Lightweight Deep Unrolling Network With Enhanced Robustness For Infrared Small Target Detection

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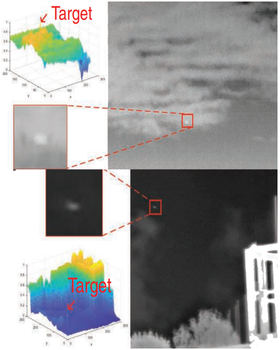
Joint work with Yinchao Han (SHU), Jingjing Liu (SHU) and Wanquan Liu (SYSU)

ISTD

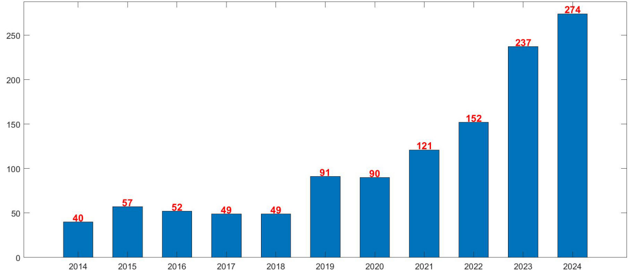
- Infrared small target detection (ISTD)



- Difficulties: small size, low SNR, weak contrast
- Advantages: strong concealment, good anti-interference

ISTD

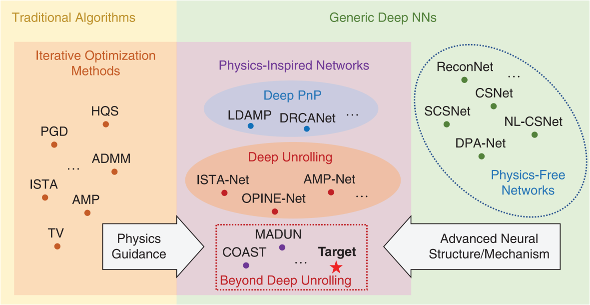
- Trends of "infrared small target detection" on Google Scholar



- Existing methods
  - Filter-based: spatial domain, transformed domain
  - Local information-based: local contrast, local entropy
  - Data structure-based: subspace, dictionary, tensor representation
  - Deep learning-based

DUN

- From iterative optimization to deep unrolling networks
  - Gregor-LeCun, ICML, 2010
  - Yang-Sun-Li-Xu, IEEE TPAMI, 2020
  - Zhang-Chen-Xiong-Zhang, IEEE SPM, 2023
  - Chen-Liu-Yin, Science China Mathematics, 2024

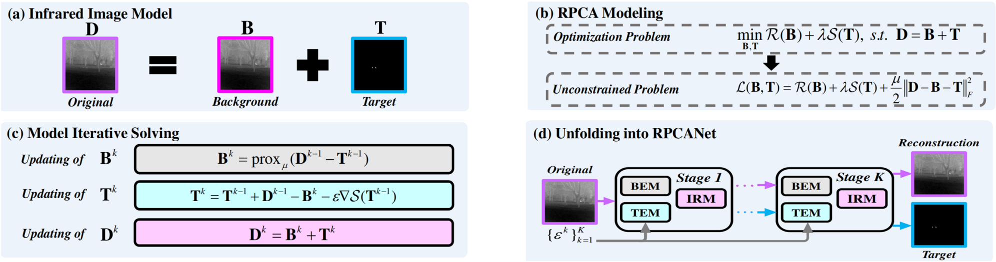


- https://github.com/xianchaoxiu/AI4OPT

RPCANet

- From RPCA to RPCANet

$$\min_{B,T} \|B\|_* + \lambda \|T\|_1 \quad \text{s.t.} \quad D = B + T$$



How to enhance robustness? How to realize lightweight?

Methodology

- From RPCANet to RPCANet+

$$\min_{B,T} \quad \|B\|_* + \lambda \|T\|_1 \qquad \text{s.t.} \quad D = B + T$$

$$\Downarrow$$

$$\min_{B,T,N} \quad \|B\|_* + \lambda \|T\|_1 + \mu \|N\|_F^2 \qquad \text{s.t.} \quad D = B + T + N$$

$$\Downarrow$$

$$\min_{B,T,N} \quad \mathcal{R}(B) + \lambda \mathcal{S}(T) + \mu \mathcal{G}(N) \qquad \text{s.t.} \quad D = B + T + N$$

- Unconstrained version

$$\mathcal{L}(B, T, N) = \mathcal{R}(B) + \lambda \mathcal{S}(T) + \mu \mathcal{G}(N) + \frac{\alpha}{2} \|D - B - T - N\|_F^2$$

Update B

- Bcakgound estimation module + squeeze-and-excitation network (SEBEM)

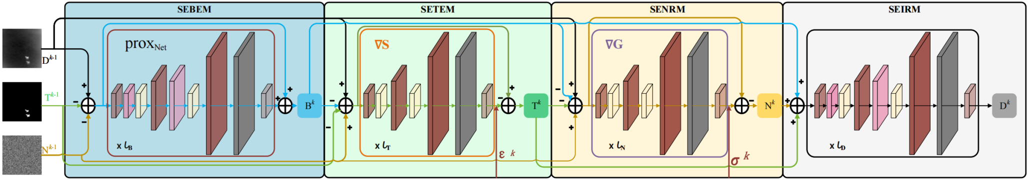
$$B^k = \arg\min_B \ \mathcal{R}(B) + \frac{\alpha}{2}\|D^{k-1} - B - T^{k-1} - N^{k-1}\|_F^2$$

$$\Downarrow$$

$$B^k = \mathrm{prox}_\alpha(D^{k-1} - T^{k-1} - N^{k-1})$$

$$\Downarrow$$

$$B^k = D^{k-1} - T^{k-1} - N^{k-1} + \mathcal{W}^k(D^{k-1} - T^{k-1} - N^{k-1})$$



Update T

- Target estimation module + squeeze-and-excitation network (SETEM)

$$T^k = \arg\min_T \ \lambda \mathcal{S}(T) + \frac{\alpha}{2}\|D^{k-1} - B^k - T - N^{k-1}\|_F^2$$

$$\Downarrow$$

$$T^k = \arg\min_T \ \frac{\lambda L_{\mathcal{S}}}{2}\|T - T^{k-1} + \frac{1}{L_{\mathcal{S}}}\nabla \mathcal{S}(T^{k-1})\|_F^2 + \frac{\alpha}{2}\|D^{k-1} - B^k - T - N^{k-1}\|_F^2$$

$$\Downarrow$$

$$T^k = \frac{\lambda L_{\mathcal{S}}}{\lambda L_{\mathcal{S}} + \alpha} T^{k-1} + \frac{\alpha}{\lambda L_{\mathcal{S}} + \alpha}\left(D^{k-1} - B^k - N^{k-1}\right) - \frac{\lambda}{\lambda L_{\mathcal{S}} + \alpha}\nabla \mathcal{S}(T^{k-1})$$

$$\Downarrow$$

$$T^k = \gamma T^{k-1} + (1-\gamma)(D^{k-1} - B^k - N^{k-1}) - \varepsilon \nabla \mathcal{S}(T^{k-1})$$

Update T

- Set $\gamma = 0.5$

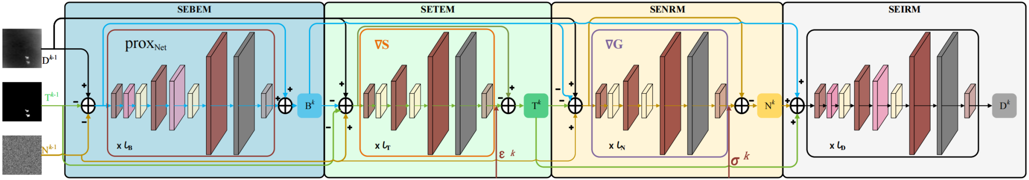
$$T^k = \gamma T^{k-1} + (1-\gamma)(D^{k-1} - B^k - N^{k-1}) - \varepsilon \nabla \mathcal{S}(T^{k-1})$$

$$\Downarrow$$

$$T^k = T^{k-1} + D^{k-1} - B^k - N^{k-1} - \varepsilon \nabla \mathcal{S}(T^{k-1})$$

$$\Downarrow$$

$$T^k = T^{k-1} + D^{k-1} - B^k - N^{k-1} - \varepsilon^k \mathcal{H}^k(T^{k-1} + D^{k-1} - B^k - N^{k-1})$$



Update N

- Noise reduction module + squeeze-and-excitation network (SENRM)

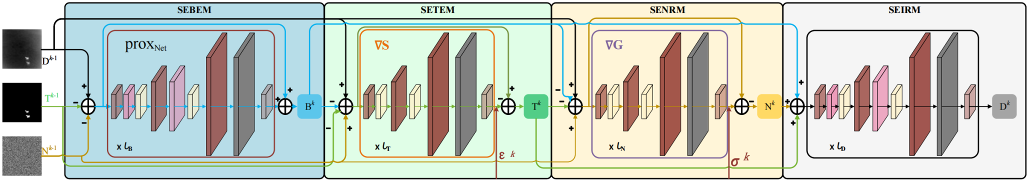
$$N^k = \arg\min_N \; \mu\mathcal{G}(N) + \frac{\alpha}{2}\|D^{k-1} - B^k - T^k - N\|_F^2$$

$$\Downarrow$$

$$N^k = \arg\min_N \; \frac{\mu L_N}{2}\|N - N^{k-1} + \frac{1}{L_N}\nabla\mathcal{G}(N^{k-1})\|_F^2 + \frac{\alpha}{2}\|D^{k-1} - B^k - T^k - N\|_F^2$$

$$\Downarrow$$

$$N^k = N^{k-1} + D^{k-1} - B^k - T^k - \sigma^k \mathcal{F}^k(N^{k-1} + D^{k-1} - B^k - T^k)$$



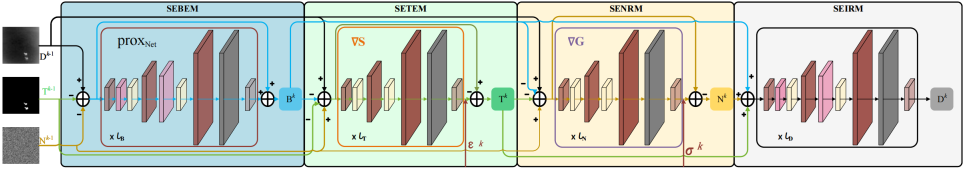
Update D

- Image reconstruction module + squeeze-and-excitation network (SEIRM)

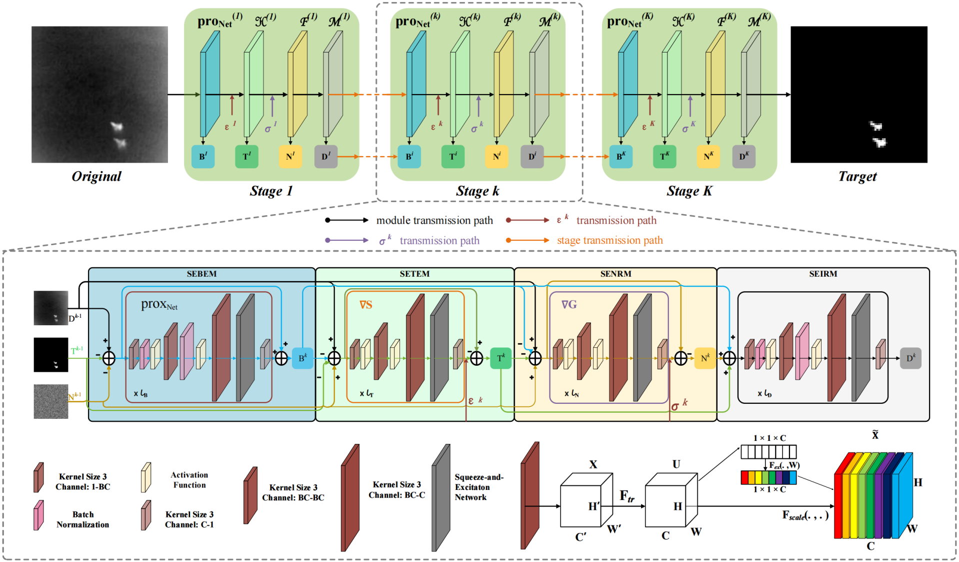
$$D^k = B^k + T^k + N^k$$

$$\Downarrow$$

$$D^k = \mathcal{M}^k(B^k + T^k + N^k)$$



Architecture



Experiment

- Compared methods
  - IPI: Gao-Meng-Yang-Wang-Zhou-Hauptmann, IEEE TIP, 2013
  - MPCM: Wei-You-Li, PR, 2016
  - PSTNN: Zhang-Peng, RS, 2019
  - AGPCNet: Zhang-Li-Cao-Pu-Peng, IEEE TAES, 2023
  - UIUNet: Wu-Hong-Chanussot, IEEE TIP, 2023
  - MSHNet: Liu-Liu-Zheng-Wang-Fu, CVPR, 2024
  - RPCANet: Wu-Zhang-Li-Huang-Peng, WACV, 2024
- Evaluation metrics
  - Mean intersection over union (mIoU $\uparrow$), F_1-score ($\mathrm{F}_1 \uparrow$), Probability of detection ($\mathrm{P}_\mathrm{d} \uparrow$)
  - False alarm rate ($\mathrm{F}_\mathrm{a} \downarrow$)
- Loss function

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{segmentation}} + \eta\mathcal{L}_{\text{fidelity}} = \left(1 - \frac{1}{M_t}\sum_{i=1}^{M_t}\frac{\mathrm{TP}}{\mathrm{FP}+\mathrm{TP}+\mathrm{FN}}\right) + \frac{\eta}{M_t M}\sum_{i=1}^{M_t}\|D^K - D\|_F^2$$

Performance

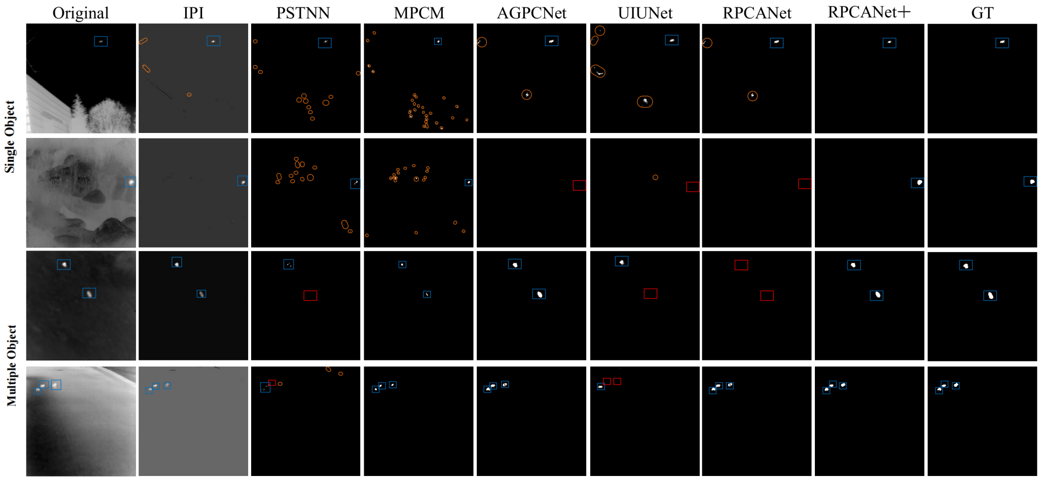
- Quantitative results

Methods	#Params	NUDT-SIRST				IRSTD-1k				SIRST-Aug				Time(s)
		mIoU ↑	F_1 ↑	P_d ↑	F_a ↓	mIoU ↑	F_1 ↑	P_d ↑	F_a ↓	mIoU ↑	F_1 ↑	P_d ↑	F_a ↓	CPU/GPU
IPI	–	34.83	51.49	92.58	7.14	18.67	31.48	78.54	11.11	21.90	35.97	80.36	**2.20**	3.0972/-
PSTNN	–	25.46	40.58	78.52	7.95	14.87	25.89	68.73	6.51	19.76	33.00	93.40	3.14	0.2249/-
MPCM	–	25.96	40.78	78.59	7.91	14.81	25.93	69.03	6.51	19.49	33.00	93.58	3.04	0.0624/-
AGPCNet	12.360M	85.41	92.15	98.10	4.72	61.00	75.75	89.35	5.34	72.36	83.83	99.03	35.56	-/0.0205
UIUNet	50.540M	88.71	94.01	91.43	1.89	63.06	77.35	**93.60**	6.57	71.80	83.59	98.35	28.29	-/0.0317
MSHNet	4.065M	75.99	86.57	96.07	2.63	64.50	77.55	91.68	4.46	71.64	84.16	90.78	23.09	-/0.0245
RPCANet	0.680M	89.31	94.35	97.14	2.87	63.21	77.45	88.31	**4.39**	72.54	84.08	98.21	34.14	-/0.0096
RPCANet+	**0.216M**	**92.37**	**96.04**	**98.41**	**1.79**	**64.68**	**78.55**	89.39	4.66	**74.56**	**85.43**	**99.17**	29.78	-/**0.0072**

	NUDT-SIRST	IRSTD-1k	SIRST-Aug
#Size	256 × 256	512 × 512	256 × 256
#Training	663	800	8525
#Testing	662	201	545

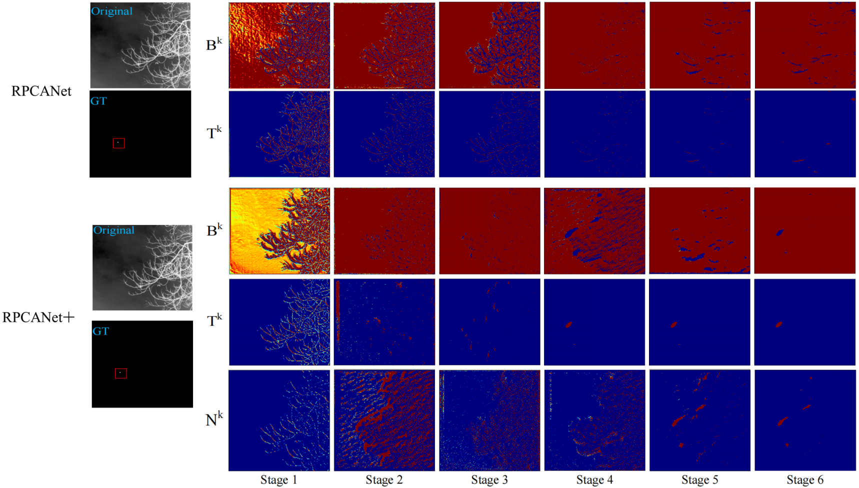
Visualization

- Comparisons on IRSTD-1k



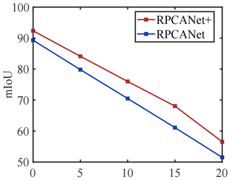
Visualization

- A close look at stages

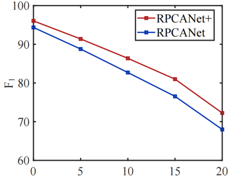


Robustness

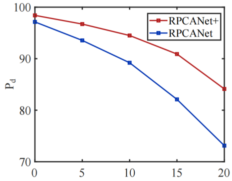
- Gaussian noise



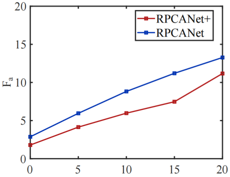
(a) mIoU



(b) F_1

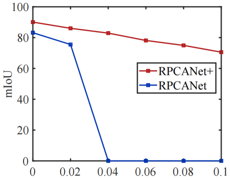


(c) P_d

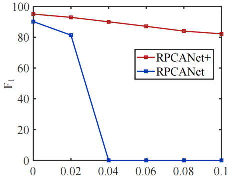


(d) F_a

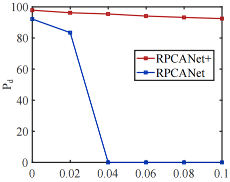
- Salt-and-pepper noise



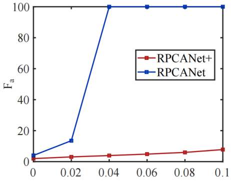
(a) mIoU



(b) F_1



(c) P_d



(d) F_a

Discussion

- Effects of stage K

K	#Params	NUDT-SIRST		IRSTD-1k		SIRST-Aug	
		mIoU ↑	F_1 ↑	mIoU ↑	F_1 ↑	mIoU ↑	F_1 ↑
1	0.0360M	72.83	84.28	91.39	95.51	61.26	75.98
2	0.0720M	72.96	84.37	91.61	95.62	61.59	76.24
3	0.1080M	73.58	84.78	91.53	95.58	62.60	77.00
4	0.1439M	73.81	84.93	90.06	95.06	61.98	76.53
5	0.1799M	74.28	85.24	91.64	95.64	63.45	77.63
6	**0.2159M**	**74.56**	**85.43**	**92.37**	**96.04**	**64.68**	**78.55**
7	0.2519M	72.29	83.92	88.53	93.58	62.29	76.76

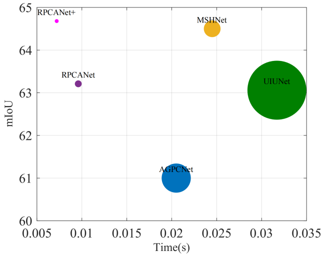
- Effects of bottleneck channel (BC) and total channel (TC)

#BC	#TC	mIoU ↑	F_1 ↑
4	**32**	**74.56**	**85.43**
4	40	72.54	83.08
4	48	72.10	82.59
4	56	70.34	80.08
4	64	68.54	78.35
8	32	73.96	85.03
16	32	71.19	83.17

Conclusion

- Conclusion
  - How to enhance robustness? $\Rightarrow$ RPCA + noise reduction + attention mechanism
  - How to realize lightweight? $\Rightarrow$ intermediate bottleneck + multi-layer mapping

Methods	mIoU ↑	F_1 ↑	P_d ↑	F_a ↓
IPI	25.13	39.65	83.83	6.81
PSTNN	20.03	33.16	80.22	5.87
MPCM	20.09	33.24	80.40	**5.82**
RPCANet+	**77.20**	**86.67**	**95.66**	**12.08**



- What about the convergence?
  - Ryu-Liu-Wang-Chen-Wang-Yin, ICML, 2019
  - Mukherjee-Hauptmann-Öktem-Pereyra-Schönlieb, IEEE SPM, 2023

References

- Gao-Meng-Yang-Wang-Zhou-Hauptmann, Infrared Patch-Image Model for Small Target Detection in A Single Image, IEEE TIP, 2013
- Zhang-Ghanem, ISTA-Net: Interpretable Optimization-Inspired Deep Network for Image Compressive Sensing, CVPR, 2018
- Zhao-Li-Li-Hu-Ma-Tao, Single-Frame Infrared Small-Target Detection: A Survey, IEEE GRSM, 2022
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- Wu-Zhang-Li-Huang-Peng, RPCANet: Deep Unfolding RPCA Based Infrared Small Target Detection, WACV, 2024

Thank you for your attention!

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