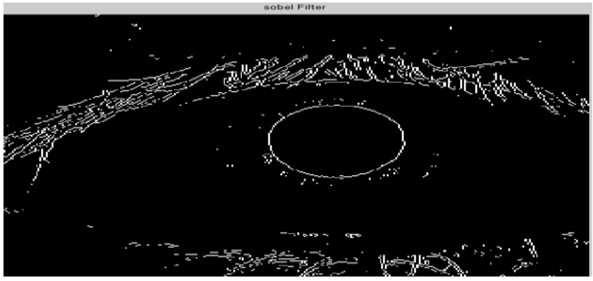

Fig.5.4 Detection of edges using Sobel mask.

All of the above discussed edge detectors are good to detect edges but not applicable to distant objects perfectly and also they contain noise factor as well. So, to overcome these problems advanced techniques also had been developed.

5.2 Edge detection using advanced techniques

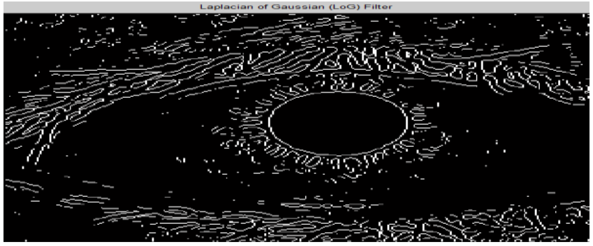

Fig.5.5 Detection of edges using LoG edge detector.

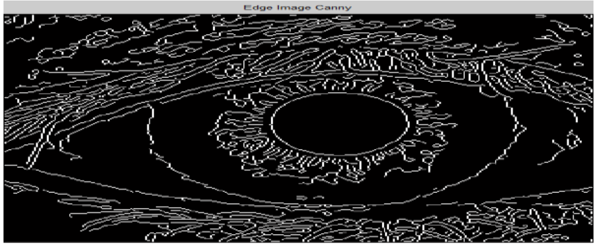

Fig.5.6 Detection of edges using canny edge detector.

Both of the above methods are good in detecting edges but still contains noise factor which can be overcome by combining the best aspects of both fuzzy and canny logic.

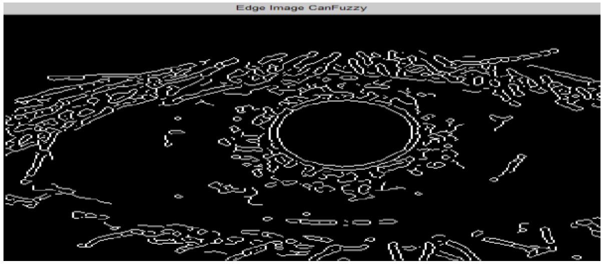

Fig.5.7 Detection of edges using Fuzzy-Canny logic.

6. Conclusion

The fuzzy – Canny edge detector presented in this paper uses both global (gray level histogram) and local (membership function for window) information and finally an important step of canny i.e. edge linking. The information which appears to be local is fuzzified using a modified Gaussian membership function. Contrast intensification operator is used to enhance the required level of visual quality by using entropy optimization of parameters *fh* and *xc*. Thereafter, the local edge detection operator is applied on the enhanced image using parameters α and β , which are again obtained from entropy optimization. Then on the resulting image edge thresholding is applied and thereafter 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.

References

[1] Canny, J.F., “A computational approach to edge detection”*IEEE Trans. on Pattern Analysis and Machine Intelligence, 8(6), 1986, 679-698.*

[2] Marr, D., and Hildreth, E.C., “Theory of edge detection”,*Proc. of the Royal Society of London, b207, 1980, 187-217.*

[3] Smith, S.M., and Brady, J.M., “SUSAN – A new approachto low level image processing”, *International Journal ofComputer Vision*, 23(1), 1997.

[4] Bloch I., “Fuzzy sets in image processing”, *ACM Symposiumon Allied Computing, 1994*.

[5] Ho, K.H.L., and Ohnishi, N., “FEDGE – Fuzzy edge detection by fuzzy categorization and classification of edges”, *Fuzzy Logic in Artificial Intelligence*, Springer, IJCAI’95 Workshop, Montreal, Canada, 1188:182-196.

[6] M. Hanmandlu, D. Jha, and R. Sharma, “Color image enhancement using fuzzification”, Pattern Recognition Letters, Vol. 24(1-3) 2003, pp. 81-87. [3]

[7] Chi, Z.R., Yan, H., Pham, T., Fuzzy Algorithms: with applications to image processing and pattern recognition, *World Scientific, Singapore, River Edge, N.J., 1996*.

[8] Pal N.R. and Pal S.K., “Entropy: A new definition and its applications, *IEEE Trans. Sys., Man, Cybernetics*, SMC-21(5).

[9] ter Haar Romeny, *B.M., Front-End Vision and Multi-Scale Image Analysis, Kluwer Academic Publishers, 2002*.

[10]Azriel Rosenfeld, Mark Thurston and Yung-Han Lee “Edge and curve detection:Further Experiments” *IEEE Transactions on Computers, Vol. C-21, No. 7, July 1972.*