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Implementation of Histogram based Tsallis Entropic Thresholding Segmentation for Plasma Detection from Visible Images of TOKAMAK

Payal Patel[1], Bhargav Shah[2], Pritesh Saxena[3], Chintan Panchal[4]

[1]M.E. Student, Electronics & Communication Department, Dr. S. & S. S. Ghandhy Government Engineering College, Surat, Gujarat, India.

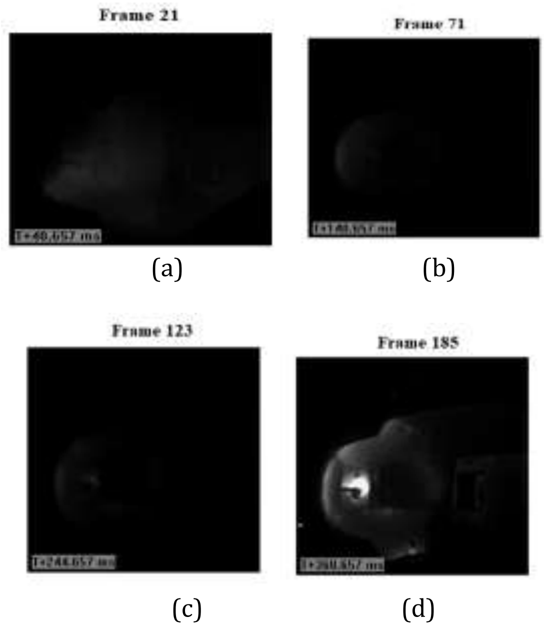
[2,3,4]Assistant Professor, Electronics & Communication Department, Sarvajanik College of Engineering & Technology, Surat, Gujarat, India.

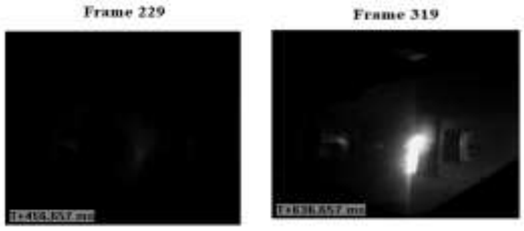
Abstract - *Image segmentation is to find the desired object presented in the image. Gray Level Local Variance (GLLV), Gray Level Local Entropy (GLLE), Gray Level Spatial Correlation (GLSC) are different 2D histogram methods used to do the segmentation using Tsallis Entropy. In this paper, visible images of Plasma of TOKAMAK are used to extract the desired bright spots from images using different 2D histogram Segmentation Methods, which can further be used to find the position of the plasma. Due to unavailability of ground truth image, unsupervised parameter Uniformity Value is used as an evaluation parameter. Result shows that GLSC based Segmentation provides better result in terms of Uniformity Value compared to the other methods.*

***Key Words*: Image Segmentation, Tsallis Entropy, Image Thresholding, Gray Level Local Variance (GLLV), Gray Level Local Entropy (GLLE), Gray Level Spatial Correlation (GLSC), Uniformity Value, Image Processing**

1. INTRODUCTION

Image segmentation is the process of dividing an image into some meaningful and non-overlapping regions according to a certain similarity criterion. In one region, the image's characteristics such as gray level, texture and colour are similar, whereas they are obviously different in different regions [14]. In image processing and image analysis, local features like regions, shapes, textures play an important role. Image segmentation uses these local features to portion the image into non- overlapping regions such that each region is homogenous and union of two adjacent region is heterogeneous [1][2]. Image segmentation can be used in image, video and computer vision applications such as defect detection, character recognition, document analysis, etc [1]. Segmentation technique can be classified into four groups: Thresholding based segmentation, Boundary based segmentation, and Region based segmentation and Hybrid technique. From all these four techniques, thresholding-based segmentation is the simplest yet effective method for converting the image into background and Region of interest (Object) using the difference of gray level [1]. In other words, Thresholding converts the gray image into black and white by finding the optimum threshold. Gray level above threshold will convert into white and others are converted into black. In image processing, the maximum entropy principle is generally recognized as having a relevant role in the initial part of image elaboration. The first step of processing in fact, sees the entropy used to determine the segmentation of the image that is used to determine objects and background in it. Entropy is a measure of uncertainty in an information source, and has received increasing attention from researchers for the selection of thresholding values [20]. The visible images of Plasma from tokamak machines are used to extract the bright plasma region using the thresholding-based segmentation. The extracted regions can be further used to find the position of plasma while it is in active state. High speed cameras are installed in tokamaks to monitor the discharge evolution and any transient interaction of the plasma with the first wall. A fast-visible camera is installed in tokamak Aditya, using an imaging fiber bundle on a re-entrant viewport, just below the midplane of the machine. When the TOKAMAK is in running mode, fast visible camera continuously captures the video of physical activity happening inside the machine. Captured Video can be converted into the frames to do further processing on it. Fig. 1 shows some Frames extracted from the video. Video is having total 323 frames.





(e) (f)

Fig -1: Extracted frames from video. a) Frame 21 b) Frame 71 c) Frame 123 d) Frame 185 e) Frame 229 f) Frame 319

2. LITERATURE REVIEW

Bi-level and multilevel thresholding are the main two categories of thresholding-based segmentation. In bi-level thresholding, one threshold is selected to partition the image into background and desired object. In multilevel thresholding, more than one threshold is obtained to divide the image into multiple classes using histogram. Global and Local threshold are further classification of the thresholding-based image segmentation technique [1, 2]. In Global threshold method, the threshold is computed based on the image histogram while in Local threshold, the threshold is computed locally using neighboring window [2]. The local global threshold holds to be computational expensive than the global threshold [2]. The popular technique of global thresholding is Entropic approach. Obtaining of Best threshold using entropic approach was first proposed by Pun [3]. It was corrected with improved result by Kapoor by maximizing the sum of the two class entropies of the background and object [4]. Albuquerque generalized Kapoor entropy into the Tsallis entropy [5]. All these entropies are 1D entropy. The 1D entropic approach does not take the spatial correlation into consideration and hence results into the same threshold output for different images having same histogram. This is the biggest drawback of the 1D entropic approach. To find the solution to this, many literatures has appeared. Abutaleb present novel thresholding method using 2D entropy [6]. He used the gray level pixel value and the local average gray value of the pixel to compute 2D histogram using. Brinks provided a better approach by maximizing the entropies of the background and foreground [7]. Sahoo refines the approach of abutaleb using 2-D Renyi's entropy [8]. Sahoo and Arora proposed a Tsallis entropic thresholding approach [2]. To incorporate the edge information with the background and object information, Xiao proposed Gray level Spatial Correlation (GLSC) histogram using the pixel's gray level and the similarity of the pixels with their local neighboring pixels [9]. Gray level local variance (GLLV) Histogram method was proposed to segment the image, which is constructed by using the gray level information of pixels and its local variance in a neighborhood [20]. Gray level local entropy (GLLE) method was proposed, which is first calculates the local entropy of a pixel and then construct a novel 2D histogram by combining the local entropy and gray level of pixels [14]. Using the local features, which represent the edge properties of the local neighborhood, to compute the 2-D histogram could give better results for image thresholding. 2-D direction histogram is determined by the gray levels of the pixels and the local features of corresponding local neighborhoods [1].

In this paper, Implementation of Gray Level Local Variance (GLLV), Gray Level Spatial Correlation (GLSC) and Gray Level Local Entropy (GLLE) Histogram based Tsallis Entropic thresholding methods are presented.

The rest of the paper is organized as follows. Tsallis entropy is presented in section 3. Image thresholding using generation of 2D Histogram using Gray Level Local Variance (GLLV), Gray Level Local Entropy (GLLE) and Gray Level Spatial Correlation (GLSC) methods with Tsallis entropy is presented in section 4. The experimental results are presented in section 5. At last, section 6 contains the conclusion.

3. TSALLIS ENTROPY

Probability distribution can be used to find the entropy of a discrete source, where p = {pi} is the probability of finding the each possible state i[5]. Therefore,

$$0 \le p_i \le 1 \ (1)$$

And

$$\sum_{i=1}^{k} p_i = 1 \ (2)$$

Where k is the total number of states. The Shanon entropy can be described as

$$H = \sum_{i=1}^{k} p_i \ln(p_i) \ (3)$$

Tsallis entopy is the extension of the Shannon entropy having the from as

$$H_\alpha = \frac{1-\sum_{i=1}^{k} p(i)^\alpha}{q-1} \ (4)$$

Two dimensional Tsallis entropy can be derived from one dimensional form as:

$$H_\alpha = \frac{1-\sum_{i=1}^{k}\sum_{j=1}^{s} p(i,j)^\alpha}{\alpha-1} \ (5)$$

Where k is the total number of possibilities of the system and α is the entropic index that characterize the degree of nonextensivity. When α=1, Tsallis entropy converts to Boltzmann-Gibbs-Shannon (BGS) entropy. The Tsallis entropy follow the pseudo additivity rule

$$H_\alpha(A+B) = H_\alpha(A) + H_\alpha(B) + (1-q)H_\alpha(A)H_\alpha(B) \ (6)$$

Considering Hα>=0, entropy can be classified in three way based on α as

Subextensive entropy (α<1)

$$H_\alpha(A+B) < H_\alpha(A) + H_\alpha(B) \ (7)$$

Extensive entropy (α=1)

$$H_\alpha(A+B) = H_\alpha(A) + H_\alpha(B) \ (8)$$

Superextensive entropy (α>1)

$$H_\alpha(A+B) > H_\alpha(A) + H_\alpha(B) \ (9)$$

4. THE TE SEGMENTATION BASED ON GLLV, GLSC AND GLLE 2D HISTOGRAM

4.1 GLLV Histogram

Let I be an image of size M×N with gray level ranging in {0, 1, … , L-1} and I(x, y) be the gray value of the pixel located at (x, y), where x = 1, 2, …, M and y = 1, 2, …, N, L = 256 for an 8-bit image. The final goal is to segment the coherent structure from the image. In Global threshold selection methods Grey level histogram of the image can be used. Grey level distribution of the image and some other features of the image can be used to optimize the suitable criteria to obtain the optimal threshold.

For each pixel at (x, y), its local variance with neighborhood size n×n is calculated as

$$g(x, y) = \frac{1}{n^2-1} \sum_{i=-\frac{n-1}{2}}^{\frac{n-1}{2}} \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} [I(x+i, y+j) - I1(x, y)]^2 \quad (10)$$

where I1(x, y) is the mean of pixels in the neighborhood, and is calculated as

$$I1(x, y) = \frac{1}{n^2} \sum_{i=-\frac{n-1}{2}}^{\frac{n-1}{2}} \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} I(x+i, y+j) \quad (11)$$

Letting n_{ij} be the total number of pixel pairs that I (x, y) = i and g (x, y) = j in the image, then the GLLV histogram is defined as

$$p_{ij} = \frac{n_{ij}}{M \times N} \quad (12)$$

GLLV histogram P = {p_{ij}; i =0, 1, …, L-1, j =0, 1, …, L'-1} is a matrix with size L×L', which is shown in Figure 2.

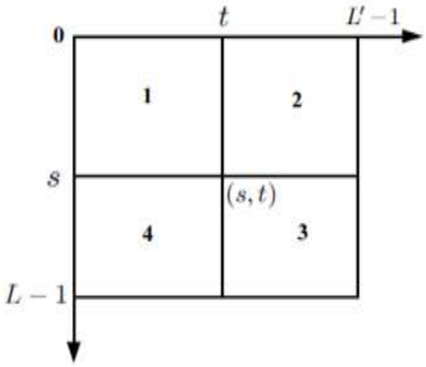


Fig -2: 2D Histogram having dimension of L× L'

4.2 GLLE Histogram

Let I be an image, I (x, y) be the grey level at pixel (x, y), where x= 1, 2, …, M; y= 1, 2, …, N. I (x, y) ε 0, 1, …, L-1}. The number of pixels with grey level k is denoted as n_k, the entropy of the image is defined as

$$E = -\sum_{k=0}^{L-1} p_k \log p_k \quad (13)$$

where

$$p_k = \frac{n_k}{M \times N} \quad (14)$$

is the probability of grey level k appeared in the image.

When moving a neighborhood window with size m×n pixel by pixel within the image from left to right and top to down, one can obtain the local entropy value of each pixel. Then, the number of pixel pairs such that I (x, y) = i and J(x, y) = j is calculated, denoted as n_{ij}. GLLE histogram is defined as

$$p_{ij} = \frac{n_{ij}}{M \times N} \quad (15)$$

4.3 GLSC Histogram

Let f (m, n) is the gray value of a pixel located at the point (m, n). In a digital image [f (m, n)|m ∈ {1, 2,. . . , M}, n ∈ {1, 2, . . . , N}] of size M×N, let the histogram be h(x) for x ∈ {0, 1, 2,…, L−1}, where L = 256 for an 8 bit image. For convenience, we denote the set of all gray levels {0, 1, 2, …, 255} as G. Global threshold selection methods generally use the gray level histogram of the image. The optimal threshold is determined by optimizing a suitable criterion function obtained from the gray level distribution of the image and some other features of the image.

In order to compute the 2D histogram of a given image, the average gray value of the neighborhood of each pixel is calculated. Let g(x, y) be the average of the neighbourhood of the pixel located at the point (x, y). The average gray value for the 3×3 neighborhood of each pixel is calculated as

$$g(x, y) = \left[\frac{1}{9} \sum_{i=-1}^{1} \sum_{j=-1}^{1} f(x+i, y+j)\right] \quad (16)$$

where [r] denotes the integer part of the number r. The pixel's gray value f(x, y) and the average of its neighborhood g(x, y) are used to construct a 2D histogram using:

$$h(i, j) = \text{probe } (f(x, y) = i \text{ and } g(x, y) = j) \quad (17)$$

where i, j ∈ G. For a given image, there are several methods to estimate this density function. One of the most popular methods is the method of relative frequency. The normalized histogram is approximated as follows:

$$p_{ij} = \frac{n_{ij}}{M \times N} \quad (18)$$

where M×N denotes the image size and denotes the index of a pixel whose gray value equals i and local average value equals j.

Threshold vector (t, s) divides the 2D histogram plane into four regions, where threshold for pixel intensity is t and s are another threshold for the normalized local average of pixels. Region of interest (Hot Spot) and background can be represented in 1st and 3rd quadrants respectively. 2nd and 4th quadrants have the mostly edge and noise information, so we can ignore them [1]. Normalization is accomplished by using posteriori class probabilities P1 (t, s) and P3 (t, s), where

$$P1(t,s) = \sum_{i=0}^{s}\sum_{j=1}^{t} p(i,j) \quad (19)$$
$$P3(t,s) = \sum_{i=t+1}^{L-1}\sum_{j=s+1}^{L'-1} p(i,j) \quad (20)$$

As per our assumption, the contributions of 2nd and 4th quadrants are negligible. Hence it can be approximated as P3 (t, s) ≈1− P1 (t, s).

Thresholding an image at a threshold t is equivalent to partitioning the set G into two disjoint subsets as G0 = {0, 1, 2, …, t} and G1 = {t+1, t+2, …, 255}.

The Tsallis entropy associated with class 1 (object) and class 2 (background) can be described in the following way:

$$H_a(t,s) = \frac{1}{\alpha-1}\left[1 - \sum_{i=0}^{s}\sum_{j=1}^{t}\left(\frac{p_{ij}}{p_{st}}\right)^{\alpha}\right] \quad (21)$$
$$H_b(t,s) = \frac{1}{\alpha-1}\left[1 - \sum_{i=s+1}^{255}\sum_{j=t+1}^{255}\left(\frac{p_{ij}}{1-p_{st}}\right)^{\alpha}\right] \quad (22)$$

From the above stated equations, threshold (t,s) for GLSC 2D bi level Tsallis Entropy can be found maximizing the following expression:

$$\varphi_\alpha(t,s) = \left(\begin{bmatrix} H_a^{\alpha}(t,s) + H_b^{\alpha}(t,s) + \\ (1-\alpha)H_a^{\alpha}(t,s)H_b^{\alpha}(t,s) \end{bmatrix}\right) \quad (23)$$

The optimum threshold vector (t, s) is one that maximizes the total Tsallis entropy of object and background, i.e.,

$$(t,s) = \arg\max \phi_\alpha(t,s) \quad (24)$$

Once the optimal threshold vector (t, s) is obtained, segmentation of image can be done as,

$$seg(x,y) = \begin{cases} 0 & I(x,y) \le t \text{ and } G(x,y) \le s \\ 1 & I(x,y) > t \text{ and } G(x,y) > s \end{cases} \quad (25)$$

5. RESULTS

Gray Level Local Variance (GLLV), Gray Level Local Entropy (GLLE), Gray Level Spatial Correlation (GLSC) based Entropy thresholding methods are applied on extracted images of Visible imaging video to detect the plasma. Following table shows the threshold value obtain using different methods on different frames of video sequence.

Table -1: Optimum Threshold Values T for Different Thresholding Methods for Alpha =0.1

Video	Frame no.	GLLV Method	GLLE Method	GLSC Method
1901	21	17	17	19
	71	10	15	16
	123	11	12	12
	185	61	60	74
	229	8	11	10
	319	78	60	92

Here we have shown the threshold value for some arbitrarily taken frames for video sequence. GLLV, GLLE, GLSC Methods applied on all the frames of the video.
Alpha Parameter plays the important role in the segmentation result while using the Tsallis Entropy based segmentation technique. We use different values of alpha on all the videos sequences to find out the optimal value. We use 0.1 to 0.9 in step size of 0.1 as alpha value. Based on the experiments, we find that alpha = 0.1 provides the better result compared to other values.

Unsupervised objective measure – Uniformity Parameter is used to estimate the performance of the proposed method. The reason to choose unsupervised objective measure is that, no ground truth data are available for these discharge videos. The uniformity measure describes region homogeneity [1]. It has the range between the 0 and 1. Higher the value, better is the segmentation. It is defined by

$$U(t) = 1 - \frac{\sigma_B^2(t) + \sigma_F^2(t)}{C} \quad (26)$$
$$C = \frac{1}{2}\left(g_{max} - g_{min}\right)^2 \quad (27)$$
$$\mu_B^t = \frac{\sum_{(x,y)\in B} f(x,y)}{n_B^t} \quad (28)$$
$$\mu_F^t = \frac{\sum_{(x,y)\in F} f(x,y)}{n_F^t} \quad (29)$$
$$\sigma_B^2(t) = \frac{1}{n_B^t}\sum_{(x,y)\in B}\left(f(x,y) - \mu_B^t\right)^2 \quad (30)$$
$$\sigma_F^2(t) = \frac{1}{n_F^t}\sum_{(x,y)\in F}\left(f(x,y) - \mu_F^t\right)^2 \quad (31)$$

Background and Foreground regions are represented by B and F respectively, g is the image gray level, f(x,y) is the gray level of the pixel(x,y), n_B^t and n_F^t is the number of pixel in the background region and in the foreground region respectively.

Table -2: Uniformity Values for Different Thresholding Methods Using Tsallis Entropy for Different Alpha Value

Alpha	Uniformity Value		
	GLLV Method	GLLE Method	GLSC Method
0.1	0.8969	0.8989	**0.9124**
0.2	0.9003	0.8757	0.9090
0.3	0.8989	0.8640	0.9074
0.4	0.8910	0.8495	0.8850
0.5	0.8832	0.8498	0.8744
0.6	0.8782	0.8416	0.8701
0.7	0.8777	0.8292	0.8742
0.8	0.8787	0.8235	0.8847
0.9	0.8735	0.8146	0.8968

Table 2 indicate the uniformity values for plasma video. To get the uniformity value for 2D entropy-based segmentation using Tsallis entropy alpha value is considered as 0.1 to 0.9.

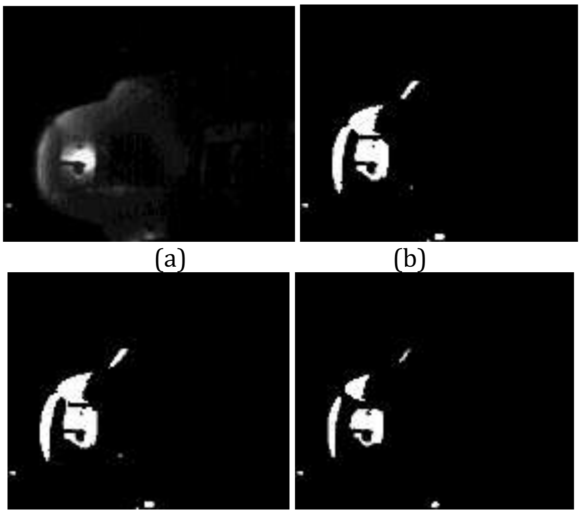

(a) (b) (c) (d)

Fig -3: Frame no. 185 of video a) Original Image b) GLLV Method c) GLLE Method d) GLSC Method

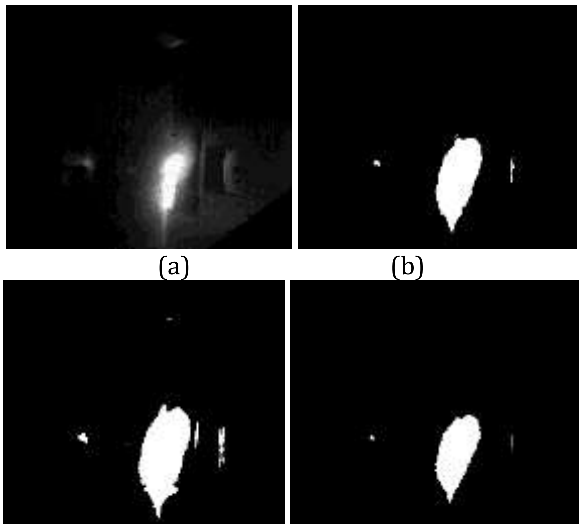

(a) (b) (c) (d)

Fig -4: Frame no. 319 of video a) Original Image b) GLLV Method c) GLLE Method d) GLSC Method

6. CONCLUSION

A Gray Level Local Variance (GLLV), Gray Level Local Entropy (GLLE) and Gray Level Spatial Correlation (GLSC) histogram-based image segmentation methods using 2D Tsallis entropy is presented in this paper. The 2D histogram was computed for different thresholding based segmented methods. The results show that GLSC method provide higher Threshold values which in turn helps to get better segmented results compared to the other methods and Also, provide good uniformity value.

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