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Implementation of Gray Level Images based on the Shannon Entropy

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Abstract: Most of the classical mathematical methods for edge detection supported the spinoff of the pixels of the initial image area unit Gradient operators, Laplacian and Laplacian of Gaussian operators. Gradient primarily based edge detection ways, like Roberts, Sobel and Prewitts, have used 2 2-D linear filters to method vertical edges and horizontal edges on an individual basis to approximate first-order spinoff of element values of the image. The Laplacian edge detection methodology has used a 2-D linear filter to approximate second-order spinoff of element values of the image. Major disadvantage of second-orderderivative approach is that the response at and round the isolated element is far stronger. during this analysis study, a unique approach utilizing Claude Shannon entropy aside from the analysis of derivates of the image in police investigation edges in grey level pictures has been projected. The projected approach solves this drawback at some extent. within the projected methodology, we've used an appropriate threshold price to section the image and succeed the binary image. when this the projected edge observeor is introduced to detect and find the sides within the image. a regular check image is employed to match the results of the projected edge detector with the Laplacian of Gaussian edge detector operator. so as to validate the results, seven totally different forms of check pictures area unit thought of to look at the flexibility of the projected edge detector. it's been discovered that the projected edge detector works effectively for various grey scale digital pictures. The results of this studywere quite promising.

Key words: Edge detection · Shannon entropy · Gradient · Laplacian · Threshold price

INTRODUCTION

Edge detection has received a lot of attention throughout the past 2 decade owing to its important importance in several analysis areas [1]. Since, the sting may be a distinguished feature of AN; it is the front-endprocessing stage in object recognition andimage understanding system. The accuracy with that this task will be performed is a crucial factor in determining overall system performance [2]. The detection results profit applications like image sweetening recognition, morphing, compression, retrieval, watermarking, hiding, restorationand registration etc [3]. Edge detection concerns localization of abrupt changes in the gray level of an image [4]. Edge detection can be defined as the boundary between two regions separated by two relatively distinct gray level properties [5]. The causes of the region dissimilarity may be due to some factors such as the geometry of the scene, the radiometric characteristics of the surface, the illumination and so on [6].

Most of the normal ways for edge detection square measure supported the primary and second order derivatives of grey levels of the pixels of the initial image like the Gradient operator and Laplacian operator [7]. Roberts, Prewitt and Sobel square measure Gradient operators that use 2nd spatial convolution masks to approximate the first-orderderivative of a picture in horizontal and vertical directions one by one. The detected edges by Gradient operators square measure thick, which can not be appropriate for a few applications, wherever the detection of the outer contour of associate degree object is needed, the Laplacian edge detection technique uses a 2nd spatial linear filter to approximate the second-order by-product of component values of the image for manufacturing sharp edges [8]. The Laplacian typically isn't employed in its original type for edge detection for many reasons: As a second-orderderivative, the Laplacian generally is intolerably sensitive to noise. The magnitude of the Laplacian produces double edges, associate degree undesirable impact as a result of it complicates segmentation [9]. For these reasons, the

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Laplacian is combined with smoothing as a precursor tofinding edges via zero-crossings. Marr and Hildreth achieved this by exploitation the Laplacian of a mathematician (LOG) operate as a filter [10]. LOG filtered pictures additionally suffer from the matter of missing edges-edges within the original image might not have corresponding edges during a filtered image. additionally, it seems to be terribly tough to mix LOG zero-crossings from totally different scales, primarily attributable to the following [11]:

- A physically significant edge doesn't match azero-crossing for quite a couple of and really limited number of scales.
- Zero-crossings in larger scales move very distant from actuality edge position as a result of poor localization of the LOG operator [12].
- There ar too several zero-crossings within the tiny scales of a LOG filtered image, most of which is as a result of noise.

To solve these problems, the study proposed a novel a novel approach supported scientific theory. engineer entropy is that the most vital among many measures of data. Edges is extracted by the detection of all pixels on the borders between completely different uniform areas. Entropy measures the randomness of intensity distribution [12]. in step with this property of entropy, the worth of entropy is low for uniform areas and is high wherever the range of grey level of pixels is large [13].

Concept of entropy: Entropy may be a conception in scientific theory. Entropy is employed to live the quantity of information [14]. Entropy is outlined in terms of the probabilistic behavior of a supply of data. In accordance with this definition, a random event A that happens with chance P(A) is alleged to contain:

$$I(A) \square \log[1/ P(A)] \square \log[P(A)]$$

Units of information. The amount I(A) is called theself-information of event A. The amount of self-information of the event is inversely related to its probability. If P(A) = 1, then I(A) = 0 and no information is attributed to it. In this case, uncertainty associated with the event is zero. Thus, if the event always occurs, then no information would be transferred by communicating that the event has occurred. If P(A) = 0.8, then some information would be transferred by communicating that the event has occurred.

The base of the exponent determines the unit that is employed to live the knowledge. If the bottom of the exponent is a pair of, then unit of data is bit. If P(A) = ½, then I(A) = -log2(½) = one bit. That is, one bit is that the quantity of data sent once one in every of 2 attainable equally seemingly events happens. an easy example of such a scenario is flipping a coin and human activity the result (Head or Tail).

The basic construct of entropy in scientific theory should do with what proportion randomness is in a very signal or in a very random event. another thanks to look into this can be to speak concerning what proportion data is carried by the signal. Entropy may be a live of randomness.

Consider a probabilistic experiment in which the output of a discrete source is observed during every unit of time (signaling interval). The source output is modeled as a discrete random variable S. S is referred as a set of source symbols [14].

$$Z \square \{s1,s2,s3,...,sj,...sK\}$$

The above set of source symbols is referred to as the source alphabet.

The set of all source symbol probabilities is denoted by P:

$$P \square \{p1,p2,p3,...,pj,...,pK\}$$

This set of probabilities must satisfy the condition:

$$\sum_{j \square 1}^{K} pj \square 1$$

The symbols generated by the source during successive signaling intervals are statistically independent. A source that satisfies such property is called a discrete memory-less source; memory-lesssource is that in which the symbol emitted at any time is independent of previous choices [13].

The amount of self-information of the event S=sjwhich occurs with probability pj is:

$$I(sj) \square \log(1/ pj)$$
$$\square \log(pj\ ),\ j \square 1,2,3,...,K$$

I(sj) Is a discrete random variable that takes on the

values I(s1), I(s2),...,I(sk) with chances p1, p2,...,pk respectively[16].The self-information generated by the assembly of one supply image is I(sj) = -log (pj). If n supply symbols square measure generated, the law of enormous numbers stipulates that, for a sufficiently massive worth of n, image sj can (on average) be output npj times. so the common self -information obtained from n outputs is given by

np1I(s1) np2I(s2) ... npKI(sK)

K
Σ npjI(sj)
J=1

k
n Σpj log (1/ pj)
j=1

k
- nΣpj log (1/ pj)
j=1

image h(x, y) is outlined as h(x, y)=1 if f(x, y)&gt; T; otherwise h(x, y)=0. Thus, pixels labeled one correspond to things, whereas pixels labeled zero correspond to the background. once T depends solely on f(x, y) (only on grey level values), the brink is named international. If T depends on f(x, y) and p(x, y), the brink is named native. If T depends on the constituent position (x, y) still as f(x, y) at that constituent position, then it's known as dynamic or reconciling threshold. In planned theme to notice edges, international threshold worth is employed.

Procedure to Select Suitable Threshold Value: The average information per source output, denoted H (Z), is:

$$H(Z) = -\sum_{j=1}^{k} pj \log(pj)$$

The important quantity H(Z) is called the entropy of a discrete memory less source with source alphabet Z. It is a measure of the average information content per source symbol. The entropy H(Z) depends only on the probabilities of the symbols in the alphabet Z in H(Z) is not an argument of a function but rather a label for a source.

Selection of Threshold Value: Threshold value is used to transform a dataset containing values that vary over some range into a new dataset containing just two values. When a threshold value is applied on to the input data, then input values that fall below the threshold are replaced by one of the output values and input values that at or above the threshold are replaced by the other output value. Image thresholding is a segmentation technique because it classifies pixels into two categories. Category1: Pixels whose gray level values fall below the threshold and category2: Pixels whose gray level values are equal or exceed the threshold. In gray level image, range of input dataset is [0, 255]. After thresholding, output dataset contains only two values 0 and 255. Thus, thresholding creates a binary image. If T is a threshold value, then any pixel (x, y) for which f(x, y)>T is called an object point; otherwise the pixel is called a background pixel. In general, the threshold can be chosen as the relation, T=T[x, y, p(x, y), f(x, y)] where f(x, y) is the gray level of the pixel(x, y) and p(x, y) denotes some local property of this pixel, for example, the average gray level of a neighborhood centered on (x, y).

Procedure to Select Suitable Threshold Value:

Step 1: Select an initial estimate for T.

Step 2: Segment the image using T. This will produce two groups of pixels:
R1 consisting of all pixels with gray level values >Tand
R2 consisting of pixels with gray level values T.

Step 3: Compute the average gray level values μ1 and μ2for the pixels in region

R1 and R2.

Step 4: Compute a new threshold value
Set TNew = (μ1 + μ2)/2 and
Set TOld=0

Step 5: While (TNew TOld) do
μ1 =Mean gray level of pixels for which f(x, y)>TNew
μ2 =Mean gray level of pixels for which f(x, y) TNew Set TOld =TNew
Set TNew = (μ1 +μ2)/2 End while

Step 6: Suitable threshold value
Set T=TNew

Step 7: Stop

Proposed Scheme for Edge Detection: In digital image processing, an image defined in the real world is considered to be a function of two real variables, for example, f(x, y) with f as the amplitude (brightness) of the image at the real coordinate position (x, y). A spatial filter mask may be defined as a (template) matrix w of size m × n. Assume that m = 2a+1 and n = 2b+1, where a, b are nonzero positive integers. Smallest meaningful size of the mask is 3×3. Such mask coefficients, showing coordinate arrangement as:

w(-1,1)	w(-1,0)	w(-1,1)
w(0,1)	w(0,0)	w(0,1)
w(1,1)	w(1,0)	w(1,1)

Image region under the above mask is shown as:

f(x-1,y-1)	f(x-1,y)	f(x-1,y+1)
f(x,y-1)	f(x, y)	f(x,y+1)
f(x+1,y-1)	f(x+1,y)	f(x+1,y+1)

Basic idea behind edge detection is:

1	1	1
1	×	1
1	1	1

In the proposed scheme, first create a binary image by choosing a suitable threshold value. Window is applied on the binary image. Set all window coefficients equal to 1 except centre, centre equal to × as shown below:

Move the window on the whole binary image and find the probability of each central pixel of image under the window. Then, the entropy of each central pixel of image under the window is calculated as:

H(centralPixel) □p log(p)

where, p is the probability of central pixel of binary image under the window. For example, at any instance the image under the window is:

Now, the probability of central pixel, p = 4/9 and the entropy of central pixel,

H(centralPixel) □p log(p) □(4 / 9) log(4 / 9) □0.3604

If, for any other instance, the image under the window is:

In this case, the probability of central pixel, p = 2/9 and the entropy of central pixel,

H(centralPixel) □p log(p) □(2 / 9) log(2 / 9) □0.3342

Table 1: p and H of central under window

Case No	P	H
1	8/9	0.1047
2	7/9	0.1955
3	6/9	0.2703
4	5/9	0.3265
5	4/9	0.3604
6	3/9	0.3662
7	2/9	0.3342
8	1/9	0.2441

Classification of all pixels that satisfy the criterion of homogeneousness
Detection of all pixels on the borders between different homogeneous areas

When the probability of central pixel, p=1, then the entropy of this pixel is zero. Thus, if the gray level of all pixels under the window homogeneous, p=1and H=0. In this case, the central pixel is not an edge pixel. Other possibilities of entropy of central pixel under window are shown in Table 1.

In case no.1, 2, the diversity for gray level of pixels under the window is low. So, in these cases, central pixel is not an edge pixel. In remaining cases, the diversity for gray level of pixels under the window is high. So, for these cases, central pixel is an edge pixel.

Thus, the central pixel with entropy greater than and equal to 0.2441 is an edge pixel, otherwise not.

Proposed Algorithm:

Step 1: Create a binary image by choosing a suitable threshold value.

```
If (f(x, y) > threshold value), then Set f(x, y) = 1
Else
Set f(x, y) = 0 End if
```

Step 2: Find edge pixels in binary image: Create a mask, w, with dimensions m×n

```
Normally, m = 3 and n = 3 Calculate
a = (m-1)/2 and b = (n-1)/2
Create an M×N output image, g:
For all pixel coordinates, x and y, do Set g(x, y) = f(x, y)
End for
Checking for edge pixels: For y = b+1 to N-b, do
For x = a+1 to M-a, do Set Sum = 0
k = -b to b For j = -a to a
If (f(x, y) = = f (x + j, y + k)), then Set Sum=Sum+1
End if End for
End for p=sum/9
H = -plog(p)
If (H<(-(1/9)log(1/9))), Then Set g(x,y)=0
Else
Set g(x,y)=1 End if
End for End for
```

Step 3: Stop

RESULTS AND DISCUSSION

The performance of the proposed scheme is evaluated through the simulation results using MATLAB 7 for a set of eight test images and the results of the proposed scheme are compared with the results of well-established edge detection operator on the same set of test images. Such edge detection operator is Laplacian of Gaussian (LOG). LOG is chosen for comparison because both approaches are rotation invariant. For this purpose, first, a standard test image eight.tif was taken from MATLAB 7 environment. Its edge was detected using LOG edge detector whose function was inbuilt in MATLAB 7. After this, the performance of proposed approach for edge detection on the same image was checked. In the proposed scheme, a suitable threshold value was calculated using the threshold evaluation procedure given in the research. Such threshold value for the test image is 0.3472 when image in normalized form (all gray level values lie between 0 and 1). The result of edge detection is shown in Fig. 1. It has been observed that the proposed method for edge detection works well as compare to LOG.

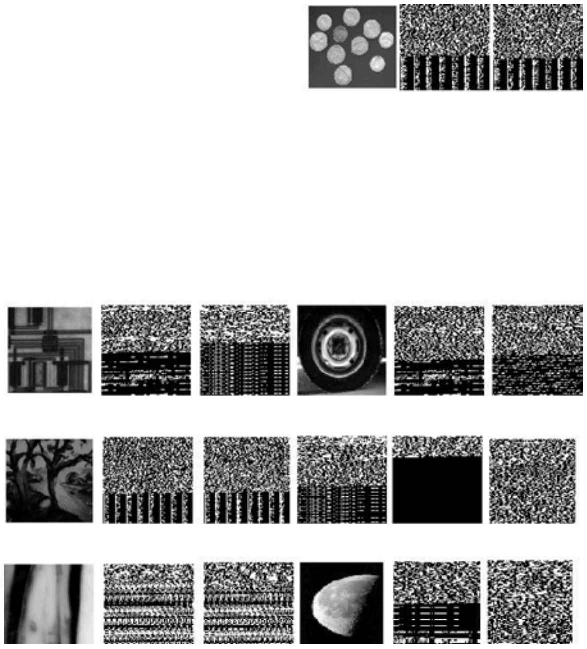

Fig. 1: Performance of Proposed Edge Detector for different images using LOG using proposedit has again been observed that the performance of the proposed edge detection scheme is found to be satisfactory for all the test images as compare to the performance of LOG.

Table 2: Threshold values for different standard images

S. No.	Image	Threshold Value
1	Coins.png	0.4943
2	Circuit.tif	0.3350
3	Ttire.tif	0.3336
4	Trees.tif	0.2408
5	Circles.png	0.5000
6	Glass.png	0.3927
7	Moon.tif	0.3520

In order to validate the results about the performance of proposed scheme for edge detection, seven different test images are considered which are present in MATLAB 7 environment. Suitable threshold values calculated by the threshold evaluation procedure for different test images are given in Table 2. The results of edge detections for these test images using LOG and proposed scheme are shown in Fig. 2. From the results;

CONCLUSION

In this study, an attempt is made to develop a new technique for edge detection. Experiment results have demonstrated that the proposed scheme for edge detection works satisfactorily for different gray level digital images. The theoretical principles and systematic development of the algorithm for the proposed versatile edge detector is described in detail. The technique has potential future in the field of digital image processing. The work is under further progress to examine the performance of the proposed edge detector for different gray level images affected with different kinds of noise [15-17].

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