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A Comparative Study of Image Segmentation Algorithms

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Abstract**—**In some applications, such as image recognition or compression, segmentation refers to the process of partitioning a digital image into multiple segments. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation is to classify or cluster an image into several parts (regions) according to the feature of image, for example, the pixel value or the frequency response. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Several image segmentation algorithms were proposed to segment an image before recognition or compression. Up to now, many image segmentation algorithms exist and be extensively applied in science and daily life. According to their segmentation method, we can approximately categorize them into region-based segmentation, data clustering, and edge-base segmentation. In this paper, we give a study of several popular image segmentation algorithms that are available.

Keywords**—**Image Segmentation, hierarchical segmentation, partitional segmentation, density estimation.

I. Introduction

IMAGE segmentation is the first stage of processing in many practical computer vision systems. Image segmentation is to separate the desired objects from the background. It can identify the regions of interest in a scene or annotate the data. Over the last few decades many segmentation algorithms have been developed. We categorize the existing segmentation algorithm into region-based segmentation, data clustering, and edge-base segmentation. Region-based segmentation includes the seeded and unseeded region growing algorithms, the JSEG, and the fast scanning algorithm. All of them expand each region pixel by pixel based on their pixel value or quantized value so that each cluster has high positional relation. For data clustering, the concept of them is based on the whole image and considers the distance between each data. The characteristic of data clustering is that each pixel of a cluster does not certainly connective. The basis method of data clustering can be divided into hierarchical and partitional clustering. Furthermore, we show the extension of data clustering called mean shift algorithm, although this algorithm much belonging to density estimation. The last classification of segmentation is edge-based segmentation. This type of the segmentations generally applies edge detection or the concept of edge. The typical one is the watershed algorithm, but it always has the over segmentation problem, so that the use of markers was proposed to improve the watershed algorithm by smoothing and selecting markers [1].

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II. Region-Based Segmentation Methods

Region-based methods mainly rely on the assumption that the neighboring pixels within one region have similar value. The common procedure is to compare one pixel with its neighbors. If a similarity criterion is satisfied, the pixel can be set belong to the cluster as one or more of its neighbors. The selection of the similarity criterion is significant and the results are influenced by noise in all instances. In this chapter, we discuss four algorithms: the Seeded region growing, the unseeded region growing, the Region splitting and merging, and the Fast scanning algorithm [2].

A. Seeded Region Growing

The seeded region growing (SRG) algorithm is one of the simplest region-based segmentation methods. It performs a segmentation of an image with examine the neighboring pixels of a set of points, known as seed points, and determine whether the pixels could be classified to the cluster of seed point or not [3]. There is no doubt that each of the segmentation regions of SRG has high color similarity and no fragmentary problem. However, it still has two drawbacks, initial seed points and time-consuming problems. The initial seed-points problem means the different sets of initial seed points cause different segmentation results. This problem reduces the stability of segmentation results from the same image. Furthermore, how many seed points should be initially decided is an important issue because various images have individually suitable segmentation number. The other problem is time-consuming because SRG requires lots of computation time, and it is the most serious problem of SRG. Fig. 1 shows the segmentation result of Lena image by using SRG. The sub-images are sorted according to the size of cluster from large to small. The display order is from left to right and from up to down.

Fig. 1 The segmentation result of Lena image using SRG

B. Unseed Region Growing

The unseeded region growing (URG) algorithm is a derivative of seeded region growing proposed by [4]. Their distinction is that no explicit seed selection is necessary. In the segmentation procedure, the seeds could be generated automatically. So this method can perform fully automatic segmentation with the added benefit of robustness from being a region-based segmentation. From Fig. 2, the segmentation result of unseen region growing seems a little over segmentation. The result will be better after the threshold is adjusted higher.

C. Region Splitting and Merging

The main goal of region splitting and merging is to distinguish the homogeneity of the image [5]. Its concept is based on quad trees, which means each node of trees has four descendants and the root of the tree corresponds to the entire image. Besides, each node represents the subdivision of a node into four descendant nodes.

Advantages:

a. The image could be split progressively according to our demanded resolution be-cause the number of splitting level is determined by us.
b. We could split the image using the criteria we decide, such as mean or variance of segment pixel value. In addition, the merging criteria could be different to the splitting criteria.

Disadvantages:

It may produce the blocky segments. The blocky segment problem could be reduced by splitting in higher level, but the tradeoff is that the computation time will arise.

Fig. 2 The segmentation result of Lena image using URG

D. Unsupervised Segmentation of Color-Texture Regions in Images and Video (JSEG)

The drawback of unsupervised segmentation is ill-defined because the segmented objects do not usually conform to homogeneous spatiotemporal regions in color, texture, or motion. Hence, in 2001, Deng et al. present the method for unsupervised segmentation of color-texture regions in images and video, called as JSEG [6]. The goal of this algorithm is to segment images and video into homogeneous color-texture regions. In this thesis, we only describe the image segmentation part of JSEG. The concept of the JSEG algorithm is to separate the segmentation process into two portions, color quantization and spatial segmentation. The color quantization quantizes colors in image into several representative classes that can differentiate regions in the image. The process of quantization is implemented in the color space without considering the spatial distribution of the colors. The corresponding color class labels replace the original pixel values and then create a class-map of the image. The CIE LUV color space is used for the color space in JSEG. In second portion, spatial segmentation executes on the class-map instead of regarding the corresponding pixel color similarity. The benefit of this separation is that respectively analyzing the similarity of the colors and their distribution is more tractable than complete them at the same time [7], [8].

E. Fast Scanning Algorithm

Unlike region growing, fast scanning algorithm do not need seed point. The concept of fast scanning algorithm [9] is to scan from the upper-left corner to lower-right corner of the whole image and determine if we can merge the pixel into an existed clustering. The merged criterion is based on our assigned threshold. If the difference between the pixel value and the average pixel value of the adjacent cluster is smaller than the threshold, then this pixel can be merged into the cluster. The regions of result are quite complete except some regions are not good in connectivity of shape. For example, the cloche in first region should be separated with the background.

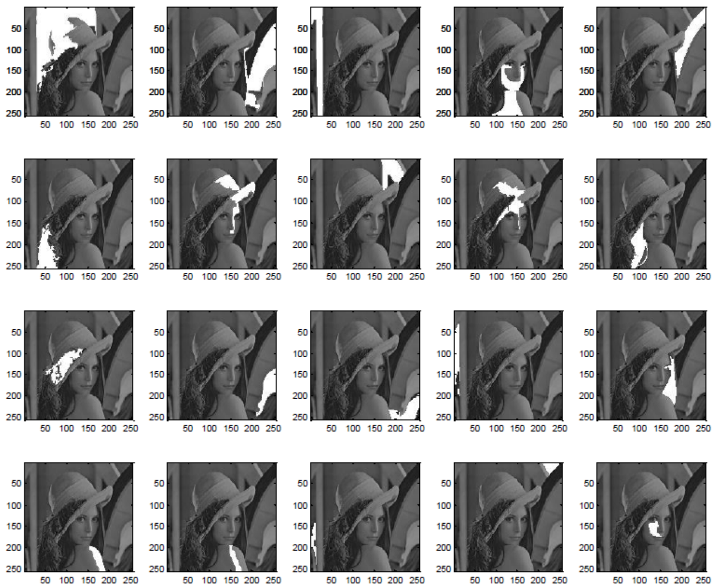

Fig. 3 The segmentation result of Lena image using the fast scanning algorithm

III. Data clustering

Data clustering is one of methods widely applied in image segmentation and statistic. The main concept of data clustering is to use the centroid to represent each cluster and base on the similarity with the centroid of cluster to classify. According to the characteristics of clustering algorithm, we can roughly divide into “hierarchical” and “partitional” clustering. Except for this two classes, mean shift algorithm is part of data clustering, too, and its concept is based on density estimation [10].

A. Hierarchical Clustering

The concept of hierarchical clustering is to construct a dendrogram representing the nested grouping of patterns (for image, known as pixels) and the similarity level set which groupings change. We can apply the two-dimensional data set to interpret the operation of the hierarchical clustering algorithm. The hierarchical clustering can be divided into two kinds of algorithm: the hierarchical agglomerative algorithm and the hierarchical divisive algorithm [11], [12]. The advantages and disadvantages of the hierarchical algorithm are concluded as below.

Advantages:

a. The process and relationships of hierarchical clustering can just be realized by checking the dendrogram.
b. The result of hierarchical clustering presents high correlation with the characteristics of original database.

c. We only need to compute the distances between each pattern, instead of calculating the centroid of clusters.

Disadvantages:

For the reason that hierarchical clustering involves in detailed level, the fatal problem is the computation time.

B. Partitional Clustering

In contrast with the hierarchical clustering constructing a clustering structure, the partitional clustering algorithm obtains a single partition of the data. It is useful to implement large data sets, but for hierarchical clustering, the construction of dendrogram needs lots of computation time. The problem of partitional clustering is that we have to select the number of desired output clusters before we start to classify data [13].

1. Squared Error Algorithm

Before we describe the steps of partitional clustering, the convergence criterion should be mentioned. The concept of partitional clustering is to start with random initial data points and keep reassigning the patterns to clusters based on the similarity between the pattern and the centroid of clusters until a convergence criterion is en-countered. One of convergence criterion frequently applied is squared error algorithm [14]. The benefit of squared error is that it works well with isolated and compact clusters.

2. K-means Clustering Algorithm

The most famous partitional clustering algorithm is k-means clustering. The steps of k-means clustering are as below.

Step1. Determine the number of clusters we want in the final classified result and set the number as N. Randomly select N patterns in the whole databases as the N centroids of N clusters.

Step2. Classify each pattern to the closest cluster centroid. The closest usually represent the pixel value is similarity, but it still can consider other features.

Step3. Recomputed the cluster centroids and then there have N centroids of N-clusters as we do after Step1.

Step4. Repeat the iteration of Step 2 to 3 until a convergence criterion is met.

The typical convergence criteria are: no reassignment of any pattern from one cluster to another, or the minimal decrease in squared error. We conclude the advantages and disadvantages of the k-means clustering algorithms as follows:

Advantages:

a. K-means algorithm is easy to implement.
b. Its time complexity is O (n), where n is the number of patterns. It is faster than the Hierarchical clustering.

Disadvantages:

a. The result is sensitive to the selection of the initial random centroids.
b. We cannot show the clustering details as hierarchical clustering does.

Fig. 4 The segmentation result of Lena image using the mean shift algorithm.

3. Mean Shift

Numerous nonparametric clustering methods can be separated into two parts: hierarchical clustering and density estimation. Hierarchical clustering composes either aggregation or division based on some proximate measure. The concept of the density estimation-based nonparametric clustering method is that the feature space can be considered as the experiential probability density function (p.d.f.) of the represented parameter. The mean shift algorithm [15], [16] can be classified as density estimation. It adequately analyzes feature space to cluster them and can provide reliable solutions for many vision tasks. The segmentation result of mean shift algorithm in Fig. 4 seems really match human sense except some fragmental regions. However, to consider the computation time, it is a time-consuming method.

IV. Edge-Based Segmentation Method

Edge-base segmentation generally indicates the segmentation method based on the edge in an image. The simple methods apply some edge detection methods before segmentation. Some edge detection methods are gradient operators [2] and Hilbert transform [17], [18]. Then the other methods only base on the concept of edge instead of using edge detection methods, for instance, watershed segmentation algorithm.

A. Watershed Segmentation Algorithm

The main goal of watershed segmentation algorithm is to find the "watershed lines" in an image in order to separate the distinct regions. To imagine the pixel values of an image is a 3D topographic chart, where x and y denote the coordinate of plane and z denotes the pixel value. The algorithm starts to pour water in the topographic chart from the lowest basin to the highest peak. In the process, we may detect some peaks disjoined the catchment basins, called as "dam". The diagram shows in Fig. 5.

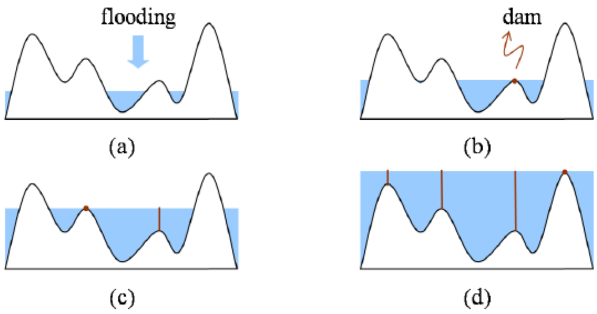

Fig. 5 The concept of watershed

We show the segmentation result of the watershed algorithm in Fig. 6 and list the advantages and disadvantages of the watershed algorithm as follows:

Advantages:

a. The boundaries of each region are continuous.

Disadvantages:

a. The segmentation result has over-segmentation problem, shown in Fig. 6 (b).
b. The algorithm is time-consuming.

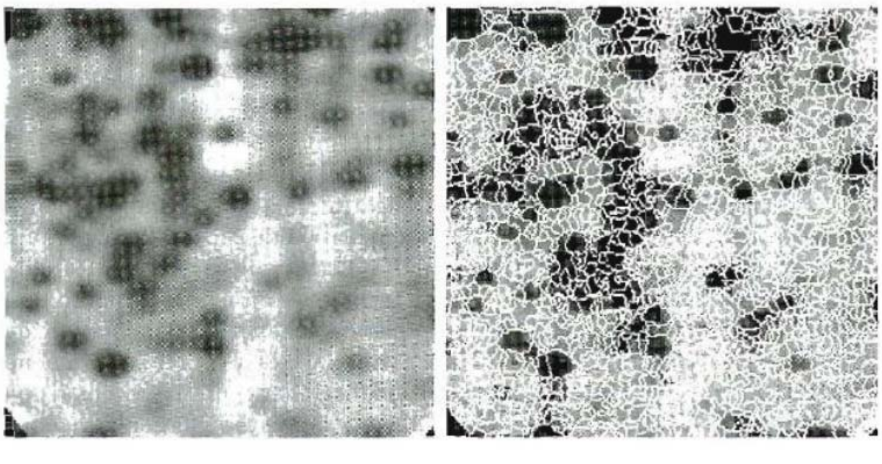

Fig. 6 (a) Electrophoresis image and (b) result of applying the watershed algorithm

B. Markers

For resolving the over-segmentation problem in the watershed algorithm, an approach based on the concept of marker is described in [1]. A marker is a connected component belonging to an image. The markers include the internal markers, associated with objects of interest, and the external markers, associated with the background. The marker selection typically consists of two steps: preprocessing and definition of a set of criteria that markers must satisfy. The preprocessing scheme is to filter an image with a smoothing filter. This step can minimize the effect of small spatial detail, in other words, this step is to reduce the large number of potential minima (irrelevant detail), which is the reason of over-segmentation.

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The definition of an internal marker is:

a. A region that is surrounded by points of higher "altitude".
b. The points in the region form a connected component.
c. All the points in the connected component have the same intensity value.

After the image is smoothed, the internal markers can be defined by these definitions, shown as light gray, blob like regions in Fig. 7 (a). Consequently, the watershed algorithm is applied to the smoothed image, under the restriction that these internal markers be the only allowed regional minima. Fig. 7 (a) shows the watershed lines, defined as the external markers. The points of the watershed line are along the highest points between neighboring markers.

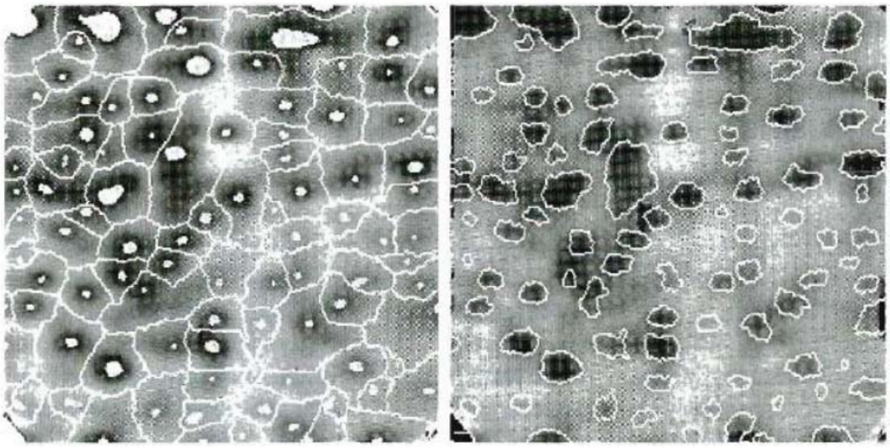

Fig. 7 (a) Image showing internal markers (light gray regions) and external markers (watershed lines).(b) Segmentation result of (a). [1]

The external markers effectively segment the image into several regions with each region composed by a single internal marker and part of the background. Then the goal is to reduce each of these regions into two: a single object and its background. The segmentation techniques discussed earlier can be applied to each individual region. Fig. 7 (b) shows the segmentation result of applying the watershed algorithm to each individual region.

V. Conclusion

In this paper, we studied several segmentation methods. For various applications, there are suitable segmentation methods that can be applied. If the requirement is that the pixels of each cluster should be linked, then region-based segmentation algorithms, especially, the JSEG and the fast scanning algorithms, are preferred, because of their better performances. If the requirement is to classify the whole image pixels but not consider the connection of cluster then data clustering, especially the k-means algorithm is the better choice. The clustering result of mean shift is fine, but it costs much computation time. The edge-based segmentation method, especially watershed, has the over-segmentation problem, so we normally combine the marker tool and watershed for overcoming the over-segmentation problem.

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