ISSN No. 0976-5697
Volume 4, No. 10, September-October 2013
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

IRMOR: A Method for Image Segmentation and Retrieval Using Mean shift Segmentation and Flood Fill Algorithm

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Abstract**—** Nowadays image retrieval plays an important role in an extraordinary number of multimedia applications which serve human society. Since a generic graph based retrieval scheme working in every situation can be quite difficult to implement due to the presence of complex scene. In this paper we investigate to deal with such problems and focuses on how to extract the object from an image using topological models. It begins with the innovative concept of initial low level segmentation of input image, which are used to construct topological model on the basis of connected regions. Using this topological model we have design a new prototype known as Iterative Region Merging and Object Retrieval (IRMOR).Using this prototype IRMOR we can extract contour based descriptors on an object from an image which contain the high level features.

In addition we focus on how to apply a region labeling and flood fill method to extract object after formation of object contour, IRMOR have special application such an image matching, object recognition, content based image retrieval, object tracking etc.

Keywords- Mean shift segmentation, Bhattacharya coefficient, Flood fill method, watershed, super pixel, object contour.

I. INTRODUCTION

Segmentation of image and retrieval of an object is very important field in image processing and it is also one of the important fundamental problems in computers vision. There has been a convincing quantity of research on image segmentation including clustering based methods [1], histogram based methods [2], adaptive threshold [3], level set methods [4], graph based methods [5,6] etc.

In this paper we have designed the prototype known as **Iterative Region Merging and Object Retrieval (IRMOR)**. This prototype is based on initial segmentation of image using mean shift. Mean shift is low level segmentation method. Low level segmentation methods include mean shift [7, 8], watershed [9] and super pixel [10]. This low level method divides image into small regions (or segments). We use mean shift method in our prototype because it divides image into less segments in comparison to watershed and super pixel [11, 10]. Mean shift also presents well edge information of the object.

Using **Iterative Region Merging and Object Retrieval (IRMOR)** method find the similarity among the different segments. It also merge the similar segments in the iterative manner. At the end of this iteratively large similarity merging process we get two types of segments. One is our desired object which is known as foreground and second one is background. With the help of this prototype IRMOR we get the object contour and extract the desired object from the image. The design prototype is very simple but it can extract the object from complex image.

In the rest of the paper we consider following sections; section 2 present the literature survey, section 3 presents the region merging process in IRMOR method, in section 4 we explain the analysis of IRMOR method and in the last section 5 we explain conclusion and future work of the paper.

II. LITERATURE SURVEY

A. Classification of Image Segmentation:

Image segmentation can be broadly classified into two types: (1) Local Segmentation, (2) Global Segmentation.

a. Local Segmentation:

In it we deals with segmenting sub-images which are small windows on a whole image. The number of pixels available for local segmentation is much lower than global segmentation.

b. Global Segmentation

Global segmentation is conquered by segmenting a whole image. It consider generally with large number of pixels segment. This makes estimated parameter values for global segment more robust. The approaches of image segmentation are:-

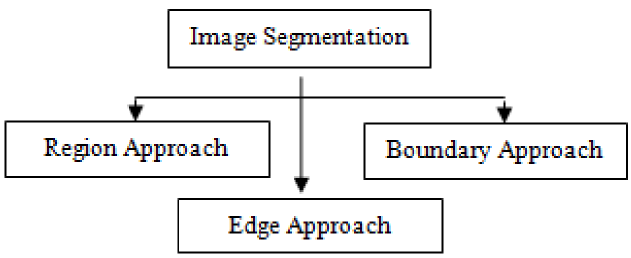

Figure1. Image Segmentation Approach

B. Classification of Image Segmentation:

a. Region Growing:

Region growing is a region approach to image segmentation in which neighbor pixels are examined and added to a region class. This process is iterated for each boundary pixel in the region, in the adjacent regions a region merging algorithm is used in which weak edges are dissolved and string edges are left intact.

Region growing approach of color image [21, 20] requires seed to being with a seed pixel. Region growing offers several advantages over conventional segmentation technique

b. Region Splitting:

It is based on top-down approach. At the start it is takes whole image and divides it up such that the segregated parts are more homogenous. For reasonable segmentation splitting alone is insufficient, as it several limits the shapes of segments. Hence, a merging phase after the splitting phase is always desirable, which is termed as the split and merge algorithm.

C. Edge Based Segmentation:

Edge-based segmentation exploits spatial information by detecting the edges in an image. Edge detection [24] is usually done with local linear gradient operators such as Prewitt, Sobel and Laplacian filters.

D. Low Level Segmentation:

Image segmentation is process which divides the image into the homogeneous regions , where as object segmentation is to separate the desired objects from the background scene. In general, the color and texture features in a natural image are very complex so that the fully automatic segmentation of the object from the background is very hard. Therefore semi-automatic segmentation methods incorporation user interactions have been proposed [25, 26, 27, 28] and are becoming more and more popular. For instance, in the active contour model (ACM) or snake algorithm [28], a proper selection of the initial curve by the user could lead to a good convergence to the true object contour. The low level image segmentation methods, such as mean shift [7, 8], watershed [9], level set [29] and super-pixel [10], usually divide the image into many small regions. Although it may have several over segmentation, these low level segmentation methods provide a good basis for the subsequent high level operations such as region merging. As a popular segmentation scheme for color image, mean-shift can have less over segmentation than watershed while preserving well the edge information of the object. Various methods used for low level segmentation are discussed below:

a. Mean Shift Segmentation:

The main problem of different segmentation methods and its similar approach are to identify a number of parameters of a pre-determined probability density function. Mean-shift segmentation avoids estimation of the probability density function and consists of two main steps discontinuities preserving filtering and mean shift clustering.

Mean shift procedure [8] is a nonparametric technique for the analysis of a complex multi-model feature space and identification of feature clusters. In number of image processing and computer vision tasks mean shift approach is used like object tracking [30] etc. The goal of the feature space analysis is delineation of the underlying cluster. Better thing for mean shift is the free from parameters size and shape of the region of interest of more precisely identification of the multivariate density kernel function. Example of image segmentation using mean shift method is shown in Fig 2.

b. Active Contour Models (Snakes Algorithm)

The active contour model is a semi-supervised technique of image segmentation and development of active contour models and they offer a solution to a variety of tasks in image processing and computer vision. Active contour model is based on the energy minimization approach to achieve goals [31].

c. Traditional Snakes and Balloons:

The energy function is minimized by using a weighted combination of internal and external forces. The snake is defined by parametric equation as $z(s) = [x(s),y(s)]$, Here $x(s)$, $y(s)$ are X, Y co-ordinates and $s \in [0, 1]$.A snake attracted to edges of image object and a termination of closed contour. In the active contour model we can impose constraints either by a user or some other higher-level process which may force the snake toward or away from particular features. If the snake is near to some desirable feature the energy minimization will pull the snake the rest of the way. However, if the snake settles in a local energy minimum that a higher-level process determine as incorrect, an area of energy peak may be made at this location to force the snake away to a different local minimum.

d. Gradient Vector Flow:

Two main limitations of snake algorithm that are common to these approaches are the requirement of snake initialization being close to the desired solution, and difficulties in segmenting concave portions of the boundary. To overcome these problems, gradient vector flow (GVF) fields and their use in snake image segmentation were reported in [32]. GVF field is a non-irrotational external force field that points toward the boundaries when in their proximity and varies smoothly over homogeneous image regions all the way to image borders. In comparison to the classical snake approach [27] in which similar behavior can be attempted by blurring the edge image of using pressure forces, it does not suffer from edge localization problems caused by edge distortion from their smoothing. The GVF field is derived from an image by minimization of energy function by solving decoupled linear partial differential equations via diffusing the gradient vectors of the edge image. The GVF is then used as an external force in the snake equations forming a GVF snake.

E. Watershed Segmentation:

Thus for we have discussed segmentation based on three principle concepts:

(a) Detection of discontinuities,
(b) Thresholding,
(c) Region Processing.

In this section we discuss an approach based on the concept of so called morphological watersheds. As will become evident in the following segmentation by watersheds embodies many of the concepts of the other three approaches and, as such, often produces more stable segmentation results including continuous segmentation boundaries.

The concept of watershed is based on visualizing an image in three dimensions: two spatial coordinates versus gray-levels. In such a topographic interpretation we consider tree types of points: (a) points belonging to regional minimum (b) pints at which a drop of water, if placed at the location at any of those points, would fall with certainty to a single minimum, and (c) point at which water would be equally likely to fall to more than one such minimum. For a particular regional minimum satisfying condition (b) is called catchments basin or watershed of that minimum. The points satisfying condition (c) form crest lines on the topographic surface and arc termed divide lines or watershed lines.

The catchments basin [9] or watershed region is defined as the region over which all points flow "downhill" to a common point. The idea originates from geology but has been applied to vision as will. In geology one might not seem to be applicable to intensity based regions but it makes sense if we apply them to gradient magnitude images.

Meyer and Beucher [33] one way of defining the maximal curves (ridges) is as the boundaries of watershed regions everything on one side flows downhill to one side and everything on the other flows to the other side. Thus, as you cross from one watershed region to another you've had to cross over some local properties but instead require building the regions first. First build a gradient magnitude image, find watershed regions of image.

F. Region Merging:

Image segmentation is the first and key step for image analysis and pattern recognition [34]. Its goal is twofold: from a semantic point of view, image segmentation is a first level abstraction providing an image representation closer to the object representation than the set of pixels and from a practical point of view, a region based representation of the image reduces the number of elementary primitives and allows a more robust estimation of parameters and descriptors.

In other words, segmentation simplifies the image providing a representation that is more semantically meaningful and easier to analyze [1]. By using the region merging we merge the segmented regions. Region merging algorithms can be specified in [35], a merging criterion that defines the cost of merging two regions, a merging order, determining the sequence in which regions are merged based on the merging criterion and a region model that determines how to represent the union of regions. They can be efficiently implemented using graph based approaches such as the recursive shortest spanning tree (RSST) algorithm [36, 37]. In the literature, there is an explicit division between two types of region models. For the first type, where the color of the pixels belonging to the region is assumed to be approximately constant, first order statistics such as mean [38], or median [39] color values are used as region model.

For instance, this assumption is common in object oriented image segmentation. The region merging is applied on segments of texture, region models which are based on second or higher order statistics. Or in transformations [21], such as wavelets or Global filters [22].

III. REGION MERGING PROCESS IN IRMOR

In our design prototype IRMOR we firstly apply the low level segmentation method for getting initial segmentation, this initial segmentation partitions the image into homogeneous regions for merging. For this we use any existing low level segmentation method which includes watershed [9], super-pixel [10], mean-shift [7, 8] and level set [12]. We use mean shift method in our prototype because it divides image into less segments in comparison to other existing low level segmentation method and mean shift also presents well edge information of the object.

(a.) Original Image (b.) Mean- Shift segmentation

Figure2. Initial Segmentation

For obtaining initial segmentation of an image we use EDISON (Edge Detection and Image Segmentation) system [13], which is software of mean-shift segmentation. The initial segmentation map using EDISON software show in fig. 2

A. Similarity Measure of Regions:

After initial segmentation using mean-shift segmentation method in IRMOR, we now have number of homogeneous segments. In our design prototype IRMOR we iteratively merge the most similarity region. For merging we first find out the similarity between segments. We can describe the region in many properties e.g. shape and size, texture [14] and color edge [15] of region. Color information of an image is very important as compared to other properties of an image because for the same region having different shapes but high color similarity, we use the color histogram. To generate color histogram for each region we will use RGB color space. After generating color histogram now we have a problem that is how to find out the similarity between the regions for merging on the basis of their color histogram. So here we need to a use formula to measure the similarity between the regions. There are some existing methods like Euclidean metric, Bhattacharya coefficient and log-likelihood ratio statistic [16].

In our design prototype IRMOR we use the Bhattacharya coefficient [16, 17, 18, 19] formula to measure the similarity between the region for merging process. Let A and B are the two segmented regions of an image then according to the Bhattacharya coefficient:

$$P\,(A, B) = \sum_{u=1}^{4096} \sqrt{\mathrm{Hist}_A{}^u \ \mathrm{Hist}_B{}^u} \qquad (1)$$

In equation 1 $Hist_A$ and $Hist_B$ are the normalized histogram of regions A and B, and u represent the u^{th} element of them.

$$\cos\theta = \left(\sqrt{\mathrm{Hist}_A{}^1 \ldots \ \mathrm{Hist}_A{}^{4096}}\right)^T \left(\sqrt{\mathrm{Hist}_B{}^1 \ldots \ \mathrm{Hist}_B{}^{4096}}\right)^T (2)$$

If two regions are having same histogram then the Bhattacharya coefficient is very high between them and θ is very low. Bhattacharya coefficient is very efficient and simple method to compute the similarity between the regions and it works well in our design prototype IRMOR.

B. Region Merging and Object Retrieval Process:

We retrieve the object in two stages. In the first stage we merge the similar regions, this merging process is in iterative fashion and at each iteration we will check whether desired object contour is achieved or not. We end the iterative region merging process after having achieve the desired object contour. We also apply region labeling after achieving object contour in first step.

In the second stage we will apply the flood fill algorithms using 8-connectivity and retrieve the object.

a. Designed Algorithm for object retrieval:

Input: We take an image as input and get its initial segmentation using the mean-shift segmentation method.

Output: Desired retrieval object from an input image.

Merge segments iteratively until the desired contour is achieved.

a) First we generate the initial segment of an image using the mean-shift segmentation.
b) We calculate the Bhattacharya coefficient of adjacent regions and merge them if they have higher Bhattacharya coefficient.
c) We iteratively apply the merging process (step 2) until we get the desired object contour and go to step 4.
d) After getting the object contour from step 3, label regions of the image.

b. Region Labeling (I):

a) let n→2
b) for all image coordinate (u, v) we do
    4.2.1 If I (u, v) = 1 then
    4.2.2 Flood fill (I, u, v, n)
    4.2.3 n→n+1
c) return to the labeling image I

We apply flood fill algorithm using 8-connectivity after region labeling:

(a.) flood fill (I, u, v, label)
5.1 Generate empty queue q
5.2 ENQUEUE (q, (u, v))
5.3 Until queue q is not empty do-
5.4 (x, y) ← DEQUEUE (q)
5.5 If (x, y) is inside the image and label of (x, y) = 1 then
5.6 set I (x, y) label
5.7 ENQUEU (q, (x-1, y+1))
5.8 ENQUEU (q, (x, y+1))
5.9 ENQUEU (q, (x+1, y+1))
5.10 ENQUEU (q, (x-1, y))
5.11 ENQUEU (q, (x+1, y))
5.12 ENQUEU (q, (x-1, y-1))
5.13 ENQUEU (q, (x, y-1))
5.14 ENQUEU (q, (x+1, y-1))
5.15 return

Above designed algorithm guarantees that it gives us the object contour after some iterative merging steps, for example let X and Y are the segmented regions of an image and Bhattacharya coefficient is higher between them i.e. X and Y are higher similar to each other, then according to design prototype IRMOR we merge X and Y i.e. X = X ∪ Y. In IRMOR first stage merging process is repeated iteratively and number of regions in the image is reduced, because the numbers of regions in the image are finite so we obtain our desired object contour after certain finite iteration.

So IRMOR prototype obtains the desired object contour and label every region of an image, label region is either background or object.

IV. IRMOR ANALYSIS

In our design prototype IRMOR method we use mean-shift method for initial segmentation of input image, Bhattacharya coefficient for measuring the similarity between the two regions and flood fill algorithm for extracting the object contour from an image. In this section we will discuss that why IRMOR method is efficient and simple for of object retrieval.

A. Image Segmentationu:

In our design prototype IRMOR, we firstly divide the image into small regions and after it we iteratively merge similar regions for getting the desired object contour. If the number of regions is less, then the time taken to merge the similar region is also less. Therefore time taken to obtain the desired object contour from the image which is segmented by mean shift segmentation method takes less time as compared to obtain desired object contour from an image which is segmented by the watershed and super-pixel segmentation method. Fig.3. show the watershed, mean-shift and super pixel segmented image.

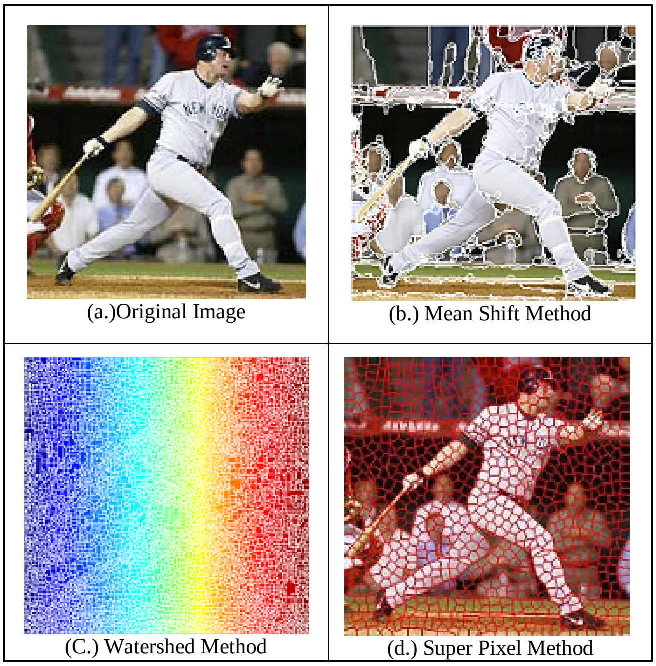

Figure3. Low Level Segmentation Methods

By observing the images (a),(b) and (c) we can say that image (c) where is watershed segmented image has large number of regions and image (b) mean shift segmented image has small number of regions. So when we use mean shift segmentation method in our design prototype IRMOR we get less number of initial segments and it decreases the object retrieval time which is advantage of our IRMOR method.

B. Object Contour Retrieval:

Our design prototype IRMOR method is based on iterative similar region merging and flood fill method. In this section we compare our object retrieval method with Hybrid Graph Model (HGM) and Normalize Cut method. Graph model and normalize cut model are based on pixel, in our prototype we extend pixel based graph cut to region based graph cut. So nodes of the graph represent the mean shift segmented regions instead of pixels. Region based node of graph take less time as compared to the pixel based graph node to retrieve object. It is also one of the major advantages in our design prototype IRMOR

V. CONLUSION AND FUTURE WORK

In our design prototype IRMOR method we use mean shift segmentation method to generate the initial segments of an input image and iteratively merge the similar regions by comparing their Bhattacharya coefficient. When we obtain the desired object contour then we stop the region merging process and retrieve it. For retrieving the object we choose one seed point in the object contour and apply flood fill algorithm.

In our future work we will implement IRMOR method on images to retrieve the object. We also use RGB, YC_bC_r and HSV color images to retrieve the object and compare the efficiency of our IRMOR method. We will also compare our retrieved object quality with the watershed retrieved object quality.

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