LEARNING FULL PAIRWISE AFFINITIES FOR SPECTRAL SEGMENTATION

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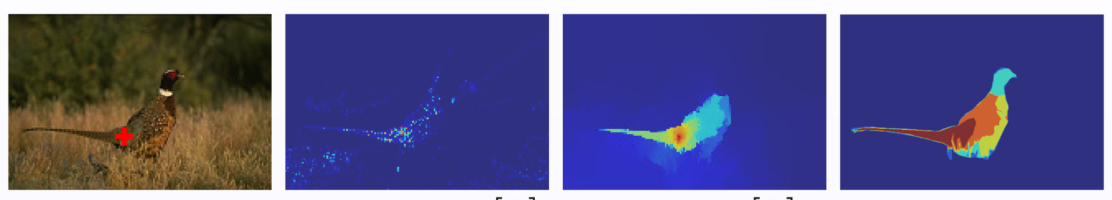
Abstract

This paper studies the problem of learning a full range of pairwise affinities gained by integrating local grouping cues for spectral segmentation. By employing a semi-supervised learning technique, optimal affinities are learnt from the test image without iteration in a multi-layer graph with pixels and regions as nodes. These pairwise affinities are then used to simultaneously cluster all pixel and region nodes into visually coherent groups across all layers in a framework of Normalized Cuts.

Introduction

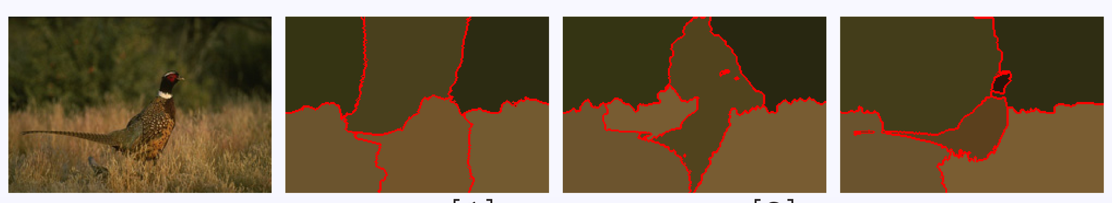
For unsupervised segmentation,

1) Integration of grouping cues across **a Full Range of Pairwise Connections** by **SSL**[3]



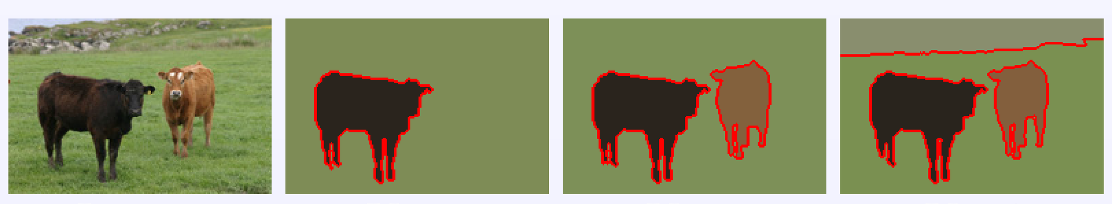
Input | By Conv.[2] | By SSL[3] | By Human

2) High-quality segmentation results in **a Multi-Layer Framework of NCut**



Input | NCut[1] | MNCut[2] | FNCut

Overview of FNCut:



Input | K=2 | K=3 | K=4

EVEC:1 | EVEC:2 | EVEC:3 | EVEC:4

Conventional Affinity Model

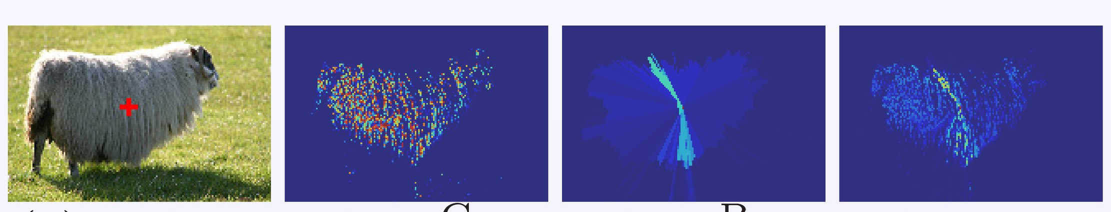
- Directly compute affinities $W = [w_{ij}]_{N \times N}$:

$$w_{ij} = \sqrt{w_{ij}^{\mathrm{C}} \times w_{ij}^{\mathrm{B}}} + \alpha w_{ij}^{\mathrm{B}} \quad \textbf{in [2]}$$

Color cue: $w_{ij}^{\mathrm{C}} = exp(-\theta_x \|x_i - x_j\|^2 - \theta_g \|g_i - g_j\|^2)$

Boundary cue: $w_{ij}^{\mathrm{B}} = exp(-\max_{i' \in \overline{ij}} \theta_f \|f_{i'}\|^2)$

- $\vec{w}_m = [w_{im}]_{N \times 1}$: Affinity vec. from a node m



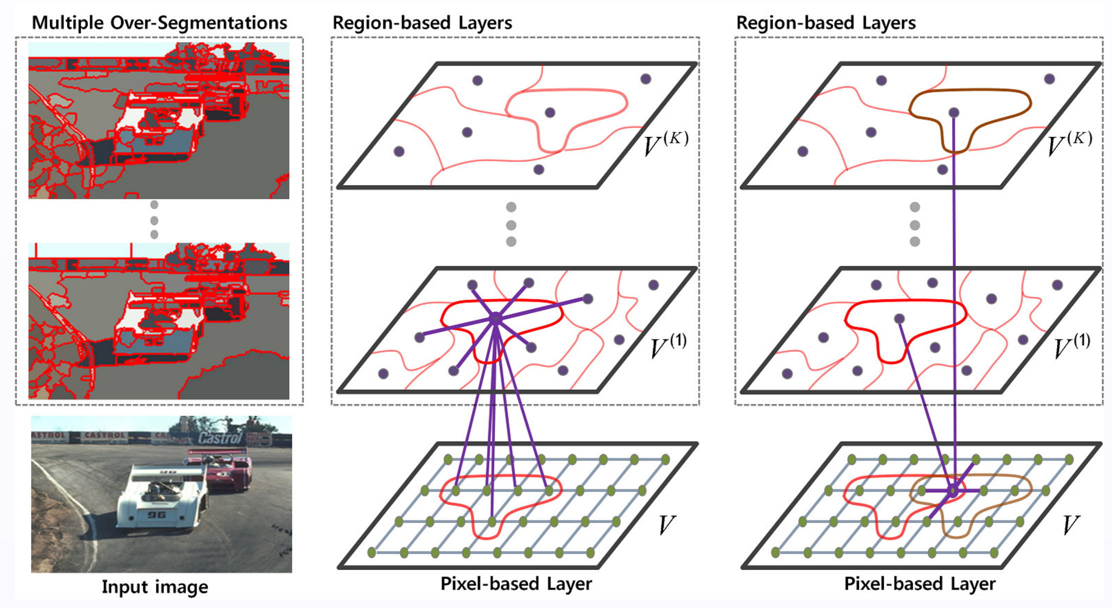
(a) Node m | by w_{im}^{C} | by w_{im}^{B} | by w_{im}

- It still has **some weakness in the long-range affinity estimation!!**

Proposed Affinity Model

To estimate full pairwise affinities,

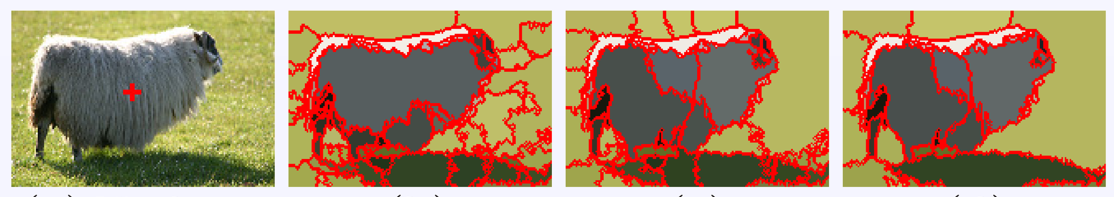
1) Construct **Multi-Layer Graph** G^*



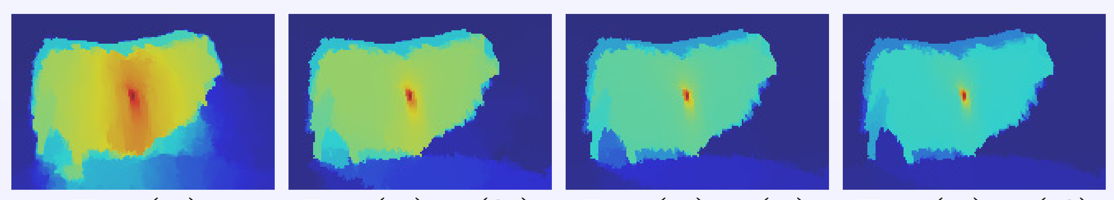
2) Learning **Full Affinities** by **SSL**[3]

- $\vec{\pi}_m = [\pi_{im}]_{\hat{N} \times 1}$: Affinity vec. from a node m

$$\vec{\pi}_m = c\,(\mathbf{D}^* - (1-c)\mathbf{W}^*)^{-1}\,\vec{b}_m$$



(a) Node m | (b) | (c) | (d)



By (a) | By (a)−(b) | By (a)−(c) | By (a)−(d)

- Total Affinities $\mathbf{\Pi} = [\vec{\pi}_1, \cdots, \vec{\pi}_{\hat{N}}]$:

$$\mathbf{\Pi} = c\,(\mathbf{D}^* - (1-c)\mathbf{W}^*)^{-1}$$

Segmentation Criterion

- Labeling problem in which one label $k \in \{1, ..., K\}$ is assigned to each node i

- $\vec{y}_k = [y_{ik}]_{\hat{N} \times 1}$: Partitioning vec. with $y_{ik} = 1$ if i belongs to the k-th segment and 0 otherwise

$$\text{maximize } \mathcal{C}(\mathbf{Y}) = \frac{1}{K} \sum_{k=1}^{K} \frac{\vec{y}_k^{\,T} \mathbf{\Pi} \vec{y}_k}{\vec{y}_k^{\,T} \mathbf{D} \vec{y}_k} \quad : \text{ NCut}$$

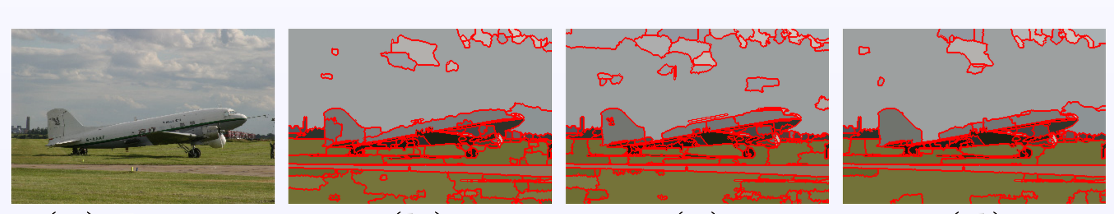
$$\text{subject to } \mathbf{Y} = [\vec{y}_1, \cdots, \vec{y}_K] \text{ \& } \mathbf{Y}\mathbf{Y}^T = \mathbf{I}^*.$$

Multi-Layer Spectral Clustering

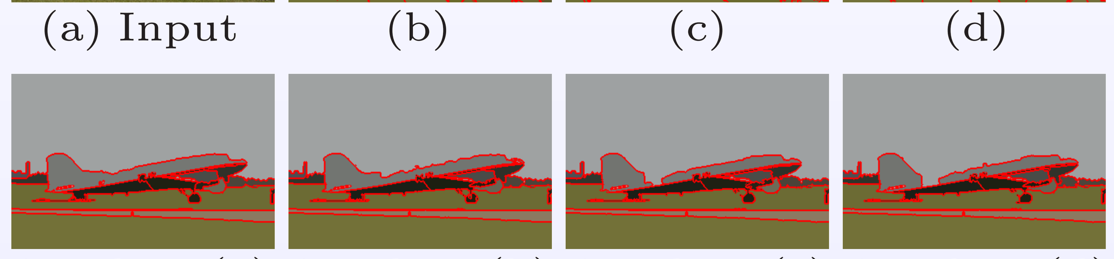
- Its solution is the subspace spanned by the K largest eigenvectors of $\mathbf{D}^{-\frac{1}{2}} \mathbf{\Pi} \mathbf{D}^{-\frac{1}{2}}$ $(= c\mathbf{B}^{-1})$

- Instead, we find the K smallest eigenvectors of $\mathbf{B} = \mathbf{D}^{\frac{1}{2}}\,(\mathbf{D}^* - (1-c)\mathbf{W}^*)\,\mathbf{D}^{\frac{1}{2}}$

- $\mathbf{D} = diag(\vec{d})$ with $\vec{d} = c(\mathbf{D}^* - (1-c)\mathbf{W}^*)^{-1}\,\vec{1}$.



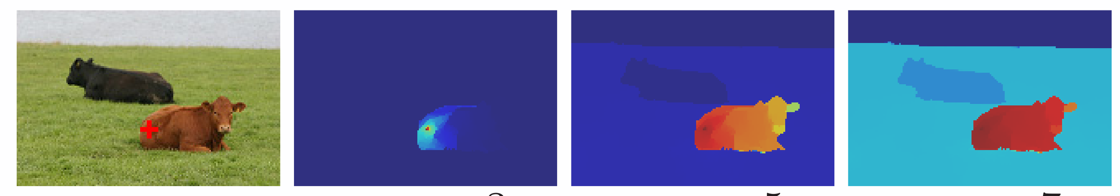
(a) Input | (b) | (c) | (d)



Result at (a) | Result at (b) | Result at (c) | Result at (d)

Experimental Results

1) Affinities with respect to the variation of c



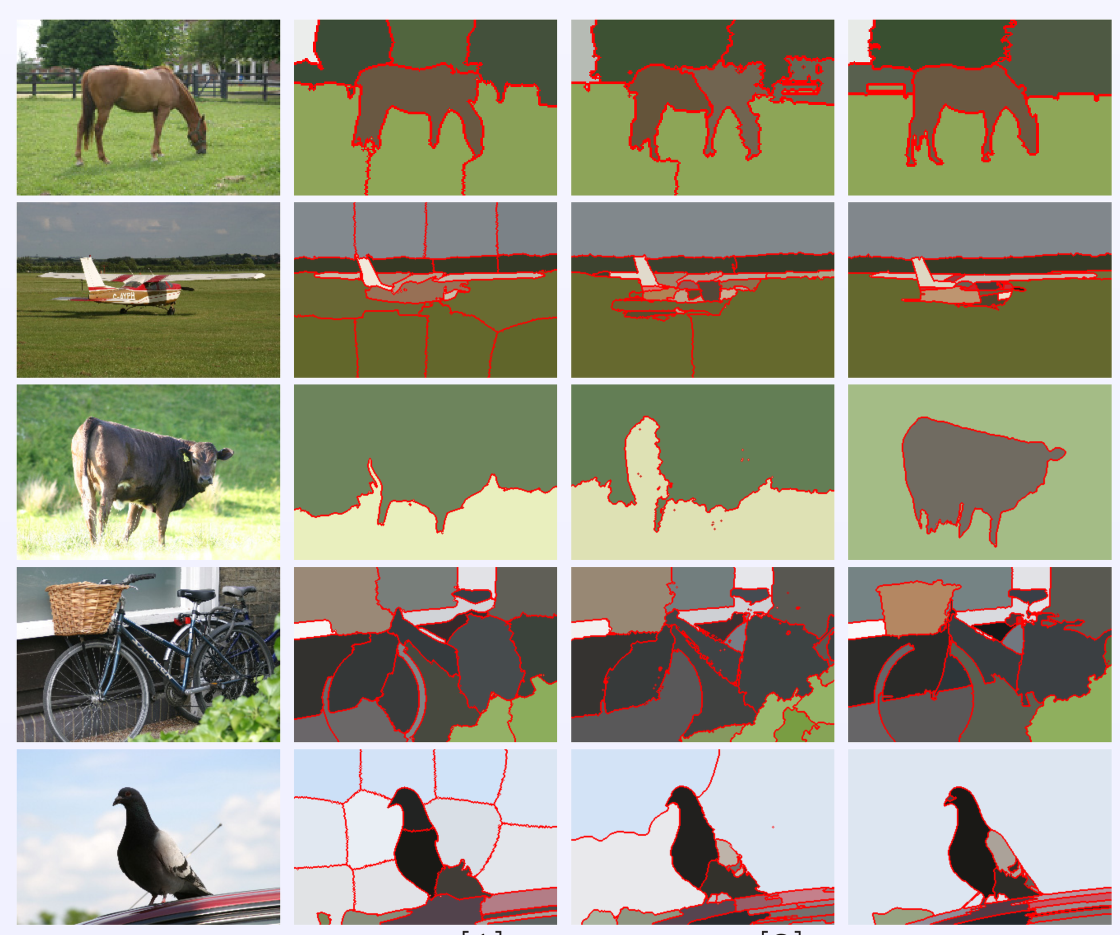
(a) Node m | c=10^{-3} | c=10^{-5} | c=10^{-7}

2) Comparison on the Berkeley Database

Methods/Score	PRI	VoI	GCE	BDE
MShift	0.7958	1.9725	0.1888	14.41
NCut	0.7242	2.9061	0.2232	17.15
JSEG	0.7756	2.3217	0.1989	14.40
GBIS	0.7139	3.3949	0.1746	16.67
MNCut	0.7559	2.4701	0.1925	15.10
NTP	0.7521	2.4954	0.2373	16.30
Saliency	0.7758	1.8165	0.1768	16.24
TBES	0.80	1.76	-	-
Our algorithm	0.8146	1.8545	0.1809	12.21

Input | NTP | TBES | FNCut

3) Comparison on the MSRC Database



Input | NCut[1] | MNCut[2] | FNCut

References

[1] **J. Shi et al.** PAMI,2000.
Normalized cuts and image segmentation

[2] **T. Cour et al.** CVPR,2005.
Spectral segmentation with multiscale graph decomposition

[3] **D. Zhou et al.** NIPS,2003.
Learning with local and global consistency

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