SEGMENTATION OF VARIOUS IMAGES USING ENTROPY BASED METHOD AND PERFORMANCE EVALUATION WITH OTSU METHOD

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Abstract: -Image segmentation quality is usually governed by two main parameters associated with a particular segmentation method: threshold selection and seed-point selection. Various methods such as the histogram method, entropy based method, busyness measure methods, etc. are well known for threshold selection in the image segmentation problems. In this thesis, threshold selection is done on the basis of different entropy measures on both grayscale and color images. Study of the Shannon and non-Shannon entropies (Renyi, Havrda-Charvat, Kapur and Vajda) with Otsu Method is done to obtain image segmentation. We classify these methods according to their evaluation criteriaviz. PRI (Probabilistic Rand Index), VOI (Variation of Information) and GCE (Global Consistency Error).These underlying metrics and combination methods help in determining the performance of an evaluation measure. It is observed through the simulation experiments performed on images, that the position of the smallest minima obtained in the entropy versus gray-level plot is different for each entropy measure. For a particular definition of the entropy plots are generated and the threshold values obtained from these plots possess the segmentation results. It is observed that Havrda-Charvat entropy measure is better matched with Otsu Method than other entropy measures.

Keywords:- Entropy; Otsu; PRI; VOI; GCE; Threshold;

I. INTRODUCTION

Image segmentation entails the division or separation of the image into regions of similar attributes and is a vitalstep in a series of processes aimed towards understanding a given image [1]-[6].The aim of the division is to make the image more meaningful and to simplify the analysis easier. Typically, Image segmentation helps to proper specify the objects and boundaries (lines, curves, etc.) in an image. More appropriately, the process of image segmentation assigns a label to each pixel of an image such that pixels with the same label share certain visual characteristics[7].The result of image segmentation gives a set of segments also called a set of contours extracted from the image. In a region, each of the pixels is similar in the sense of intensity, texture. This specialty is different for adjacent areas. Applications of image segmentation include identification of objects, feature extraction, etc. [1]-[6]. Segmentation of simple gray-level images also provides useful information about the surfaces in the scene [1].

In this paper, threshold selection is done on the basis of various entropy measures and Otsu Method to enhance the gray and color images. Comparative study of various entropies (Shannon, Kapur, Havrda-Charvat, Renyi and Vajda) and Otsu Method is done to obtain the image segmentation. It is observed through simulation experiments performed on various images, the smallest minima conditions obtained in the entropy versus gray-level plot are different for each entropy measure. For a particular definition of the entropy plots are generated and the threshold values obtained from these plots possess the segmentation results.

Then, all results of Entropies are compared with the standard Otsu Method. Quantitative evaluation of the quality of the images is also a significant issue. Different measures have been proposed in the literature for this task.

II. ENTROPYBASEDIMAGESEGMENTATION

The simplest method of segmentation is Thresholding Method.Thresholding Method gives an optimum threshold value that converts an image into a binary image and this threshold value separates the foreground from background [8].

Threshold selection in image segmentation is not an easy task. It provides important information about the image and play important role in segmentation of image. There are various methods to compute threshold value, threshold value can be computed manually or can be computed automatically by using thresholding algorithms, which is called automatic thresholding [7]-[8]

Various threshold selection techniques are well known in the literature.

(a) Basic Global Thresholding.

(b)Clustering methods

(c) Histogram-based method

(d) Region growing method

Here in this work we will have a major discussion on Entropy based image segmentation methods.

A. Entropy Based Image Segmentation

To segmentize the image gray level co-occurrence matrix and Shannon entropy measure is illustrated in [5]. In this work we extend this methodology using the co-occurrence matrix with non- Shannon entropy measures (such as Renyi, Havrda-Charvat, Kapur and Vajda entropy) on gray level and color images. The basic steps of the algorithm are reproduced here for the sake of convenience [5]:

a) First of all, the co-occurrence matrix C_{m_1,m_2} [5] of the image to be segmented is generated.

b) Now, from co-occurrence matrix C_{m_1,m_2} probability distribution $p_{m_1,m_2} = C_{m_1,m_2}/MN$ is generated.

c) Entropy function for each entropy definition, as defined below, are then calculated for each $t \in [0,1,2,\ldots,L-2]$ for a given image to be segmented using the probabilty distribution p_{m_1,m_2}.

d) The entropy versus gray level plot gives the minima points. And the smallest minima can be considered as threshold value.

Next, we discuss different entropy measures [5]-[7], which are used in this work for a comparative study in image segmentation problems.

A. Shannon Entropy:

Shannon's entropy measure provides an absolute limit on the best possible lossless compression of a signal under certain constraints [3]. It is defined as:

$$H_s(p_{m_1,m_2}) = -\sum_{m_1}\sum_{m_2} p_{m_1,m_2}\log p_{m_1,m_2} \quad (1)$$

Where p_{m_1,m_2} is the probability distribution associated with the 2-D random variable. In this work, we have computed the values of p_{m_1,m_2} from the entries of the gray level co-occurrence matrix [5], [4] of the given image as given by the relation $p_{m_1,m_2} = C_{m_1,m_2}/MN$ where M, N represents the image dimensions along x and y directions respectively. The entropy function for the purpose of the calculation of threshold for image segmentation is then computed from the expression given as:

$$\text{Entropy}(t) = -\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1,m_2}\log p_{m_1,m_2} - \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1,m_2}\log p_{m_1,m_2} \quad (2)$$

Where, L represents the maximum number of gray level present in a particular image.

B. Kapur Entropy:

Kapur's entropy $H_k(p_{m_1,m_2})$ of order α and type β defined as [3], [5]:

$$H_k(p_{m_1,m_2}) = \left(\frac{\sum_{m_1}\sum_{m_2} p_{m_1,m_2}^{\alpha+\beta-1}}{\sum_{m_1}\sum_{m_2} p_{m_1,m_2}^{\beta}} - 1\right)(2^{1-\alpha}-1)^{-1} \quad (3)$$

The corresponding entropy function is given by

$$\text{Entropy}(t) = \sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1}\left(\frac{p_{m_1,m_2}^{\alpha+\beta-1}}{p_{m_1,m_2}^{\beta}} - 1\right)(2^{1-\alpha}-1)^{-1} + \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t}\left(\frac{p_{m_1,m_2}^{\alpha+\beta-1}}{p_{m_1,m_2}^{\beta}} - 1\right)(2^{1-\alpha}-1)^{-1} \quad (4)$$

C. Vajda Entropy:

Vajda entropy measure $H_v(p_{m_1,m_2})$ is a special case of Kapur's entropy where β=1 is taken. It provides the advantage of faster calculations over Kapur's entropy measure and is defined as [3]:

$$,H_v(p_{m_1,m_2}) = \left(\frac{\sum_{m_1}\sum_{m_2} p_{m_1,m_2}^{\alpha}}{\sum_{m_1}\sum_{m_2} p_{m_1,m_2}} - 1\right)(2^{1-\alpha}-1)^{-1} \quad (5)$$

and corresponding entropy function is given by

$$.\ \text{Entropy}(t) = \left(\frac{\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1,m_2}^{\alpha}}{\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1,m_2}} - 1\right)(2^{1-\alpha}-1)^{-1} + \left(\frac{\sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1,m_2}^{\alpha}}{\sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1,m_2}} - 1\right)(2^{1-\alpha}-1)^{-1} \quad (6)$$

D. *Renyi Entropy*:

The generalized version of Shannon Entropy is Renyi Entropy.The Renyi entropy quantify the diversity, uncertainty or the randomness of a system. It is defined as [3], [6];

$$H_r(p_{m_1,m_2}) = \frac{\log\left(\sum\sum(p_{m_1,m_2})^{\alpha}\right)}{1-\alpha}, \alpha \neq 1, \alpha > 0 \quad (7)$$

and corresponding entropy function is given by

$$Entropy(t) = -\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1}\frac{\log\left(\sum\sum(p_{m_1,m_2})^{\alpha}\right)}{1-\alpha} - \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t}\frac{\log\left(\sum\sum(p_{m_1,m_2})^{\alpha}\right)}{1-\alpha}$$

(8)

E.*Havrda-Charvat Entropy*:

The Havrda–Charvát entropy $H_{hc}(p_{m_1,m_2})$ of degree α introduced by Havrda and Charvát and later on modified by Daróczy is often used in statistical physics and is defined as follows [3]:

$$H_{hc}(p_{m_1,m_2}) = \frac{\sum\sum p_{m_1,m_2}^{\alpha} - 1}{2^{1-\alpha} - 1} \quad (9)$$

and corresponding entropy function is given by

$$Entropy(t) = \frac{1}{2^{1-\alpha}-1}\left(\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1,m_2}^{\alpha} - 1\right) + \frac{1}{2^{1-\alpha}-1}\left(\sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1,m_2}^{\alpha} - 1\right) \quad (10)$$

III. OTSUMETHOD

Otsu method gives maximum between class variance and minimum within class variance of gray level and this gray level is selected as threshold value. Let Lgray levels $[0,1 \ldots L-1]$ represent the pixels of a given picture.The total number of pixels is denoted by$N = n_0 + n_1 + \cdots + nL - 1$ and pixels at level i is denoted by n_i. In order to explain in more easier form, thedistribution of probability is given by [13]:

$$p_i = n_i/N, p_i \geq 0, \sum_{i=0}^{L-1} p_i = 1 \quad (11)$$

Now, at level t, by using a threshold we divide pixels in two classes C_0 and C_1; C_0 denotes level of pixels [0….t] and C_1 denotes level of pixels [t+1….L-1]. Then class occurrence and class mean levels probabilities are given by

$$\omega_0 = \Pr(C_0)$$

$$= \sum_{i=0}^{t} p_i = \omega(t) \quad (12)$$

$$\omega_1 = \Pr(C_1)$$

$$= \sum_{i=t}^{L-1} P_i = 1 - \omega(t) \quad (13)$$

And

$$\mu_0 = \sum_{i=0}^{t} i \Pr(i|C_0)$$

$$= \sum_{i=0}^{t} ip_i/\omega_0$$

$$= \mu(t)/\omega(t) \quad (14)$$

$$\mu_1 = \sum_{i=t+1}^{L-1} i \Pr(i|C_1)$$

$$= \sum_{i=t+1}^{L-1} ip_i/\omega_1$$

$$= \frac{\mu_T - \mu(t)}{1-\omega(t)} \quad (15)$$

Where

$\omega(t) = \sum_{i=0}^{t} p_i$(16)

And

$\mu(t) = \sum_{i=0}^{t} i p_i$ (17)

Here, (16) and (17) represent histogram of zeroth and first order cumulative moments, and

$\mu_T = \mu(L-1) = \sum_{i=0}^{L-1} i p_i$(18)

represent the mean level of the picture. The following relation may be verified for any value of t:

$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T, \qquad \omega_0 + \omega_1 = 1$ (19)

The class variances are given by

$$\sigma_0^2 = \sum_{i=0}^{t} (i-\mu_0)^2 \Pr(i|C_0)$$

$= \sum_{i=0}^{t} (i-\mu_0)^2 p_i/\omega_0$(20)

$$\sigma_1^2 = \sum_{i=t+1}^{L-1} (i-\mu_1)^2 \Pr(i|C_1)$$

$= \sum_{i=t+1}^{L-1} (i-\mu_1)^2 p_i/\omega_1$(21)

Now, to estimate the goodness, we can use the following analysis of measure shown in (12)

$\sigma_B = \omega_0(\mu_0-\mu_T)^2 + \omega_1(\mu_1-\mu_T)^2$(22)

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-class variance is the difference between two parts. If the between-class variance is increased then this also increase difference between two parts. The between class variance is decreased if there is a mistake between foreground and background. Hence, the probability of error will be minimum if only between class variance is maximum. A threshold may be considered as a good threshold if it gives the perfect separation of classes in gray-levels. That is the Otsu algorithm.

By using general quantities (9) and (10), or distinctly using (12)-(8), the optimal threshold t* can be obtained for various values of t from 0 to L-1, and this threshold maximizes σ_B^2 and can be given as:

$$\sigma_B^2(t) = \frac{[\mu_T\omega(t)-\mu(t)]^2}{\omega(t)[1-\omega(t)]}(23)$$

And the optimal threshold t is

$\sigma_B^2(t^*) = \text{Arg} \max_{0<t<L-1}[\sigma_B^2(t)]$ (24)

Algorithm of Otsu Method:

1. Read image with gray levels of $t = [1 \ldots L]$.
2. Calculate probability and histogram of all intensity level.
3. Set up $\omega_i(0) = 0$ and $\mu_i = (0)$

4. Step through all possible thresholds $t = [1 \dots L]$ maximum intensity.
5. Compute ω_i and μ_i.
6. Compute $\sigma_B^2(t)$
7. Desired threshold corresponding to the maximum $\sigma_B^2(t)$.

IV. IMAGESEGMENTATIONINDICES

A.Probabilistic Rand Index (PRI)

Comparing two different partitions that have different number of classes is a problem in the image segmentation field. The Rand Index is a property that computes the pair wise relationships of label of this different partition.

In this technique pairs of pixels are counted whose labelling is relevant between the ground truth and computed segmentation. It superimposes the desirable statistical properties of the Rand index so that the refinements can be accommodated properly. Consider an image $X = \{x_1, x_2, \dots x_i, \dots, xN\}$, here subscript shows a pixel from N pixels and consider an image $\{S_1, S_2, \dots \dots, S_k\}$, which is manually segmented. The segmentation of test image is given by Stest and PRI is defind as[20]:

$$PR(Stest, \{Sk\}) = \frac{1}{N} \sum_{\substack{i,j \\ i<j}} [c_{ij}p_{ij} + (1 - c_{ij})(1 - p_{ij})]$$

Here c_{ij} denote the event of a pair of pixels i and j having the same label in the test image $Stest$:

$$C_{ij} = I(l_i^{Stest} = l_j^{Stest})$$

This measure takes values in [0, 1] – 0 when Stestand $\{S_1, S_2, \dots \dots, S_k\}$ have no similarities and 1 whenall segmentations are identical.

B. Global Consistency Error (GCE)

The Global Consistency Error scales the extent to which one segmentation can be inquired as a defecation of the other. Region-based Segmentation is used in GCE, which present the consistency between different image segmentations. It compares manually segmented images with the results of algorithms. Let there are two segmentation S_1 and S_2. Consider x_i(pixel) and the classes (segments) in that x_i in S_1 and S_2. These sets S_1 and S_2 may be expressed by pixels C (S_1, x_i) and C (S_2, x_i) respectively [11].

$$GCE(S_1, S_2) = \frac{1}{n} \min\left\{\sum_i x_i (S_1, S_2), \sum_i x_i (S_2, S_1)\right\}$$

C. Variation of Information

Between the two classes, the VOI scales sum of information loss and information gain, and thus due to this property one class can be understand by other. If the VOI metric shows lower values it means that there are major similarity between two classes and VOI always give nonnegative values. More appropiately, when there is changing from one class to another class VOI scales the quantity of information that is lost or gained.

The VOI gives a scale of the distance between two classes. A class with pixels$X_1, X_2, \dots, X_k$ is represented by a random variable X with X= {1 ….K} such that $p_i = |X_i|/n, i \in X$ and $n = \sum i\, X_i$ the variation of information between two class X and Y so represented is defined to be [11]

$$VI(X, Y) = H(X) + H(Y) - 2I(X, Y)$$

Where H(X) is entropy of Xand I(X, Y) is mutual information.

V. RESULTS&SIMULATION

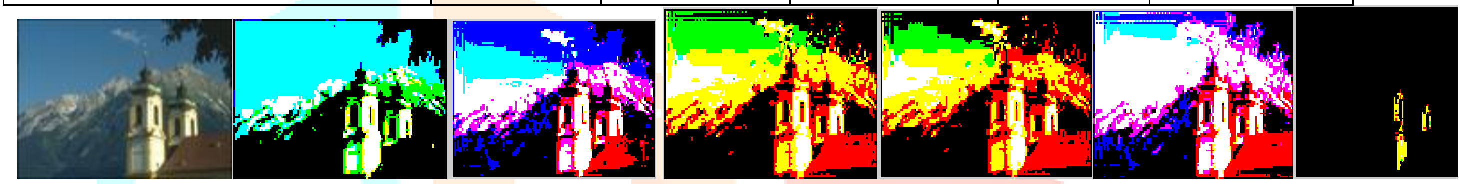
In this chapter, we present the simulation results performed in MATLAB on variety of different gray and color images. To segment these images Shannon and various Non-Shannon entropies viz. Kapur, Havrda-Charvat, Renyi, Vajda Entropies and Otsu Method is used. The entropy of these images is computed using entropy versus gray level plot obtained for different definitions of entropy and the plots and images are shown for reference. And segmented results from Otsu Method are also shown. Then, all these Entropy results are compared with simulation results of Otsu Method on the basis of three parameters viz. Probabilistic Rand Index (PRI), Variation of Information (VOI) and Global Consistency Error (GCE) to investigate that which method give best suitable results for different types of images.

(a) (b) (c) (d) (e) (f) (g)

Fig.1. (a)Gray Input Image, Output Image for (b) Otsu, (c) Havrda, (d) Vajda (e) Kapur, (f) Reny, (g) Shannon

TABLE.1 Comparison of different methods using PRI, VOI, GCE and Threshold Value for Output Image

Parameter/Methods	**Havarda VS OTSU**	**Vajda Vs OTSU**	**Kapur VS OTSU**	**Reny Vs OTSU**	**Shannon Vs OTSU**
PRI(probabilistic Rand Index)	0.9219	0.6521	0.5953	0.5953	0.5177
VOI(variation of information)	0.4092	0.7452	1.2629	1.2629	1.3421
GCE(Global Consistency Error)	0.0734	0.3254	0.2930	0.2930	0.2504
Threshold	109/117	148/117	152/117	152/117	168/117



(a) (b) (c) (d) (e) (f) (g)

Fig.2. (a) Color Input Image, Output Image for (b) Otsu, (c) Havrda, (d)Vajda (e) Kapur, (f) Reny, (g) Shannon

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