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An Efficient Approach for Edge Detection in Gray-Scale Images

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Abstract: Edges in a digital image provide important information about the objects contained within the image since they constitute boundaries between objects in the image. This paper proposes a new approach based on both Tsallis and Kapur entropy together. The performance of our method is compared against other methods such as Sobel and Canny edge detector by using various tested images. Experimental results reveal that the proposed method exhibits better performance and may efficiently be used for the detection of edges in images.

Keywords: Non-extensive Entropy ; Edge Detection; Threshold Value, Gray-scale images.

I. INTRODUCTION

Edge Detection has been very useful low-level image processing tool for image analysis in computer vision and pattern recognition field. In image, edges carries essential information of an object of interest in image as they separate dissimilar regions in an image. Specific linear time-invariant filters is the most common procedure applied to the edge detection problem, and the one which results in the least computational effort. In the case of first-order filters, an edge is interpreted as an abrupt variation in gray level between two neighbor pixels. the goal in this case is to determine in which points in the image the first derivative of the gray level as a function of position is of high magnitude. By applying the threshold to the new output image, edges in arbitrary directions are detected.

Edge Detection Techniques are classified as follows: the primary order by-product of selection in image process is that the gradient. The second order derivatives of selection in image process are typically computed exploitation Laplacian. For Sobel, a Prewitt & Roberts technique performs finding edges by thresholding the gradient for the log[1]. By default edge perform mechanically computes the edge to use. For Sobel & Prewitt strategies, we are able to opt to discover horizontal edges, vertical edges or each. Laplacian of a Gaussian (LOG) [2,3] finds edges by searching for zero crossing once filtering with a Gaussian filter. Zero crossing finds edges by searching for Zero crossing once filtering with a user-specified filter[4]. Clever finds by searching for native maxima of the gradient. The gradient is calculated exploitation the by-product of a Gaussian filter[5]. The strategy used 2 thresholds to discover sturdy & weak edges, and includes the weak edges within the output provided that they're connected to sturdy edges. Therefore; this technique is a lot of doubtless to discover true weak edges. Sobel edge detector technique is somewhat tough than Prewitt edge detector. Prewitt edge detector technique is slightly easier to implement computationally than the Sobel detector. However it tends to supply somewhat noisier results[1].

Parliamentarian edge detector is one amongst the oldest and simplest edge detectors in digital image process. It's still used oftentimes in hardware implementations wherever simplicity and speed are dominant factors. This detector is employed significantly but the others. Attributable to partly to its restricted practicality. Log smoothes the image (thus reducing noise) and it computes the Laplacian that yields a double edge image. Zero crossing edge detector supported same thought because the LOG technique however the convolution, is disbursed employing a nominal filter. Canny [6] proposed a method to counter noise problems from gradient operators, where 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.

In this proposed work we present a new hyper approach to detect edges of gray scale images based on information theory, which is Tsallis-Kapur entropy based thresholding. The proposed method is decrease the computation time as possible as can and the results were very good compared with the other methods.

A brief introduction of entropy is given in Section 2. Section 3 presents the entropy thresholding and details of the threshloding algorithm. Illustration of the proposed approach applied to gray scale images is presented in Section 4. In Section 5, some particular images will be analyzed using proposed method based algorithm and moreover, a comparison with some existing methods will be provided for these images., and conclusions is included in Section 6.

II. ENTROPY

Entropy is an uncertainty measure first introduced by Shannon[7-9] into information theory to describe how much information is contained in a source governed by a probability law.

Let $p_1, p_2, \cdots\cdots, p_k$ be the probability distribution of a discrete source. Therefore, $0 \le p_i \le 1$, $i = 1,2,\cdots,k$ and $\sum_{i=1}^{k} p_i = 1$, where k is the total number of states. The entropy of a discrete source is often obtained from the probability distribution.

The Shannon Entropy can be defined as[7]

$$H(p) = -\sum_{i=1}^{k} p_i \ln(p_i) \qquad (1)$$

This formalism has been shown to be restricted to the domain of validity of the Boltzmann–Gibbs–Shannon (BGS) statistics. These statistics seem to describe nature when the effective microscopic interactions and the microscopic memory are short ranged. Generally, systems that obey BGS statistics are called extensive systems. If we consider that a physical system can be decomposed into two statistical independent subsystems A and B, the probability of the composite system is $p^{A+B} = p^A \cdot p^B$, it has been verified that the Shannon entropy has the extensive property (additive):

$$H(A+B) = H(A) + H(B). \quad (2)$$

Rènyi entropy[10,11] for the generalized distribution can be written as follows:

$$H_\alpha^R(p) = \frac{1}{1-\alpha} \ln \sum_{i=1}^{k} (p_i)^\alpha, \quad \alpha > 0,$$

This expression meets the BGS entropy in the limit $\alpha \longrightarrow 1$. Rènyi entropy has a nonextensive property for statistical independent systems, defined by the following pseudo additivity entropic formula

$$H_\alpha(A+B) = H_\alpha(A) + H_\alpha(B) + (\alpha - 1) \cdot H_\alpha(A) \cdot H_\alpha(B).$$

Tsallis[12-14] has proposed a generalization of the BGS statistics, and it is based on a generalized entropic form,

$$H_\alpha^T(p) = \frac{1 - \sum_{i=1}^{k} (p_i)^\alpha}{\alpha - 1}, \quad (3)$$

Where k is the total number of possibilities of the system and the real number α is an entropic index that characterizes the degree of nonextensivity. This expression meets the BGS entropy in the limit $\alpha \longrightarrow 1$. The Tsallis entropy is nonextensive in such a way that for a statistical independent system, the entropy of the system is defined by the following pseudo additive entropic rule

$$H_\alpha(A+B) = H_\alpha(A) + H_\alpha(B) + (1-\alpha) \cdot H_\alpha(A) \cdot H_\alpha(B) \quad (4)$$

The generalized entropies of Kapur of order α and type β [15,16] is

$$H_{\alpha,\beta}(p) = \frac{1}{\alpha - \beta} \ln \left(\frac{\sum_{i=1}^{k} p_i^\alpha}{\sum_{i=1}^{k} p_i^\beta} \right), \ \alpha \neq \beta, \alpha, \beta > 0 \quad (5)$$

In the limiting case, when $\alpha \longrightarrow 1$ and $\beta \longrightarrow 1$, $H_{\alpha,\beta}(p)$ reduces to $H(p)$ and when $\beta = 1$, $H_{\alpha,\beta}(p)$ reduces to $H_\alpha^R(p)$. Also, $H_{\alpha,\beta}(p)$ is a composite function which satisfies pseudo-additivity as:

$$H_{\alpha,\beta}(A+B) = H_{\alpha,\beta}(A) + H_{\alpha,\beta}(B) + (1-\alpha) \cdot H_{\alpha,\beta}(A) \cdot H_{\alpha,\beta}(B). \quad (6)$$

III. ENTROPIC THRESHOLDING

The concept of entropy becomes increasingly important in image processing, since an image can be interpreted as an information source with the probability law given by its image histogram[17-21].

For an image with k gray-levels, let $p_1, p_2, \ldots, p_t, p_{t+1}, \ldots, p_k$ be the probability distribution for an image with k gray-levels, where p_t is the normalized histogram i.e. $p_t = h_t/(M \times N)$ and h_t is the gray level histogram. From this distribution, we can derive two probability distributions, one for the object (class A) and the other for the background (class B), are shown as follows:

$$p_A: \frac{p_1}{P_A}, \frac{p_2}{P_A}, \ldots, \frac{p_t}{P_A},$$

$$p_B: \frac{p_{t+1}}{P_B}, \frac{p_{t+2}}{P_B}, \ldots, \frac{p_k}{P_B}, \quad (7)$$

where

$$P_A = \sum_{i=1}^{t} p_i, \ P_B = \sum_{i=t+1}^{k} p_i, t \text{ is the threshold value.} \quad (8)$$

In terms of the definition of Tsallis entropy of order , the entropy of Object pixels and the entropy of background pixels can be defined as follows:

$$H_\alpha^A(t) = \frac{1 - \sum_{i=1}^{t} \left(\frac{p_i}{P_A}\right)^\alpha}{\alpha - 1}, \alpha > 0$$

$$H_\alpha^B(t) = \frac{1 - \sum_{i=t+1}^{k} \left(\frac{p_i}{P_B}\right)^\alpha}{\alpha - 1}, \ \alpha > 0. \quad (9)$$

The Tsallis entropy $H_\alpha(t)$ is parametrically dependent upon the threshold value t for the object and background. It is formulated as the sum each entropy, allowing the pseudo-additive property for statistically independent systems, as defined in (4). We try to maximize the information measure between the two classes (object and background). When $H_\alpha(t)$ is maximized, the luminance level t that maximizes the function is considered to be the optimum threshold value. This can be achieved with a cheap computational effort.

$$t^{opt} = \text{Arg max } [H_\alpha^A(t) + H_\alpha^B(t) + (1-\alpha) \cdot H_\alpha^A(t) \cdot H_\alpha^B(t)]. \quad (10)$$

When $\longrightarrow 1$, the threshold value in (4), equals to the same value found by Shannon Entropy. Thus this proposed method includes Shannon's method as a special case. The following expression can be used as a criterion function to obtain the optimal threshold at $\alpha \longrightarrow 1$.

$$t_{Sh}^{opt} = \text{Arg max } [H_\alpha^A(t) + H_\alpha^B(t)]. \quad (11)$$

Now, we can describe the Tsallis Threshold algorithm to determine a suitable threshold value t^{opt} and α as follows:

ALGORITHM 1: THRESHOLD VALUE SELECTION (TSALLIS THRESHOLD)

1. **Input:** A digital grayscale image I of size $M \times N$.
2. Let $f(x,y)$ be the original gray value of the pixel at the point $(x,y), (x = 1,2,\cdots,M, \ y = 1,2,\cdots,N)$
3. Calculate the probability distribution p_i, $0 \leq i \leq 255$
4. For all $t \in \{0,1,\ldots,255\}$,
   I. Apply Equations (7) and (8) to calculate P_A, P_B, p_A . and p_B
   II. ***if*** $0 < \alpha < 1$ ***then***
      Apply Equation (10) to calculate optimum threshold value t^{opt}.
   else
      Apply Equation (11) to calculate optimum threshold value t_{Sh}^{opt}.
   end-if
5. **Output**: The suitable threshold value t^{opt} of *I*, for $\alpha > 0$.

IV. EDGE DETECTION ALGORITHM

A spatial filter mask may be defined as a matrix *w* of size $m \times n$. So, we will use the usual masks for detecting the edges[1]. The process of spatial filtering consists simply of moving a filter mask *w* of order $m \times n$ from point to point in an image. At each point (x,y), the response of the filter at that point is calculated a predefined relationship. Assume that $m = 2a+1$ and $n = 2b+1$, where a, b are nonnegative integers. For this purpose, smallest meaningful size of the mask is 3×3, as shown in Figure 1.

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

Figure 1: Mask coefficients showing coordinate arrangement

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

Figure. 2

Image region under the above mask is shown in Figure 2. In order to edge detection, firstly classification of all pixels that satisfy the criterion of homogeneousness, and detection of all pixels on the borders between different homogeneous areas. In the proposed scheme, first create a binary image by choosing a suitable threshold value using Tsallis entropy. Window is applied on the binary image. Set all window coefficients equal to 1 except centre, centre equal to × as shown in Figure 3.

1	1	1
1	×	1
1	1	1

Figure. 3

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 $H(CP) = -p_c \ln(p_c)$.

Table I. p and H of central pixel under window

p	1/9	2/9	3/9	4/9	5/9	6/9	7/9	8/9
H	0.244	0.334	0.366	0.360	0.326	0.270	0.195	0.104

Where, p_c is the probability of central pixel CP of binary image under the window. When the probability of central pixel $p_c = 1$ then the entropy of this pixel is zero. Thus, if the gray level of all pixels under the window homogeneous, then $p_c = 1$ and $\boldsymbol{H} = 0$. In this case, the central pixel is not an edge pixel. Other possibilities of entropy of central pixel under window are shown in Table I.

In cases $p_c = 8/9$, and $p_c = 7/9$, 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, $p_c \leq 6/9$, 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.

The following Algorithm summarize the proposed technique for calculating the optimal threshold values and the edge detector.

ALGORITHM 2: EDGE DETECTION

1. Input: A grayscale image I of size $M \times N$ and t^{opt}, that has been calculated from algorithm 1.

2. Create a binary image: For all x, y,
if $I(x,y) \leq t^{opt}$ ***then*** $f(x,y) = 0$ ***else*** $f(x,y) = 1$.

3. Create a mask w of order $m \times n$, in our case ($m = 3$, $n = 3$)

4. Create an $M \times N$ output image g: For all x and y, Set $g(x,y) = f(x,y)$.

5. Checking for edge pixels:
Calculate: $a = (m-1)/2$ and $b = (n-1)/2$.
For all $y \in \{b+1, \dots, N-b\}$, and $x \in \{a+1, \dots, M-a\}$,
$sum = 0$;
For all $l \in \{-b, \dots, b\}$, and $j \in \{-a, \dots, a\}$,
if ($f(x,y) = f(x+j, y+l)$) ***then***
$sum = sum + 1$.
if ($sum > 6$) ***then*** $g(x,y) = 0$ ***else*** $g(x,y) = 1$

6. **Output**: The edge detection image g of I.

The steps of our proposed technique are as follows:

<u>Step 1</u>: Find global threshold value (t_1) using Tsallis entropy . The image is segmented by t_1 into two parts, the object (Part1) and the background (Part2).

<u>Step 2</u>: By using Kapur entropy, we can select the locals threshold values (t_2) and (t_3) for Part1 and Part2, respectively.

<u>Step 3</u>: Applying Edge Detection Procedure with threshold values t_1, t_2 and t_3.

<u>Step 4</u>: Merge the resultant images of step 3 in final output edge image.

In order to reduce the run time of the proposed algorithm, we make the following steps: Firstly, the run time of arithmetic operations is very much on the $M \times N$ big digital image, I , and its two separated regions, Part1 and Part2. We are use the linear array p (probability distribution) rather than I, for segmentation operation, and threshold values computation t_1, t_2 and t_3. Secondly, rather than we are create many binary matrices f and apply the edge detector procedure for each region individually, then merge the resultant images into one. We are create one binary matrix f according to threshold values t_1 , t_2 and t_3 together, then apply the edge detector procedure one time. This modifications will reduce the run time of computations.

V. EXPERIMENTAL RESULTS

To demonstrate the efficiency of the proposed approach, the algorithm is tested over a number of different grayscale images and compared with traditional operators. The images detected by Canny, LOG, Sobel, Prewitt and the proposed method, respectively. All the concerned experiments were implemented on Intel® Core™ i3 2.10GHz with 4 GB RAM using MATLAB R2007b. As the algorithm has two main phases – global and local enhancement phase of the threshold values and detection phase, we present the results of implementation on these images separately.

The proposed scheme used the good characters of Tsallis-Kapur entropy, to calculate the global and local threshold values. Hence, we ensure that the proposed scheme done better than the traditional methods.

In order to validate the results, we run the Canny, LOG, Sobel and Prewitt methods and the proposed algorithm 10 times for each image with different sizes. As shown in Figure. 4. It has been observed that the proposed edge detector works effectively for different gray scale digital images as compare to the run time of Canny method.

Some selected results of edge detections for these test images using the classical methods and proposed scheme are shown in Figures.5(a)-(d). From the results; it has again been observed that the performance of the proposed method works well as compare to the performance of the previous methods (with default parameters in MATLAB)..

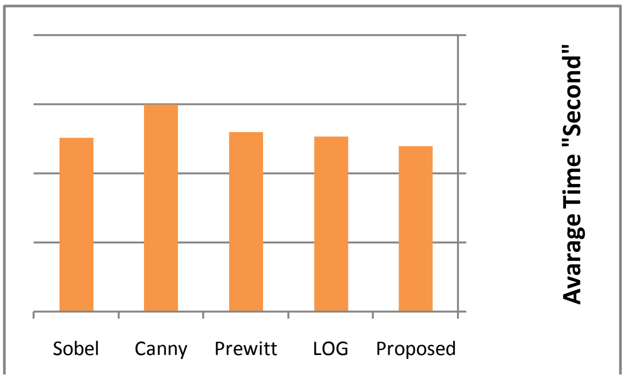

Figure. 4: Chart time for proposed method and classical methods with 512×512 pixel test images

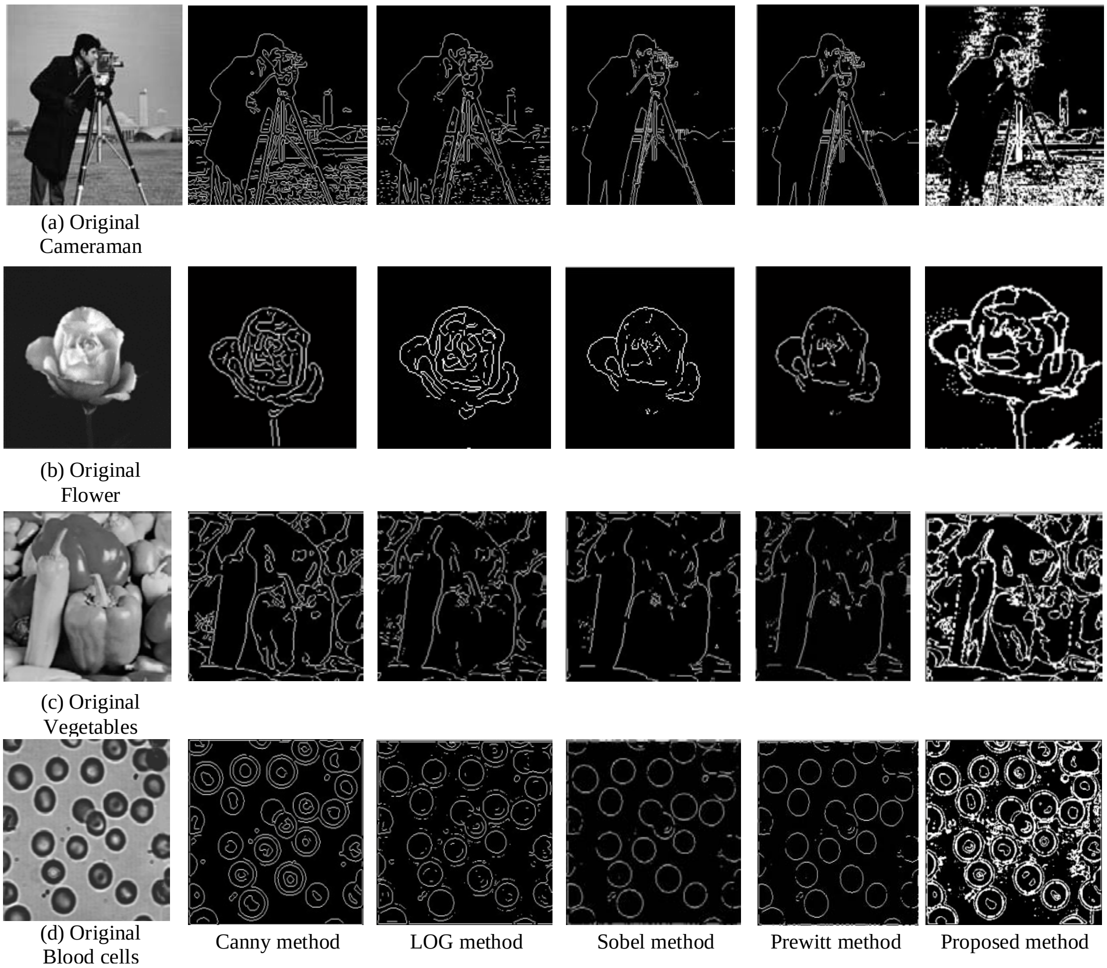

Figure. 5: Performance of Proposed Edge Detector for various images

VI. CONCLUSION

An efficient approach using Tsallis-Kapur entropy for detection of edges in grayscale images is presented in this paper. The proposed method is compared with traditional edge detectors. On the basis of visual perception and edgel counts of edge maps of various grayscale images it is proved that our algorithm is able to detect highest edge pixels in images. The proposed method is decrease the computation time as possible as can with generate high quality of edge detection. Also it gives smooth and thin edges without distorting the shape of images. Another benefit comes from easy implementation of this method.

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