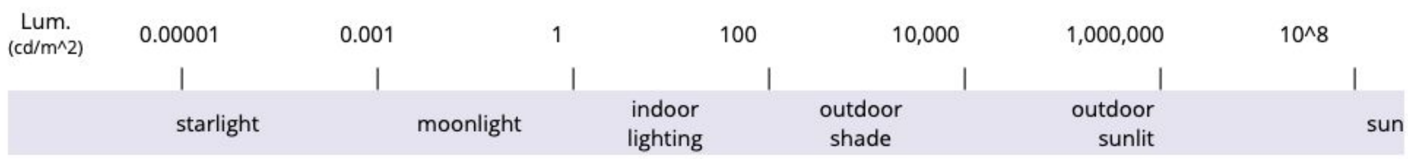
HDR imaging
using Deep Learning

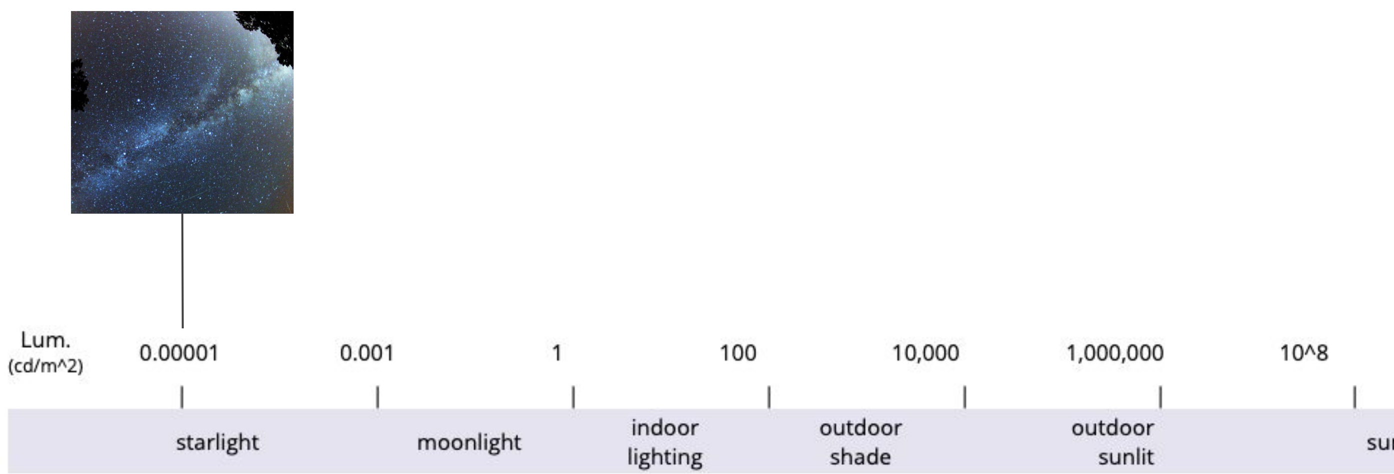
Mukul Khanna, IIT Gandhinagar

HDR

High Dynamic Range

Dynamic Range


Lum.
(cd/m^2)
0.00001
0.001
1
100
10,000
1,000,000
10^8
starlight
moonlight
indoor lighting
outdoor shade
outdoor sunlit
sun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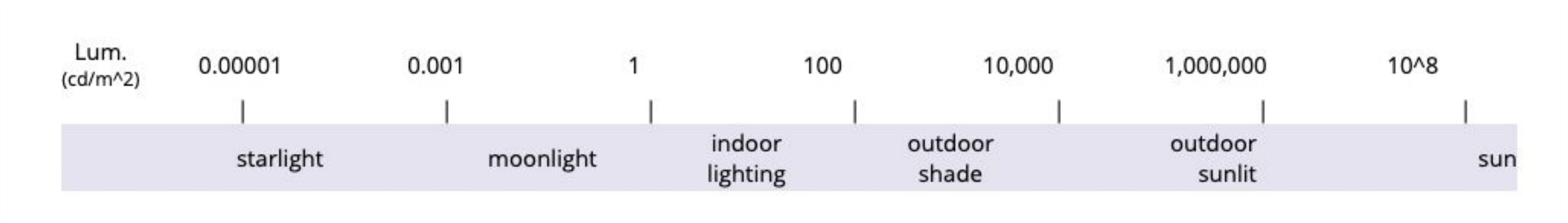
Introduction

- Common digital cameras can not capture the wide range of light intensity levels in a natural scene.



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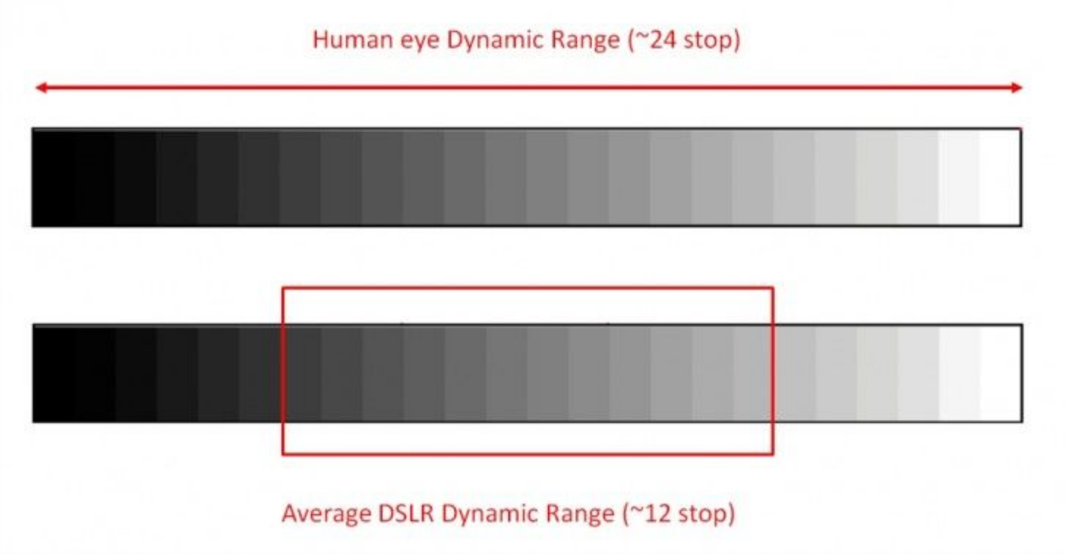

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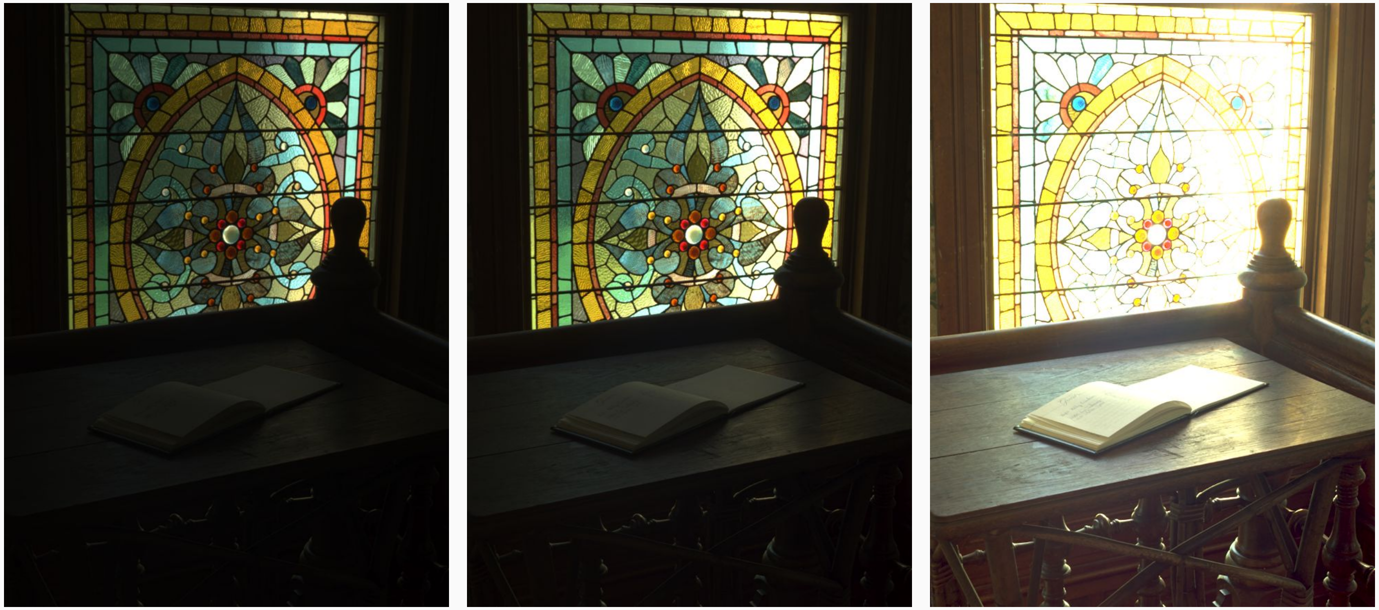
Courtesy: OpenHDR (viewer.openhdr.org)

Introduction

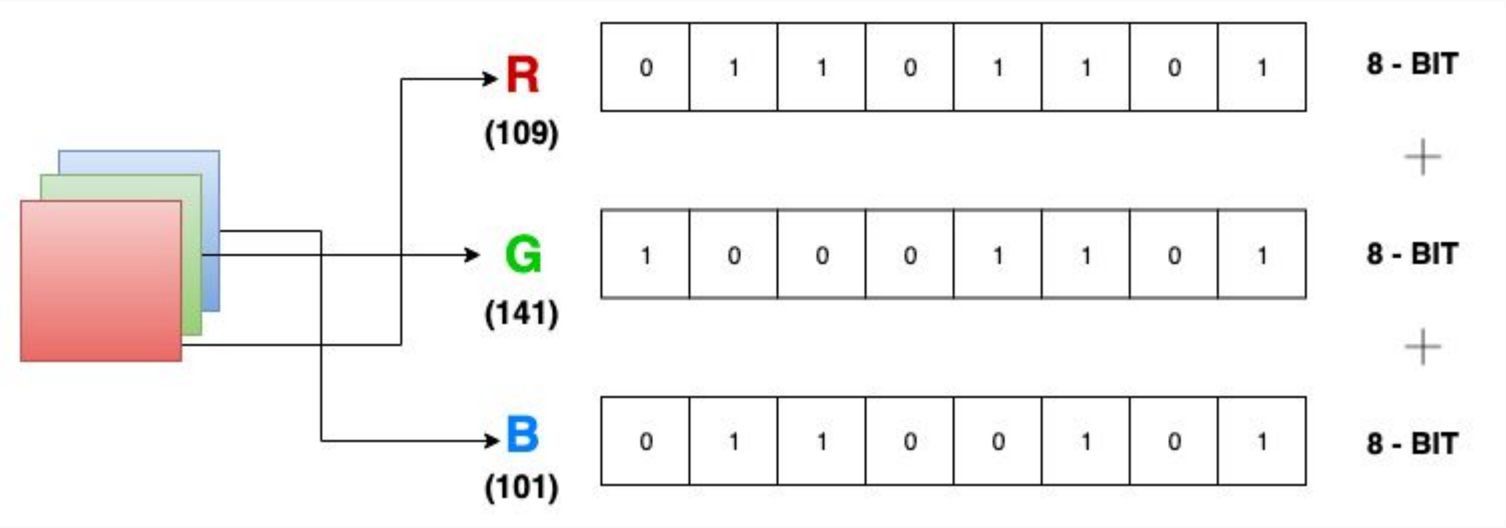
- To recover the lost information and represent the wide range of illuminance in an image, **High Dynamic Range (HDR)** images need to be generated.



HDR IMAGE ENCODING

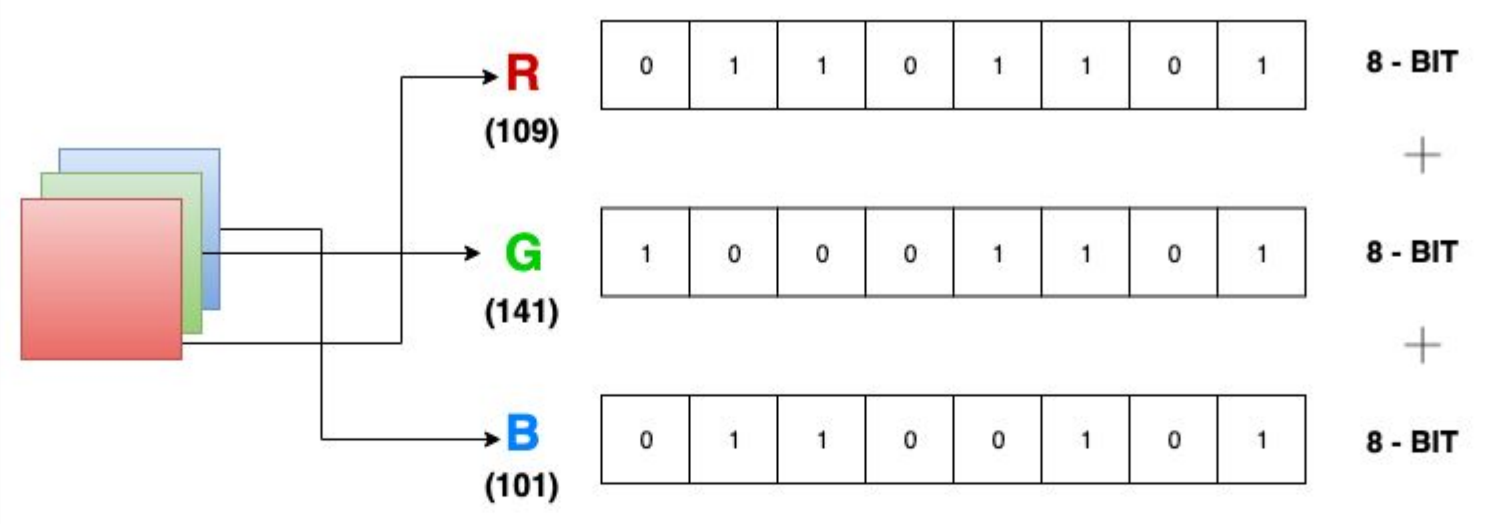
HDR image encoding

- Commonly, the images that we see on our phones and computers, are 8-bit (per channel) encoded RGB images.



HDR image encoding

- Each pixel's value is stored using 24-bit representations, 8-bit for each channel (R, G, B). Each channel of a pixel has a range of 0–255 intensity values.



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- To solve this problem, HDR images are encoded using 32-bit floating point numbers, for each channel. This allows us to capture the wide uncapped range of HDR images.
- There are various formats for writing HDR images, the most common being **.hdr** and **.exr**.

DISPLAYING HDR IMAGES

Displaying HDR images

- Most off the shelf display devices are incapable of delivering the wide uncapped range of HDR images.
- They expect the input source to be in the three-channel 24-bit (3x8) RGB format.
- Due to this reason, the wide dynamic range needs to be toned down to be able to accommodate it in the 0–255 range of RGB format.

Tone-mapping

- Tone mapping addresses the problem of strong contrast reduction from the scene radiance to the displayable range while preserving the image details and color appearance important to appreciate the original scene content.

HDR IMAGE GENERATION

APPROACHES

- Non-learning based
- Learning based

Non learning based approach

Non learning based approach

- Conventionally, HDR images are developed by merging images captured at different exposures.

Non learning based approach

- These images are merged using a software algorithm and are saved as a single HDR image, in a way that the best portions of each image make it to the final image.

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Caveats

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Learning based approach

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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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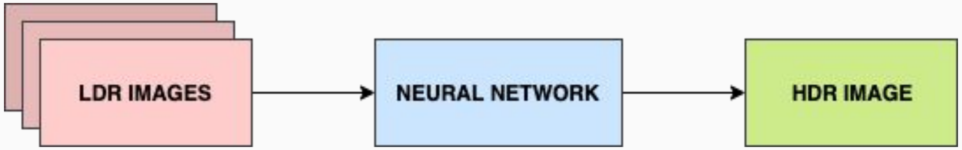
Approaches - learning based

- Learning based approaches can be broken down into two types -

    - Single LDR input
    - Multiple LDR inputs



Learning based - multiple LDR inputs

- Multiple exposure input

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

Single LDR input approaches

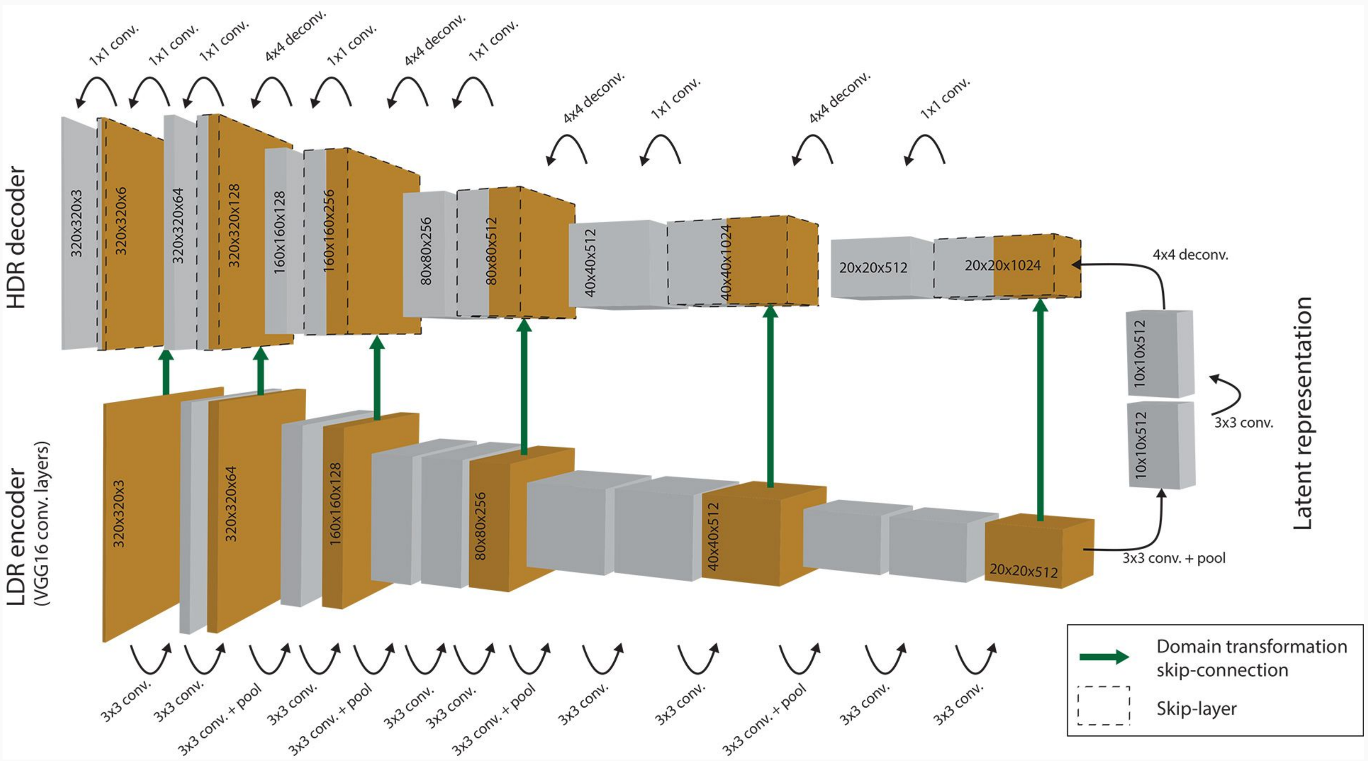
Learning based - single LDR input

- 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

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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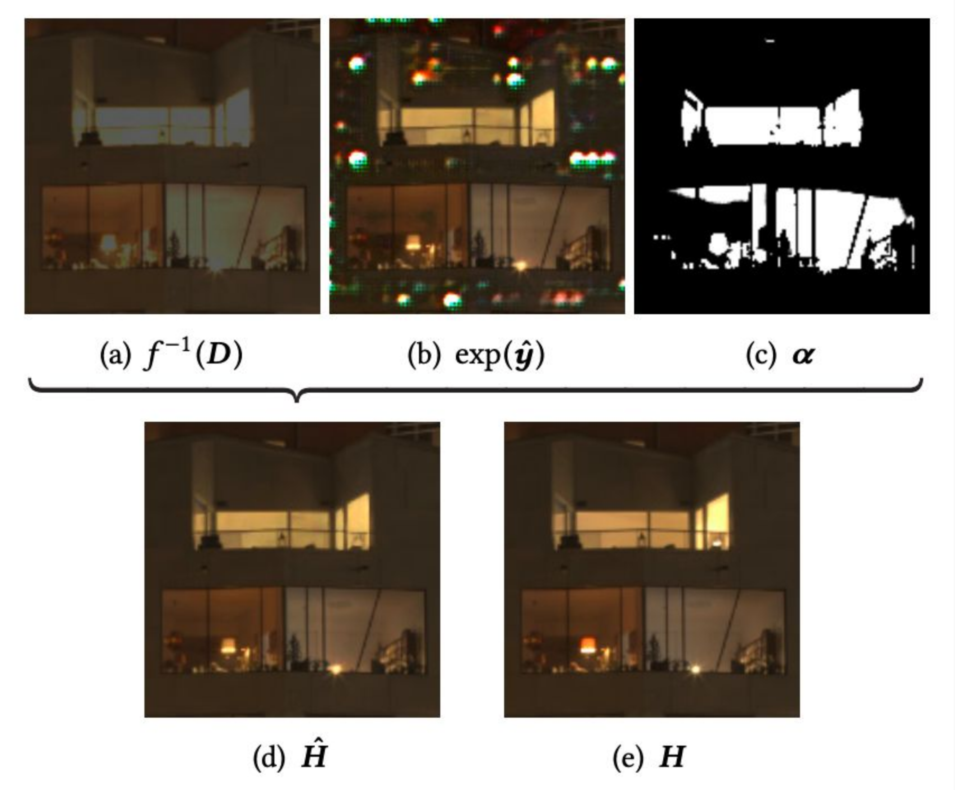
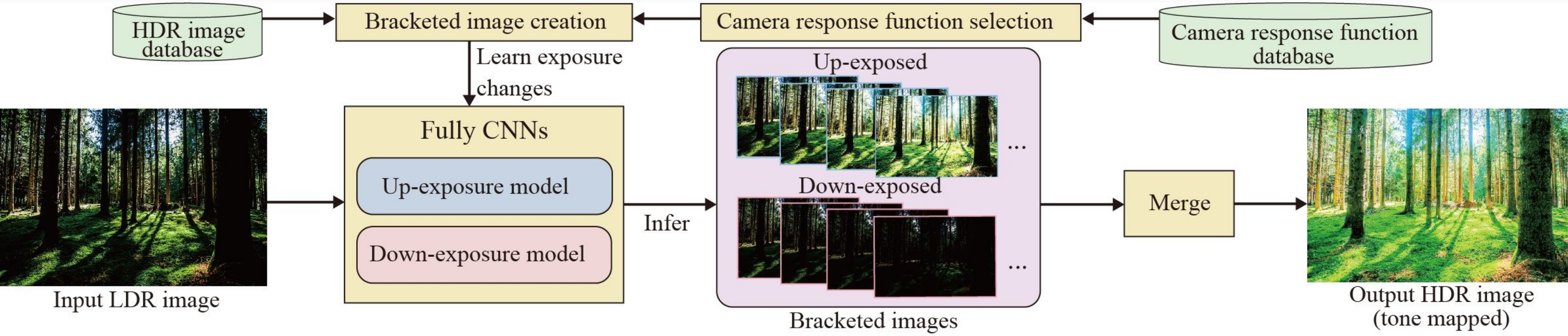


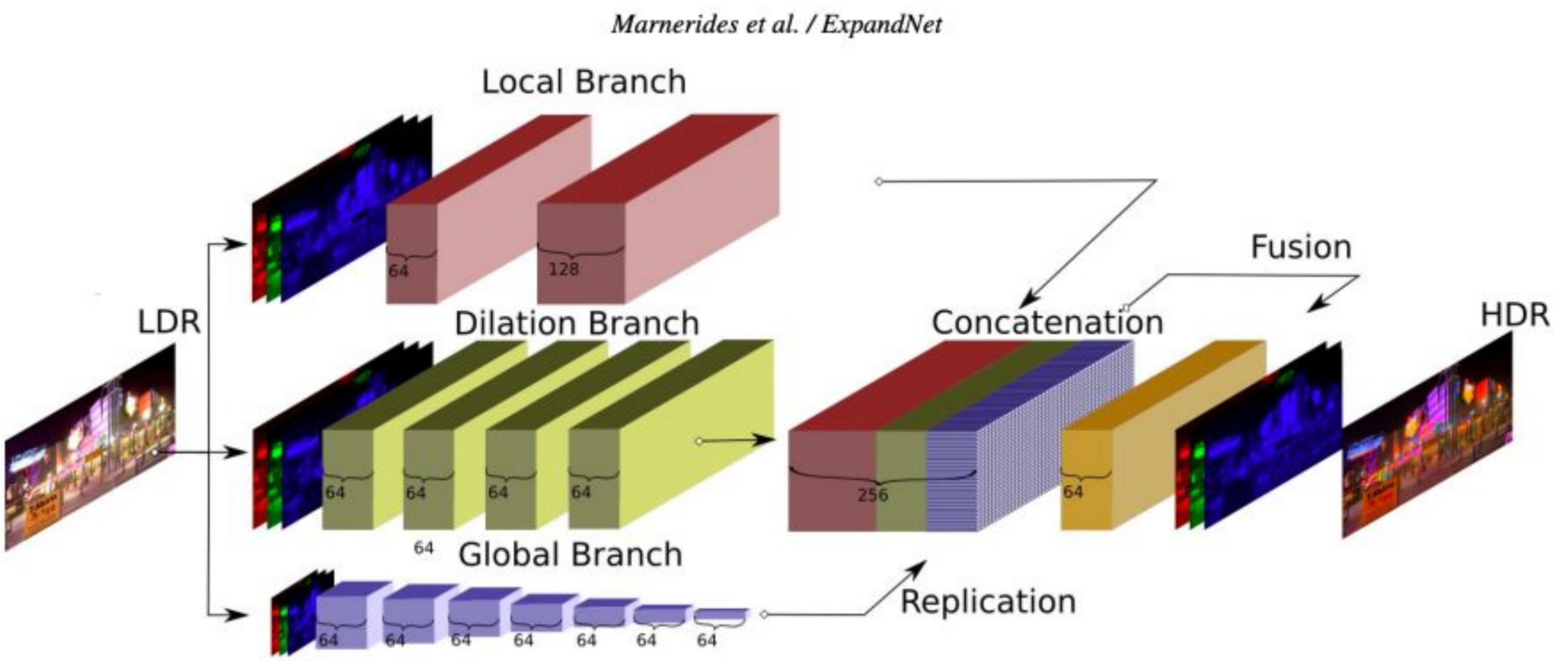
Deep reverse tone mapping

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.



Caveats

- Not end-to-end trainable

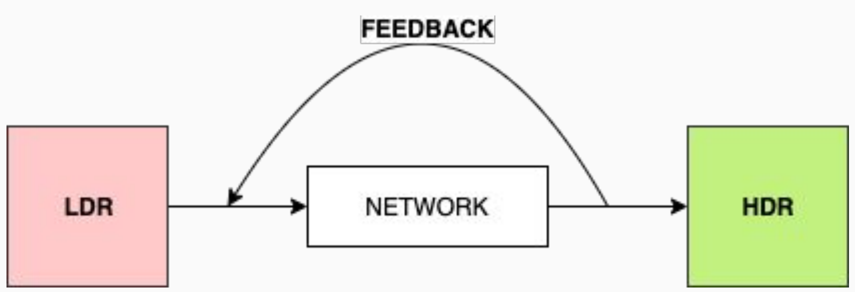
    OR/AND
- Only overexposed regions are recovered

    OR/AND
- High network parameter count

Our approach

Feedback networks

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



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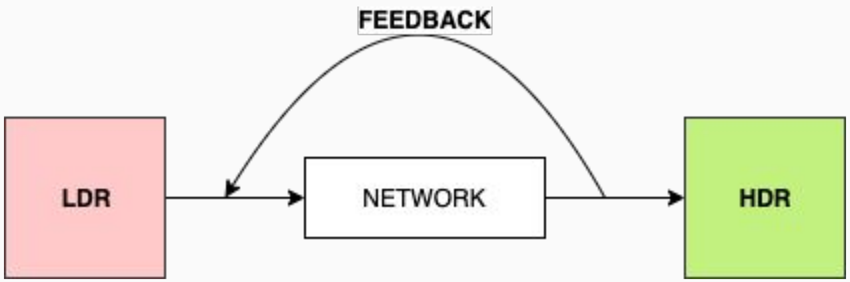
- Feedback systems are adopted to influence the input based on the generated output.
- Initial low level features are guided by the high level features using a hidden state of a Recurrent Neural Network over n iterations.



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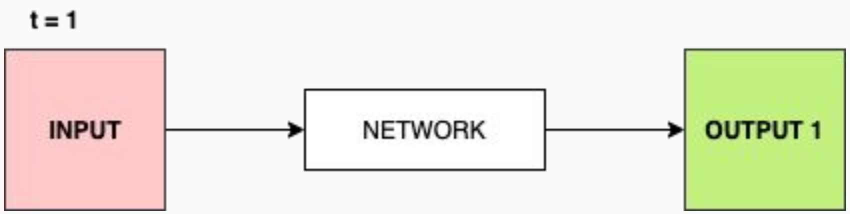

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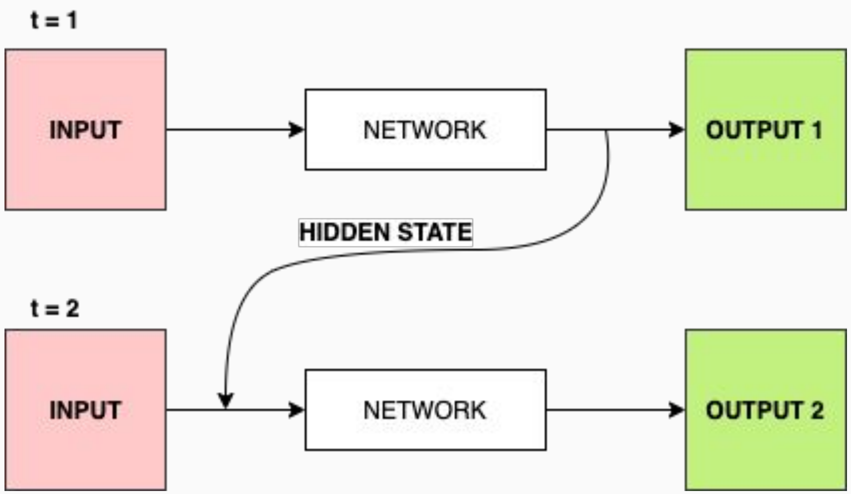

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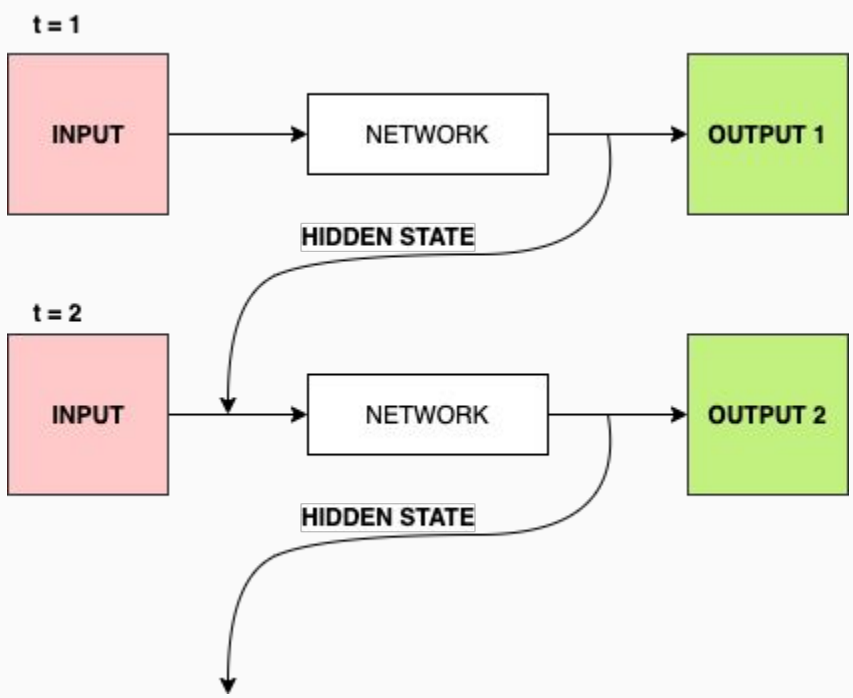

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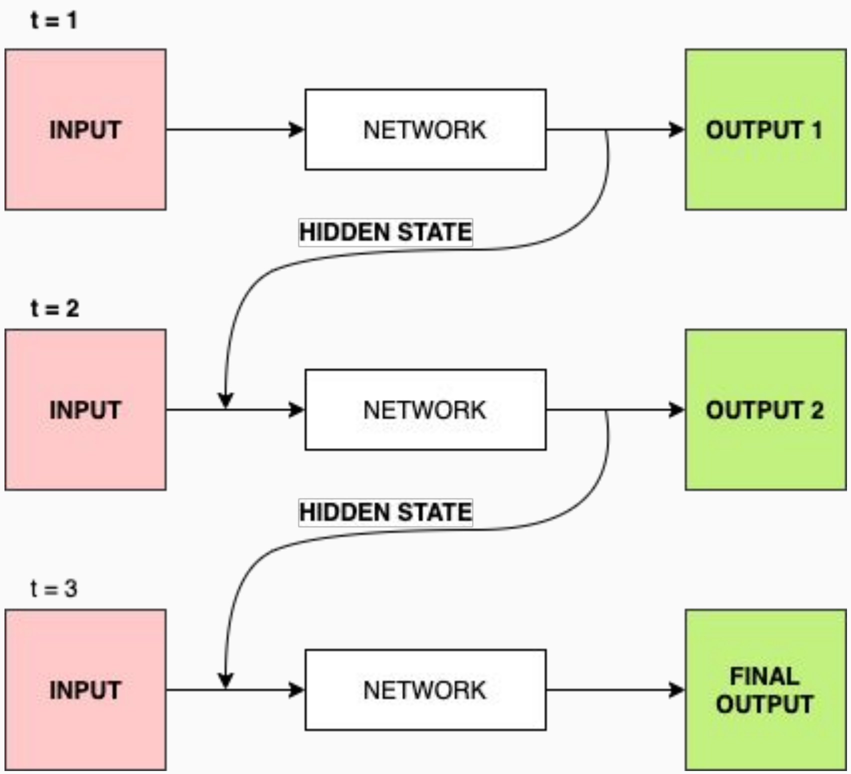
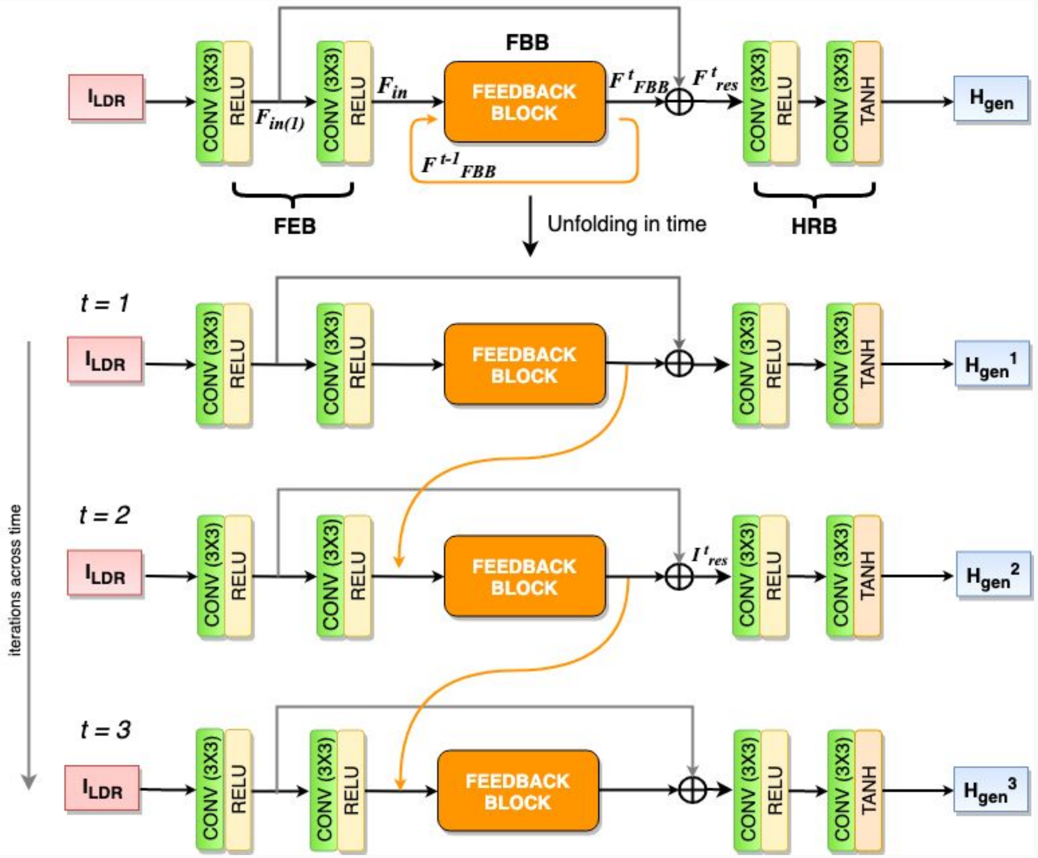
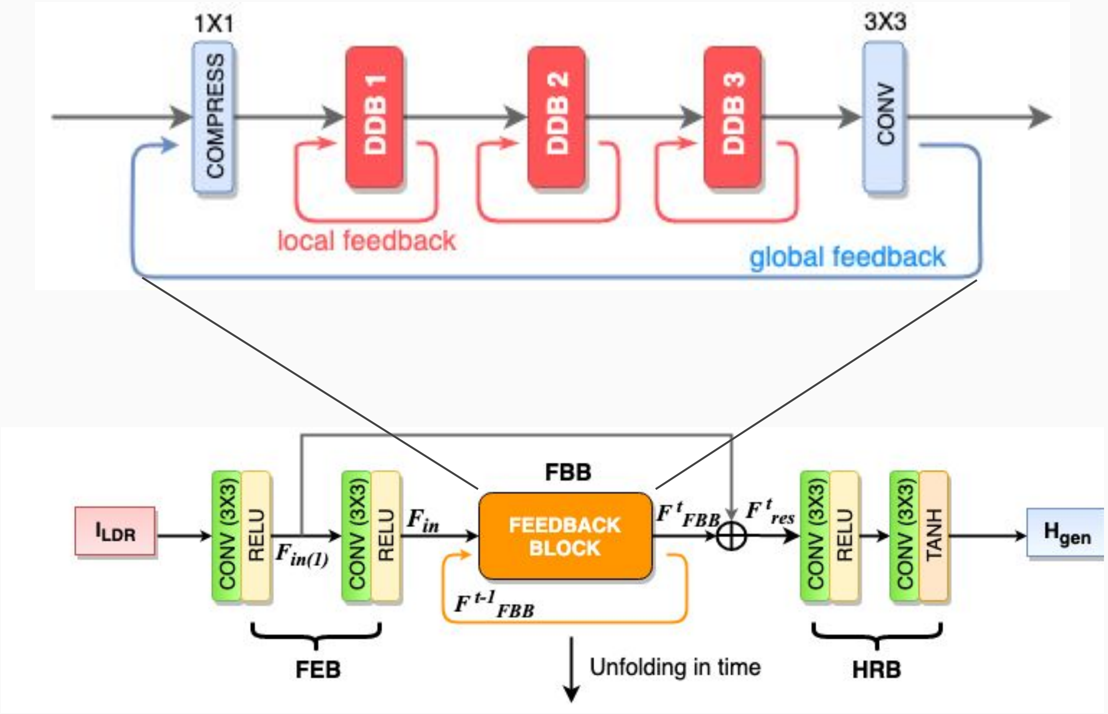


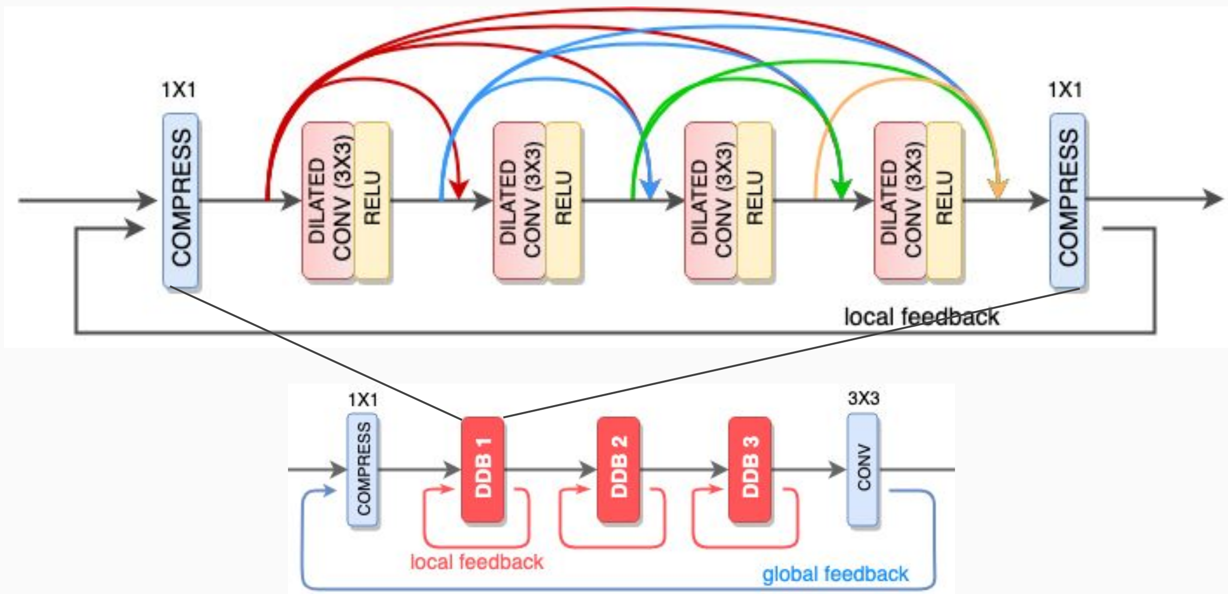
Model architecture

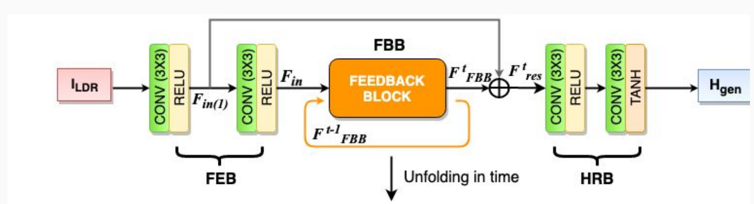


Feedback block

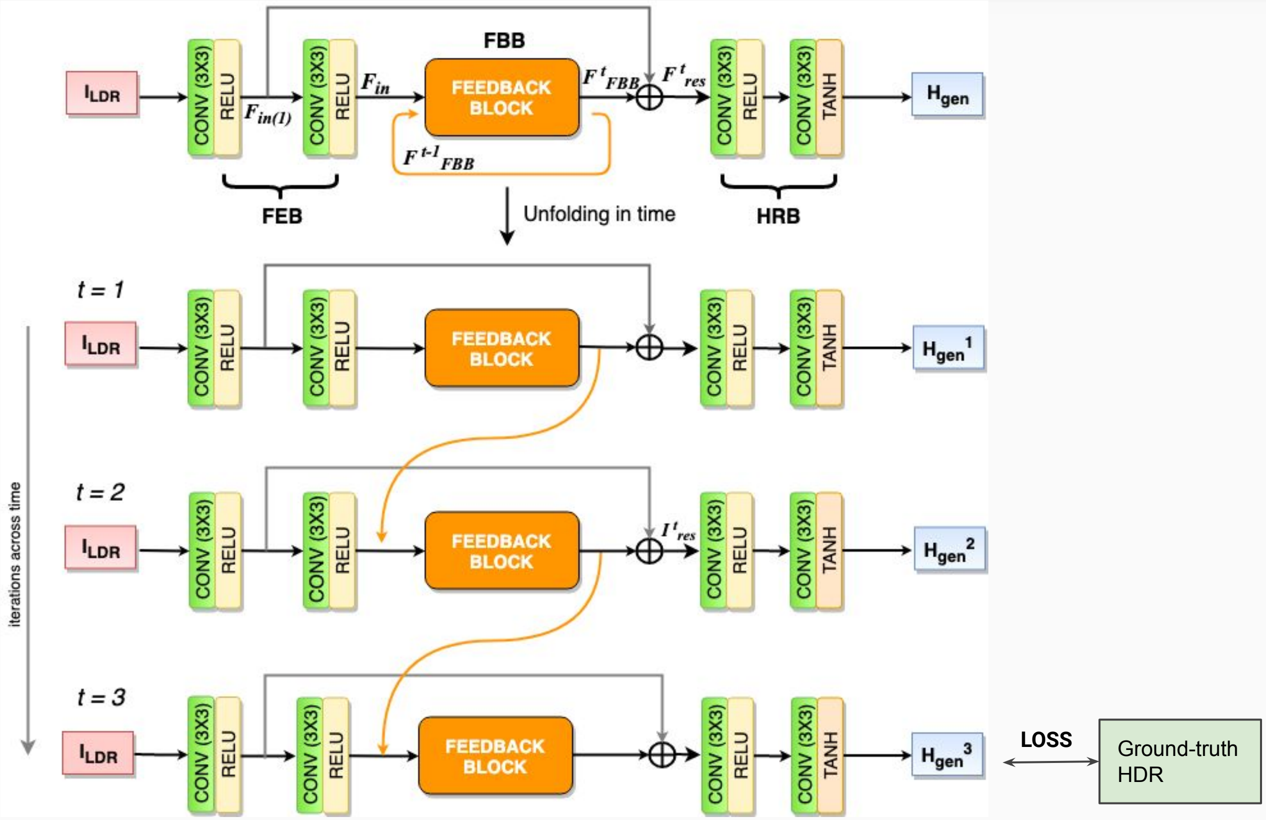


Dilated Dense Block (DDB)





Loss function



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$$T(H_{gen}^{t}) = \frac{log(1 + \mu H_{gen}^{t})}{log(1 + \mu)}$$

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

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

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

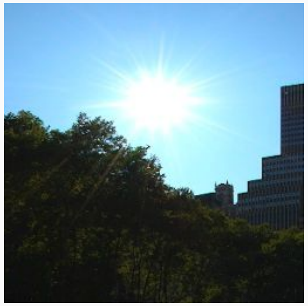
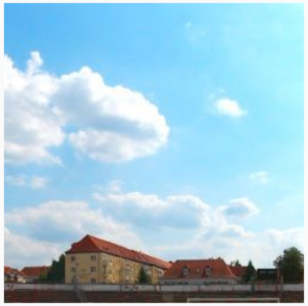
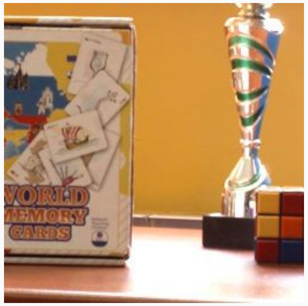
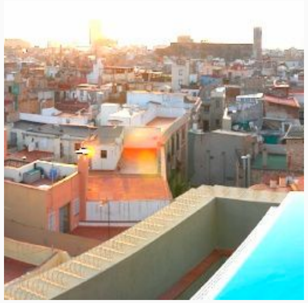




Datasets

The performance of the network was evaluated over two datasets-

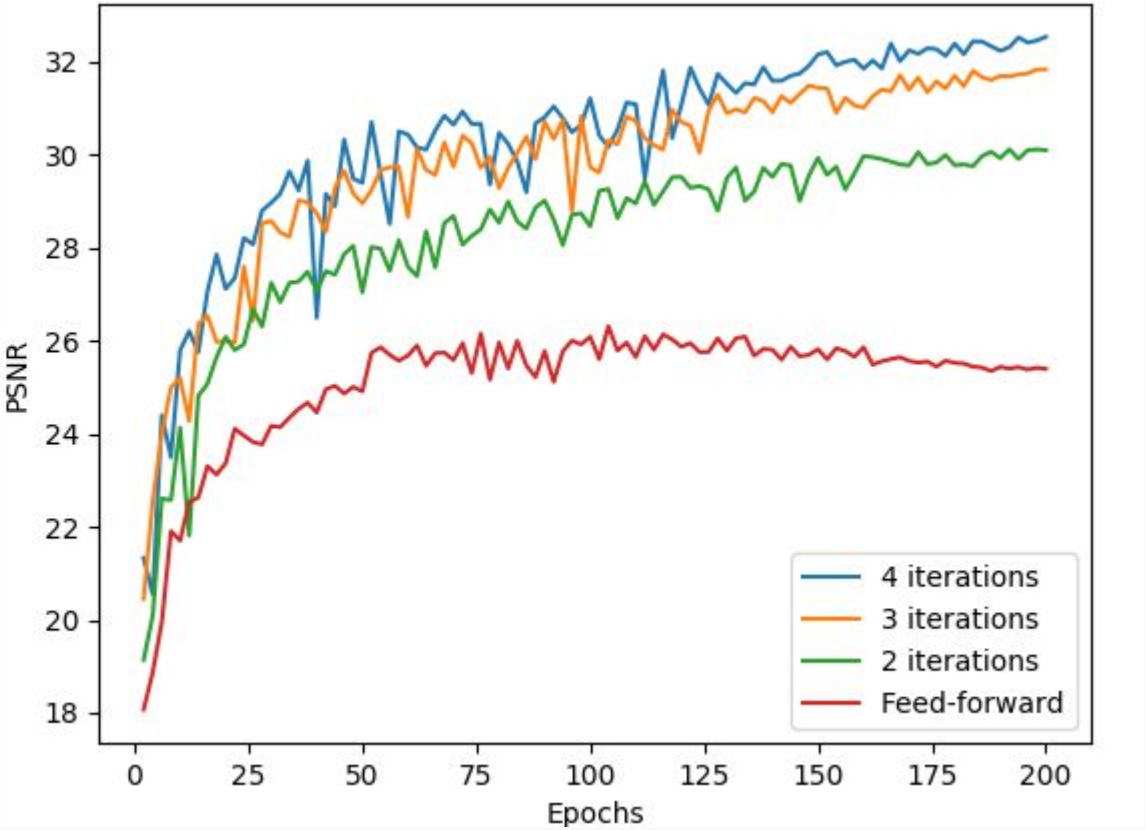
- Curated dataset
    - 256 x 256 size
    - Training set - 11,262 LDR-HDR image pairs
    - Testing set - 500 image pairs (512 x 512)


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

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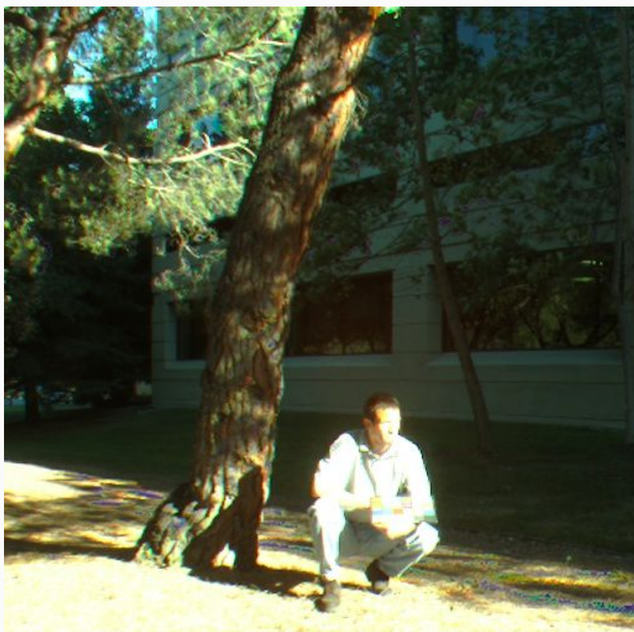
Qualitative evaluation



LDR

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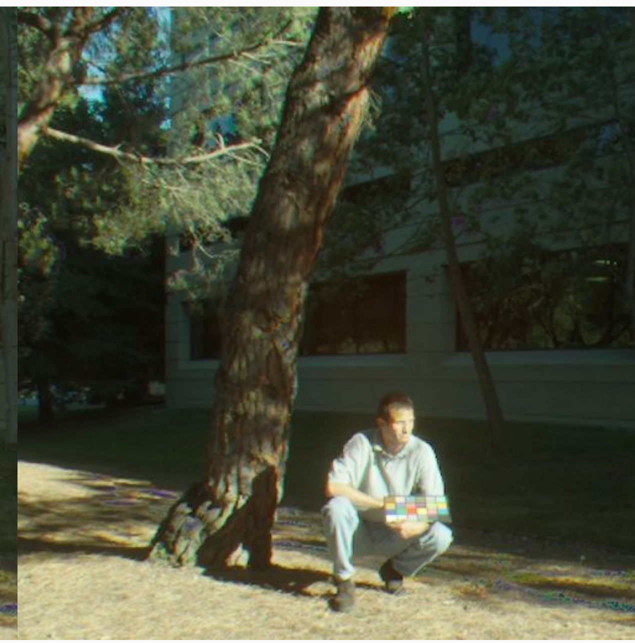

GROUND TRUTH

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**

HDR VIDEO

HDR VIDEO GENERATION

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  - Multiple exposure LDR sequences to HDR

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- RNNs, LSTMs to propagate temporal information across sequences.
- Adversarial training using temporal discriminators.

Conclusion

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- Deep learning helps - outperforms traditional approaches, again.

Thank you

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