International Journal of Latest Trends in Engineering and Technology
Special Issue SACAIM 2016, pp. 126--133
e-ISSN:2278-621X

ALGORITHMS FOR IMAGE SEGMENTATION

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Abstract- Image segmentation is one of the emerging research topics in the field of image processing. Image segmentation is one of the most important steps to the analysis of processed image data; its main goal is to divide an image into parts that have a strong correlation with objects of areas of the real world contained in the image. There are several issues related to image segmentation that require detailed review. One of the common problems encountered in image segmentation is choosing a suitable approach for isolating different objects from the background. In this paper the different types of algorithm used for image segmentation have been discussed.

Keywords –Intensity,Thresholding , Brightness, Edge, Gray-level, Region, Watershed,clustering

I. INTRODUCTION

Image segmentation is one of the primary steps in image analysis for object identification. The main aim is to recognize homogeneous regions within an image as distinct and belonging to different objects. Segmentation stage does not worry about the identity of the objects. They can be labeled later. The segmentation process can be based on finding the maximum homogeneity in gray levels within the regions identified.

There are several issues related to image segmentation that require detailed review. One of the common problems encountered in image segmentation is choosing a suitable approach for isolating different objects from the background. The segmentation doesn't perform well if the gray levels of different objects are quite similar. Image enhancement techniques seek to improve the visual appearance of an image. They emphasize the salient features of the original image and simplify the task of image segmentation. The type of operator chosen has a direct impact on the quality of the resultant image. It is expected that an ideal operator will enhance the boundary differences between the objects and their background making the image segmentation task easier. Issues related to segmentation involve choosing good segmentation algorithms, measuring their performance, and understanding their impact on the image processing system.

II.SEGMENTATION TECHNIQUES

The study is focused on finding the object regions in gray-level images. Image segmentation has been used for a wide variety of applications.

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Segmentation algorithm for monochrome images are based on the following two basic properties [1][2]:

1. Intensity values 2. Discontinuity and similarity

In the first case partition of the images is done by changing the intensity of the image like edges. In the second case partitioning is done by dividing an image into regions which are similar according to a set of predefined criteria.

The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each and every pixels of a particular region are similar with respect to some of the characteristic or computed property like color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristics.

Types of segmentation techniques:Thresholding based segmentation , Edge Based Segmentation, Region-based segmentation,Watershed based segmentation, Clustering based Segmentation[1].

A. Thresholding

Gray-level thresholding is the simplest segmentation process. Many objects or image regions are characterized by constant reflectivity or light absorption of their surfaces; a brightness constant or threshold can be determined to segment objects and background. Thresholding is computationally inexpensive and fast. It is the oldest segmentation method and is still widely used in simple applications; thresholding can easily be done in real time using specialized hardware.

A complete segmentation of an image R is a finite set of regions R1,…Rs,

$$R=R1+R2+\ldots Rs \qquad R_i \cap R_j \qquad i \neq j$$

Complete segmentation can result from thresholding in simple scenes. Thresholding is the transformation of an input image f to an output (segmented) binary image g as follows:

$$g(i,j) = 1 \text{ for } f(i,j) \geq T$$
$$= 0 \text{ for } f(i,j) < T$$

Where T is the threshold, g(i,j) = 1 for image elements of objects, and g(x,y)=0 for image elements of the background(or vice versa)[1][2].Figure (4) shows the result of thresholding with T = 120 of the input image in Figure (3).

B. Edge-Based Segmentation

Edge-Based segmentation represents large group of methods based on information about edges in the image; it is one of the earliest segmentation approaches and still remains very important. Edge-based segmentations rely on edges found in an image by edge detecting operators-these edges mark image locations of discontinuities in gray-level, color, texture etc.

The most common problems of edge-based segmentation, caused by image noise or unsuitable information in an image, are an edge presence in locations where there is no border, and no edge presence where a real border exists.**Edge image thresholding** is based on construction of an edge image that is processed by an appropriate threshold.Different types of edge based segmentation are Sobel, Prewit, Roberts, Laplacian of a Gaussian, zero crossing, Canny[2]. The result figure after applying Prewit, Sobel, Canny algorithms are shown in figure (5),figure (6),and figure (7).

C. Region-based segmentation

It is easy to construct regions from their borders, and it is easy to detect borders of existing regions. Segmentation as based on edge based method and region growing methods are not exactly same. Usually the partition based on combination of both will be more effective. For noisy image region growing techniques are better in which the borders are very difficult to detect.

Homogeneity is an important property of regions and is used as the main segmentation criterion in region growing, whose basic idea is to divide an image into zones of maximum homogeneity. The criteria for homogeneity can be based on gray-level, color, texture, shape, mode etc. Properties chosen to describe regions influence the form, complexity, and amount of prior information in the specific region-growing segmentation method.

Region growing segmentation should satisfy the following condition of complete segmentation:

$R = \bigcup_{i=1}^{S} R_i \quad R_i \cap R_j = \emptyset \quad i \neq j$ Eq-1

And the maximum region homogeneity conditions

$H(Ri) = TRUE \quad i = 1,2,\ldots,S$ Eq.2

$H(R_i \cup R_j) = FALSE \quad i \neq j$, Rj adjacent to R_j Eq.3

Three approaches to region growing exist; region merging, region splitting, and split-and-merge region growing.

Region merging starts with an over segmented image in which regions satisfy equation (Eq.2). Regions are merged to satisfy condition (Eq.3) as long as equation Eq.2 remains satisfied.

Region splitting is the opposite of region merging. Region splitting begins with an under segmented image which does not satisfy condition (Eq.2). Therefore, the existing image regions are sequentially split to satisfy conditions (Eq.1,2 and.3).

If we combine splitting and merging it will give a good result having advantages of both. Split and merge approaches typically use pyramid image representations. Since split and merge options both can be used at the starting segmentation no need to satisfy either condition (Eq.2 or 3)[2].

D. Watershed Segmentation

In the case of watershed segmentation the regions of the segmented image is represented by the catchment basin. The first approach for the watershed segmentation approach begins with locating a downstream path from each pixel of the image to local minima of the image surface altitude. The catchment basin can be defined as the set of pixels to which the respective downstream path all terminated in the same altitude minimum.

In the second approach, each gray-level minimum represents one catchment basin and the strategy is to start filling the catchment basin from the bottom[2][1].Figure (8) shows the result of watershed segmentation of the input image in figure (1).

E. Clustering based segmentation

From the different technique one of the most efficient methods is the clustering method. Again there are different types of clustering: *K*-means clustering, Fuzzy *C*-means clustering, mountain clustering method and subtractive clustering method.

One of most used clustering algorithm is *k*-means clustering. It is simple and computationally faster than the hierarchical clustering. And it can also work for large number of variable. But it produces different cluster result for different number of number of cluster. Therefore it is require to initializing proper number for numbers of cluster, k2. Again, it is required to initialize the *k* number of centroid. Different value of initial centroid would result different cluster. So selection of proper initial centroid is also an important task [3].

a. Contrast Enhancement using Partial Contrast Stretching

Contrast enhancement technique such as Partial Spatial Starching (PCS) is used to improve the image quality and contrast of the image. It is done by stretching and compression process. By applying this technique, the pixel range of lower threshold value and upper threshold value will be mapped to a new pixel range and stretched linearly to a wide range of pixels within new lower stretching value, and the remaining pixels will experience compression (Figure1)[3].

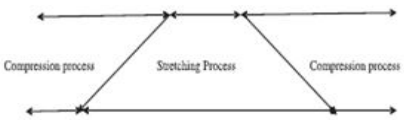


Figure (1) Partial contrast stretching process

b. Subtractive Clustering Algorithm

Subtractive clustering is a method to find the optimal data point to define a cluster centroid based on the density of surrounding data points. This method is the extension of Mountain method, proposed by Chiu1.Mountain method is very simple and effective. It estimates the number and initial location of the cluster centers. It distribute the data space into gridding point and compute the potential for each data point base on its distance to the actual data point. So the grid point with many data point nearby will have high potential value. And so this grid point with highest potential value will be choose as first cluster centre. So after selecting the first cluster centre we will try to find the second cluster centre by calculating the highest potential value in the remaining grid points.

As grid points near the first cluster center will reduce its potential value, the next cluster center will be grid with many data point nearby other than first cluster center grid point. So this procedure of acquiring new cluster center and reducing the potential of surrounding grid point repeat until potential of all grid points falls below a threshold value. Therefore this method is considered as one among the simplest and effective methods to find the cluster centers.

But with increase in the dimension of data, its computation complexity grows exponentially. So, subtractive clustering algorithm solves the computational method associated with mountain method.This algorithm makes use of data points as the candidates for the cluster centre. And the computation of this method is proportional to the size of the problem.

Consider a collection of n data points: $X = \{x1, x2, x3 \ldots xn\}$. Then each point is considered as a potential cluster center. The potential of data point's $xn$is defined as:

$$P_n = \sum_{i=1}^{n} e^{\frac{-4x_n - x_i^2}{r_a^2}}$$

where$ra$is hyper sphere cluster radius in data space and it is a positive constant which is used to define the neighborhood. The symbol $\|\cdot\|$ denotes the Euclidean distance. So the measure of the potential for the data point is a measure of function of distance to all other data points.

After finding the potential of each data points, select the data point with maximum potential as the first cluster centre. Let us consider $x1$ and $p1$ as first cluster centre and its corresponding potential respectively. The potential of each data point is then revised for each data point by using the formula as follows:

$$P_n = P_n - P_1 e^{\frac{-4 x_n - x_1^2}{r_b^2}}$$

*rb*is the hyper sphere penalty radius in data space and it is a positive constant. Here an amount of potential is subtracted from each data point as a function of distance from the first cluster center. So the data points near the first cluster center will have greatly reduced potential, and therefore it have less chance to select as next cluster center. After calculating the revise potential of each data points, find the next highest potential as the next cluster center. These processes are repeated till a required number of cluster centers are obtained [3].

c. K-Means Clustering Algorithm

Clustering method divide a set of data into a specific number of groups. It's one of the popular method is *k*-means clustering. In *k*-means clustering, it partitions a collection of data into a *k* number group of data. A given set of data can be classified into k number of disjoint clusters by this method. *K*-means algorithm consists of two separate phases.

In the first phase it calculates the *k* centroid and in the second phase it takes each point to the cluster which has nearest centroid from the respective data point. There are different methods to define the distance of the nearest centroid and one of the most used methods is Euclidean distance. Once the grouping is done it recalculate the new centroid of each cluster and based on that centroid, a new Euclidean distance is calculated between each center and each data point and assigns the points in the cluster which have minimum Euclidean distance.

In this partition each cluster is defined by means of its member objects and also by its centroid. The point to which the sum of the distances from all the objects in that cluster is minimized is called centroid of that cluster. K-means clustering is an iterative algorithm. It minimizes the sum of the distances from each object to its cluster centroid in all clusters. An image with resolution of x x y is considered and this image has to be cluster into k number of cluster.

Let us consider p(x,y) is an input pixels to be cluster and ck be the cluster centers.

The algorithm for *k*-means clustering is following as:

1. Initialize number of cluster *k* and centre.
2. For each pixel of an image, calculate the Euclidean distance *d,* between the center and each pixel of an image using the relation given below.

$$d = \| p(x, y) - c_k \|$$

3. Assign all the pixels to the nearest centre based on distance *d*.
4. After all pixels have been assigned, recalculate new position of the centre using the relation given below.

$$c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} p(x, y)$$

5. Repeat the process until it satisfies the tolerance or error value.
6. Reshape the cluster pixels into image.

Although *k*-means has the great advantage of being easy to implement, it has some drawbacks. The quality of the final clustering results is depends on the arbitrary selection of initial centroid. So if the initial centroid is randomly chosen, it will get different result for different initial centers. Therefore the initial center will be chosen carefully to get our required segmentation. And also computational complexity is another term which we need to consider while designing the *K*-means clustering. It depends on the number of data elements, number of iteration and number of clusters. The following figure 5 shows how the original images figure 2(a) and figure (2) b are transformed after applying K-means clustering algorithm [3].

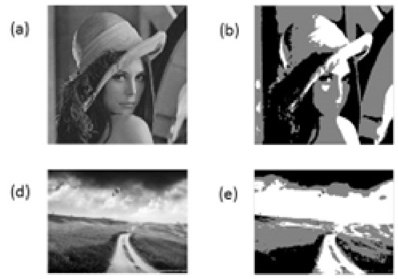


Figure (2): (a),(d) Original images; (b),(e) K-means algorithm

III. EXPERIMENT AND RESULT

A. Implementation using matlab

The judy image is taken for measurement. The following operations are done on the image.

Threshold
Edge detection by prewitt
Edge detection by soble
Edge detection by canny
Watershed segmentation

```
% Image Segmentation
I=imread('d:\matlab704\work\judy2.bmp');
figure,imshow(I),title('input image');
g= abs(g);
figure,imshow(gbot,[ ])
T=120;
g=g>=T;
figure,imshow(g),title('threshold');
g=edge(I,'prewitt',0.15);
figure,imshow(g),title('edge detection by prewitt');
ts=edge(I,'sobel',0.15);
figure,imshow(ts),title('edge detection by sobel');
tc=edge(I,'canny',0.5);
figure,imshow(tc),title('edge detection by canny');
l=watershed(I);
figure,imshow(l),title('watershed');
```

B. Screen shots

The judy image is taken for measurement. The following operations are done on the image.

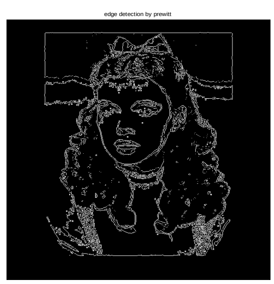
Threshold
Edge detection by prewitt
Edge detection by soble
Edge detection by canny
Watershed segmentation

The result of the program provides the following

The input image and the result of threashold method is as shown below

Figure (3): Input Image Figure (4): The result of Threshold

The result of edge detection by Prewitt Method and Soble Method is shown below.



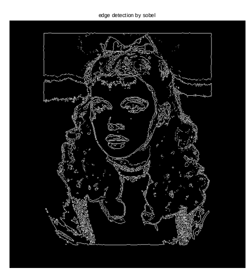
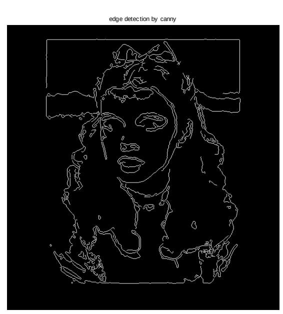


Figure (5): result of prewitt Figure (6): result of sobel

The result of edge detection by Canny method and watershed method is shown below



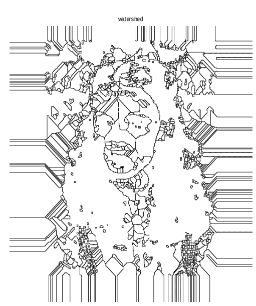


Figure (7): result of canny Figure (8): result of watershed

IV.CONCLUSION

Segmentation is an essential preliminary step in object recognition and image understanding. Based on the objects of interest of the problem the image can be divided into number of objects. Segmentation process will be repeated till the object of interest is obtained. Different types of algorithms are discussed. The choice of the algorithm generally based on the application area and the requirement.Segmentation is very much useful for detailed analysis of any image. It will be very much useful for analyzing medical images. In medical image processing segmentation techniques are useful for transforming the raw image in to meaningful quantifiable form to be useful for diagnosis and analysis. Segmentation can also be used for computer vision, robotics, remote sensing and other industrial applications.

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