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Segmentation of Images Using Different Aggregation Steps

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ABSTRACT: *Beginning with an image, we execute a sequence of bottom-up aggregation steps in which pixels are gradually merged to produce larger and larger regions. In each step, we consider pairs of adjacent regions and provide a probability measure to assess whether or not they should be included in the same segment. The overall formulation takes intensity and texture distributions into an account around each region. It further incorporates prior based on the geometry of the regions. Our intensity and texture features can be obtained by summation of the corresponding feature values over all pixels in a region. The probabilistic approach provides a complete hierarchical segmentation of the image. The algorithm complexity is linear in the number of the image pixels and it requires almost no user tuned parameters. We test methods on a variety of gray scale images and compare our results to several existing segmentation algorithms.*

I. INTRODUCTION

Segmentation algorithms aim at partitioning an image into regions of coherent properties as a means for separating objects from their backgrounds. As objects may be separable by any of a variety of cues, intensity, color, texture or boundary continuity, many recent algorithms have been designed to utilize and combine multiple cues. Typically in such algorithms cue is handled by a separate module whose job is to assess the coherence of nearby pixels. The utilization of multiple cues aggravates an old problem [1]. In many multi-cue segmentation algorithms each module comes with its own set of parameters intended to control the relative influence of each module. These parameters may depend non-trivially on the particular statistics on the input image. The common practice is to leave those parameters to be set by the use, but in effect most users leave the parameters in their default values. Allowing these parameters to automatically adapt to an image can greatly simplify the use of segmentation algorithms and potentially allow them to consistently provide better results. Proposed algorithms tends to achieve segmentation which will ne parameter-free on various training sets [Fig: 1].In this paper we explore a different approach which relies primarily on local information available within the image to be segmented. Beginning with an image, we execute a sequence of steps in which pixels are gradually merged to produce larger and larger regions. In each step we consider pairs of adjacent regions and provide a probability measure to assess whether or not they should be in evaluation. Here the approach has been designed to work with bottom-up merge strategies for segmentation.

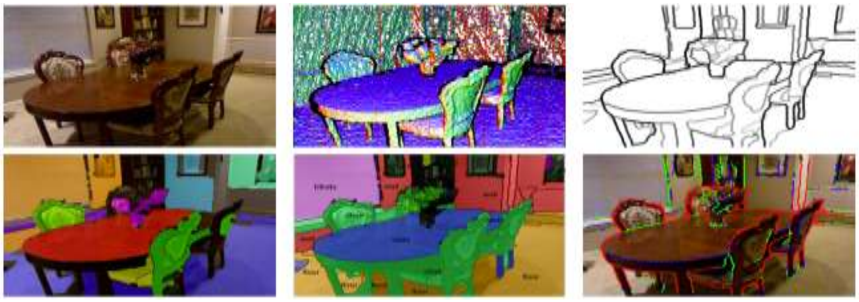

Figure 1: Parameter – Free Segmentation Of Images

A large methods approach segmentation using bottom-up merge strategies, beginning with the classic agglomerative clustering algorithm. Merge algorithms generate a hierarchy of segments, allowing subsequent algorithms to choose between possible segmentation hypotheses. Further test parameter- free approach on a database with manually segmented images and compare results with several existing algorithms [2]. In order to determine the edge weights at every level need to compute posterior probabilities. The computation of these posteriors uses the average intensity and histogram of filter responses computed for every region, as well as the length of boundaries between every two neighboring regions. The merge strategy enables us to compute these properties efficiently for every node, by averaging the same properties computed for its descendants. Unary features are computed for a single region.

II. RELATED WORK

In previously used segmentation algorithms there is a common limitation faced is that the number of segments is specified by a human user. The feasibility of this method is to determine in which situations it will and will not work. Instead of operating at the pixel level, [Fig: 2] advocates the use of super pixels as the basic unit of class segmentation. We construct a classifier on the histogram of local features found in each super pixel. By aggregating histograms in the neighborhood of each super pixel and then refine results further by using the classifier in a conditional random field operating on the super pixel graph.

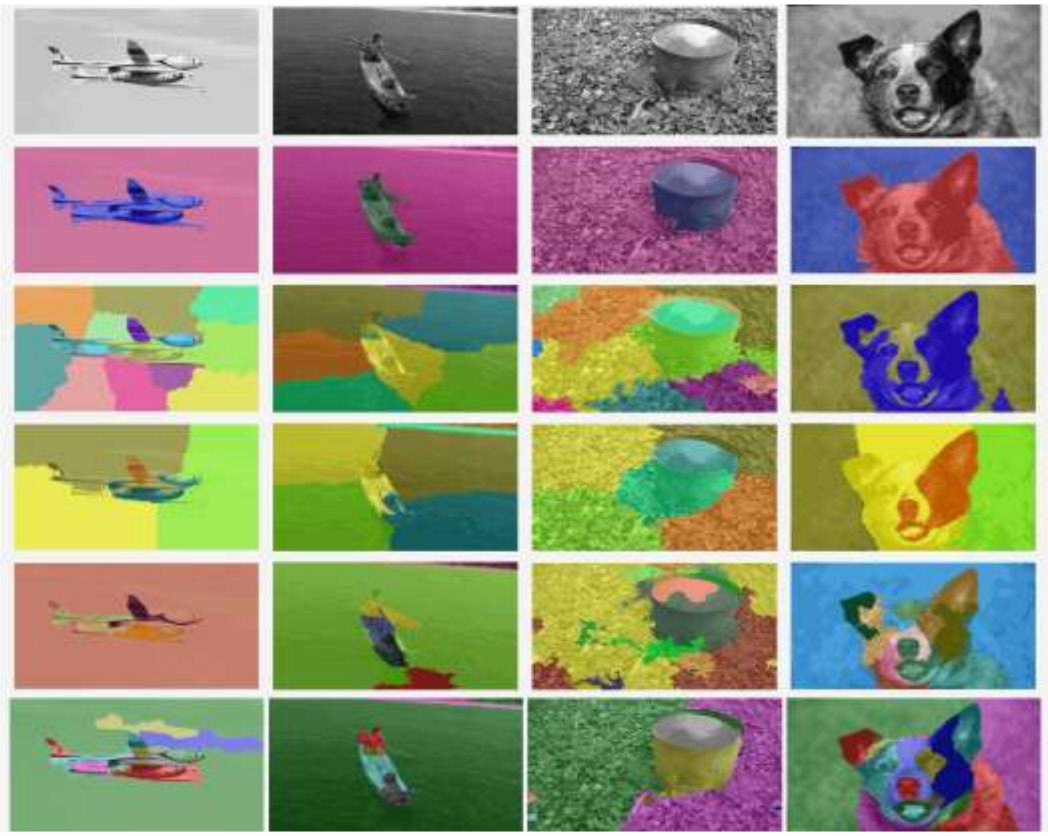

Figure 2: Pixel level Segmentation of the given Image

III.FORMING SUPER PIXELS BY GROWING PIXELS

A size of an image m*n is divided into average lattices. The seed pixels of the super pixels are stationed at the minimum gradient points in the average lattices on the image. When estimating super pixels, pure texture features display blurring of the true edges so that the super pixels boundary information is weakened. For placing accurate boundaries in growing super pixels we integrate RGB channel [3]. A pixels color texture descriptor is denoted by F(R, G, B, U')The growing process of super pixels is implemented in the adjacent lattice over the seed pixels for compact and uniform super pixels with complete textures. The calculation is done for the normalized distance between the pixels and regions in the combined feature space. For keeping the real boundaries and homogeneous regions, the explicit iteration argument is in proportion to the pixel number in super pixels S/2. The boundaries affinity comparison of the method against SLIC, Turbo, and LSC with combined features F (R, G, B, U') are displayed.

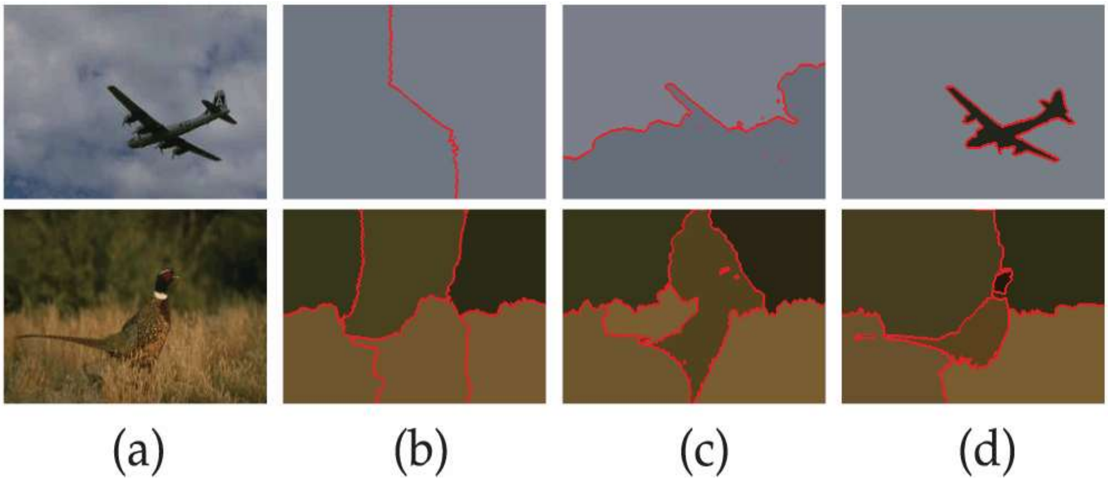

Figure 3: Boundary Affinity with Super pixels of image

This method obtains the better boundaries affinity [Fig: 3] with manual boundaries and gets uniform super pixels with complete textures. From the preliminary results, the average boundaries precision of segmentations with 900 super pixels is higher than 95% compared with the ground truth, which can meet the requirement of the segmentation task. Furthermore, super pixels will gain the computation complexity of merging and characteristics calculation, and it is not conducive to calculate the complete description of the texture in single super pixels. Hence, we set the super pixels number K =900 to ensure the boundary accuracy and texture integrity in the growing procedure.

IV.GRAPH BASED MUMFORD – SHAH OPTIMAL REGION MERGING:

The basic merging benchmark which confides on color homogeneity always suffers from small and meaningless regions. Some other merging algorithms use global optimization energy terms, region number and the region area to control the merging process rather than setting termination condition. To acquisition, an optimal sequence of merging which produces a union of optimal labeling for all regions, the minimization of a certain objective function F is required. At the same time, M–S function is a variation model proposed for segmentation, and it detects optimal result by using the objective function. M–S segmentation uses the energy functional to judge all pixels whether can be merged into homogeneous regions and obtain qualitative region boundaries.

In addition to the merging approach, feature selection is the key issue for reliable segmentation. A combined aspect including color-texture information is projected to explain the region properties, which is a reliable similarity measurement for region discrimination and the standard deviation is introduced for further control of the merging process [4]. Therefore, we design a hybrid constraints merging method based on the M–S model that can optimize multiple features of an image for reasonable merging.

1. Mumford–Shah Model:

The M-S model has a key issue which is to design a decisive minimization energy function to merge the 2-D feature and 1-D constraints together and act related effects. Two typical M–S segmentation models are studied to design the merging strategy [5]. One model is trying to identify the largest energy decrease by using the heuristic greedy manner and it will combine two regions when the largest decrease comes into view. The energy model is simplified to keep an in equality relations between the boundary and regional. The other model assumes the two neighboring regions contain pixels number Ni and Nj with average intensity as CI and CJ, the distance of the common border between the region is r. This model defines the energy function for the stage of before and after merging with region aspects and common boundaries. If the difference of the energy after merging becomes smaller, two regions should be merged.

2. Hybrid Region Histogram Feature and Distance Metric:

In this area, a statistical histogram features as an assistant descriptor of super pixels with color and texture information is designed for two reasons: 1) histogram is a rotation invariant aspect of super pixels and 2) complex regions cannot be properly characterized by simplex color information. The histograms feature defined is able to describe the local color distribution feature and build up the categorized ability of super pixels. The number of pixels in super pixels is different and the number of colors that can be discerned visually is limited, a quantized image is sufficient to describe the color distribution of the local area for segmentation. Quantization on the basis of uniform cutting of color space is too scattered, thus it will generate an error and unnecessary texture.[6] Therefore, an image is quantized to 64 colors by the minimum variance method to assure the least color distortion, which is able to reduce the computing time. After texture coding of pixels, adding up all LCP values of pixels with the same color in the super pixel serves as texture weights of corresponding color bins, then multiply the probability of quantitative colors and texture weights to obtain the composite histogram aspects of super pixels. Hence, the distribution characteristic of super pixels is defined.

3. Hybrid Feature Fusion Mumford–Shah Merging Model:

In this field, an accelerated optimization merging method based on the M–S model is proposed. Simple greedy search strategy easily leads to deviating from the correct segmentation results, so we employ both M–S minimization and standard deviation-based threshold to constrain the merging process for getting a more rational merging sequence.

Standard Deviation-Based Threshold:

The hybrid histogram is a combined aspect of pixels group that has the advantage of discriminating various regions. To explain the merging threshold, the standard deviation is a validated measure of dispersion of data set in statistics, and it is an important index to describe the differences between samples [8]. Thus, the standard deviation of all image super pixels (K super pixels) features is computed for setting termination condition. From the analysis, it is found that the standard deviation changes too fast to control the merging speed, which may lead to over-segmentation. Hence, we introduce an exponential function to modify the standard deviation.

V .EXPERIMENTAL RESULTS

Evaluating the results is really challenging in case of segmentation algorithms, as it is difficult to come up with test sets. This is partly because manual delineation of segments in everyday complex images can be laborious. Furthermore, people often tend to incorporate into their segmentations semantic considerations which are beyond the scope of data driven segmentation algorithms. For this reason many existing algorithms show only few segmentation. An important attempt to produce an extensive evaluation database for segmentation was recently done. This database however has its own limitations, as can be noticed by the differences between subjects. In many cases images are under-segmented, and semantic considerations seem to dominate the annotated segmentations. Many researchers have developed the merging techniques in various aspects. The technique generated an initial set of regions by extracting dominant colors in the input image using a non-parametric density estimation methodology.

To evaluate our method and compare it to recent algorithms we have compiled a database containing 100 gray level images along with ground truth segmentations. The database was designed to contain a variety of images with objects that differ from their surroundings by either intensity, texture, or other low level cues [11]. To avoid potential ambiguities we only selected images that clearly depict one object in the foreground. To obtain ground truth segmentations we asked about 50 subjects to manually segment the images into two classes, foreground and background, with each image segmented by three different human subjects. We further declared a pixel as foreground if it was marked as foreground by at least two subjects.

We evaluated segmentation results by assessing its consistency with the ground truth segmentation and its amount of fragmentation. The amount of fragmentation is given simply by the number of segments needed to cover the foreground object. We applied our segmentation algorithm to all 100 images in the database and compared our results with several state of the art algorithms [10]. As we mentioned in the beginning, we integrate segmentation decisions from different cues using a local mixture of experts. This model allows us to control the influence of each cue and adapt it to the information contained in each region. Thus, when we compare two textured regions we can discount the effect of intensity and by this overcome brightness variations due to lighting.

VI. CONCLUSION

We have presented a parameter – free approach to image segmentation. Our approach uses a bottom – up aggregation procedure in which regions are merged based on probabilistic considerations. The framework utilizes adaptive parametric distributions whose parameters are estimated locally using image information. Segmentation relies on a integration of intensity and texture cues, with priors determined by the geometry of the regions. We further applied the method to a large database with manually segmented images and compared its performance to several recent algorithms obtaining favorable results.

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