

# Review of Image segmentation Techniques

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**Abstract-** Segmentation was used to identify the object of image that users are interested. Three approaches to do it. The first is Edge detection. The second is to use threshold. The third is the region-based segmentation. It does not mean that these three of that method can solve all of the problems that user met, but these approaches are the basic methods in segmentation. To segment the images, using segmentation techniques edge detection, thresholding, region growing are considered for this study. Segmentation algorithms are based on two properties similarity and discontinuity. This paper focuses on the various methods that are widely used to segment the image.

**Keywords –** Segmentation, Edge detection, Threshold, Region based Segmentation, Watermarking.

## I. INTRODUCTION

Image segmentation is the method of sorting out an image into multiple constituent segments i.e. set of pixels. The main aim of segmentation is to simplify and/or change the depiction of an image into something that is more consequential and easier to analyze. The intensity to which the division is carried depends on application. Segmentation should stop when the objects of concern in an application have been isolated. It can be used for diverse applications in computer vision and digital image processing. Many applications require high accurate and computationally faster image processing algorithms.

Image segmentation is usually used to trace objects and boundaries like lines, curves in images. Image segmentation is the route of assigning a label to all pixels in an image such that pixels with the equivalent label share certain characteristics. The outcome of image segmentation is a set of segments that jointly wrap the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some quality or computed characteristics, such as color, intensity, or texture. Nearby regions are considerably different with respect to the same characteristic. When applied to an image, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms. Image segmentation algorithms usually based on one of two basic categories of intensity values discontinuity and similarity. The first approach is to partition an image based on rapid changes in intensity, such as edges in an image. Similarly in second approach is based upon partitioning an image into regions that are related according to set of predefined criteria. For example Threshold, region splitting, region growing and merging.

## II. IMAGE SEGMENTATION

### A. Discontinuity Detection –

There are several techniques available for detecting gray-level discontinuities in image like points, lines, and edges. For finding discontinuities in image is need to just run a mask through the image. For  $3 \times 3$  mask, this process involves computing the sum of products of coefficients with the gray-levels contained in the region included by the mask i.e. response of mask in the image is given by

$$R=W_1Z_1+W_2Z_2+\dots\dots\dots + W_9Z_9 +\dots\dots$$

Where  $Z_i$  is gray-level of pixel associated with mask coefficient  $W_i$  and reaction of the mask is defined with respect to its middle location.

### B. Edge Based Segmentation –

The focal point of this section is on the segmentation methods based on detection in sharp, local changes in intensity. Edge pixels are pixels at which the intensity of pixels changes quickly. The local changes in intensity can be detected using first-order and second-order derivatives and they are particularly well suited for this purpose. Normally first order derivatives generate thicker edges in an image; Second-order derivative produces fine detail, such as thin lines, isolated points, and noise. Second-order derivatives also produce a double-edge response. The indication of the second derivative can be used to determine whether a transition into an edge is from light to dark or dark to light.

### C. Point Detection –

Point detection should be based on the second order derivative, so Laplacian mask is expected.

-1	-1	-1
-1	8	-1
-1	-1	-1

This mask is used to scan the all point of image, and compute the response of every point, if the response of point is greater than T(threshold), the point belongs to 1(light), if not, it belongs 0(dark).

$$G(x, y) = \begin{cases} 1 & \text{if } |R(x,y)| \geq T \\ 0 & \text{otherwise} \end{cases}$$

### D. Line Detection –

The second order derivative have stronger response and to produce thinner lines than first order derivative. There are four different direction of mask.

#### Horizontal

-1	-1	-1
2	2	2
-1	-1	-1

+45°

-1	-1	2
-1	2	-1
2	-1	-1

#### Vertical

2	-1	-1
-1	2	-1
-1	-1	2

-45°

-1	2	-1
-1	2	-1
-1	2	-1

The four masks are used to decide which direction of mask is better than others. Let  $R_1$ ,  $R_2$ ,  $R_3$  and  $R_4$  denote the response of the masks shown above. If at a point in the image,  $|R_k| > |R_j|$ , for all  $j \neq k$ .  $|R_1| > |R_j|$  for  $j=2, 3, 4$ , that point is said to be more likely associated with a line in the direction of mask  $k$ .

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### E. Edge Detection –

The magnitude of first-order derivative can be used to detect an edge at a point in an image. The second-order derivative have two properties one is it produces two values for every edge in an image and another is its zero crossings can be used for locating the center of thick edges.

The image gradient is used to find edge strength and direction at location (x,y) of image, and defines as the vector.

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

The magnitude (length) of vector  $\nabla f$ , denoted as  $M(x,y)$

$$\text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

The direction of the gradient vector is given by the angle

$$\alpha(x, y) = \tan^{-1} \left[ \frac{g_y}{g_x} \right]$$

The direction of an edge at an arbitrary point (x,y) is orthogonal to the direction.

The edge-detection algorithm may be summarized as follow:

1. Filter the input image with an  $n \times n$  Gaussian low pass filter (It can smooth the large numbers of small spatial details).
2. Compute the Laplacian of the image resulting from Step1 using.
3. Finding the zero crossings of the image from Step2.

### F. Thresholding –

#### Basic Global Thresholding

As the fact that only the histogram of the image is needed to segment it, segmenting images with Threshold Technique does not involve the information of the images. Therefore, some problem may be caused by noise, blurred edges, or outlier in the image. That is why this method is the simplest concept to segment images.

When the intensity distributions of objects and background pixels are sufficiently distinct, it is possible to use a single(global) threshold applicable over the entire image. The following iterative algorithm can be used for this purpose:

1. Select an initial estimate for the global threshold,  $T$ .
2. Segment the image using  $T$  as

$$g(x, y) = \begin{cases} 1 & \text{if } f(x,y) \geq T \\ 0 & \text{if } f(x,y) < T \end{cases}$$

This will produce two groups of pixels:  $G_1$  consisting of all pixels with intensity values  $> T$ , and  $G_2$  consisting of pixels with values  $\leq T$ .

3. Compute the average(mean) intensity values  $m_1$  and  $m_2$  for the pixels in  $G_1$  and  $G_2$ .
4. Compute a new threshold values:

$$T = \frac{1}{2}(m_1 + m_2)$$

5. Repeats Step2 through 4 until the difference between values of  $T$  in successive iterations is smaller than a predefined parameter.

### Optimum Global and Adaptive Thresholding

Thresholding may be viewed as a statistical-decision theory problem whose objective is to minimize the average error incurred in assigning pixels to two or more groups.

Let  $\{0, 1, 2, \dots, L-1\}$  denote the  $L$  distinct intensity levels in a digital image of size  $M \times N$  pixels, and let  $n_i$  denote the number of pixels with intensity  $i$ . The total number,  $MN$ , of pixels in the image is  $MN = n_0 + n_1 + n_2 + \dots + n_{L-1}$ . The normalized histogram has components  $p_i = n_i / MN$ , from which it follows that

$$\sum_{i=0}^{L-1} p_i = 1, p_i \geq 0$$

Now, we select a threshold  $T(k) = k, 0 < k < L-1$ , and use it to threshold the input image into two classes,  $C_1$  and  $C_2$ , where  $C_1$  consist with intensity in the range  $[0, k]$  and  $C_2$  consist with  $[k+1, L-1]$ .

Using this threshold,  $P_1(k)$ , that is assigned to  $C_1$  and given by the cumulative sum.

$$P_1(k) = \sum_{i=0}^k p_i$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)$$

The validity of the following two equations can be verified by direct substitution of the preceding result:

$$P_1 m_1 + P_2 m_2 = m_G \quad P_1 + P_2 = 1$$

In order to evaluate the “goodness” of the threshold at level  $k$  we use the normalized, dimensionless metric

$$\eta = \frac{\sigma_B^2(k)}{\sigma_G^2}$$

Where  $\sigma_G^2$  is the *global variance*

$$\sigma_G^2 = \sum_{i=0}^{L-1} (i - m_G)^2 p_i$$

And  $\sigma_B^2$  is the *between-class variance*, define as :

$$\sigma_B^2 = P_1 (m_1 - m_G)^2 + P_2 (m_2 - m_G)^2$$

$$\sigma_B^2(k) = P_1 P_2 (m_1 - m_2)^2 = \frac{(m_G P_1(k) - m(k))^2}{P_1(k)(1 - P_1(k))}$$

Indicating that the *between-class variance* and  $\eta$  is a measure of *separability* between class.

Then, the optimum threshold is the value,  $k^*$ , that maximizes  $\sigma_B^2(k)$

$$\sigma_B^2(k^*) = \max_{0 \leq k \leq L-1} \sigma_B^2(k)$$

In other word, to find  $k^*$  we simply evaluate (2.7-11) for all *integer values* of  $k$ . Once  $k^*$  has been obtain, the input

image  $f(x, y)$  is segmented as before:  $g(x, y) = \begin{cases} 1 & \text{if } f(x,y) \geq k^* \\ 0 & \text{if } f(x,y) < k^* \end{cases}$

For  $x = 0, 1, 2, \dots, M-1$  and  $y = 0, 1, 2, \dots, N-1$ . This measure has values in the range

$$0 \leq \eta(k^*) \leq 1$$

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### G. Region Based Segmentation –

#### Region Growing

Region growing segmentation is an approach to examine the neighboring pixels of the initial “seed points” and determine if the pixels are added to the seed point or not.

- Step1. Selecting a set of one or more starting point (seed) often can be based on the nature of the problem.
- Step2. The region are grown from these seed points to adjacent point depending on a threshold or criteria(8-connected) we make.
- Step3. Region growth should stop when no more pixels satisfy the criteria for inclusion in that region

Several important issues about region growing :

1. The suitable selection of seed points is important. The selection of seed points is depending on the users.
2. More information of the image is better. Obviously, the connectivity or pixel adjacent information is helpful for us to determine the threshold and seed points.
3. The value, “minimum area threshold”. No region in region growing method result will be smaller than this threshold in the segmented image.
4. The value, “Similarity threshold value“. If the difference of pixel-value or the difference value of average gray level of a set of pixels less than “Similarity threshold value”, the regions will be considered as a same region.
5. The result of an image after region growing still have point’s gray-level higher than the threshold but not connected with the object in image.

The advantages and disadvantages of region growing:

Advantages:

1. Region growing methods can correctly separate the regions that have the same properties define.
2. Region growing methods can provide the original images which have clear edges the good segmentation results.
3. The concept is simple. Only need a small numbers of seed point to represent the property, then grow the region.
4. It can choose the multiple criteria at the same time.  
It performs well with respect to noise, which means it has a good shape matching of its result.

Disadvantage:

1. The computation is consuming, no matter the time or power.
2. This method may not distinguish the shading of the real images.

In conclusion, the region growing method has a good performance with the good shape matching and connectivity. The most serious problem of region growing method is the time consuming.

#### Region Splitting and Merging

An alternative method is to subdivide an image initially into a set of arbitrary, disjoint regions and then merge and/or split the region. The quadrants means that subdivide that quadrant into sub quadrants, and it is the following as:

1. Split into four disjoint quadrants any region  $R_i$  for which  $Q(R_i) = FALSE$  (means the region don’t satisfy same logic in  $R_i$ ).
2. When no further splitting is possible, merge any adjacent region  $R_j$  and  $R_k$  for which  $Q(R_j \cup R_k) = TRUE$  (means that  $R_j$  and  $R_k$  have similarity we define in somewhere).
3. Stop when no further merging is possible.

*Advantage of region splitting and merging :*

It can split the image by choosing the criteria user want, such as segment variance or mean of the pixel-value. And the splitting criteria can be different from the merging criteria.

*Disadvantages:*

1. Computation is intensive.
2. Probably producing the blocky segments.

The blocky segment problem effect can be reduced by splitting for higher resolution, but at the same time, the computational problem will be more serious.

### III. CONCLUSION

Image segmentation forms the basics of pattern recognition and scene analysis problems. The segmentation techniques are numerous in number but the choice of one technique over the other depends only on the application or requirements of the problem that is being considered. In this paper a few techniques are considered. But the numbers of techniques are so large they cannot be all addressed.

### REFERENCES

- [1] Rafael C. Gonzalez and Richard E. Woods ,“ Digital Image Processing”, 2006.
- [2] B. Sumengen, B. S. Manjunath, C. Kenney, "Image Segmentation using Curve Evolution and Flow Fields," Proceedings of IEEE International Conference on Image Processing (ICIP), Rochester, NY, USA, September 2002.
- [3] W. Ma, B.S. Manjunath, "Edge Flow: a technique for boundary detection and image segmentation," Trans. Image Proc., pp. 1375-88, Aug. 2000.
- [4] Jin Wang," Image segmentation Using curve evolution and flow fields", written reports 2003.
- [5] Waseem Khan, "Image Segmentation Techniques: A Survey", Journal of Image and Graphics, Vol. 1, No. 4, December 2013.
- [6] Lijun Ding, Ardeshir Goshtasby, "On the Canny edge detector", Pattern Recognition 34 (2001), 721-725
- [7] Matei Mancas, Bernard Gosselin, Benoît Macq," Segmentation Using a Region Growing Thresholding".
- [8] Sonam Saluja, Aradhana Kumari Singh, Sonu Agrawal,"A Study of Edge-Detection Methods", International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 1, January 2013
- [9] Ms. Chinki Chandhok, Mrs.Soni Chaturvedi, Dr A.A Khurshid," An Approach to Image Segmentation using K-means Clustering Algorithm", International Journal of Information Technology (IJIT), Volume – 1, Issue – 1, August 2012 ISSN 2279 – 008X.
- [10] <http://www.mathworks.com/>