Image Segmentation using Seeded Region growing

Mrs. Musale Shital S

Bharati Vidyapeeth,College of Engineering Kolhapur, Shivaji University,

shital.musale12@gmail.com

Prof. Pawar Sanjay S.
Asst. Professor
Bharati Vidyapeeth,College of Engineering Kolhapur, Shivaji University,

pawarsanjay2@rediffmail.com

***Abstract*:.** *Segmentation through seeded region growing is widely used because it is fast, robust and free of tuning parameters. However, the seeded region growing algorithm requires an automatic seed generator, and has problems to label unconnected pixels (unconnected pixel problem). This paper introduces a new automatic seeded region growing algorithm called ASRG-IB1 that performs the segmentation of colour (RGB) and multispectral images. The seeds are automatically generated via histogram analysis; the histogram of each band is analyzed to obtain intervals of representative pixel values. An image pixel is considered seed if its gray values for each band fall in some representative interval. After that, our new seeded region growing algorithm is applied to image*.

Keyword: *Image Segmentation, Seeded Region Growing, Instance based learning, Colour image.*

Introduction:

Meaning of image segmentation?

The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application[1].Usually image segmentation is an initial and vital step in a series of processes aimed at overall image understanding .Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous .Let F be the set of all pixels and P() be a uniformity (homogeneity) predicate defined on groups of connected pixels, then segmentation is a partitioning of the set F into a set of connected subsets or regions (S1, S2,…...Sn) such that [ni=1Si = F with Si \ Sj = when i 6= j. The uniformity predicate P(Si) is true for all regions Si and P(Si [Sj) is false when Si is adjacent to Sj .

Process of image segmentation:

A fairly general approach to morphological segmentation involves three steps: image simplification, marker extraction, and contour definition.

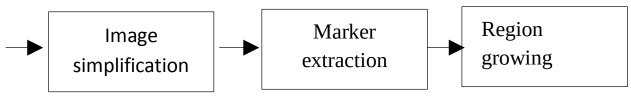

Fig.1 Block diagram of image segmentation.

The scheme of this process is presented in Fig. 1.In the first step, images are simplified for ease of segmentation; in the second step, markers are extracted; then in the last step, a region-growing algorithm is used to decide the boundaries. The second step, marker extraction, which will get the first estimation of the partition, is the most important step of the whole process, because the general view of the final partition is decided by this step on the whole. The marker-extraction step is also the most difficult step of the whole process, because it is not an easy task to extract markers exactly: too many markers will lead to extreme over segmentation and too fewer markers will merge different objects. In this paper, we simplify images by area morphological operators. This method is different from standard morphology which uses a structuring element, and avoids its disadvantages. We propose a new design for marker extraction, which makes use of both luminance and color information. In the third step, we use a region-growing algorithm to assign the remaining pixels, which follows the principles of with a modification on color distance definition.

Classification of image segmentation:

The existing image segmentation technique is classified as 1)threshold-based technique 2) Histogram based technique 3) Edge detection technique 4)Region-based technique 5) Watershed Transformation Technique. We see all methods in details one by one [1].

Threshold based:

This is a technique mainly used for grey scale images and is very simple to implement. Here the decisions done based on the local pixel information of the age. An image is assumed to be divided into two parts: foreground and background. The interesting objects in the image are a foreground and the rest is a background. Threshold T is first finalized by analyzing all the pixel intensity. Consider a pixel f(x,y) classification is done as

1)F(x,y) > T :Foreground.

2) F(x,y) > T:Background

Problem associated with the Thresholding technique is that it will ignore the partial information of the pixel values [10] and hence they are inefficient for images that blur at object boundaries or for multiple image component segmentation [1].

Basic Global and Local Thresholding may be viewed as an operation that involves tests against a function T of the form,

$$T = T[x, y, p(x, y), f(x, y)]$$

Where $f(x, y)$ is the gray level and p (x, y) is some local property. Simple Tresholding schemes compare each pixels gray level with a single global threshold. This is referred to as **Global Tresholding.** If T depends on both f(x, y) and p(x, y) then this is referred to a **Local Thresholding**.

Histogram based:

A histogram plots the relative frequency of each pixel value that occurs in a gray scale image. The histogram provides a convenient summary of the intensities in an image, but is unable to convey any information regarding spatial relationships between pixels.

It is also a quiet easy technique when compared with other segmentation techniques. In this type of segmentation histogram of all the pixels are calculated and according to the peaks and valleys different clusters are formed. In case of colour images, threshold combined with histogram can be used for segmentation. Each pixel is characterized by three RGB values. A 3D histogram can be built from that and k-significant clusters are formed. Images can be segmented by assigning arbitrary values to a pixel whose RGB components are closer to one cluster and another value to other pixel in the image. A problem associated with this technique is that, because of noise the profiles of the histograms are rather jagged giving rise to spurious peaks and thus to segmentation ambiguities.

Edge-based technique:

Edge detection is the approach used most frequently for segmenting images based on abrupt changes in intensity .There are three types of edge model that are classified according to their intensity profile. A step edge involves transition between two intensity levels occurring ideally over the distance of 1 pixel. Ideal edges can occur over the distance of 1 pixel, provided that no additional processing is used to make them look real. Roof edges are model of lines through a region, with the base of a roof edge being determined by the thickness and sharpness of the line [2]. First and second order derivatives like gradient and laplacian are used for detection of edges in an image. A problem associated with this technique is that, Edge detection algorithms need additional post processing by using linking procedures to assemble edge pixel into meaningful edges.

Region based technique:

The goal of segmentation is to partition the image into several disjoint regions. Region Based technique is used to determine the regions directly. While performing region based segmentation, every pixel in an image should be grouped in a region. To perform this grouping initially some seed pixels are selected based on some criteria (e.g. Color, intensity, texture). After selecting the initial seeds a homogeneous region of an image is obtained by growth process (i.e.) it tries to find an accurate segmentation of images into regions with the property that each connected component of a region meets exactly one of the seed [1]. This is said to be seeded region growing (SRG). The problem related with SRG is in selecting the initial seed to get more accurate segmentation of image [5]

Watershed transformation technique:

The **watershed transformation** is a powerful tool for image segmentation. Boucher and Lantuejoul were the first to apply the concept of watershed and divide lines to segmentation problems They used it to segment images of bubbles and SEM metallographic pictures. Unfortunately, this transformation very often leads to an over-segmentation of the image. To overcome this problem, a strategy has been proposed by Meyer and Boucher. This strategy is called marker-controlled segmentation. This approach is based on the idea that machine vision systems often roughly "know" from other sources the location of the objects to be segmented. This approach is applied as follows: first, we define the properties which will be used to mark the objects. These markers are called **object markers**. The same is done for the background, i.e., for portions of the image in which we are sure there is no pixel belonging to any object. These markers constitute the **background markers**. The rest of the procedure is Straightforward and is the same for all applications: the gradient image is modified in order to keep only the most significant contours in the areas of interest between the markers. This gradient modification consists in changing the **homotopy** of the function. Then, we perform the final contour search on the modified gradient image by using the watershed transformation. No supervision, no parameter and no heuristics is needed to perform the final segmentation. The parameterization controlling the segmentation is concentrated in the marker construction step where it is easier to control and validate it. The gradient image is often used in the watershed transformation, because the main criterion of the segmentation is the homogeneity of the grey values of the objects present in the image. But, when other criteria are relevant, other functions can be used. In particular, when the segmentation is based on the shape of the objects, the **distance function** is very helpful. In the first part, we describe the main morphological tools used in segmentation: gradient, distance function, geodesic distance function and watershed transformation. For this last transformation, some algorithms are presented. In the second part, we introduce the concept of markers and the homotopy modification of the transformed function for solving over-segmentation problems. Many examples illustrate this methodology. This tool is particularly efficient for defining different levels of segmentation starting from a graph representation of the images based on the **mosaic image transform**.

Segmentation using seeded region growing algorithm:

Seeded Region Growing is an algorithm used for image segmentation. Initial seeds are selected based on some criteria and then segmentation is done by region growing process [2]

Automatic Seed Generation:

An overview of the automatic seed generation algorithm is shown in Fig.2 The first step divides the histogram in subintervals.

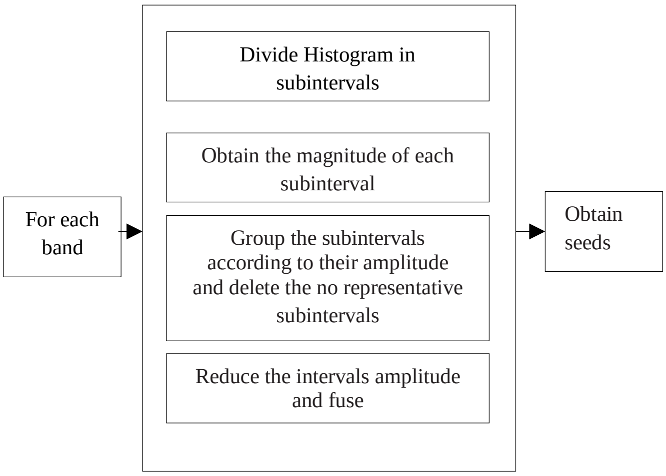

Fig.2 Overview of the automatic seed generation algorithm

Let *hb*(*p*) be the histogram function, this function receives a gray value *p* ($0 \le p \le 255$) and returns the number of pixels of band *b* with gray value equal to *p*. To divide the histogram we must find the *cut points*. All the gray values *p* that satisfy the next two conditions will be taken as cut points,

$$\textbf{1. } hb(p-1) \ge hb(p)$$

$$\textbf{2. } hb(p+1) > hb(p)$$

The cut points indicate the end and the beginning of each subinterval. Table 1 shows the subintervals *Sj* obtained from a given histogram function *hb*(*p*) with *q* cut points, where *Ci* is a cut point ($1 \le i \le q$), *Sj* is a subinterval ($1 \le j \le m$) and *m* is the number of resultant subintervals.

Table.1: Resultant subinterval table

S1=[0,C1]
S2= [C1+1, C2]
……….
Sm = [Cq,255]

Subintervals *Sj* obtained from a given histogram function *hb*(*p*) with *q* cut points. The second step obtains the amplitude of each subinterval. For a given subinterval *Sj* = [*Sj*,1, *Sj*,2] the amplitude is given by:

$$amp(Sj) = Sj,2 - Sj,1 + 1$$

The third step groups the subintervals according to their amplitude to delete the non representative subintervals. For all subintervals *Sj* with amplitude $amp(Sj) = \alpha$, The fourth step reduces the representative intervals amplitude. For a given representative subinterval *Sj* = [*Sj*,1, *Sj*,2] of band *b*, A gray value γ of a representative subinterval *Sj* of band *b* is representative if:

$$\boldsymbol{hb(\gamma) > 1/2mrg(Sj)}$$

All the no representative gray values must be removed from the interval, producing a reduced interval. Depending of the application, the consecutive resultant reduced intervals can be merged. For example, the reduced intervals [12-18], [19-25] produces the new merged interval [12-25]. Interval merging lower the quantity of homogeneous seeds, and must be avoided if the application needs the highest separation between seeds (i.e. the user needs the maximum level of homogeneity in the Regions). The final step is to generate the seeds. A pixel *x* is considered as a seed if its gray values on each band fall inside a representative interval of the same band. If the gray values of two seed pixels fall inside the same representative intervals, the pixels will be labeled with the same region ID. The output of the seed generator is a set with *n* seeds *A*1, *A*2, . . .,*An*.

Region Growing and Instance-based Learning:

The region growing algorithm is shown in Fig 3.The automatically generated seeds are used to construct the classifier using the region ID as the class of the pixel. Before the region growing step, the sets of pixels to label *P* and unallocated (non labeled) pixels *Q* must be defined [2].

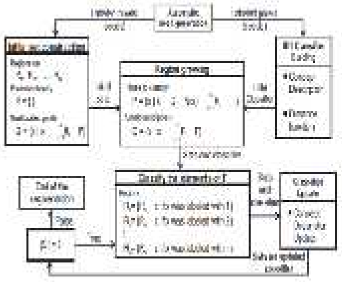

Fig.3 Region growing algorithm.

All the seeds must be grouped according to their region ID (region sets *R*). The region growing step obtains the pixels that must be labelled (set *P*) and updates the set *Q*. We use the IB1 classifier to label the regions. Because all the pixels are considered without concerning what regions they meet, pixels that in the original seeded region growing algorithm cannot be reached by the region to which they belong (unconnected pixel problem) are labelled. After labelling, the IB1 classifier must be updated to consider the newly labelled instances. The algorithm stops when set *Q* is empty.

At this point, the algorithm has obtained the homogeneous regions of the image, these regions represent a segmentation at the lowest level of abstraction. To complete the task it is necessary to merge the regions according to the user needs.

Ownership tables allow the user to merge regions according to his needs. The user manually selects the regions that must be merged and those regions ID's are stored in a table. An ownership table indicates which regions must be merged to form the concept that the user wants, so, the concept must be completely defined by its ownership table, and distinct concepts cannot have the same table. The elements of an ownership table can be of two kinds, ambiguous and unambiguous.

Experimental result:

This section shows the results of the proposed algorithm on RGB leukemia medical images [2]. Leukemia is a cancer of the blood characterized by an abnormal proliferation of white blood cells (leukocytes). Experiments were made over thirty distinct images, with the objective of segmenting white blood cells of the image to study their characteristics and determine if a given patient has leukemia. There is not a generally accepted methodology (in the field of computer vision) which elucidates on how to evaluate segmentation algorithms.

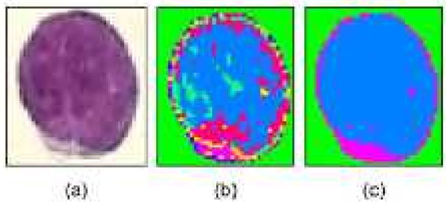

Fig.4.RGB image of a white blood cells with cytoplasm. (b) Image segmented With SRG-IB1. (c) Image segmented after region merging

Applications:-

- Optical character recognition (OCR).
- Automatic Target Acquisition.
- Colorization of Motion Pictures.
- Detection and measurement of bone, tissue, etc, in medical images.

Conclusion:-

Image segmentation is a fundamental task in many image processing applications. Segmentation using seeded region growing and merging is found to be very effective for Segmenting colour images. This proposed method is found to be very interactive since it uses separate threshold values for region merging and region growing. This method allows control over the degree of segmentation by changing the powers of HSI in its Euclidean distance. Experimental results show that our algorithm is robust to various colour images.

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