Inharmonious Region Localization by Magnifying Domain Discrepancy

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AAAI 2022

Motivation

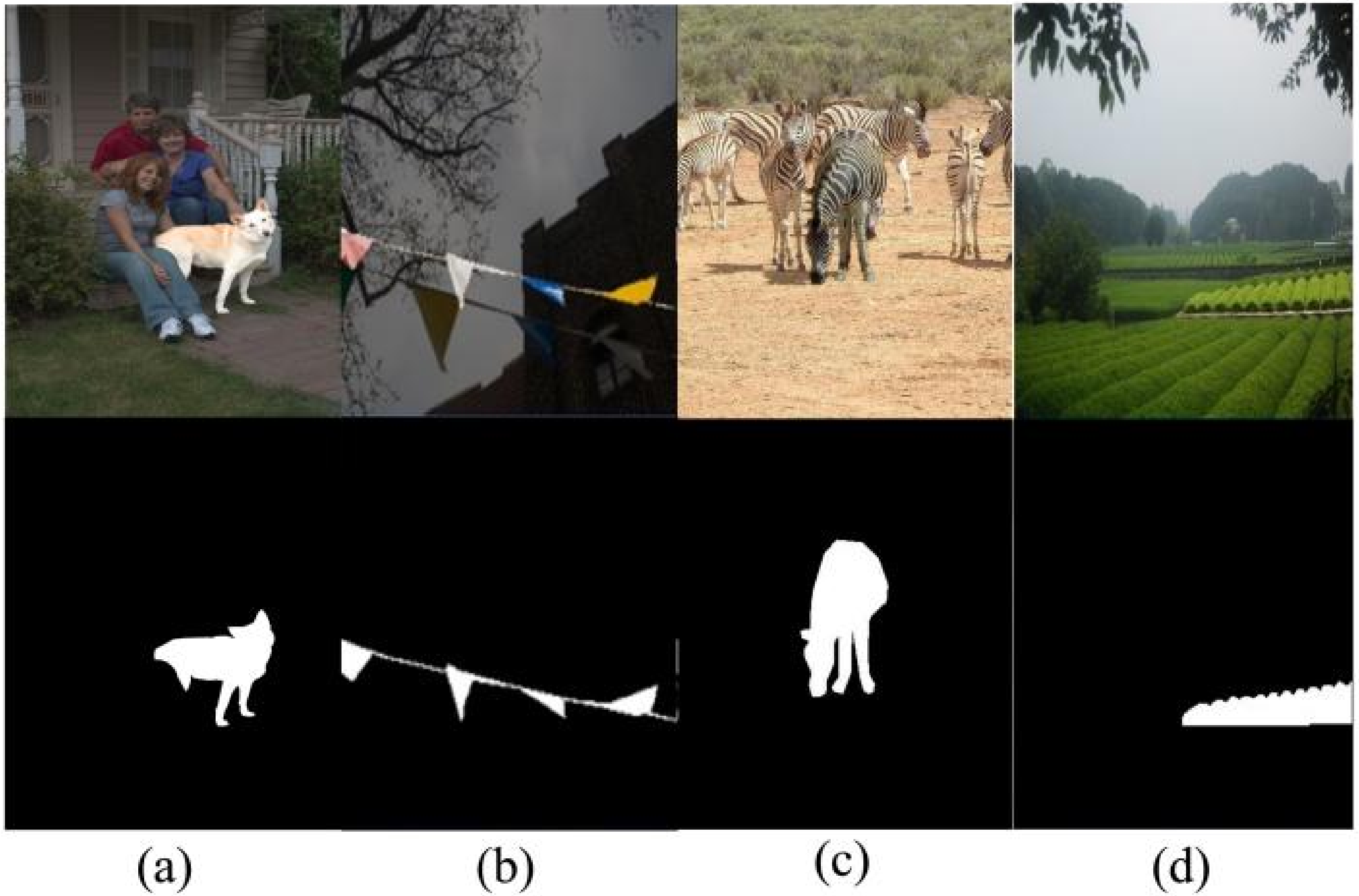


Figure 1: We show the examples of inharmonious synthetic images in the top row and their inharmonious region masks in the bottom row.

Motivation

- The only existing inharmonious region localization method is DIRL, which attempted to fuse multi-scale features and avoid redundant information. However, DIRL is a rather general model without exploiting the uniqueness of this task, that is, the discrepancy between inharmonious region and background.
- We refer to each suite of color and illumination statistics as one domain following. Thus, the inharmonious region and the background belong to two different domains.

To achieve this goal, we propose a framework composed of two components: one **color mapping module** and one inharmonious region localization network.

Contributions

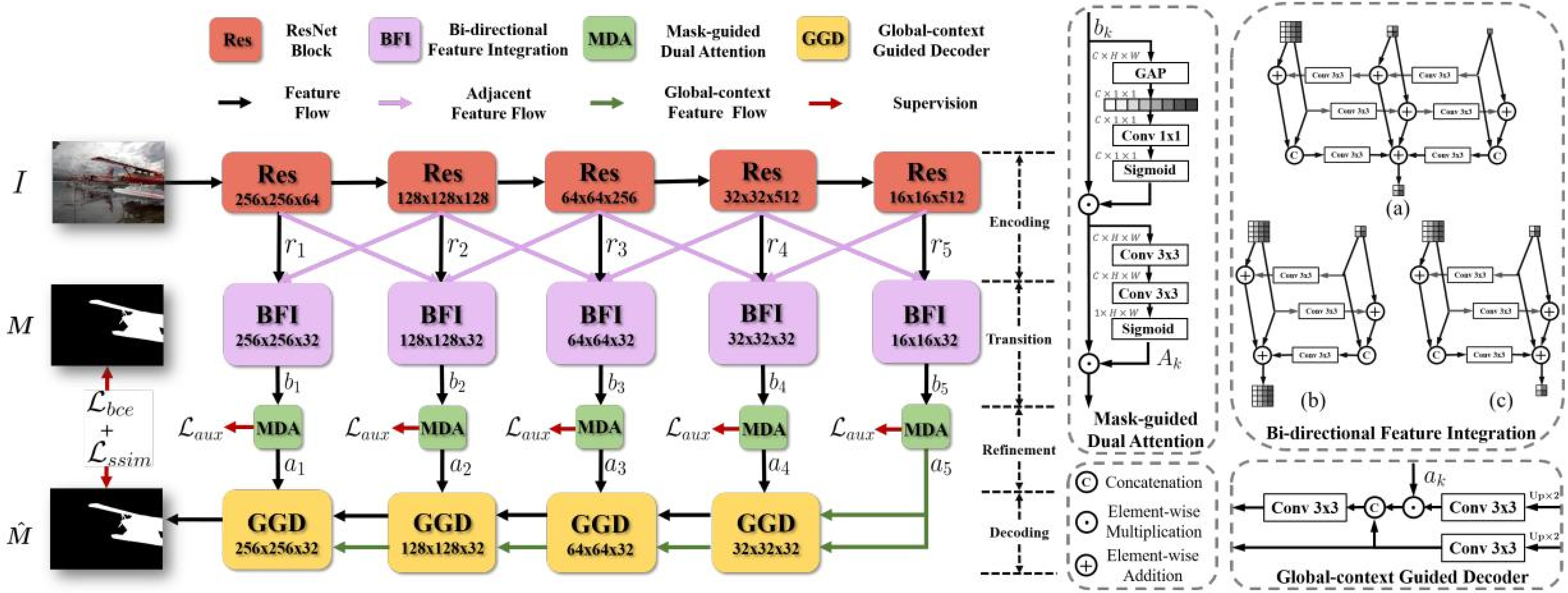
(a) We devise a simple yet effective inharmonious region localization framework which can accommodate any region localization method.

(b) We are the first to introduce adaptive color transformation to inharmonious region localization, in which improve HDRNet is used as the color mapping module.

(c) We propose a novel domain discrepancy magnification loss to magnify the domain discrepancy between inharmonious region and background.

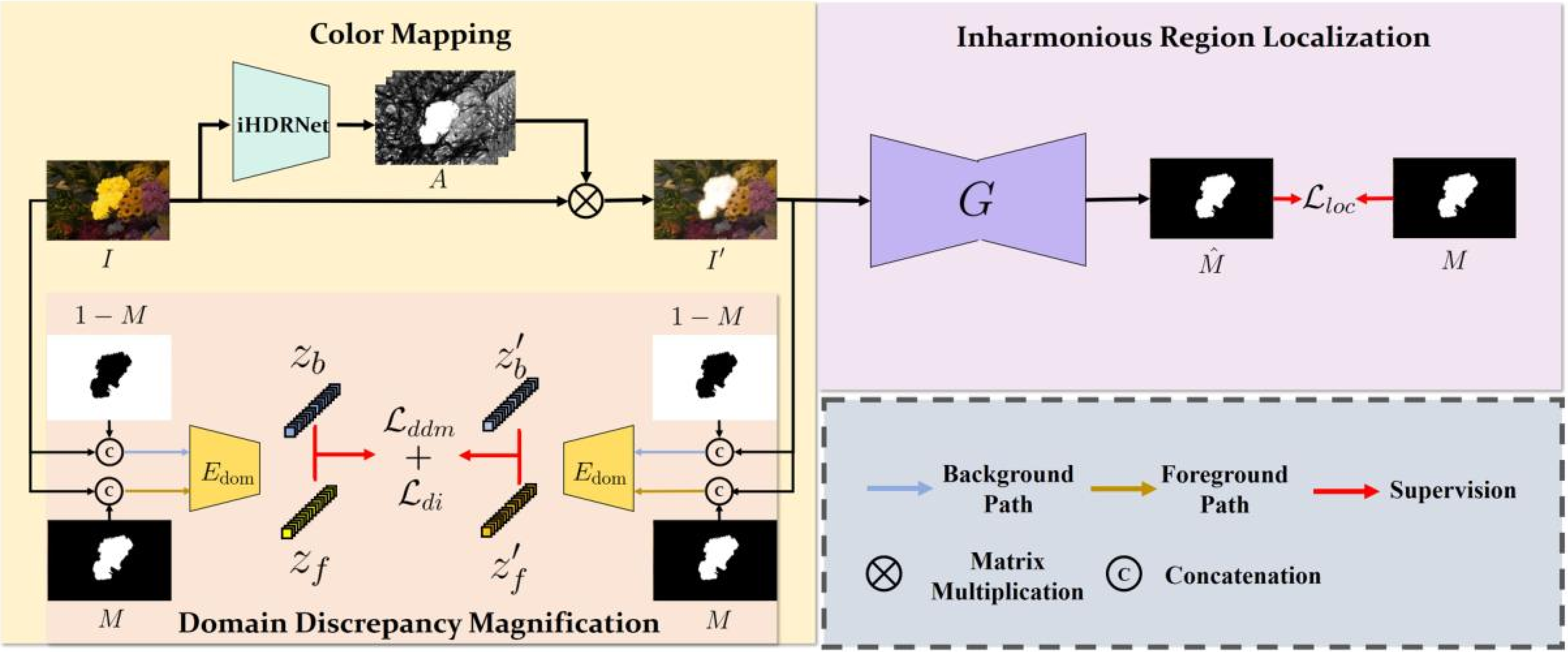
(d) Extensive experiments demonstrate that our framework outperforms existing methods by a large margin (e.g., IoU is improved from 67.85% to 74.44%).

DIRL



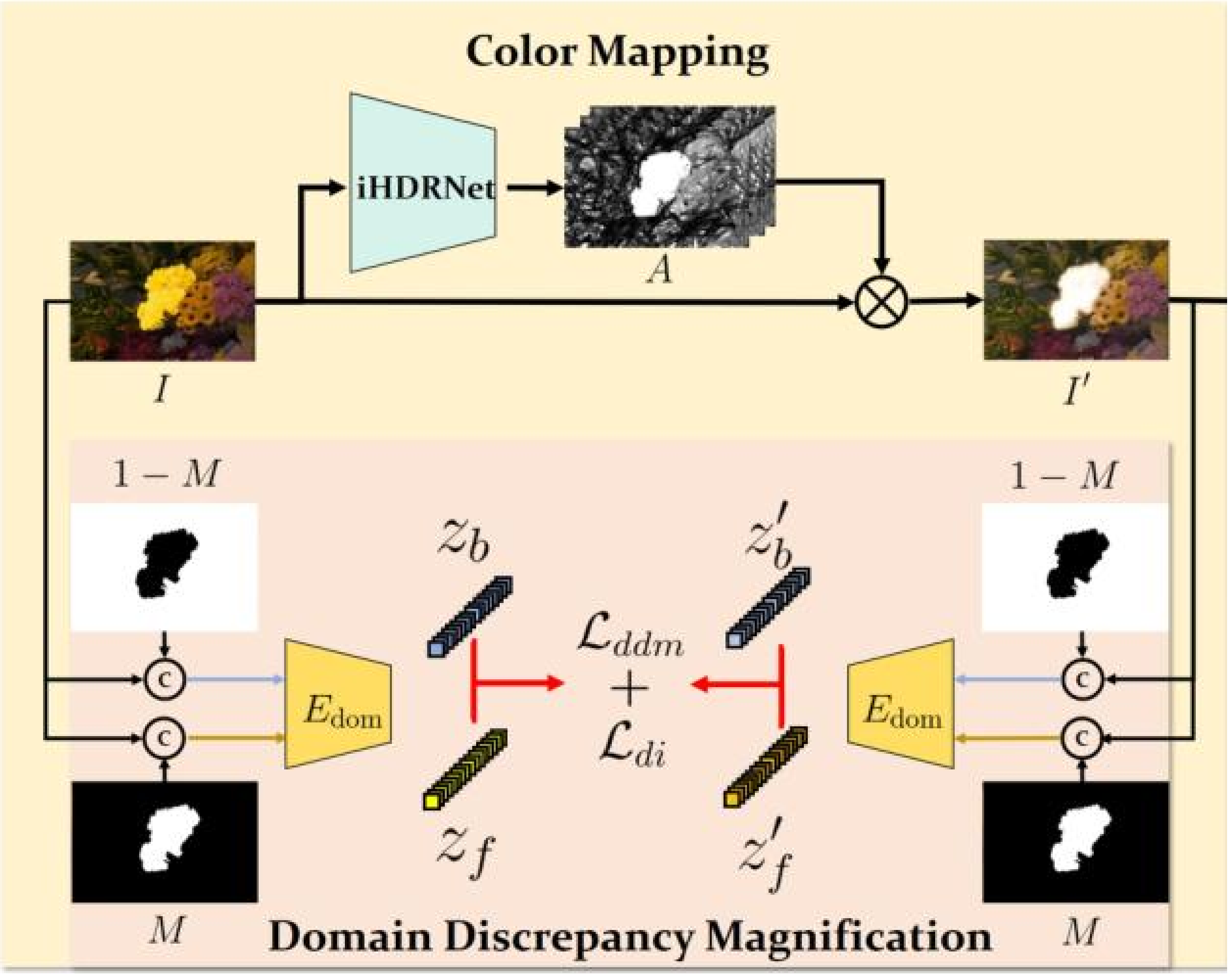
[1] *Liang, Jing, Li Niu, and Liqing Zhang. Inharmonious Region Localization. IEEE International Conference on Multimedia and Expo (ICME), 2021.*

MadisNet



Color Mapping
iHDRNet
A
I
I'
Inharmonious Region Localization
G
$\hat{M}$
$\mathcal{L}_{loc}$
M
1 − M
z_b
z_b'
$\mathcal{L}_{ddm}$
+
$\mathcal{L}_{di}$
E_{dom}
z_f
z_f'
M
Domain Discrepancy Magnification
Background Path
Foreground Path
Supervision
Matrix Multiplication
Concatenation

Methodology



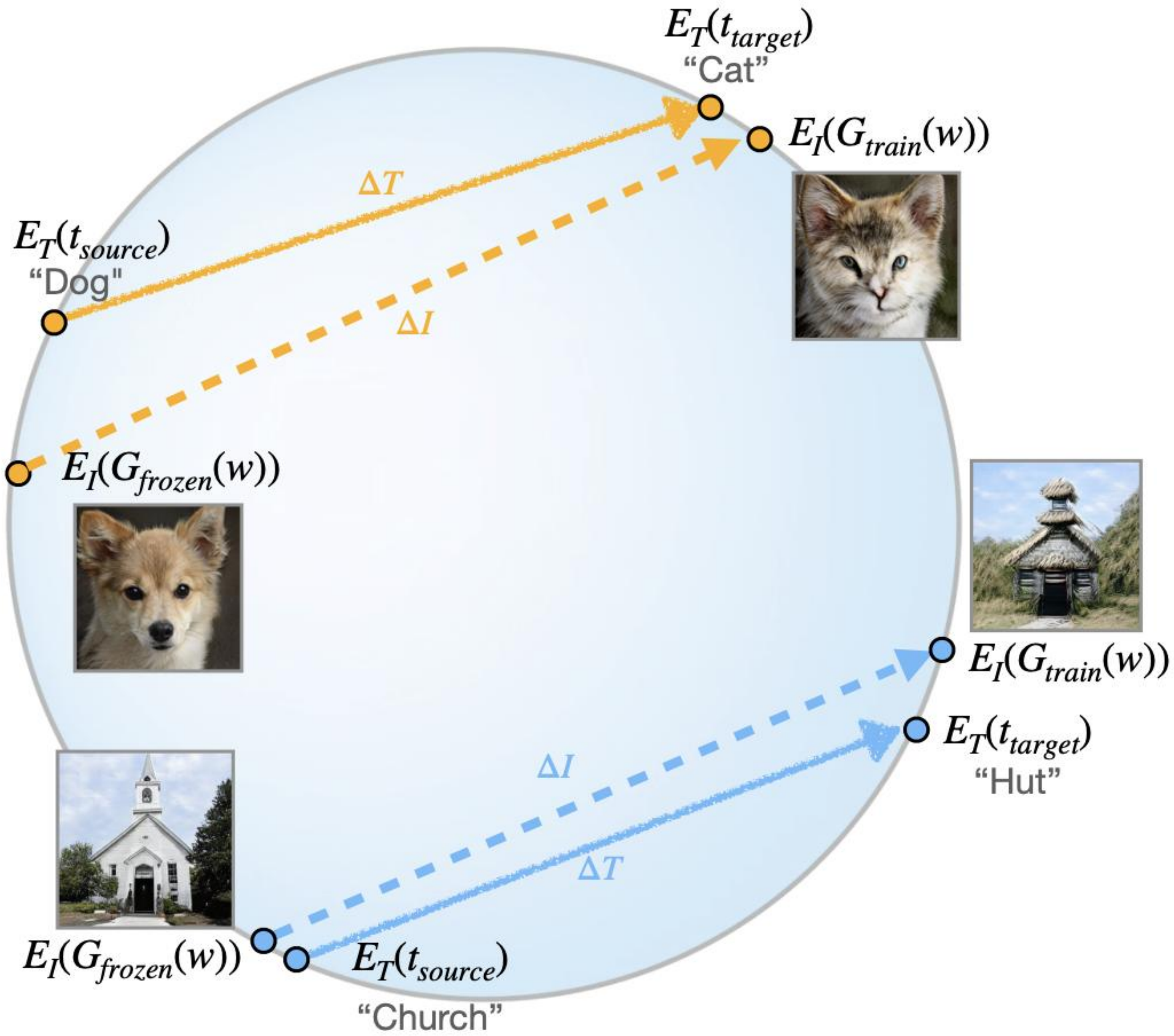
Domain Discrepancy Magnification (DDM) loss:

$$\mathcal{L}_{ddm} = \max\left(d(\boldsymbol{z}_f, \boldsymbol{z}_b) - d(\boldsymbol{z}'_f, \boldsymbol{z}'_b) + m, 0\right), \quad (1)$$

Direction Invariance Loss:

$$\mathcal{L}_{di} = 1 - \langle \Delta z, \Delta z' \rangle, \quad (2)$$

Methodology



Direction Invariance Loss:

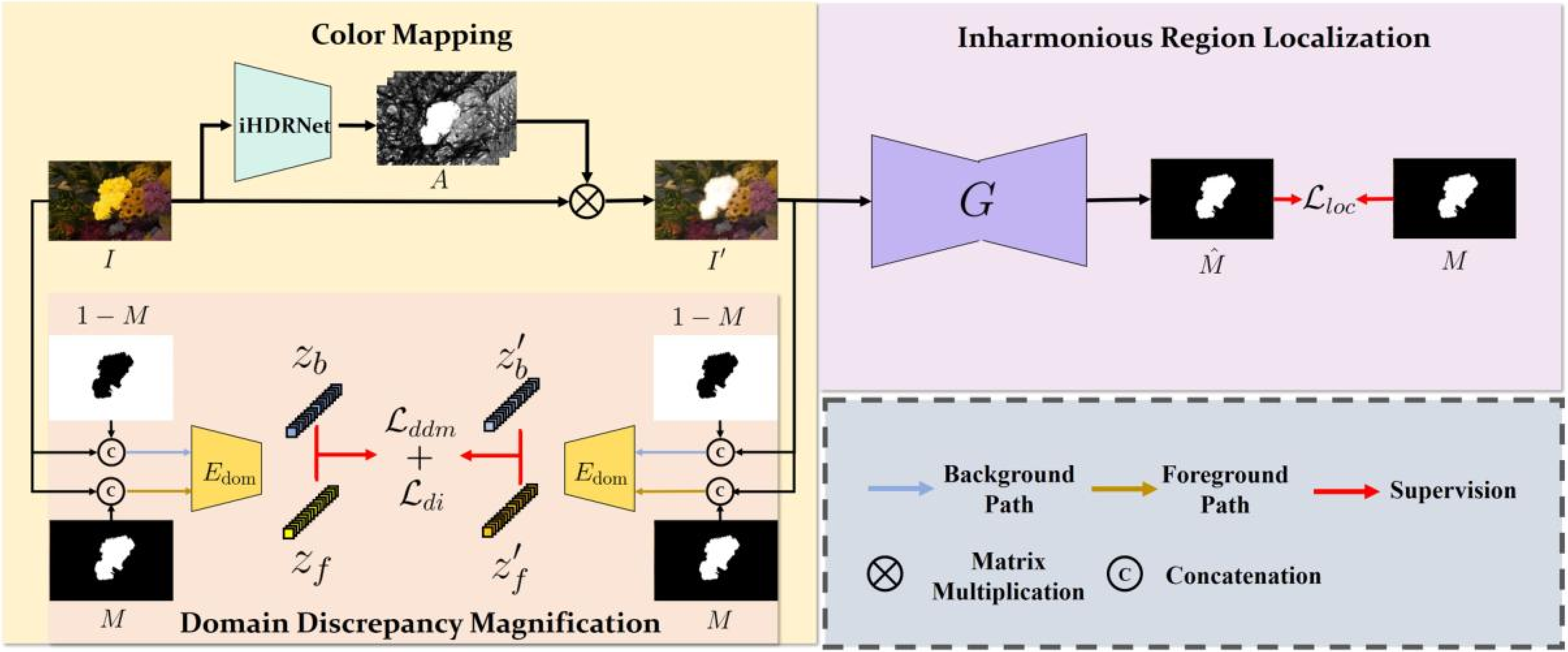
$$\mathcal{L}_{di} = 1 - \langle \Delta z, \Delta z' \rangle, \quad (2)$$

$$\Delta z = z_f - z_b$$

$$\Delta z' = z'_f - z'_b$$

[1] *Gal, Rinon, et al. StyleGAN-NADA: CLIP-guided domain adaptation of image generators. ACM Transactions on Graphics (TOG) 41.4 (2022): 1-13.*

MadisNet



$$\mathcal{L}_{total} = \lambda_{ddm}\mathcal{L}_{ddm} + \lambda_{di}\mathcal{L}_{di} + \mathcal{L}_{loc}, \qquad (3)$$

Experiments

Methods	Evaluation Metrics		
	AP(%) ↑	F_1 ↑	IoU(%) ↑
UNet	74.90	0.6717	64.74
DeepLabv3	75.69	0.6902	66.01
HRNet-OCR	75.33	0.6765	65.49
MFCN	45.63	0.3794	28.54
MantraNet	64.22	0.5691	50.31
MAGritte	71.16	0.6907	60.14
H-LSTM	60.21	0.5239	47.07
SPAN	65.94	0.5850	54.27
F3Net	61.46	0.5506	47.48
GATENet	62.43	0.5296	46.33
MINet	77.51	0.6822	63.04
S2AM	43.77	0.3029	22.36
DIRL	80.02	0.7317	67.85
MadisNet(UNet)	81.15	0.7372	67.28
MadisNet(DIRL)	**85.86**	**0.8022**	**74.44**

Table 1: Quantitative comparison with baseline methods on iHarmony4 dataset. The best results are denoted in boldface.

Experiments

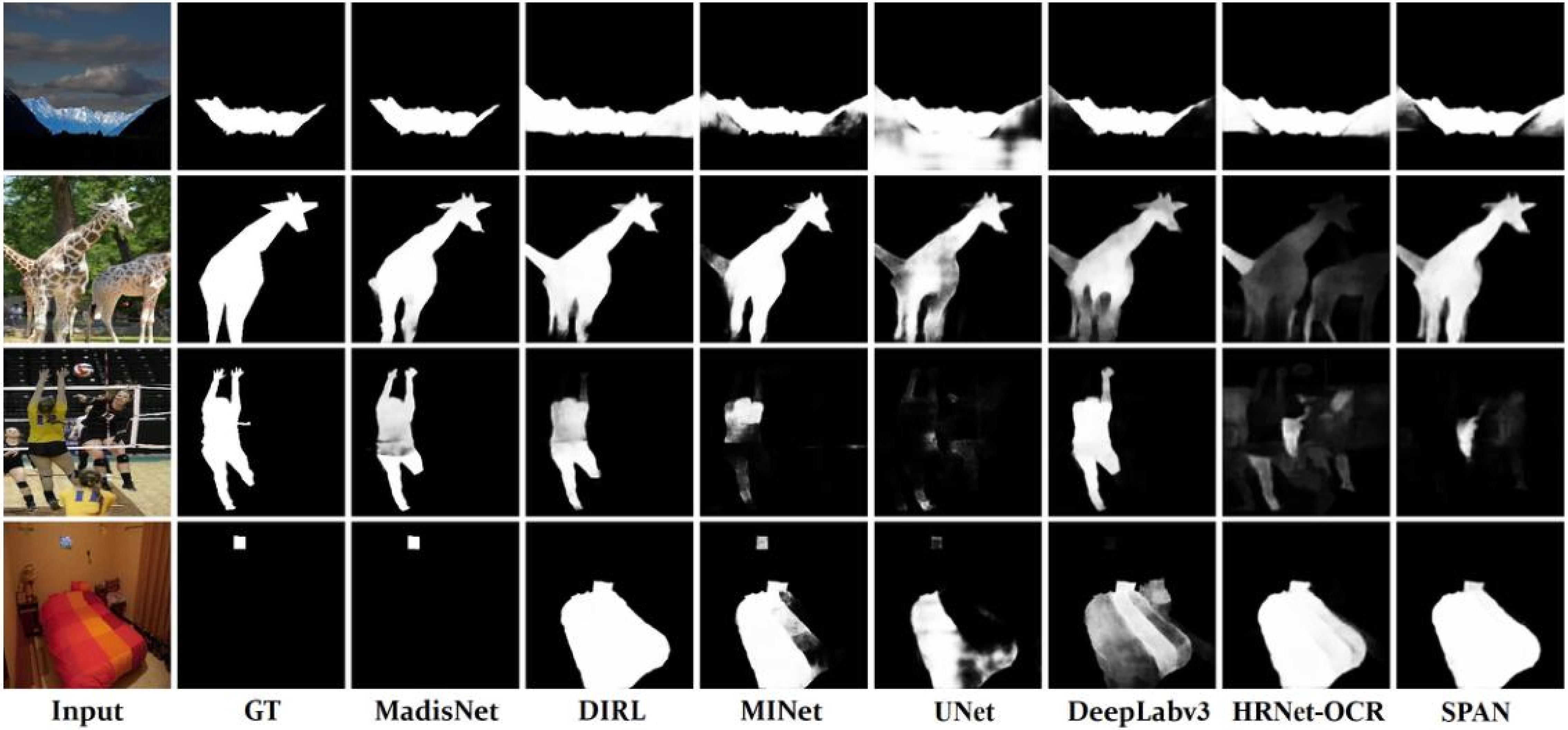


Figure 3: Qualitative comparison with baseline methods. GT is the ground-truth inharmonious region mask.

Q&A

Thank you!