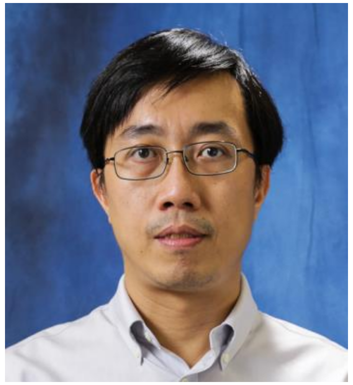
Direction-aware Spatial Context Features for Shadow Detection


Xiaowei Hu*


Lei Zhu*


Chi-Wing Fu


Jing Qin


Pheng-Ann Heng

The Chinese University of Hong Kong

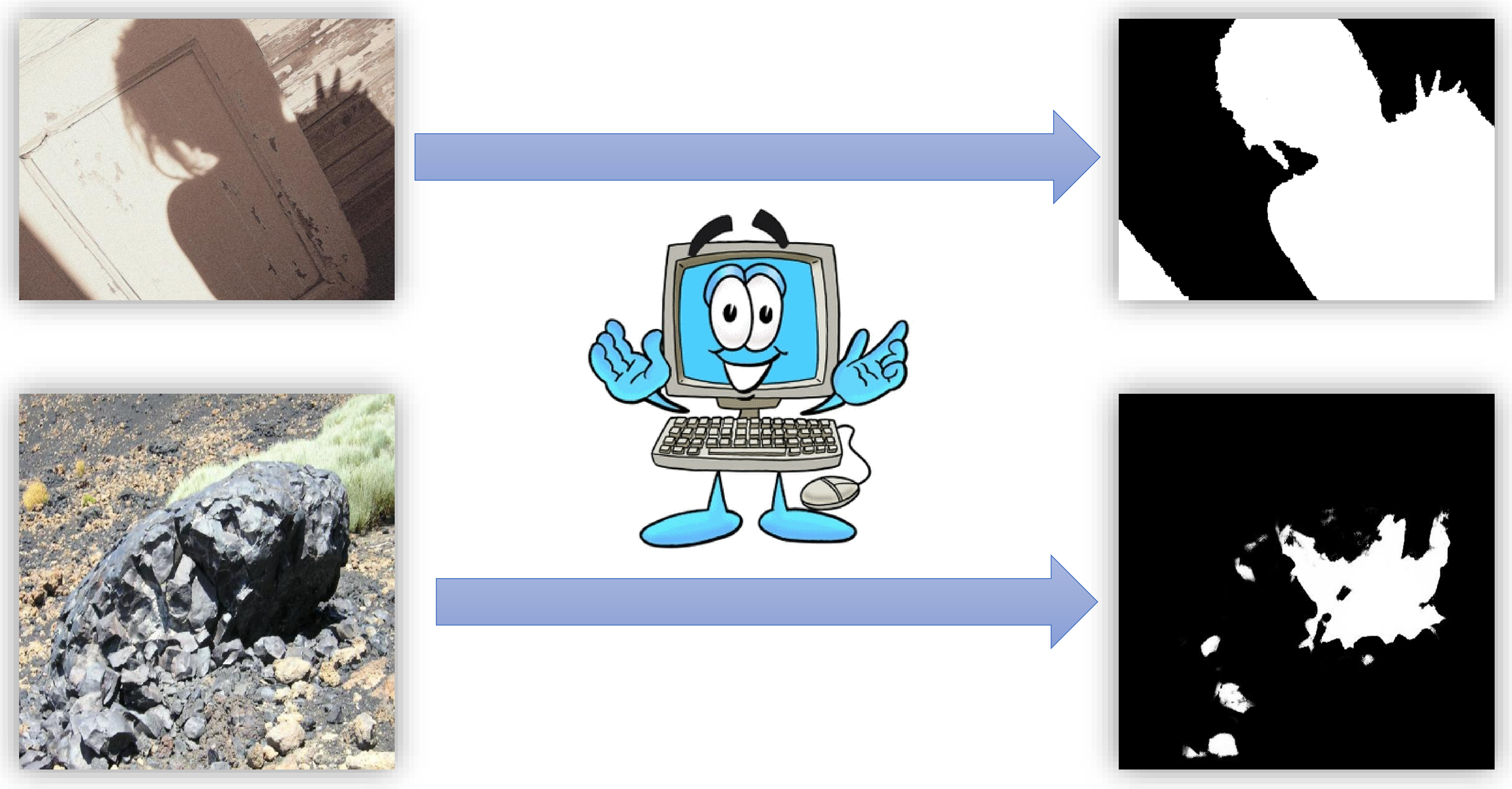
The Hong Kong Polytechnic University

Shenzhen Institutes of Advanced Technology

2018 CVPR

SALT LAKE CITY • JUNE 18-22

Problem



Related Works

2017	ICCV	V. Nguyen, et al.	Shadow detection with conditional generative adversarial networks.
2016	ECCV	T. F. Y. Vicente, et al.	Large-scale training of shadow detectors with noisily-annotated …
2016	Pattern Rec.	J. Tian, et al.	New spectrum ratio properties and features for shadow detection.
2015	CVPR	L. Shen, et al.	Shadow optimization from structured deep edge detection.
2015	ICCV	Y. Vicente, et al.	Leave-one-out kernel optimization for shadow detection.
2014	CVPR	S. H. Khan, et al.	Automatic feature learning for robust shadow detection
2011	CVPR	R. Guo, et al.	Single-image shadow detection and removal using paired regions.
2011	ICCV	X. Huang, et al.	What characterizes a shadow boundary under the sun and sky?
2011	CVPR	A. Panagopoulos, et al.	Illumination estimation and cast shadow detection through …
2010	CVPR	J. Zhu, et al.	Learning to recognize shadows in monochromatic natural images.
2010	ECCV	J.-F. Lalonde, et al.	Detecting ground shadows in outdoor consumer photographs.
…	…	…	…
1999	ICCV	T. Horprasert, et al.	A statistical approach for real-time robust background subtraction …
1995	BMVC	P.L. Rosin, et al.	Image difference threshold strategies and shadow detection.
1990	ICASSP	J.M. Scanlan, et al.	A shadow detection and removal algorithm for 2-D images

Related Works

- Data-driven approaches by learning the features using deep neural networks.

inputs scGAN stacked-CNN

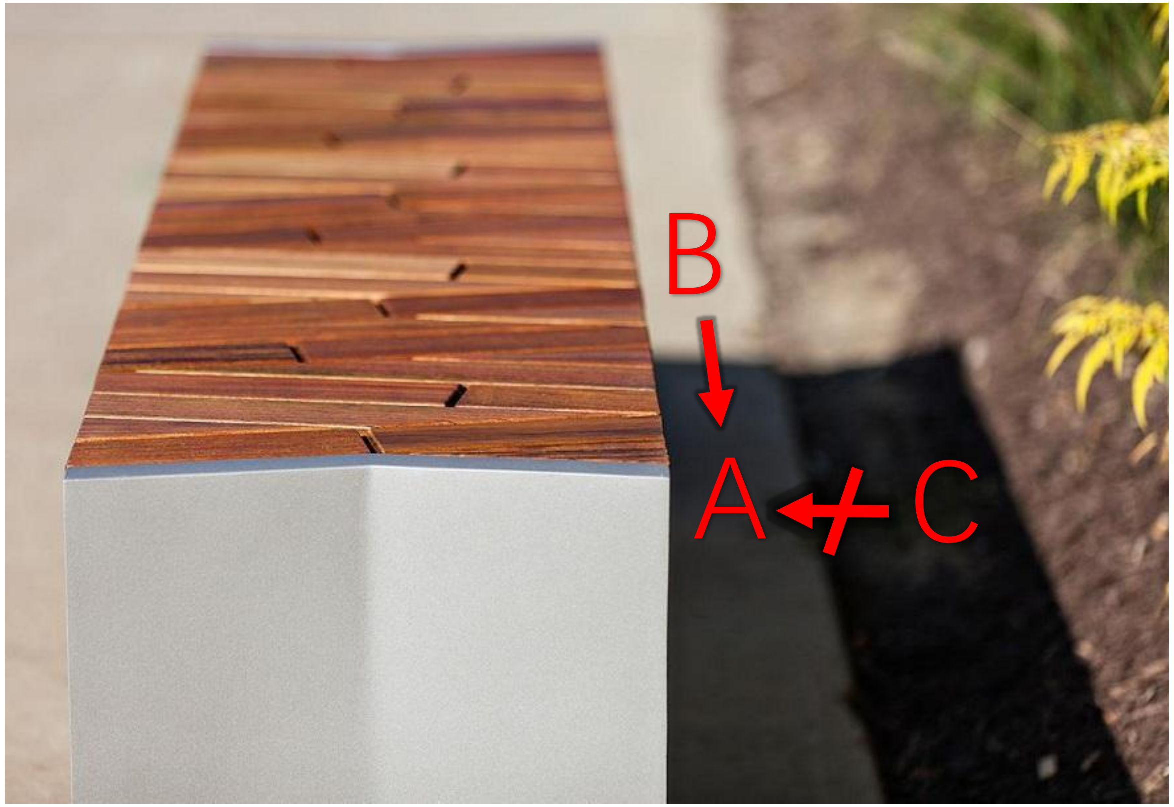
scGAN: V. Nguyen, et al., “Shadow detection with conditional generative adversarial networks,” In *ICCV*, 2017.
stacked-CNN: T. F. Y. Vicente, et al., “Large-scale training of shadow detectors with noisily-annotated shadow examples,” in *ECCV*, 2016.

Motivation

Motivation #1: Global Context

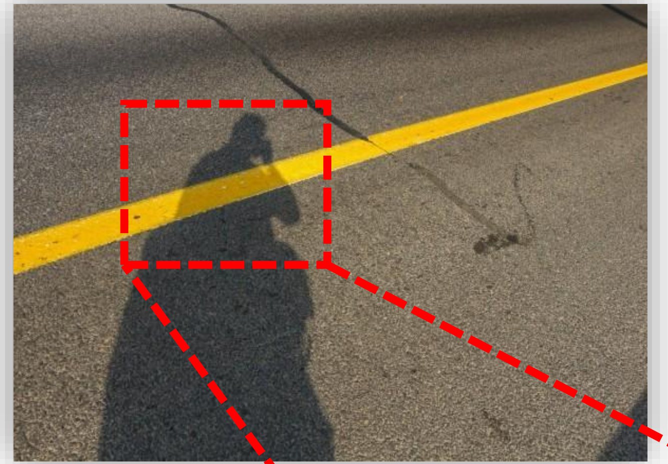
- Shadow detection requires an understanding of the ***global image context***

Motivation #2: Direction-aware Context

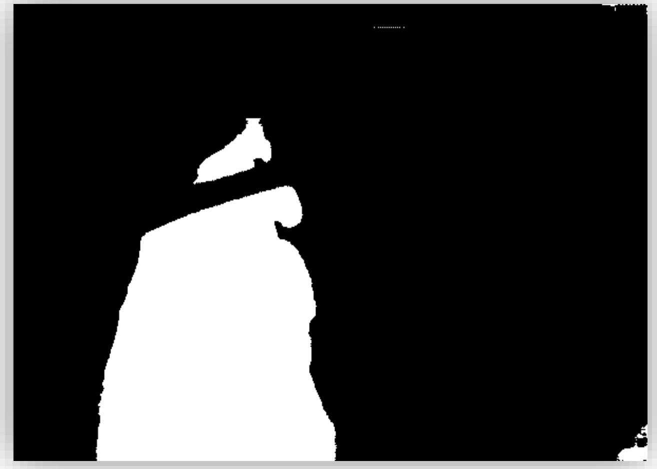


- Analyze the global image context in a ***direction-aware manner***

Motivation #2: Direction-aware Context

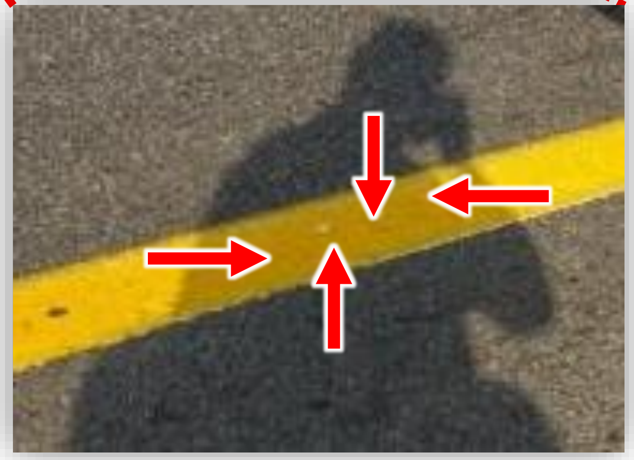


inputs



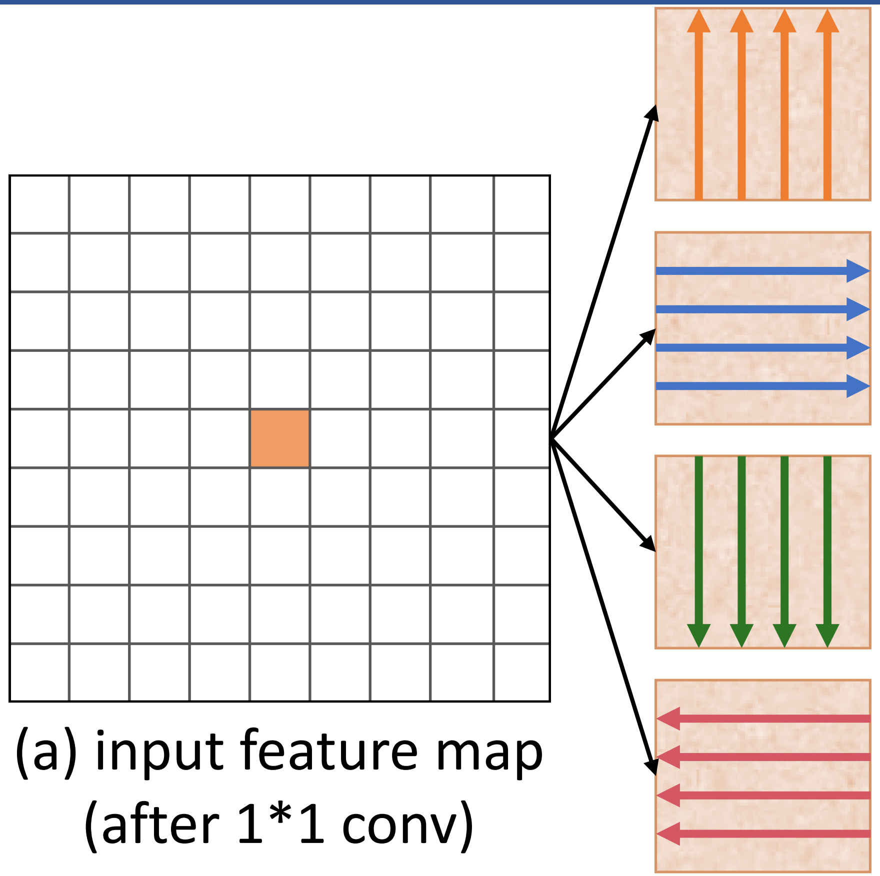
scGAN

stacked-CNN



ours

Spatial Recurrent Neural Network (RNN)



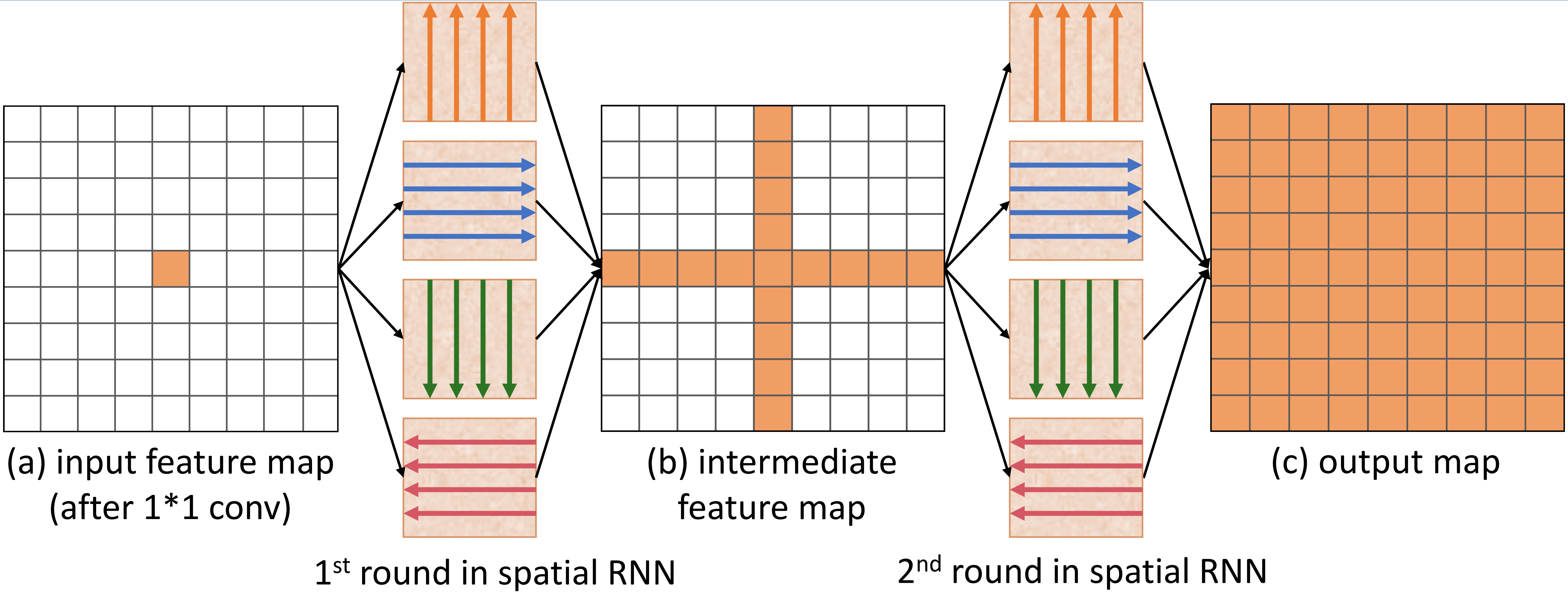
(a) input feature map
(after 1*1 conv)

1st round in spatial RNN

$$f_{i,j} = \max(\ \alpha_{\text{right}}\ f_{i,j-1} + f_{i,j}\ ,\ 0\ )$$

S. Bell, et al., "Inside-outside net: Detecting objects in context with skip pooling and recurrent neural networks," in *CVPR*, 2016.

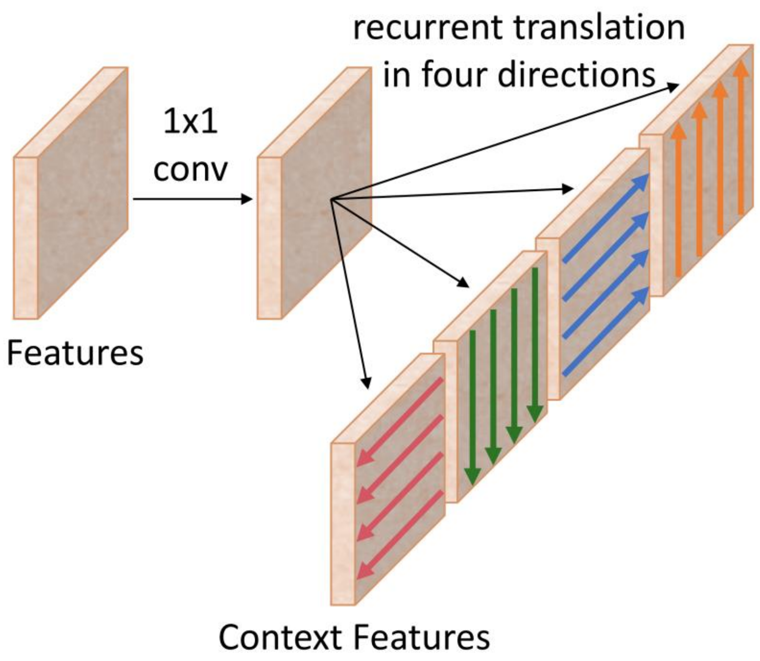
Spatial Recurrent Neural Network (RNN)

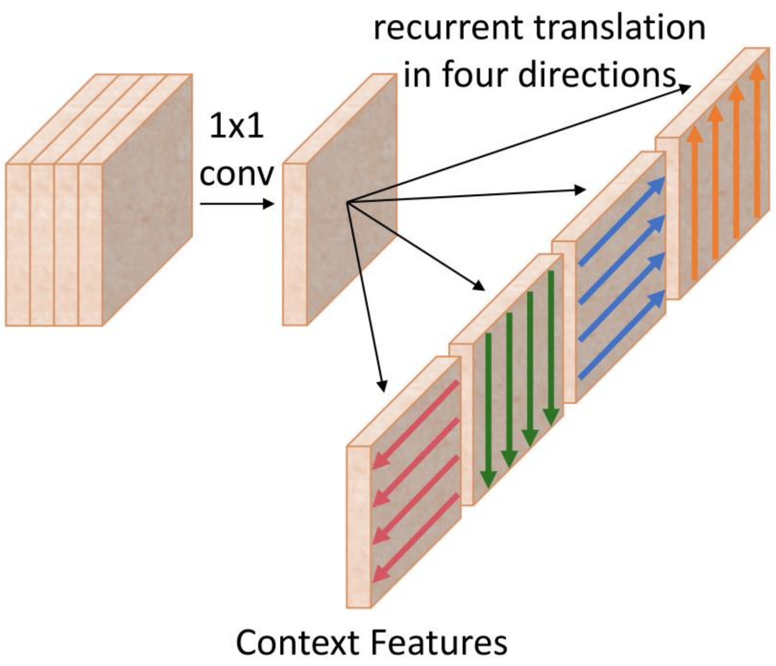


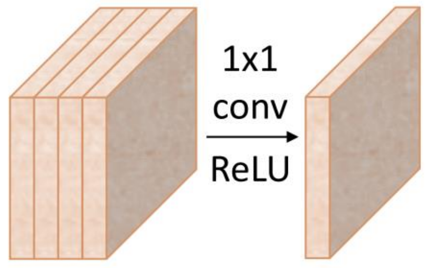
$$f_{i,j} = \max(\ \alpha_{\text{right}}\ f_{i,j-1} + f_{i,j}\ ,\ 0\ )$$

S. Bell, et al., "Inside-outside net: Detecting objects in context with skip pooling and recurrent neural networks," in *CVPR*, 2016.

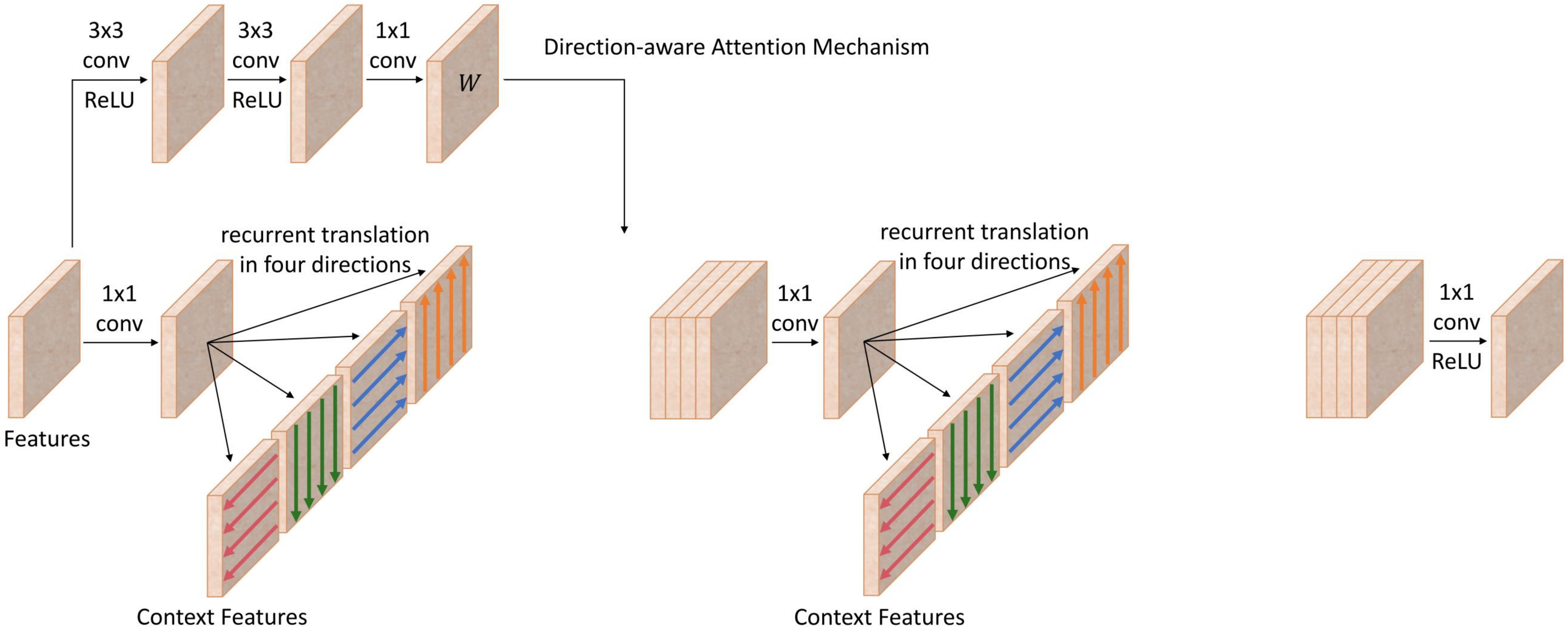
Spatial Recurrent Neural Network (RNN)



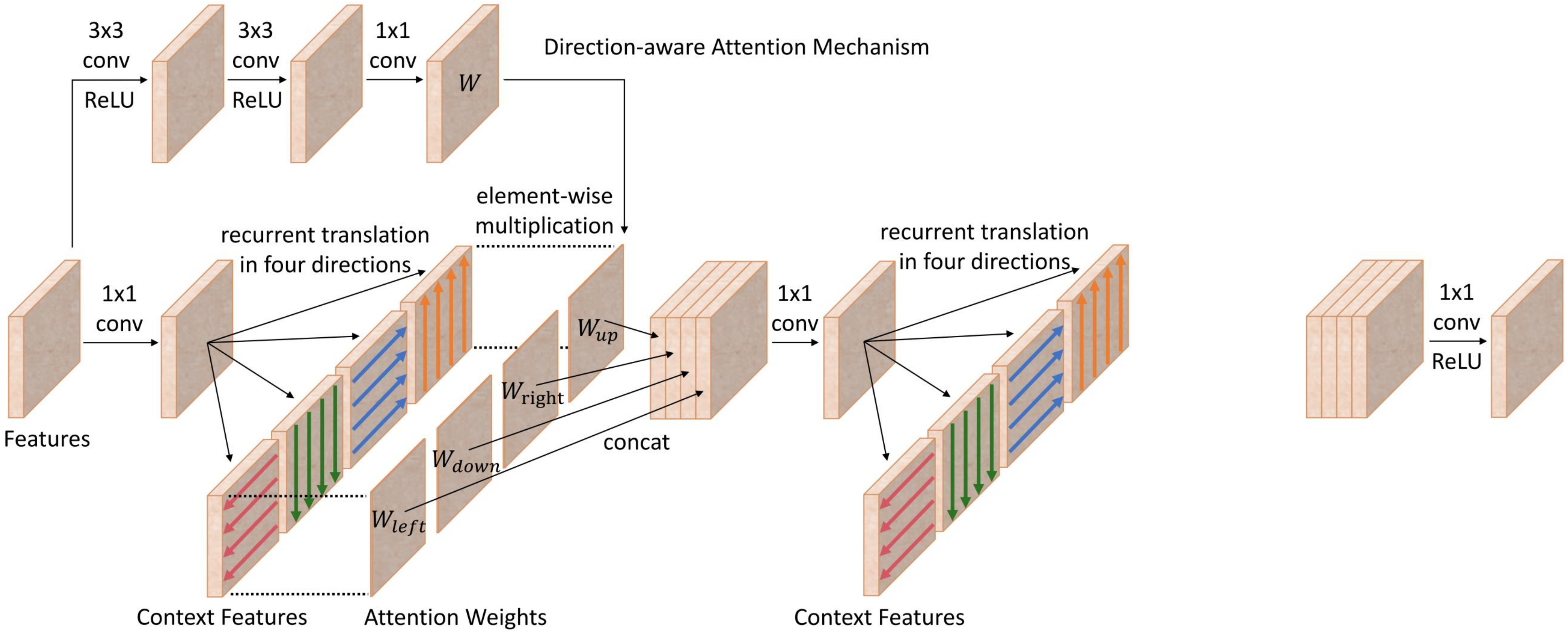




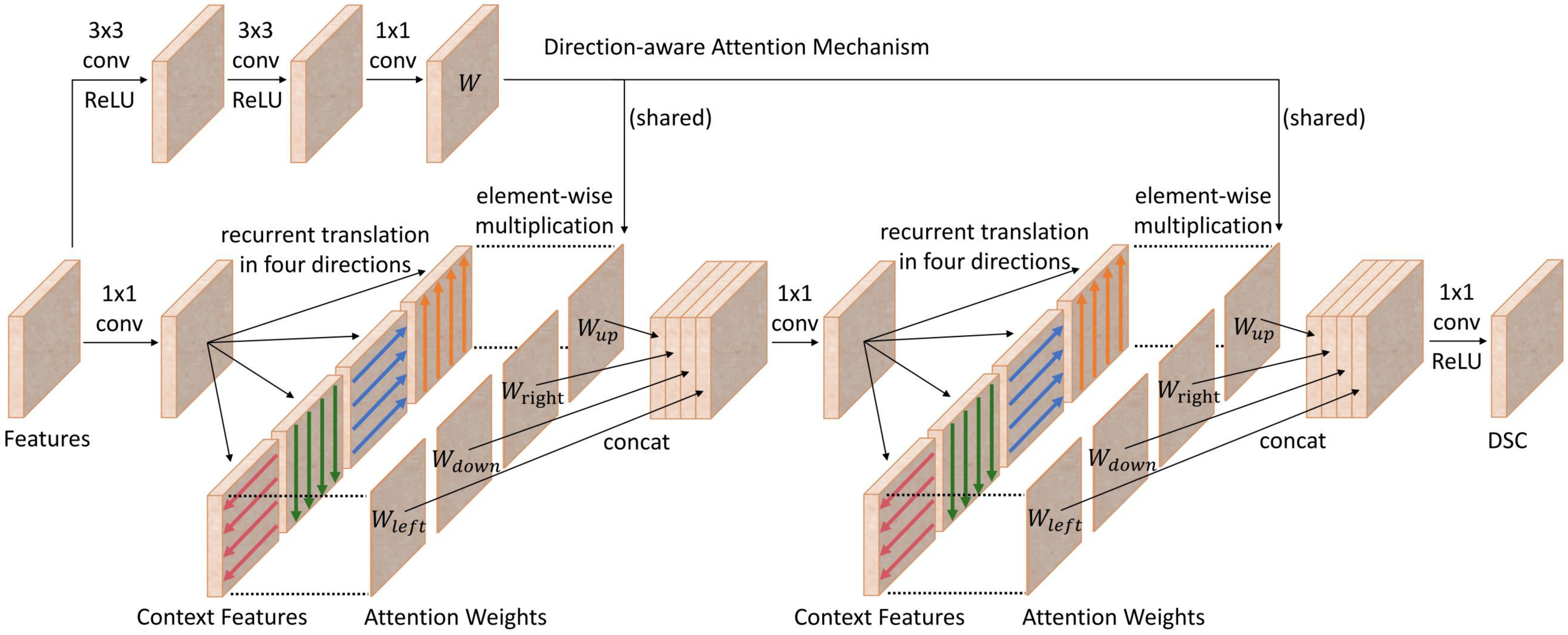
Direction-aware Spatial Context (DSC) Module



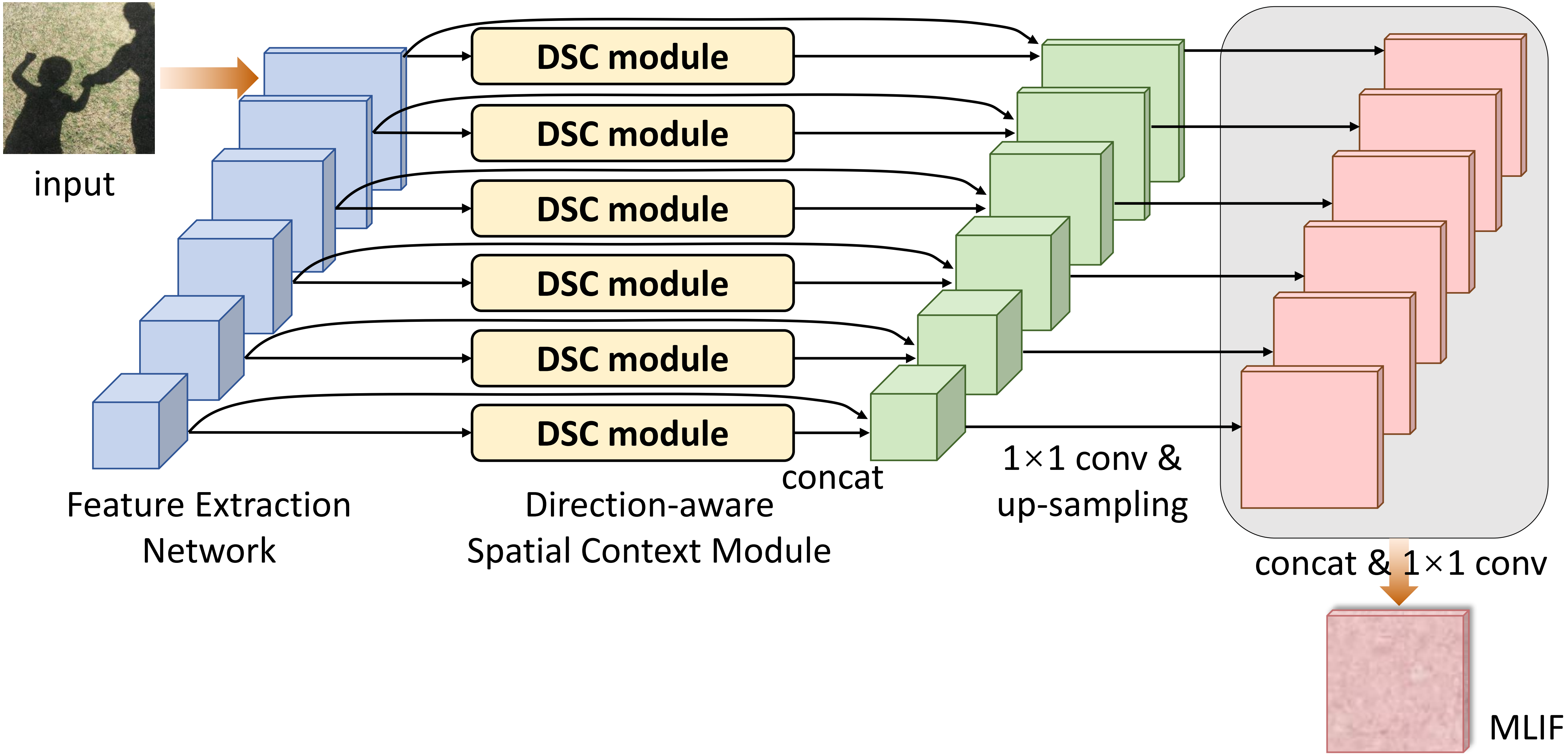
Direction-aware Spatial Context (DSC) Module



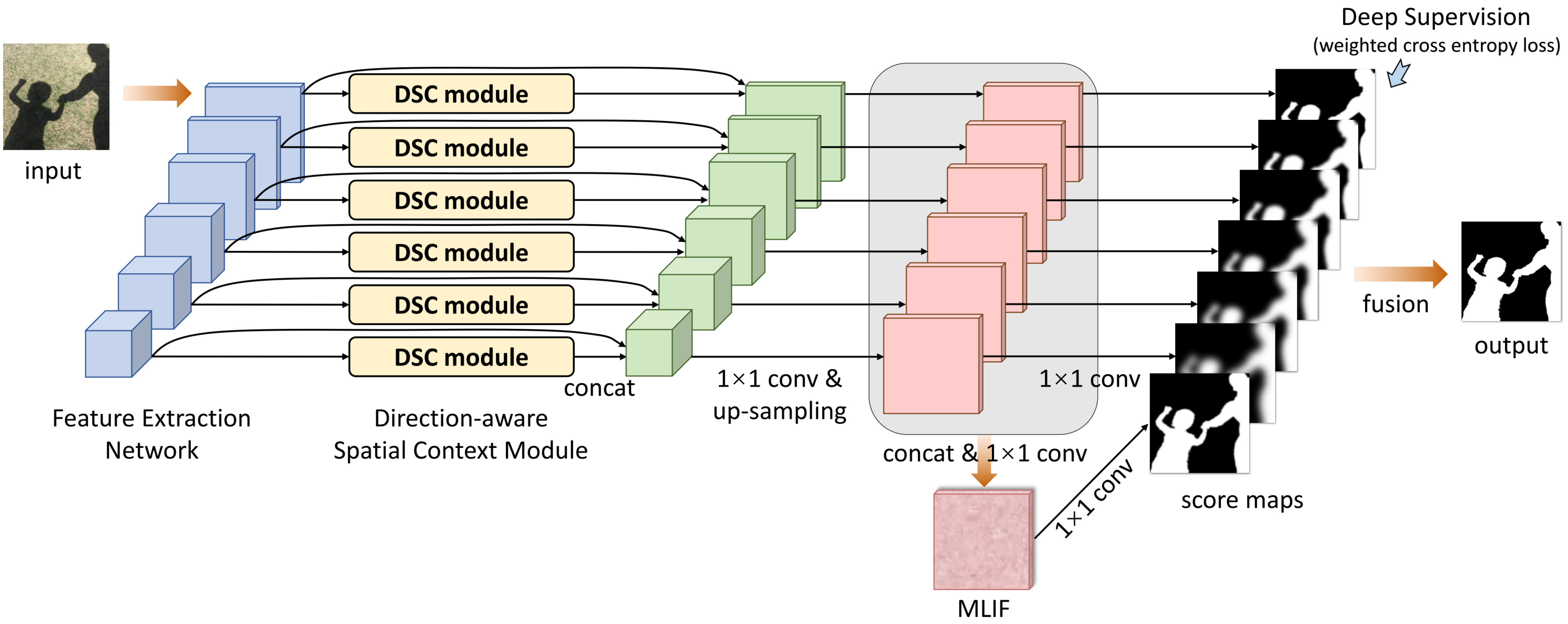
Direction-aware Spatial Context (DSC) Module



Method Overview



Method Overview



Training and Testing

Datasets:

- Training: SBU training set (4089 images)
- Testing: SBU testing set (638 images) and UCF testing set (76 images)

Loss Function:

- Weighted cross entropy loss: $L_1 + L_2$

$$L_1 = -(\frac{N_n}{N_p + N_n})y\log(p) - (\frac{N_p}{N_p + N_n})(1-y)\log(1-p)$$

$$L_2 = -(1 - \frac{TP}{N_p})y\log(p) - (1 - \frac{TN}{N_n})(1-y)\log(1-p)$$

y: ground truth value p: prediction label N_n: the number of non-shadow pixels
N_p: the number of shadow pixels TP: true positive TN: true negative

SBU: T. F. Y. Vicente, et al., "Large-scale training of shadow detectors with noisily-annotated shadow examples," in *ECCV*, 2016.
UCF: J. Zhu, et al., "Learning to recognize shadows in monochromatic natural images," in *CVPR*, 2010.

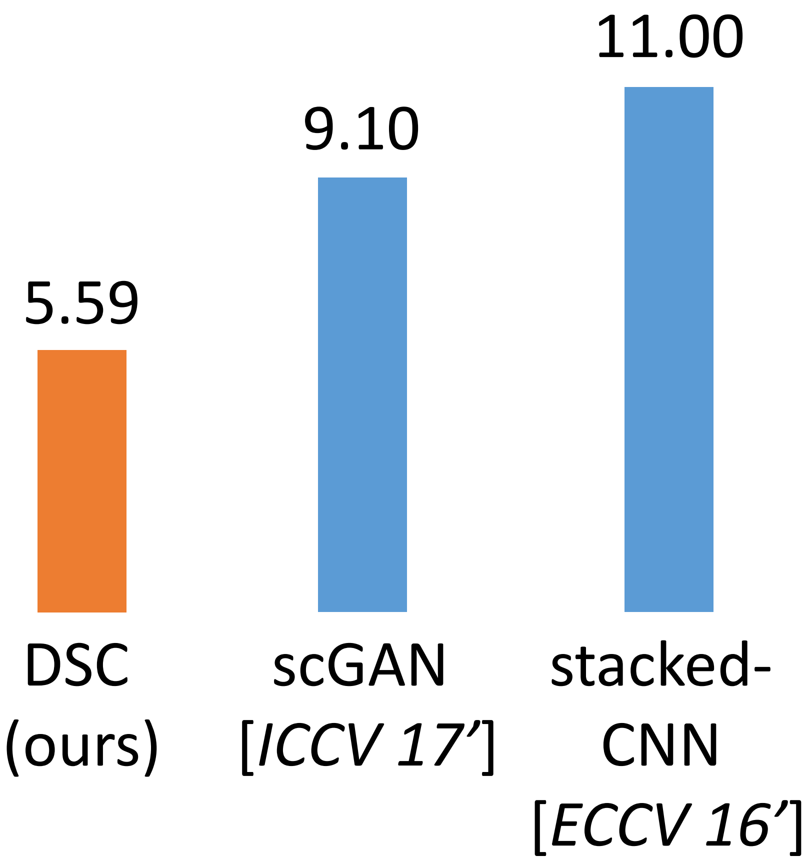
Training and Testing

Testing:

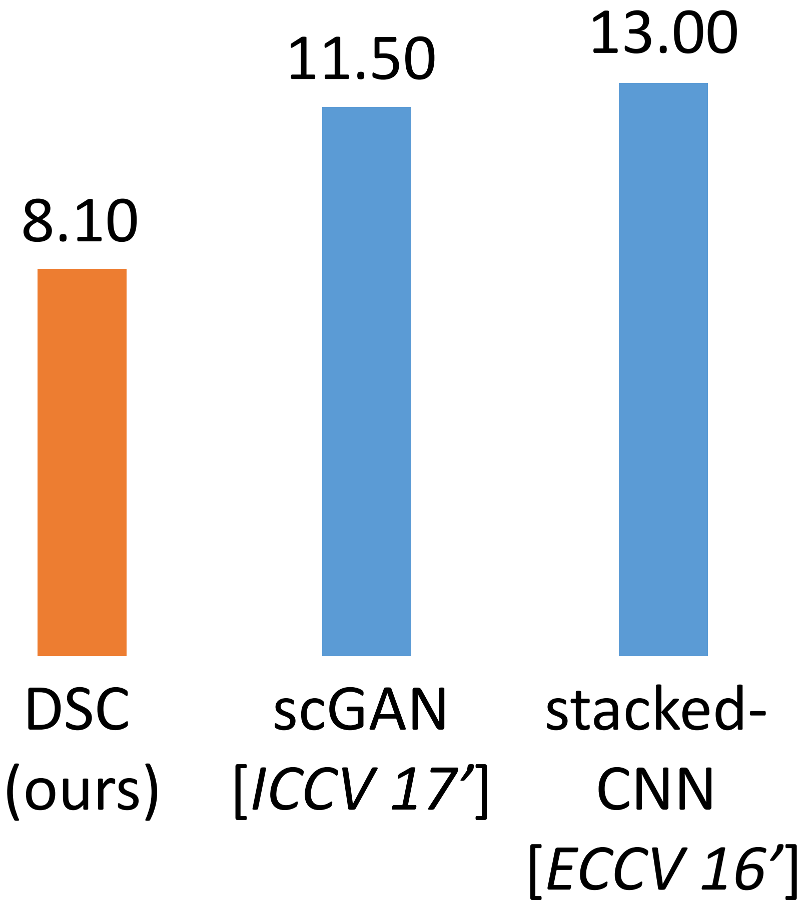
- Shadow map: the mean of the score maps over the MLIF layer and the fusion layer
- Post-processing: conditional random field (CRF)

Results - Balance Error Rate (%)

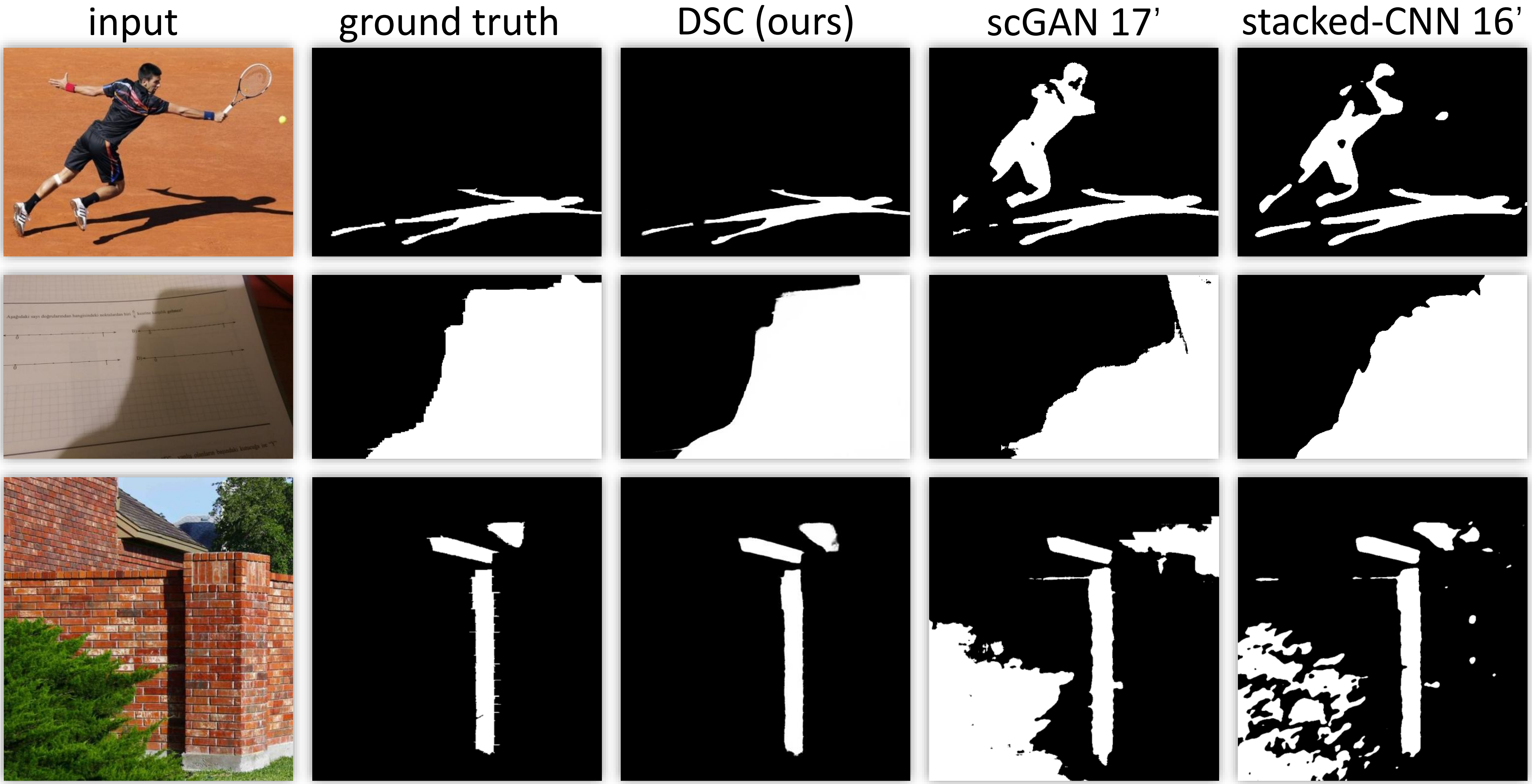
SBU testing set



UCF testing set

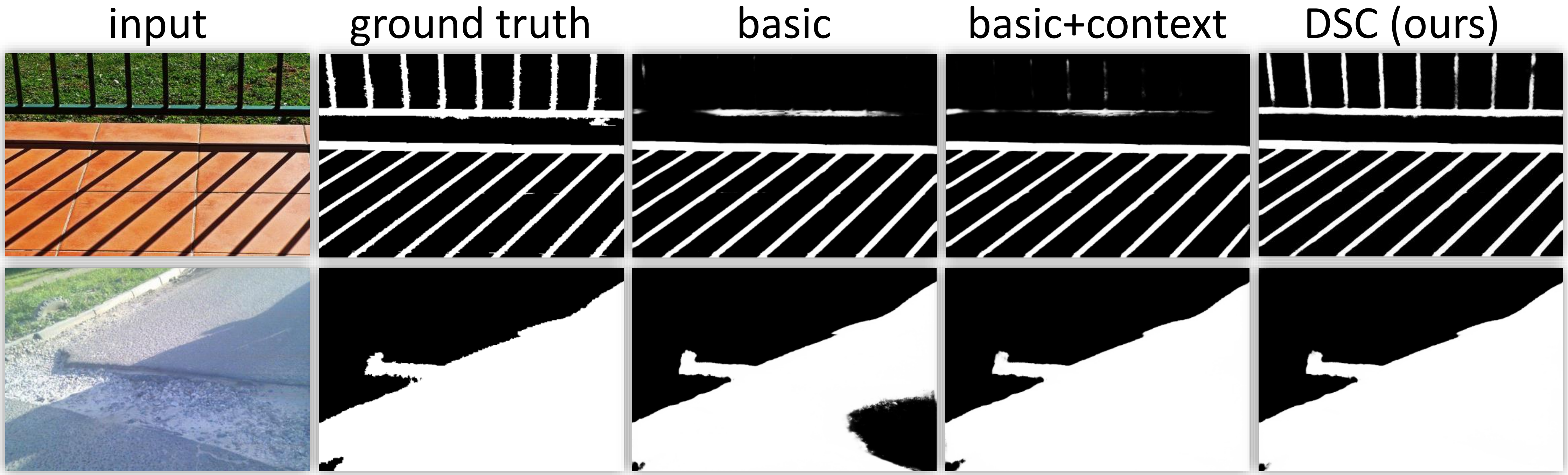


Visual Comparison Results

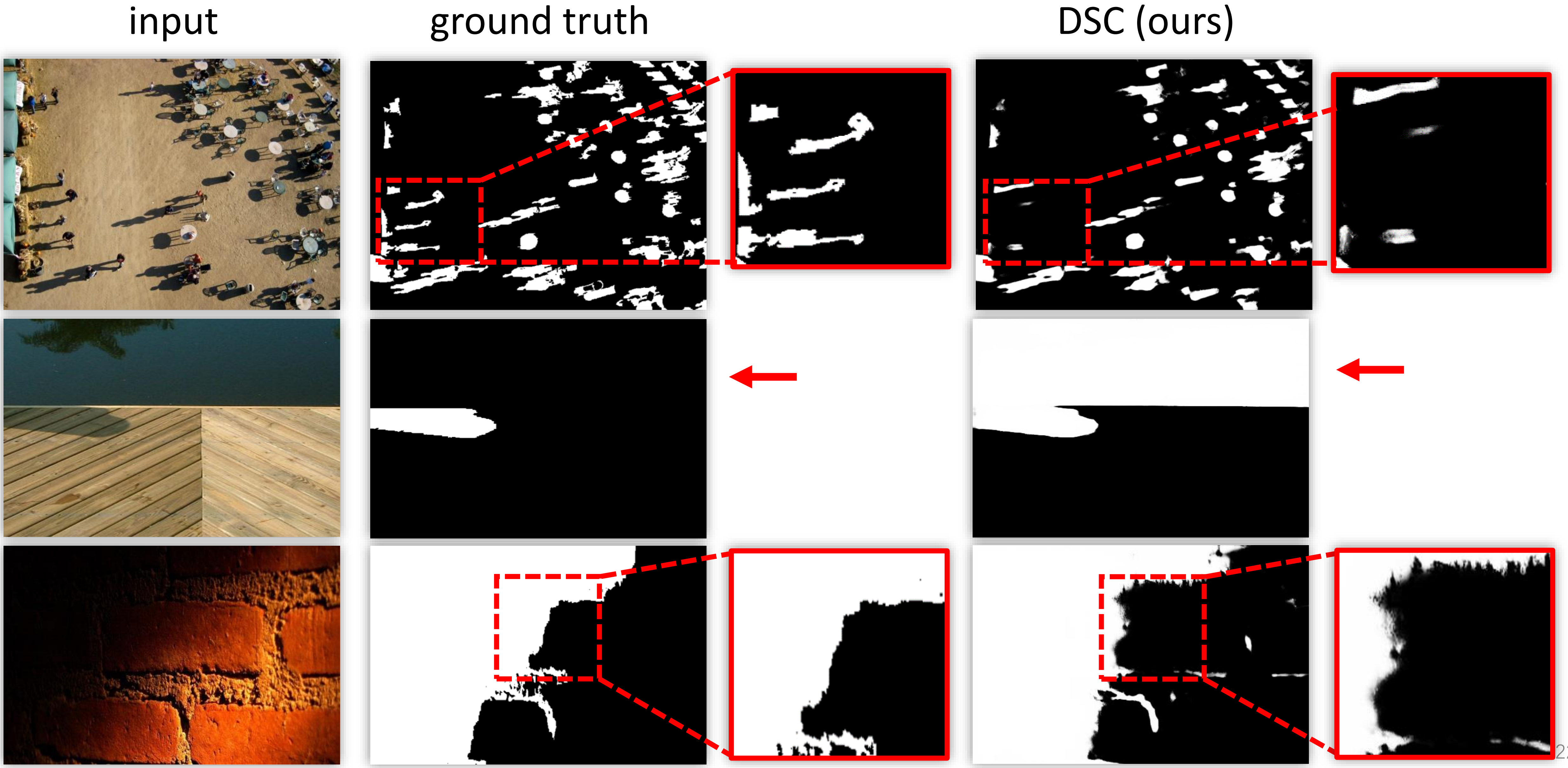


Network Design Evaluation

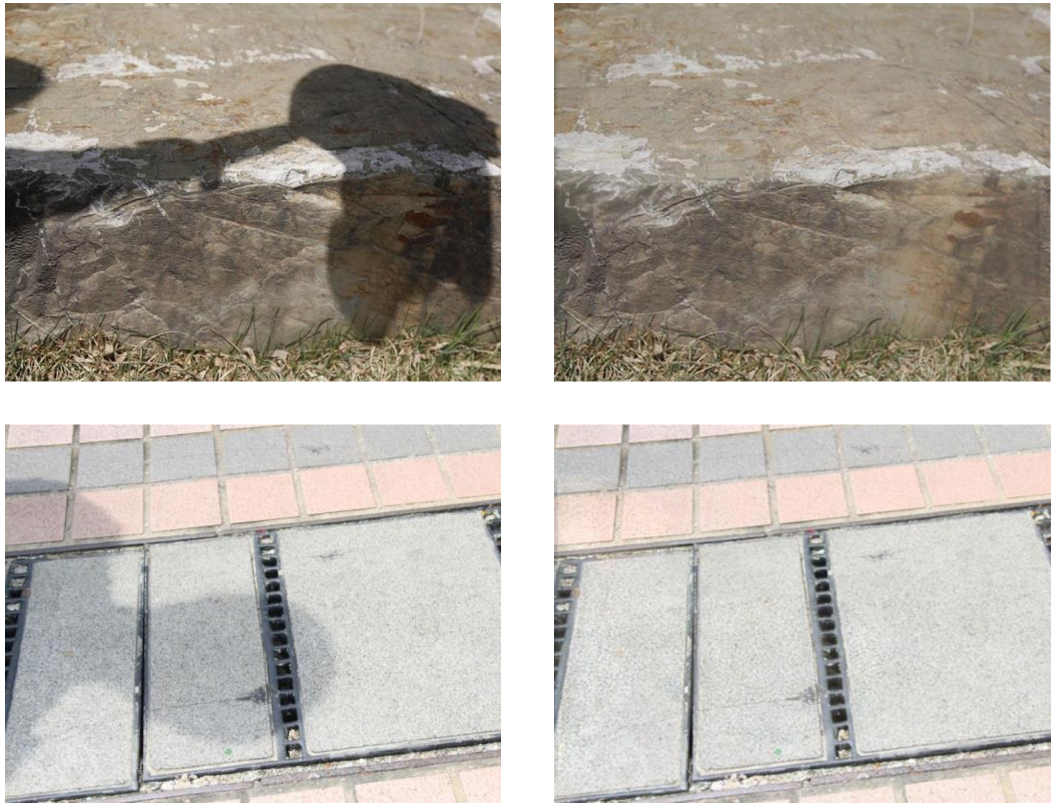
network	BER	improvement
basic	6.55	-
basic+context	6.23	4.89%
DSC	**5.59**	10.27%



Failure Cases



Our Recent Extension - Shadow Removal



	SRD	ISTD
DSC (ours)	**6.21**	**6.67**
ST-CGAN [*CVPR*, 2018]	-	7.47
DeshadowNet [*CVPR*, 2017]	6.64	-
Gong *et al.* [*BMVC*, 2014]	8.73	8.53
Guo *et al.* [*TPAMI*, 2013]	12.60	9.30
Yang *et al.* [*TIP*, 2012]	22.57	15.63

Xiaowei Hu, Chi-Wing Fu, Lei Zhu, Jing Qin, and Pheng-Ann Heng. *Direction-aware Spatial Context Features for Shadow Detection and Removal.* arXiv preprint arXiv:1805.04635, 2018.

Conclusion

- Direction-aware spatial context features for shadow detection and removal.
- Achieve the state-of-the-art performance on two benchmark datasets for shadow detection and another two benchmark datasets for shadow removal.

Code & Results:

https://github.com/xw-hu/DSC

Poster: D12

Q&A

Thank you!

Code & Results:

https://github.com/xw-hu/DSC

Poster: D12