A Multi-Layer Graphical Model for Constrained Spectral Segmentation

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Abstract

Spectral segmentation is a major trend in image segmentation. Specially, constrained spectral segmentation, inspired by the user-given inputs, remains its challenging task. Since it makes use of the spectrum of the affinity matrix of a given image, its overall quality depends mainly on how to design the graphical model. In this work, we propose a sparse, multi-layer graphical model, where the pixels and the over-segmented regions are the graph nodes. Here, the graph affinities are computed by using the must-link and cannot-link constraints as well as the likelihoods that each node has a specific label. They are then used to simultaneously cluster all pixels and regions into visually coherent groups across all layers in a single multi-layer framework of Normalized Cuts. Although we incorporate only the adjacent connections in the multi-layer graph, the foreground object can be efficiently extracted in the spectral framework. The experimental results demonstrate the relevance of our algorithm as compared to existing popular algorithms.

1. Introduction

Constrained segmentation algorithms, inspired by the user-inputs (*e.g.* pixels which provide a partial image labeling), have gained popularity since they give a user the ability to affect the segmentation results as necessary for a particular application. The main directions are focused on graph cuts [1] to find the minimum cut between two different labels via a maximum flow computation, and random walker [2] to determine the labeling of an image via the label propagation on a weighted graph.

In natural images, many problems make segmentation difficult, such as finding the faint object boundaries and separating the highly cluttered background. As a popular way to solve these problems, many methods are based on the image regions, obtained by unsupervised segmentation. Unlike previous works, inspired by the hard constraint whereby pixels constituting a particular region should have the same label, several recent works [3][4] to combine multiple over-segmentations of the same image have been proposed. In [3], the higher-order potential functions defined in the regions, are coupled with conventional unary and pairwise constraints in higher-order CRF. Since the connections between the regions are not considered in [3], there are some limitations to propagate the local grouping cues into larger image area. In [4], the authors proposed a generative model which has the ability of utilizing nonparametric higher-order cues defined in the regions. Although the full connections between the regions are used in [4], a few errors may occur far away from the user-given foreground and background pixels.

In this work, we propose a constrained spectral segmentation algorithm to cluster the neighboring pixels for each label. In detail, we first construct a multi-layer graph with pixels and regions as nodes, similarly to [4]. Given an initial labeling of some pixels, namely seeds, we extract the must-link and cannot-link pairwise constraints, which specify that two nodes should be assigned to the same segment and the different segments respectively, and the likelihoods that each node has a specific label, estimated by using the user-given color information. We then define the affinity model based on the pairwise constraints and the likelihoods in the small neighborhood system. Finally, this affinity model is effectively and efficiently used for spectral segmentation.

2. Proposed Algorithm

The overall quality of spectral segmentation depends mainly on the graphical model. Therefore, to propagate local grouping cues to a large image area, we first construct a multi-layer graph with the user-inputs. We then partition this graph into multiple groups in a Normalized Cuts framework [5].

2.1. Graphical Model

Let us construct a multi-layer graph $G=(V,E)$, where the nodes $V=\{X,Y\}$ are a set of pixels X and the sets of regions $Y=\{Y_1\cup\dots\cup Y_L\}$. The subset Y_l corresponds to the N_l non-overlapping regions, obtained by mean shift [6], at the l-th region-based layer. The use of L over-segmentations by varying the mean shift parameters is helpful in reducing the errors of regions that may contain several object parts. An undirected edge $e_{ij} \in E$ between two nodes i and j exists with the following weight w_{ij}:

$$w_{ij} = \begin{cases} 1 & (i,j) \in M \\ 0 & (i,j) \in C \\ e^{-\frac{\|\pi_i - \pi_j\|}{\sigma_d}} & (i,j) \notin \{M, C\}, j \in N_i \,(\text{or } N_i^{(l)}), \\ & i,j \in X \,(\text{or } Y_l) \\ \tau & (i,j) \notin \{M, C\},\ i \in j, \\ & i \in X,\ j \in Y_l \\ 0 & otherwise \end{cases}, \quad (1)$$

where M (or C) is a set of must-links (or cannot-links), and N_i (or $N_i^{(l)}$) is a set of neighboring nodes from node i in the same layer X (or Y_l). We first connect (or disconnect) the must-links (or cannot-links) M (or C). We then define the intra-layer edge between two adjacent nodes in the same layer. For its weight, the likelihood vector $\pi_i = [\pi_{ik}]_{k=1,\ldots K}$, where K is the number of labels, are used as the features of node i, instead of color or texture information. In this paper, we estimate the likelihood π_{ik} that the node i has a label l from the user-given seeds, similarly in [4]. Here, σ_d is a constant that controls the strength of w_{ij}. Finally, a parameter τ controls the strength of relationship between pixel- and region-based layers.

2.2. Multi-Layer Spectral Segmentation

We consider the image segmentation as a labeling problem in which one label $k \in \{1,\ldots,K\}$. Let $v_k = [v_{ik}]_{i=1,\ldots,N}$, where $N = |V|$ is the number of nodes, denote a partitioning vector with $v_{ik} = 1$ if i belongs to the k-th segment and 0 otherwise. Here the segmentation criterion follows the Normalized Cuts [5]:

$$\max \frac{1}{K} \sum_{k=1}^{K} \frac{v_k^T W v_k}{v_k^T D v_k}, \quad (2)$$

where the weight matrix $W = [w_{ij}]_{N \times N}$ in (1), the degree matrix $D = diag([d_1, \ldots, d_N])$ with the diagonal element $d_i = \sum_{j=1}^{N} w_{ij}$, and the partitioning matrix $V = [v_1, \ldots, v_K]$ with $VV^T = I$. The optimal solution in (2) is the subspace spanned by the K largest eigenvectors of the matrix $L = D^{-1/2} W D^{-1/2}$. Since the matrix L is large but very sparse, we can easily find this solution.

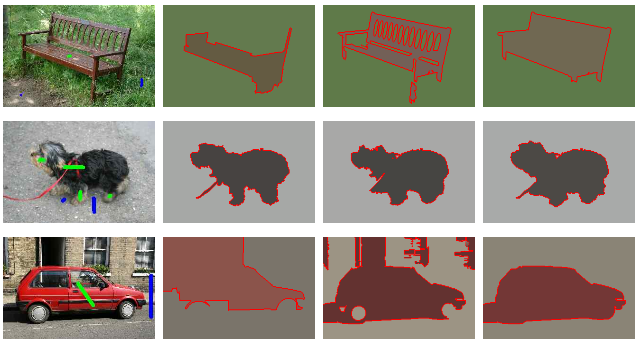
3. Experimental Results

We empirically obtain the regions Y from the $L = 3$ different region-based layers by varying the bandwidth parameters $(h_s, h_r) = \{(5,7),(7,5),(7,7)\}$ for the spatial and range domains in mean shift, and set $\tau = 0.001$ in (1).

We demonstrate the quality of our algorithm on the Microsoft GrabCut database which consists of 50 images with tri-maps and ground truth segmentations. Table 1 presents the comparative evaluation of the constrained segmentation algorithms: Graph Cut [1], Random Walker [2], Robust P^n Model [3], Generative Model [4], and our proposed algorithm. Our algorithm quantitatively has better performance than other conventional algorithms. Fig. 1 shows a more visual comparison in natural images. Our algorithm perceptually produces high-quality segmentation results that detect larger textured regions.

Segmentation model	Error rate
Graph Cust	6.62%
Random Walker	6.70%
Robust Pn model	5.28%
Generative Model	4.15%
Our algorithm	3.83%

Table 1. Percentage of mislabeled pixels in the area to be classified in the Microsoft GrabCut database.



(a) (b) (c) (d)

Figure 1. Visual comparison of our algorithm with the state-of-the-art algorithms in natural images. (a) Images with seeds having two green and blue labels. Segmentation results by (b) Robust P^n Model, (c) Generative Model, and (d) Our algorithm.

4. Conclusion

In this paper, the constrained segmentation algorithm based on spectral clustering is proposed. Since our multi-layer graphical model is efficiently designed from the user-inputs, our algorithm produces high-quality segmentation results with object details in the spectral framework.

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