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Study & Comparision of Image Segmentation Algorithm for Better Analyzing of Different Images

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Abstract: Image segmentation is an important processing step in many image, video and computer vision applications. Extensive research has been done in creating many different approaches and algorithms for image segmentation, but it is still difficult to assess whether one algorithm produces more accurate segmentations than another, whether it be for a particular image or set of images, or more generally, for a whole class of images.

To date, the most common method for evaluating the effectiveness of a segmentation method is subjective evaluation, in which a human visually compares the image segmentation results for separate segmentation algorithms, which is a tedious process and inherently limits the depth of evaluation to a relatively small number of segmentation comparisons over a predetermined set of images.

This paper presents an objective and quantitative study of segmentation algorithms. This study distinguished from other studies by considering both evaluation and comparison, treating algorithm selected from distinct technique groups.

Keywords: PSNR, GCE, PRI

I. INTRODUCTION

1.1 Image Processing

Image processing is any form of signal processing for which the input is an image as a two-dimensional signal; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Before processing an image, it is converted into a digital form. Digitization includes sampling of image and quantization of sampled values. After converting the image into bit information, processing is performed. This processing technique may be image enhancement, image reconstruction, and image compression.

1.2 Image Segmentation

Definition

It 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 [2] 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.

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

Where $S_j \bigcap S_k = \varphi$ for $k \neq j$ and each S_j is connected and *n* is number of objects of interest. Thus the goal of image segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze [2].

1.3 Applications

Image segmentation is useful in many applications. It can identify the regions of interest in a scene or annotate the data. Some of the practical applications of image segmentation are:

- Content-based image retrieval
- Medical Imaging
- Locate objects in satellite images (roads, forests, etc.)
- Face Recognition
- Fingerprint Recognition
- Iris recognition
- Traffic Control System
- Video surveillance

1.4 Problem Formulation

Image segmentation is fundamental problem in image processing and computer vision. Image segmentation is partitioning the image into multiple regions based on some predefined criteria. This problem is well studied in literature and there are many techniques which conation different variational models and mathematical formulation. Various techniques are suited to various type of images and quality of particular technique is rigorous to measure.

In my dissertation work, Ostu method, Watershed method and Color-Based Segmentation Using K-Means Clustering are used. Comparison of these algorithms are done using performance metrics.

1.5 Objectives

1. Study and analysis of different Image Segmentation techniques.
2. Implementation of different Image Segmentation Techniques for computation of Probabilistic Random Index, Variation of Information, Global Consistency Error, Peak Signal-To-Noise ratio (PSNR) .
3. Application of Image Segmentation techniques applied on Berkeley Dataset.
4. Comparison of results obtained using image segmentation techniques.

II. METHODOLOGY

2.1 Ostu's Thresholding Method

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:

$$p_i = \frac{n_i}{n} \qquad (2)$$

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 :

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

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

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.

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

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:

$$t^* = Arg \max_{0 \le t \le L} \{ \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2 \} \qquad (11)$$

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 [23]. Ostu Thresholding Segmentation follows the procedure that is shown in fig 2.1

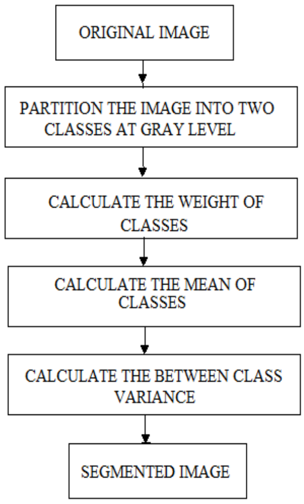


Figure 2.1: Flow Chart of Ostu Method

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 drawbacks 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 [18], 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 transforms works well if you can identify, or "mark," foreground objects and background locations [24]. Watershed Segmentation follows the procedure that is shown in fig 3.2.

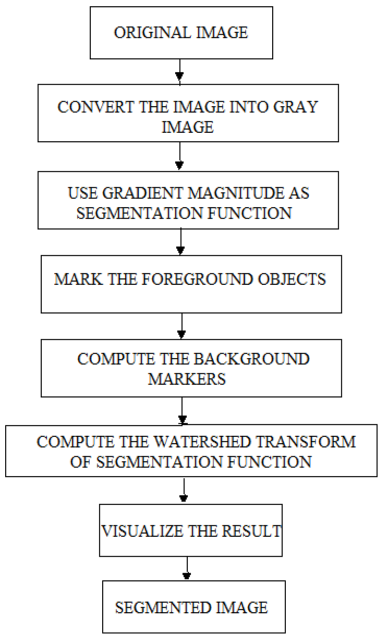


Figure 3.2: Flow Chart of Watershed Method

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 K-Means.
5. Resultant image that segment the image by color.

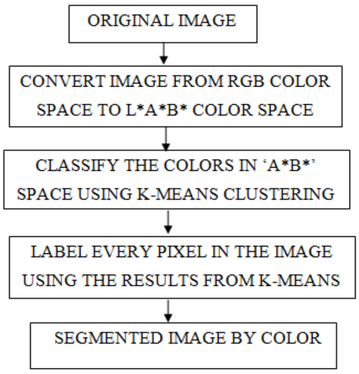


Figure 3.3: Flow Chart of color-based segmentation using K-Means

III. RESULTS AND DISCUSSIONS

3.1 Matlab

MATLAB (matrix laboratory) is most adapatable research tool used for number of research applications including the image processing, sensor network, mobile network etc. It itself define a high level language and very interactive environment to perform different tasks. It also provide the integration with different languages like C, C++, Java etc. Different features of matlab environment are

1. User friendly environment
2. Developing Algorithms and Applications
3. Analyzing and Accessing Data
4. Visualizing Data
5. Performing Numeric Computation
6. Publishing Results and Deploying Applications

MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. Using the MATLAB product, you can solve technical computing problems faster than with traditional programming languages, such as C, C++, and Fortran.

3.1.1 Development Tools

MATLAB includes development tools that help to implement algorithm efficiently. These include the following:

- MATLAB Editor - Provides standard editing and debugging features, such as setting breakpoints and single stepping .
- Code Analyzer – Checks code for problems and recommends modifications to maximize performance and maintainability .
- MATLAB Profiler - Records the time spent executing each line of code .
- Directory Reports - Scan all the files in a directory and report on code efficiency, file differences, file dependencies, and code coverage .
- Workspace - In windowed version of Matlab, Workspace item is in the view menu .
- Command Window - The window in which commands are entered.

3.2 Performance Metrics

For evaluating the performance of segmented image, we used different types of metrics.

3.2.1 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. Stest is the segmentation of a test image, and then PRI is defined as: $PR(S_{test}, \{S_k\}) = \frac{1}{\binom{N}{2}} \sum_{\substack{i,j \\ i<j}} \left[c_{ij} p_{ij} + (1 - c_{ij})(1 - p_{ij})\right]$ Here c_{ij} denote the event of a pair of pixels i and j having the same label in the test image S_{test}:

$$c_{ij} = I\left(l_i^{S_{test}} = l_j^{S_{test}}\right)$$

3.2.2 Global Consistency Error (GCE)
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 [25].

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

3.2.3 Variation of Information (VOI)
It measures the sum of information loss and information gain between the two classes, 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 class 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 classes (partitions of elements). A class with pixels $X_1,X_2, , , , ,X_k$ is represented by a random variable X with X={1 ….K} such that $p_i=|X_i|/n$ and $n=\sum_i X_i$ the variation of information between two class X and Y so represented is defined to be

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

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 [25] .

3.2.4 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 .

3.3 Experimental Results and Discussion
For segmentation, Original images are taken from Berkeley Dataset .

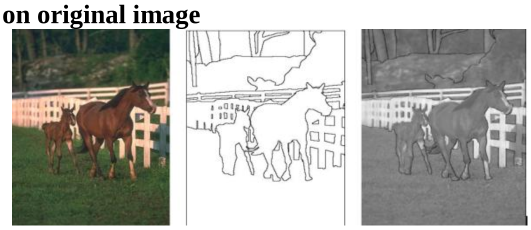
Image segmentation is done by using:

(1) Ostu Method

(2) Watershed Method

(3) Color-based segmentation using K-Means clustering

3.3. 2 Mask image superimposed on original image



Original Image Image Mask Ground Truth

3.3.2 Image 2 Segmentation

Ostu Image Watershed Image Colour based segmentation using K-Means clustering

After segmentation we need to find the best segmentation technique. For this purpose we use performance metrics. These are PRI, GCE, VOI and PSNR. For better result PRI should be high and GCE, VOI and PSNR should be low. Ground truth image is compared with original image.

Table 3.1 : Comparison of segmented image 1 using performance metrics

METRICS	OSTU IMAGE	WATERSHED IMAGE	COLOR BASED SEGMENTATION IMAGE
PRI	0.7028	0.7967	0.7526
GCE	0.2838	0.4678	0.3531

VOI	4.2737	5.8398	4.8218
PSNR	8.5943	11.5312	8.4734

Table 3.1 shows the PRI, GCE, VOI & PSNR of Ostu image, Watershed image & color- based segmentation using K-Means clustering image of image 2. This shows PRI, GCE, VOI of Ostu Image is lower than the other methods and PSNR of Watershed image is high as compare to other.

IV. CONCLUSION

Image segmentation is important consideration in computer vision. Image segmentation partition the image into multiple regions. For segmentation different methods have proposed.

In this work, I have used three image segmentation techniques named as Ostu Threholding, Watershed Method and Color-Based Segmentation using K-Means Clustering. The performance of these techniques has been evaluated in terms of PRI, GCE, VOI and PSNR. Five images have taken from Berkeley dataset for experimentation. In many cases Ostu is better while in other cases color-based segmentation using K-Means clustering is better.

For better segmentation result, value of GCE,VOI and PSNR should be smaller. From Experiments for image 1 PRI, GCE of Ostu technique is higher than the other methods and VOI of Ostu technique is low as compare to other methods. But for all other Images GCE, VOI of Ostu is lower than the Watershed method.

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