CVPR Nashville JUNE 11-15, 2025

Exploiting Deblurring Networks for Radiance Fields

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[1] kt

[2] POSTECH COMPUTER GRAPHICS

Radiance Fields from Blurry Images

- NeRF assumes that input images are well captured and calibrated.
- 3DGS requires high-quality input images and a good point cloud initialization.

Ground Truth

Real-world Conditions

- Various degradations (e.g., blur, noise)
- Blur makes it difficult to aggregate accurate 3D information from input images.

Camera motion blur

Ground Truth

Defocus blur

Problem Statement

- Input : Multi-view blurry images (camera motion blur / defocus blur).

Blurry training views

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- Input : Multi-view blurry images (camera motion blur / defocus blur).
- Output : High-quality radiance fields where we can synthesize sharp novel views

Novel-view synthesis

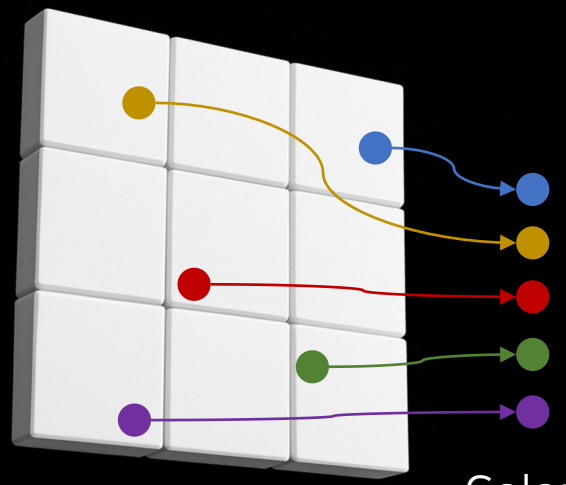
Radiance fields

Limitations of Related Works (1)

- Rely on linear blur models, describing a blurred pixel as linear combinations of sharp pixels.

$$b_p = c_p * h$$

  - $\mathrm{b_p}$: the corresponding blurry color
  - $\mathrm{c_p}$: the color of sharp pixel at p
  - h : the blur kernel centered at p



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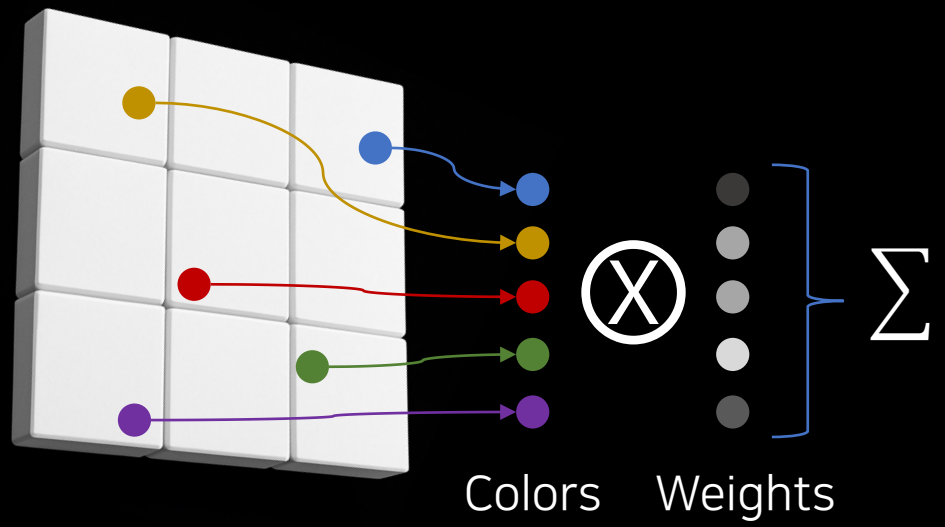

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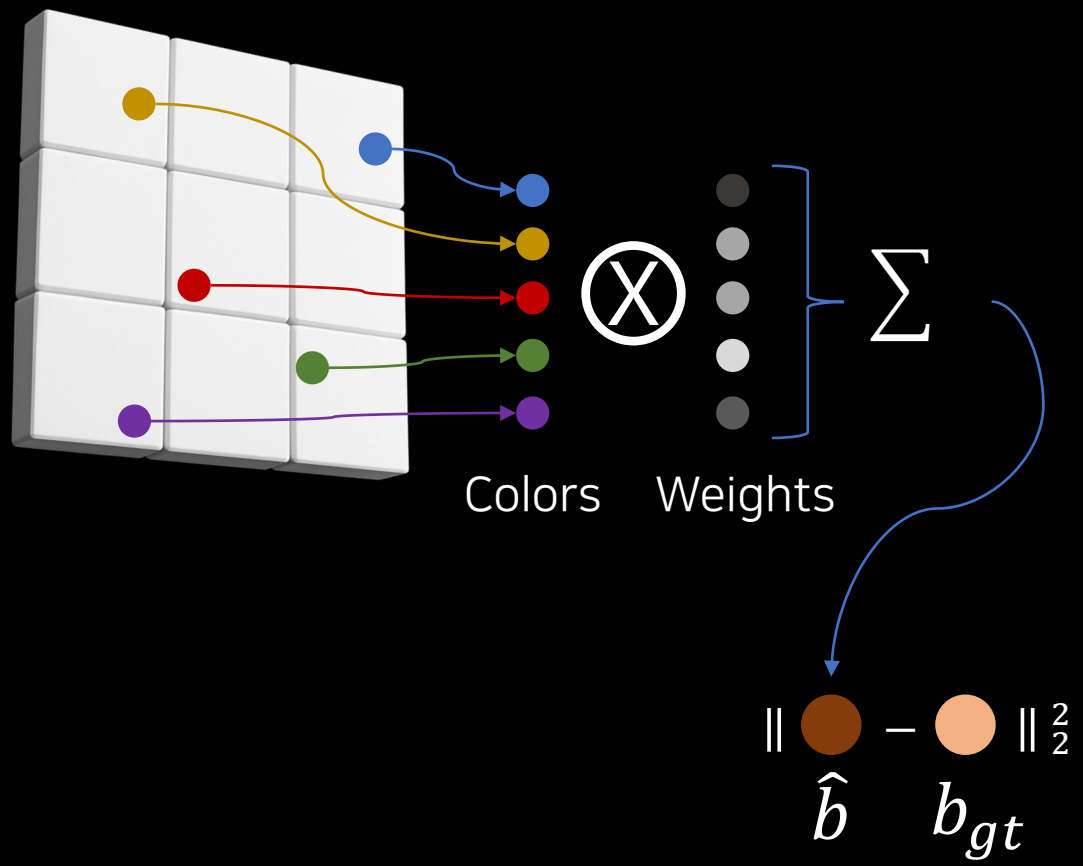

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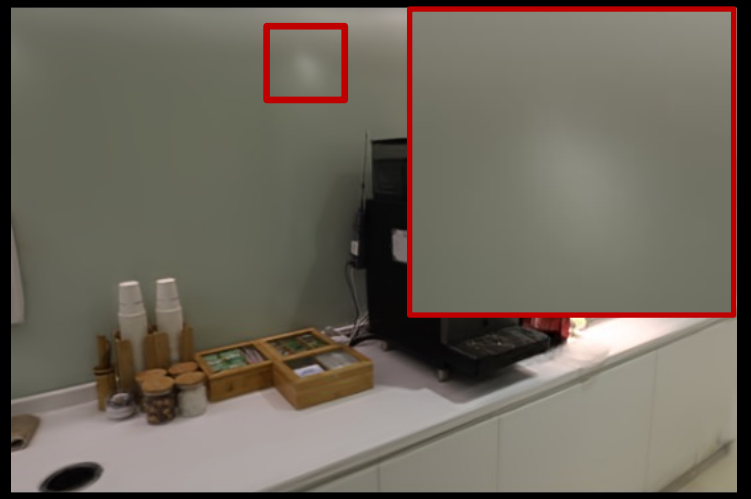
Training view

Deblur-NeRF (CVPR 2022)



BAGS (ECCV 2024)

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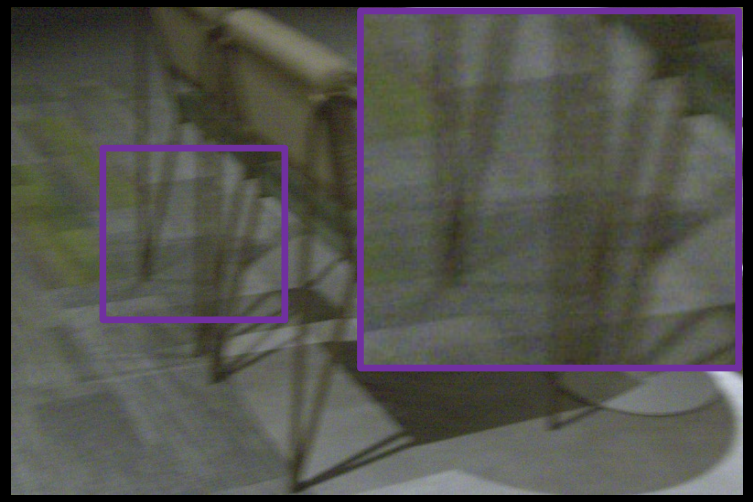

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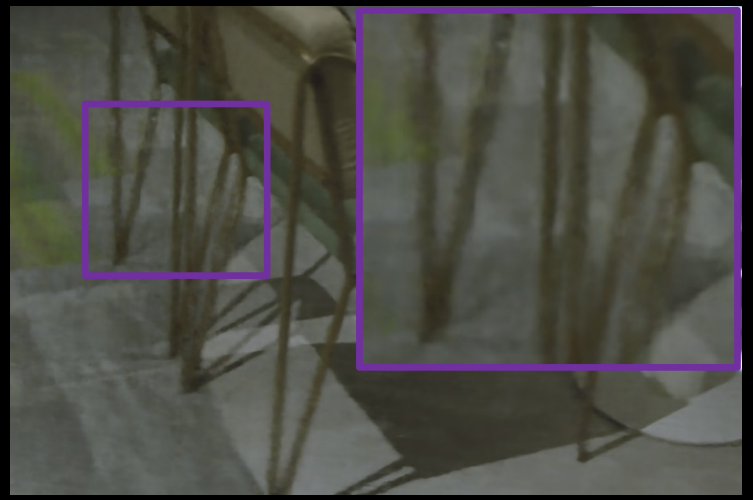

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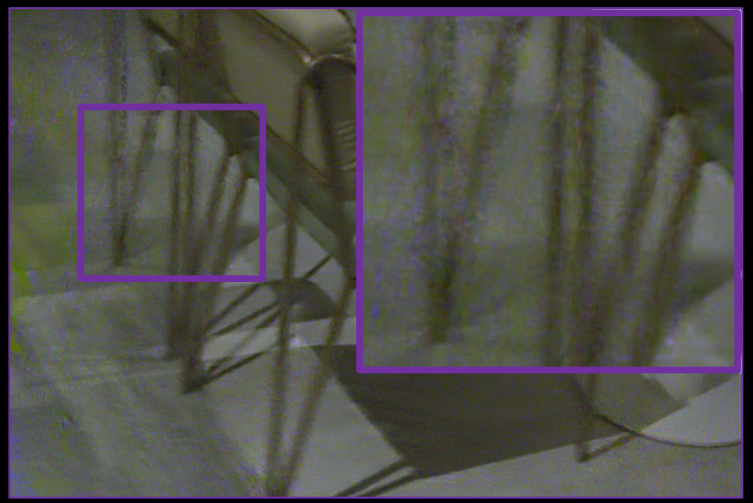

BAGS (ECCV 2024)

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- No priors on sharp images, relying solely on information from different views.
- Completely fail when all input views exhibit same blur directions, akin to classical multi-frame deblurring methods

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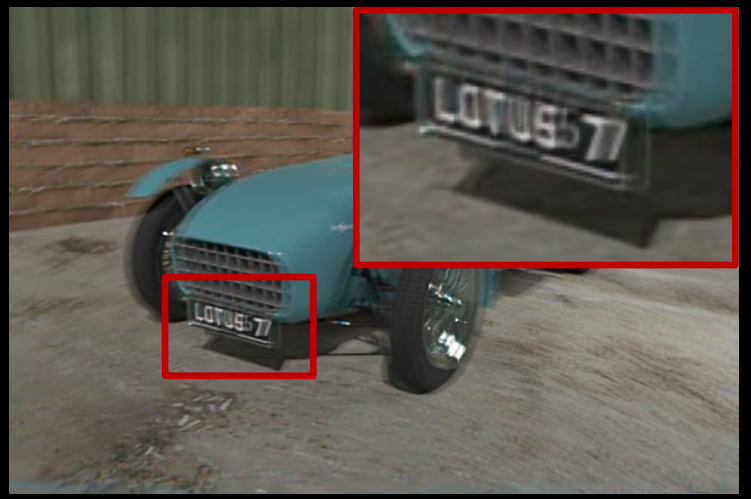

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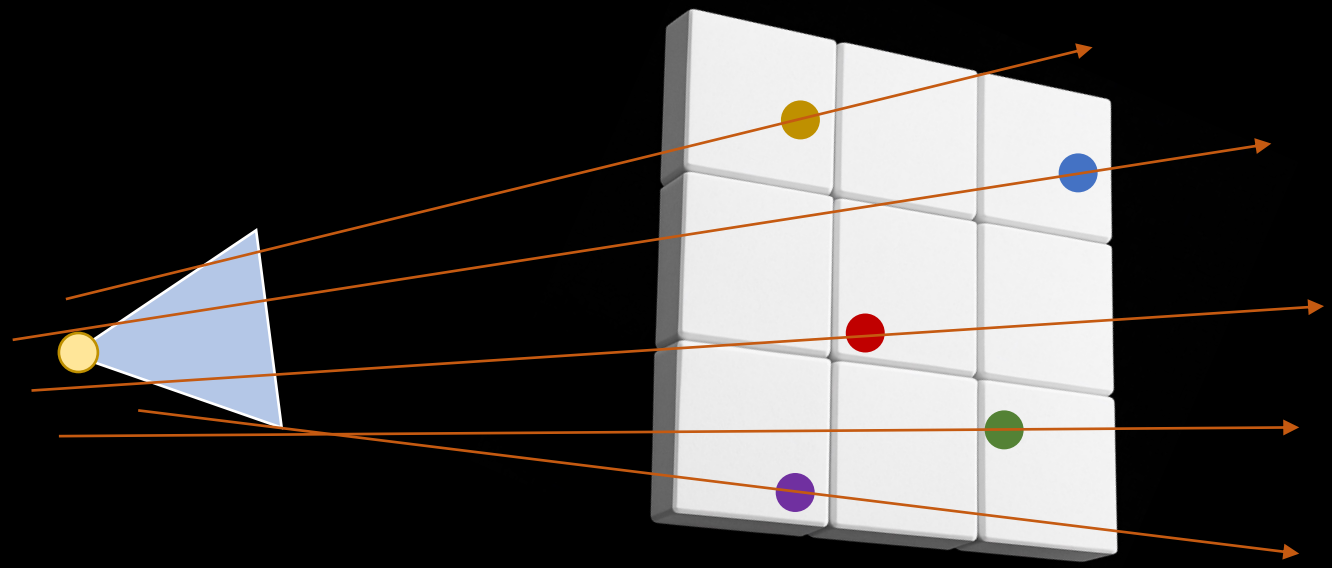
- High computation time.



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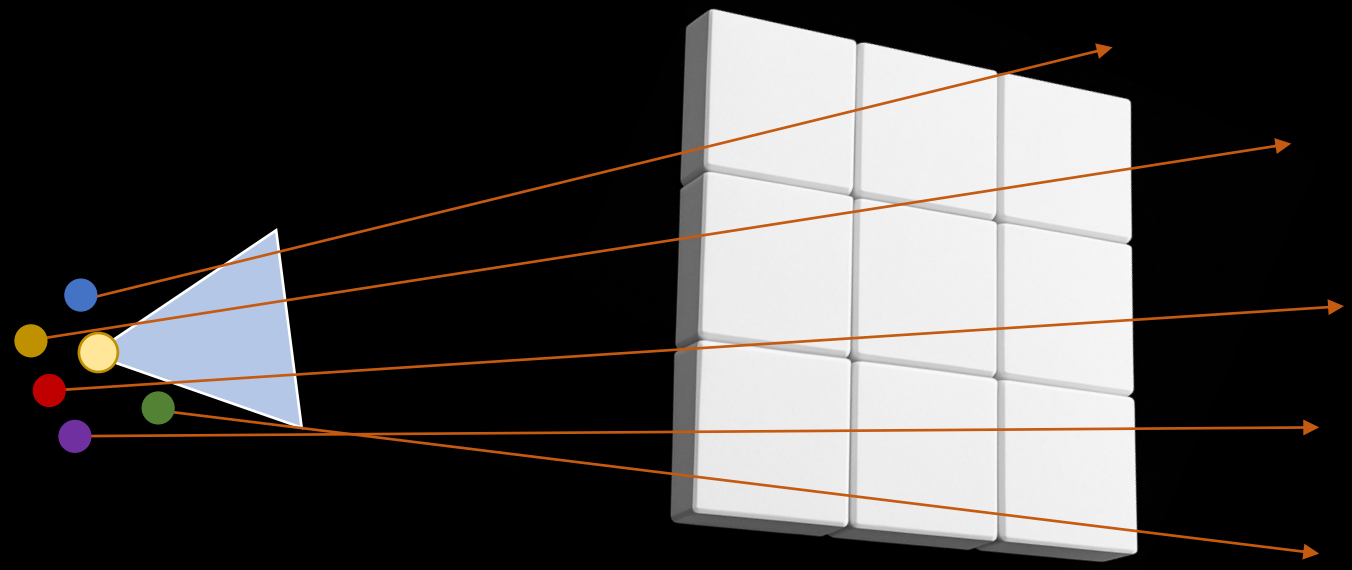

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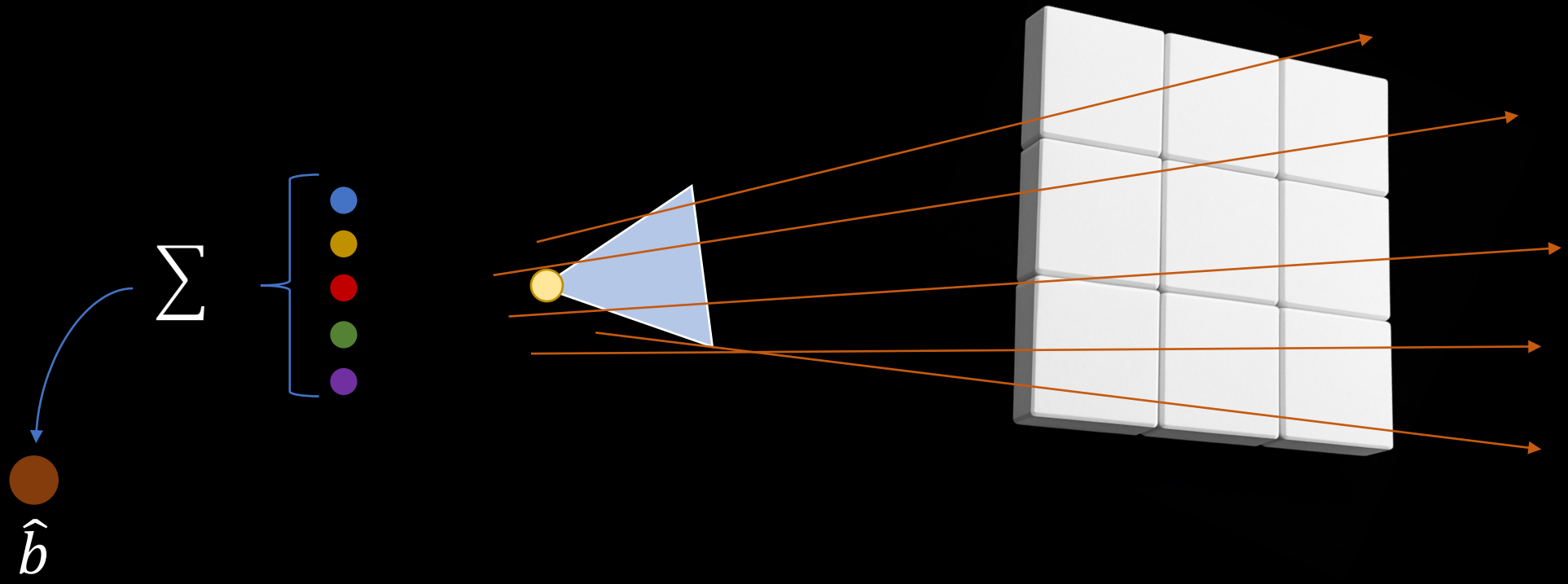

📌 DNN-based Image Deblurring

- Do not rely on linear blur models but learn deblurring from large-scale datasets.
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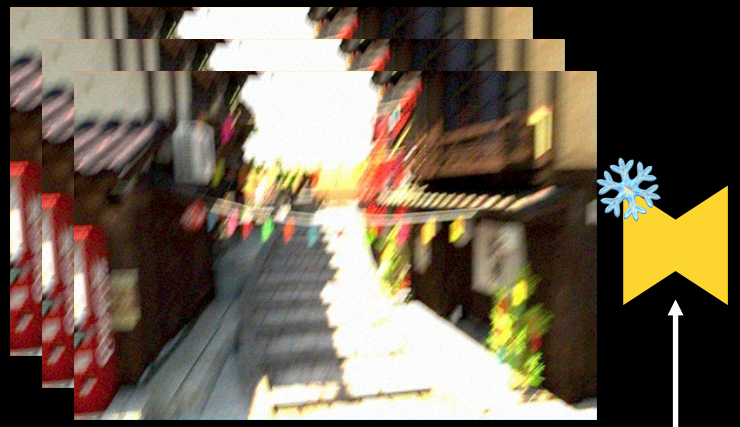

Blurry training views

Single-image
deblurring network

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Deblurred training views

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- Unsatisfactory results.
- Limited performance of single-image deblurring due to insufficient information available in a single image.

Blurry training view

Deblurred training view

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Rendered novel view

Reference

⭐ DeepDeblurRF

1. Initial deblurring
2. Radiance field (RF) construction
3. RF-guided deblurring

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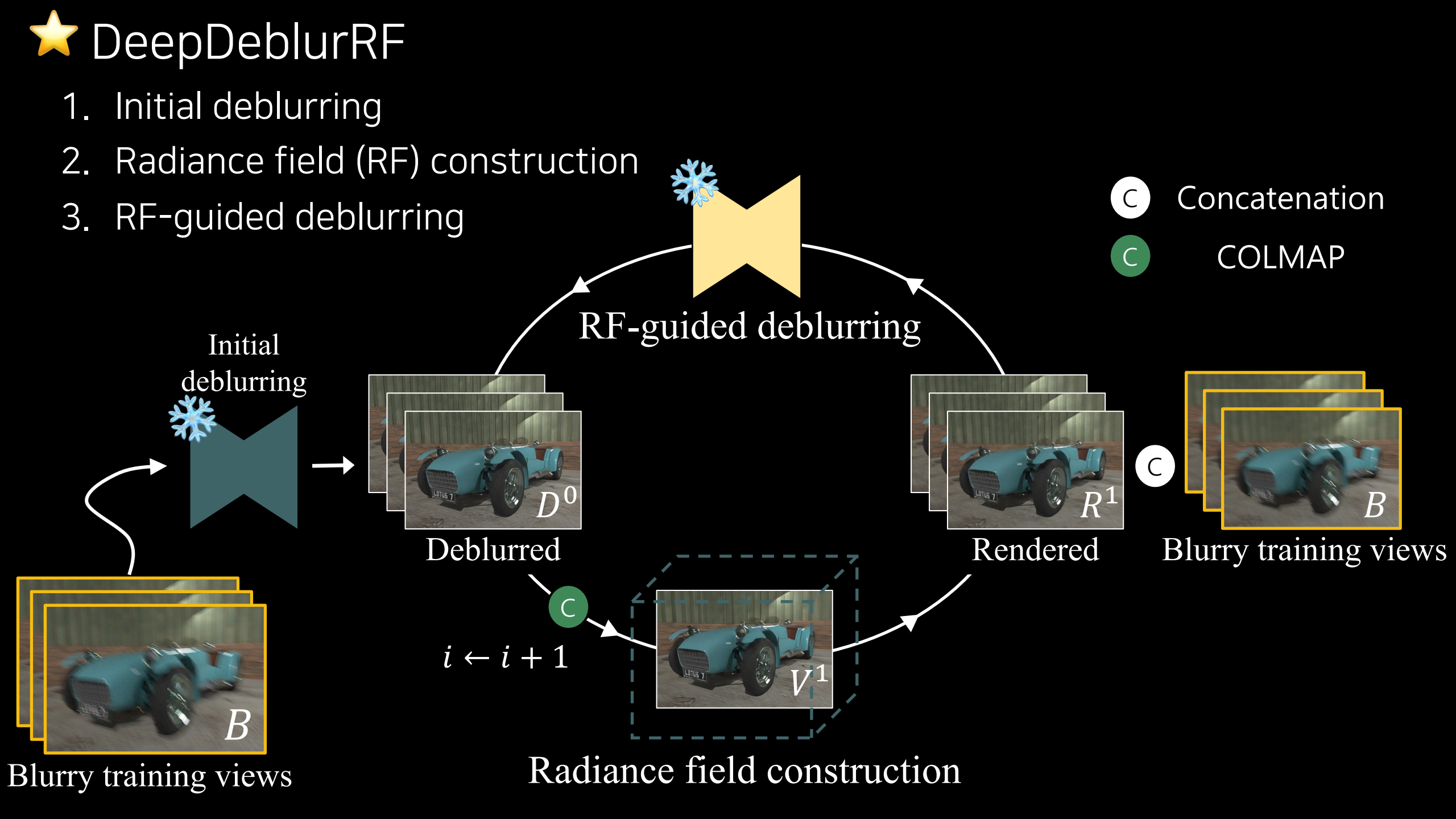
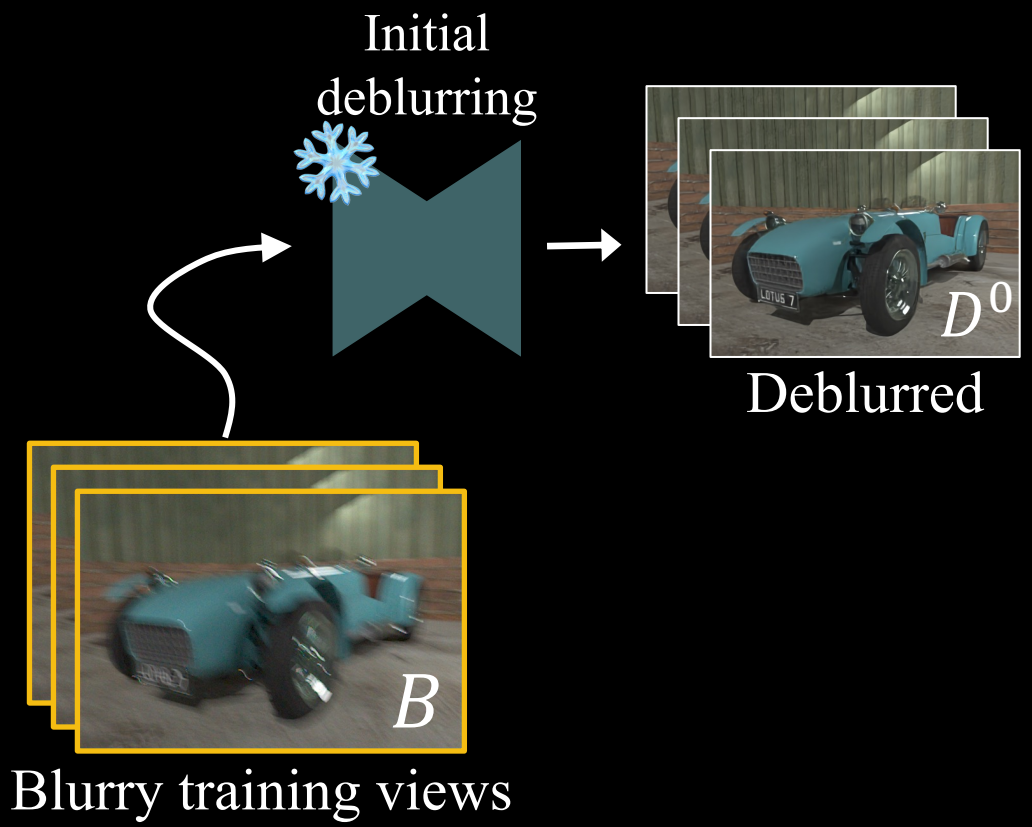


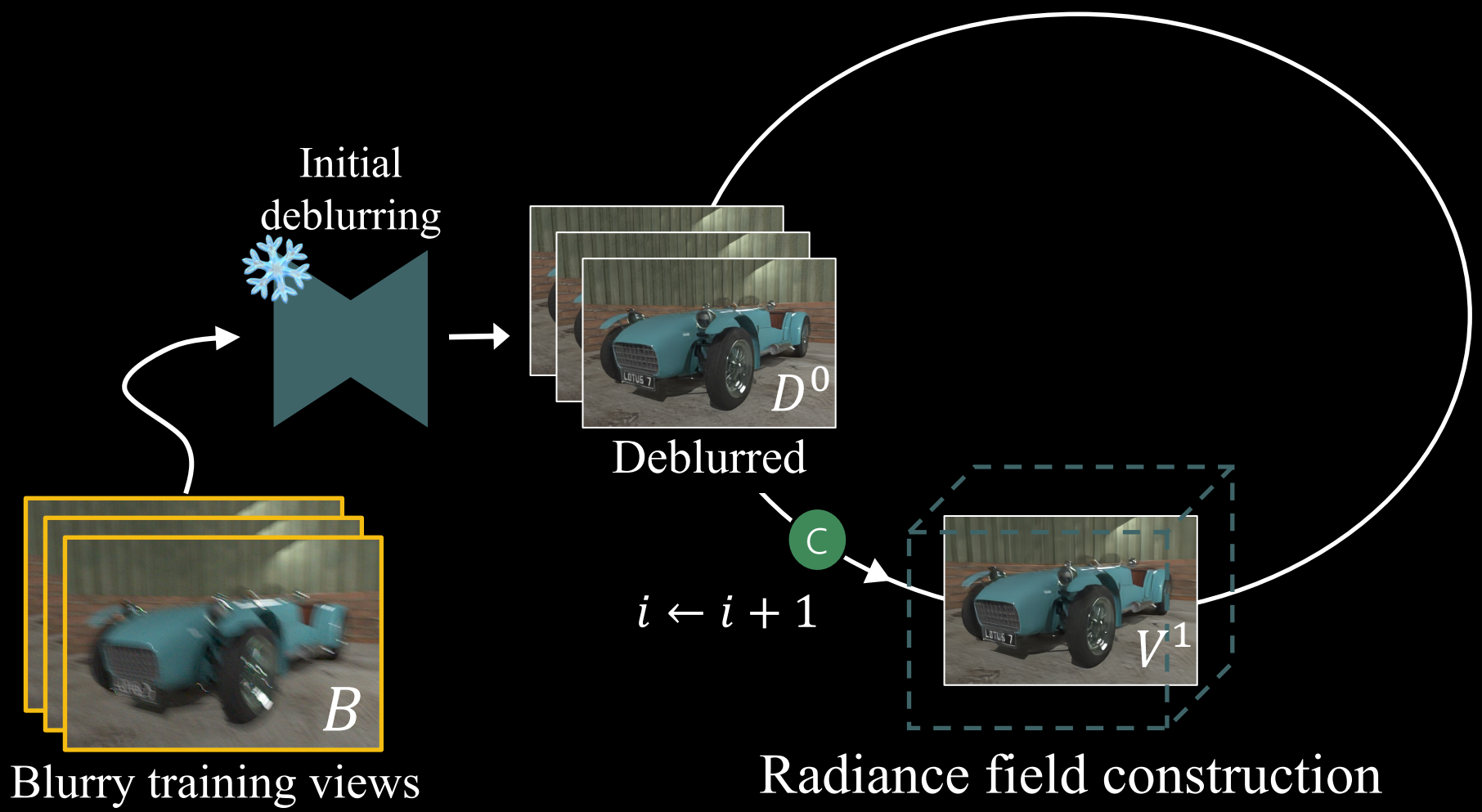
1. Initial deblurring

- Single-image deblurring network : NAFNet



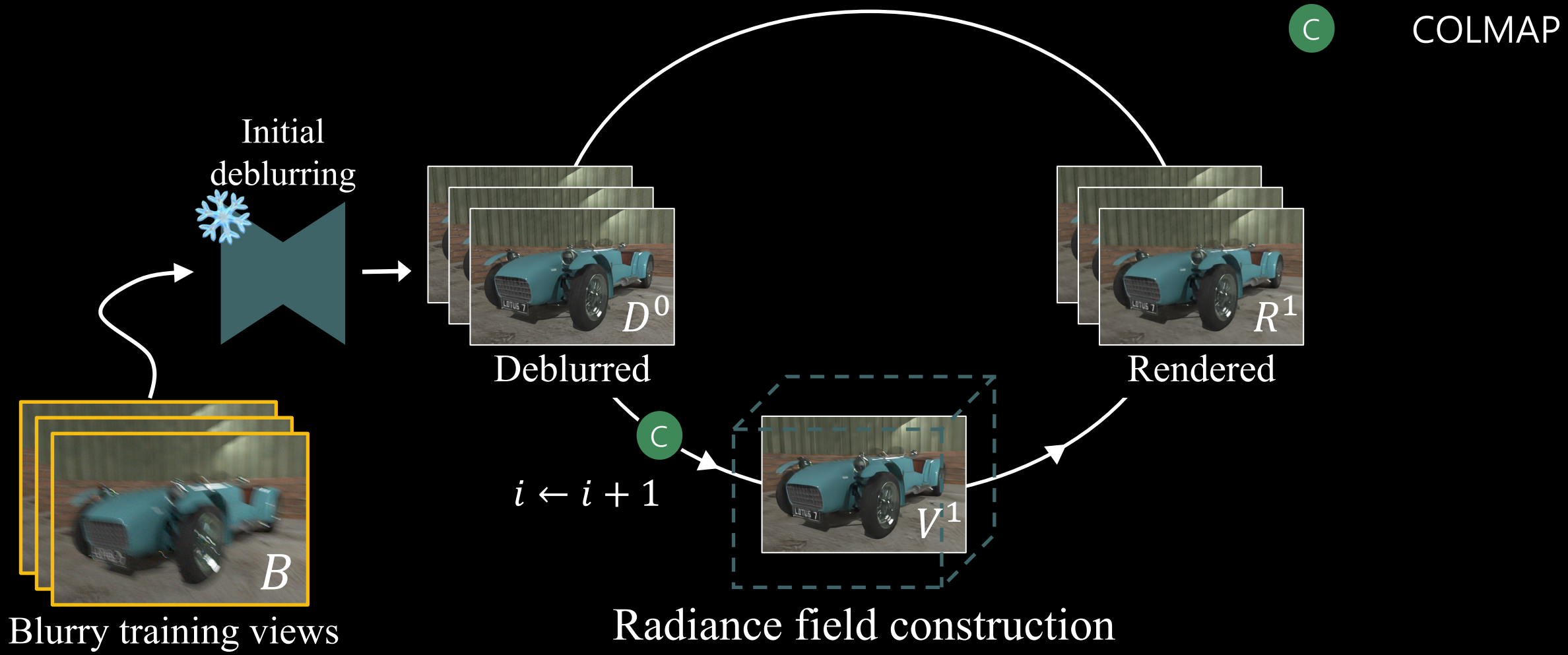
2. Radiance field (RF) construction

- DeepDeblurRF-P : Plenoxels
- DeepDeblurRF-G : 3D Gaussian splatting



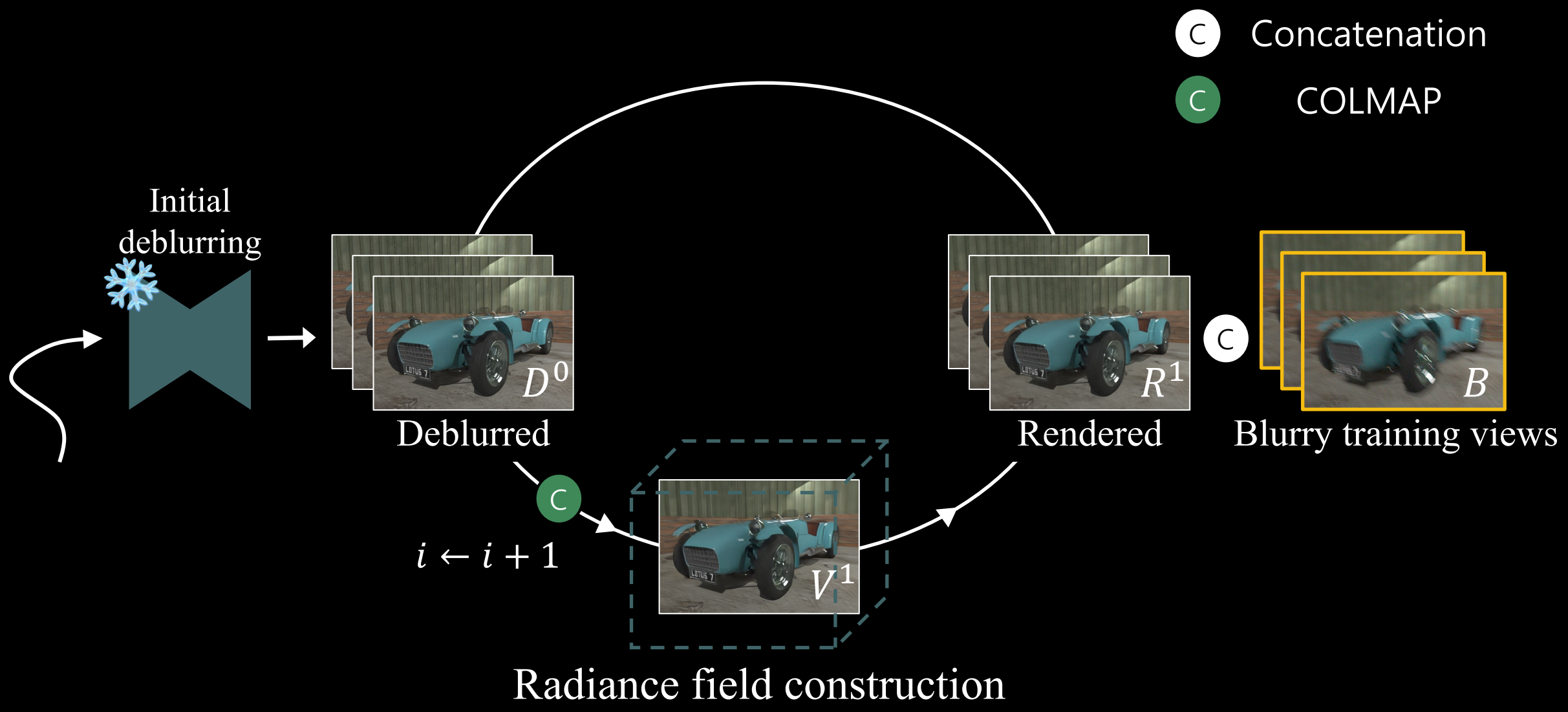
DeepDeblurRF

- R share the same content with B.
- R contain fewer artifacts and finer details.



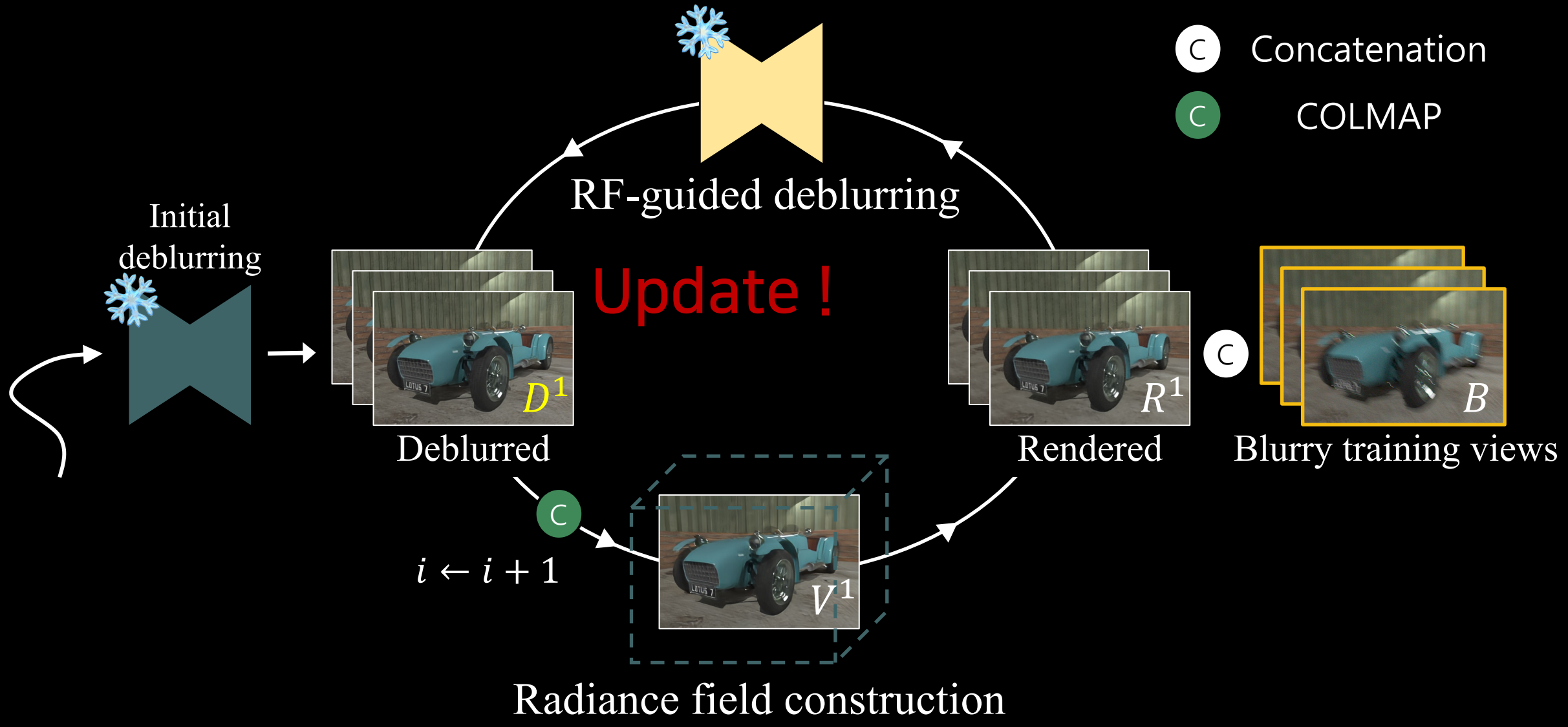
3. RF-guided deblurring

- Guide the deblurring process with the aggregated information in R.



3. RF-guided deblurring

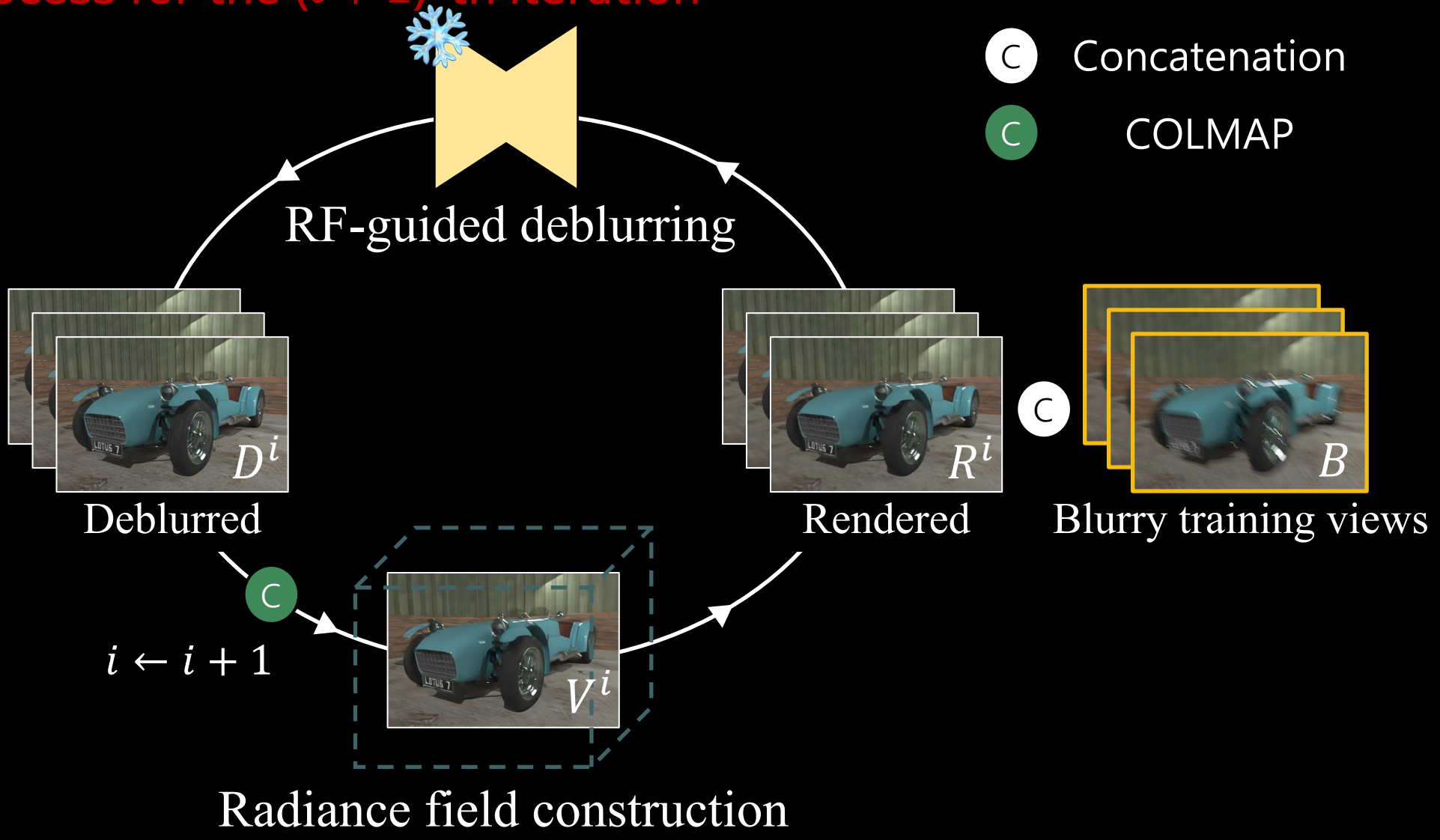
- Network : Modified NAFNet



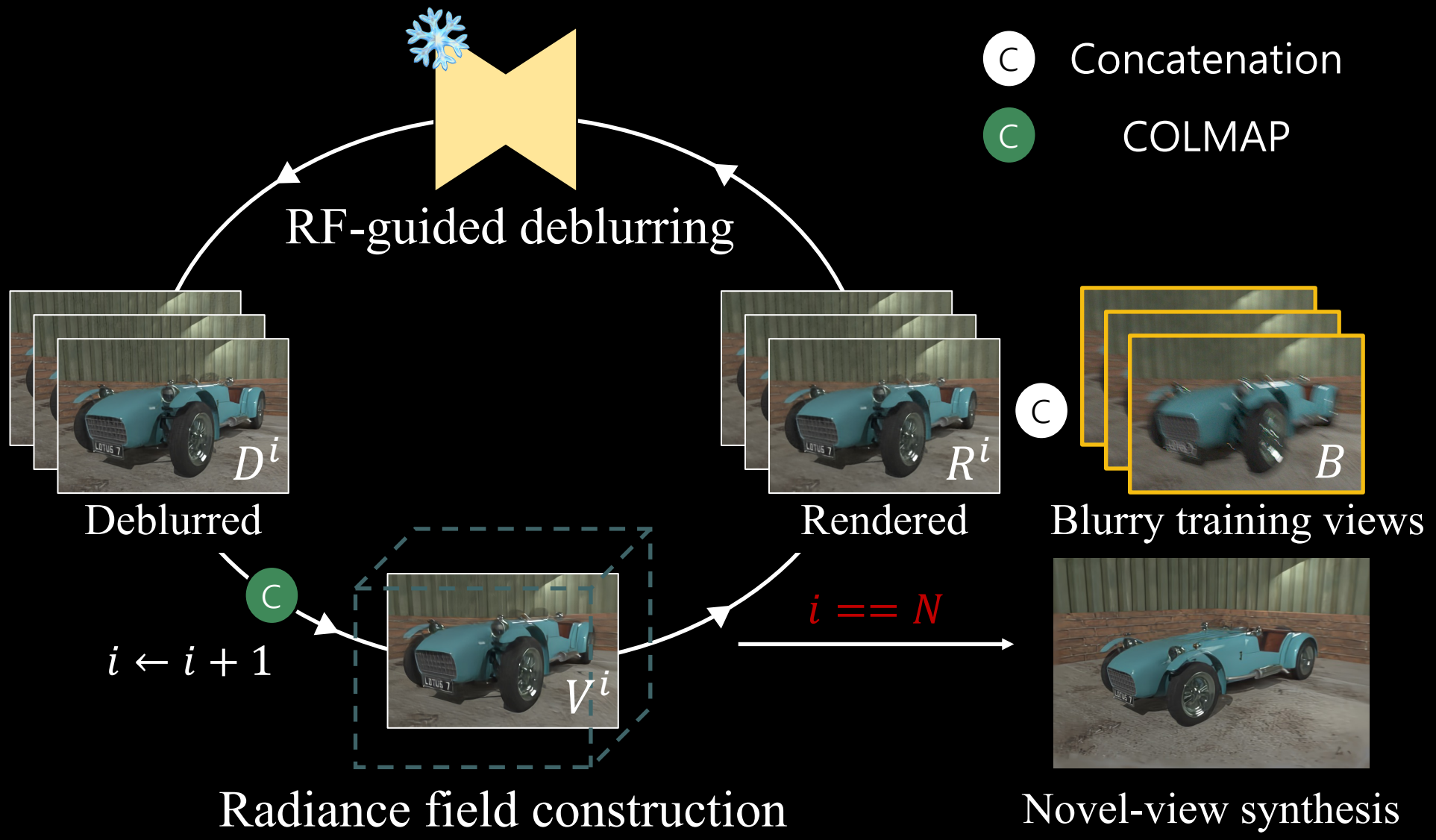
4. Alternates between two stages

Return to the RF construction step.

Carry out the process for the $(i+1)$-th iteration



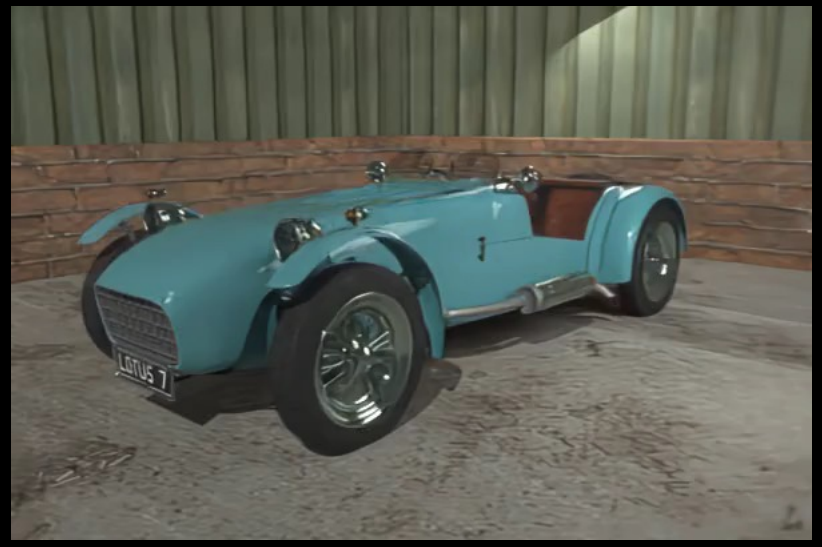
5. Novel-view Synthesis



More results on the website



Blurry Input Views




DeepDeblurRF-P

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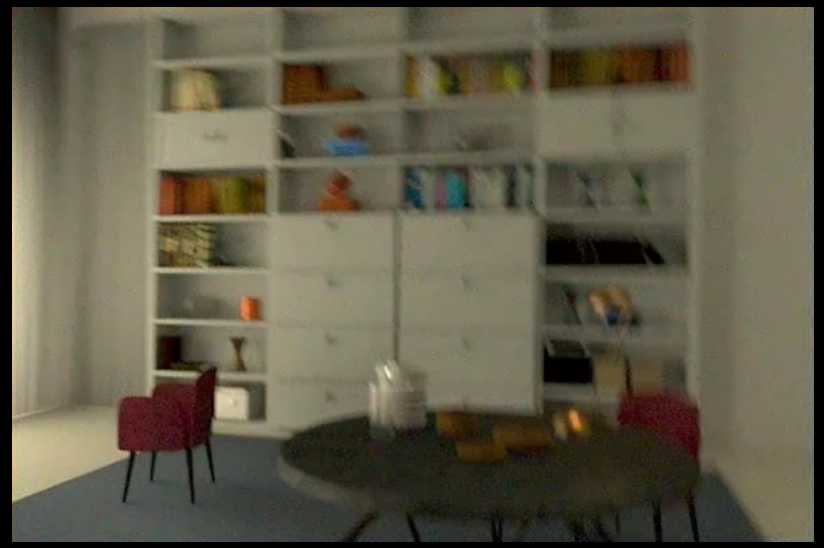

Blurry Input Views



DeepDeblurRF-G

Thank You

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