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Background Recognition in Outdoor Images Using Image Segmentation and Boundary Detection

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Abstract: In this paper, my research objective is to explore detecting object boundaries in outdoor scene images solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on a priori knowledge of the specific objects. Here in order to distinguish the unstructured and structured objects in an outdoor scene, image segmentation is performed. After that the boundary of the foreground object alone is extracted. Then using sobel edge detection method all the edges in the image is detected. In the second round of grouping image fusion is performed using alpha factor which can be varied to realize the contribution of foreground and background objects. After background objects are identified, we roughly know where the structured objects are and delimit perceptual organization in certain areas of an image. This paper shows that, for many fairly articulated objects, recognition may not be a requirement for segmentation. The geometric relationships of the constituent parts of the objects provide useful cues indicating the memberships of these parts.

Keywords: POM, boundary detection, GDS and BSDS

I.INTRODUCTION

Image segmentation is considered to be one of the fundamental problems for computer vision. A primary goal of image segmentation is to partition an image into regions of coherent properties so that each region corresponds to an object or area of interest. In general, objects in outdoor scenes can be divided into two categories, namely, unstructured objects (e.g., sky, roads, trees, grass, etc.) and structured objects (e.g., cars, buildings, people, etc.). Unstructured objects usually comprise the backgrounds of images. The background objects usually have nearly homogenous surfaces and are distinct from the structured objects in images. Many recent appearance-based methods have achieved high accuracy in recognizing these background object classes. Without certain knowledge about an object, it is difficult to group these parts together. Some studies tackle this difficulty by using object-specific models. However, these methods do not perform well when the images contain objects that have not been seen before. Different from these studies, in this paper, our research objective is to explore detecting object boundaries in outdoor scene images solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on *a priori* knowledge of the specific objects. It has been long known that perceptual organization plays a powerful role in human visual perception. Perceptual organization, in general, refers to a basic capability of the human visual system to derive relevant groupings and structures for main image without prior knowledge of its contents. The main contribution of this paper is a developed perceptual organization model (POM) for boundary detection. The POM quantitatively incorporates a list of Gestalt laws and therefore is able to capture the *nonaccidental* structural relationships among the constituent parts of a structured object. With this model, we are able to detect the boundaries of various salient structured objects under different outdoor environments. The experimental results show that our proposed method outperformed two state-of-the-art studies on two challenging image databases consisting of a wide variety of outdoor scenes and object classes.

The remainder of this paper is organized as follows: In Section II, we discuss some related studies, including image segmentation and boundary detection methods. In Section III, we describe our POM and scene image segmentation algorithm. The experimental results are presented in Section IV, and Section V concludes this paper.

II. RELATED WORK

Bottom-up image segmentation methods only utilize low-level features such as colors, textures, and edges to decompose an image into uniform regions. Bottom-up methods can be divided into two categories, namely, region-based and contour-based approaches. A group of approaches treats image segmentation as a graph cut problem. Shi and Malik proposed the normalized cut criterion that removes the trivial solutions of cutting small sets of isolated nodes in the graph. Felzenszwalb and Huttenlocher proposed an efficient graph-based generic image segmentation algorithm. As with the normalized cut method, this method also tries to capture nonlocal image characteristics. Comiciu and Meer treated image segmentation as a cluster problem in a spatial-range

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feature space. Their mean-shift segmentation algorithm has illustrated excellent performance on different image data sets and has been considered as one of the best bottom-up image segmentation methods. Some of these region-based methods have been widely used to generate coherent regions called super pixels for many applications model

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III. IMAGE SEGMENTATION ALGORITHM

Here, we present a novel image segmentation algorithm for outdoor scenes. Our research objective here is to explore detecting object boundaries solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on object-specific knowledge. Our image segmentation algorithm is inspired by a POM, which is the main contribution of this paper. The POM quantitatively incorporates a list of Gestalt cues. By doing this, the POM can detect many structured object boundaries without having any object-specific knowledge of these objects. We first give the formal definition of salient structured objects and object parts in images:

Definition 1: A salient structured object refers to a structured object with an independent and detectable physical boundary. An independent physical boundary means that the boundary of the object should not be contained in another structured object. For example, the window of a building should be treated as a part of the building because the whole physical boundary of the window is contained in the building's physical boundary. In addition, the physical boundary of a salient object should be detectable by state-of-the-art computer vision algorithms. For a group of people, if each individual is too small or several people wear the same color clothes, making it difficult to clearly detect each individual's boundary with today's computer vision technology, then the whole group of people should be treated as a salient object.

Definition 2: An object part refers to a homogenous portion of a salient structured object surface in an image. Based on our empirical observation, most object parts have approximately homogenous surfaces (e.g., color, texture, etc.).Therefore, the homogenous patches in an image approximately correspond to the parts of the objects in the image. Throughout this paper, we use this definition for object parts. In the remainder of this section, we first introduce how to recognize the common background objects such as skies, roads, and vegetation in outdoor natural scenes. Then, we present our POM and the boundary detection algorithm. Finally, we describe our image segmentation algorithm based on the POM.

A novel image segmentation algorithm for outdoor scenes is proposed. The research objective here is to explore detecting object boundaries solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on object-specific knowledge. Image segmentation algorithm is inspired by a POM, which is the main contribution of this project. The POM quantitatively incorporates a list of Gestalt cues. By doing this, the POM can detect many structured object boundaries without having any object-specific knowledge of these objects. Most studies to date apply Gestalt laws on zero- or 1-D image features (e.g., points, lines, curves, etc.). Different to these studies, proposed method applies Gestalt laws on 2-D image features, i.e., object parts. First give the formal definition of salient structured objects and object parts in images:

Definition 3: A salient structured object refers to a structured object with an independent and detectable physical boundary. An independent physical boundary means that the boundary of the object should not be contained in another structured object. For example, the window of a building should be treated as a part of the building because the whole physical boundary of the window is contained in the building's physical boundary. In addition, the physical boundary of a salient object should be detectable by state-of-the-art computer vision algorithms. For a group of people, if each individual is too small or several people wear the same color clothes, making it difficult to clearly detect each individual's boundary with today's computer vision technology, then the whole group of people should be treated as a salient object.

Definition 4: An object part refers to a homogenous portion of a salient structured object surface in an image. Based on the empirical observation, most object parts have approximately homogenous surfaces (e.g., color, texture, etc.). Therefore, the homogenous patches in an image approximately correspond to the parts of the objects in the image. Throughout this project, use this definition for object parts.

A. *Background Identification In Outdoor Natural Scenes*

Objects appearing in natural scenes can be roughly divided into two categories, namely, unstructured and structured objects. Unstructured objects typically have nearly homogenous surfaces, whereas structured objects typically consist of multiple constituent parts, with each part having distinct appearances (e.g., color, texture, etc.). The common backgrounds in outdoor natural scenes are those unstructured objects such as skies, roads, trees, and grasses. These backgrounds objects have low visual variability and, in most cases, are distinguishable from other structured objects in an image. For instance, a sky usually has a uniform appearance with blue or white colors; a tree or a grass usually has a textured appearance with green colors. Therefore, these background objects can be accurately recognized solely based on appearance information.

The key for this method is to use textons to represent object appearance information. The term texton is first presented in for describing human textural perception. The whole textonization process proceeds as follows: First, the training images are converted to the perceptually uniform CIE color space. Then, the training images are convolved with a 17-D filter bank. Use the

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same filter bank as that, which consists of Gaussians at scales 1, 2, and 4; and derivatives of Gaussians at scales 2 and 4; and Laplacians of Gaussians at scales 1, 2, 4, and 8. The Gaussians are applied to all three color channels, whereas the other filters are applied only to the luminance channel. By doing so, we obtain a 17-D response for each training pixel. The 17-D response is then augmented with the CIE, channels to form a 20-D vector. This is different from [41] because found that, after augmenting the three color channels, can achieve slightly higher classification accuracy. Then, the Euclidean-distance –means clustering algorithm is performed on the 20-D vectors collected from the training images to generate cluster centers. These cluster centers are called textons. Finally, each pixel in each image is assigned to the nearest cluster center, producing the texton map. After this textonization process, each image region of the training images is represented by a histogram of textons. Then use these training data to train a set of binary Adaboost classifiers to classify the unstructured objects (e.g., skies, roads, trees, grasses, etc.). The classifiers also achieve high accuracy on classifying these background objects in outdoor images.

B. *POM*

Most images consist of background and foreground objects. Most foreground objects are structured objects that are often composed of multiple parts, with each part having distinct surface characteristics (e.g., color, texture, etc.). Assume that use a bottom-up method to segment an image into uniform patches, then most structured objects should be over segmented to multiple patches (parts). After the background patches are identified in the image, the majority of the remaining image patches correspond to the constituent parts of structured objects. The challenge here is how to piece the set of constituted parts of a structured object together to form a region that corresponds to the structured object without any object-specific knowledge of the object. To tackle this problem, develop a POM. Accordingly, image segmentation algorithm can be divided into the following three steps.

1) Given an image, use a bottom-up method to segment it into uniform patches.

2) Use background classifiers to identify background patches.

3) Use POM to group the remaining patches (parts) to larger regions that correspond to structured objects or semantically meaningful parts of structured objects.

Now go through the details of the POM. Even after background identification, there are still a large number of patches (parts) remaining. Use the Gestalt laws to guide us to find and group these kinds of regions. Strategy is that, since there always exists some special structural relationships that obey the principle of non accidentalness among the constituent parts of a structured object, may be able to piece the set of parts together by capturing these special structural relationships. The whole process works as follows: First pick one part and then keep growing the region by trying to group its neighbors with the region. The process stops when none of the region's neighbors can be grouped with the region. To achieve this, develop a measurement to measure how accurately a region is grouped. The region goodness directly depends on how well the structural relationships of parts contained in the region obey Gestalt laws. In other words, the region goodness is defined from perceptual organization perspective. With the region measurement, find the best region that contains the initial part. In most cases, the best region corresponds to a single structured object or the semantically meaningful part of the structured object.

The POM can capture the special structural relationships that obey the principle of non accidentalness among the constituent parts of a structured object. To apply the proposed POM to real-world natural scene images, need to first segment an image into regions so that each region approximately corresponds to an object part. In the implementation, make use of Felzenszwalb and Huttenlocher's approach to generate initial super pixels for an outdoor scene image. Choose this method because it is very efficient and the result of the method is comparable to the mean-shift algorithm. However, the initial super pixels are, in many cases, still too noisy. To further improve the segmentation quality, apply a segment-merge method on the initial super pixels to merge the small size regions (i.e., region size 0.03% of the image size) with their neighbors. These small size regions are often caused by the texture of surfaces or by the inhomogeneous portions of some part surfaces. Since these small size image regions contribute little to the structure information (shape and size) of object parts, merge them together with their larger neighbors to improve the performance of POM. In addition, if two adjacent regions have similar colors, also merge them together. By doing so, obtain a set of improved super pixels. Most of these improved super pixels approximately correspond to object parts. Now turn to the image segmentation algorithm. Given an outdoor scene image, first apply the segment-merge technique described above to generate a set of improved super pixels. Most of the super pixels approximately correspond to object parts in that scene.

This perceptual organization procedure is repeated for multiple rounds until no components in can be grouped with other components. In practice, find that the result of two rounds of grouping is good enough in most cases. At last, in a post process procedure, merge all the adjacent sky and ground objects together to generate final segmentation. A novel image segmentation algorithm for outdoor scenes is to explore detecting object boundaries solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on object-specific knowledge. Image segmentation algorithm is inspired by a POM, which is the main contribution of this project. The POM

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quantitatively incorporates a list of Gestalt cues. By doing this, the POM can detect many structured object boundaries without having any object-specific knowledge of these objects.

IV RESULTS AND SCREENSHOTS

Figure1 shows the input image that is to be processed. Input image can be any one of the image formats JPEG, PNG and BMP. First the input image is passed to the MATLAB and then it is resized using a threshold value 0.5. This resized image is shown in the figure1.

Figure 1: Input image

Figure2 shows the segmentation maps. After resizing the input image using the fixed threshold value as show in the figure1, convert it into gray scale image. Then segmentation is performed on this gray scale image. Parts of the image having similar properties are grouped together and given a separate color for each group.

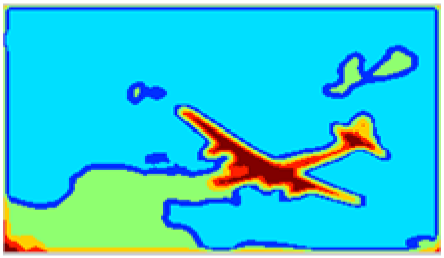

Figure 2: Segmented map image

B. *Boundary Detection*

Figure3 shows the boundary detection. In this figure the boundary of the foreground object (In this case the foreground object is aircraft) is extracted from the background objects. The sobel edge detection method is used for this purpose.

Figure 3: Boundary detected image

After this first round grouped as shown in figure4 in which the boundaries are shown in red lines.

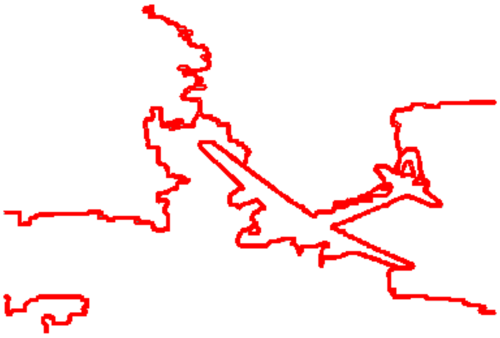

Figure 4: First round grouped image

Result of the first round perceptual organization. Notice that the different parts of the aeroplane have been grouped into two big pieces. These two big pieces are aligned. Bottom: final segmentation result after second round.

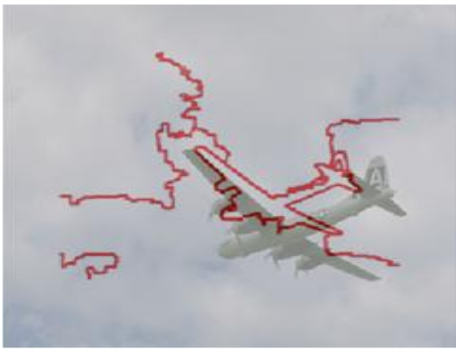

Figure 5: second round group image

V. CONCLUSION

A novel image segmentation algorithm for outdoor natural scenes proposed. The main contribution is that we develop a POM. The experimental results show that the proposed method outperformed two competing state-of-the-art image segmentation approaches (Gould09 and global probability of boundary) and achieved good segmentation quality on two challenging outdoor scene image data sets

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(GDS and BSDS). It is well accepted that segmentation and recognition should not be separated and should be treated as an interleaving procedure. The method basically follows this scheme and requires identifying some background objects as a starting point. Compared to the large number of structured object classes, there are only a few common background objects in outdoor scenes. These background objects have low visual variety and hence can be reliably recognized. After background objects are identified, roughly know where the structured objects are and delimit perceptual organization in certain areas of an image. For many objects with polygonal shapes, such as the major object classes appearing in the streets (e.g., buildings, vehicles, signs, people, etc.) and many other objects, the method can piece the whole object or the main portions of the objects together without requiring recognition of the individual object parts. In other words, for these object classes, the method provides a way to separate segmentation and recognition. This is the major difference between the method and other class segmentation methods that require recognizing an object in order to segment it. This project shows that, for many fairly articulated objects, recognition may not be a requirement for segmentation.

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