Deep Snapshot HDR Imaging Using Multi-Exposure Color Filter Array

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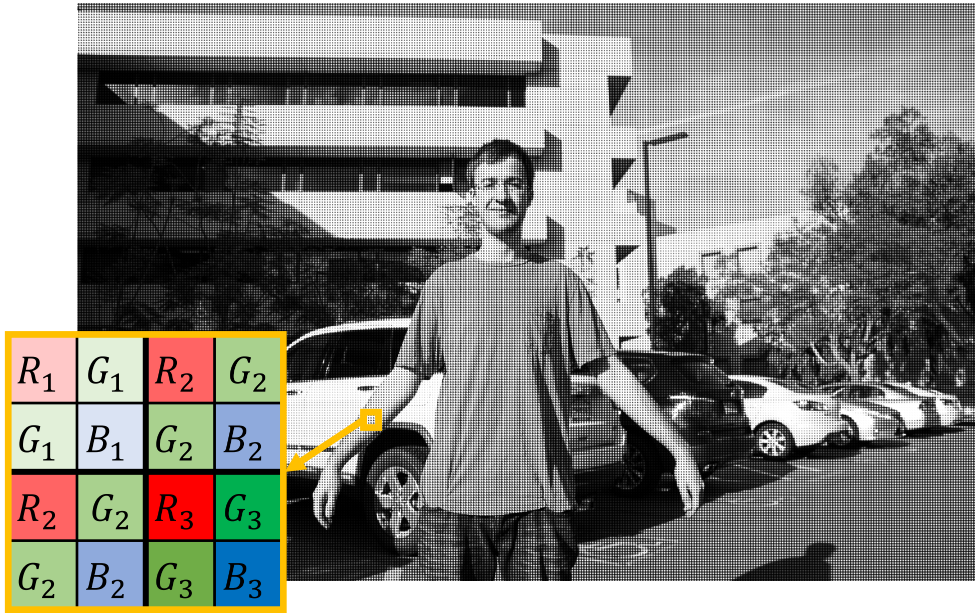
ACCV2020

Our Topic: Snapshot HDR Imaging



Multi-exposure CFA RAW data
(ME-CFA RAW data)

Reconstructed HDR image

Related Works

Multi-LDR-images-based methods

+ Rich spatial and exposure information
− Ghost artifacts for dynamic scenes

Multi LDR images

HDR image

Single-LDR-image-based methods

+ One-shot HDR image generation
− Inpainting artifacts for saturated or blacked-out areas

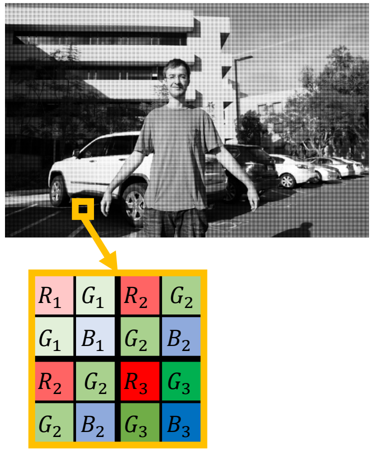
Single LDR image

HDR image

Snapshot methods

+ One-shot acquisition of multi-exposures information
− Demosaicking is required to interpolate missing color information

ME-CFA RAW data



HDR image

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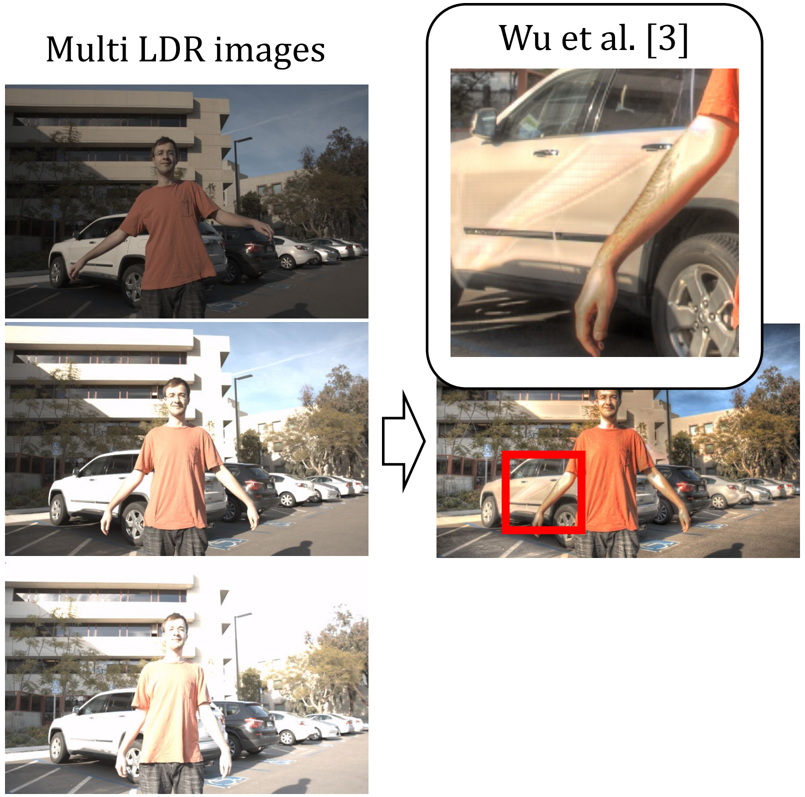
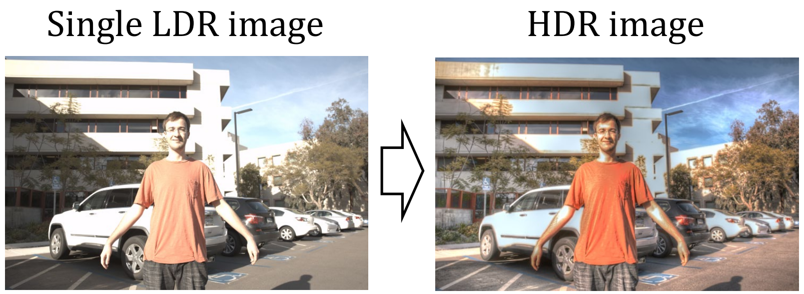


Single-LDR-image-based methods

\+ One-shot HDR image generation

− Inpainting artifacts for saturated or blacked-out areas



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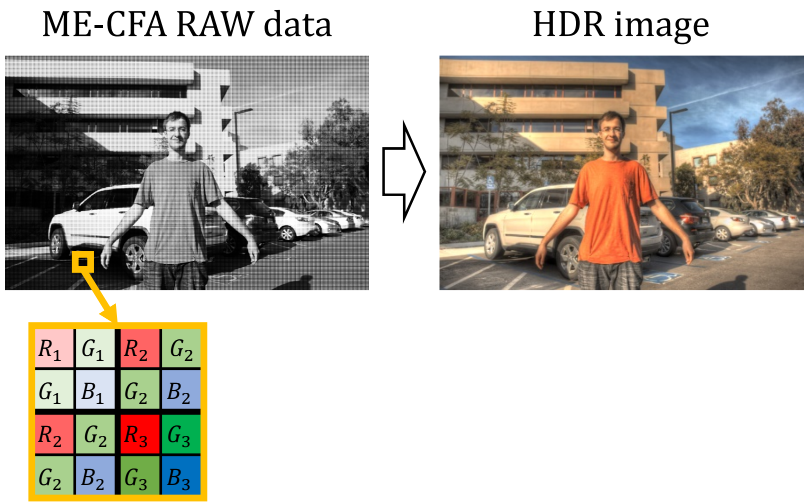

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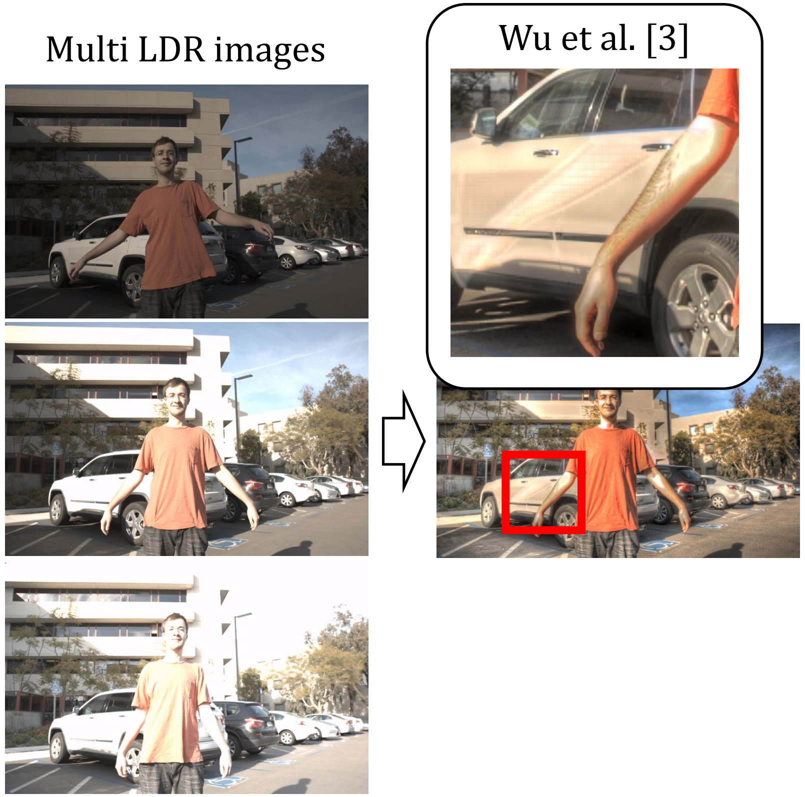
Multi LDR images



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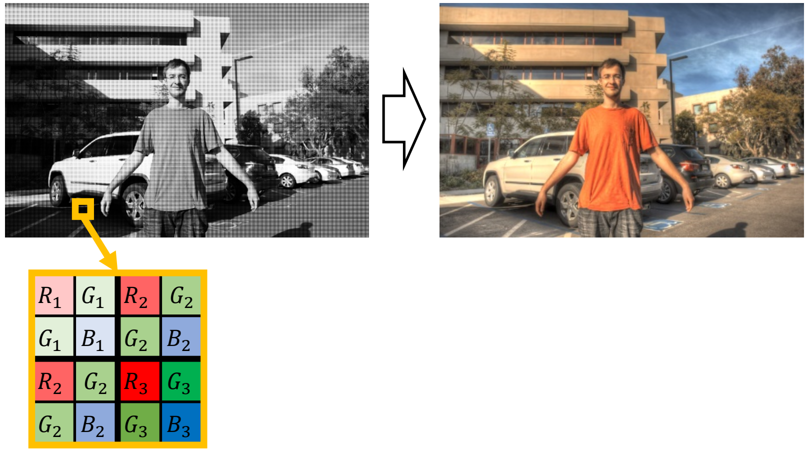

Related Works

Multi-LDR-images-based methods

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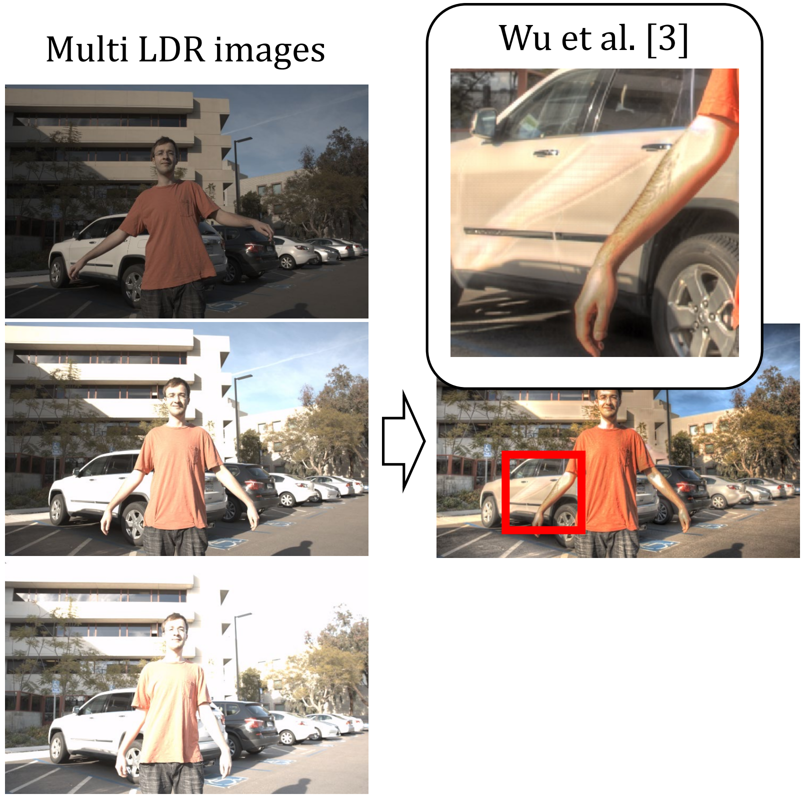

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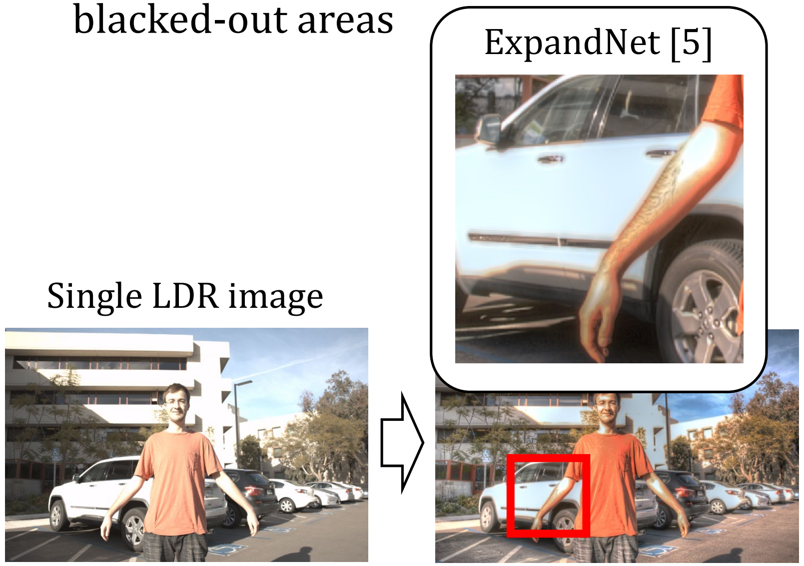

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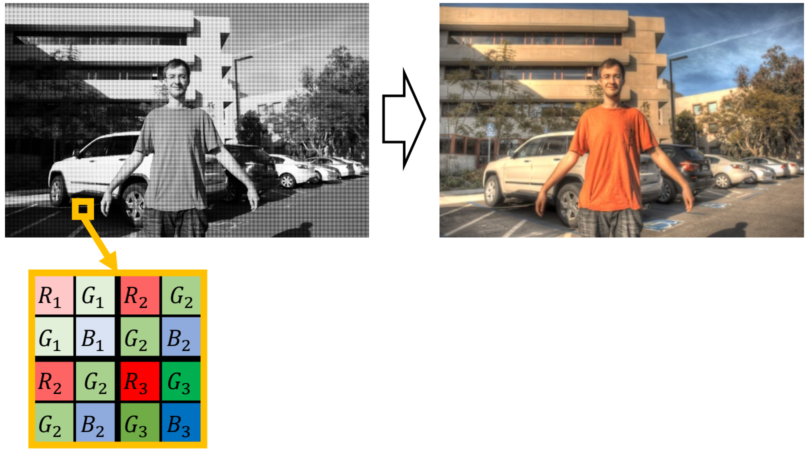

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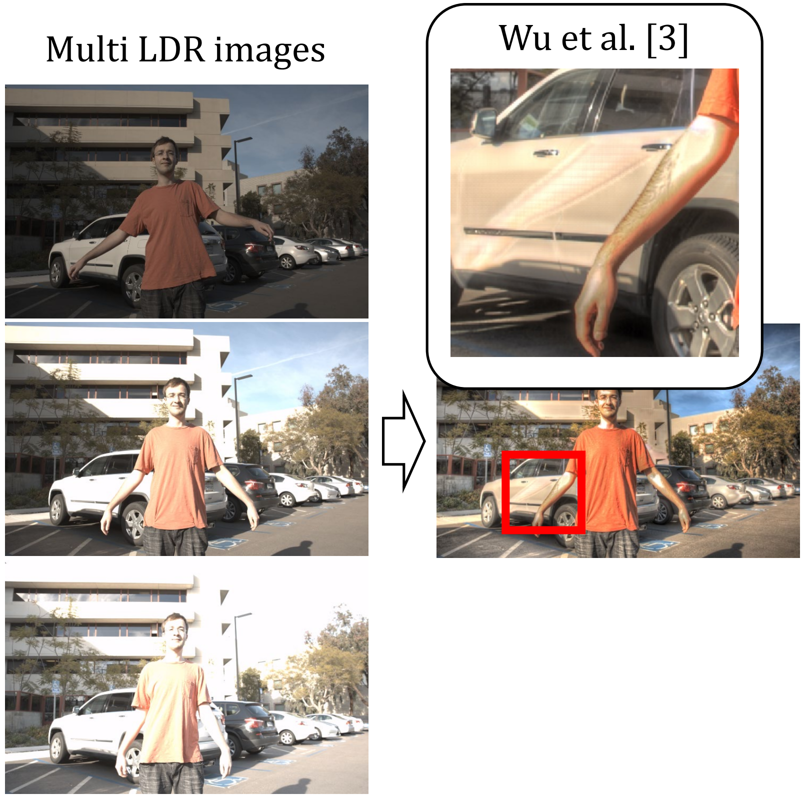

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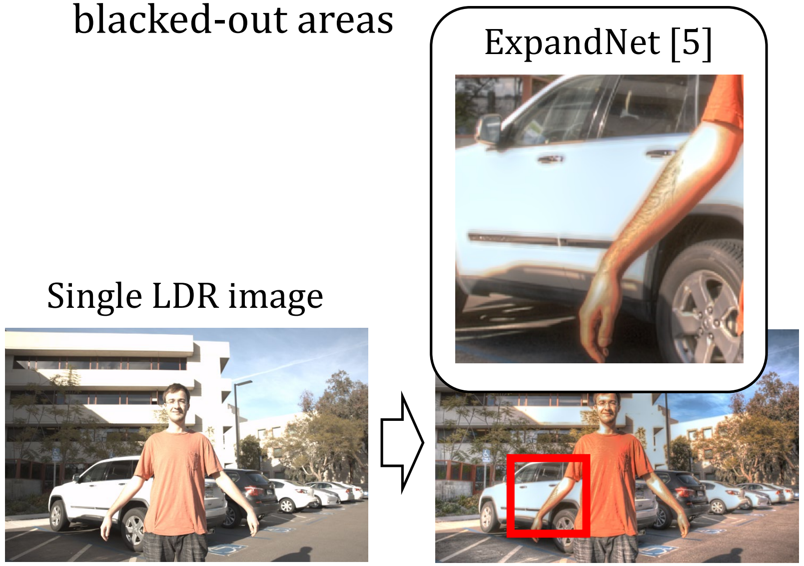

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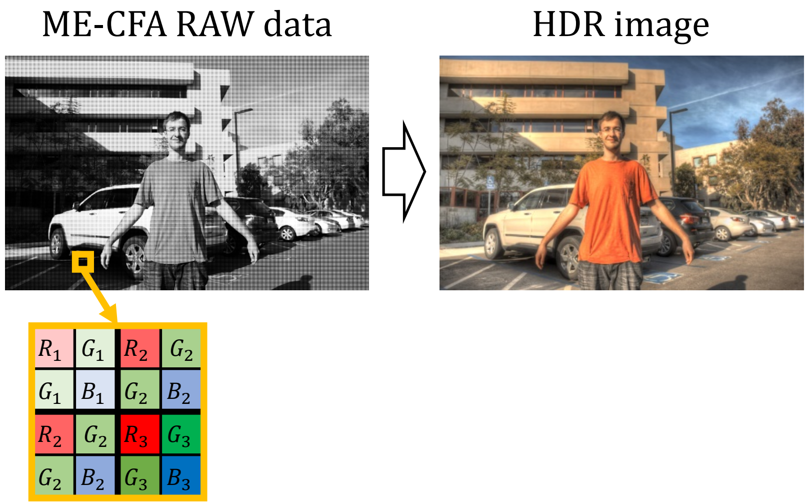
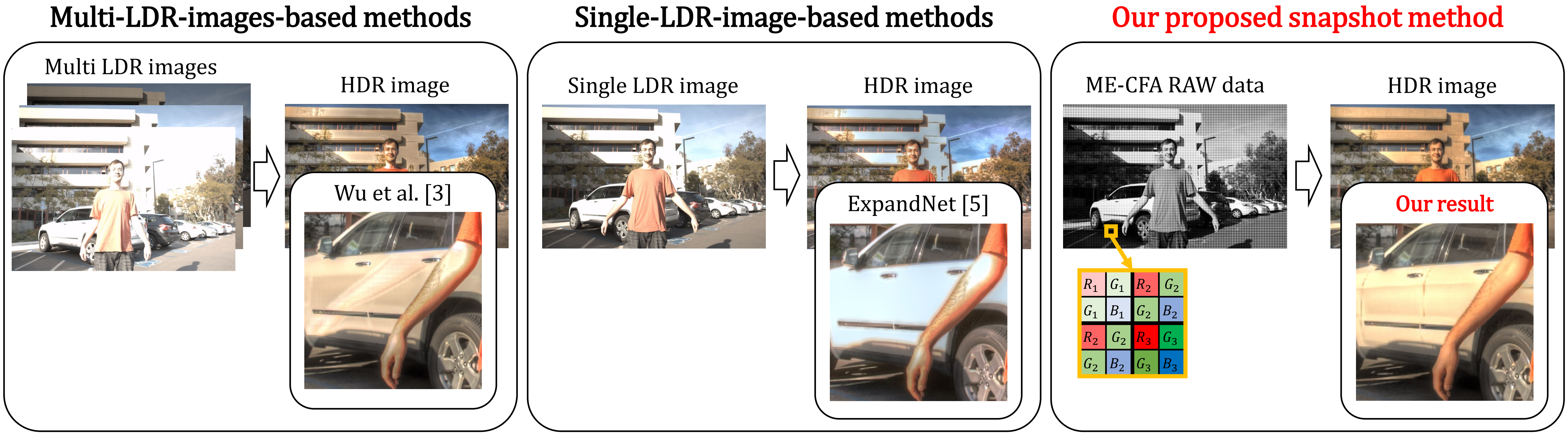


Our Main Contributions

- We propose a novel deep learning framework that effectively solves the joint demosaicking and HDR reconstruction problem.

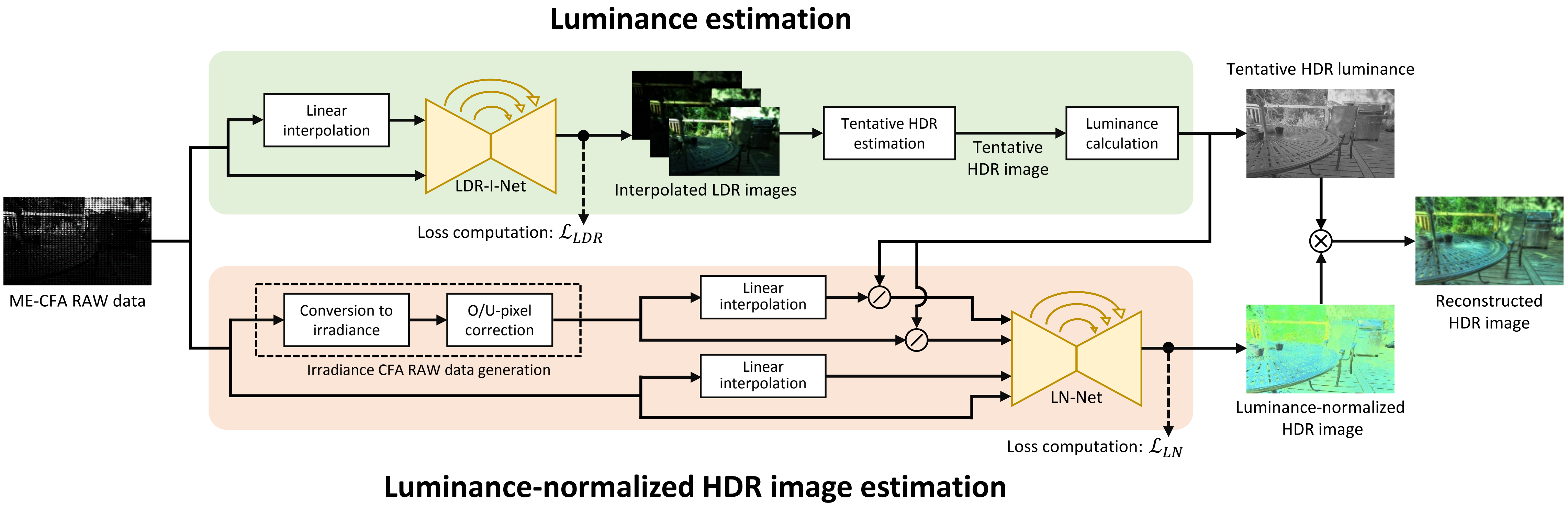
- We propose the idea of luminance normalization that enables an effective consideration of relative local image contrasts.



Proposed Method

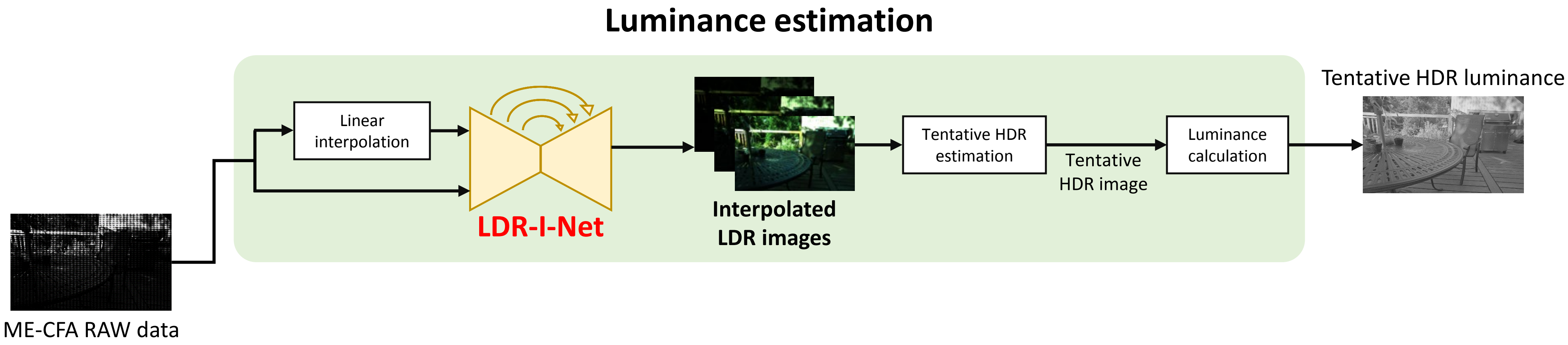
Our Proposed Method Overview

- Our method mainly consists of two parts:
  1. Luminance estimation
  2. Luminance-normalized HDR image estimation



Training Steps

- Step 1: Training LDR interpolation network (LDR-I-Net) for luminance estimation



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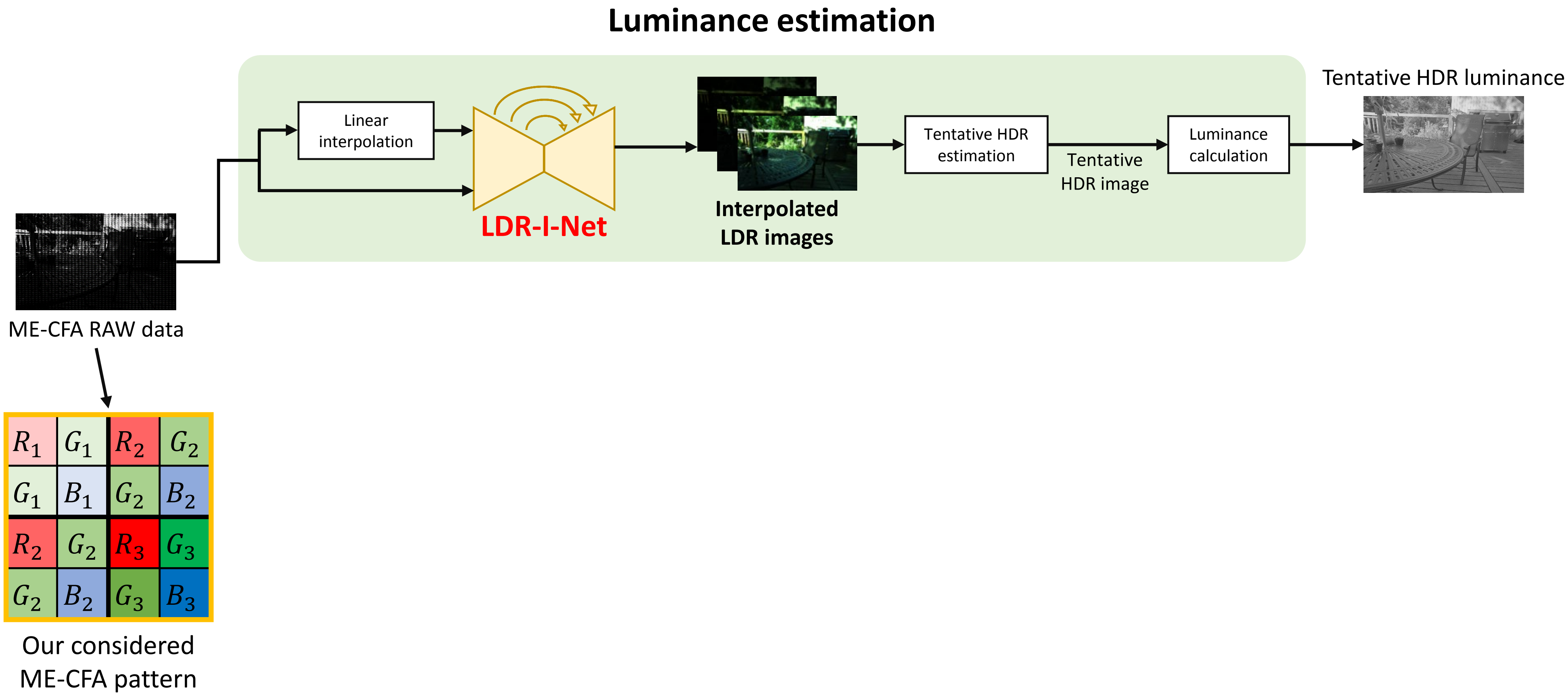

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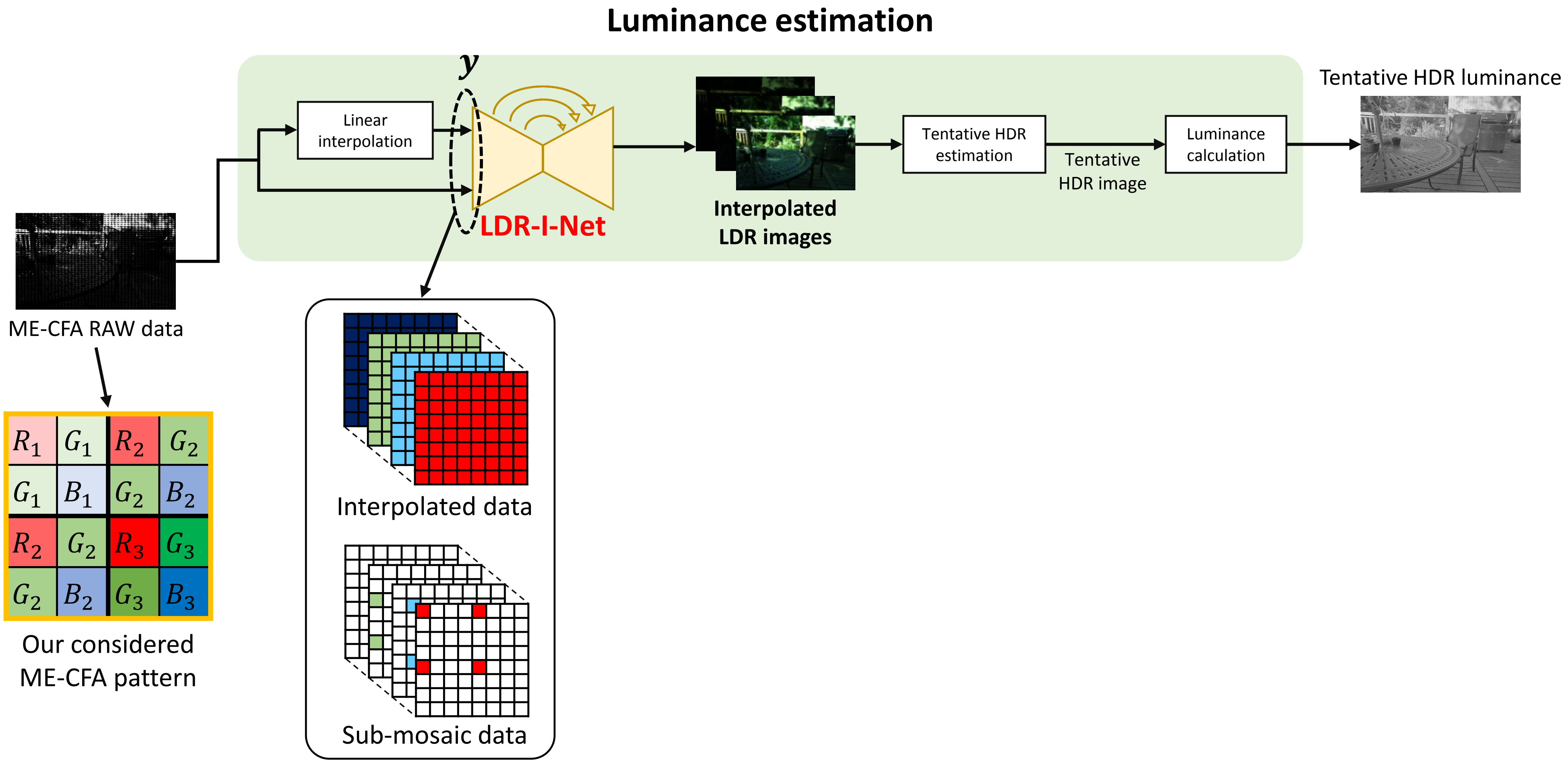

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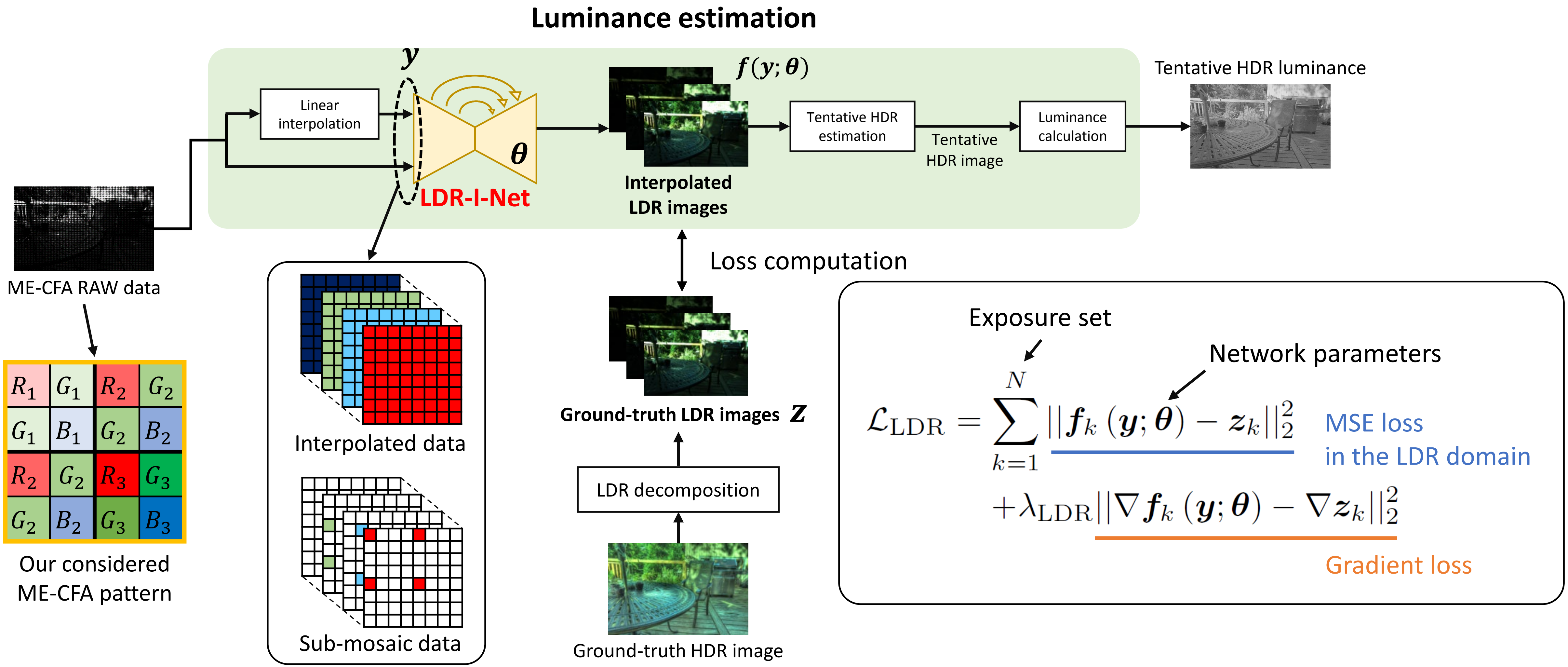

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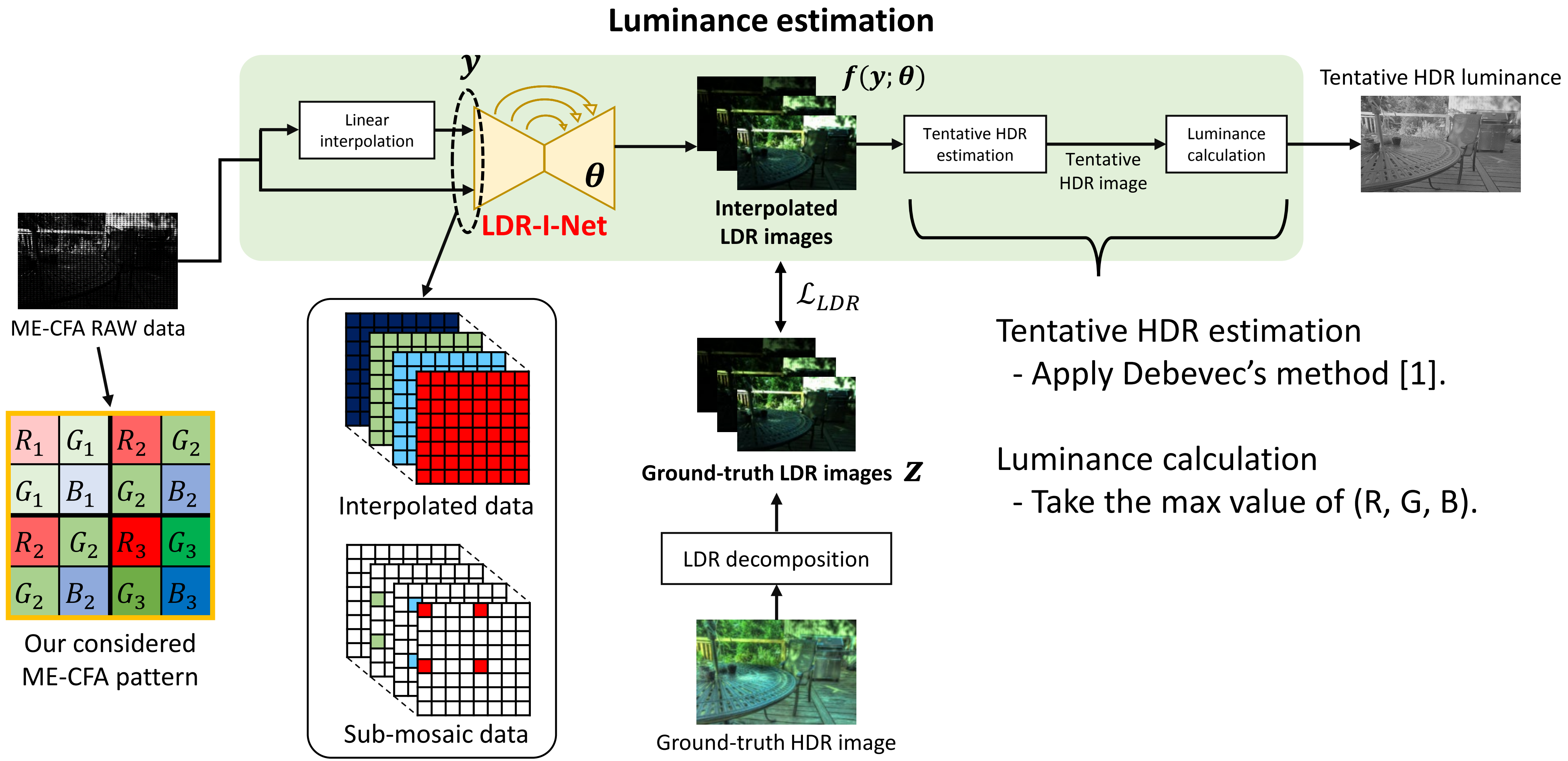
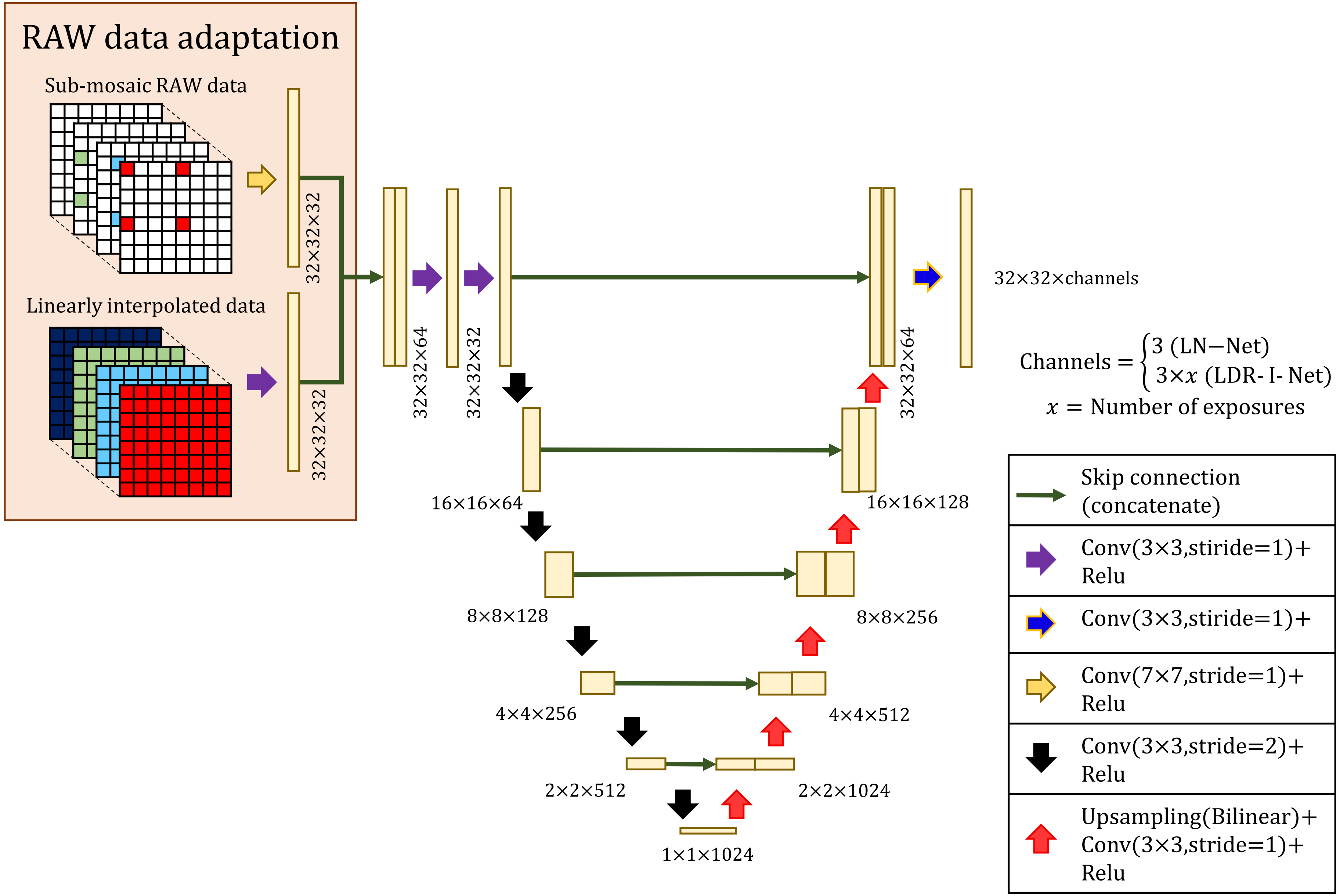


Tentative HDR estimation
- Apply Debevec's method [1].

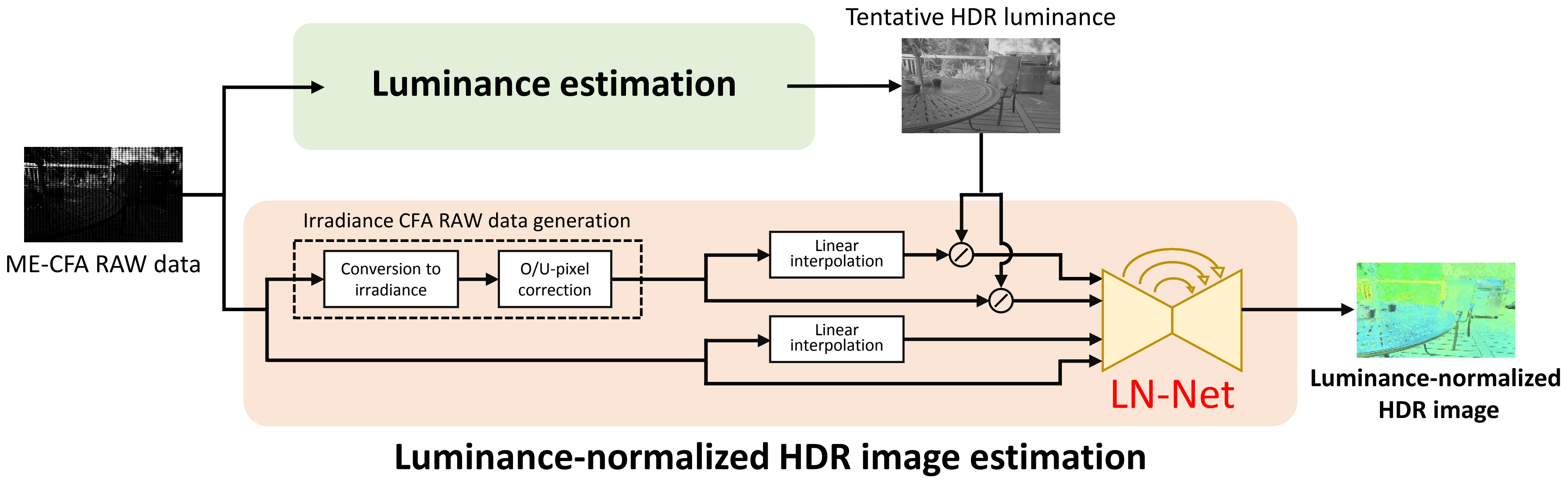
Luminance calculation
- Take the max value of (R, G, B).

Network Architecture



Training Steps

- Step 2: Training luminance-normalized network (LN-Net) for HDR image estimation



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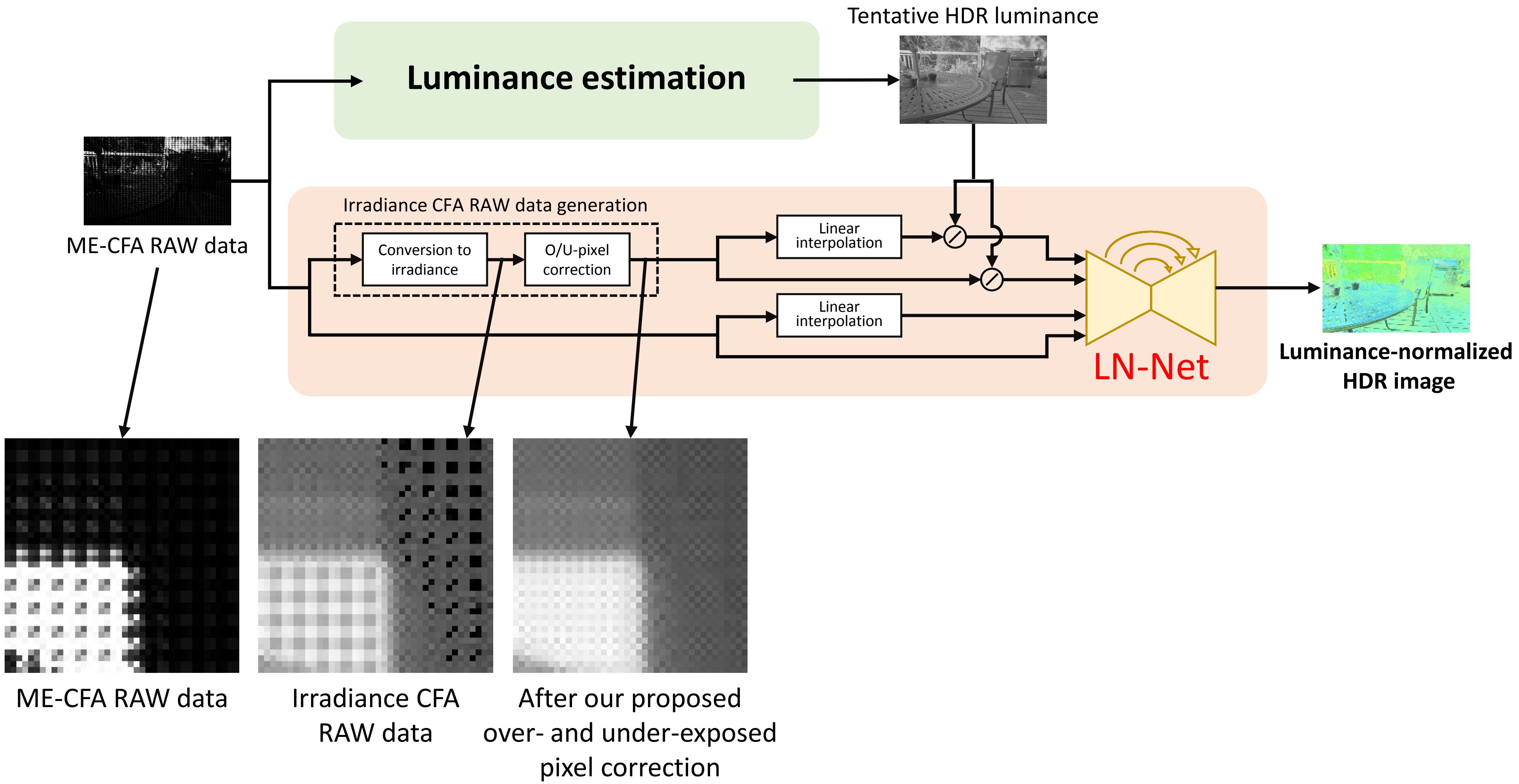

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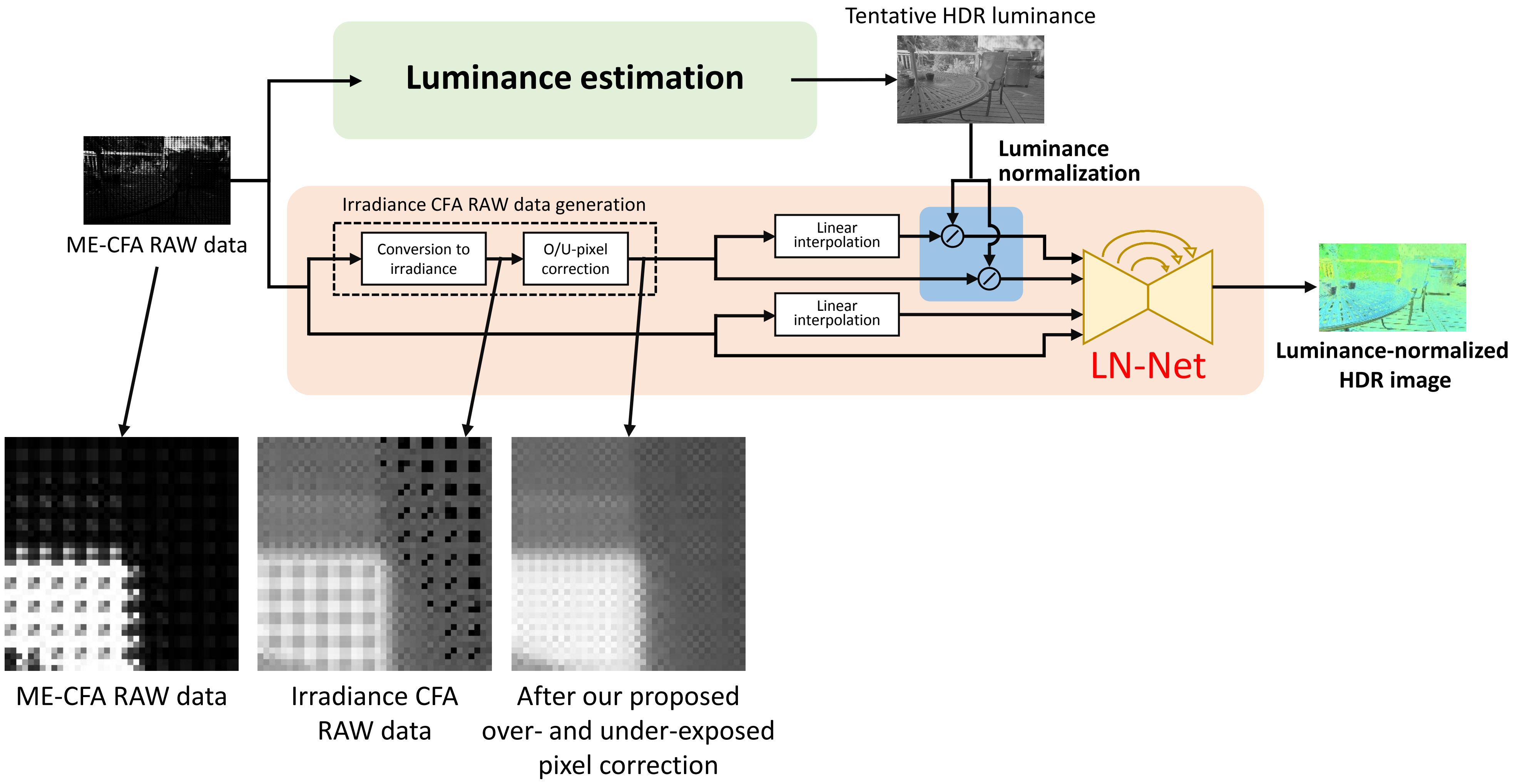

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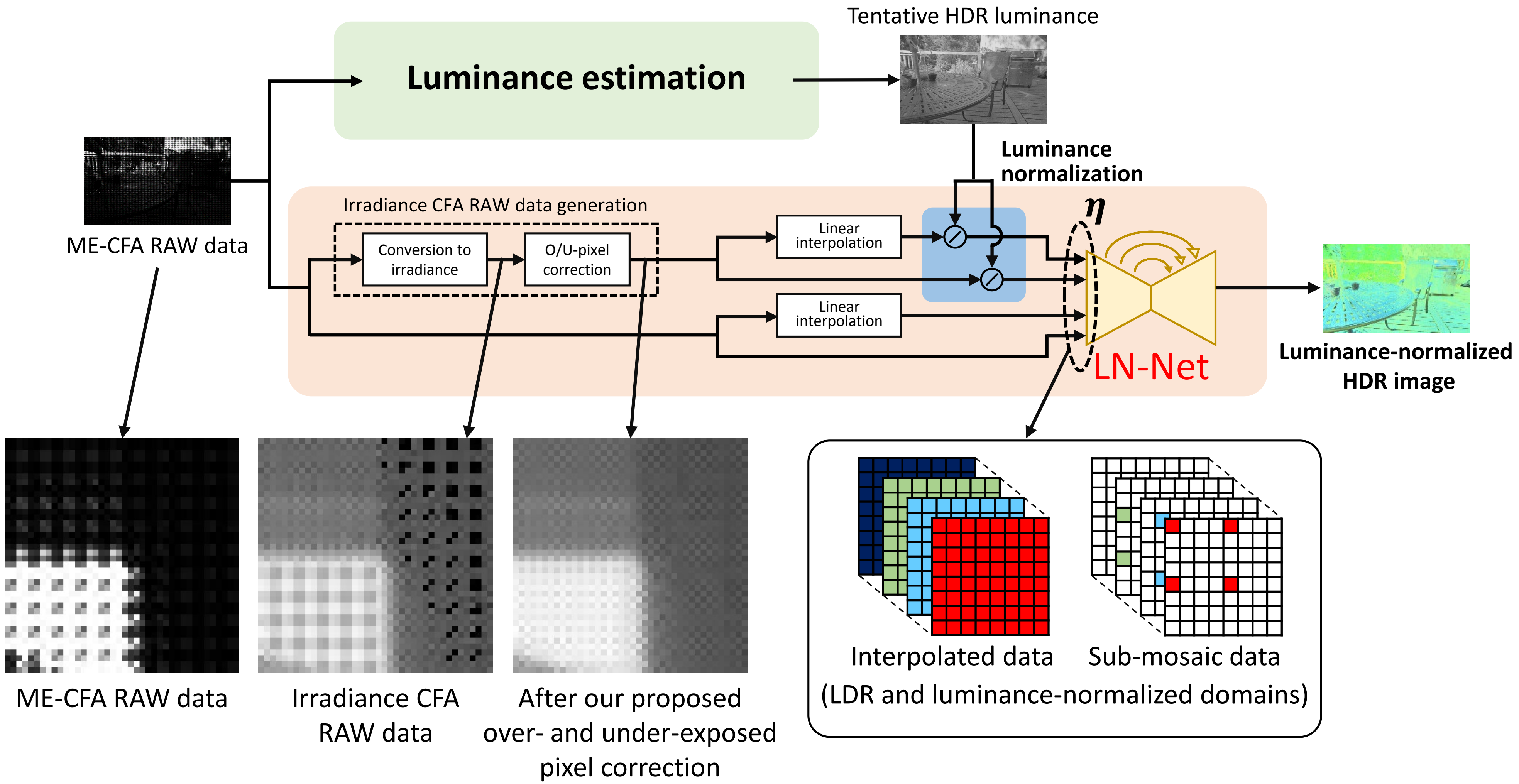

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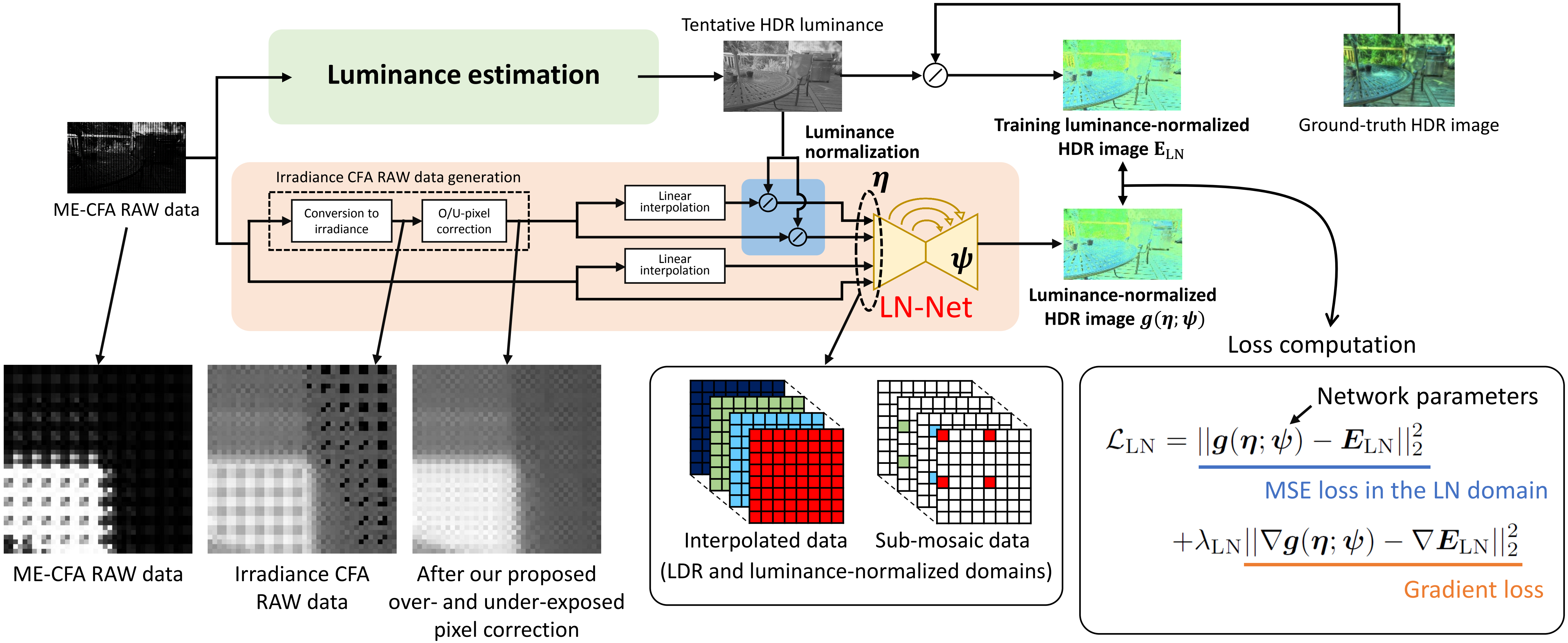
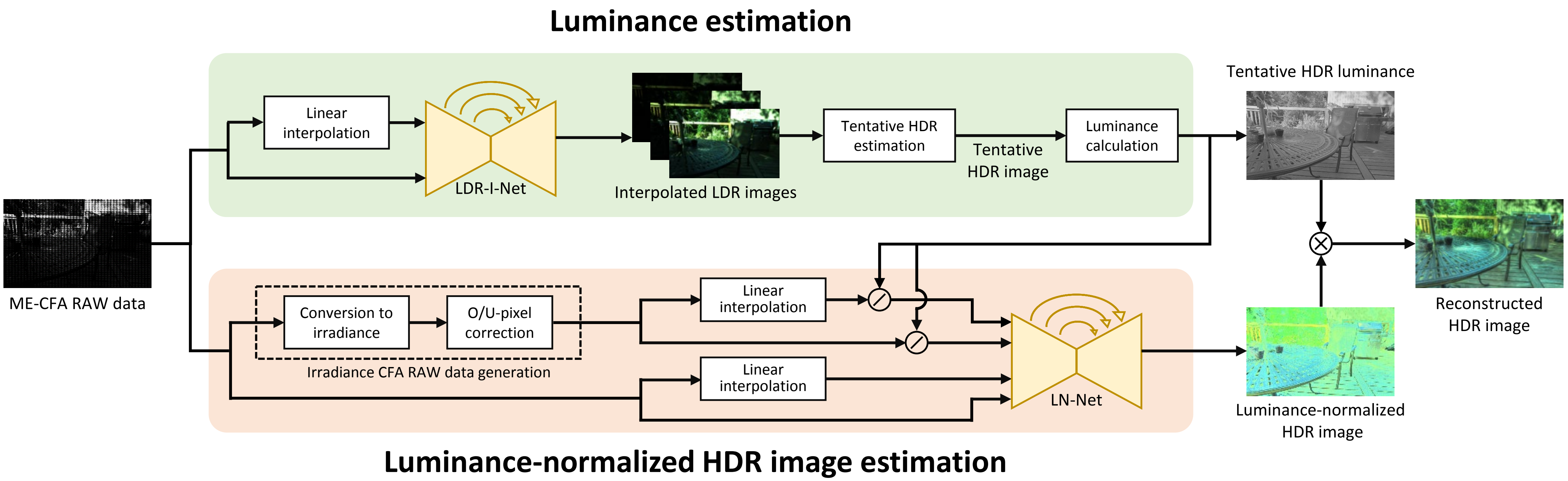


Inference Step

- HDR image is reconstructed through the trained two networks



Experimental Results

Datasets

- Funt's dataset [52]
  - 224 static scenes
    - 211 images for training
    - 13 images for testing
- Kalantari's dataset [2]
  - 89 dynamic scenes
    - 74 images for training
    - 15 images for testing

Example ground-truth HDR images (Funt's dataset)

LDR inputs

Ground-truth HDR image

Example LDR inputs and ground-truth HDR images (Kalantari's dataset)

Ablation Study

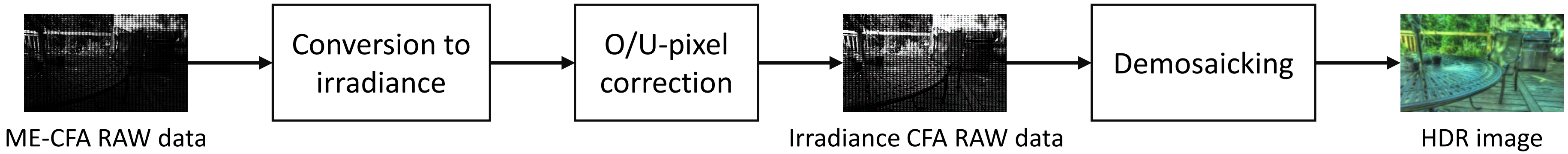
	CPSNR	G-CPSNR	L-CPSNR	HDR-VDP-2	LN-MSE
Ours (full version)	**48.57**	**41.94**	**40.38**	**80.57**	**0.0585**
without luminance normalization	46.70	30.24	29.29	77.97	0.1289
without O/U-pixel correction	42.30	36.60	34.45	78.51	0.0913
without gradient term in the loss	41.76	36.14	35.76	65.41	0.4364
without RAW data adaptation	46.19	39.45	37.77	78.16	0.0688

- Evaluation metrics
  - CPSNR: CPSNR in the liner HDR domain
  - G-CPSNR: CPSNR in the global tone-mapped domain using Kalantari et al. tone-mapping [2]
  - L-CPSNR: CPSNR in the local tone-mapped domain using MATLAB local tone-mapping function
  - HDR-VDP-2: Common evaluation metric for HDR images (Mantiuk et al. [54])
  - LN-MSE: Mean squared error in the luminance normalized domain

Comparison with Other Snapshot Methods (Funt's Dataset)

Framework	Demosaicking/SR	CPSNR	G-CPSNR	L-CPSNR	HDR-VDP-2	LN-MSE
Demosaicking-based framework: Irradiance CFA RAW data generation → Demosaicking	ARI [55]	46.14	38.15	36.69	75.68	0.0712
	Kokkinos [48]	41.06	26.27	26.65	69.32	0.1840
	CDMNet [47]	46.32	38.37	37.12	58.00	0.0713
LDR-interpolation-based framework: LDR interpolation by SR → HDR reconstruction	ESRGAN [56]	30.66	25.21	21.87	53.55	0.2720
	WDSR [57]	35.75	30.97	29.32	60.16	0.3796
	EDSR [58]	39.19	32.57	29.95	66.04	0.1190
	LDR-I-Net	43.38	35.64	34.54	76.30	0.1030
Our deep snapshot HDR imaging framework		**48.57**	**41.94**	**40.38**	**80.57**	**0.0585**

Demosaicking-based methods



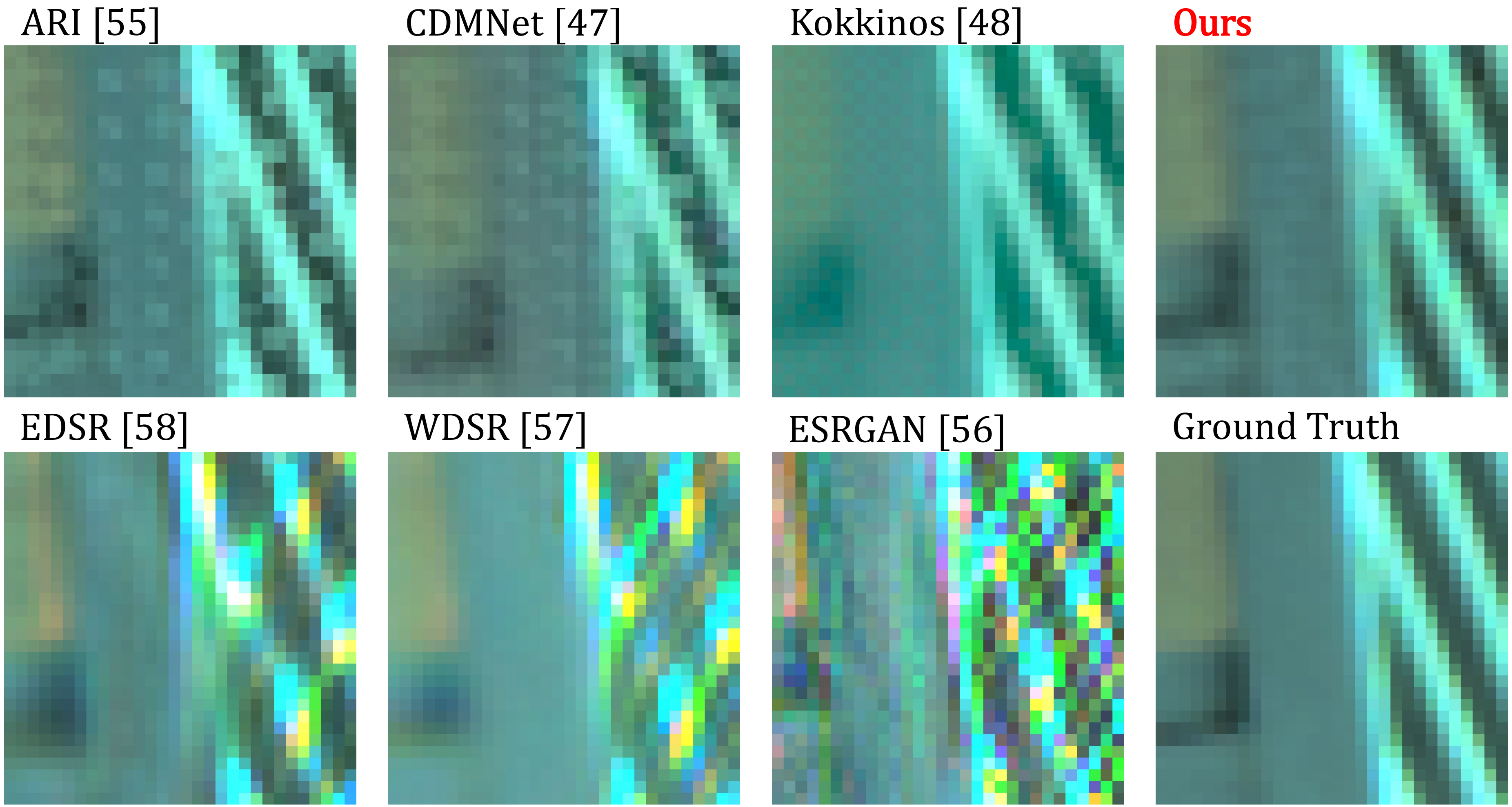
LDR-interpolation-based methods

Comparison with Other Snapshot Methods

Ground-truth HDR image

Demosaicking-based methods

LDR-interpolation-based methods

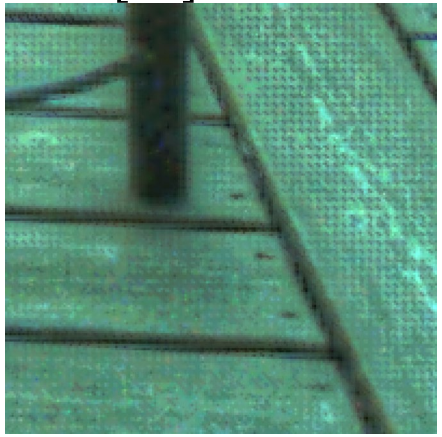


Comparison with Other Snapshot Methods

Ground-truth HDR image

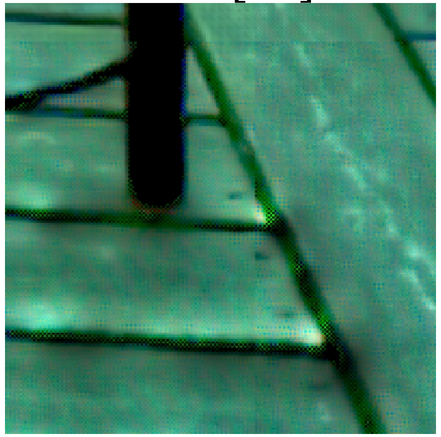
Demosaicking-based methods

ARI [55]

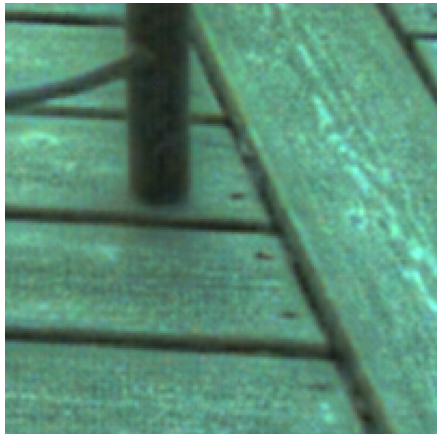


CDMNet [47]

Kokkinos [48]

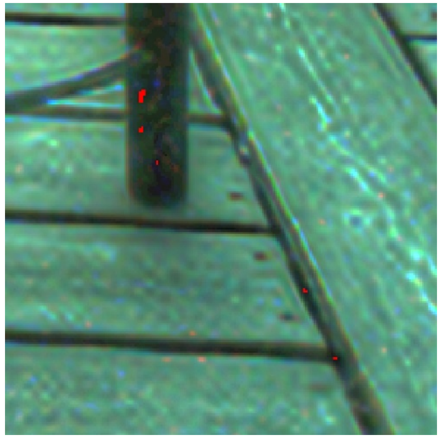


Ours

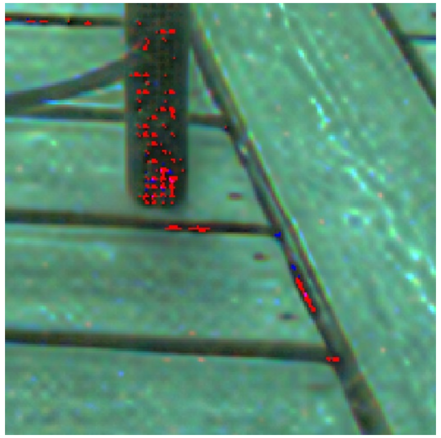


LDR-interpolation-based methods

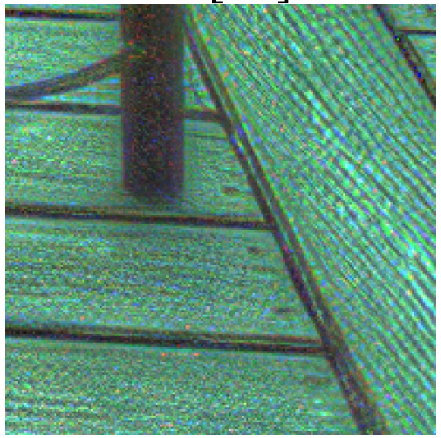
EDSR [58]



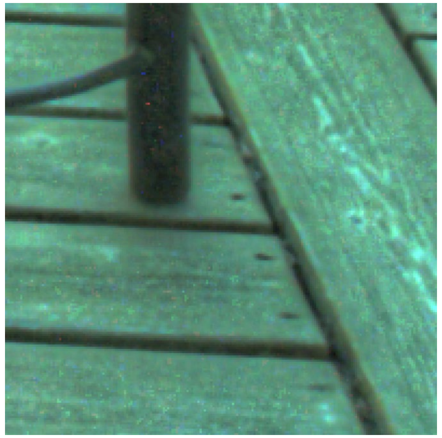
WDSR [57]



ESRGAN [56]



Ground Truth



Comparison with State-of-the-Art Methods (Kalantari's Dataset)

Input sources	Methods	CPSNR	G-CPSNR	L-CPSNR	HDR-VDP-2	LN-MSE
Multiple LDR images	Sen [17]	38.05	40.76	36.13	61.08	0.0389
	Kalantari [2]	41.15	**42.65**	**38.22**	64.57	**0.0306**
	Wu [3]	40.88	42.53	37.98	65.60	0.0338
Single LDR image (Second exposure)	HDRCNN [6]	12.92	14.13	34.80	54.48	4.1082
	DrTMO [31]	18.23	14.07	25.32	56.78	8.7912
	ExpandNet [5]	22.09	22.37	28.03	57.34	1.2923
ME-CFA RAW data	Ours	**41.43**	38.60	35.23	**66.59**	0.0832

Comparison with State-of-the-Art Methods

Sen [17]

Kalantari [2]

Wu [3]

Ours

Multi-LDR-images-based methods

HDRCNN [6]

DrTMO [31]

ExpandNet [5]

Ground-truth HDR image

Single-LDR-image-based methods

Comparison with State-of-the-Art Methods

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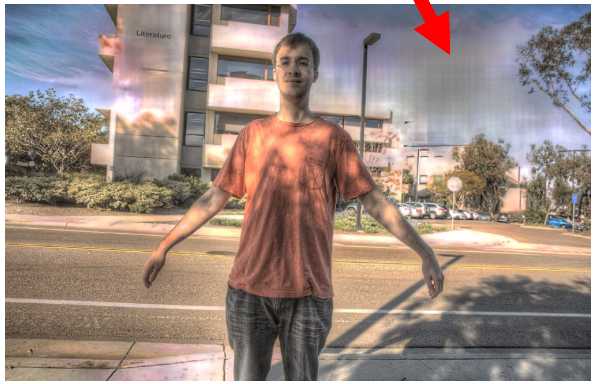
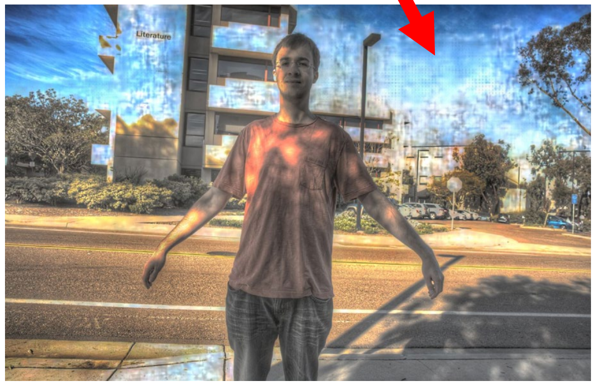
HDRCNN [6]



DrTMO [31]

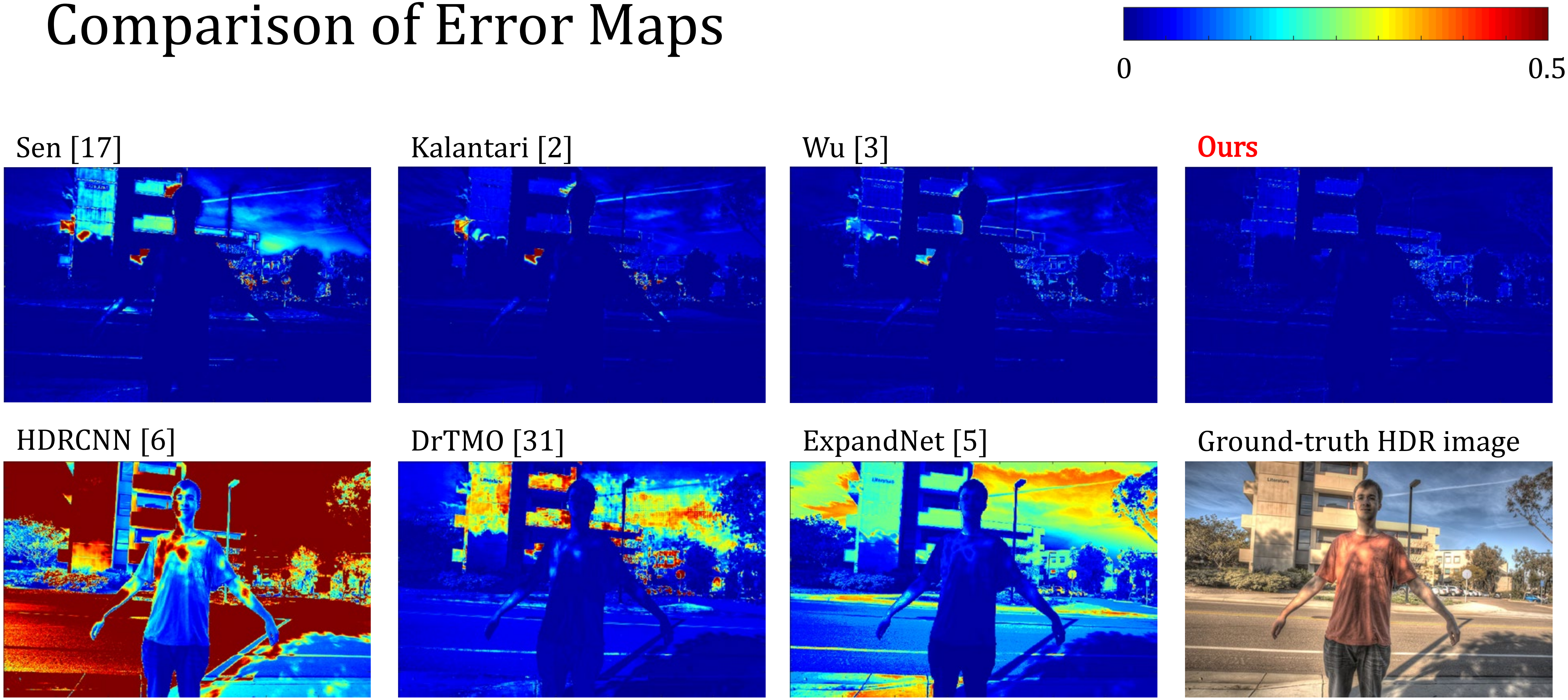


ExpandNet [5]

Ground-truth HDR image

Single-LDR-image-based methods

Comparison of Error Maps



Conclusions

- We have proposed a novel deep learning-based framework that can effectively address the joint demosaicking and HDR reconstruction problem for snapshot HDR imaging using an ME-CFA.
- We have introduced the idea of luminance normalization that effectively considers relative local image contrasts.
- We have demonstrated that our framework can produce HDR images with much fewer visual artifacts compared with other snapshot methods and also state-of-the-art HDR imaging methods.