Mask-ShadowGAN: Learning to Remove Shadows from Unpaired Data

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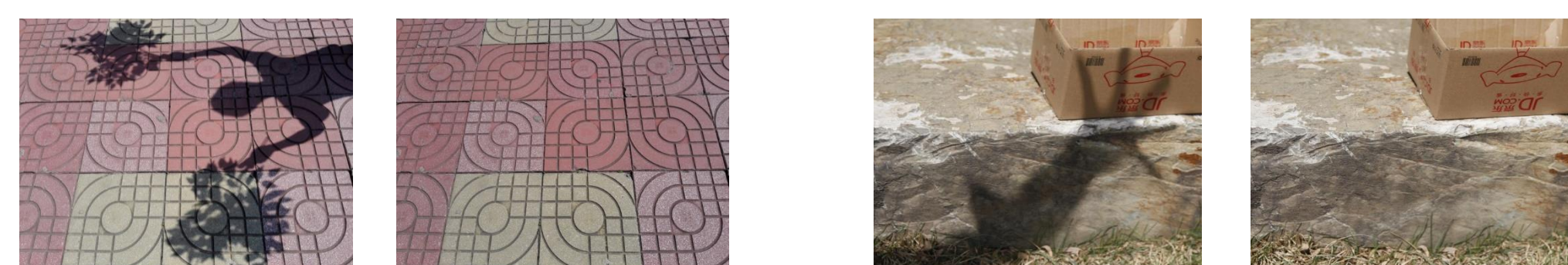
ICCV 2019
Seoul, Korea

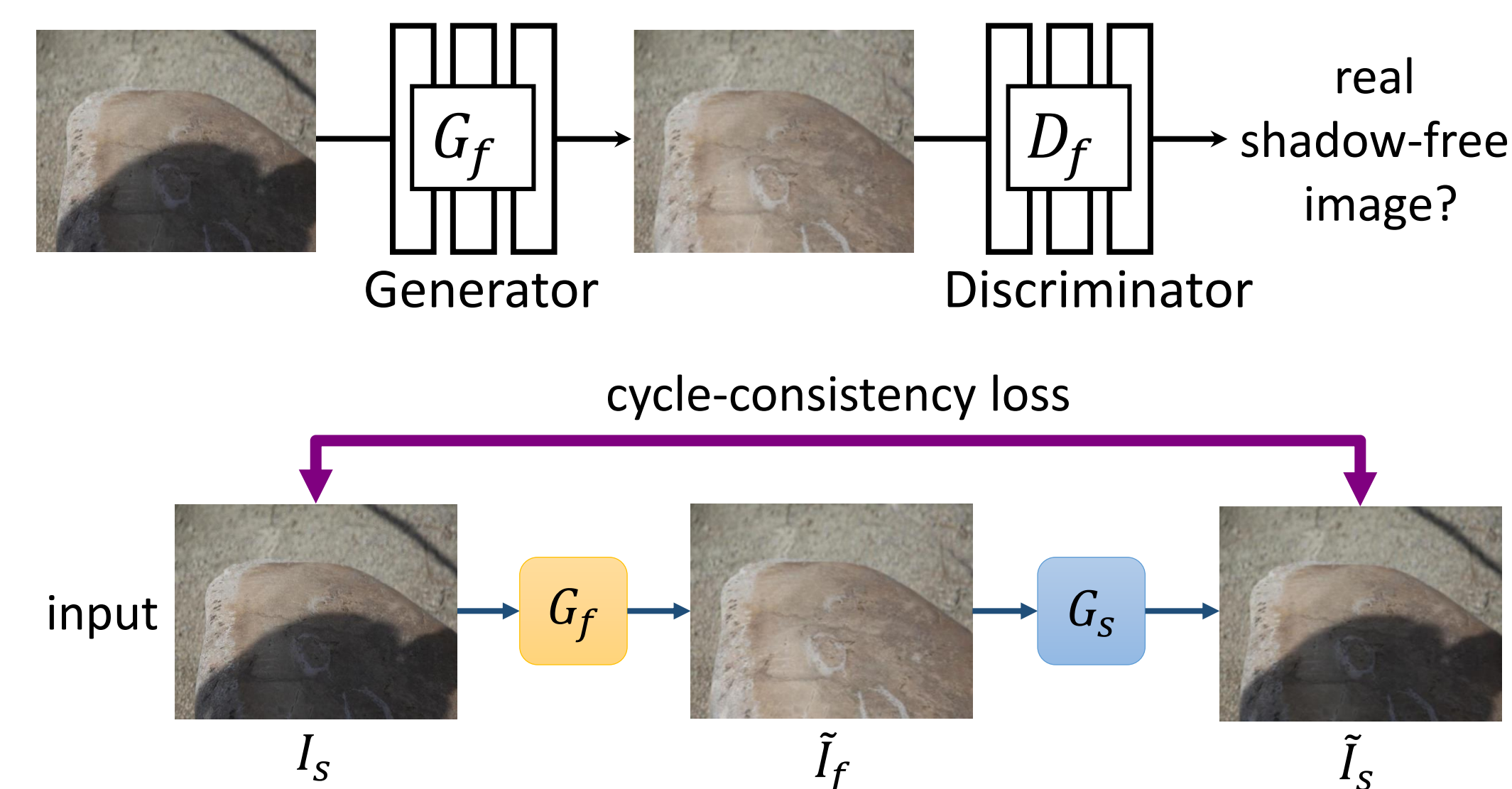## Motivation #1:

Limitations of paired training data:

➤ It is very tedious to prepare the training data.

➤ The approach limits the kinds of scenes that data can be prepared.

➤ Training pairs may have inconsistent colors or shift in camera views.

Learn to remove shadows from unpaired training data:

Shadow Domain

Shadow-free Domain

G_f Generator D_f Discriminator   real shadow-free image?

cycle-consistency loss

input I_s G_f $\tilde{I}_f$ G_s $\tilde{I}_s$

Our Unpaired Shadow Removal Dataset - USR

➤ 2,445 shadow images (training : testing = 1,956 : 289)

➤ 1,770 shadow-free images (training)

➤ Shadows are cast by various kinds of objects, e.g., trees, buildings, traffic signs, persons, umbrellas, railings, etc.

➤ Existing datasets cover only hundreds of different backgrounds, while ours cover over a thousand different backgrounds.

Motivation #2:

not match

G_f G_s

not match

vs.
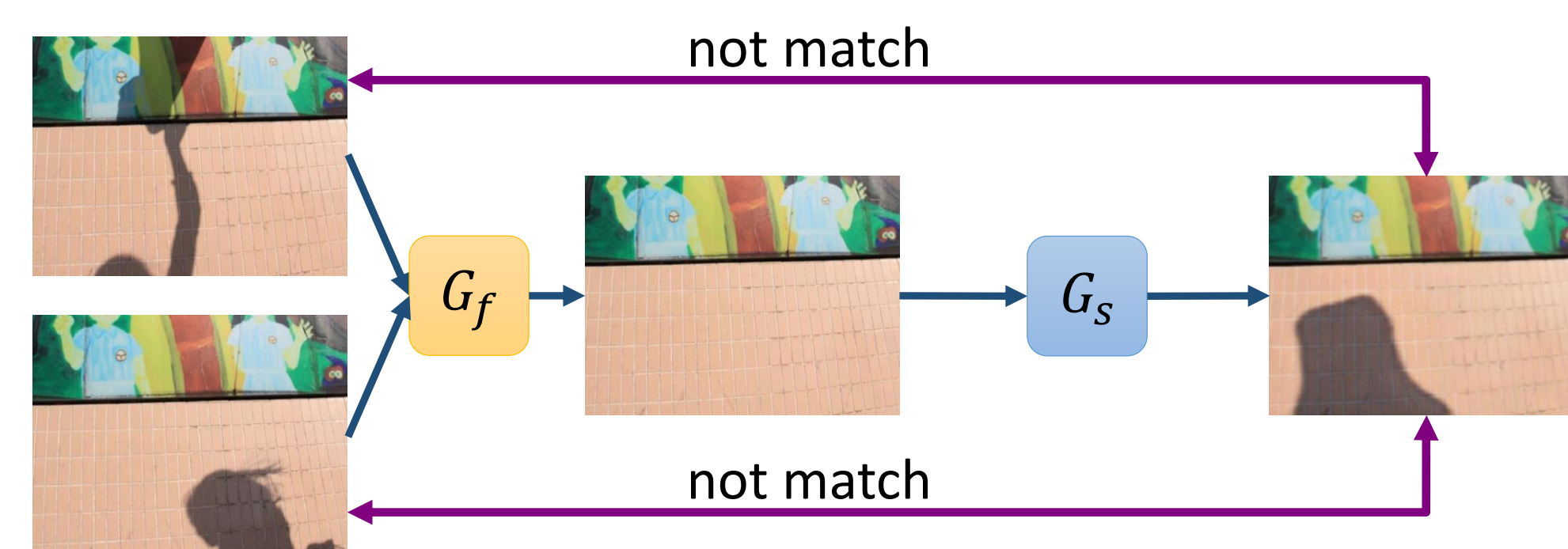
(a) Cycle-consistency constraint (conventional)

➤ On the same background, we may have different shadows.

➤ However, the generator G_s can only produce a unique shadow image from a given shadow-free image (background).

➤ The generated shadow image cannot match different input shadow images (leftmost) and the cycle-consistency constraint cannot hold.
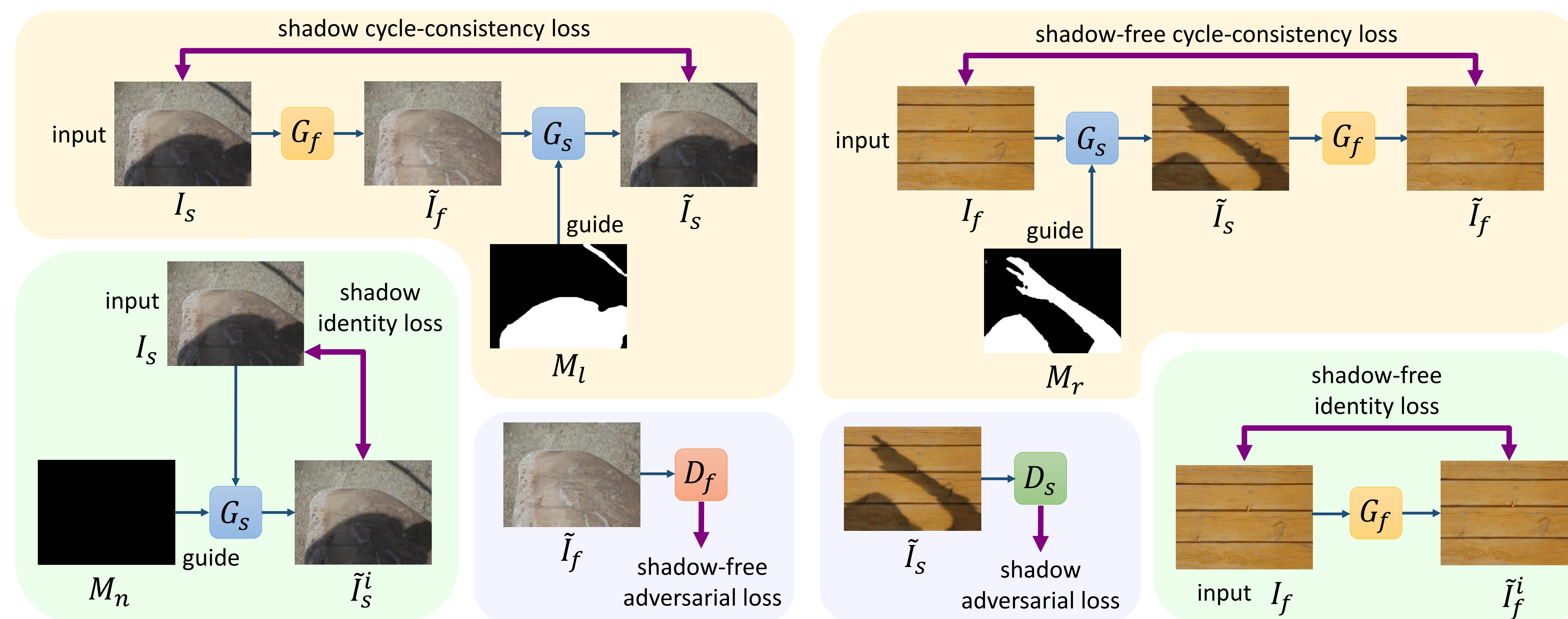
match

G_f $\ominus$ G_s

$\ominus$

match
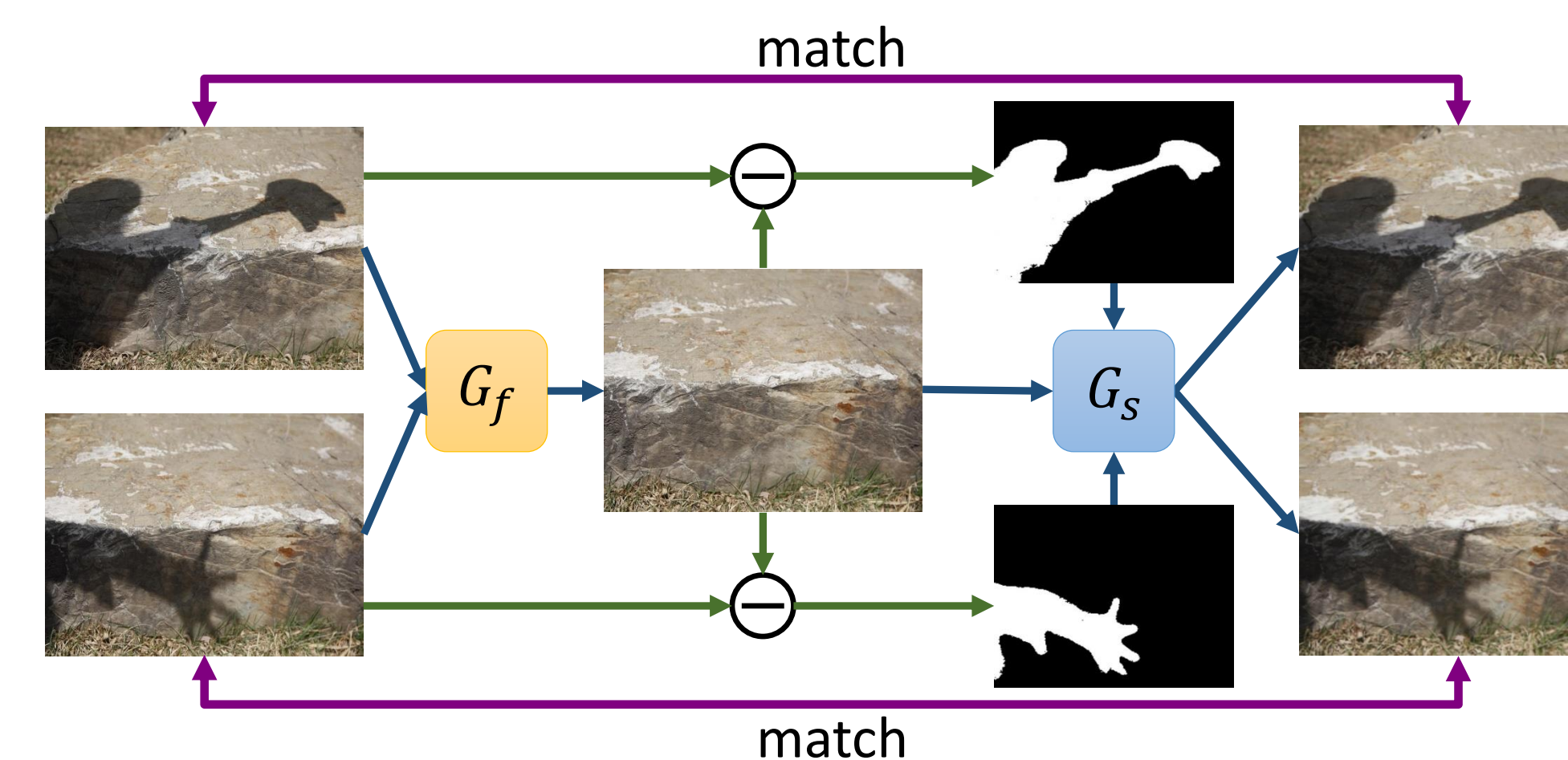
(b) Mask-guided cycle-consistency constraint (ours)

➤ On the same background, Mask-ShadowGAN can generate different shadow images.

➤ Our key idea is to first learn to produce a shadow mask from the input shadow image during the training and generate the shadow images with the help of shadow masks.

Mask-ShadowGAN

shadow cycle-consistency loss

input I_s G_f $\tilde{I}_f$ G_s $\tilde{I}_s$ guide M_l

input I_s shadow identity loss G_s guide $\tilde{I}_s^i$ M_n

$\tilde{I}_f$ D_f shadow-free adversarial loss

(a) Learning from shadow images

shadow-free cycle-consistency loss

input I_f G_s guide $\tilde{I}_s$ G_f $\tilde{I}_f$ M_r

$\tilde{I}_s$ D_s shadow adversarial loss

shadow-free identity loss G_f input I_f $\tilde{I}_f^i$

(b) Learning from shadow-free images

Experimental Results

● Comparison using USR testing set (user study)

	Methods	Rating (mean & standard dev.)
Trained on USR (unpaired)	**Mask-ShadowGAN**	**6.30 ± 2.97**
Trained on ISTD (paired)	DSC-I [TPAMI 19']	4.78 ± 2.92
	DSC-S [TPAMI 19']	4.60 ± 2.66
Trained on SRD (paired)	Gong et al. [BMVC 14']	2.82 ± 1.76
	Guo et al. [TPAMI 13']	2.31 ± 1.90

● Comparison using SRD & ISTD testing sets (RMSE)

Training data	Methods	SRD	ISTD
unpaired	**Mask-ShadowGAN**	**7.32**	**7.61**
	CycleGAN [ICCV 17']	9.14	8.16
paired	DSC [TPAMI 19']	6.21	6.67
	ST-CGAN [CVPR 18']	-	7.47
	DeshadowNet [CVPR 17']	6.64	-
-	Gong [BMVC 14']	8.73	8.53
	Guo et al. [TPAMI 13']	12.60	9.30
	Yang et al. [TIP 12']	22.57	15.63

● Comparison with CycleGAN

inputs   CycleGAN   Mask-ShadowGAN

inputs   CycleGAN   Mask-ShadowGAN

Code & data:
https://github.com/xw-hu/Mask-ShadowGAN