Image segmentation by MAP-ML Estimation

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ABSTRACT: Image segmentation plays an important role in computer vision and image analysis. In this paper, image segmentation is formulated as a labeling problem under a probability maximization framework. To estimate the label configuration, an iterative optimization scheme is proposed to alternately carry out the maximum a posteriori (MAP) estimation and the maximum likelihood (ML) estimation. The MAP estimation problem is modeled with Markov random fields (MRFs) and a graph cut algorithm is used to find the solution to the MAP estimation. The ML estimation is achieved by computing the means of region features in a Gaussian model. Our algorithm can automatically segment an image into regions with relevant textures or colors without the need to know the number of regions in advance. Its results match image edges very well and are consistent with human perception. Comparing to six state-of-the-art algorithms, extensive experiments have shown that our algorithm performsthe best.

KEYWORDS –Image segmentation, graph cuts, maximum likelihood, maximum a posteriori, Markov random fields.

I. INTRODUCTION

1.1 IMAGE SEGMENTATION

In computer vision segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixel). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. 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 (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). Some of the practical applications of image segmentation are medical imaging, pattern recognition, finger print recognition, face recognition etc. The problem of image segmentation and visual grouping has received extensive attention since the early years of computervision research. It has been known that visual grouping playsan important role in human visual perception. Many computer vision problems, such as stereo vision, motion estimation, image retrieval, and object recognition, can be solved better with reliable results of image segmentation. For example results of stereo vision based on image segmentation are more stable than pixel-based results . Although the problem of image segmentation has been studied for more than three decades, great challenges still remain in this research.

1.2 CLASSIFICATION OF IMAGE SEGMENTATION

Available image segmentation algorithms can be classified into two groups: contour-based approaches and region-based approaches. Contour-based approaches try to find the boundaries of objects in an image, while region-based approaches attempt to split an image into connected regions.

The main idea of contour-based approaches is to start with some initial boundary shape represented in the form of a spline curve, and iteratively modifies it by shrink and expansion operations to minimize some energy function. These approaches are physics-based models that deform under the laws of Newton mechanics, in particular, by the theory of elasticity expressed in the Lagrange dynamics. Many contour based segmentation algorithms have been developed in the past two decades.

Region-based approaches try to classify an image into multiple consistent regions or classes.

1.3 DRAWBACKS IN EXISTING SYSTEM

One problem existing in these algorithms is that they are easy to get trapped in local minima. In addition, they need manually specified initial curves close to the objects of interest. Region-based approaches try to classify an image into multiple consistent regions or classes. Thresholding is the simplest segmentation method but its performance is usuallyfar from satisfactory. Watershed segmentation is one of the traditional region-based

approaches. The watershed transform is often used to segment touching objects. It finds intensity valleys in an image if the image is viewed as asurface with mountains (high intensity regions) and valleys(low intensity regions). Morphological operations are alwaysused to handle the over-segmented problem in the output obtained by the watershed transform. Usually, watershed is used for the segmentation of foreground and background (twoclass)of an image. For a general color image with many different regions, it often gives a bad result. It is also sensitive to the morphological structuring element.

1.3.1   PROPOSED ALGORITHM FOR IMAGE SEGMENTATION

This paper1 proposes a new image segmentation algorithm based on a probability maximization model. An iterative optimization scheme alternately making the MAP and the maximum likelihood (ML) estimations is the key to the segmentation. We model the MAP estimation with MRFs and solve the MAP-MRF estimation problem using graph cuts. The result of the ML estimation depends on what statistical model we use. Under the Gaussian model, it is obtained by finding the means of the region features.

It is shown that other statistical models can also fit in our framework. The main contributions of this work include:

1) a novel probabilistic model and anIterative optimization
scheme for image segmentation, and

2) Using graph cuts to solve the multiple region segmentation Problem with the number of regions automatically adjusted according to the properties of the regions.

Our algorithm can cluster relevant regions in an image well, with the segmentation boundaries matching the region edges. Extensive experiments show that our algorithm can obtain results highly consistent with human perception. The qualitative and quantitative comparisons demonstrate that our algorithm outperforms six other state-of-the-art image segmentation.

II. AN ITERATIVE OPTIMISATION SCHEME FOR IMAGE   SEGMENTATION

2.1 ALGORITHM DESCRIPTION

Input: an RGB color image.

Step 1: Convert the image into L*a*b* space and   Calculate the texture contrast.

Step 2: Use the *K*-means algorithm to initialize Φ .

Step 3: Iterative optimization.

3.1: MAP estimation — Estimate the label Configuration *f* based on current Φ using the graph
Cut algorithm.

3.2: Relabeling — Set a unique label to each Connecting region to form a new cluster, obtaining a new *f*.

3.3: ML estimation — Refine Φ based on current *f*

Step 4: If Φ and *f* do not change between two successive iterations or the maximum number of
iterations is reached, go to the output step;
otherwise, go to step 3.

Output: Multiple segmented regions of the image.

2.2   COLOUR SPACE CONVERSION

Generally every digital image should be in the form of RGB colour space which represent red, green and blue colour respectively. in our algorithm in order to label the pixels of the colour image the RGB colour image is converted into L*a*b colour space where L represents the lightness of the pixel, a and b represents the horizontal and vertical dimensions' of the image respectively. this conversion is carried out in order to ease the segmentation process easier and to provide an effective segmentation.

2.3   K-MEANS ALGORITHM FOR CLUSTERING

In order to carry out the iteration process in our algorithm initially we have to cluster the regions in the images. In order to carry out the clustering we are using K-means algorithm. Now we analyse the computational complexity of the algorithm. In step 2, the *K*-means algorithm takes $O(NdKT_k)$time , where N is the number of pixels in an image, *d* is the number of features used to represent a pixel/region, K is the number of clusters, and T_k is the number of iterations. In our application, $d = 4$, K is set to 10, and T_k is set to100.

3. A NEW PROBABILISTIC MODEL

3.1 LABELING CONFIGURATION

In this section, we first introduce the features used to describe   the properties of each pixel, and then present the new probabilistic model. For a given image P, the features of every pixel p are expressed by a four-dimensional vector

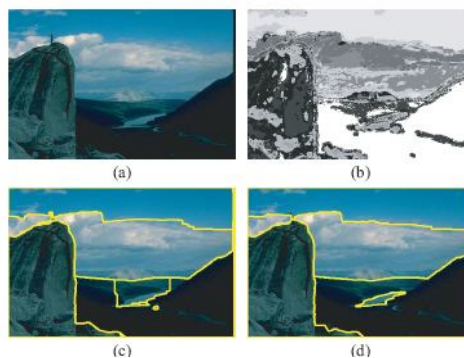$$I(p) = (I_L(p), I_a(p), I_b(p), I_t(p))^T \qquad (1)$$

where $I_L(p)$, $I_a(p)$, and $I_b(p)$ are the components of p in the L*a*b* color space, and $I_t(p)$ denotes the texture feature of p.
    The task of image segmentation is to group the pixels of an image into relevant regions. If we formulate

it as a labeling problem, the objective is then to find a label configuration $f = \{f_P \mid p\}$ where f_p is the label of pixel p denoting which Region this pixel is grouped into. Generally speaking, a "good" segmentation means that

the pixels within a region i should share homogeneous features represented by a vector $\phi(i)$ that does not change rapidly except on the region boundaries.

IVSIMULATION RESULTS:

V.CONCLUSION

In this phase of project work, I did clustering of regions in the image using K-means algorithm then I implemented MAP estimation for labeling the pixels in the regions with initial region features. in order to carry out iteration process for a complete image segmentation I need to implement ML estimation to find the region features with current label value of each pixels. Then I need implement graph cut algorithm to reduce data term and smoothness term of the image. I will complete this two modules in my next phase of the project and their by performing iterations I will segment the image with high resolution.

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