

Outdoor Scene Image Segmentation for background recognition using Perceptual organization model

Anupama J Patil¹, Sanjay S. Pawar²

¹ME(Student) Electronics & Telecommunication

Bharati Vidyapeeth's college of Engineering, Kolhapur.

²Assistant Professor

Bharati Vidyapeeth's college of Engineering, Kolhapur

Abstract— In this paper we recognize the background objects like sky, tree, ground. In processing we improve the quality of input image (auto contrast) by thresholding & then bottom up segmentation applied on it for clustering of similar patch. After that Edge detection principle is used for the identification of any type of boundaries. Finally Perceptual Organization Model which mainly include list of Gestalt's laws & capture structural object. Our proposed method outperformed on Berkeley image data set & natural outdoor images.

Index Terms— POM (Perceptual Organization Model)

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). 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 a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Edge detection is used for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in image processing.

Human can immediately detect relationships such as co linearity, parallelism & connectivity this phenomenon called perceptual organization. Providing such facility in terms of model can result in better image segmentation results. By using different Gestalt laws POM is able to capture relation between structured & non structured objects.

II. RELATED WORK

In this paper, we study the problem of image understanding in indoor scenes from color and depth data. Our system produces contour detection and bottom up segmentation, grouping by a modal completion, and semantic labeling of objects and scene surfaces[1] A method for the detection of salient non-local structures in vector graphics. Non-local structures may consist of similar graphical objects—the constituents of a vector graphics—or

of objects which are orderly arranged. They may be perceived immediately, but they are not explicitly represented in the internal description of a graphics. Information on such cognitive relevant structures may serve as additional indices to the graphics data base of a graphics retrieval system or may guide higher scene interpretation routines. Nonlocal structures emerge as a result of grouping processes of visual perception. The method used to detect non-local structures is the simulation of models of organizing phenomena of human visual perception.[2]

In this paper, we propose a novel outdoor scene image segmentation algorithm based on background recognition and perceptual organization. We recognize the background objects such as the sky, the ground, and vegetation based on the color and texture information. For the structurally challenging objects, which usually consist of multiple constituent parts, we developed a perceptual organization model that can capture the non accidental structural relationships among the constituent parts of the structured objects and, hence, group them together accordingly without depending on *a priori* knowledge of the specific objects.[3] Finally, we review some previous efforts attempting to apply Gestalt laws to guide image segmentation. A number of studies [4], [5], [6], [7] only applied one or two Gestalt laws (e.g., *proximity*, *curvilinear*, *continuity*, *closure*, or *convexity*, etc.) on 1-D image features (e.g., lines, curves, and edges) to find closed contours in images. Lowe [4] and Mahamud *et al.* [6] integrated *proximity* and *continuity* laws to detect smooth closed contour bounding unknown objects in real images. Ren *et al.*[7]

III. PROPOSED METHOD

In our proposed method we first of all improved the quality of input image by adjusting its brightness. Thresholding technique is used to implement this auto contrast to original input image.



Fig.1 Input image

Fig.2 Auto contrast of input

1) Edge detection:

Edge detection is an image processing technique for finding the boundaries of objects within images. We propose sobel technique for edge detection. Where a general formulation for edge detection that can be applied, in principle, to the identification of any type of boundaries, such as general edges from low-level static cues. A boundary separates different image regions, which in the absence of noise are almost constant, at some level of image interpretation or processing. For example, at the lowest level, a region could have constant intensity. At a higher-level, it could be a region delimiting an object category, in which case the output of a category-specific classifier would be constant.



Fig.1 Edge detection by Sobel technique.

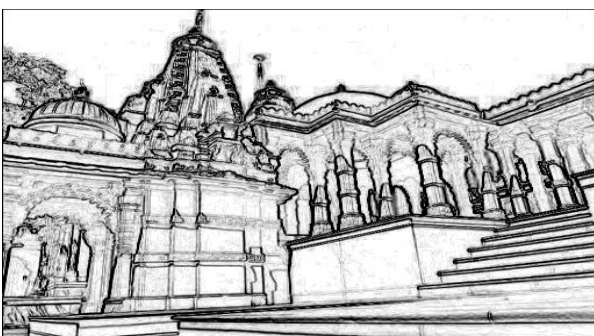


Fig.4 Edge detection by Sobel technique with filled object area

2) Initial segmentation

After the edge detection, result of image segmentation is a set of contours extracted from the edges detected image. Then to initialize the segmentation, we used

K-means segmentation algorithm. K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them.

K-means is the clustering algorithm used to determine the natural spectral groupings present in a data set. This accepts from analyst the number of clusters to be located in the data. The algorithm then arbitrarily seeds or locates, that number of cluster centers in multidimensional measurement space. Each pixel in the image is then assigned to the cluster whose arbitrary mean vector is closest. The procedure continues until there is no significant change in the location of class mean vectors between successive iterations of the algorithms

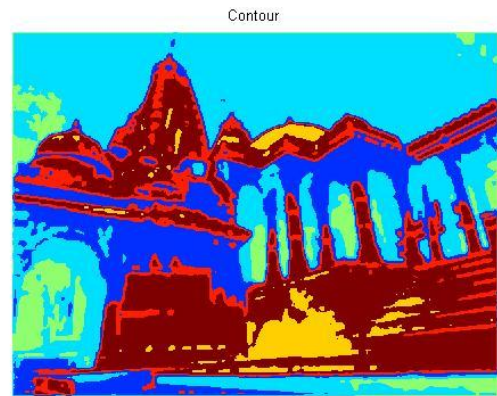


Fig.3 segmented by K-means clustering

3) POM Model:

Human can immediately detect relationships such as co linearity, parallelism & connectivity this phenomenon called perceptual organization. Providing such facility in terms of model can result in better image segmentation results. By using different Gestalt laws POM is able to capture relation between structured & non structured objects. POM model is used for the recognition of background in original input image by which the relation between structured & non structured objects also recognized.

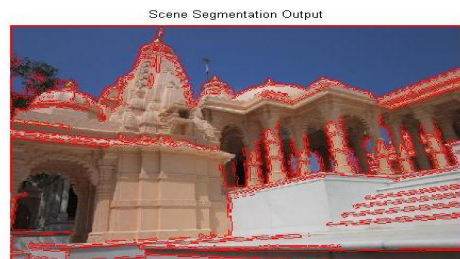


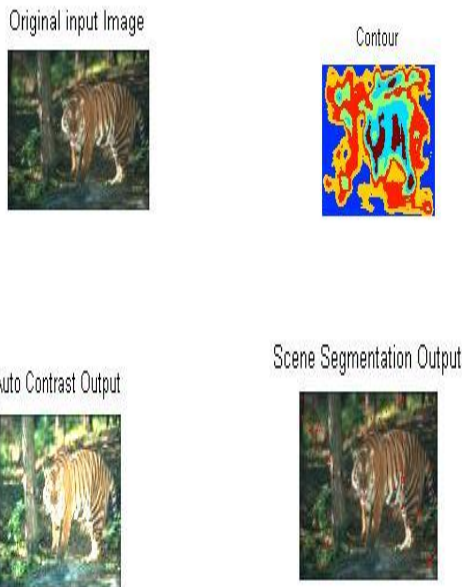
Fig.5 output of POM model

IV. RESULT

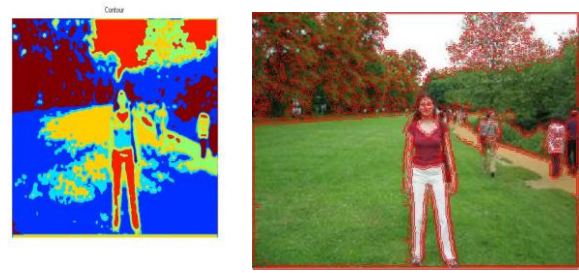
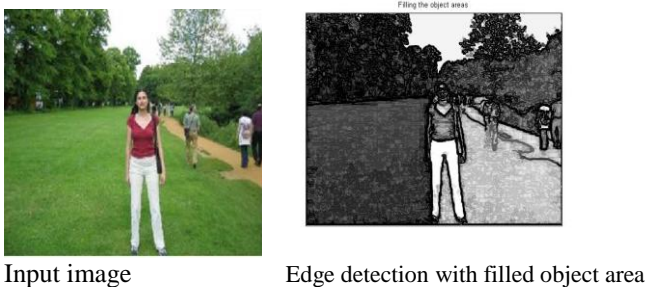
We first test our image segmentation algorithm on a Gould image data set (GDS) [52]. This data set contains 715 images of urban and rural scenes assembled from a collection of public image data sets. The images on this data set are down sampled to approximately 320 pixels 240 pixels. The images contain a wide variety of man-made and biological objects such as buildings, signs, cars, people, cows, and sheep.

Furthermore, we evaluate our POM image segmentation method on the Berkeley segmentation data set (BSDS) [60]. BSDS contains a training set of 200 images and a test set of 100 images. For each image, BSDS provides a collection of hand-labeled segmentations from multiple human subjects as ground truth. BSDS has been widely used as a benchmark for many boundary detection and segmentation algorithms in technical literature. We directly evaluate our POM method on the test set of BSDS. The sizes of images in this data set are 481* 321 ,which are larger than the sizes of images in GDS. Then applied on real time images taken by author.

Results for Berkeley segmentation data set



Results for GDS



segmented by K-means clustering

POM Output

V. CONCLUSION

Our method outperformed on two datasets as GDS & BSDS. It recognizes the common outdoor backgrounds like sky, tree, grass, water, road etc. It works better on images having smaller size. If size of the image is too big then it takes very much time for processing or sometimes it is unable to process. It can't perform well on images having very high brightness.

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