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Boundary Detection of Structured Objects

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Abstract: Efficient and effective detection of objects in the images is an important task in many image processing applications. This paper presents a region merging approach for detecting the foreground objects in the image. The foreground objects are the structured objects with an independent and detectable boundary. The proposed approach identifies objects in the given image based on general properties of the objects without depending on the prior knowledge about specific objects. The regions of the structured foreground objects in the image are separated by using region contrast information. The perceptual organization laws of human visual system are used in the region merging process to identify the boundaries of various objects. The system is adaptive to the image content. The results of the experiments show that the proposed scheme can reliably extract object boundary from the background.

Keywords: Contrast, Histogram, Region merging, Seed region, Threshold

I. INTRODUCTION

Image segmentation is used to separate the foreground objects from the background. The objects in the images are of two types: Unstructured objects and Structured objects. Unstructured objects form the background in images. e.g. sky, trees, roads, etc. Structured objects are the foreground objects. Structured objects have an independent and detectable boundary in the image. e.g.car, bird etc. The detection of structured foreground objects in an image is an important task in many applications like image classification, image retrieval, content-aware image resizing etc. These applications require accurate detection of boundary of objects.

The backgrounds in images usually have homogeneous appearance (e.g. color, texture etc.) and are distinct from the structured objects in images. Therefore these unstructured objects can be identified by using region contrast information. The structured objects are more difficult to identify as they are composed of multiple parts. An object part refers to a homogeneous portion of a structured object. Different parts of object may have distinct surface characteristics (e.g. colors, texture etc.). Hence the use of a general purpose segmentation algorithm to detect the structured objects may result in over-segmentation of the object. S.Gould, J.Rodgers [5] used a multi-class segmentation technique to detect objects. This method uses object-specific models to identify the objects. Each region in the image is assigned to one of the specific predefined classes. However this method fails to detect objects when the images contain objects that are not in training data.

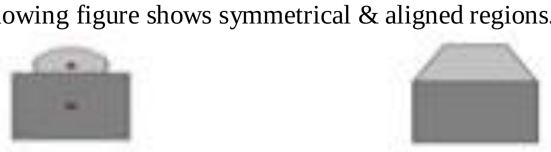
The proposed approach tries to detect the structured objects in the image using region contrast information and perceptual organization of object parts. The approach is based on the general properties of real-world objects (e.g. similarity, proximity etc.) and hence does not depend on specific properties of objects.

The structured foreground objects usually have high contrast to their background. Hence region contrast information is used to distinguish among the regions that belong to unstructured and structured objects. Perceptual organization is defined as the basic capability of human visual system to identify relevant groupings and structures from an image without any prior knowledge of image content. The Gestalt Laws are based on human visual perception of objects. In the proposed approach following Gestalt laws are used to group the regions together to form a region that constitutes a structured object in an image.

Law of Similarity:
Regions that have similar attributes (e.g. color) are more likely to be organized together.

Law of Symmetry:
Regions that are symmetrical are grouped together.

Law of Alignment:
Regions will be grouped as a whole if they are co-linear or follow a direction.
Following figure shows symmetrical & aligned regions.



(a) (b)

Fig.1(a) Symmetrical Regions: red dots indicate the region centroid (b) Aligned Regions.

Law of Proximity:
The regions that are closer are perceived as a group.

The proposed approach applies Gestalt laws to image regions using color and structural information of regions and merge the regions together so as to identify one single region that corresponds to a structured object.

II. LITERATURE REVIEW

There are several algorithms and techniques available for image segmentation to detect boundary of objects. The choice of a segmentation technique over another and the level of segmentation depends on the particular type of image and characteristics of the problem being considered.

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Top down approach of image segmentation uses prior knowledge about an object such as its shape, color or texture to guide the segmentation. The complexity in this approach increases because of the large unevenness in the shape and appearance of objects. In bottom-up approach the pixels are grouped according to the similarity among low-level features such as color, textures etc. The limitation of this approach is that an object may be over-segmented into numerous regions. In the graph based image segmentation approach each pixel of the image is equivalent to a node in the graph and edges represent adjacent pixels. Weights on each edge represent the dissimilarity between pixels. The boundaries between regions are defined by measuring the dissimilarity between the neighbouring pixels. Shi and Malik[4]used normalized cut(Ncut) criteria for image segmentation. Ncut method organizes nodes into groups so that within the group the similarity is high and between the groups the similarity is low. In the region-based approach, each pixel is assigned to a particular region. In region growing method of image segmentation a seed region is chosen and a new region is identified by merging as many neighboring pixels with the seed region. Martin et al.[11]implemented boundary detection as a supervised learning problem. A large data set of human-labelled boundaries in natural images is used to train a boundary model. The model can then predict the possibility of a pixel being a boundary pixel based on a set of low-level cues such as brightness, color and texture extracted from local image patches. S.Gould, J.Rodgers[5] proposed a multi-class image segmentation technique. Multi-class image segmentation uses one of a number of classes (e.g., road, sky, water, etc.) for labelling every pixel in an image. In this method the image is first segmented into superpixels (i.e. small coherent regions) and then each region is classified. However training classifiers and classification of regions in image is computationally expensive. Also this method fails to detect objects in image that are not in the training set. McCafferty[6] used Gestalt grouping laws for segmenting an image. They used boundary energy functions to identify the regions that can be grouped together. The energy function is defined on the space of boundaries in the image domain, and includes information about the region. Chang Cheng, Andreas Koschan[14] implemented Gestalt Laws in terms of energy function. The energy function measures the accuracy of grouping the regions. The limitation of this method is that, it fails to detect complex objects in the image.

III. METHODOLOGY

The objective of the proposed approach is to detect boundary of structured objects in an image based on some general properties of real world objects, without depending on the *a priori* knowledge of specific objects. The structured objects should be detected accurately from an image without over-segmentation.

The proposed system takes an image as input and produces an output image with structured objects segmented from the background in the image.

Following figure shows the block diagram of the proposed system.

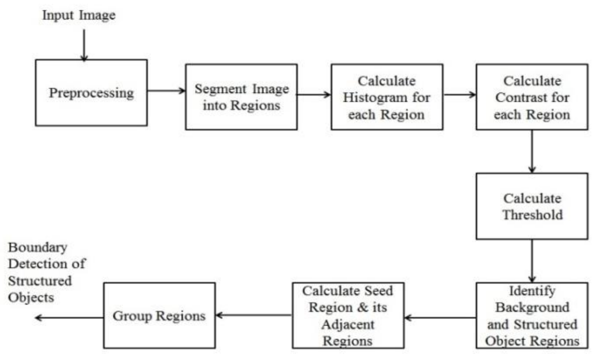

Fig. 2 Block diagram for boundary detection of structured objects.

A. Pre-processing the image

The input to the system is an image in the RGB color format. The pre-processing step involves applying Gaussian smoothing filter to the image. It is used to remove noise from the image.

B. Initial Segmentation

Since working on every pixel of the image is computationally expensive, the input image is first segmented into multiple uniform regions (i.e. superpixels). The Felzenszwalb and Huttenlocher's [3] segmentation algorithm is used to generate initial regions. To improve the output quality, the small size regions (i.e. region_size < 0.03 of the image_size) are merged with their adjacent regions. There are two advantages of initially segmenting the image into superpixels: First regions carry more information for describing object nature and second is since number of regions is significantly fewer than number of pixels in the image, it largely speeds-up the region merging process.

C. Histogram calculation

Next a color histogram is created for each region. Histogram of the regions provides a convenient summary about the colour statistics. The histogram provides more insight about image contrast.

D. Calculate contrast for each region

The region contrast information is used to separate regions that belong to structured object and background. For each region its color contrast is calculated based on region's histogram, by measuring its color contrast to all the other regions in the image.Then for a region r_k, its color contrast RC to all other regions in the image is measured as,

$$RC(r_k) = \sum_{r_k \neq r_i} w(r_i)\, D_r(r_k, r_i) \quad (1)$$

where $w(r_i)$ is the weight of the region r_i (i.e. number of pixels in r_i). D_r is the color distance between two regions defined as,

$$D_r(r_1, r_2) = \sum_{i=1}^{n1}\sum_{j=1}^{n2} f(c_{1,i}) f(c_{2,j}) D(c_{1,i}, c_{2,j}) \quad (2)$$

Where $f(c_{1,i})$is frequency of the i-th color $c_{k,i}$ among all $n_k$colors in the k-th region r_k with k= {1, 2}.

$D(c_{1,i}, c_{2,j})$ is the Euclidean distance between two colors.

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E. Calculate threshold

Thresholding is a useful technique for establishing boundary of objects in images that contain solid objects residing on contrasting background.

The system uses global threshold i.e. one threshold value is used to separate the initial regions into structured objects regions and background regions.

A threshold of region contrast is calculated as,
Threshold=meanregion_contrast+ 0.1*stddevregion_contrast

F. Identify background and structured object regions

The regions having region contrast more than threshold are considered as regions that belong to structured objects. The regions having region contrast less than threshold are considered as regions that belong to background (i.e. unstructured objects).

G. Calculate seed region and its adjacent regions

As initially the input image is segmented into multiple regions, the structured object may span multiple regions. Hence these multiple regions (i.e. object parts) are grouped together to detect a structured object. To start with, we identify a seed region from the set of regions that belong to structured objects. The seed region is a region with highest region contrast value.

H. Group Regions

A seed region from the set of structured object regions having maximum value of region contrast is selected at the beginning of grouping procedure. The seed region R_o is grouped with its neighbouring regions by using perceptual organization laws. The regions are grouped based on similarity, symmetry, alignment and proximity between regions. The output of region grouping is a single region, that corresponds to a structured object. The accuracy of region grouping depends on how well the constituent regions satisfy perceptual organization laws. The region accuracy is measured by defining a boundary energy function $E[bR]$. The output region R_a is a region with minimum value of boundary energy. This is because, as the regions are grouped, the convexity of output region increases which results in decrease of boundary energy.

$$R_a = \arg\min_R (E[bR]) \quad \text{with } R \in R_s \tag{3}$$

The energy function E[bR] is defined as

$$E[bR] = \frac{-\iint f(x,y)dxdy}{L(bR)} \tag{4}$$

where bR denotes boundary of region R and $L(bR)$ is boundary length of region R.

f(x,y) is the weight function used to identify structural relationship between neighbouring parts a and i in region R. This function is used to encode the Gestalt laws i.e symmetry, alignment and proximity. f(x,y) is defined as ,

$$f(x,y) = e^{-\theta.\eta(Si-Sa)} \tag{5}$$

where vector $S_i = [B_i\ C_i]$ encodes structure information of image patch i. S_a encodes structure information of image patch a. θ is a constant. B_i is boundary complexity of image patch i.

$$B_i = \frac{4\Pi S}{P^2} \tag{6}$$

where S is the area and P is perimeter of patch i.

C_i is the cohesiveness strength that measures how tightly image patch i is attached to remaining parts of structured object. C_i is calculated as

$$C_i = \max_j (e^{-\phi_{ij}\varphi_{ij}\lambda_{ij}} C_j) \tag{7}$$

where ϕ_{ij} measures the symmetry of image patches i and j as

$$\phi_{ij} = 1- \delta(y_i,y_j) \tag{8}$$

y_i and y_j are the column coordinates of the centroids of i and j. This means, if the image patches i and j are symmetric along a vertical axis then they mostly belong to the same object.

φ_{ij} measures the alignment of patches i and j.

$$\varphi_{ij} = \begin{cases} 0 \ if \ e(bij) \cap bi = \Phi \wedge e(bij) \cap bj = \Phi \\ 1 \ if \ e(bij) \cap bi \neq \Phi \vee e(bij) \cap bj \neq \Phi \end{cases} \tag{9}$$

where bi and bj are the boundaries of regions i and j. $e(bij)$ is the extension of common boundary between i and j. This is used to indicate that if two object parts are strictly aligned along a direction then the boundary of the union of two parts will have a continuation.

λ_{ij} measures the proximity of two object parts i and j.

$$\lambda_{ij} = \beta * \exp\left(-\alpha \frac{(\cos w) * L(bij)}{L(bi)+L(bj)}\right) \tag{10}$$

The proximity depends on the ratio of the common boundary length between i and j to the sum of the boundary lengths of i and j. If regions i and j share a long common boundary, this means that i and j are in close *proximity* to each other.

w is the angle between the line connecting the two ends of bij and the horizontal line starting from one end of bij. cosw is used to control the cohesiveness strength of two attaching patches according to the attachment orientation. α and β are constants.

Following is the algorithm for boundary detection of structured objects using perceptual organization.

Algorithm : Boundary detection of structured objects

Input : Set of structured object regions R_s ,Seed region R_o
Output: Region R_a with minimal boundary energy value such that R_a corresponds to structured object.

1) Let $R_a = R_o$
2) Let NR_a is the set of neighbor regions of R_a.
3) Repeat steps 4 to 7 for q =1 to n
4) Select a subset u of NR_a with q regions such that there exist a path among the regions in u.
5) Measure the boundary energy of $R_a \cup u$ with equation[4].
6) If $E[b(Ra \cup u)] < E[b(R_a)]$, set $R_a = R_a \cup u$, goto step 2
7) Otherwise select the next set of u from NR_a and repeat steps 4-7 until all possible u have been tested.
8) Return R_a

IV. RESULTS & DISCUSSION

The objective is to accurately detect the boundary of structured objects in the image. The system is tested on Berkley dataset. The dataset contains images with a wide variety of man-made and biological objects with various types of backgrounds. The size of the images are 481 X 321.This dataset also provides ground truth object segmentation. Following figures shows the results of the boundary detection.

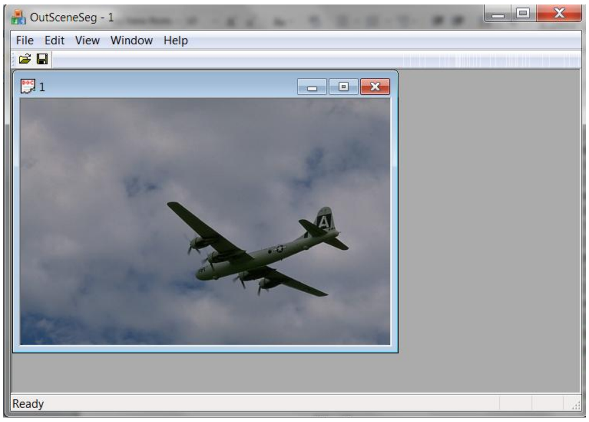

Fig. 3 Input image.

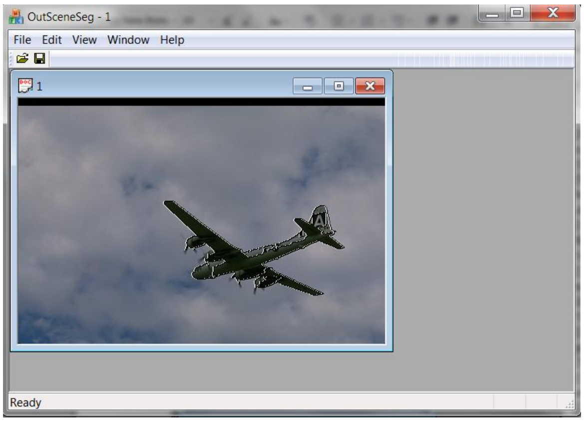

Fig. 4 Output image with boundary detection of structured objects.

V. CONCLUSION

The proposed system identifies boundary of structured objects in the image by using general properties of real world objects without requiring object-specific knowledge. The method combines contrast information and structural information of regions to detect foreground structured objects in the image. The proposed system can detect different types of objects without requiring object-specific knowledge. Thus the proposed method overcomes the requirement of training a set of classifiers to detect objects. The system is adaptive to the image content. In future, the system will be enhanced to detect overlapping objects in image.

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