IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

An Inventive Marker based Section Assimilation Technique using Concept of Seeding

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Abstract

Efficient and effective object extraction of image in image segmentation is an important task in pattern recognition and computer vision. It is very hard to find a fully automatic object extraction method in practical applications for natural images, interactive schemes. Schemes with a few simple user inputs are good solutions. However, they are tedious and not effective in some situations like extracting object from complex background. Therefore, this paper proposes a novel unsupervised image segmentation framework to deal with the above problem. A still image is divided into many small regions by some low level segmentation methods (mean shift in this case) at first, then the users needs to roughly indicate the location and region of the object and background by using strokes, which are called markers. A novel maximum-correlation based section assimilation mechanism is proposed to guide the merging process with the help of markers. A region R is merged with its adjacent region Q if Q has the highest similarity with Q among all Q's adjacent regions. The proposed method automatically merges the regions that are initially segmented by mean shift segmentation, and then effectively extracts the object contour by labeling all the non-marker regions as either background or object. The section assimilation process is adaptive to the image content and it does not need to set the similarity threshold in advance. The extensive experiments demonstrate the efficiency and effectiveness of the proposed method.

Keywords: Seeding, Assimilation.

Introduction

Object segmentation is one of the most important and challenging issues in image analysis and computer vision. Image segmentation is to separate the desired objects from the background. 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. It facilitates a number of object-driven high-level applications, such as object recognition and scene understanding. Interaction-aware methodologies have been the most widely used techniques for object segmentation.

Numerous methods have already been proposed for image segmentation, the low level image segmentation methods, such as mean shift [1, 2], watershed [3], level set [4] and super-pixel [5], usually divide the image into many small regions. Although may have severe over segmentation, these low level segmentation methods provide a good basis for the subsequent high level operations, such as section assimilation, clustering based methods [6], histogram based methods [7], region growing methods [3], and more recent ones such as adaptive thresholding methods [8] and graph based methods among others. Clustering based methods, which generally define the segmentation problem as finding the labeling of all pixels in an image that minimizing a specific energy function, are unable to handle unbalanced elongated clusters. When one cluster has much more points than a neighboring cluster, it will erroneously split the larger cluster into artificial sub-clusters. Image thresholding methods are also popular due to their simplicity and efficiency. Traditional histogram-based thresholding algorithms, however, cannot separate those areas which have the same gray level but do not belong to the same part. In addition, they cannot process images whose histograms are nearly unimodal.

Maximum-Correlation based Section Assimilation

In this paper, we choose to use the mean shift method for initial segmentation because it has less over segmentation and can well preserve the object boundaries. Fig. 2.1 b shows an example of the mean shift initial segmentation.

ISSN: 2277-9655
Impact Factor: 1.852

Fig. 2.1(a) Original Image (b) Initial mean shift segmentation

Region representation and correlation measure

After mean shift initial segmentation, we have many small regions available. To guide the following section assimilation process, we need to represent these regions using some descriptor and define a rule for merging. A region can be described in many aspects, such as the color, edge [9], texture [10], shape and size of the region. Among them the color histogram is an effective descriptor to represent the object color feature statistics and it is widely used in pattern recognition [11] and object tracking [12], etc. In the context of section assimilation based segmentation, color histogram is more robust than the other feature descriptors. This is because the initially segmented small regions of the desired object often vary a lot in size and shape, while the colors of different regions from the same object will have high correlation. Therefore, we use the color histogram to represent each region in this paper.

The RGB color space is used to compute the color histogram in this paper. We uniformly quantize each color channel into 16 levels and then the histogram of each region is calculated in the feature space of 16×16×16 = 4096 bins. Denote by $Hist_R^u$the normalized histogram of a region R. The next problem is how to merge the regions based on their color histograms so that the desired object can be extracted. In the interactive image segmentation, the users will mark some regions as object and background regions. The key issue in section assimilation is how to determine the correlation between the unmarked regions with the marked regions so that the similar regions can be merged with some logic control. Therefore, we need to define a correlation measure ρ(R, Q) between two regions R and Q to accommodate the comparison between various regions. There are some well-known goodness-of-fit statistical metrics such as the Euclidean distance, Bhattacharyya coefficient and the log-likelihood ratio statistic [13]. Here we choose to use the Bhattacharyya coefficient [14,13,12] to measure the correlation between R and Q

$$\rho(R, Q) = \sum_{u=1}^{4096} \sqrt{Hist_R^u . Hist_Q^u} \qquad (1)$$

Where$Hist_R^u$ and $Hist_Q^u$are the normalized histograms of R and Q, respectively, and the superscript u represents the u_{th} element of them. Bhattacharyya coefficient ρ is a divergence-type measure which has a straightforward geometric interpretation. It is the cosine of the angle between the unit vectors

$(\sqrt{Hist_R^1}, \ldots, \sqrt{Hist_R^{4096}})^T$ and

$(\sqrt{Hist_Q^1}, \ldots, \sqrt{Hist_Q^{4096}})^T$

The higher the Bhattacharyya coefficient between R and Q is, the higher is the correlation between them.

Object and background marking

In the interactive image segmentation, the users need to specify the object and background conceptually. Similar to [15,16,17], the users can input interactive information by drawing markers, which could be lines, curves and strokes on the image. The regions that have pixels inside the object markers are thus called object marker regions, while the regions that have pixels inside the background markers are called background marker regions. Fig. 1b shows examples of the object and background markers by using simple lines. We use green markers to mark the object while using blue markers to represent the background.

Maximum correlation based merging rule

After object/background marking, it is still a challenging problem to extract accurately the object contour from the background because only a small portion of the object/background features are indicated by the user. The conventional section assimilation methods merge two adjacent regions whose correlation is above a preset threshold. These methods have difficulties in adaptive threshold selection. A big threshold will lead to incomplete merging of the regions belonging to the object, while a small threshold can easily cause over-merging, i.e. some object regions are merged into the background. Moreover, it is difficult to judge when the section assimilation process should stop.The marker regions cover only a small part of the object and back-ground. Those object regions that are not marked by the user, i.e. the non-marker object regions, should be identified and not be merged with the background. Since they are from the same object, the non- marker object regions will usually have higher correlation with the marker object regions than the background regions. Therefore, in the automatic section

ISSN: 2277-9655
Impact Factor: 1.852

assimilation process, the non-marker object regions will have high probabilities to be identified as object.

The merging process

The whole MSRM process can be divided into two stages, which are repeatedly executed until no new merging occurs. Our strategy is to merge background regions as many as possible while keep object regions from being merged. Once we merge all the background regions, it is equivalent to extracting the desired object.

Block Diagram of proposed Method

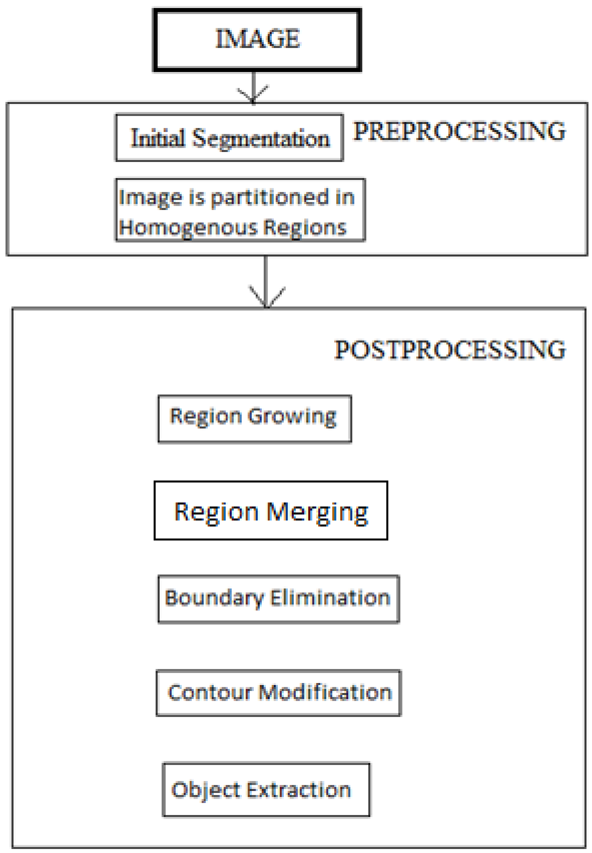

Fig 2.2 Block Diagram

Experimental Results

The proposed method is essentially an adaptive section assimilation method. With the markers input by the user, it will automatically merge regions and label the non-marker regions as object or background.

Experimental analysis of the proposed method

Fig. 3.1 shows an example to extract the portrait (Mona Lisa) from a picture. After the initial segmentation of mean shift, the user inputs some interactive information: the green marker represents the object while the blue markers represent the background. Refer to Fig. 3.1 a, the initial marker regions cover only part but representative features of the object and background regions. As shown in Figs. 3.1 b–d, the object and background marker regions will propagate to all non-marker regions via iteratively implementing the two stage section assimilation process. Finally, Fig. 3.1 e shows that the portrait is well extracted from the complex background.

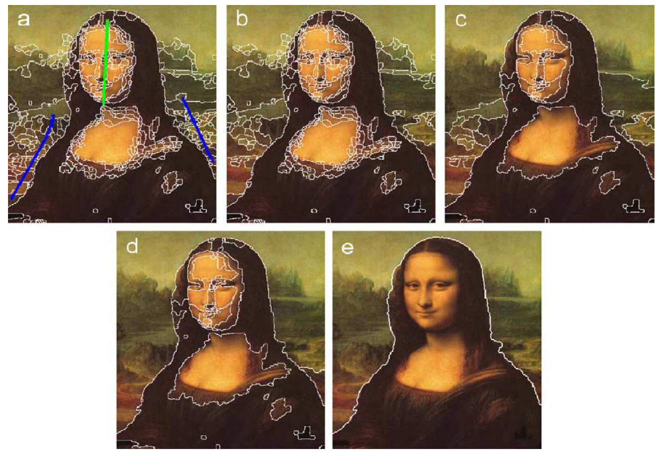

Fig.3.1.Section assimilation process: (a) the initial mean shift segmentation results and the markers input by the user; (b) the first stage (1st round); (c) the second stage (1st round); (d) the first stage (2nd round); and (e) the extracted object contour.

Fig. 3.2 shows the result of proposed method on images of Bird and Dogs.

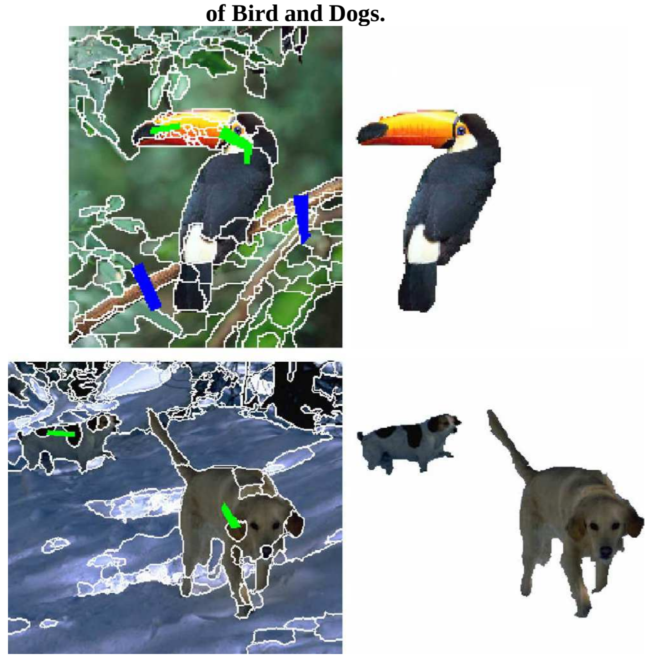

Fig 3.2 Left column: initial segmentation by mean shift and the user input interactive information; Right column: section assimilation result

Conclusion

This paper proposed a novel section assimilation based interactive image segmentation method. The image is initially segmented by mean shift segmentation and the users only need to roughly indicate the main features of the object and background by using some strokes, which are called markers. Since the object regions will have high correlation to the marked object regions and so do the background regions, a novel maximum correlation based section assimilation mechanism was proposed to extract the object. The proposed scheme is simple yet powerful and it is image content adaptive. With the correlation based merging rule, a two stage iterative merging algorithm was presented to gradually label each non-marker region as either object or background. Extensive experiments were conducted to validate the proposed method in extracting single and multiple objects in complex scenes. The proposed scheme efficiently exploits the color similarity of the target object so that it is robust to the variations of input markers.

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