Random Walk on Pixel Manifolds for Anomaly Segmentation of Complex Driving Scenes

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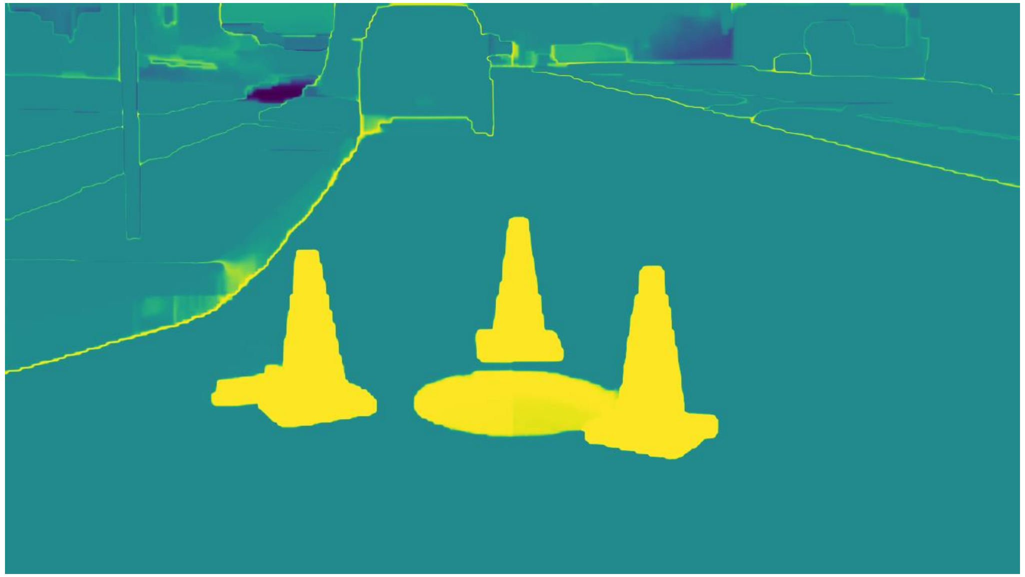
The 18th European Conference on Computer Vision ECCV 2024

Anomaly Segmentation for Driving Scenes

- Given a driving scene image, anomaly segmentation detects all anomalous objects on the road.

A input image [1]

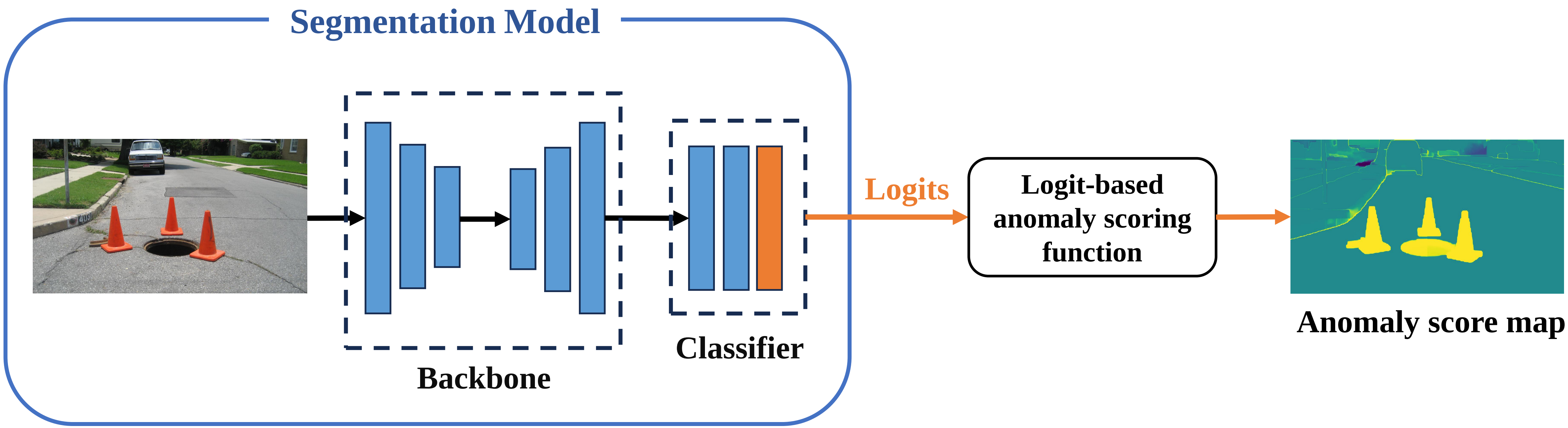


The result of anomaly segmentation

[1] Chan, Robin, et al. "Segmentmeifyoucan: A benchmark for anomaly segmentation." *NeurIPS 2021*.

Anomaly Segmentation for Driving Scenes

- Most existing state-of-the-art methods design and utilize anomaly scoring functions to calculate anomaly scores for each pixel.



Accurately predicting the logits is crucial for precisely inferring the anomaly score.

Motivation

- The diversity of driving scenes.

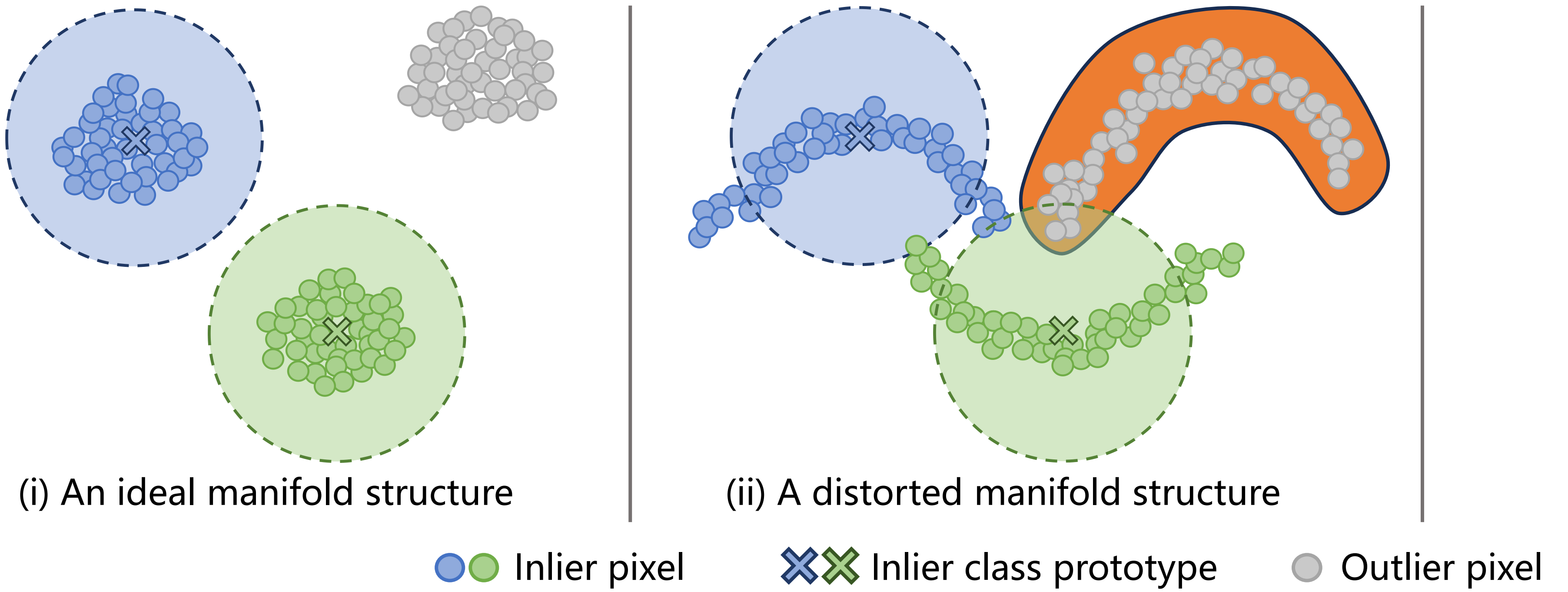
Training data [2]

Test data [3] in various environmental factors.

[2] Cordts, Marius, et al. "The cityscapes dataset for semantic urban scene understanding." *CVPR 2016*.
[3] Chan, Robin, et al. "Segmentmeifyoucan: A benchmark for anomaly segmentation." *NeurIPS 2021*.

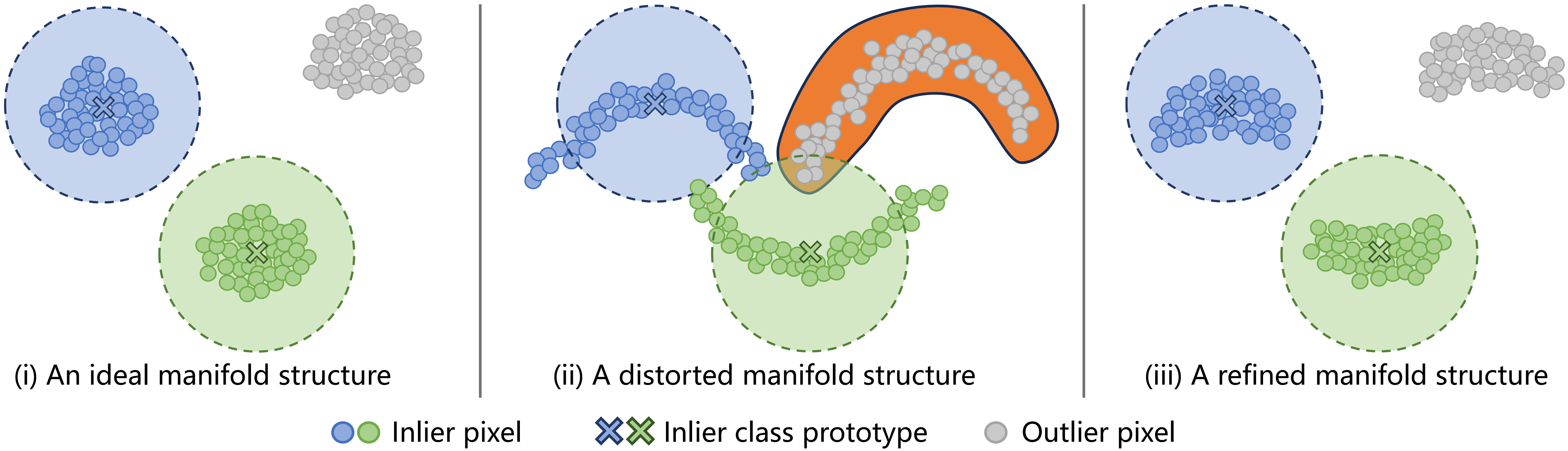
Motivation

- The diversity of driving scenes often result in distorted manifolds.



Motivation

- The structure of data manifolds implicitly contains the intrinsic relationship among pixel points.



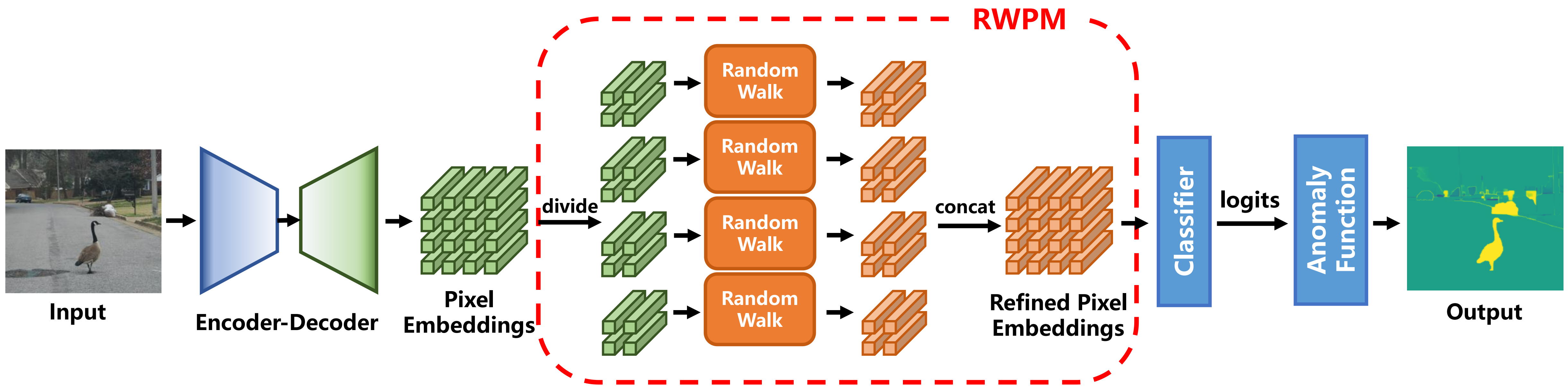
Proposed Method

- Random Walk on Pixel Manifolds (RWPM): RWPM can be directly integrated into existing anomaly segmentation frameworks in the inference phase.

Random Walk on Pixel Manifolds (RWPM)

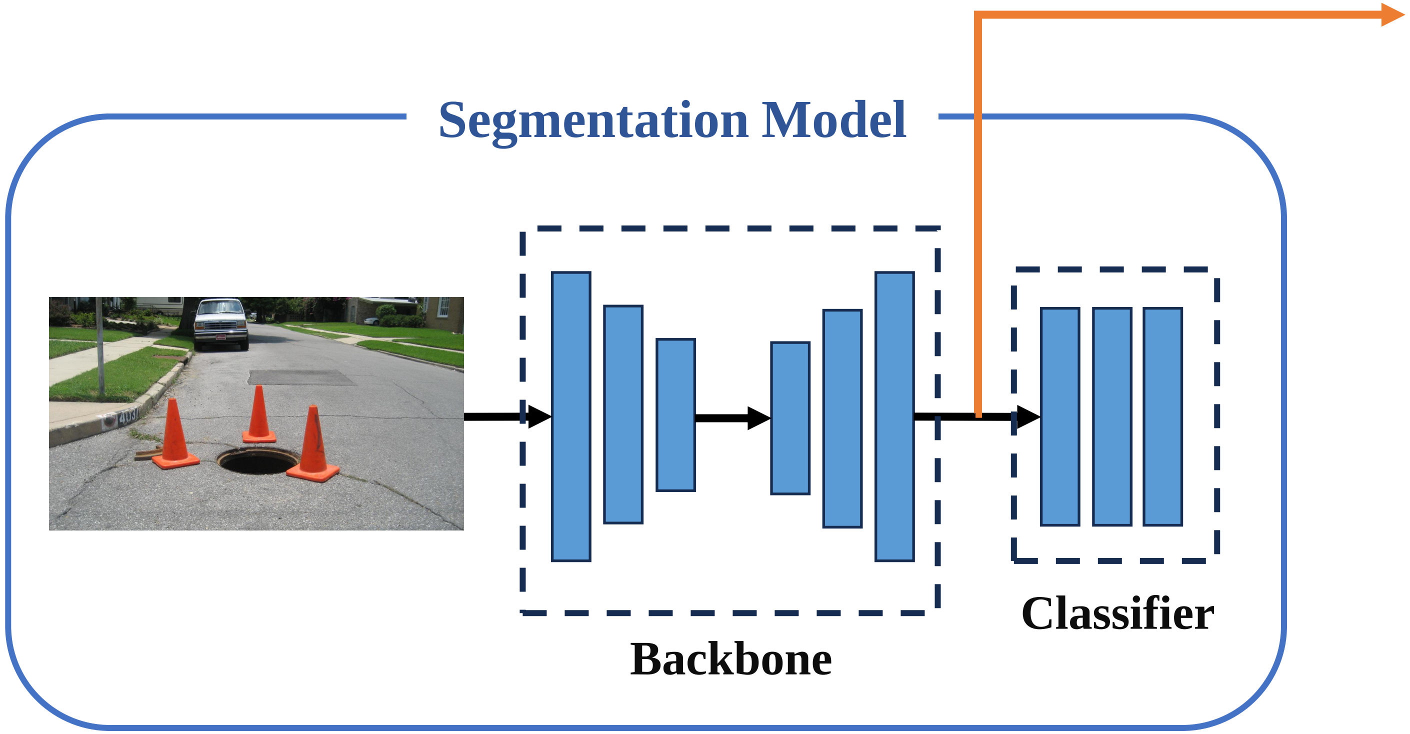
- **Overview**

RWPM consists of 3 parts: *Graph Construction*, *Random Walk Process* and *Partial Random Walk*



Random Walk on Pixel Manifolds (RWPM)

- Graph Construction



Pixel embeddings: $\boldsymbol{p} \in \mathbb{R}^{d\times H\times W}$

$\xrightarrow{\text{Reshape}}$ $\boldsymbol{p}^r \in \mathbb{R}^{HW\times d}$

$\xrightarrow{\text{Normalize}}$ $\widehat{\boldsymbol{p}}_i^r = \boldsymbol{p}_i^r / \|\boldsymbol{p}_i^r\|.$

Affinity matrix:

$$\mathbf{W}_{ij} = \begin{cases} \langle \widehat{\boldsymbol{p}}_i^r, \widehat{\boldsymbol{p}}_j^r \rangle & i \neq j \\ 0 & i = j \end{cases},$$

Locally constrained graph:

$$\mathbf{S}_{ij} = \begin{cases} \frac{\exp(\mathbf{W}_{ij}/\tau)}{\sum_{i=1, i\neq j}^{HW} \exp(\mathbf{W}_{ij}/\tau)} & i \neq j \\ 0 & i = j \end{cases},$$

Random Walk on Pixel Manifolds (RWPM)

- Random Walk Process

Initialization:

$$\mathbf{m}^0 \xrightarrow{\text{Initialize as}} \boldsymbol{p}^r$$

Iteration:

$$\mathbf{m}^{t+1} = \alpha \mathbf{S} \mathbf{m}^t + (1-\alpha)\,\mathbf{m}^0,\ \alpha \in (0,1),$$

$$\xrightarrow{\text{Closed-form}} \boxed{\mathbf{m}^{\infty}} = (1-\alpha)\,(\mathbf{I}-\alpha\mathbf{S})^{-1}\,\mathbf{m}^0,$$

Refined pixel embeddings

Random Walk on Pixel Manifolds (RWPM)

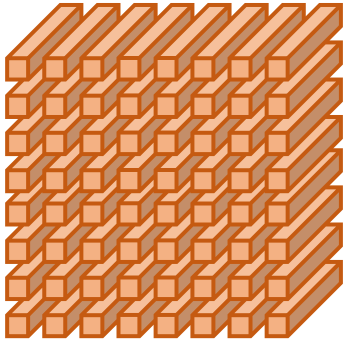
- Partial Random Walk

1024

512

524288

524288

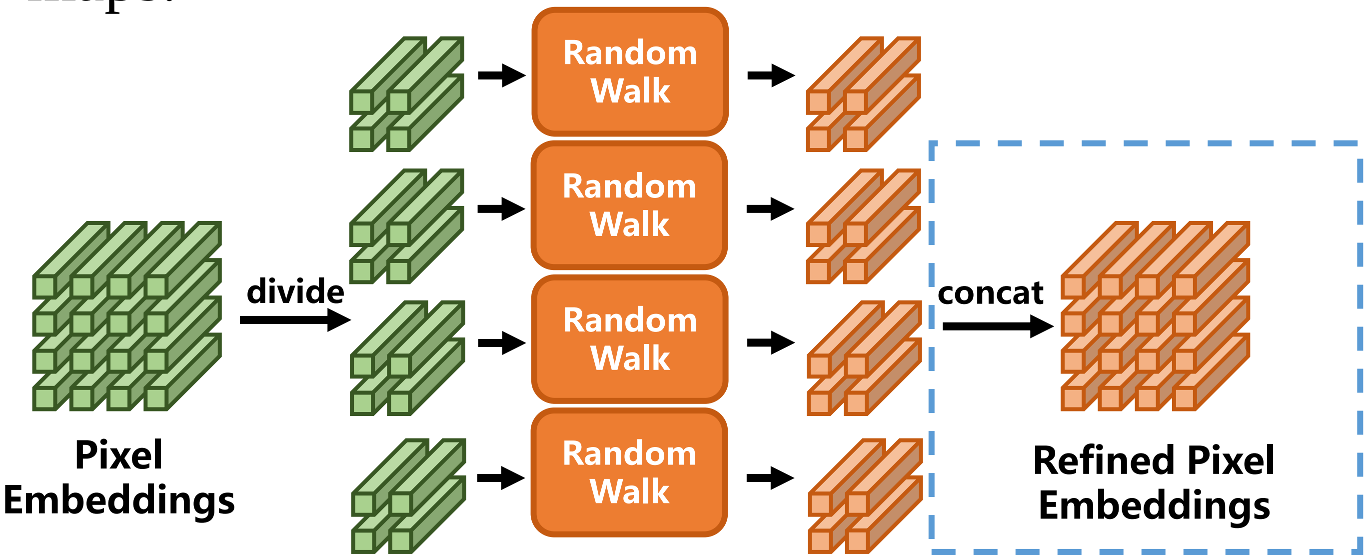


Random Walk on Pixel Manifolds (RWPM)

- Partial Random Walk
  1. Limited iteration: Iterate only T time

$$\mathbf{m}^{t+1} = \alpha \mathbf{S} \mathbf{m}^{t} + (1-\alpha)\,\mathbf{m}^{0},\ \alpha \in (0,1),$$

  2. Embedding map partitioning: Equally divide the pixel embedding map into some sub-maps.



Optional Step: Use calibration to smooth out the difference between patches.

Experiments

- We integrate RWPM with 4 representative anomaly segmentation methods.

Benchmark→		Fishyscapes Lost&Found			Road Anomaly		
Method ↓	Arch	AuROC↑	AP↑	FPR95↓	AuROC↑	AP↑	FPR95↓
PEBAL [38]	Pixel-base	98.96	58.81	4.77	87.63	45.10	44.58
PEBAL + RWPM† (Ours)	Pixel-base	**99.20**	**66.85**	**3.68**	**89.48**	**50.29**	**36.81**
Balanced Energy [12]	Pixel-base	99.03	67.07	2.93	88.31	41.48	41.46
Balanced Energy + RWPM† (Ours)	Pixel-base	**99.29**	**72.95**	**2.38**	**90.51**	**48.26**	**32.10**
Mask2Anomaly[1] [37]	Mask-base	95.41	69.44	9.22	96.54	80.04	13.95
Mask2Anomaly + RWPM (Ours)	Mask-base	**95.92**	**69.54**	**8.13**	**97.44**	**80.09**	**7.45**
RbA [35]	Mask-base	98.62	70.81	6.30	97.99	85.42	6.92
RbA + RWPM (Ours)	Mask-base	**98.82**	**71.16**	**6.12**	**98.04**	**87.34**	**5.27**

Experiments

- Pixel level evaluation: Comparison with state-of-the-art anomaly segmentation methods.

Benchmark→		Fishyscapes L&F		Road Anomaly		Anomaly Track		Obstacle Track		Average	
Method ↓	Arch	AP↑	FPR95↓	AP↑	FPR95↓	AP↑	FPR95↓	AP↑	FPR95↓	AP↑	FPR95↓
Synboost [15] (CVPR'21)	Pixel-based	60.58	31.02	41.84	59.72	56.44	61.86	71.34	3.15	57.46	38.94
SML [26] (ICCV'21)	Pixel-based	22.74	33.49	25.82	49.47	46.8	39.5	3.4	36.8	24.69	39.82
Meta-OOD [7] (ICCV'21)	Pixel-based	41.31	37.69	48.84	31.77	85.47	15.00	85.07	0.75	65.13	21.30
Learning Embedding [5](IJCV'21)	Pixel-based	4.65	24.36	-	-	37.52	70.76	0.82	46.38	-	-
Void Classifier [5](IJCV'21)	Pixel-based	10.29	22.11	-	-	36.61	63.49	10.44	41.54	-	-
GMMSeg-DL [28] (NeurIPS'22)	Pixel-based	43.47	13.11	34.42	47.90	-	-	-	-	-	-
DenseHybrid [18] (ECCV'22)	Pixel-based	69.79	5.09	31.39	63.97	77.96	**9.81**	87.08	0.24	65.56	19.78
PEBAL [38] (ECCV'22)	Pixel-based	58.81	4.77	45.10	44.58	49.14	40.82	4.98	12.68	39.58	25.71
Balanced Energy [12] (CVPR'23)	Pixel-based	67.07	2.93	41.48	41.46	-	-	-	-	-	-
RPL-CoroCL [33] (ICCV'23)	Pixel-based	70.61	**2.52**	71.61	17.74	83.49	11.68	85.93	0.58	77.91	8.13
Mask2Anomaly [37] (ICCV'23)	Mask-based	69.44	9.22	80.04	13.95	88.62	14.57	93.10	**0.20**	82.87	9.49
M2F-EAM [19] (CVPRW'23)	Mask-based	52.03	20.51	66.67	13.42	76.3	93.9	66.9	17.9	65.48	36.43
RbA [35] (ICCV'23)	Mask-based	70.81	6.30	85.42	6.92	90.9	11.6	91.8	0.5	84.73	6.33
RbA + RWPM (Ours)	Mask-based	**71.16**	6.12	**87.34**	**5.27**	**92.20**	10.15	**93.30**	0.28	**86.00**	**5.46**

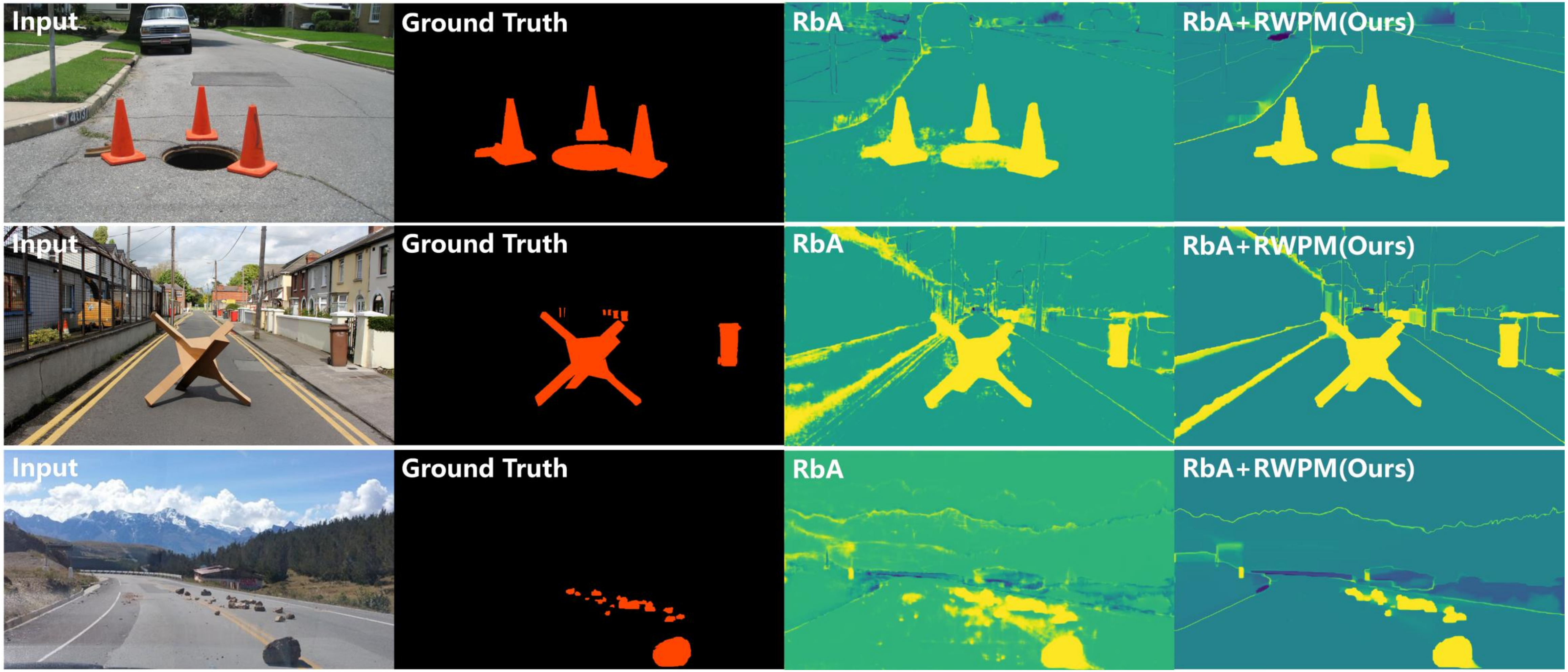
Experiments

- Component level evaluation: Comparison with state-of-the-art anomaly segmentation methods.

Benchmark→		Anomaly Track			Obstacle Track		
Method ↓	Arch	sIoU ↑	PPV↑	mean F1↑	sIoU ↑	PPV↑	mean F1↑
Synboost [15] (CVPR'21)	Pixel-based	34.68	17.81	9.99	44.28	41.75	37.57
SML [26] (ICCV'21)	Pixel-based	26.00	24.70	12.20	5.10	13.30	3.00
Meta-OOD [7] (ICCV'21)	Pixel-based	49.31	39.51	28.72	47.87	63.64	48.51
Void Classifier [5](IJCV'21)	Pixel-based	21.14	22.13	6.49	6.34	20.27	5.41
Learning Embedding [5](IJCV'21)	Pixel-based	33.86	20.54	7.90	35.64	2.87	2.31
JSRNet [39] (ICCV'21)	Pixel-based	20.20	29.27	13.66	18.55	24.46	11.02
DenseHybrid [18] (ECCV'22)	Pixel-based	54.17	24.13	31.08	45.74	50.10	50.72
PEBAL [38] (ECCV'22)	Pixel-based	38.88	27.20	14.48	29.91	7.55	5.54
RPL-CoroCL [33] (ICCV'23)	Pixel-based	49.76	29.96	30.16	52.61	56.65	56.69
Mask2Fromer [37] (ICCV'23)	Mask-based	25.20	18.20	15.30	5.00	21.90	4.80
Maskomaly [2] (BMVC'23)	Mask-based	55.4	51.6	50.0	-	-	-
RbA [35] (ICCV'23)	Mask-based	55.69	52.14	46.80	58.36	58.78	60.85
RbA + RWPM (Ours)	Mask-based	**57.00**	**61.25**	**58.44**	**59.47**	**72.51**	**69.85**

Experiments

- Qualitative Result.



Thank you !

The Code Link

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