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Comparitive Analysis of Image Segmentation Techniques

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Abstract –Image segmentation is the process of partitioning an image into multiple segments, so as to change the representation of an image into something that is more meaningful and easier to analyze. Several general-purpose algorithms and techniques have been developed for image segmentation. In this paper, we present ostu method, watershed method and Color-Based Segmentation Using K-Means Clustering for image segmentation. Then evaluation of these method is done using four evaluation metrics: probabilistic Rand index, global consistency error, variation of information and peak signal to noise ratio. We intend to find out the best algorithm using evaluation metrices.

Keywords: Image segmentation, Threshold, Ostu method, Watershed, Color-Based Segmentation Using K-Means Clustering, PRI, GCE, VOI, PSNR,

1. Introduction

Image Segmentation is a common process in an image analysis especially in the field of vision and tracking. Segmentation is defined as a method that subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the object of interest in an application have been isolated [1].

Mathematical Form

Mathematically if the domain of image is given by *I*, then the segmentation problem is to determine the sets S_j , whose union is entire Image *I.* Thus the sets that make up segmentation must satisfy

$$I = \bigcup_{j=1}^{n} S_j \qquad (1)$$

where $S_j \cap S_k = \varphi$ for $k \neq j$ and each S_j is connected and n is number of objects of interest .

Image Segmentation Techniques

Many algorithms and methods have been developed for image segmentation. The simplest method of image segmentation is called the thresholding method. This method is based on a threshold value to turn a gray-scale image into a binary image. Another image segmentation method is Edge based Method that is more common for detecting discontinuities in gray level than detecting isolated points and thin lines because isolated points and thin lines so not occur frequently in most practical images[2]. Another method Graph Based Segmentation is a fast and efficient method of generating a set of segments from an image.The graph based image segmentation is based on selecting edges from a graph, where each pixel corresponds to a node in the graph[3].In this paper, Ostu Thresholding Algorithm, Watershed Algorithm and Color-Based Segmentation Using K-Means Clustering are studied. Comparison of these algorithm are done using performance metrics. Predicted dataset is compared with ground truth data.

2 Methodology

2.1 Ostu's Thresholding Method

Ostu [4] proposed a dynamic thresholding selection method in 1979. This method suggests maximizing the weighted sum of between-class variances of foreground and background pixels to establish an optimum threshold.

Ostu's thresholding technique is based on a discriminate analysis which partitions the image into two classes C_0 and C_1 at gray level t such that $C_0 = \{1,2,3,....,t\}$ and $C_1 = \{ t+1,t+2,....,L-1\}$, where L is the total number of the gray levels of the image. Let the number of pixels at the ith gray level be n_i and n be the total number of pixels in a given image. The probability of occurrence of gray level i is defined as:

$$pi = \frac{ni}{n} \qquad (2)$$

C_0 and C_1 are normally corresponding to the object of interested and the background, the probabilities of the two classes are ω_0 and ω_1:

$$\omega_0 = \sum_{i=0}^{t} pi \qquad (3)$$

$$\omega_1 = \sum_{i=t+1}^{L-1} pi \qquad (4)$$

Thus, the means of the two classes can be computed as:

$$\mu_0(t) = \sum_{i=0}^{t} \frac{ip_i}{\omega_0(t)\mu_1(t)} \qquad (5)$$

$$\mu_1(t) = \sum_{i=t|+1}^{L-1} \frac{ip_i}{\omega_1(t)} \qquad (6)$$

Let σ_B^2 and σ_T^2 be the between-class variance and total variance respectively. An optimal threshold t^* can be obtained by maximizing the between-class variance.

$$t^* = Arg\left\{\max_{0\le i\le L-1}\left(\frac{\sigma_B^2}{\sigma_T^2}\right)\right\} \qquad (7)$$

Where, the between-class variance σ_B^2 and σ_T^2 are defined as:

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \qquad (8)$$

$$\sigma_T^2 = \sum_{i=0}^{L-1} (i - \mu_T)^2 \qquad (9)$$

The total mean of the whole image μ_T is defined as:

$$\mu_T = \sum_{i=0}^{L-1} ip_i \qquad (10)$$

An equivalent formula for obtaining optimal threshold t^* is as follows:

$$t^* = Arg \max_{0\le t\le L} \left\{ \omega_o(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \right\} \qquad (11)$$

Ostu's method of thresholding gray level images is efficient for separating an image into two classes where two types of fairly distinct classes exist in the image [5] .

2.2 Watershed Algorithm

The watershed transform finds "catchments basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low. One of the most important drawback associated to the watershed transform is the over segmentation that commonly results. The usual way of predetermining the number and approximate location of the regions provided by the watersheds technique consists in the modification of the homotopy of the function to which the algorithm is applied. This modification is carried out via a mathematical morphology operation, geodesic reconstruction [6], by which the function is modified so that the minima can be imposed by an external function (the marker function). All the catchment basins that have not been marked are filled by the morphological reconstruction and so transformed into non minima plateaus, which will not produce distinct regions when the final watersheds are calculated. Segmentation using the watershed transform works well if you can identify, or "mark," foreground objects and background locations [7].

2.3 Color-Based Segmentation Using K-Means Clustering

Color-Based Segmentation using K-Means follows the following steps:-

1.Read the color image.

2.Convert image from RGB color space to L*A*B* color space.

3.Classify the colors in 'A*B*' space using K-Means Clustering.

4.Label every pixel in the image using the results from KMeans.

5.Create Images that segment the image by color.

3 Performance Metrics

For evaluating the performance of segmented image, we use following metrics.

3.1 Probabilistic Rand Index (PRI)

Rand Index is the function that converts the problem of comparing two partitions with possibly differing number of classes into a problem of computing pair wise label relationships.

PRI counts the fraction of pairs of pixels whose labelling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. It is a measure that combines the desirable statistical properties of the Rand index with the ability to accommodate refinements appropriately. Since the latter property is relevant primarily when quantifying consistency of image segmentation results.

Consider a set of manually segmented (ground truth) images $\{S_1, S_2, \ldots, S_K\}$ corresponding to an image $X = \{x_1, x_2, \ldots x_i, \ldots, x_N\}$, where a subscript indexes one of N pixels. S_{test} is the segmentation of a test image, and then PRI is defined as:

$$PR(S_{test},\{S_k\}) = \frac{1}{\binom{N}{2}} \sum_{\substack{i,j \\ i<j}} [c_{ij} p_{ij} + (1-c_{ij})(1-p_{ij})] \quad (12)$$

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

$$c_{ij} = I(l_i^{S_{test}} = l_j^{S_{test}}) \quad (13)$$

This measure takes values in [0, 1] – 0 when S_{test} and $\{S_1, S_2, \ldots, S_K\}$ have no similarities and 1 when all segmentations are identical[8].

3.2 Global Consistency Error (GCE)

The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other [9].It is a Region-based Segmentation Consistency, which measures to quantify the consistency between image segmentations of differing granularities. It is used to compare the results of algorithms to a database of manually segmented images. Let S_1 and S_2 be two segmentation as before. For a given point x_i (pixel), consider the classes (segments) that contain x_i in S_1 and S_2. These sets are denoted in the form of pixels by C (S_1, x_i) and C (S_2, x_i) respectively [10].

$$GCE(S_1,S_2) = \frac{1}{n} \min\{ \textstyle\sum_i x_i(S_1,S_2), \sum_i x_i(S_2,S_1)\} \quad (14)$$

3.3 Variation of Information (VOI)

It measures the sum of information loss and information gain between the two class, and thus it roughly measures the extent to which one class can explain the other. The VOI metric is nonnegative, with lower values indicating greater similarity. It is based on relationship between a point and its class. It uses mutual information metric and entropy to approximate the distance between two classes across the lattice of possible classes. More precisely, it measures the amount of information that is lost or gained in changing from one class to another (and, thus, can be viewed as representing the amount of randomness in one segmentation which cannot be explained by the other).
The variation of information is a measure of the distance between two class (partitions of elements). A class with pixels $X_1, X_2, \ldots, X_k$ is represented by a random variable X with X={1 ….K} such that $p_i = |X_i|/n$ i€X and $n = \sum_i X_i$ the variation of information between two class X and Y so represented is defined to be

$$VI(X,Y) = H(X) + H(Y) - 2I(X,Y) \quad (15)$$

where $H(X)$ is entropy of X and $I(X,Y)$ is mutual information between X and Y. VI(X,Y) measures how much the pixel assignment for an item class X reduces the uncertainty about the item's pixel in class Y [10].

3.4 Peak signal to noise ratio (PSNR)

PSNR is used to measure the difference between two images. It is defined as

PSNR = 20 * log10(b/rms)

where b is the largest possible value of the signal (typically 255 or 1), and rms is the root mean square difference between two images. The PSNR is given in decibel units (dB), which measure the ratio of the peak signal and the difference between two images[10].

4 Experimental evaluation

For Segmentation, Original images and Image Mask are taken form Berkeley Database .

Image segmentation is done by using three techniques: (1) Ostu Method (2) Watershed Method

(3) Color-Based Segmentation Using K-Means Clustering

Experiment 4.1 : Ostu Method

1. Read image with gray levels of t=[1,… …L]
2. Compute histogram and probabilities of each intensity level
3. Set up initial $\omega_i(0) = 0$ and $\mu_i(0) = 0$
4. Step through all possible thresholds t=[1,… …L] maximum intensity
   - Compute ω_i and μ_i
   - Compute $\sigma_B^2(t)$
5. Desired threshold corresponds to the maximum $\sigma_B^2(t)$.


ORIGINAL IMAGE OTSU IMAGE

Figure 4.1 : Ostu Image Segmentation

Experiment 4.2 : Watershed Method

1. Read the color image and convert it to gray scale.
2. Use the gradient magnitude as segmentation function.
3. Mark the foreground objects.
4. Compute the background markers.
5. Compute the watershed transform of the segmented function.
6. Visualize the result.


ORIGINAL IMAGE WATERSHED IMAGE

Figure 4.2 : Watershed Image Segmentation

Experiment 4.3 : Color- Based Segmentation Using K-Means Clustering

1. Read the color image.
2. Convert image from RGB color space to L*A*B* color space.
3. Classify the colors in ‘A*B*’ space using K-Means Clustering.
4. Label every pixel in the image using the results from KMeans.
5. Create Images that segment the image by color.


ORIGINAL IMAGE COLOR-BASED SEGMENTATION USING K-MEANS CLUSTERING

Figure 4.3 : Color-Based Segmentation Using K-Means Clustering

Experiment 4.4 : Ground Truth

For Ground Truth , we superimposed Image Mask on Original Image.

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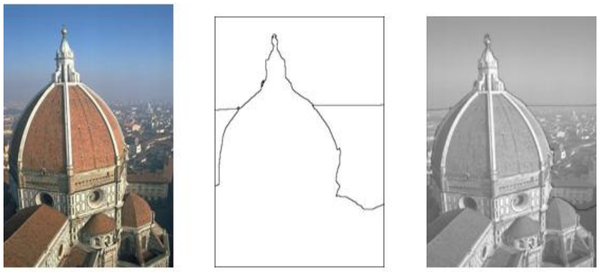

Figure 4.4 : Mask Image Superimposed On Original Image

Experiment 4.5 : Experiments Perform on Different Images

We perform experiment on different images from Berkeley dataset. One of the image is considered in this paper. Now we have to find which segmentation algorithm is best. For this we take image and image mask from Berkeley Database. Ground truth is obtained by superimposed the image mask on original image. Ostu Image, Watershed Image and Color-Based Segmentation using K-Means Clustering is result as shown in fig.

Figure 4.5 : OSTU, WATERSHED & COLOR-BASED SEGEMENTATION USING K-MEANS CLUSTERING IMAGE

Table 4.1 shows the PRI, GCE, VOI & PSNR of Ostu Image, Watershed Image & Color- Based Segmentation Using K-Means Clustering Image of Image 1. This shows PRI, GCE of Ostu Image is higher than the other methods and VOI of Ostu Image is low as compare to other methods. So using PRI, GCE, VOI, PSNR we conclude that Ostu Mehtod is better than other methods.

METRICS	OSTU IMAGE	WATERSHED IMAGE	Color-Based Segmentation Using K-Means Clustering IMAGE
PRI	0.6456	0.4610	0.5270
GCE	0.0461	0.0457	0.0430
VOI	1.4977	3.7308	1.6121
PSNR	7.2947	9.8827	4.9413

Table 4.1 : Comparison Using Parameter PRI, GCE, VOI,PSNR

References

[1] Linda G. Shapiro and George C. Stockman "Computer Vision", Upper Saddle River, New Jersey: Prentice Hall, pp. 279-325, 2001.

[2] Salem Saleh Al-amri, Dr. N.V. Kalyankar and Dr. Khamitkar S.D "Image Segmentation by Using Edge Detection" International Journal on Computer Science and Engineering ,Vol. 02, No. 03,pp. 804-807,2010.

[3] Sandeep Chalasani "Graph Based Image Segmentation"

[4] N. Otsu, A threshold selection method from gray-level histogram, IEEE Transactions on Systems Man Cybernet, pp. 62-66, 1978.

[5] WANG Hongzhi, DONG Ying "An Improved Image Segmentation Algorithm Based on Otsu Method" International Symposium on Photoelectronic Detection and Imaging 2007: Related Technologies and Applications, Vol. 6625,2008.

[6] Ashwin Kumar, Pradeep Kumar "A New Framework for Color Image Segmentation Using Watershed Algorithm" Journal of Electronic Imaging,Vol. 2,No. 3,pp. 41-46,2011.

[7] Mandeep Kaur, Gagandeep Jindal "Medical Image Segmentation using Marker Controlled Watershed Transformation" IJCST Vol. 2, Issue 4, 2011.

[8] R. Unnikrishnan C. Pantofaru M. Hebert,"A Measure for Objective Evaluation of Image Segmentation Algorithms" Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition ,Vol. 03,Page 34,2005.

[9] Allan Hanbury, Julian Stottinger, " On segmentation evaluation metrics and region count."

[10] Manisha Sharma, Vandana Chouhan "Objective Evaluation Parameters of Image Segmentation Algorithms" International Journal of Engineering and Advanced Technology (IJEAT) Vol. 2, Issue 2, 2012.