RUN: Reversible Unfolding Network for Concealed Object Segmentation

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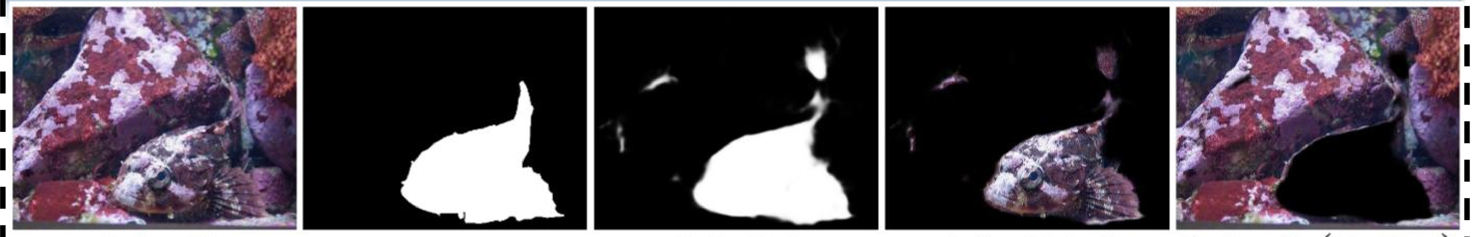
Introduction



(a) C (b) GT (c) M (d) C•M (e) C•(I-M)

Challenges:

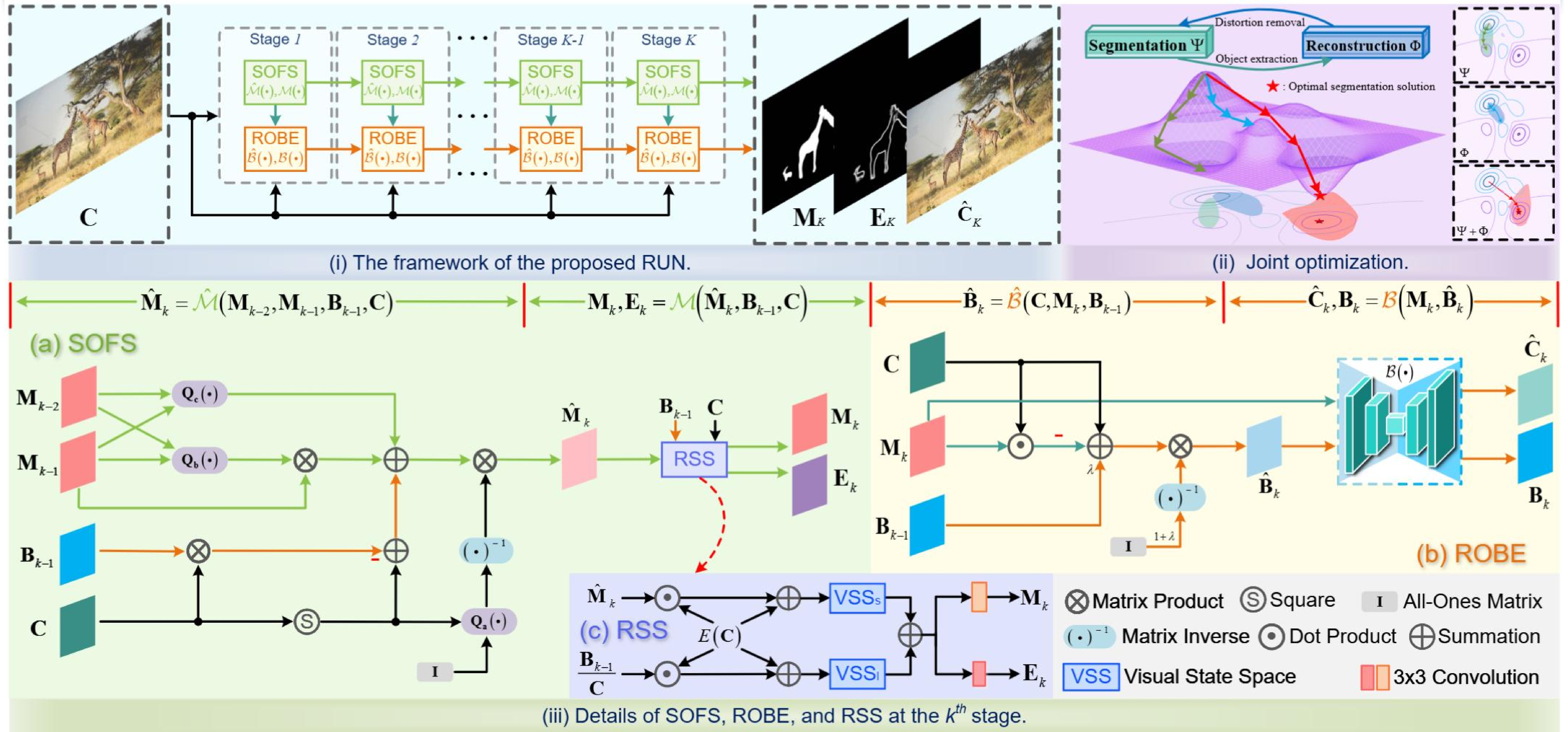
Reversible modeling improves segmentation by focusing on uncertain mask regions (pixels with values between 0 and 1) to extract subtle discriminative cues. Current strategies, however, **are limited to the mask level**, overlooking the the RGB domain. As shown in (d) and (e) in the figure, this RGB uncertainty often **manifests as color distortion** when reversibly separating foreground and background. Addressing these color distortions could further refine segmentation by enabling more precise delineation.

Contribution:

1. We propose RUN, **the first deep unfolding network**, for the COS task, balancing interpretability and generalizability.
2. RUN proposes a novel COS model designed to **reduce segmentation uncertainties** and introduces SOFS and ROBE modules to integrate model-based optimization solutions with deep networks. RUN **directs the network's focus to uncertain regions**, thereby reducing false-positive and false-negative outcomes.
3. Experiments on **five** COS tasks, as well as salient object detection, validate the superiority of our RUN method in effectiveness and generalizability.

1. I am looking for a summer internship in the US in 2026. Feel free to contact me!
2. Our lab is looking for research assistants. Feel free to email me directly and cc Prof. Sina Farsiu.

Network architecture

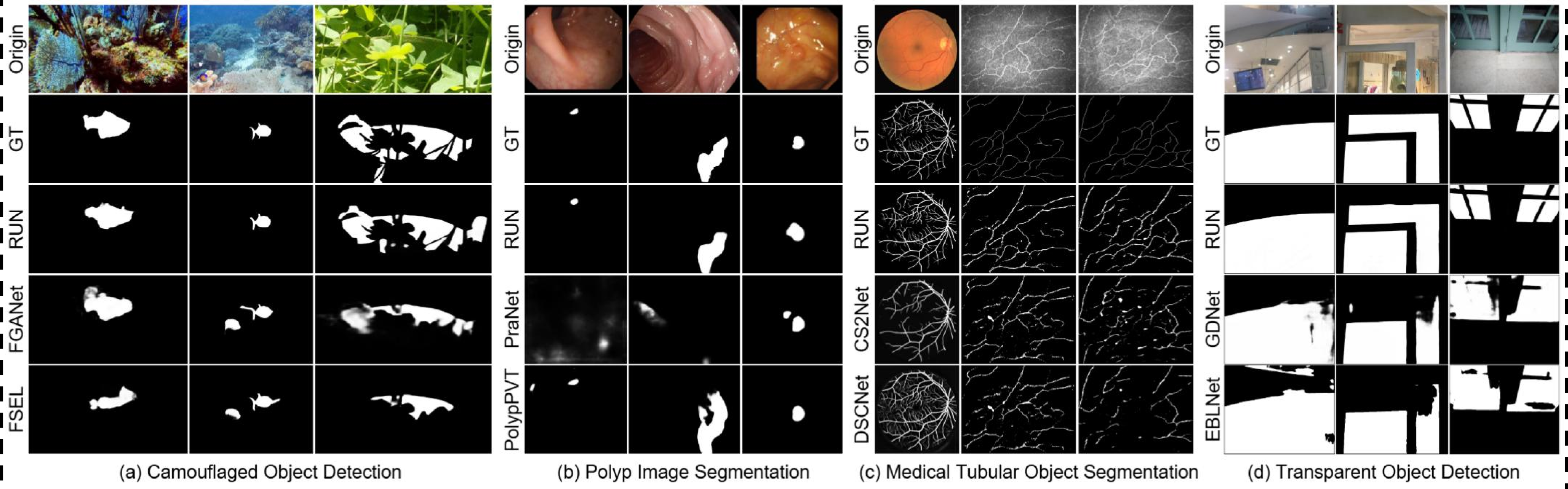


Framework of our RUN. The network connects in the first part of SOFS and ROBE are derived strictly based on mathematical principles, thus enhancing interpretability. Panel (ii) illustrates that the joint optimization of image segmentation and reconstruction tasks.

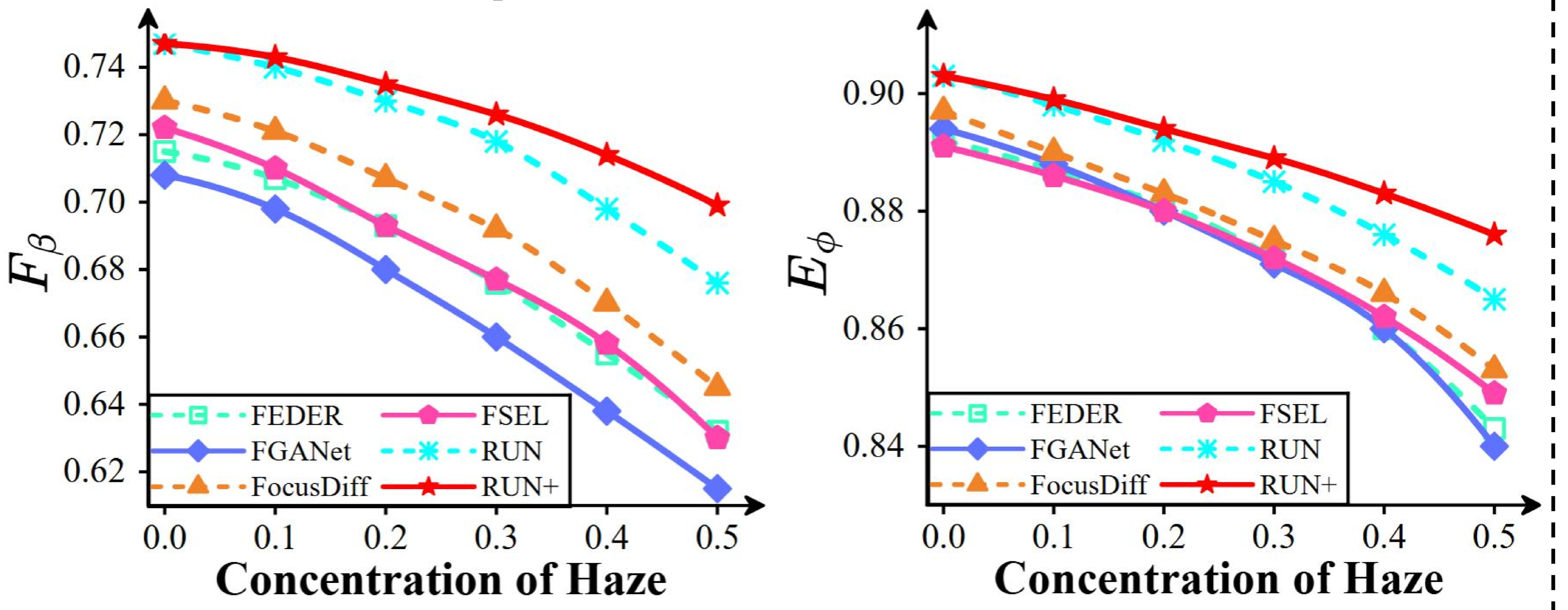
Experiment

Methods	Backbones	CHAMELEON $M\downarrow$	CHAMELEON $F_\beta\uparrow$	CHAMELEON $E_\phi\uparrow$	CHAMELEON $S_\alpha\uparrow$	CAMO $M\downarrow$	CAMO $F_\beta\uparrow$	CAMO $E_\phi\uparrow$	CAMO $S_\alpha\uparrow$	COD10K $M\downarrow$	COD10K $F_\beta\uparrow$	COD10K $E_\phi\uparrow$	COD10K $S_\alpha\uparrow$	NC4K $M\downarrow$	NC4K $F_\beta\uparrow$	NC4K $E_\phi\uparrow$	NC4K $S_\alpha\uparrow$
Common Setting: Single Input Scale and Single Stage																	
SINet (Fan et al., 2020a)	ResNet50	0.034	0.823	0.936	0.872	0.092	0.712	0.804	0.745	0.043	0.667	0.864	0.776	0.058	0.768	0.871	0.808
LSR (Lv et al., 2021)	ResNet50	0.030	0.835	0.935	0.890	0.080	0.756	0.838	0.787	0.037	0.699	0.880	0.804	0.048	0.802	0.890	0.834
FEDER (He et al., 2023b)	ResNet50	0.028	0.850	0.944	0.892	0.070	0.775	0.870	0.802	0.032	0.715	0.892	0.810	0.046	0.808	0.900	0.842
FGANet (Zhai et al., 2023)	ResNet50	0.030	0.838	0.945	0.891	0.070	0.769	0.865	0.800	0.032	0.708	0.894	0.803	0.047	0.800	0.891	0.837
FocusDiff (Zhao et al., 2024)	ResNet50	0.028	0.843	0.938	0.890	0.069	0.772	0.883	0.812	0.031	0.730	0.897	0.820	0.044	0.810	0.902	0.850
FSEL (Sun et al., 2024)	ResNet50	0.029	0.847	0.941	0.893	0.069	0.779	0.881	0.816	0.032	0.722	0.891	0.822	0.045	0.807	0.901	0.847
RUN (Ours)	ResNet50	**0.027**	**0.855**	**0.952**	**0.895**	0.070	**0.781**	0.868	0.806	**0.030**	**0.747**	**0.903**	**0.827**	**0.042**	**0.824**	**0.908**	**0.851**
BSA-Net (Zhu et al., 2022)	Res2Net50	0.027	0.851	0.946	0.895	0.079	0.768	0.851	0.796	0.034	0.723	0.891	0.818	0.048	0.805	0.897	0.841
FEDER (He et al., 2023b)	Res2Net50	0.026	0.856	0.947	0.903	**0.066**	0.807	0.897	0.836	0.029	0.748	0.911	0.844	0.042	0.824	0.913	**0.862**
RUN (Ours)	Res2Net50	**0.024**	**0.879**	**0.956**	**0.907**	**0.066**	**0.815**	**0.905**	**0.843**	**0.028**	**0.764**	**0.914**	**0.849**	**0.041**	**0.830**	**0.917**	0.859
HitNet (Hu et al., 2023)	PVT V2	0.024	0.861	0.944	0.907	0.060	0.791	0.892	0.834	0.027	0.790	0.922	0.847	0.042	0.825	0.911	0.858
CamoFocus (Khan et al., 2024)	PVT V2	0.023	0.869	0.953	0.906	**0.044**	**0.861**	0.924	0.870	0.022	**0.818**	0.931	0.868	0.031	0.862	0.932	0.886
RUN (Ours)	PVT V2	**0.021**	**0.877**	**0.958**	**0.916**	0.045	**0.861**	**0.934**	**0.877**	**0.021**	0.810	**0.941**	**0.878**	**0.030**	**0.868**	**0.940**	**0.892**

Results on camouflaged object detection.



Visual comparison on COD, PIS, MTOS, and TOD tasks.



Performance in degraded COS scenarios.

Metrics	FEDER	FEDER-R	FGANet	FGANet-R	FSEL	FSEL-R
$M\downarrow$	0.032	0.031	0.032	0.032	0.032	0.031
$F_\beta\uparrow$	0.715	0.721	0.708	0.716	0.722	0.725
$E_\phi\uparrow$	0.892	0.897	0.894	0.897	0.891	0.890
$S_\alpha\uparrow$	0.810	0.812	0.803	0.805	0.822	0.825

Potential of RUN to serve as a refiner.

Metrics	FEDER	FEDER+	FGANet	FGANet+	FSEL	FSEL+
$M\downarrow$	0.032	0.031	0.032	0.031	0.032	0.030
$F_\beta\uparrow$	0.715	0.726	0.708	0.730	0.722	0.738
$E_\phi\uparrow$	0.892	0.902	0.894	0.901	0.891	0.905
$S_\alpha\uparrow$	0.810	0.816	0.803	0.808	0.822	0.830

Generalization of RUN.

Personal Information

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Related Works

1. FEDER, CVPR23.
2. WS-SAM, NeurIPS23.
3. Camouflageator, ICLR24.
4. SEE, TPAMI.