Learning Full-Range Affinity for Diffusion-based Saliency Detection

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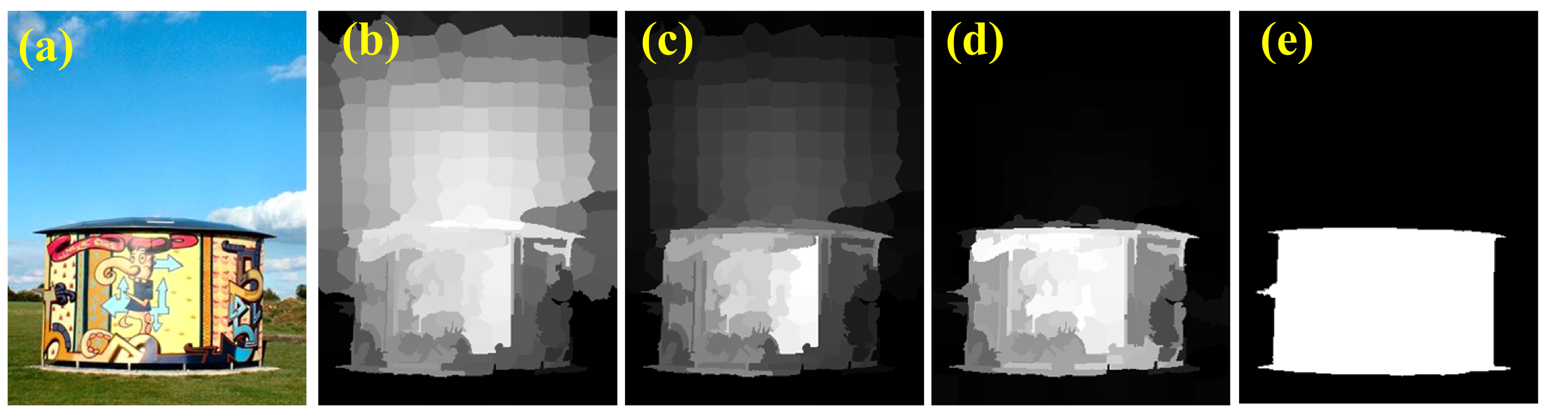
1. Overview

Addressed Problem

- **Salient object detection** by diffusion-based techniques.



Diffusion from image borders. (a) input image; (b) manifold ranking [1]; (c) quadratic model [3]; (d) the proposed diffusion scheme; (e) ground truth.

Motivation

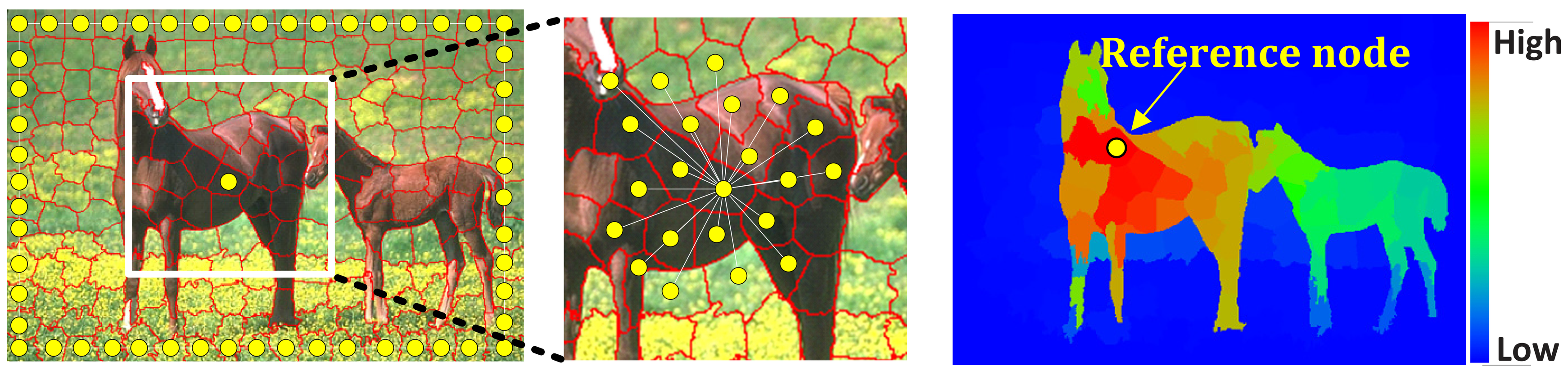
- Existing diffusion models [1-3] suffer from inhomogeneous seed ingredient and complex image contents like textures.
- The diffusion process could be formulated in two-stages: 1) learning a full-range affinity matrix; 2) applying global propagation.
- Graph-based semi-supervised learning (GSSL) can be a choice for full-range affinity learning.

Main Contribution

- A robust diffusion method: **Affinity Learning-based Diffusion (ALD)**.
- An enhanced saliency detector by using ALD, where salient object detection only requires one-stage diffusion without refinement.

2. Proposed Method

Affinity Learning-based Diffusion (ALD)



Superpixel segmentation *Graph construction* *Affinity image of a node*

1. Construct a local neighbor graph $G = (V, E, \mathbf{W})$.
2. Learn a full-range affinity matrix $\mathbf{A}$, where entry a_{ij} $(a_{ij} \geq 0)$ encodes pairwise affinity between *i*th and *j*th nodes.
3. Formulate the diffusion process as $\mathbf{s} = \mathbf{D}_{\mathbf{A}}^{-1}\mathbf{A}\mathbf{y}$

where $\mathbf{D}_{\mathbf{A}}$ is the diagonal degree matrix of $\mathbf{A}$, and $\mathbf{y}$ is the seed vector.

Determine A by Semi-Supervised Learning

- Use Manifold Regularization (MR) in graph-based semi-supervised learning (GSSL) to obtain relevance scores for nodes (unlabeled) w.r.t. a reference node (labeled). The affinity vector corresponding to the *k*th node is :

$$\underbrace{\mathbf{A}_{:,k}}_{\text{Affinity vector}} = \underbrace{(\mathbf{I} - \alpha\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}})^{-1}}_{\text{Manifold regularization}}\underbrace{\mathbf{b}_k}_{\text{A label vector}}$$

where $\mathbf{b}_k$: b_{ki}=1 (ref. node) or b_{ki}=0 (unlabeled nodes).

Hence the learned affinity matrix is:

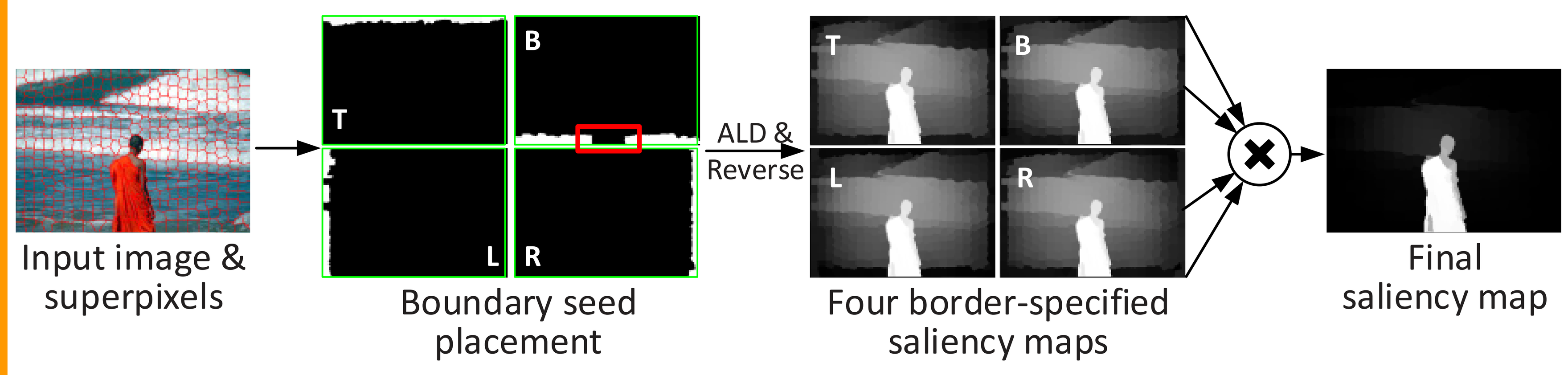
$$\begin{aligned}\mathbf{A} &= [\mathbf{A}_{:,1}, \mathbf{A}_{:,2}, ..., \mathbf{A}_{:,N}] \\ &= (\mathbf{I} - \alpha\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}})^{-1}[\mathbf{b}_1, \mathbf{b}_2, ..., \mathbf{b}_N] \\ &= (\mathbf{I} - \alpha\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}})^{-1}\end{aligned}$$

- Consider four commonly used MR models [9,10] in GSSL:

Model	Learned Affinity	Regularization formulation
MR_{sn}	$\mathbf{A} = (\mathbf{I} - \alpha\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}_{\mathbf{W}}^{-\frac{1}{2}})^{-1}$	$E(\mathbf{A}_{:,k}) = \sum_{i,j=1}^{N}\frac{1}{2}w_{ij}(\frac{a_{ik}}{\sqrt{d_i}} - \frac{a_{jk}}{\sqrt{d_j}})^2 + \mu\sum_{i=1}^{N}(a_{ik} - b_{ki})^2$
MR_{un}	$\mathbf{A} = (\mathbf{D}_{\mathbf{W}} - \alpha\mathbf{W})^{-1}$	$E(\mathbf{A}_{:,k}) = \sum_{i,j=1}^{N}\frac{1}{2}w_{ij}(a_{ik} - a_{jk})^2 + \mu\sum_{i=1}^{N}d_i(a_{ik} - \frac{b_{ki}}{d_i})^2$
MR_{sp}	$\mathbf{A} = (\mathbf{D}_{\mathbf{W}} - \mathbf{W} + \mu\mathbf{I})^{-1}$	$E(\mathbf{A}_{:,k}) = \sum_{i,j=1}^{N}\frac{1}{2}w_{ij}(a_{ik} - a_{jk})^2 + \mu\sum_{i=1}^{N}(a_{ik} - b_{ki})^2$
MR_{ln}	$\mathbf{A} = (\mathbf{I} - \alpha\mathbf{D}_{\mathbf{W}}^{-1}\mathbf{W})^{-1}$	$E(\mathbf{A}_{:,k}) = \sum_{i,j=1}^{N}\frac{1}{2}w_{ij}(a_{ik} - a_{jk})^2 + \mu\sum_{i=1}^{N}d_i(a_{ik} - b_{ki})^2$

2. Proposed Method (Cont'd)

Saliency Detection by using ALD



- Incorporate color and edge cues for $\mathbf{W}=[w_{ij}]_{N\times N}$:

$$w_{ij} = \sqrt{\underbrace{\exp(-\lambda_c||\mathbf{c}_i - \mathbf{c}_j||)}_{\text{color term}} \cdot \underbrace{\exp(-\lambda_e \max_{i' \in \overline{ij}} f_{i'})}_{\text{edge term}}}$$

- Refine background seed vectors (e.g., the red rectangle) using the boundary connectivity measure [13].

3. Test Results and Performance

Compare Diffusion Performance by MR Models

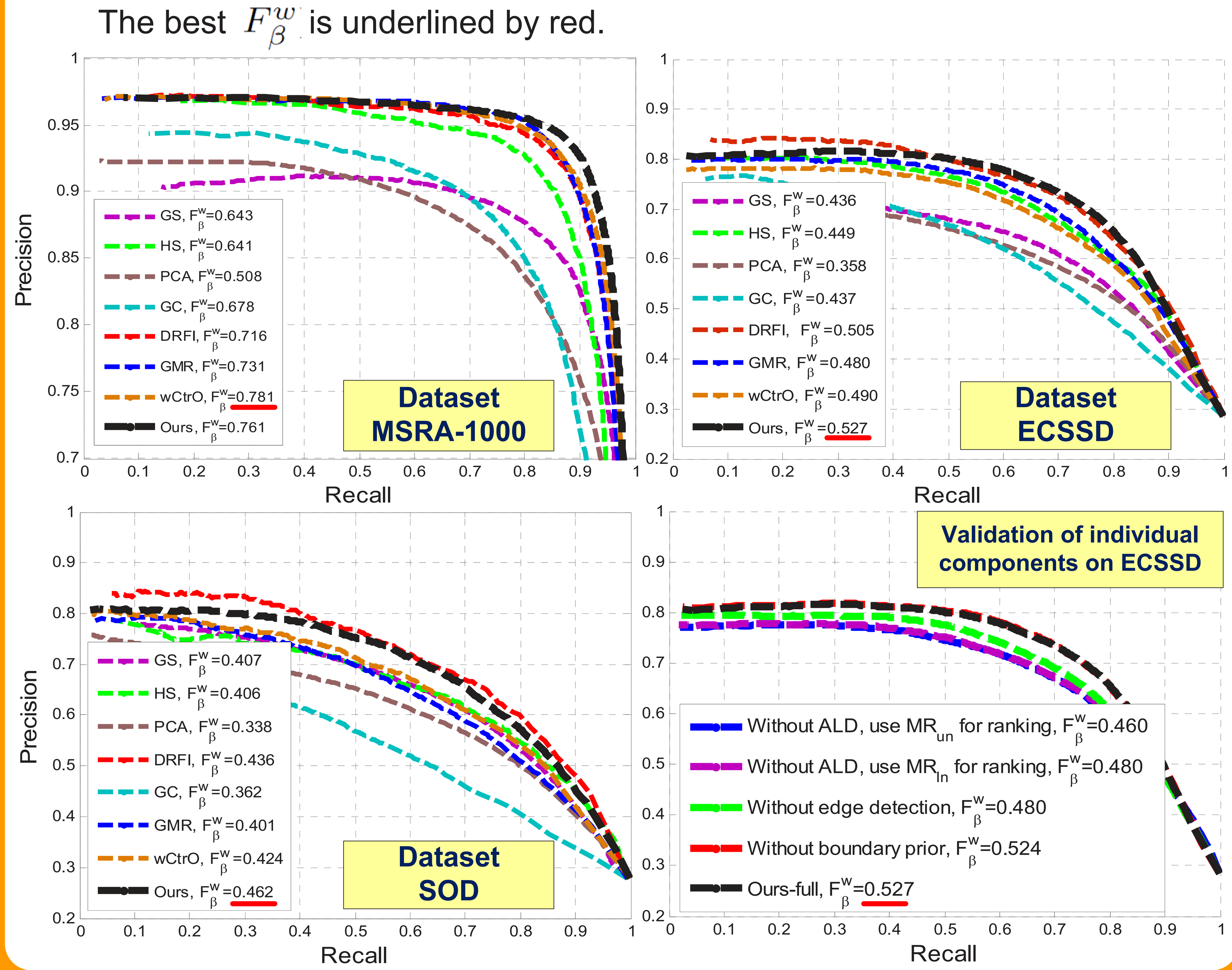
- Besides affinity learning, all four MR Models in GSSL are used directly to perform regularization on the seed vectors in the tests, similar to [1,3].

Benchmarks: Evaluation by weighted F-measure. (B) or (F): diffusion seeds are from the background or foreground. Numbers in ( ) are ranking positions on a dataset. The best score is in bold font.

Methods	MSRA(B)	ECSSD(B)	SOD(B)	MSRA(F)	ECSSD(F)	SOD(F)
MR_{ln}	0.709(4)	0.466(3)	0.398(3)	0.666(5)	0.423(2)	0.371(3)
MR_{ln}_ALD	0.609(7)	0.374(6)	0.312(8)	0.557(7)	0.363(6)	0.322(7)
MR_{sp}	0.651(6)	0.352(7)	0.330(6)	0.679(4)	0.372(5)	0.333(5)
MR_{sp}_ALD	0.717(3)	0.434(5)	0.373(5)	**0.694(1)**	0.403(4)	0.356(4)
MR_{un}	0.660(5)	0.440(4)	0.381(4)	0.617(6)	0.340(7)	0.323(6)
MR_{un}_ALD	**0.763(1)**	0.471(2)	**0.408(1)**	0.681(3)	0.420(3)	**0.377(1)**
MR_{sn}	0.509(8)	0.331(8)	0.325(7)	0.349(8)	0.272(8)	0.245(8)
MR_{sn}_ALD	0.747(2)	**0.479(1)**	**0.408(1)**	0.682(2)	**0.427(1)**	0.376(2)

Compare with 7 State-of-the-Art Saliency Methods

- Model MR_{un}_ALD is selected for saliency diffusion, as it works well for different datasets.
- Compare performance: precision-recall curves & weighted F-measure F_β^w. The best F_β^w is underlined by red.



4. Conclusion

- Affinity Learning-based Diffusion (ALD) consistently outperforms ranking-based diffusion when evaluating under the same settings.
- Saliency detection by ALD achieves state-of-the-art performance. It requires only a single stage diffusion and is effective.
- Experiments show that diffusion models are crucial to high quality saliency detection.

ICASSP16, IVMSP-P14.1, 25/3/2016