Deep Superpixel Cut for Unsupervised Image Segmentation

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OVERVIEW

We propose a deep learning architecture for unsupervised image segmentation, which contains two stages:

First stage, a **Superpixelwise Autoencoder** (SuperAE) is designed to learn the deep embedding and reconstruct a smoothed image, then the smoothed image is passed to generate superpixels.

Second stage, we present a novel clustering algorithm called **Deep Superpixel Cut (DSC)**, which measures the deep similarity between superpixels and formulates image segmentation as a soft partitioning problem.

SUPERPIXELWISE AUTOENCODER

The real world image usually contain noise, which would affected the segmentation and needs to be smoothed. We observe that pixels within a superpixel are more continuous in color space, so we regard this as constraint in reconstruction.

Our SuperAE formulation:

$$\mathcal{L}_{r} = \|x - x^{R}\|^{2} + \lambda \sum_{i=1}^{N} \sum_{j=1}^{M} t_{ij} \|x_{i}^{R} - v_{j}\|^{2}$$

 $v_j = \frac{\sum_{i=1}^N t_{ij} x_i}{\sum_{i=1}^N t_{ij}}$ (Superpixel RGB vector)

SuperAE aim to minimize the variance of pixel features within a superpixel, thus smoothing the regions

PIPELINE



DEEP SUPERPIXEL CUT

Regard the segmentation as a pixelwise K-class classification problem by generate pseudo-labels.

$$\mathcal{L}_1 = -\sum_{n=1}^N \sum_{k=1}^K y_n^k \log(p_n^k)$$

Regard the segmentation as a superpixelwise graph-partition problem, based on their deep

imilarity.

$$\mathcal{L}_{2} = \sum_{k=1}^{K} \sum_{a,b \in V} \mathcal{P}(a \in A_{k}, b \notin A_{k})$$

$$= \sum_{k=1}^{K} \sum_{a,b \in V} q_{k}^{a} w_{ab} (1 - q_{k}^{b})$$

$$= \sum_{k=1}^{K} Q_{k}^{T} \mathbf{W} (1 - Q_{k})$$

Intuition: If two superpixel a and b are more similar in deep features, then the probability they belong to different partitions should be lower.

Loss function

S

$$\mathcal{L}_s = \alpha \mathcal{L}_1 + \beta \mathcal{L}_2$$
$$= \alpha \sum_{n=1}^N \sum_{k=1}^K \hat{y}_n^k \log(p_n^k) + \beta$$



UNIVERSITY



Method		SC		RI		VI	
		ODS	OIS	ODS	OIS	ODS	OIS
SLIC	IMG	0.354	0.402	0.698	0.726	2.391	2.306
	SuperAE	0.376	0.415	0.710	0.745	2.360	2.286
	DSC	0.428	0.485	0.709	0.742	2.262	2.079
MS	IMG	0.515	0.535	0.771	0.805	2.450	2.429
	SuperAE	0.497	0.550	0.777	0.795	2.162	2.077
	DSC	0.504	0.543	0.739	0.762	2.014	1.849
EGB	IMG	0.458	0.467	0.770	0.775	2.334	2.325
	SuperAE	0.491	0.500	0.774	0.782	2.190	2.180
	DSC	0.506	0.548	0.737	0.779	1.989	1.853

QUANTITATIVE RESULT

Evaluate the effectiveness of SuperAE and DSC on different superpixels algorithm.

(Cross-entropy Loss)

 $\notin A_k W(a,b)$

(Differential)



QUALITATIVE RESULT



REFERENCES

- 1. Arbelaez P, Maire M, Fowlkes C, et al. Contour detection and hierarchical image segmentation[J]. *IEEE transactions on pattern* analysis and machine intelligence, 2010, 33(5): 898-916.
- 2. A. Kanezaki, "Unsupervised Image Segmentation by Backpropagation," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, 2018, pp. 1543-1547, doi: 10.1109/ICASSP.2018.8462533.

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