

Simple-to-Complex Discriminative Clustering for Hierarchical Image Segmentation

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- Contour-based methods like gPb-OWT-UCM [1] typically outperform region-based ones (e.g., SAS [2]).
- Potential issues of contour-based approaches:
 Probabilistic interpretation or theoretical supports
 Heavy memory cost (e.g., large-scale eigen problems)
 - Require training data (and possibly overfitting)

Related Works

- Discriminative clustering [3]: Classification → Clustering
 Need to determine the cluster number
- GrabCut [4]: Figure/ground segmentation by MRF
 Need prior knowledge by user interaction
- GMM clustering:
 - Assume the Gaussian

distributions of clusters



Our Proposed Framework

- Bottom-up hierarchical segmentation: clusters at $\ell \rightarrow$ segments at $\ell+1$
- At each level, we perform EM-based discriminative clustering:
 - E-step: Classify segments into clusters by MRF M-step: Train classifiers by the clustering result
- Features & classifiers considered:
 - Color I KDE, texture BoW, spatial info Gaussian







Experiments

gPb-OWT-UCM [1]

- Our method achieves state-of-the-art performances on multiple datasets in terms of optimal image scale (OIS).
- No training data is required.
 Only 120(of moments on the compared)
- Only 12% of memory costs compared with [1,5].
 Source code is available [6].

Comparisons of Unsupervised Segmentation (* indicates using the different ground truth)

	MSRC			SBD		
Methods	SegCover	PRI	Vol (↓)	SegCover	PRI	Vol (↓)
SAS (FH+MS) [2]	0.712	0.823	1.052	0.649	0.856	1.474
gPb-OWT-UCM [1]	0.745	0.850	0.989	0.642	0.858	1.527
ISCRA [5]	0.75	0.85	1.02	0.68*	0.90*	1.50*
Ours (Full)	0.772	0.862	0.920	0.681	0.870	1.425

Qualitative and Quantitative Comparisons of Unsupervised Segmentation on BSDS



Seman	Semantic Segmentation Accuracy						
	MSRC		SBD		0.65		
Method	NB	SVM	NB	SVM	0.6		
SAS (FH+MS) [2]	0.272	0.330	0.399	0.423	0.55		
gPb-OWT-UCM [1]	0.285	0.352	0.406	0.426	ື 0.5		
Ours (Full)	0.294	0.362	0.414	0.454	0.45		
Ground Truth	0.366	0.474	0.502	0.570	0		



	ISCRA [5]	0.66	0.86	1.40	0.66	0.85	1.42
Ours (Full)		0.660	0.854	1.443	0.655	0.859	1.454
	Init (w/o DC)	0.583	0.814	1.734	0.578	0.825	1.784
	Complex only	0.627	0.840	1.569	0.618	0.845	1.613
Ours	w/o MRF	0.633	0.843	1.536	0.634	0.849	1.548
	Color	0.595	0.810	1.695	0.598	0.823	1.724
	w/o Texture	0.605	0.824	1.653	0.605	0.832	1.699

0.852

0.646

1.466

0.647

1.475

0.856

Conclusion and Future Work

- Our proposed general framework can be viewed as:
 - An unsupervised version of GrabCut [4]
 - A generalization of GMM clustering
 - A Maximize Likelihood Estimation (see our paper)
- Additional features and classifiers can be easily added.
- Future directions: video, semantic & interactive seg.

Reference

[1] Arbelaez, P., et al.: Contour detection and hierarchical image segmentation. In: TPAMI. (2011)
[2] Li, Z., et al.: Segmentation using superpixels: A bipartite graph partitioning approach. In: CVPR. (2012)
[3] Xu, L., Neufeld, J., Larson, B., Schuurmans, D.: Maximum margin clustering. In: NIPS. (2004)
[4] Rother, C., et al.,: "GrabCut": interactive foreground extraction using iterated graph cuts. In: SIGGRAPH. (2004)
[5] Ren, Z., Shakhnarovich, G.: Image segmentation by cascaded region agglomeration. In: CVPR. (2013)
[6] http://mml.citi.sinica.edu.tw/papers/HDC_code_ACCV_2014/
[7] Cour, T., et al.: Spectral segmentation with multiscale graph decomposition. In: CVPR. (2005)
[8] Sharon, E., et al.: Hierarchy and adaptivity in segmenting visual scenes. In: Nature. (2006)

Acknowledgement: This work is supported in part by the National Science Council of Taiwan via NSC102-3111-Y-001-015 and NSC102-2221-E-001-005-MY2.