# Supplemental Material: Learning to See in the Dark with Events

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#### 1 Introduction

In this supplementary material, we provide:

- 1) The detailed layer/parameter configurations of the proposed network architecture (Sect. 2);
- 2) Illustration of the captured DVS-Dark dataset (Sect. 3);
- 3) Additional visual comparisons with state-of-the-art models (Sect. 4).

Note that for 3), abbreviations of different approaches are: Pix2Pix [2,3], CycleGAN [8], I2I [5], SDA [1], CIE [7], RIRM [4] and E2V [6].

#### References

- Hong, W., Wang, Z., Yang, M., Yuan, J.: Conditional generative adversarial network for structured domain adaptation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 1335–1344 (2018)
- Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A.: Image-to-image translation with conditional adversarial networks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (July 2017)
- L. Wang, S. M. Mostafavi, Y.S.H., Yoon, K.J.: Event-based High Dynamic Range Image and Very High Frame Rate Video Generation using Conditional Generative Adversarial Networks (2019)
- Munda, G., Reinbacher, C., Pock, T.: Real-time intensity-image reconstruction for event cameras using manifold regularisation. International Journal of Computer Vision 126(12), 1381–1393 (2018)
- 5. Murez, Z., Kolouri, S., Kriegman, D.J., Ramamoorthi, R., Kim, K.: Image to image translation for domain adaptation. arXiv preprint arXiv:1712.00479 (2017)

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- 2 S. Zhang, Y. Zhang, Z. Jiang, D. Zou, J. Ren, B. Zhou
- Rebecq, H., Ranftl, R., Koltun, V., Scaramuzza, D.: Events-to-video: Bringing modern computer vision to event cameras. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (June 2019)
- 7. Scheerlinck, C., Barnes, N., Mahony, R.: Continuous-time intensity estimation using event cameras. In: Asian Confence on Compututer Vision (ACCV) (2018)
- Zhu, J.Y., Park, T., Isola, P., Efros, A.A.: Unpaired image-to-image translation using cycle-consistent adversarial networks. In: Computer Vision (ICCV), 2017 IEEE International Conference on (2017)

### 2 Architecture Details

As described in Sect. 3 of the paper, the proposed architecture contains 5 main modules: the shared and private encoders  $E_c$  and  $E_p$ , the discriminator D, the reconstruction decoder R and the detail enchancing branch  $T_e$ , whose layer configurations are listed as follows. Note that the structure of the residual block is referred to Table 6.

$E_c$	Input	Kernel s	size	Stride	In	channels	Out	channels	Output			
Conv1	Events	7	1		8		32	Conv1				
Norm1	Conv1		Instance Norm + ReLU									
Conv2	Norm1	3	3 2 32 64				64	Conv2				
Norm2	Conv2		Instance Norm $+$ ReLU									
Conv3	Norm2	3	2		64		128	Conv3				
Norm3	Conv3		Norm3									
Res1	Norm3		Residual block $\times$ 9									

Table 1: Layer configurations of shared encoder  $E_c$ .

Table 2: Layer configurations of private encoder  $E_p$ .

$E_p$	Input	Kernel	size	Stride	In channels	Out channels	Output
Conv1	concatenate(Events, noise)	7		1	9	32	Conv1
Norm1	Conv1		Iı	istance	$\rm Norm + Re$	eLU	Norm1
Conv2	Norm1	3		2	32	64	Conv2
Norm2	Conv2		Iı	istance	$\rm Norm + Re$	eLU	Norm2
Conv3	Norm2	3		2	64	128	Conv3
Norm3	Conv3		Iı	nstance	e Norm + Re	eLU	Norm3
Res1	Norm3		$X_p^f$				

D	Input	Kernel size	Stride	In channels	Out channels	Output					
Conv1	$X_{DE}^f/X_{LE}^f$	5	2	128	32	Conv1					
Norm1	Conv1		Leaky ReLU								
Conv2	Norm1	5	2	32	64	Conv2					
Norm2	Conv2	Insta	Instance Norm + Leaky ReLU								
Conv3	Norm2	5	2	64	128	Conv3					
Norm3	Conv3	Insta	Instance Norm + Leaky ReLU								
Conv4	Norm3	5	1	128	256	Conv4					
Norm4	Conv4	Insta	Norm4								
Conv5	Norm4	5	1	256	1	R/F					

Table 3: Layer configurations of discriminator D.

Table 4: Layer configurations of the detail enchancing branch  $T_e$ .

$T_e$	Input	Kernel	size	Stride	In	channels	Out	channels	Output
Conv1	$concatenate(X_{DE}^f, noise)$	3		1		160		128	Conv1
Norm1	Conv1	Instance Norm + ReLU						Norm1	
Res1	Norm1	Residual block $\times$ 9						$\Delta y$	

Table 5: Layer configurations of reconstruction decoder R.

R	Input	Kernel	size	Stride	In channels	Out channels	Output			
Res1	$X_{DE}^f + \Delta y / X_{DE}^f$			Resid	ual block $\times$	9	Res1			
Deconv1	Res1	3		2	128	64	Deconv1			
Norm1	Deconv1		Instance Norm + ReLU							
Deconv2	Norm1	3		2	64	32	Deconv2			
Norm2	Deconv2		Ir	istance	Norm + Re	eLU	Norm2			
Conv1	Norm2	7		1	32	1	Conv1			
Sigmoid	Conv1	Conv1 sigmoid								

Table 6: Layer configurations of a residual block.

Residual block	Input	Kernel size	Stride	In channels	Out channels	Ouput				
Conv1	*	3	1	128	128	Conv1				
Norm1	Conv1	Iı	Instance Norm + ReLU							
Conv2	Norm1	3	3 1 128 128							
Norm2	Conv2		Instance Norm							

# 3 Illustration of the DVS-Dark Dataset



Fig. 1: Representative intensity images and the corresponding event frames of the day-light split of DVS-Dark dataset.



Fig. 2: Representative intensity images and the corresponding event frames of the low-light split of DVS-Dark dataset.

## 4 More Visual comparisons with State-of-the-Art Models



Fig. 3: Additional visual comparisons with domain-adaptation approaches Pix2Pix, CycleGAN, I2I and SDA, tested on the real low-light events.



Fig. 4: Additional visual comparisons with domain-adaptation approaches Pix2Pix, CycleGAN, I2I and SDA, tested on the real low-light events.

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Fig. 5: Additional visual comparisons with domain-adaptation approaches Pix2Pix, CycleGAN, I2I and SDA, tested on the real low-light events.



Fig. 6: Additional visual comparisons with domain-adaptation approaches Pix2Pix, CycleGAN, I2I and SDA, tested on the real low-light events.



Fig. 7: Additional visual comparisons with event based intensity reconstruction approaches CIE, RIRM, E2VID, tested on the real low-light events.



Fig. 8: Additional visual comparisons with event based intensity reconstruction approaches CIE, RIRM, E2VID, tested on the real low-light events.



Fig. 9: Additional visual comparisons with event based intensity reconstruction approaches CIE, RIRM, E2VID, tested on the real low-light events.



Fig. 10: Additional visual comparisons with event based intensity reconstruction approaches CIE, RIRM, E2VID, tested on the real low-light events.