ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 3, Special Issue 10, March 2017

Tree Structured Image Segmentation Based On Super Pixel

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Abstract

Image segmentation is used for analyzing the images for solving high-level vision problems,such as object recognition and image classification. Image segmentation also plays a significant role in helping scientists quantify and analyze image data. In this paper,a supervised hierarchical approach to object-independent imagesegmentation is proposed. The proposed algorithm uses super pixels for segmenting an image. It constructs a tree structure for merging the hierarchical region. The super pixels are merged iteratively for each time by combining the pair of neighbors in the graph.The results show that the proposed algorithm efficiently segments the images using the super pixel by constructing a tree structure and hierarchical merging.

Keywords: Segmentation, Hierarchical Merging, Super Pixel

I INTRODUCTION

One of the most important operations in image processing is image analysis and computer vision. The segmentation is an efficient method for analyzing the images. In image segmentation, the images are partitioned into multiple segments [1]. The multiple segments consist of set of pixel. The pixels in the region are similar according to the particular individual criteria.

In this paper, a supervised hierarchical approach to object-independent image segmentation is proposed. It starts with oversegmenting superpixels. The tree structure is used to represent the hierarchy of region merging, by which it reduce the problem of segmenting image regions to finding a set of label assignment to tree nodes. It also formulates the tree structure as a constrained conditional model to associate region merging with likelihoods predicted using an ensemble boundary classifier. Final segmentations can then be inferred by finding globally optimal solutions to the model efficiently. It also present an iterative training and testing algorithm that generates various tree structures and combines them to emphasize accurate boundaries by segmentation accumulation.

II RELATED WORK

Many region segmentation methods have an advantage of the edge detection methods and outputs for detecting boundary cues [2]. The proposed algorithm belongs to the region segmentation category and this sectionhighlight reviewing previous related works based on this category.In [3], a clustering algorithm that combines two different models together. Themost familiar method is K-means clustering algorithm. K-means is an unsupervised clustering algorithm and is used to segment the interest area from the background. Subtractive clustering method used to generate the initial centers and those centers are used in k-means algorithm for the segmentation of image. Then finally median filter is applied to the segmentedimage to remove any unwanted region from the image.

In [4], a conventional FCM algorithm is proposed that contains spatial information into the relationship function for clustering. The spatial function is the summing up of membership function in the locality of each pixel under consideration. The advantages of new method are: (1) it reduces the spurious blobs (2) it removes noisy spot (3) it is less sensitive to noise than any other techniques. The [3] introduces the concept of Fuzzy image segmentation, providing an algorithm to build boundaries that are difficult to build based on the existing relations between the fuzzy boundary set problem and the hierarchical image segmentation problem. A fuzzy set on set of edges is given, using these sets fuzzy image segmentation is characterized and that can be easily understood as the unclear boundary of the image.

The [4] introduces a newmethod of image segmentation that combine spectral clustering and Gaussian mixture model. The new method contains three phases: (1) Image is partitioned into small segments given by a Gaussian mixture model(GMM),and the GMM is resolved by an

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IJARMATE
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Expectation Maximization (EM) algorithm with a very newprojected Image Reconstruction Criterion, named EM-IRC. (2) Distance among GMM components are measured using Kullback-Leibler(KL) divergence, and (3) spectral clustering is applied to this enhanced similarity matrix to merge the GMM components. In [5], Image segmentation problem is a primary task and process in computer visualization and various application of image processing. It is well known that the performance of image segmentation is mainly inclined by two factors: the segmentation approaches and the feature presentation. For image segmentation techniques, clustering is one of the most popular approaches. In [6], a novel image segmentation approach is presented based on DirichletProcess clustering algorithm. Compared with the current methods,our method has several improved advantages as follows: 1) The given algorithm could directly give the cluster number of theimage based on the decision graph 2) The center of cluster could be correctly recognized 3) We could simply achieve thehierarchical segmentation according to the requirement of our application. Various experiments express the validity of thisnovel segmentation algorithm.[7] uses a different strategy for extracting salient smooth curves from the output of a local contour detector. They consider the set of short oriented line segments that connect pixels in the image to their neighboring pixels. Each such segment is either part of a curve or is a background segment [8]. They assume curves are drawn from a Markov process, the prior distribution on curves favors few per scene, and detector responses are conditionally independent given the labeling of line segments. Finding the optimal line segment labeling then translates into a general weighted min-cover problem in which the elements being covered are the line segments themselves and the objects covering them are drawn from the set of all possible curves and all possible background line segments [9]. Since this problem is NP-hard, an approximate solution is found using a greedy "cost per pixel" heuristic.

III PROPOSED WORK

The proposed algorithm consists of five phases. The first phase initializes the super pixel for segmenting a given image. The second phase calculates the boundary probability statics for given image. The third phase merges the partitioned images using the hierarchical merge tree. In fourth phase, the boundary classifier is used to calculate the score for partitioned region based on boundary features and region features. The phases of the proposed algorithm are described as follows.

Phase 1: Initial Super Pixel

The super pixels are initialized based on the intensity for partitioning the given image. The proposed algorithm is starting with the fixed initial superpixels for grouping the pixels in hierarchical manner.

Phase 2: Boundary Probability

The first iteration uses boundary probability ("Pb") statistics for merge tree generation, and the training procedure iteratively augments the training set by incorporating new samples from merge treesAt testing time, boundary probability statistics and boundary classifiers learned at each iteration are used to generate merge trees from the same initial superpixels

Phase 3: Hierarchical Merge Tree

Consider a graph, in which each node corresponds to a superpixel, and an edge is defined between two nodes that share boundary pixels with each other. Starting with the initial over-segmentation so, finding a final segmentation, which is essentially the merging of initial superpixels, can be considered as combining nodes and removing edges between them. This superpixel merging can be done in an iterative fashion: each time a pair of neighboring nodes is combined in the graph, and corresponding edges are updated. To represent the order of such merging

Phase 4: Boundary Classifier

To score each clique, we train a boundary classifier to predict the probability of each merge. To generate training labels that indicate whether the boundary between two regions exists or not, we compare both the merge and the split case against the ground truth under certain error metric.

Boundary features and region features are extracted for classification. For a pair of merging regions, boundary features provide direct cues about how it is likely the boundary truly exists, and regional features measure geometric and textural similarities between the two regions, which can both be informative to boundary classification.

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IJARMATE

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The new boundary classifier is used for merging tree generation from the sameinitial superpixels in the next iteration. Each boundary classifier is used to score merge cliques in the previous iteration.

Phase 5: Segmented Image

Segmentations are generated from each merge tree and accumulated to generate the final contour hierarchy.

The algorithm for proposed algorithm is given below.

Algorithm: Hierarchical Merging using Super Pixels

Input: Training Data
Output: Segmented Image
Step 1: Initialize the super pixels
Step 2: Apply Boundary Probability to generate hierarchical tree
Step 3: Merge the trees iteratively
Step 4: Apply Boundary Classifier to differentiate the images
Step 5: Generate final contour hierarchy
Step 6: Segmented Image

IV SIMULATION AND EXPERIMENTAL RESULTS

The proposed algorithm is implemented using MATLAB tool. The Berkely images are given as a input. The input images are partitioned based on the hierarchical splitting method. Based on the given constrains the input images are portioned into number of region.

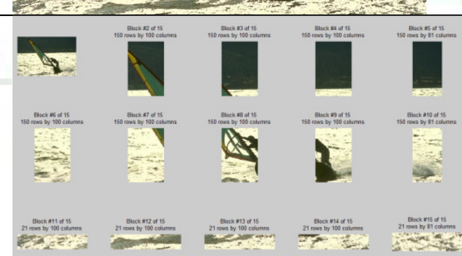
The Input and output images are shown in table 1.

Once the images are divided into number of regions, the boundary classifier is applied over a partitioned image. After that, the regions are merged with super pixels. Finally the images are merged and provide a segmented image as output.

V CONCLUSION

The proposed hierarchical image segmentation framework, namely the hierarchical merge tree model, that limits the search space to one that is induced by tree structures and thus linear with respect to the number of initial super pixels. The framework allows the use of various merging saliency heuristics and features, and its supervised nature grants its capability of learning complex conditions for merging decisions from training data without the need for parameter tuning or the dependency on any classification model. Globally optimal solutions can be efficiently found under constraints to generate final segmentations thanks to the tree structure. It also introduce a modification to the hierarchical merge tree model that iteratively trains a new boundary classifier with accumulated samples for merge tree construction and merging probability prediction and accumulates segmentation to generate contour maps.

Table1. The input and output images for proposed algorithm

Input Images		
Hierarchical Split Image		

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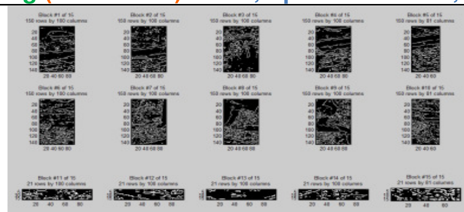
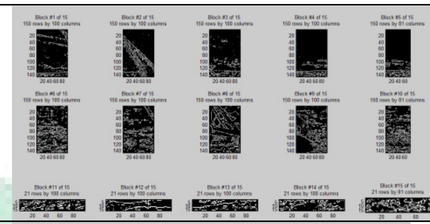
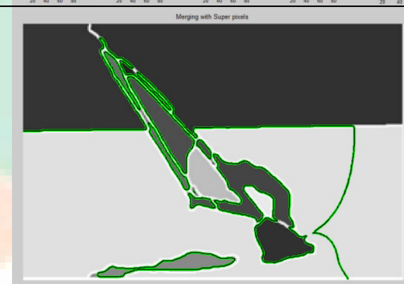
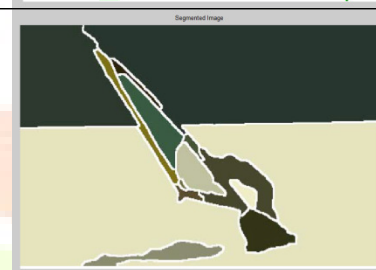
Boundary Classifier		
Merging with Super Pixels		
Segmented Image		

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ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

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