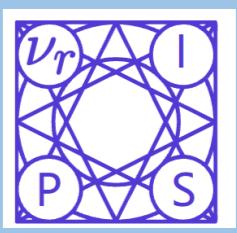




Neural Diffusion Distance for Image Segmentation

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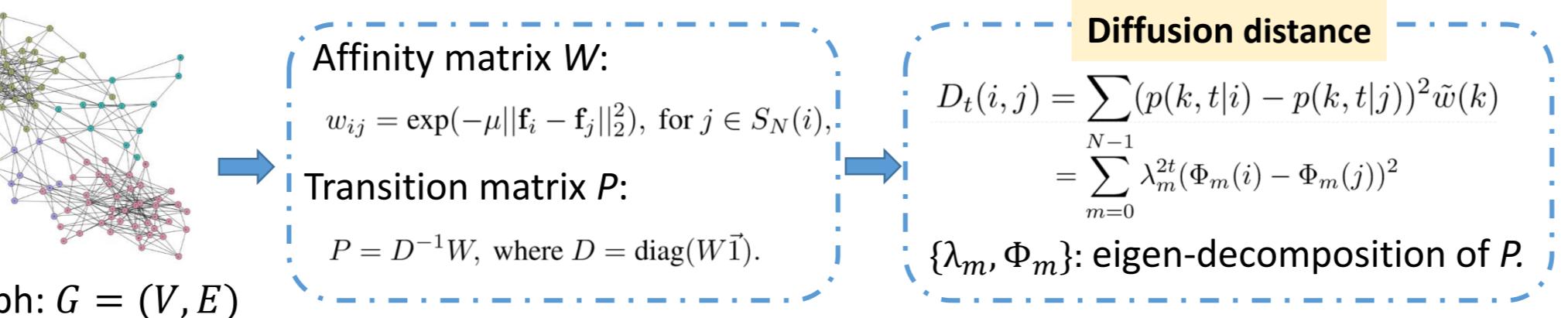
1. Contribution

General novelties: Neural diffusion distance (NDD) + applications in image segmentation.

- NDD: Learn diffusion distance by an end-to-end trainable deep network
- Produce high quality diffusion distance map for image
- A new hierarchical image segmentation method using NDD
- A weakly supervised (ws) semantic segmentation method using NDD

2. What is diffusion distance?

Pairwise distance of graph nodes considering global structure of graph by spectral analysis.



3. Neural diffusion distance

Neural Diffusion Distance: Diffusion distance computed by NDD-network, which learns node features, hyper-parameters of diffusion distance by end-to-end training.

Approximate spectral decomposition for P^{2t} (*differentiable*)

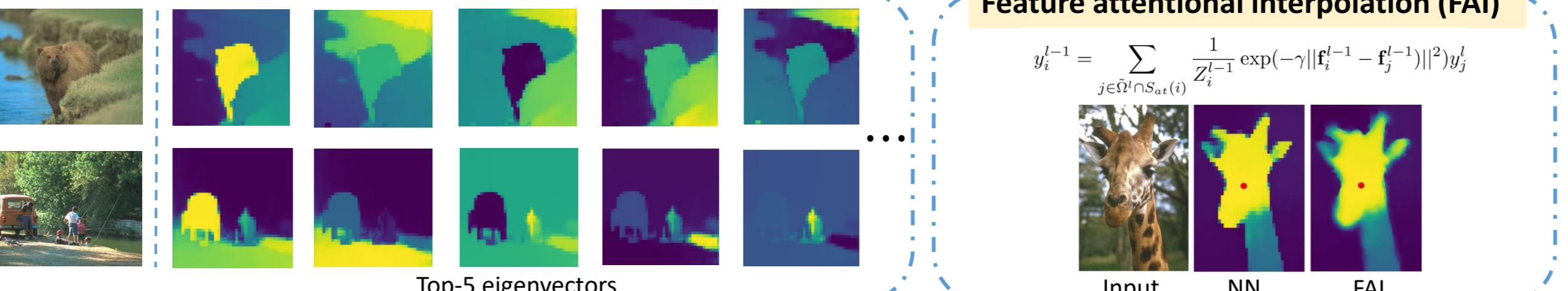
$$Z_{n+1} = P^{2t} U_n, \{U_{n+1}, R_{n+1}\} = QR(Z_{n+1}), n = 0, \dots, T$$

Top-d eigenvectors (eigenvalues)

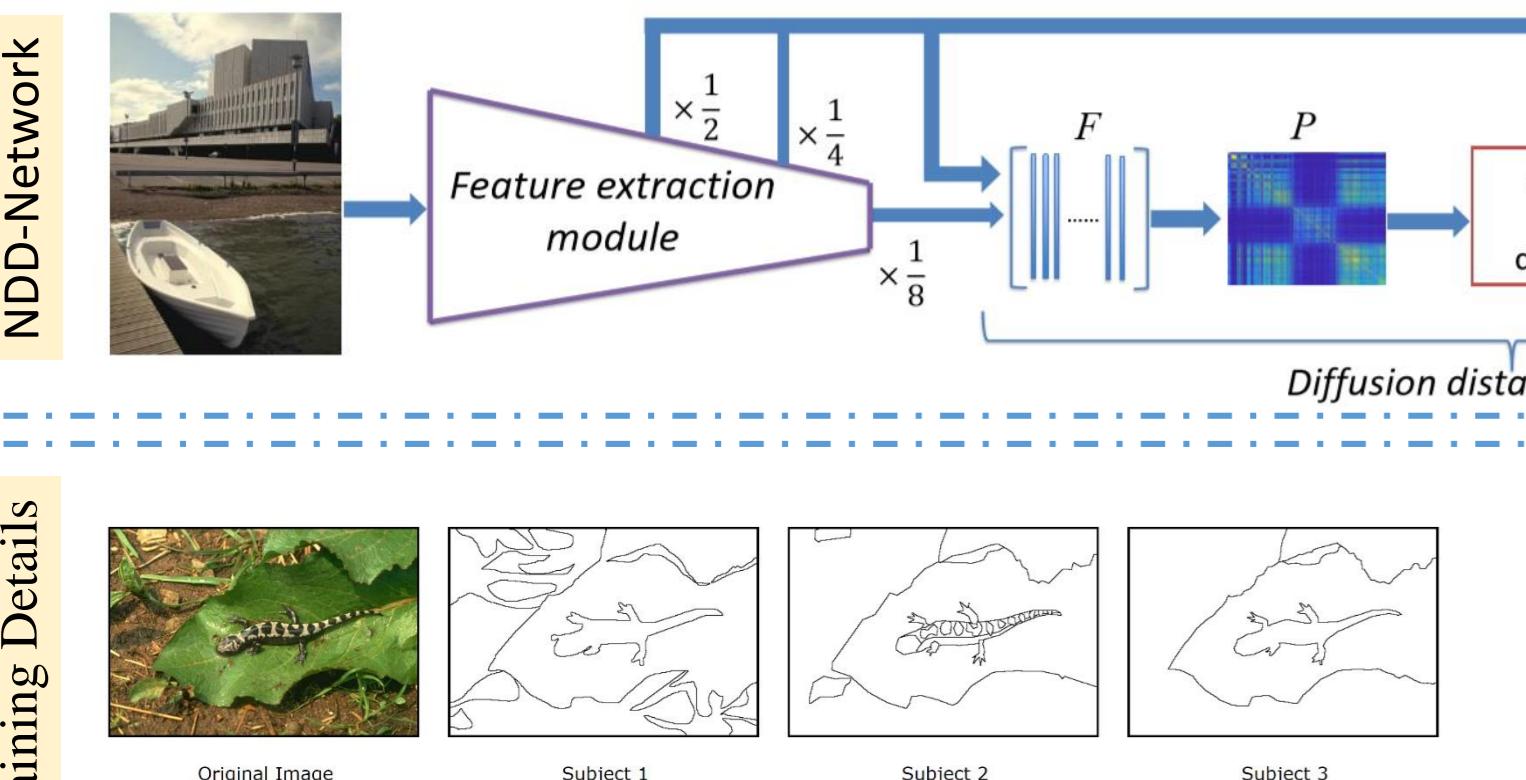
$U_T \in \mathbb{R}^{N \times N_e}$: eigenvectors as its columns

$R_T \in \mathbb{R}^{N_e \times N_e}$: eigenvalues as its diagonals

Convergence rate: $\max_{k \in [1, N_e]} \{(|\lambda_k| / |\lambda_{k-1}|)^{2t}\}$



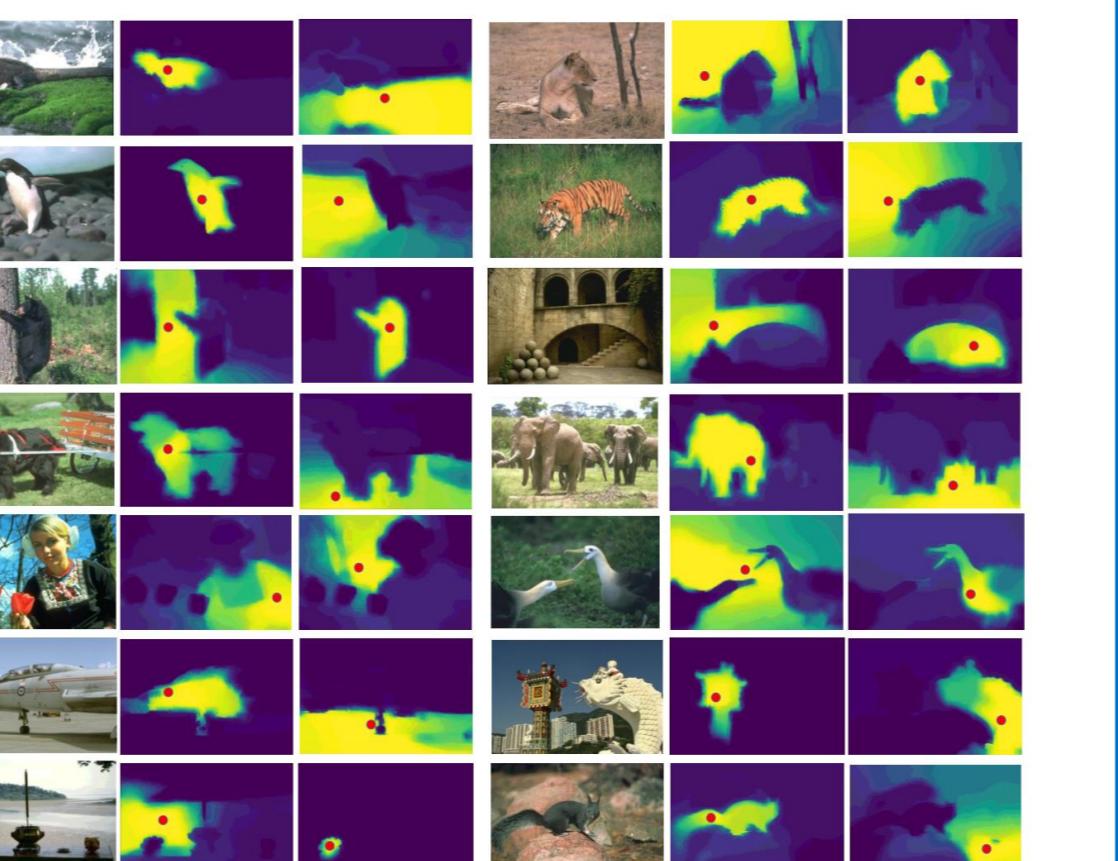
4. NDD-network



$$L_{hr}(K_D, \hat{K}_{gt}) = \sum_{i \in S} - \left\langle \hat{K}_D^i / \|\hat{K}_D^i\|, \hat{K}_{gt}^i / \|\hat{K}_{gt}^i\| \right\rangle,$$

$$+$$

$$L_{lr}(K_D, K_{gt}) = - \left\langle K_D / \|K_D\|_F, K_{gt} / \|K_{gt}\|_F \right\rangle.$$



Examples of neural diffusion distance
(shown as diffusion similarity maps w.r.t. red points)

5. Application to hierarchical image segmentation

Kernel k-means

- Initialize a set of cluster centers (C)
- Iterate until coverage map satisfies $1 - U_{cov} < \epsilon$:
- $i^* = \operatorname{argmax}_i \{K_D^i(1 - U_{cov})\}, C = C \cup \{i^*\}, U_{cov} = \min\{U_{cov} + K_D^{i^*}, 1\}$
- Run kernel k-means with diffusion similarity matrix K_D as kernel. ($K_D = \exp(-\tau D_t)$)

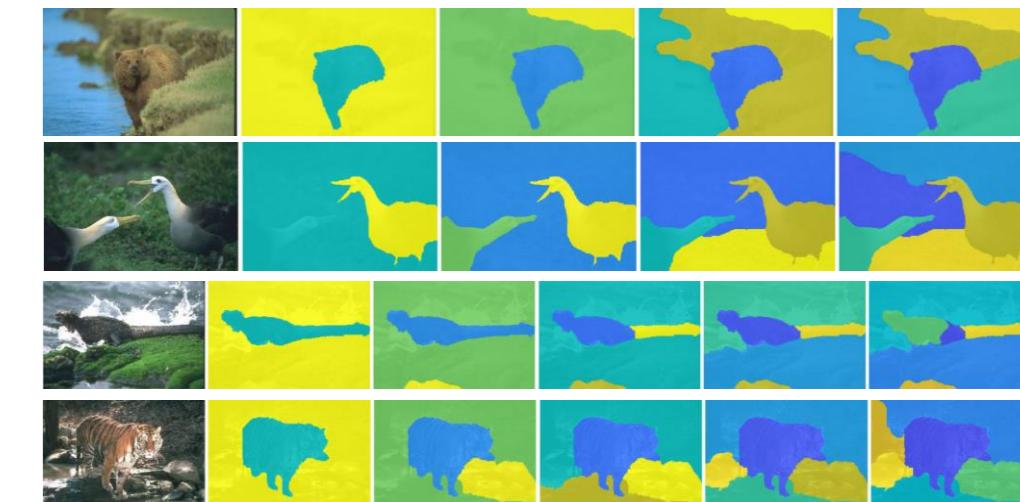
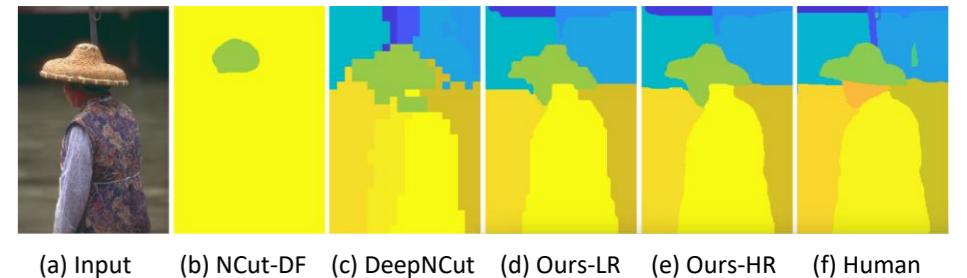


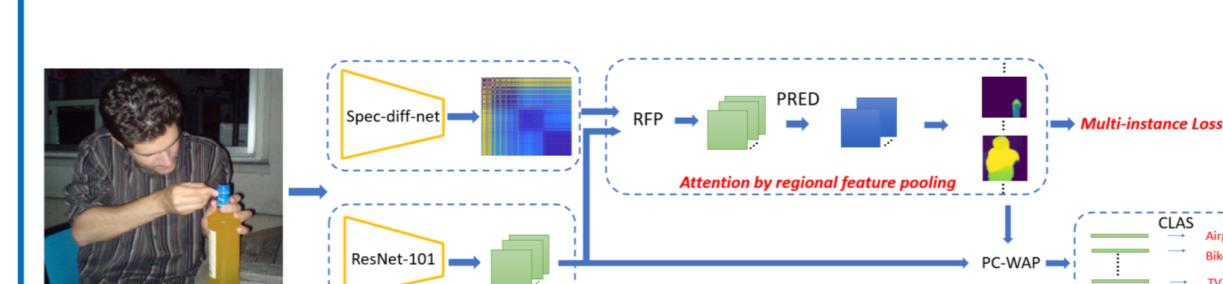
Table 2: Comparison of different segmentation methods.

Methods	NCut [31]	NCut-DF	DeepNCut [17]	Ours-LR	Ours-HR
MAX	0.53	0.56	0.70	0.78	0.80
AVR	0.44	0.48	0.60	0.68	0.69

Ncut[31]: J. Shi, et al., IEEE TPAMI, 2000
DeepNCut[17]: C. Ionescu, et al., ICCV, 2015



6. Application to ws-semantic segmentation



Key Idea: Diffusion distance-guided regional feature pooling.

Methods	GAP [38]	Embedding	Ours (w/o RFP)	Ours (w/o sharing)	Ours
Val	45.2	54.7	44.6	64.7	65.8

Methods	MIL [29]	Saliency [27]	RegGrow [16]	RandWalk [34]	AISI [10]	Ours
Val	42.0	55.7	59.0	59.5	63.6	65.8
Test	-	56.7	-	-	64.5	66.3

GAP[38]: B. Zhou, et al., CVPR 2016;
Saliency [27]: S. Oh, et al., CVPR 2017;
RandWalk[34]: P. Vernaza, et al., CVPR 2017;

MIL[29]: P. Pinheiro, et al., CVPR 2015;
RegGrow[16]: Z. Huang, et al., CVPR 2018;
AISI[10]: R. Fan, et al., ECCV 2018.

Input images ours (w/o RFP) ours (full) Input images ours (w/o RFP) ours (full)

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