

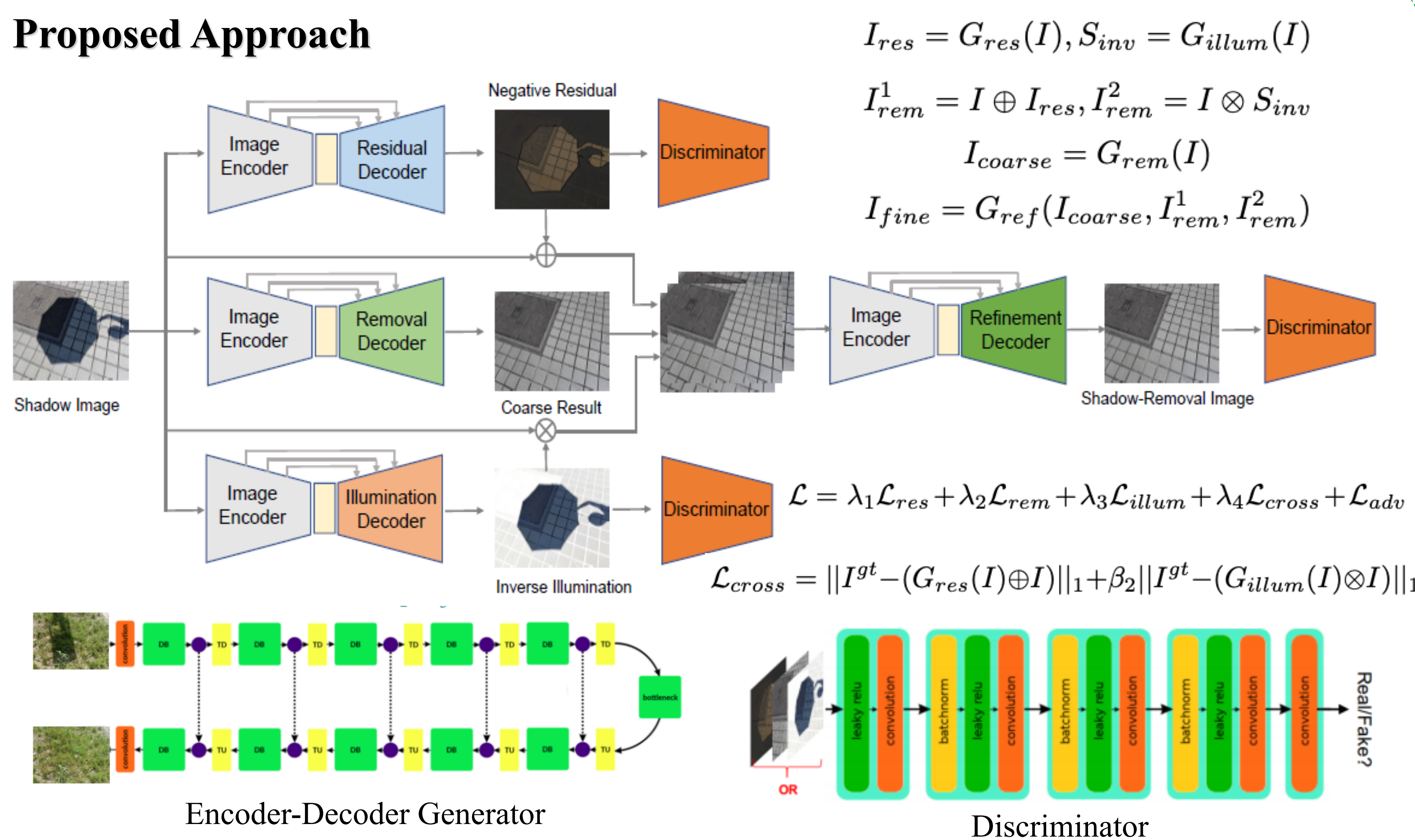
## Problem & Background

- Traditional methods rely on some prior knowledge, e.g., gradients between shadow and non-shadow regions → obvious artifacts on shadow boundaries.
- The effectiveness of learning-based methods highly depends on the training dataset and the designed network architectures.
- Most of existing deep learning methods just focus on shadow itself, without well exploring other extra information like residual and illumination for shadow removal.

## Contributions

- We are the first one to propose a general and novel framework RIS-GAN to explore residual and illumination for shadow removal, which can produce high-quality shadow removal results.
- The correlation among residual, illumination and shadow has been well explored within a cross loss function and the joint discriminator.
- The proposed framework is easy to be extended to general image-level applications.

## Proposed Approach



## Quantitative Shadow Removal Result

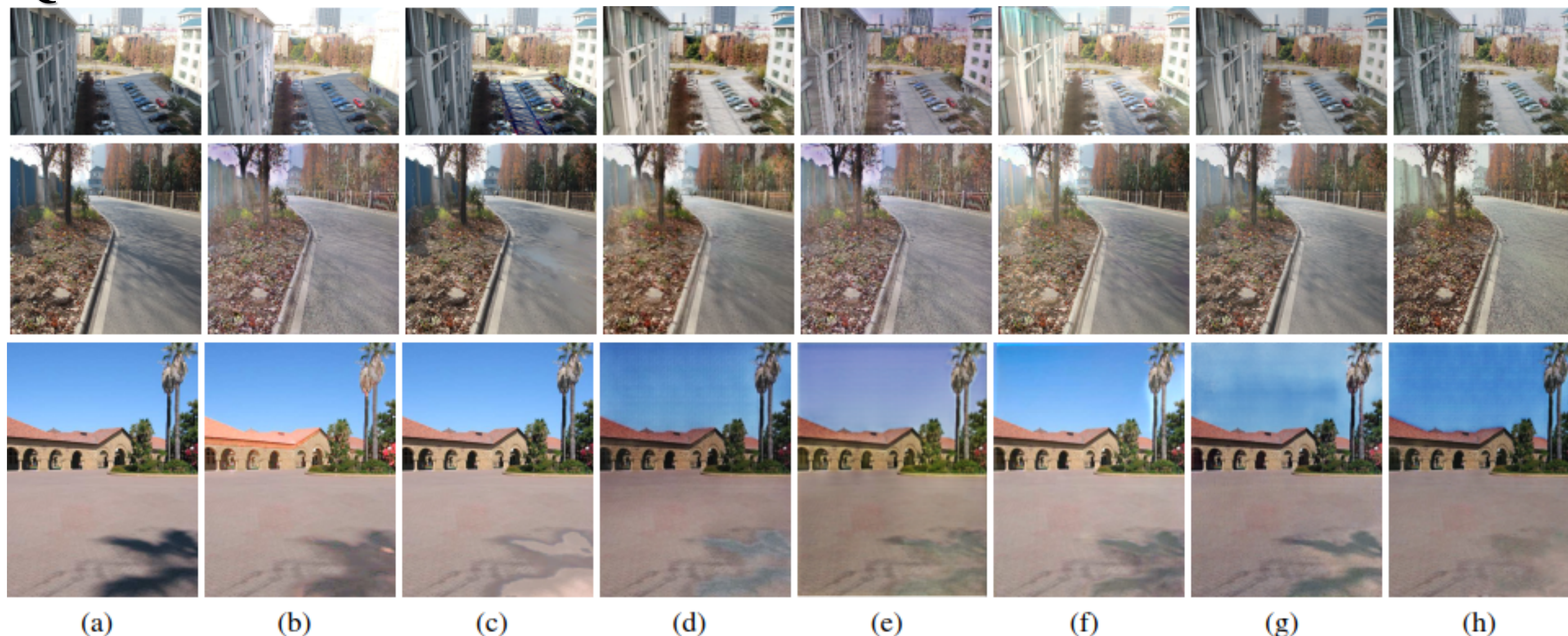
On the SRD dataset (RMSE)

Methods	Venue/Year	S	N	A
Guo	CVPR/2011	31.06	6.47	12.60
Zhang	TIP/2015	9.50	6.90	7.24
Global/Local-GAN	TOG/2017	19.56	8.17	16.33
Pix2Pix-HD	CVPR/2018	17.33	7.79	12.58
Deshadow	CVPR/2017	17.96	6.53	8.47
ST-CGAN	CVPR/2018	18.64	6.37	8.23
DSC	CVPR/2018	11.31	6.72	7.83
AngularGAN	CVPRW/2019	17.63	7.83	15.97
RIS-GAN	AAAI/2020	8.22	6.05	6.78

On the ISTD dataset (RMSE)

Methods	Venue/Year	S	N	A
Guo	CVPR/2011	18.95	7.46	9.30
Zhang	TIP/2015	9.77	7.12	8.16
Global/Local-GAN	TOG/2017	13.46	7.67	8.82
Pix2Pix-HD	CVPR/2018	10.63	6.73	7.37
Deshadow	CVPR/2017	12.76	7.19	7.83
ST-CGAN	CVPR/2018	10.31	6.92	7.46
DSC	CVPR/2018	9.22	6.50	7.10
AngularGAN	CVPRW/2019	9.78	7.67	8.16
RIS-GAN	AAAI/2020	8.99	6.33	6.95

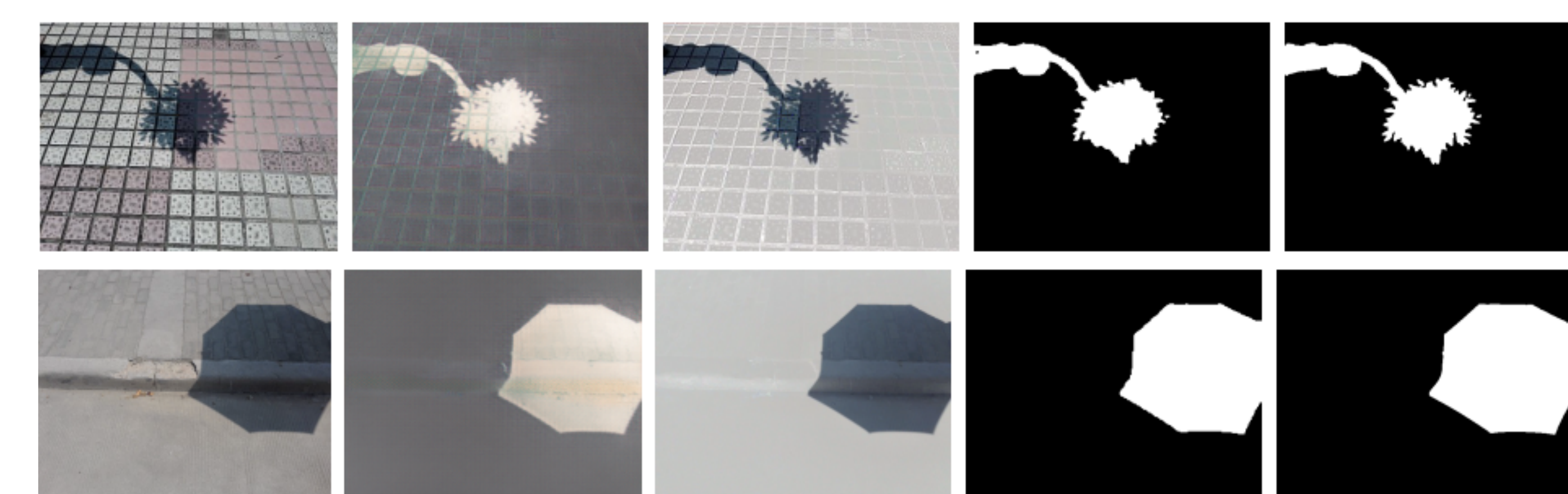
## Qualitative Shadow Removal Results



From left to right are input images (a), shadow-removal results of Guo (b), Zhang (c), DeshadowNet (d), ST-CGAN (e), DSC (f), and AngularGAN (g), and shadow-removal results of our RIS-GAN (h).

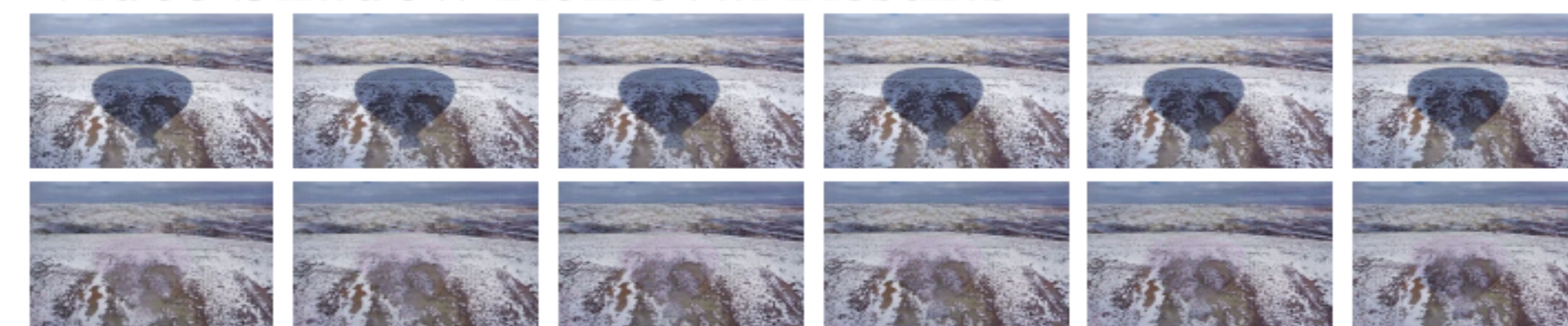
**Conclusion:** The correlation among residual, illumination and shadow has been well explored under a unified end-to-end framework, from which we are able to get complementary input sources to generate a high-quality shadow-removal image.

## Shadow Detection Results



From left to right are input images, negative residual images, inverse illumination maps, prediction shadow masks based on the explored residual and illumination, and ground-truth shadow masks, respectively.

## Video Shadow Removal Results



## Key References

- [Guo] R. Guo et al. Single-image shadow detection and removal using paired regions. CVPR, 2011.  
 [Zhang] L. Zhang et al. Shadow remover: Image shadow removal based on illumination recovering optimization. TIP, 2015.  
 [DSC] X. Hu et al. Direction-aware spatial context features for shadow detection and removal. CVPR, 2018.  
 [AngularGAN] Sidorov, O. Conditional gans for multi-illuminant color constancy: Revolution or yet another approach? CVPRW, 2019.

- [ST-CGAN] J. Wang et al. Stacked conditional generative adversarial networks for jointly learning shadow detection and shadow removal. CVPR, 2018.  
 [BDRAR] Wang, T.-C. et al. High-resolution image synthesis and semantic manipulation with conditional gans. CVPR, 2018.  
 [DeshadowNet] L. Qu et al. Deshadownet: A multi-context embedding deep network for shadow removal. CVPR, 2017.