

Single-Image HDR Reconstruction by Learning to Reverse the Camera Pipeline

박예인

Vision & Display Systems Lab.

Dept. of Electronic Engineering, Sogang University

Outline

- Introduction
- Background
 - Dynamic range / LDR / HDR
 - Multi-image HDR reconstruction
 - Single-image HDR reconstruction
- Learning to Reverse the Camera Pipeline
 - LDR image formation
 - Dequantization
 - Linearization
 - Hallucination
 - Refinement
 - Experimental Results
- Conclusion

Introduction

- Recovering a HDR image from a single LDR input image
- This paper propose a method to **reverse** the LDR image formation pipeline.
 - [HDR] \rightarrow dynamic range clipping \rightarrow non-linear mapping with a CRF \rightarrow quantization \rightarrow [LDR]
 - [LDR] \rightarrow dequantization \rightarrow linearization \rightarrow hallucination \rightarrow [HDR]



Background

- Dynamic range
 - The ratio of the maximum and minimum values of contrast
 - The ratio of brightness between the brightest and darkest areas
- LDR (Low dynamic range) : Small dynamic range
- HDR (High dynamic range) : Large dynamic range
 - Compared to the LDR image, the details in the dark and bright areas are alive, which has the advantage of adding realism to the screen.



LDR



HDR

Background

- Multi-image HDR reconstruction

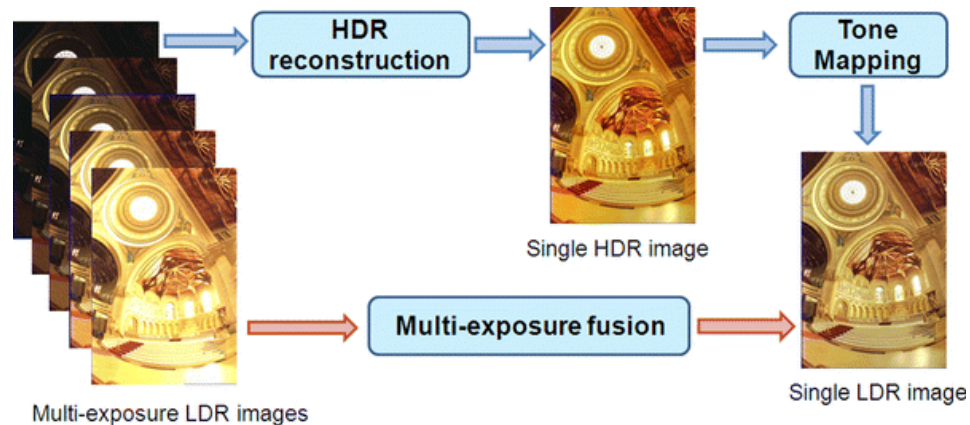
- Better performance than single-image

- Since images with various exposure values are input, there is a lot of information given, so resilience is relatively high in terms of detail and color.

- Ghost artifacts present

- Ghost artifacts

- ⚡ Afterimages that occur when the camera or object moves in the process of sequentially shooting multiple images



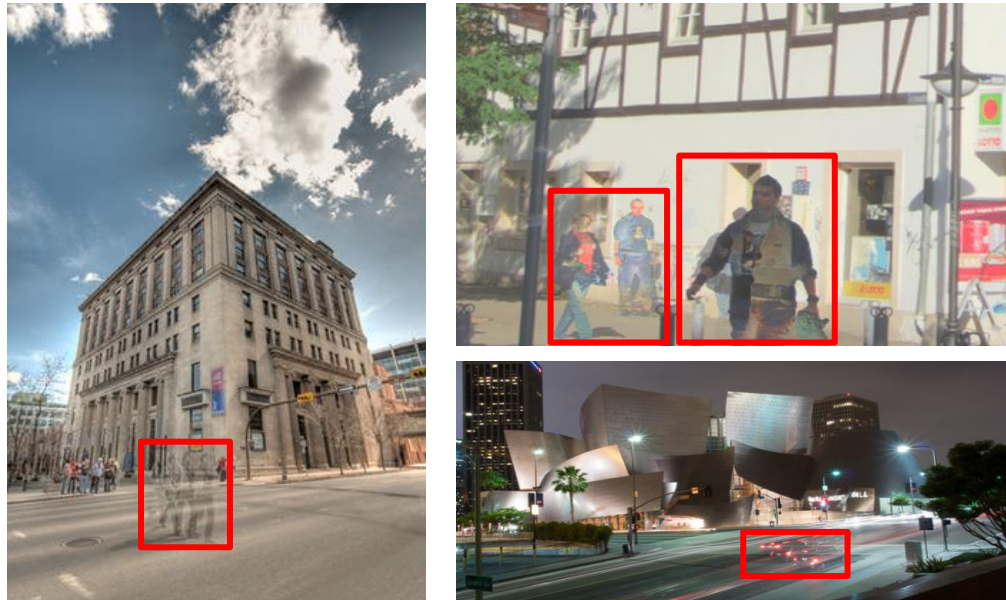
Multi-image HDR reconstruction pipeline

Background

- Multi-image HDR reconstruction

- Ghost artifacts present

- When such an afterimage effect occurs, an afterimage problem and a discoloration problem appear on the HDR restored image, resulting in deterioration of image quality.
 - Therefore, a lot of research is being conducted to solve this problem.



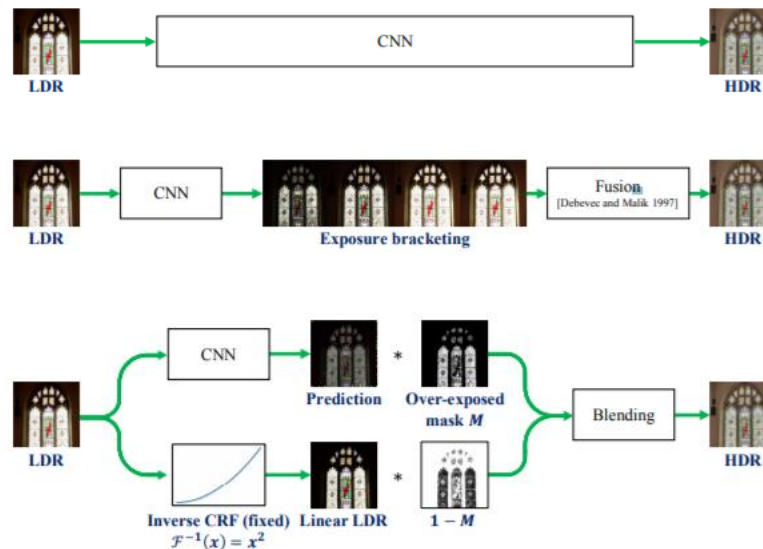
Examples of ghost artifacts

Background

- Single-image HDR reconstruction

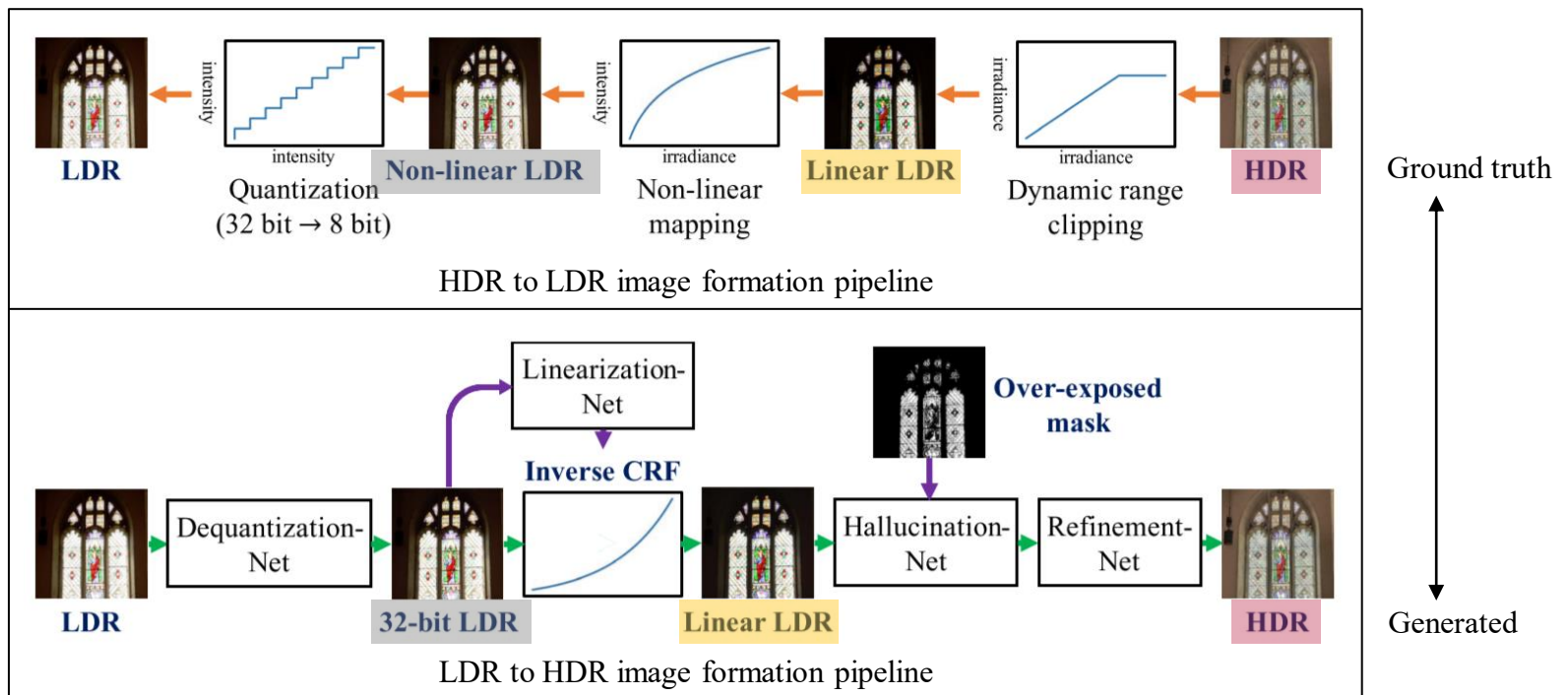
- It can be implemented without images with various exposure values
- It does not suffer from ghosting artifacts
- **More challenging compared to multi-image**

- Less information is given, resulting in poor resilience in terms of detail and color



Learning to Reverse the Camera Pipeline

- HDR to LDR image formation pipeline
 - [HDR] → dynamic range clipping → non-linear mapping with a CRF → quantization → [LDR]
- **Inverse function** of the HDR to LDR image formation pipeline
 - [LDR] → dequantization → linearization → hallucination → [HDR]



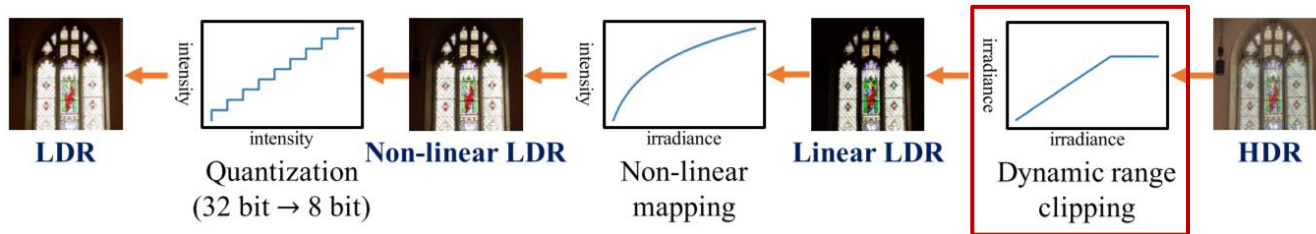
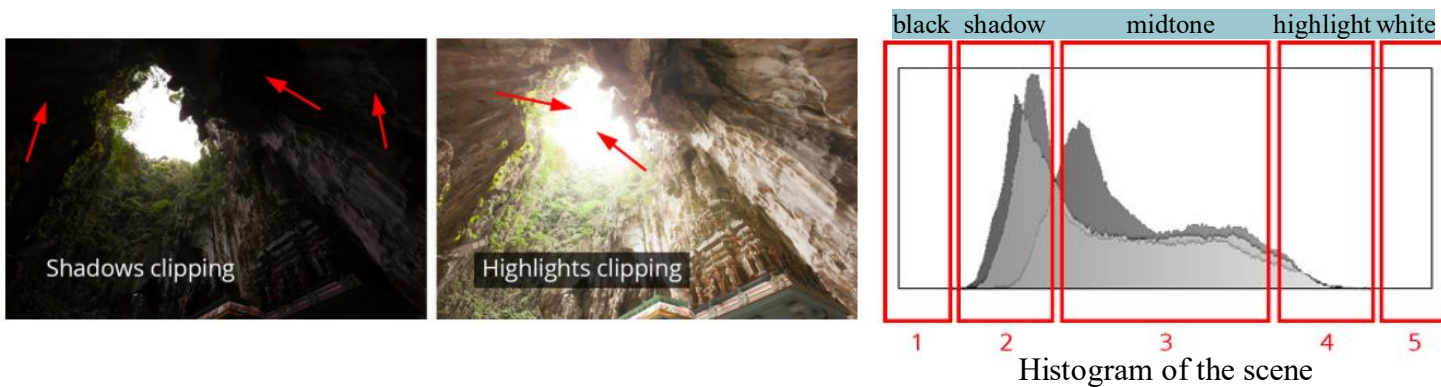
Learning to Reverse the Camera Pipeline

- HDR to LDR image formation pipeline

- Dynamic range clipping

- The camera first clips the pixel values of an HDR image to a limited range.

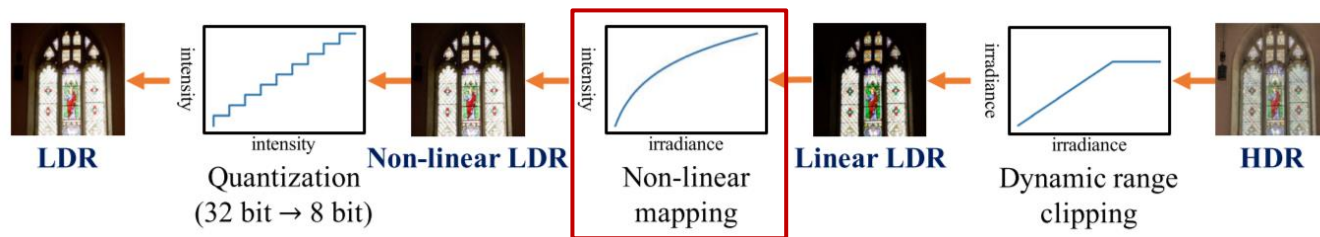
- Due to the clipping operation, there is information loss for pixels in the **over-exposed regions**.



HDR to LDR image formation pipeline

Learning to Reverse the Camera Pipeline

- HDR to LDR image formation pipeline
 - Non-linear mapping from a camera response function (CRF)
 - Non-linear mapping of linear LDR image generated by applying dynamic range clipping
 - A function that maps the irradiance of sensor to the pixel intensity of the image
 - ※ Cameras apply nonlinear CRF mapping to adjust the contrast of the captured image.
 - ✓ Calibration, tone mapping
 - ※ A CRF is unique to the camera model.
 - ✓ Non-linear characteristics are obtained through internal processing steps such as gamma correction and automatic white balance.
 - CRF estimation is a basic and necessary step in generating high dynamic range images.



HDR to LDR image formation pipeline

Learning to Reverse the Camera Pipeline

- HDR to LDR image formation pipeline

- Quantization

- After the non-linear mapping, the pixel values are quantized to 8 bits by

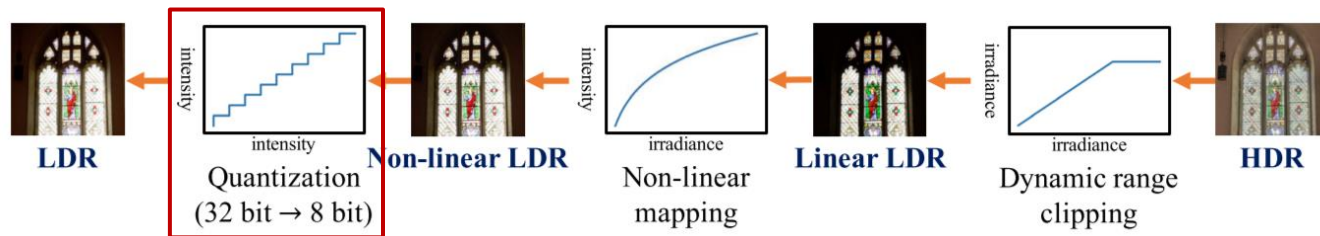
$$Q(I_n) = \lfloor 255 \times I_n + 0.5 \rfloor / 255.$$

- The quantization process leads to errors in the under-exposed regions.

- LDR image is formed by:

$$L = \Phi(H) = Q(\mathcal{F}(\mathcal{C}(H)))$$

- Φ denotes the pipeline of dynamic range clipping, non-linear mapping, and quantization steps..

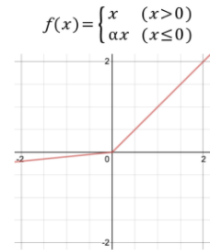


HDR to LDR image formation pipeline

Learning to Reverse the Camera Pipeline

- Dequantization-Net

- 6-level U-Net architecture with 2 conv layers followed by a leaky ReLU ($\alpha = 0.1$)
- Tanh layer is used to normalized the output of the last layer to $[-1.0, 1.0]$.
- The output of the Dequantization-Net is **added** to the input LDR image.
 - Dequantized LDR image is generated.

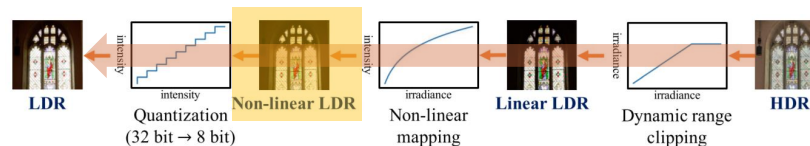
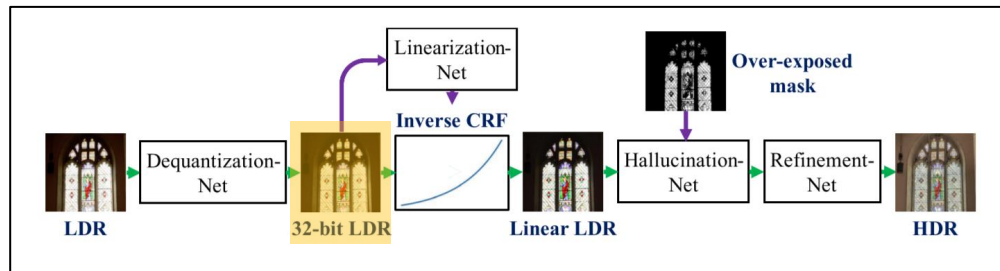


Leaky ReLU

- L2 loss

$$\mathcal{L}_{\text{deq}} = \|\hat{I}_{\text{deq}} - I_n\|_2^2$$

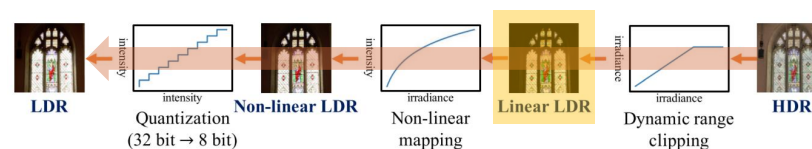
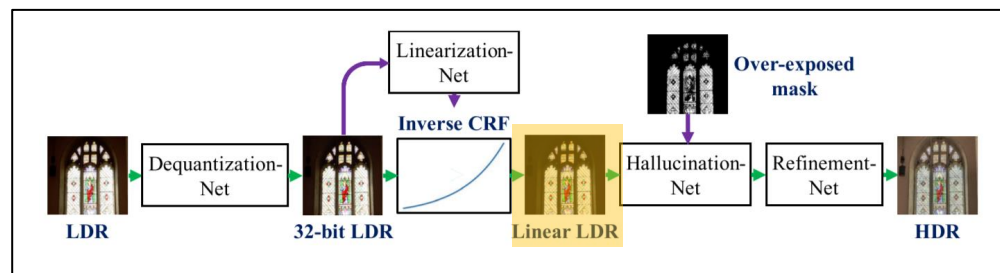
- Ground truth HDR image is constructed by dynamic range clipping and non-linear mapping.



Learning to Reverse the Camera Pipeline

- Linearization-Net

- The goal is to predict CRF and convert non-linear LDR images to linear irradiance.
- CRF is unique for each camera, but all CRFs have the following properties.
 - The function should increase monotonically.
 - The minimum and maximum input values must be mapped to the minimum and maximum output values, respectively.
 - Since it is a one-to-one mapping function, the inverse function also has the above features.



Learning to Reverse the Camera Pipeline

- Linearization-Net

- Edge and color histogram are effective in predicting inverse CRF

- Extract edge and color histogram features from non-linear LDR images

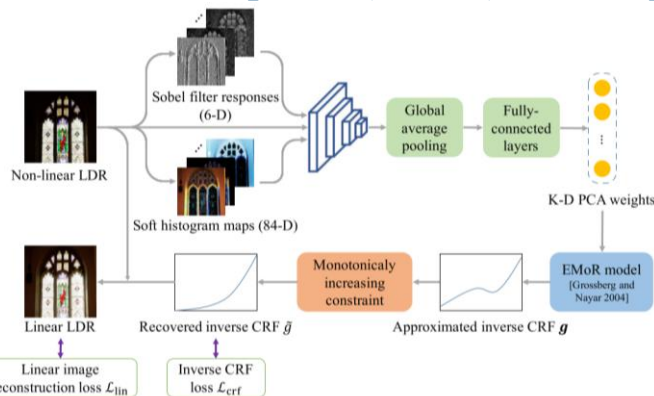
- ☼ Sobel filter

- ☼ Spatial-aware soft-histogram layer

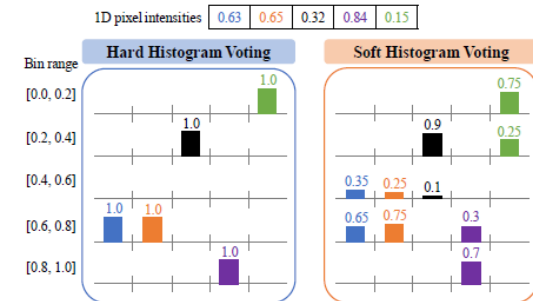
- ResNet-18

- 2 FC layer → k-dim PCA weights

- Empirical Model of Response (EMoR) model applied



$$\mathcal{L}_{lin} = \|\hat{I}_{lin} - I_c\|_2^2 \quad \mathcal{L}_{crf} = \|\tilde{g} - g\|_2^2 \quad \rightarrow \quad \mathcal{L}_{lin} + \lambda_{crf} \mathcal{L}_{crf}$$



$$h(i, j, c, b) = \begin{cases} 1 - d \cdot B, & \text{if } d < \frac{1}{B} \\ 0, & \text{otherwise} \end{cases}$$

i, j : horizontal, vertical pixel positions

c : the index of color channels

$b \in \{1, \dots, B\}$: the index for the histogram bin

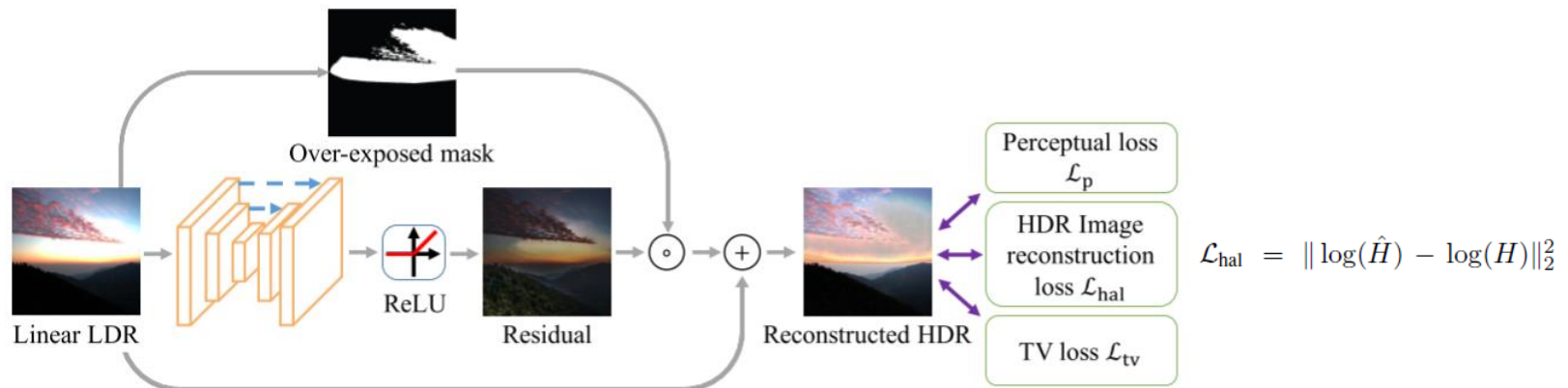
$d = |I(i, j, c) - (2b - 1)/(2B)|$: the intensity distance to the center of the b th bin

Learning to Reverse the Camera Pipeline

- Hallucination
 - The goal is to recover missing details due to dynamic range clipping.
 - Over-exposed regions
 - Encoder-decoder architecture with skip connections
 - Reconstruction HDR image

$$\hat{H} = \hat{I}_{\text{lin}} + \alpha \cdot \mathcal{C}^{-1}(\hat{I}_{\text{lin}})$$

$$\text{Over-exposed mask } \alpha = \max(0, \hat{I}_{\text{lin}} - \gamma) / (1 - \gamma) \quad (\gamma = 0.95)$$



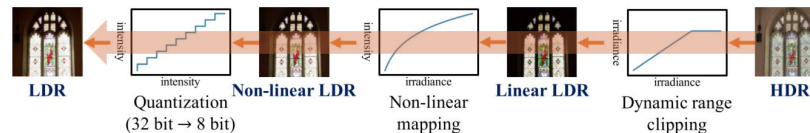
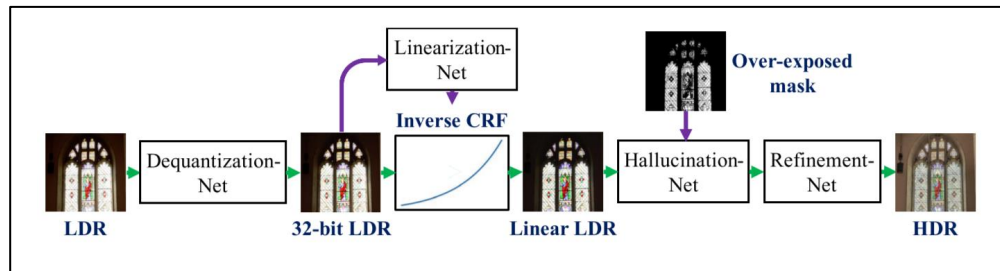
Learning to Reverse the Camera Pipeline

- Combination of loss functions

$$\lambda_{\text{deq}} \mathcal{L}_{\text{deq}} + \lambda_{\text{lin}} \mathcal{L}_{\text{lin}} + \lambda_{\text{crf}} \mathcal{L}_{\text{crf}} + \lambda_{\text{hal}} \mathcal{L}_{\text{hal}} + \lambda_{\text{p}} \mathcal{L}_{\text{p}} + \lambda_{\text{tv}} \mathcal{L}_{\text{tv}}$$

$$(\lambda_{\text{deq}} = 1, \lambda_{\text{lin}} = 10, \lambda_{\text{crf}} = 1, \lambda_{\text{hal}} = 1, \lambda_{\text{p}} = 0.001, \lambda_{\text{tv}} = 0.1)$$

- Refinement
 - Same U-Net architecture as the Dequantization-Net
 - Refine the output of the Hallucination-Net



Learning to Reverse the Camera Pipeline

- Experimental Results
 - Quantitative comparison
 - HDR-VDP-2 score
 - Proposed method has the highest performance.

Method	Training dataset	HDR-SYNTH	HDR-REAL	RAISE [10]	HDR-EYE [42]
HDRCNN+ [14]	HDR-SYNTH + HDR-REAL	55.51 ± 6.64	<u>51.38 ± 7.17</u>	56.51 ± 4.33	51.08 ± 5.84
DrTMO+ [15]	HDR-SYNTH + HDR-REAL	<u>56.41 ± 7.20</u>	50.77 ± 7.78	<u>57.92 ± 3.69</u>	<u>51.26 ± 5.94</u>
ExpandNet [40]	Pre-trained model of [40]	53.55 ± 4.98	48.67 ± 6.46	54.62 ± 1.99	50.43 ± 5.49
Deep chain HDRI [29]	Pre-trained model of [29]	-	-	-	49.80 ± 5.97
Deep recursive HDRI [30]	Pre-trained model of [30]	-	-	-	48.85 ± 4.91
Ours*	HDR-SYNTH	60.11 ± 6.10	51.59 ± 7.42	58.80 ± 3.91	52.66 ± 5.64
Ours+	HDR-SYNTH + HDR-REAL	59.52 ± 6.02	53.16 ± 7.19	59.21 ± 3.68	53.16 ± 5.92

Learning to Reverse the Camera Pipeline

- Experimental Results

- Quantitative comparison

Method	PSNR (\uparrow)	SSIM (\uparrow)
w/o dequantization	33.86 ± 6.96	0.9946 ± 0.0109
Hou et al. [18]	33.79 ± 6.72	0.9936 ± 0.0110
Liu et al. [35]	34.83 ± 6.04	0.9954 ± 0.0073
Dequantization-Net (Ours)	35.87 ± 6.11	0.9955 ± 0.0070

Comparisons on Dequantization-Net

Image	Edge	Histogram	Monotonically increasing	L2 error (\downarrow) of inverse CRF	PSNR (\uparrow) of linear image
✓	-	-	-	2.00 ± 3.15	33.43 ± 7.03
✓	✓	-	-	1.66 ± 2.93	34.31 ± 6.94
✓	-	✓	-	1.61 ± 3.03	34.51 ± 7.14
✓	✓	✓	-	1.58 ± 2.73	34.53 ± 6.83
✓	✓	✓	✓	1.56 ± 2.52	34.64 ± 6.73

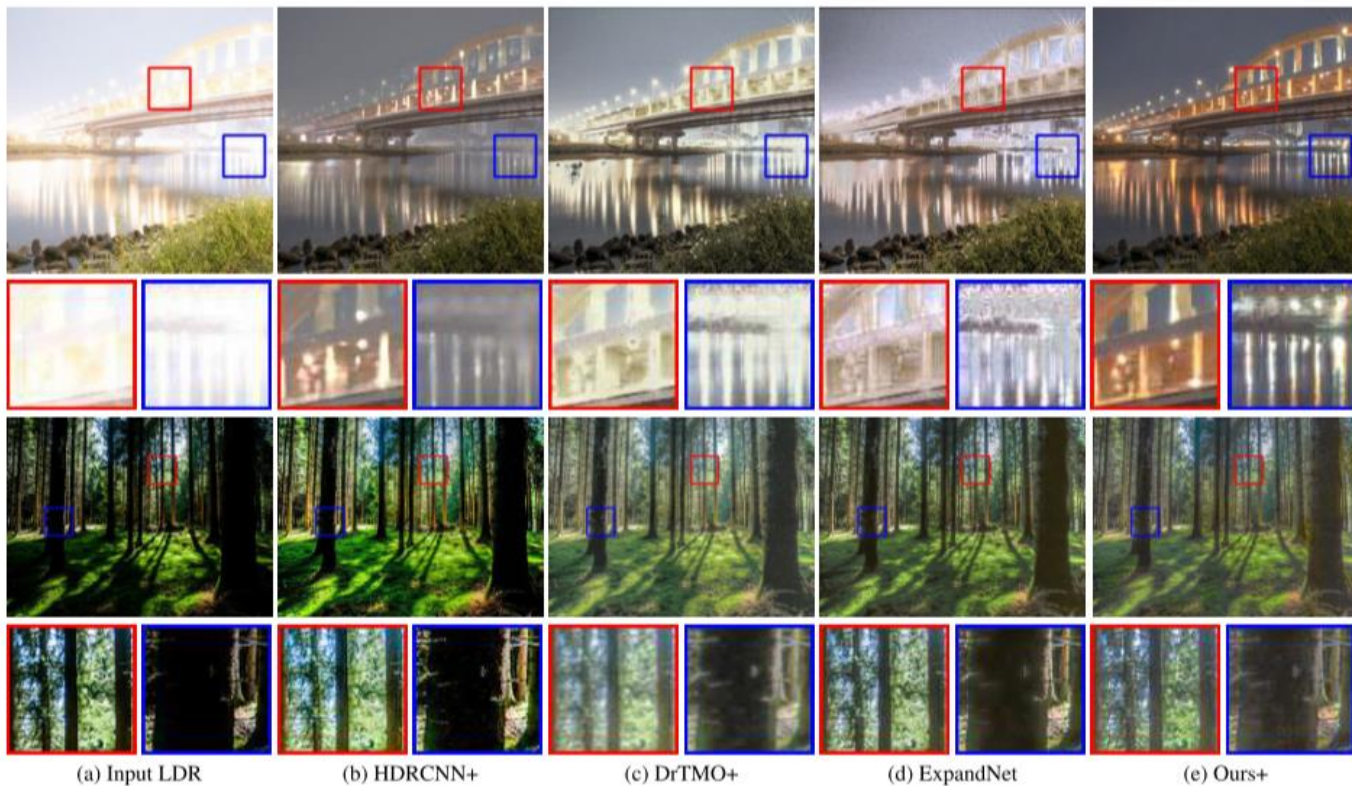
Analysis on alternatives of Linearization-Net

Positive residual	Resize convolution	Perceptual loss	HDR-VDP-2 (\uparrow)
-	-	-	63.60 ± 15.32
✓	-	-	64.79 ± 15.89
✓	✓	-	64.52 ± 16.05
✓	✓	✓	66.31 ± 15.82

Analysis on alternatives of Hallucination-Net

Learning to Reverse the Camera Pipeline

- Experimental Results
 - Visual comparison



Conclusion

- Recovering a HDR image from a single LDR input image
- This paper propose a method to reverse the LDR image formation pipeline.
 - [HDR] → dynamic range clipping → non-linear mapping with a CRF
→ quantization → [LDR]
 - [LDR] → dequantization → linearization → hallucination → [HDR]
- Experimental results validate the effectiveness of proposed method to restore visually pleasing details for a wide variety of challenging scenes.