FHDR: HDR Image Reconstruction from a Single LDR Image using Feedback Network

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Introduction

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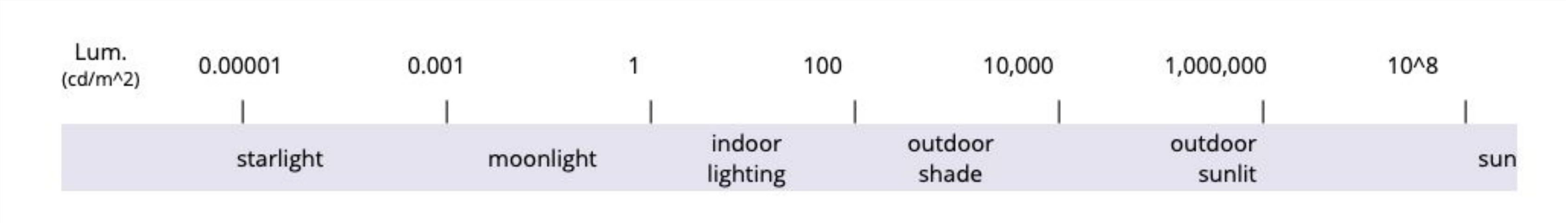

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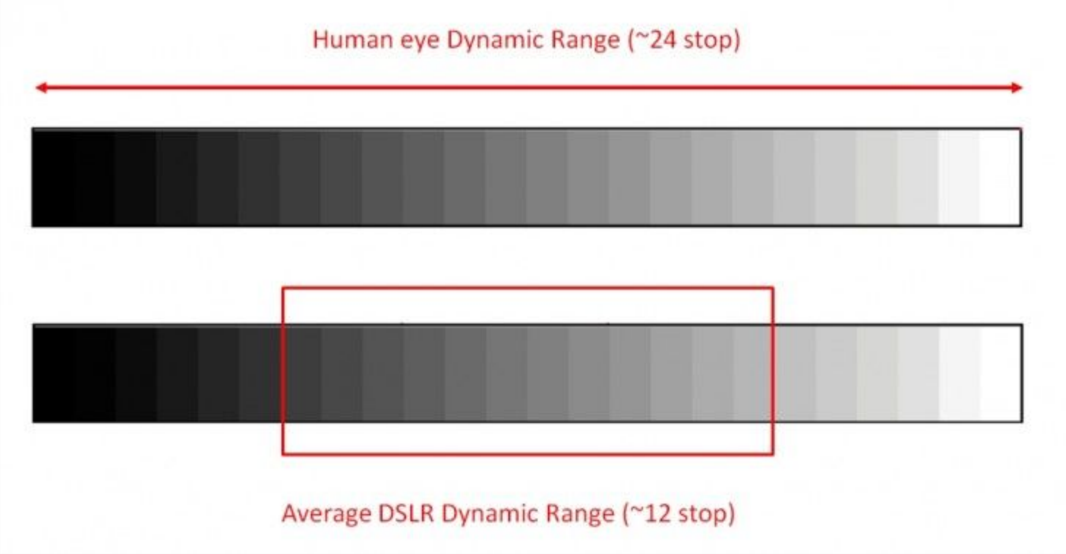

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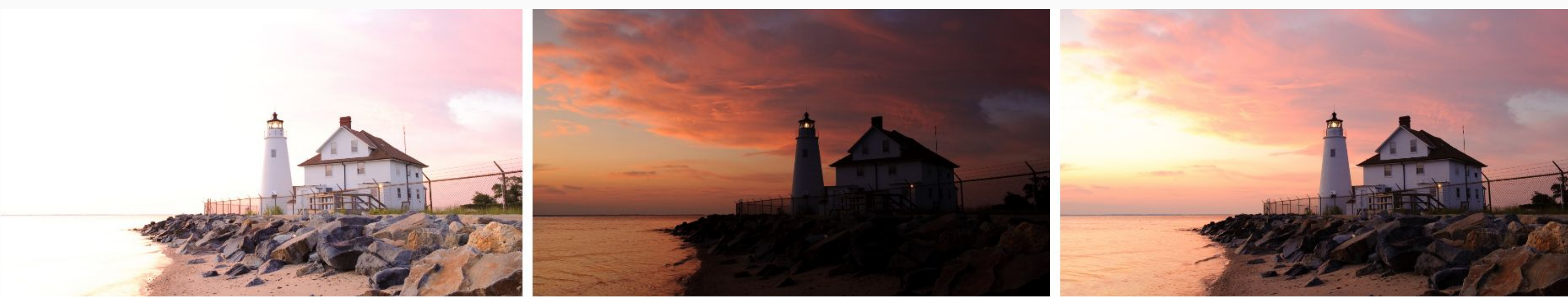
- To recover the lost information and represent the wide range of illuminance in an image, **High Dynamic Range (HDR)** images need to be generated.



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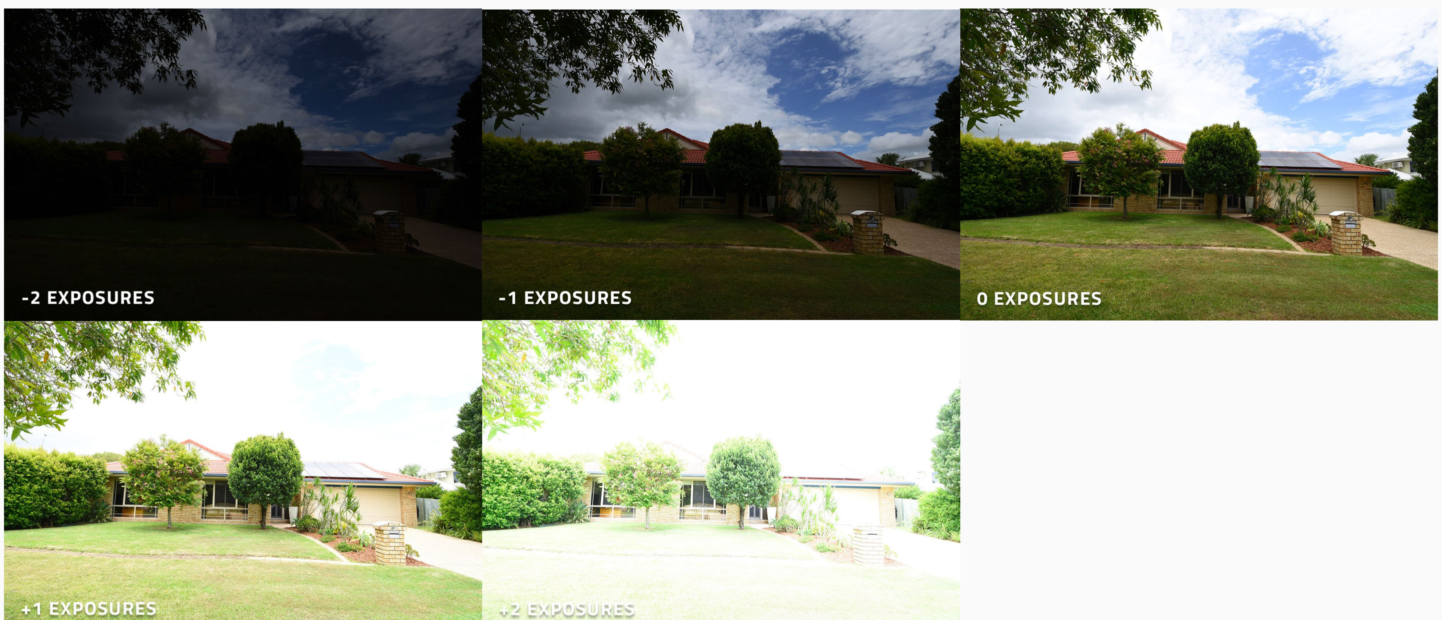

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- Such networks can do better due to -
  - improved learning based flow mechanisms
  - hallucinating HDR content in saturated regions when LDR input is limited
  - optimised, quick, low-memory alternative

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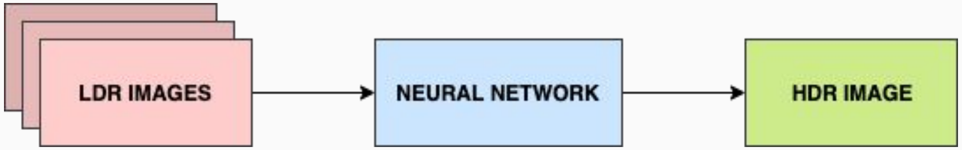

Learning based - multiple LDR inputs

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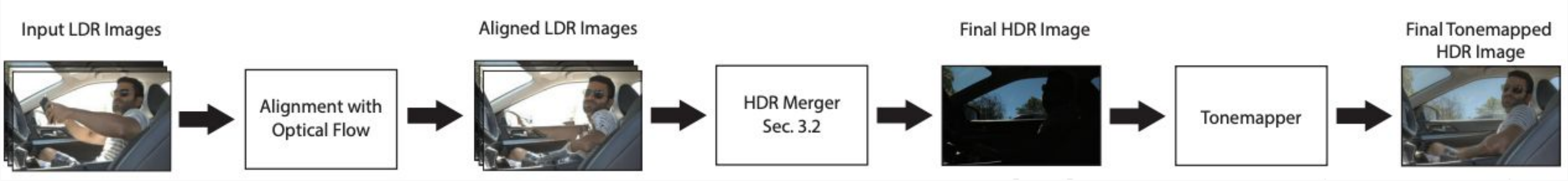
Learning based - multiple LDR inputs

- Multiple exposure input
- More dynamic range is provided to the network
- Explicit mechanism required for motion compensation
- Better results
- But input is a constraint

Related work
(multi-exposure input)

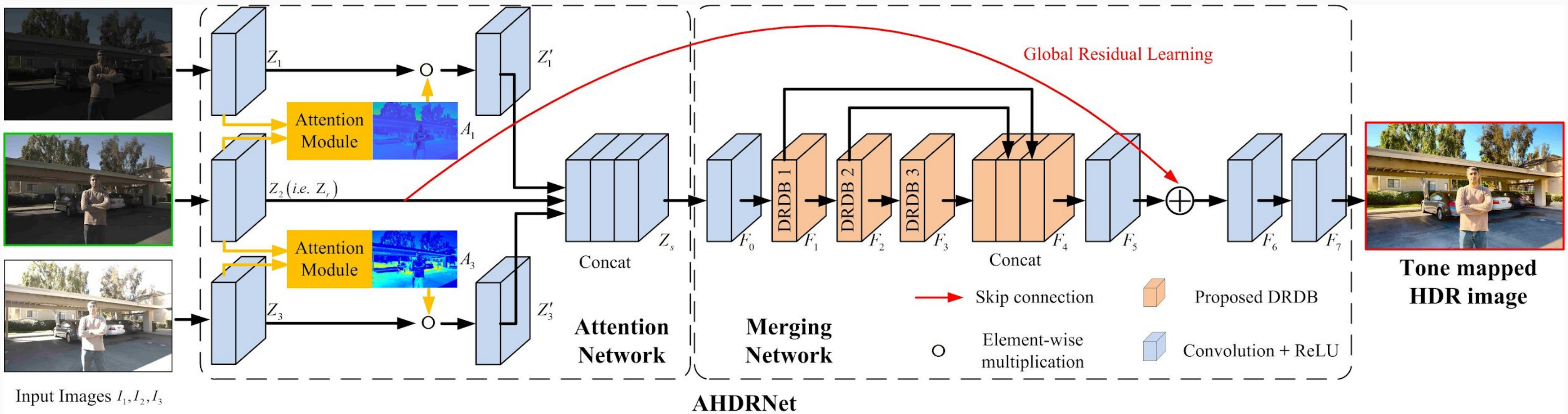
Deep HDR

N. K. Kalantari and R. Ramamoorthi, “Deep high dynamic range imaging of dynamic scenes.,” ACM Trans. Graph., vol. 36, no. 4, pp. 144–1, 2017.



AHDR-Net

Yan, Q., Gong, D. , Shi, Q., van den Hengel, A., Shen, C., Reid, I. and Zhang, Y.: Attention-guided Network for Ghost-free High Dynamic Range Imaging. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019



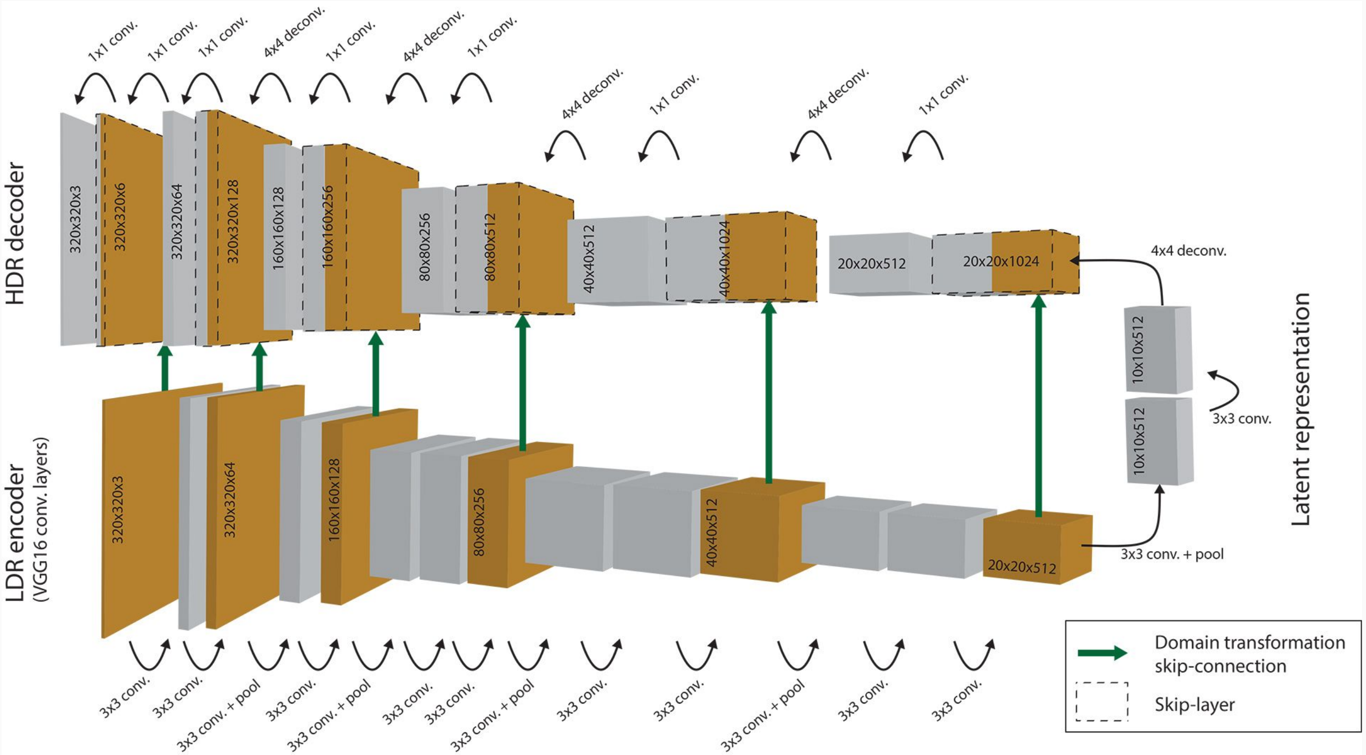
Learning based - single LDR input

- More challenging scenario
- Limited dynamic range information input
- More important for real life situations
- Heavily relies on ability of deep CNNs to hallucinate content in saturated image regions.

Related work
(single input)

HDRCNN

G. Eilertsen, J. Kronander, G. Denes, R. K. Mantiuk, and J. Unger, “Hdr image reconstruction from a single exposure using deep cnns,” ACM Transactions on Graphics (TOG), vol. 36, no. 6, p. 178, 2017



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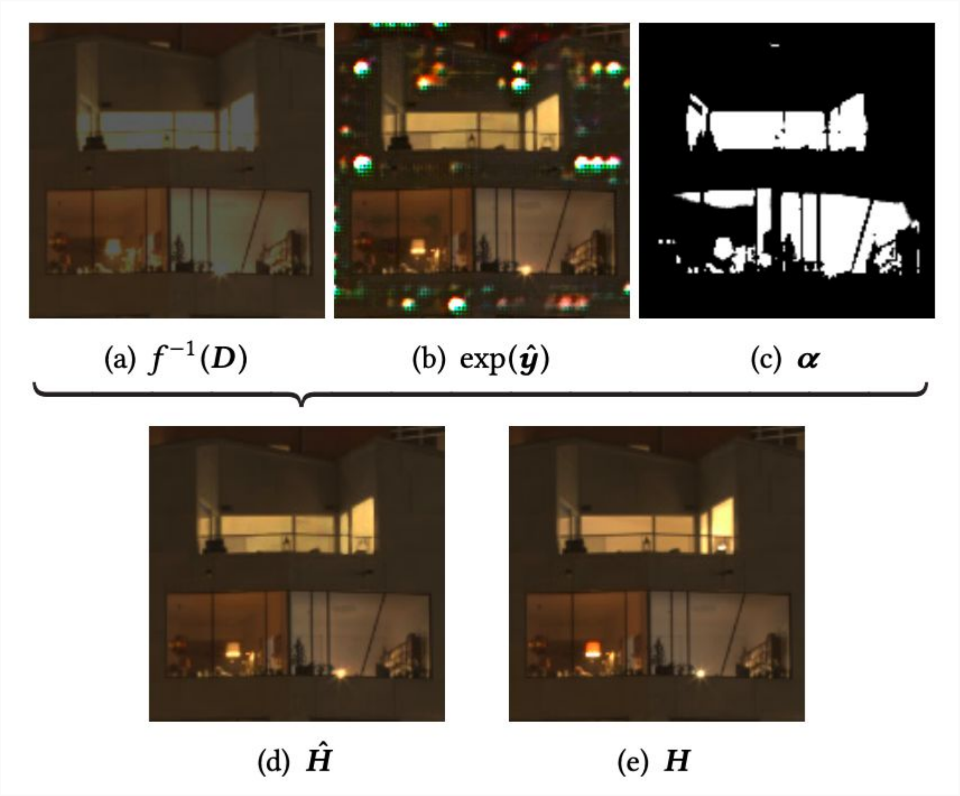
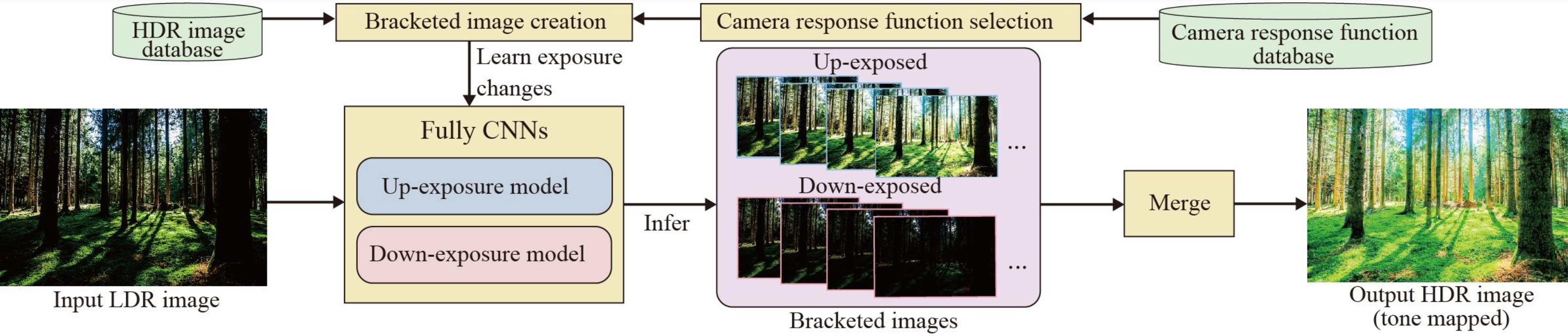


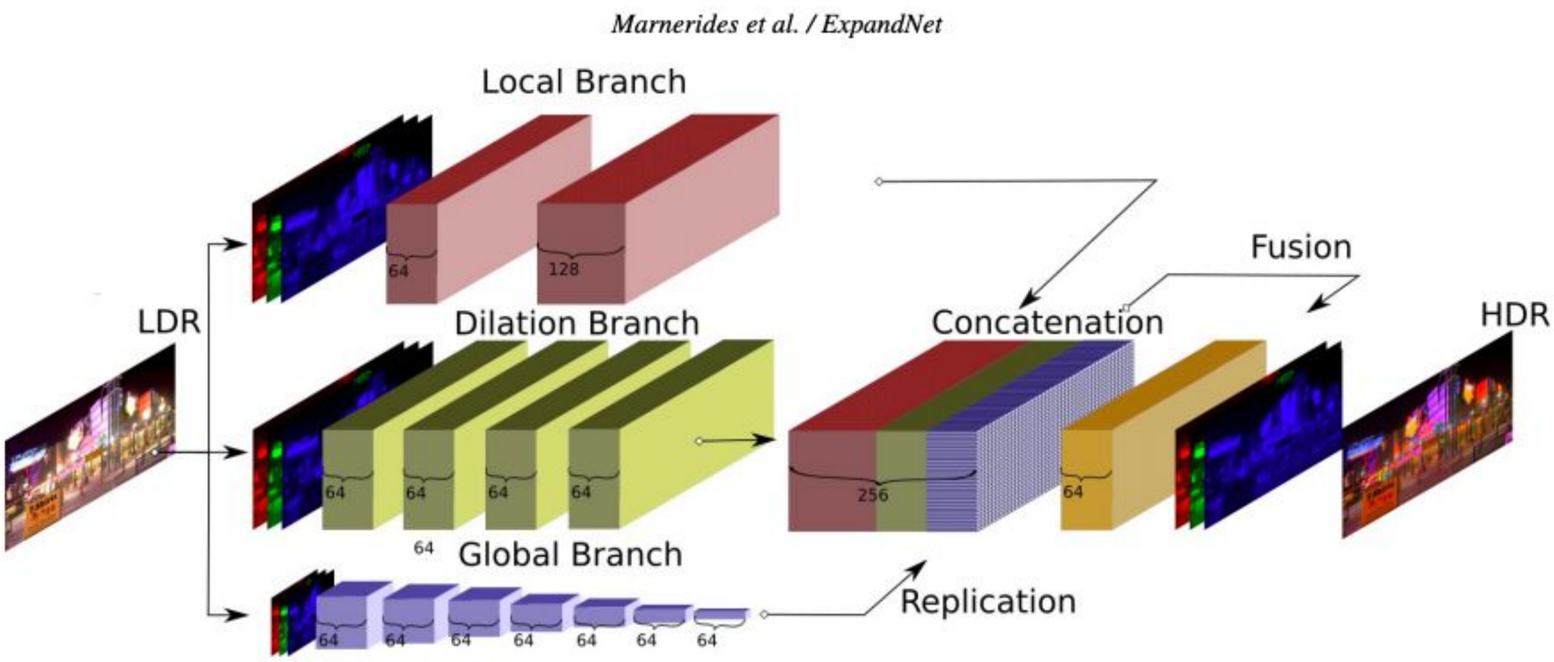
Deep reverse tone mapping

Y. Endo, Y. Kanamori, and J. Mitani, "Deep reverse tone mapping.," ACM Trans. Graph., vol. 36, no. 6, pp. 177–1, 2017.



ExpandNet

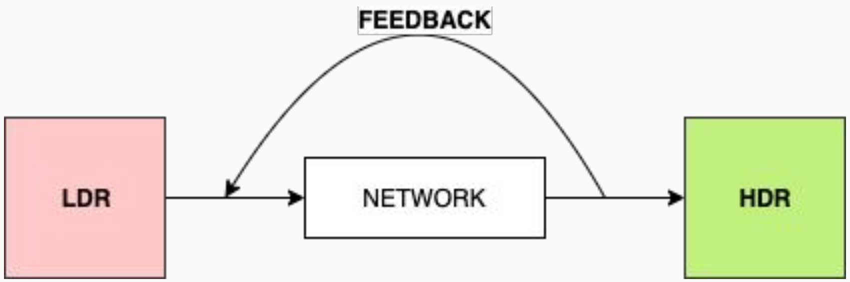
D. Marnerides, T. Bashford-Rogers, J. Hatchett, and K. Debattista, “Expandnet: A deep convolutional neural network for high dynamic range expansion from low dynamic range content,” in Computer Graphics Forum, vol. 37, pp. 37–49, Wiley Online Library, 2018.



Our approach

Feedback networks

- Feedback systems are adopted to influence the input based on the generated output.



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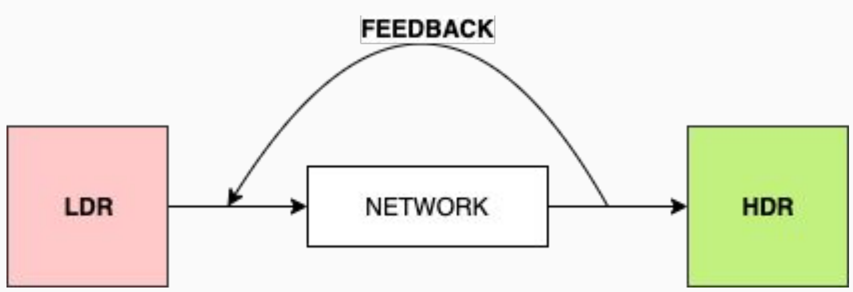

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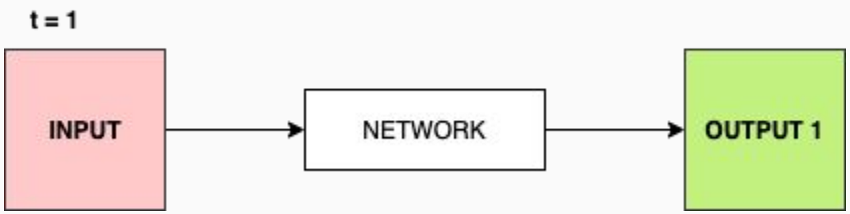

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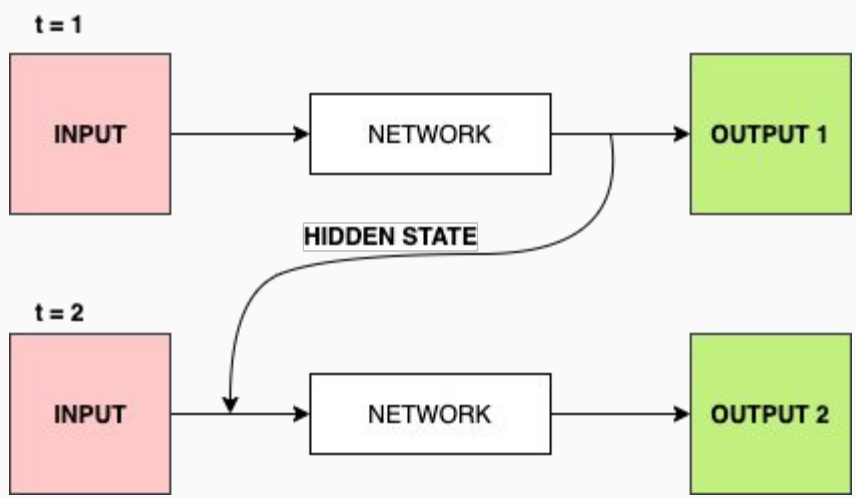

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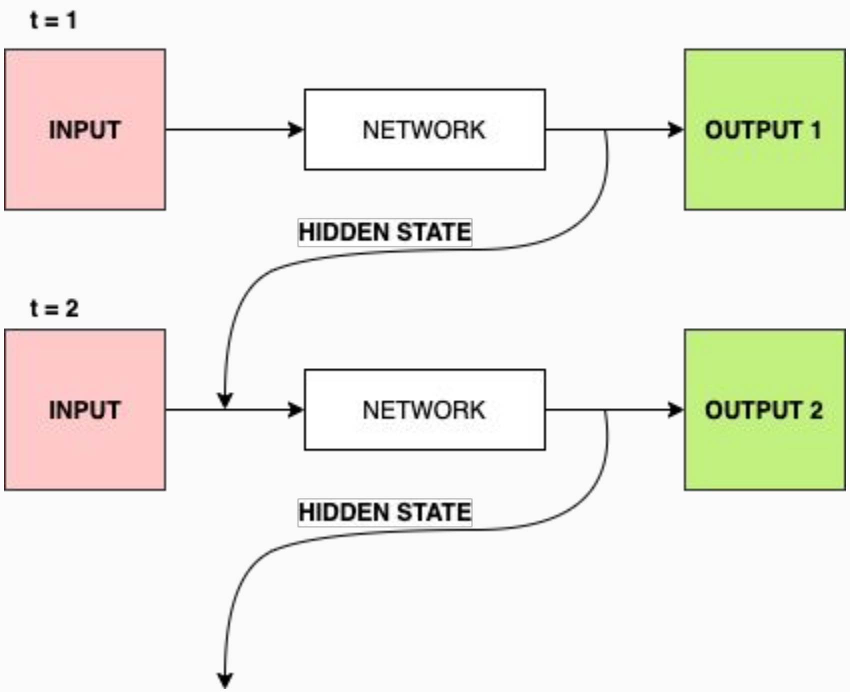

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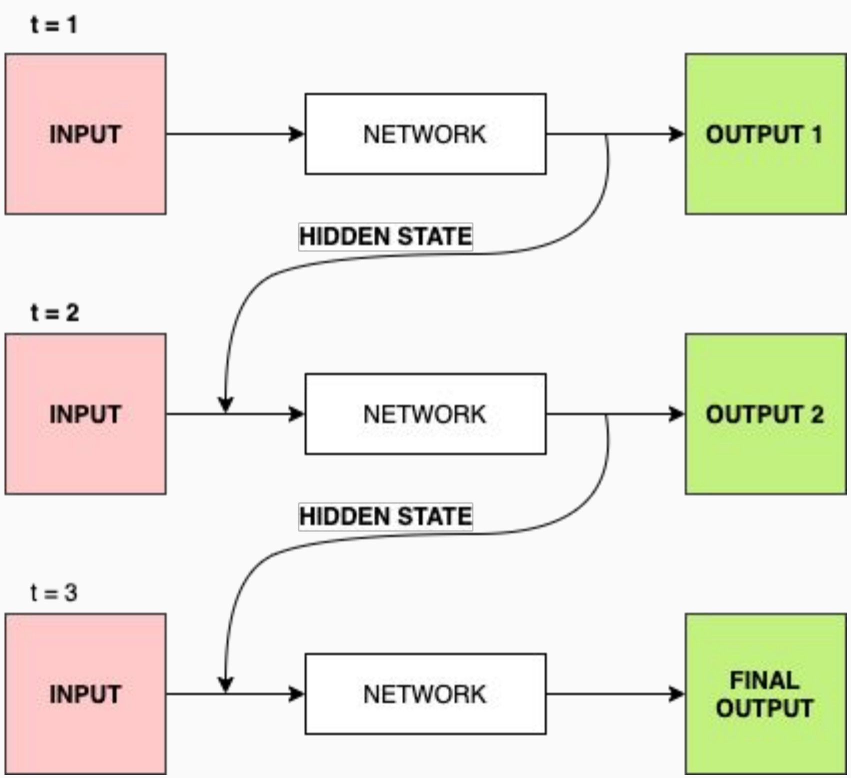

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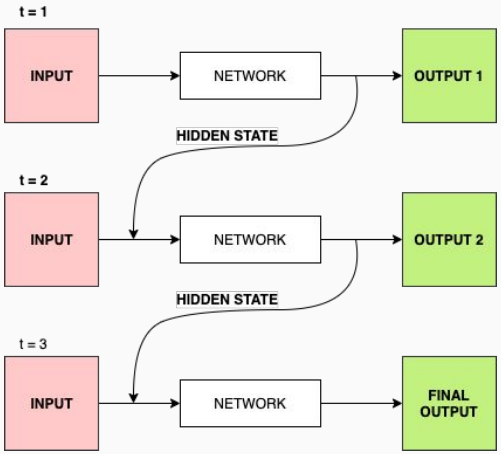
- Backpropagation in time through an unfolded RNN



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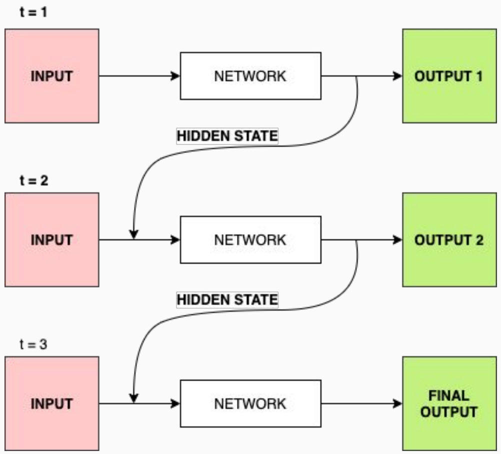
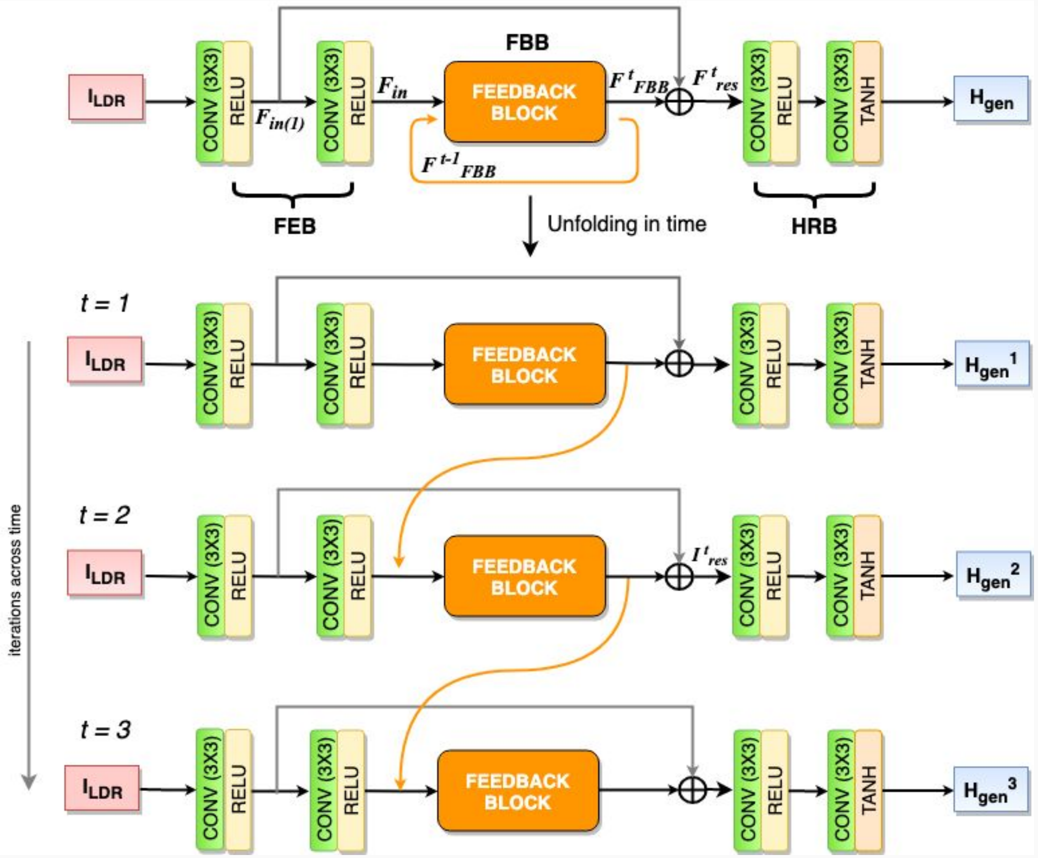
- Initial low level features are guided by the high level features using a hidden state of a Recurrent Neural Network over n iterations.
- Backpropagation in time through an unfolded RNN
- Helps in learning coarse-to-fine representations



Model architecture



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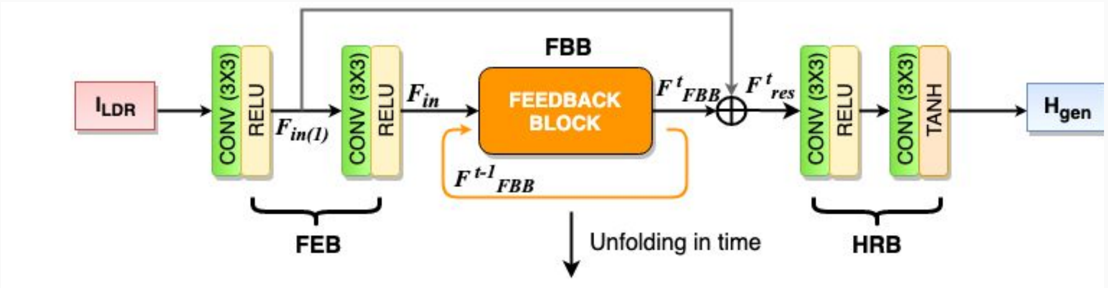
Feature Extraction Block (FEB)

- The FEB is responsible for extracting the low-level feature information F_{in} from the input LDR image ILDR.



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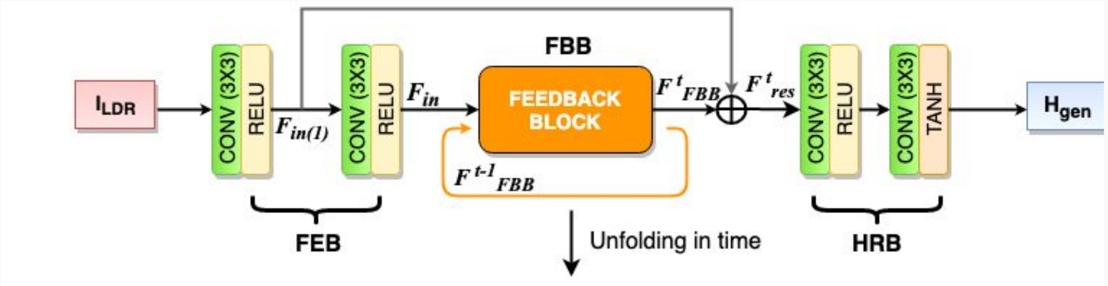

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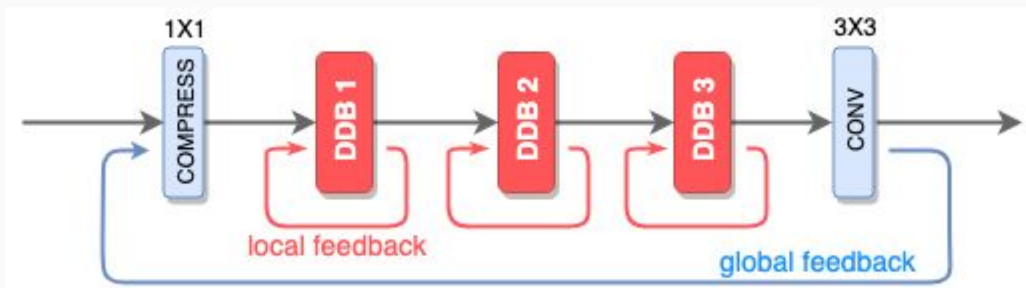
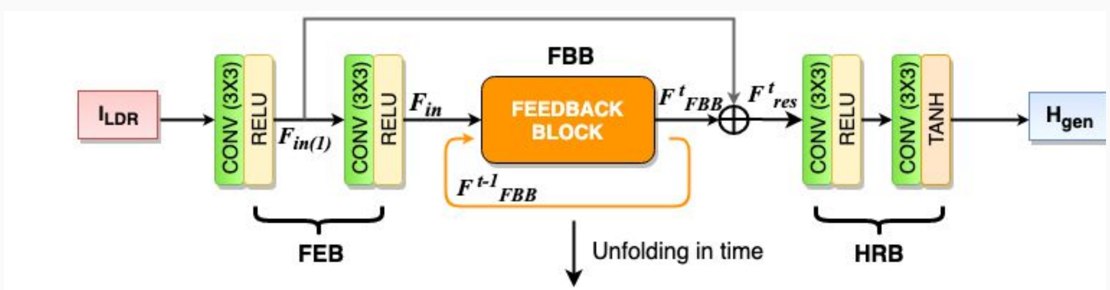
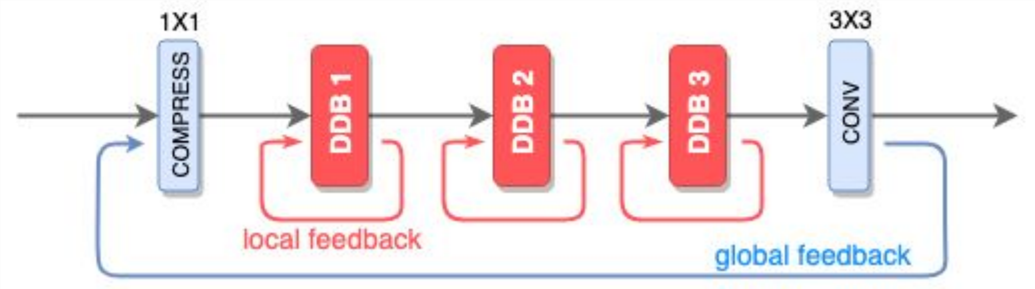




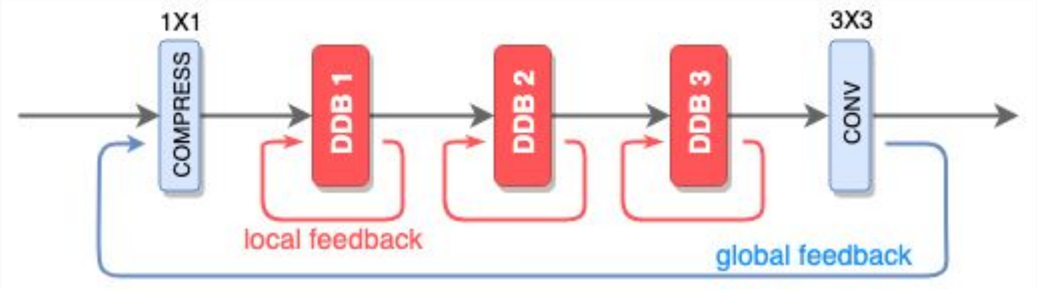
Feedback block

- Novel feedback block for the task of learning LDR-to-HDR mapping



Feedback block

- Novel feedback block for the task of learning LDR-to-HDR mapping
- The basic unit of the feedback block is a Dilated Dense Block (DDB).



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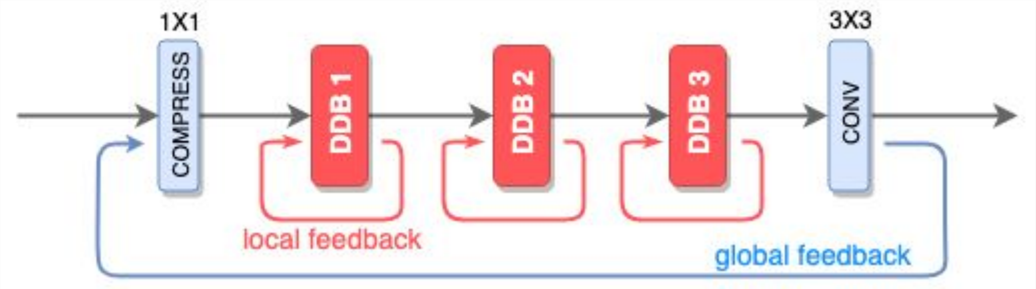

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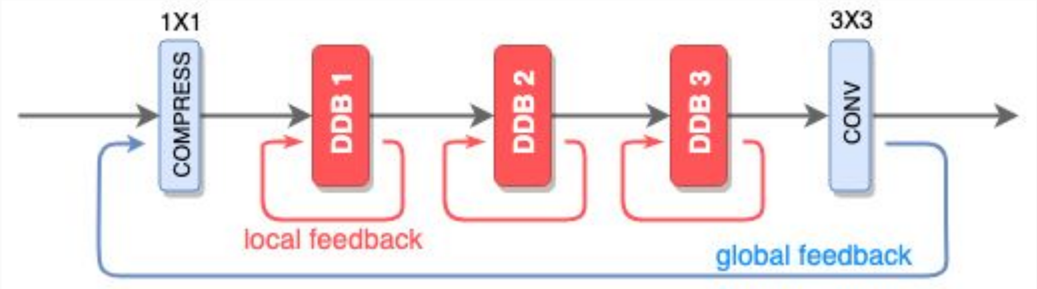
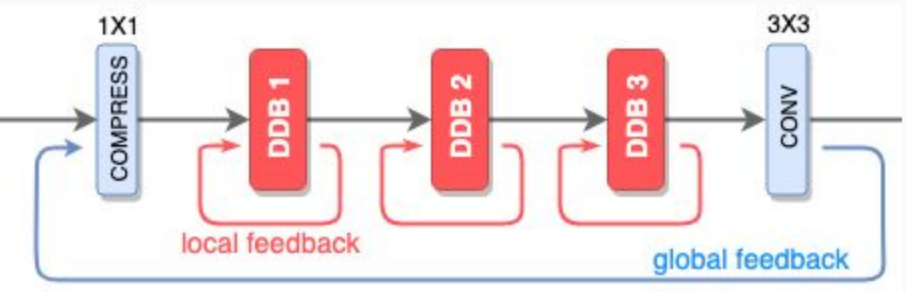
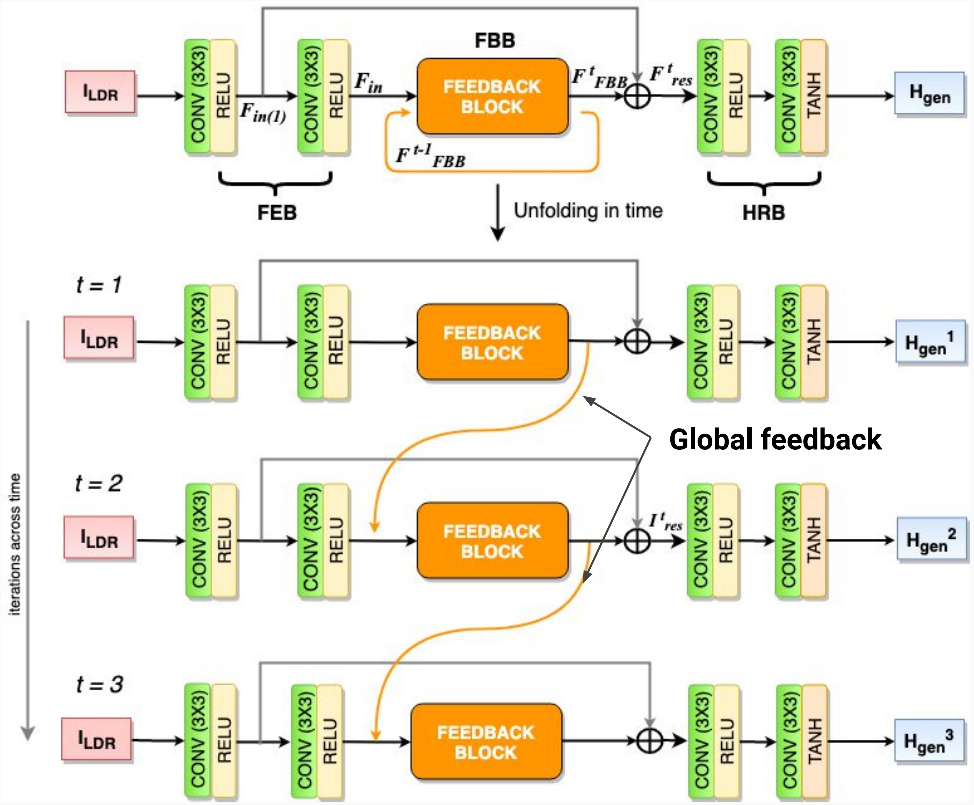
- Three DDBs are used for the feedback block of the network.



Feedback block - Global feedback





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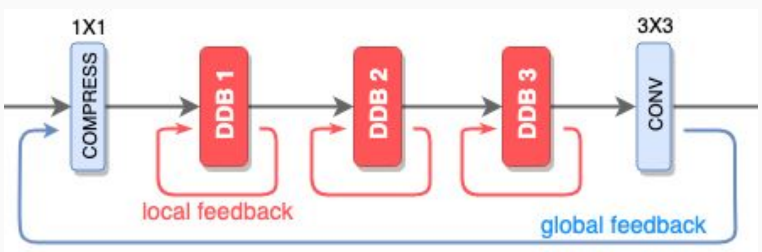

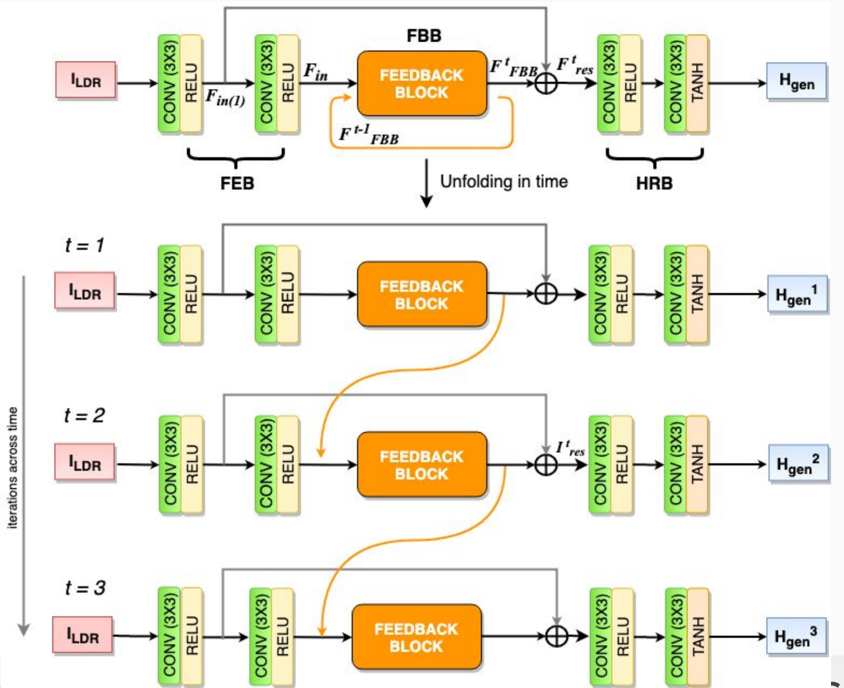

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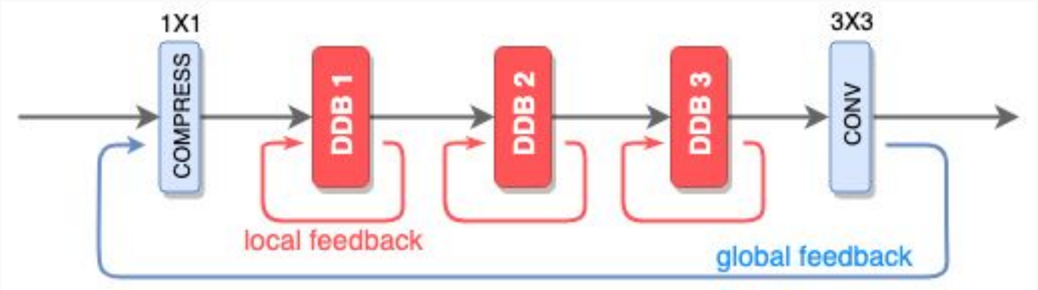

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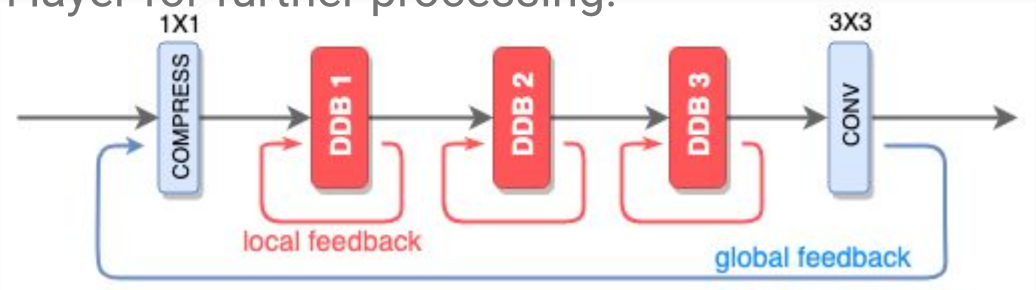
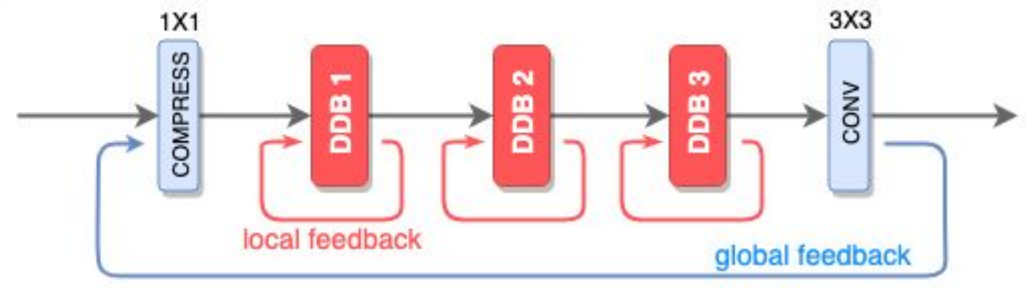
- The fused features are passed to the DDBs, followed by a 3×3 convolution layer for further processing.



Feedback block - Local feedback

- We argue that a feedback connection is always beneficial.



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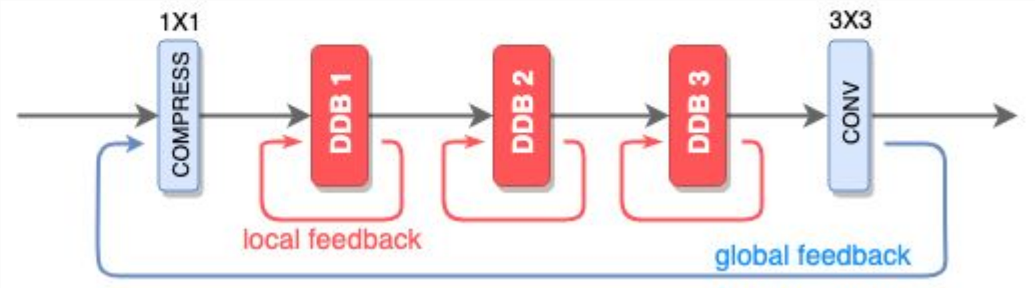

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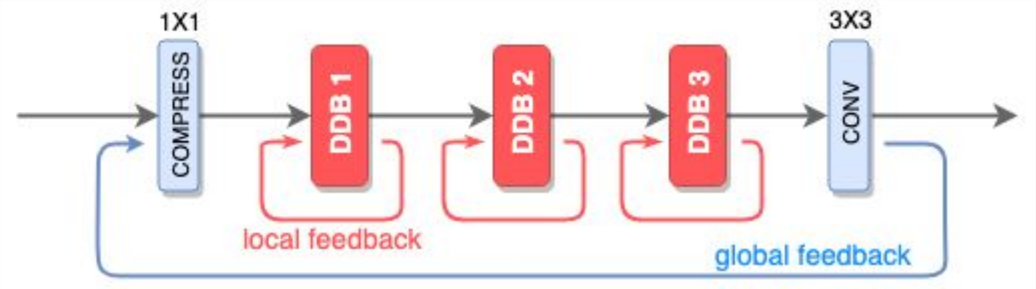

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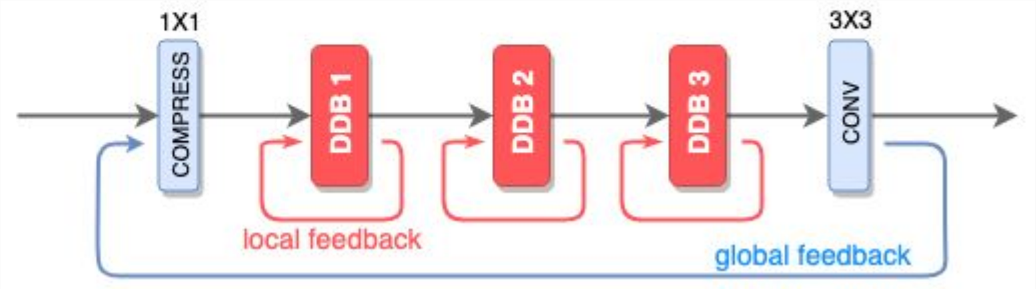
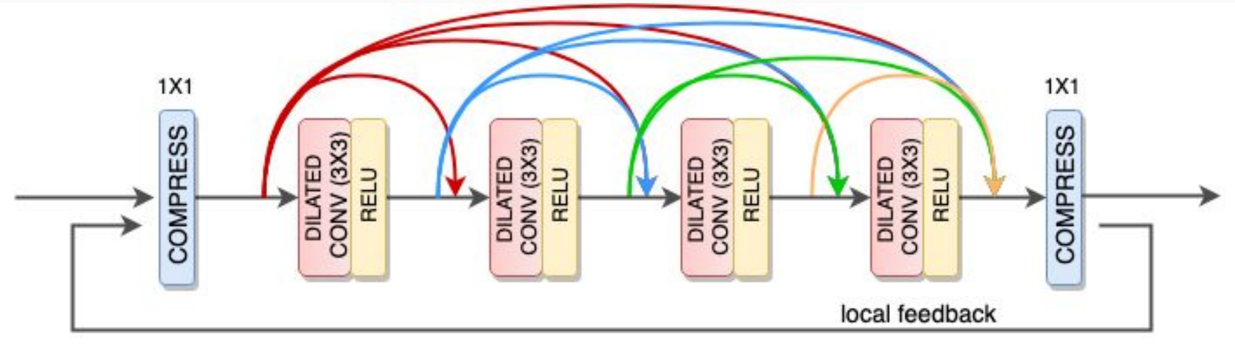
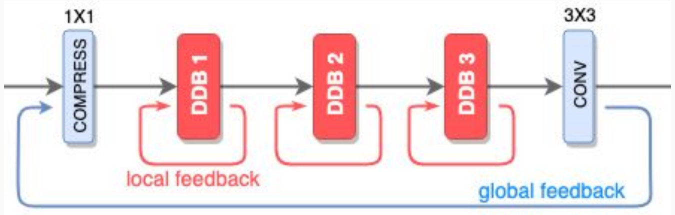
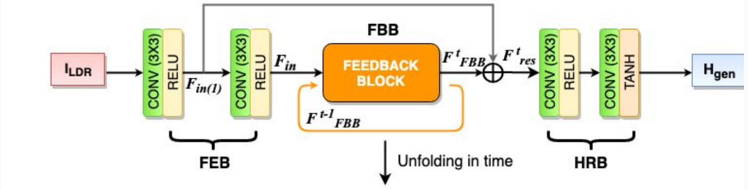
- These connections run parallel to the global feedback connections and increase the overall effectiveness of the network.



Dilated Dense Block (DDB)

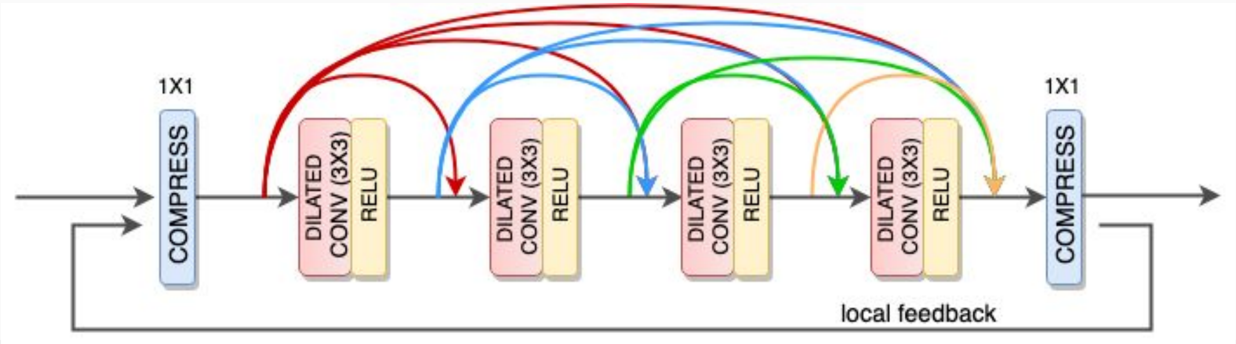






Dilated Dense Block (DDB)

- Basic unit of the feedback block



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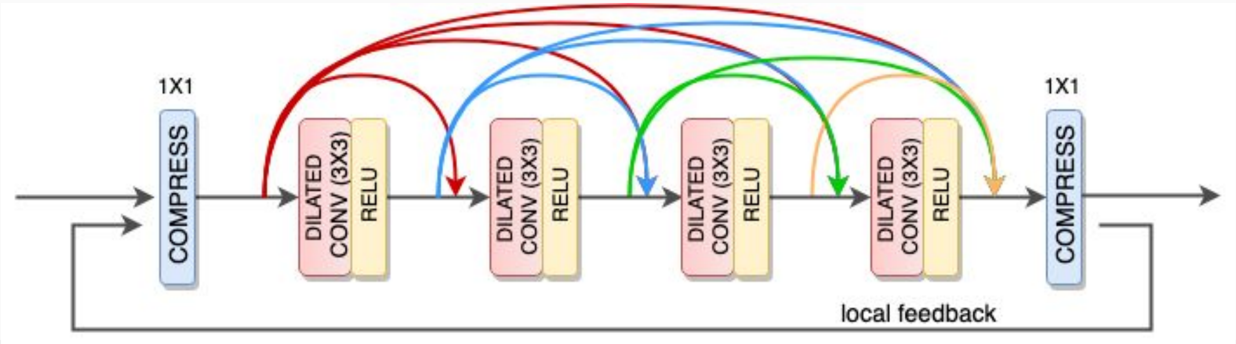
- Basic unit of the feedback block
- Dilated convolutions help in increasing the receptive field of the network.



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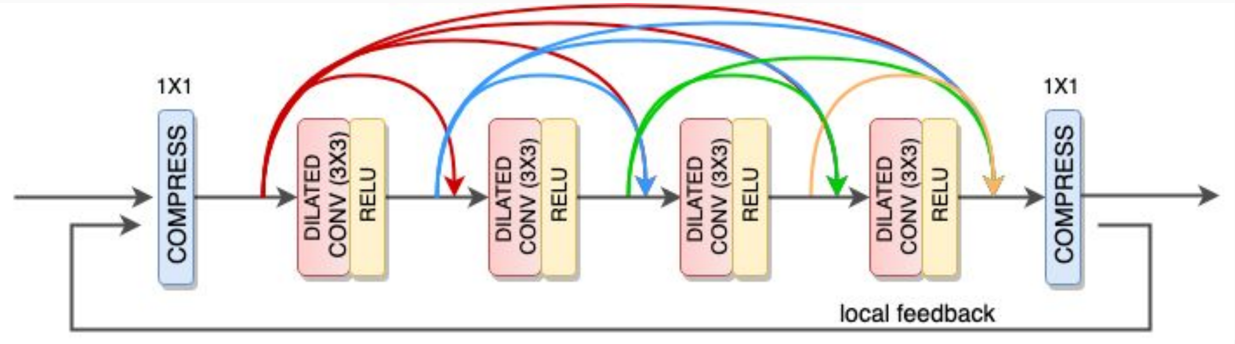

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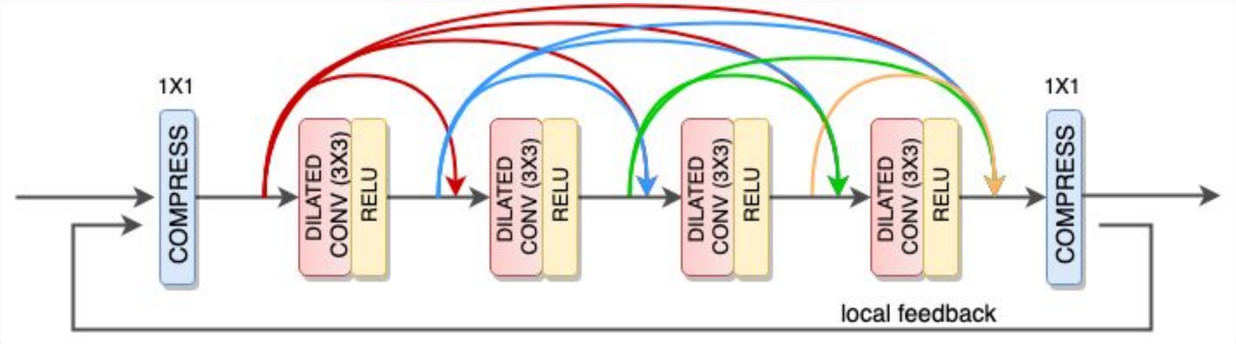
- Two 1 × 1 convolutional layers for feature compression + four dilated 3 × 3 dense convolutional layers



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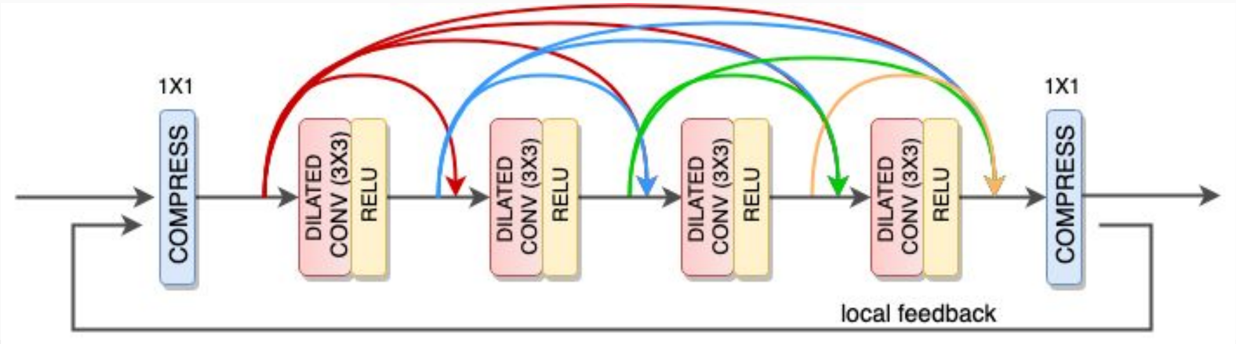
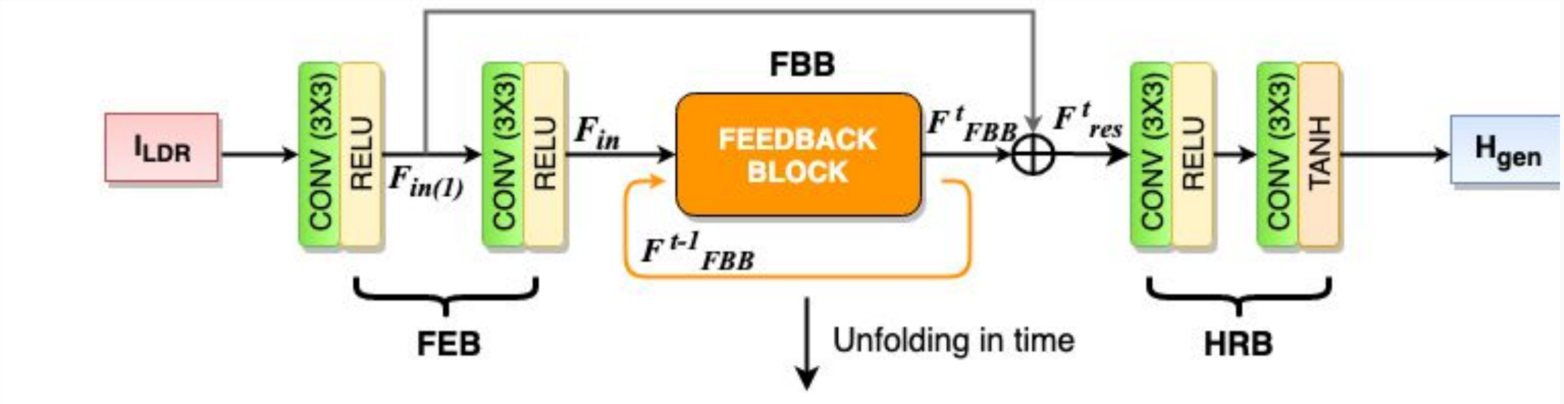
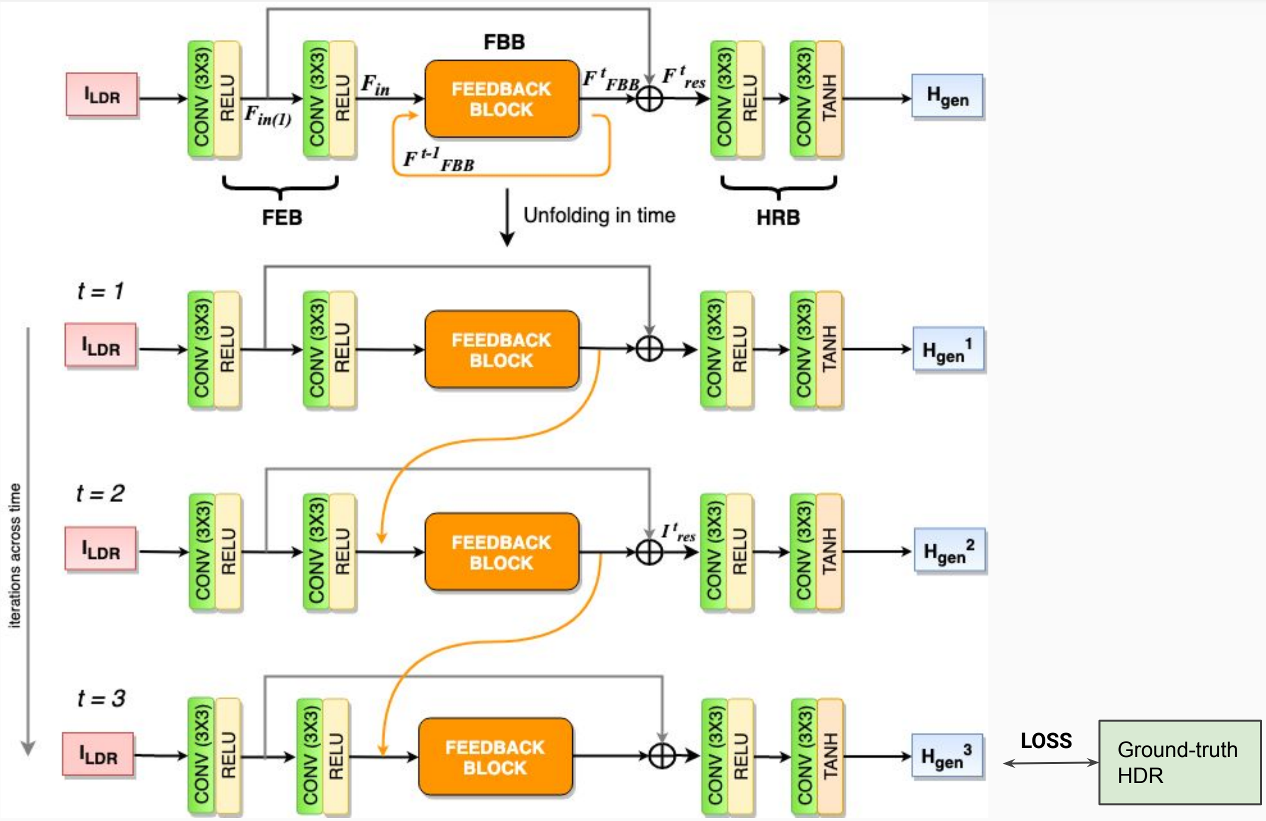
- Feature reuse, reduced network parameters, improved learning ability.



HDR Reconstruction Block (HRB)



Loss function



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- **L1 loss and Perceptual loss** ($\lambda = 0.1$)

$$\mathcal{L} = \mathcal{L}_p + \lambda \mathcal{L}_{L1}$$

Implementation

- Adam optimizer β1 = 0.5 and β2 = 0.999
- 200 epochs
- Batch size: 16 (CityScene dataset), 6 (Curated HDR dataset)
- Learning rate of 2×10^{-4} for first 100 epochs, decayed linearly over the next 100 epochs
- 2 RTX 2070 GPUs

Experiments

Datasets

The performance of the network was evaluated over two datasets-

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- CityScene dataset
  - 128 x 64 size
  - Training set - 39,460 LDR-HDR image pairs
  - Testing set - 1,672 pairs

Datasets

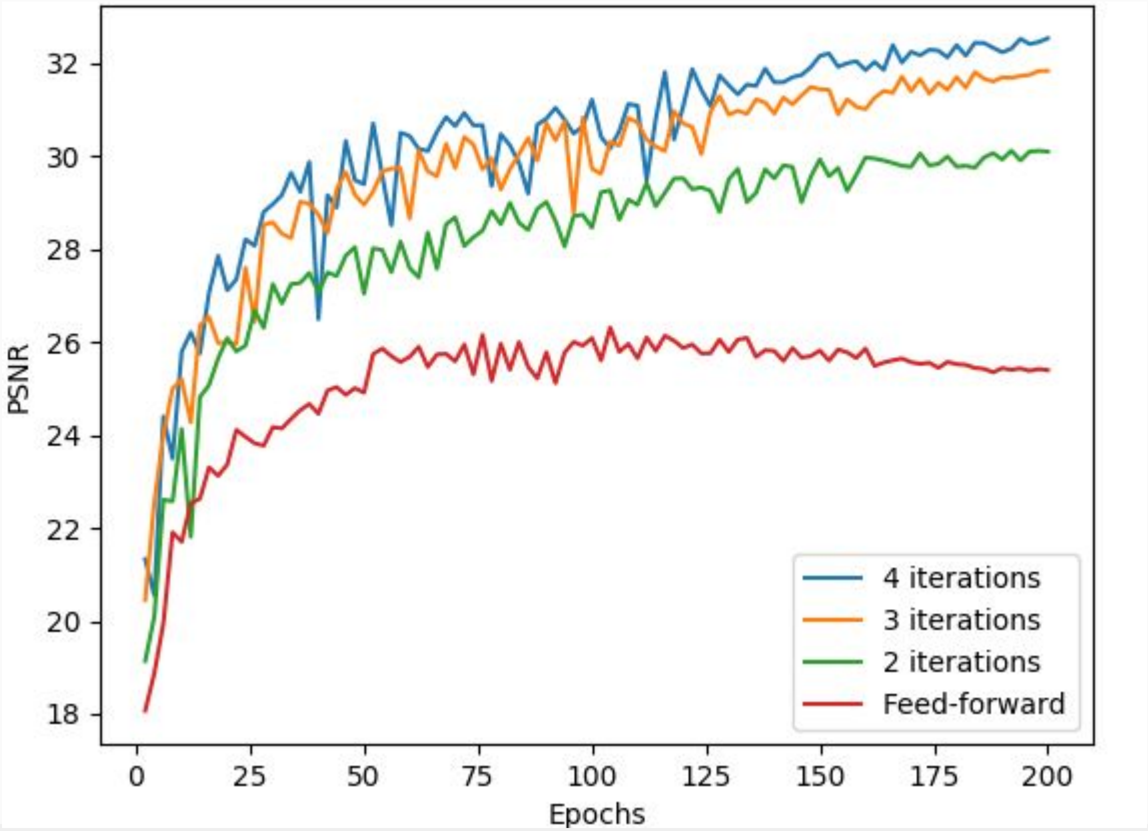
The performance of the network was evaluated over two datasets-

- Curated dataset
    - 256 x 256 size
    - Training set - 11,262 LDR-HDR image pairs
    - Testing set - 500 image pairs (512 x 512)

Evaluation metrics

- PSNR score (db) - Peak Signal-to-Noise Ratio
- SSIM score - Structural Similarity Index
- HDR-VDP2 Q-score

Feedback mechanism analysis



Results

Qualitative evaluation

LDR

GENERATED

GROUND TRUTH

Qualitative evaluation

LDR

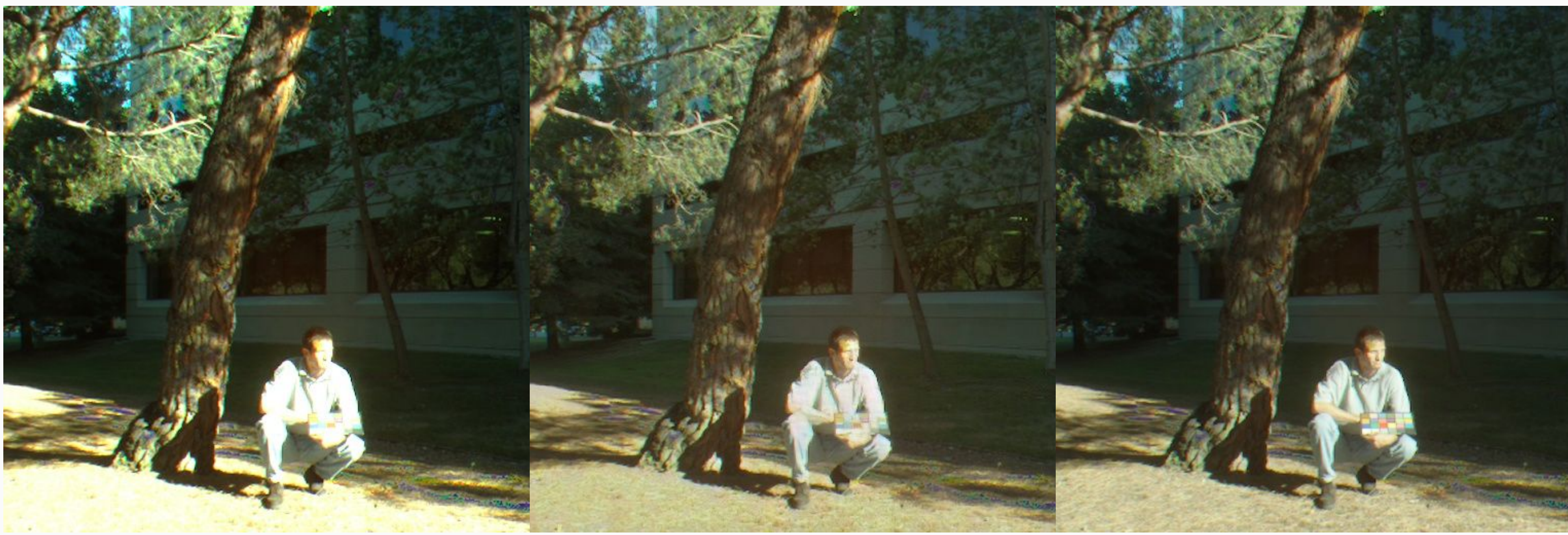
GENERATED

GROUND TRUTH

Qualitative evaluation

LDR GENERATED GROUND TRUTH

Qualitative evaluation



LDR GENERATED GROUND TRUTH

Qualitative comparisons

LDR | **DRTMO** | **FHDR** | **GROUND TRUTH**

Qualitative comparisons

LDR | HDRCNN | FHDR | GROUND TRUTH

Qualitative evaluation

LDR

GENERATED

GROUND TRUTH

Qualitative comparisons

LDR DRTMO FHDR GROUND TRUTH

Qualitative comparisons

LDR **HDRCNN** **FHDR** **GROUND TRUTH**

Quantitative evaluation

Methods	City Scene Dataset			Curated HDR Dataset		
	PSNR	**SSIM**	**Q-score**	**PSNR**	**SSIM**	**Q-score**
AKY [14]	15.35	0.44	35.40	9.58	0.20	33.47
KOV [15]	16.77	0.59	35.31	12.99	0.41	29.87
HDRCNN [1]	13.21	0.38	54.34	12.13	0.34	55.32
DRTMO [3]	-	-	-	11.4	0.28	58.85
DRHT [4]	-	0.93	61.51	-	-	-
FHDR/W	25.39	0.89	63.21	16.94	0.74	65.27
FHDR	**32.54**	**0.95**	**67.18**	**20.3**	**0.79**	**70.97**

Conclusion

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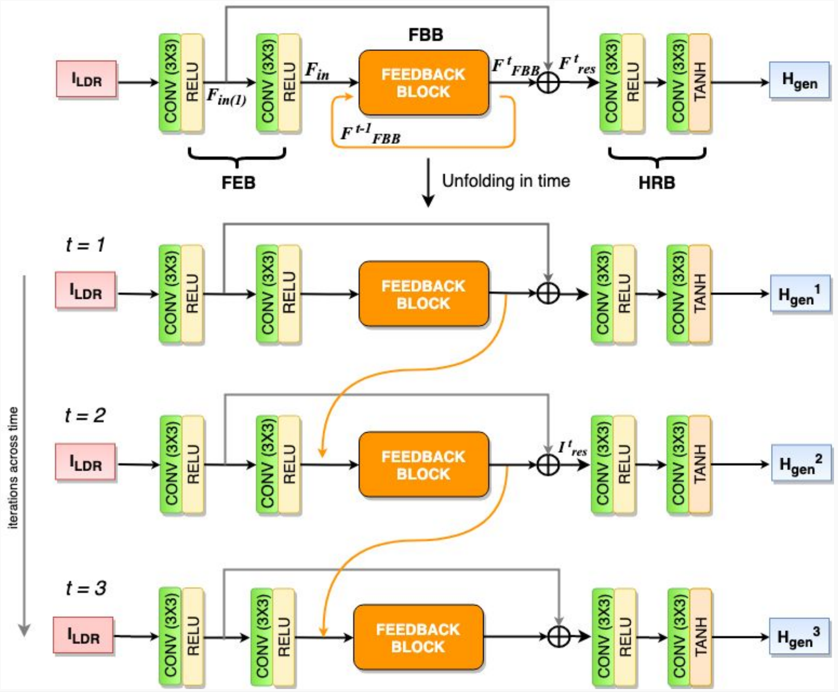
- Novel feedback network FHDR, to reconstruct an HDR image from a single exposure LDR image.



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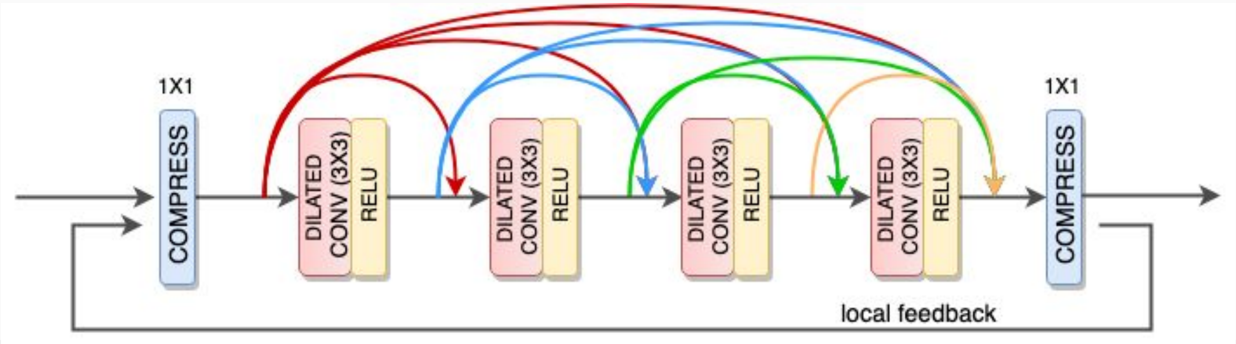

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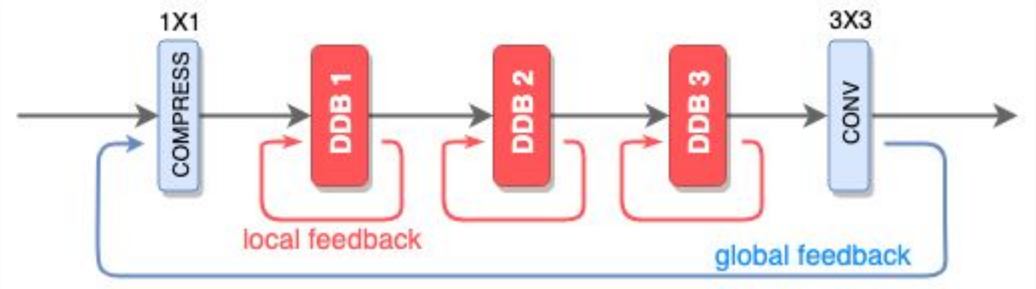

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- Iterative learning forces the network to create a coarse-to-fine representation which results in early reconstructions.
- Extensive experiments demonstrate that the FHDR network is successfully able to recover the underexposed and overexposed regions outperforming state-of-the-art methods.

Thank you

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