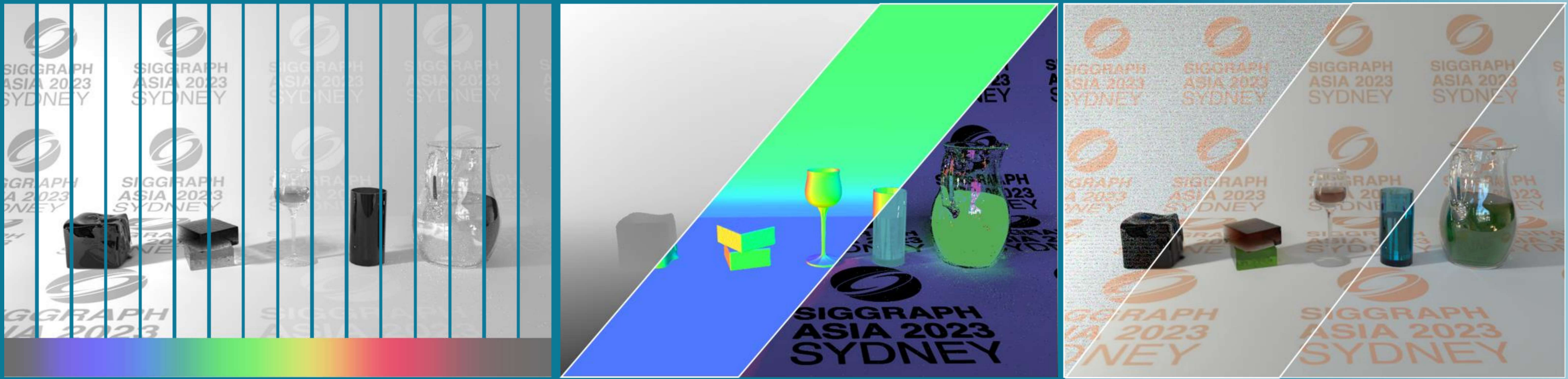
Spectral Monte Carlo Image Denoising

Mathieu Noizet, Robin Rouphael, Stéphanie Prévost, Hervé Deleau, Luiz Angelo Steffenel, Laurent Lucas



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M. Noizet[1], R. Rouphael[1,2], S. Prévost[1], H. Deleau[1], L. Steffenel[1] and L. Lucas[1]

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JCAD 2023

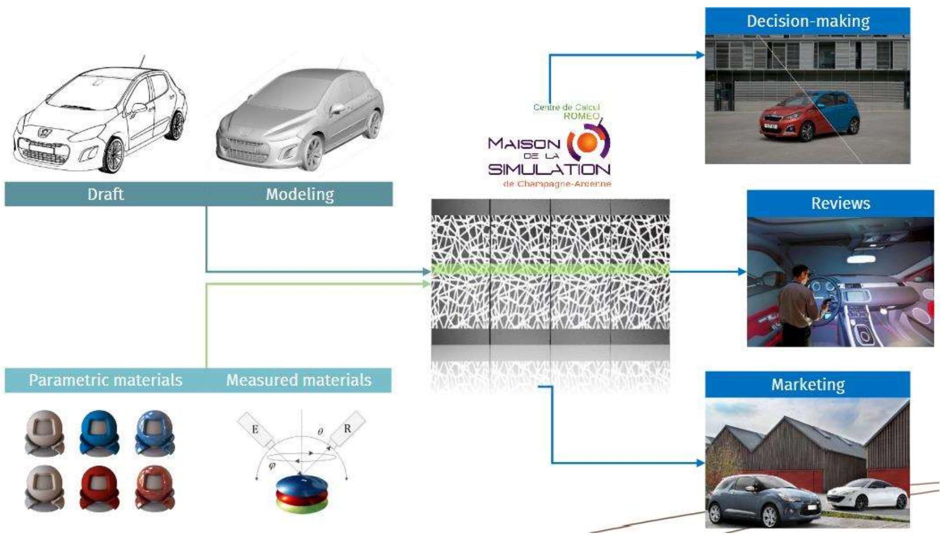
anr LUCE Light-transport SimUlation and MaChine LEarning
Université de Reims Champagne-Ardenne
UVR United Visual Researchers
LICIIS LRC DIGIT

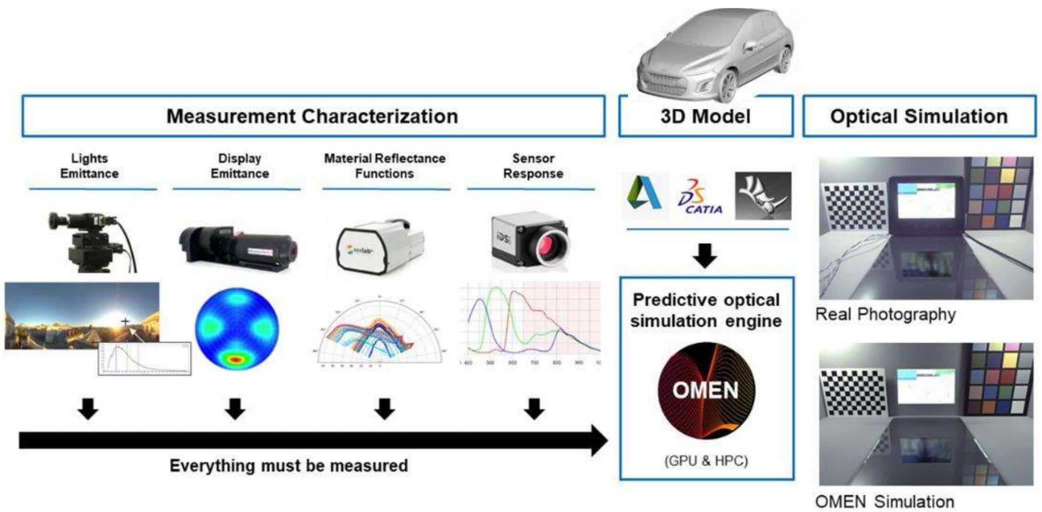
Summary

- General context
- Previous works
- Contributions and results
- Conclusion

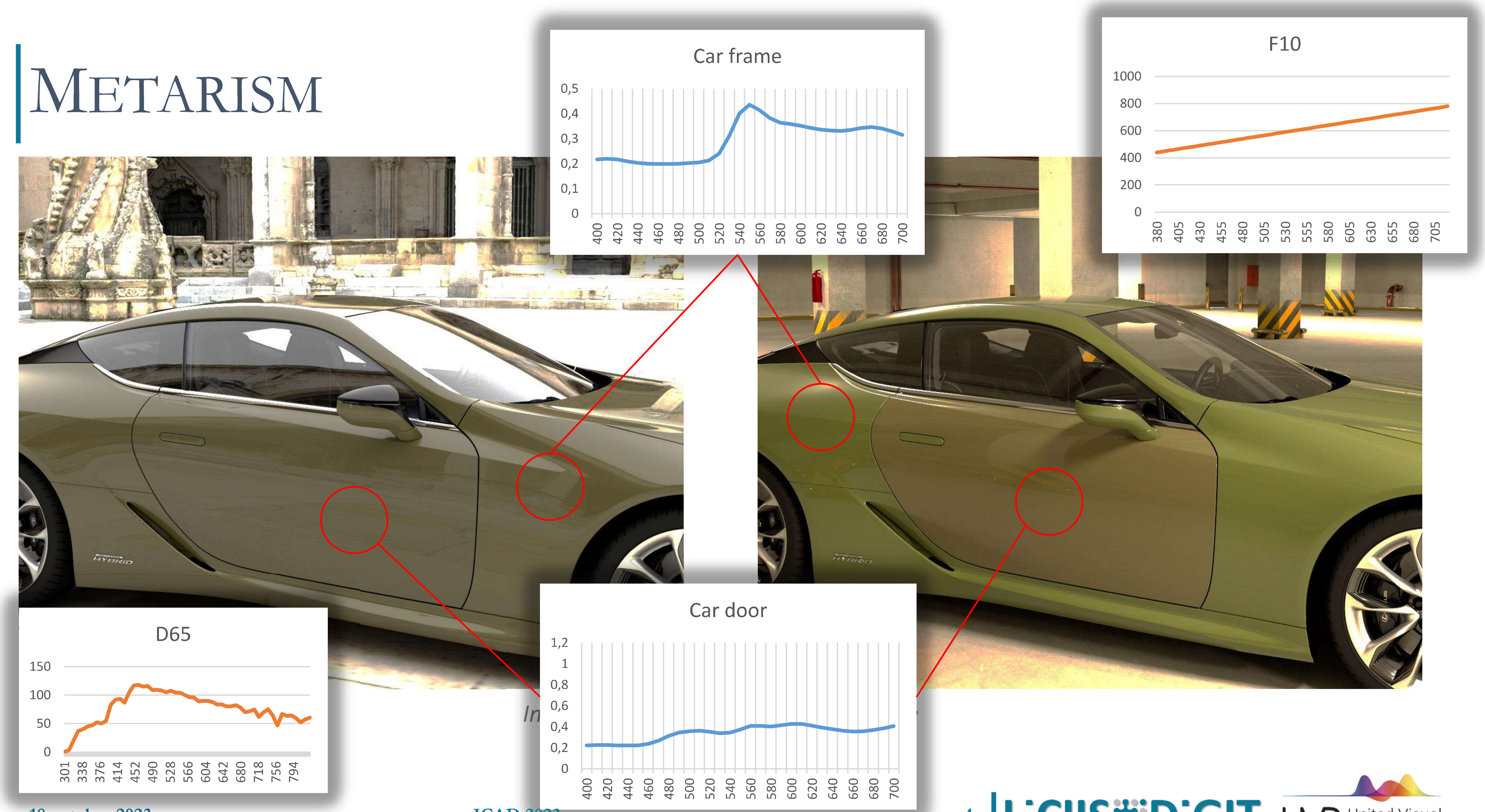
General context

- Predictive visualisation – in interactive time – of complex materials for industry (CA^{2}O)
  - ANR LUCE PRCE 2021-2024
  - Optical simulation with Spectral information
    - Generate predictive image for virtual moke-up
    - Time consuming
    - All light phenomena (metarism, polarization, etc.)





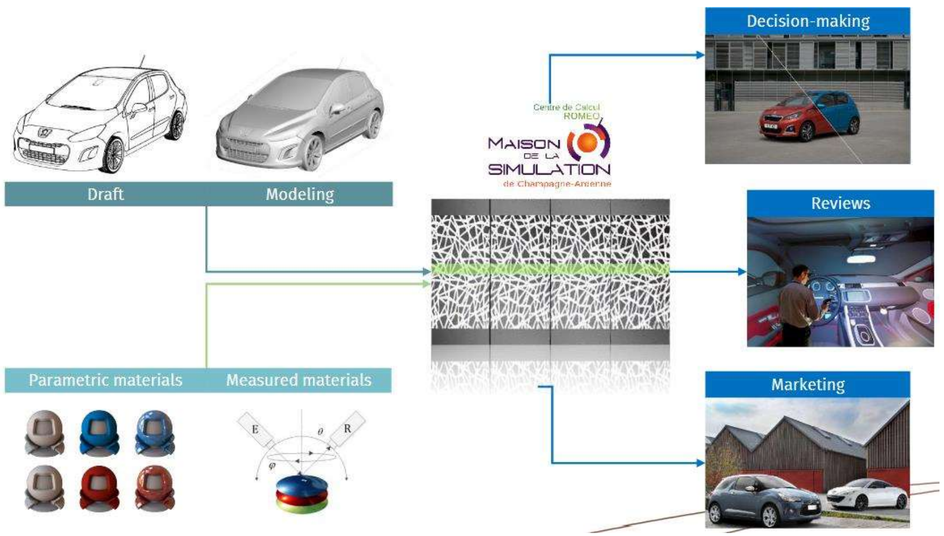
METARISM

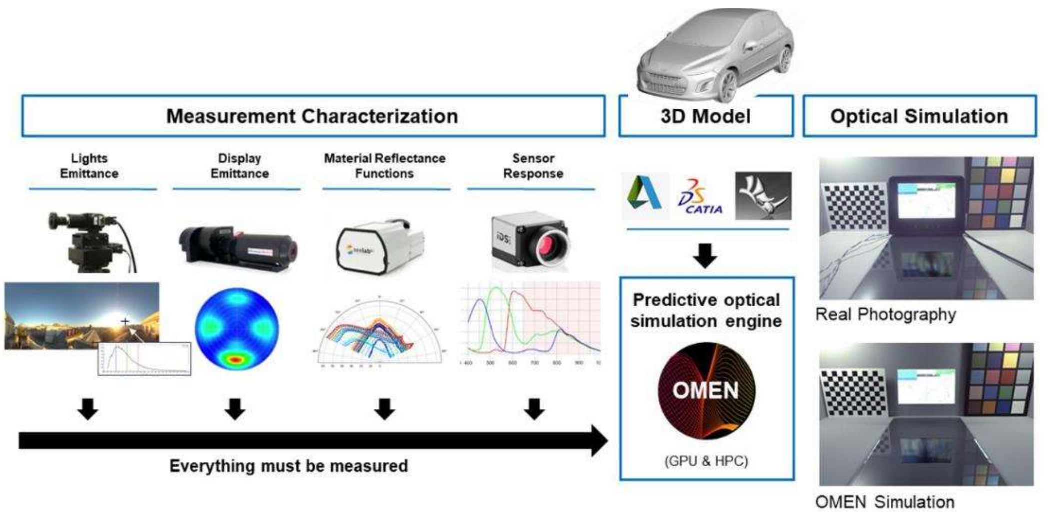


Car frame
0,5
0,4
0,3
0,2
0,1
0
400 420 440 460 480 500 520 540 560 580 600 620 640 660 680 700
F10
1000
800
600
400
200
0
380 405 430 455 480 505 530 555 580 605 630 655 680 705
D65
150
100
50
0
301 338 376 414 452 490 528 566 604 642 680 718 756 794
Car door
1,2
1
0,8
0,6
0,4
0,2
0
400 420 440 460 480 500 520 540 560 580 600 620 640 660 680 700

General context

- Predictive visualisation – in interactive time – of complex materials for industry (CA^{2}O)
  - Coupling optical simulation and machine learning
    - How can rendering methods be combined with Deep Learning?
    - How can they be adapted for HPC architecture?





Monte Carlo Rendering

Rendering by UVR Predict Engine

- Rendering equation

$$L_o(x,\omega) = L_e(\dots) + \int_{\Omega} f_r \cdot L_i(\dots) \cdot \cos\theta \, d\vec{\omega}_i$$

- Complex analytic resolution
  - Recursive
  - High dimension

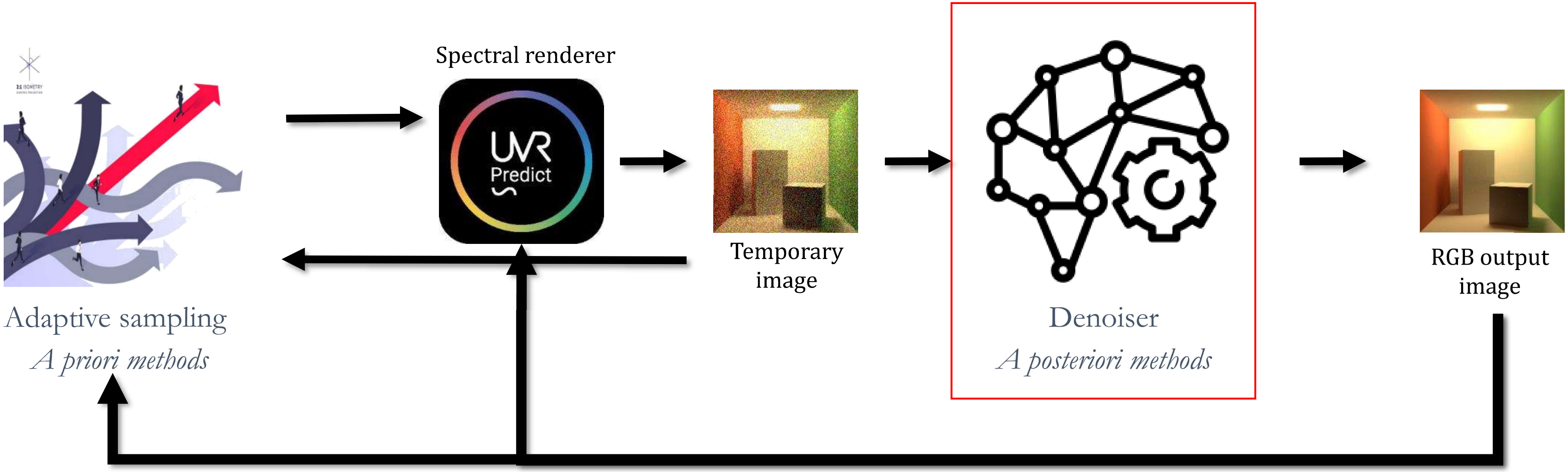
- Resolution based Monte Carlo approach

$$\langle F \rangle = \frac{1}{N}\left[\frac{f(X)}{p(X)}\right] \approx \int f(x)dx$$

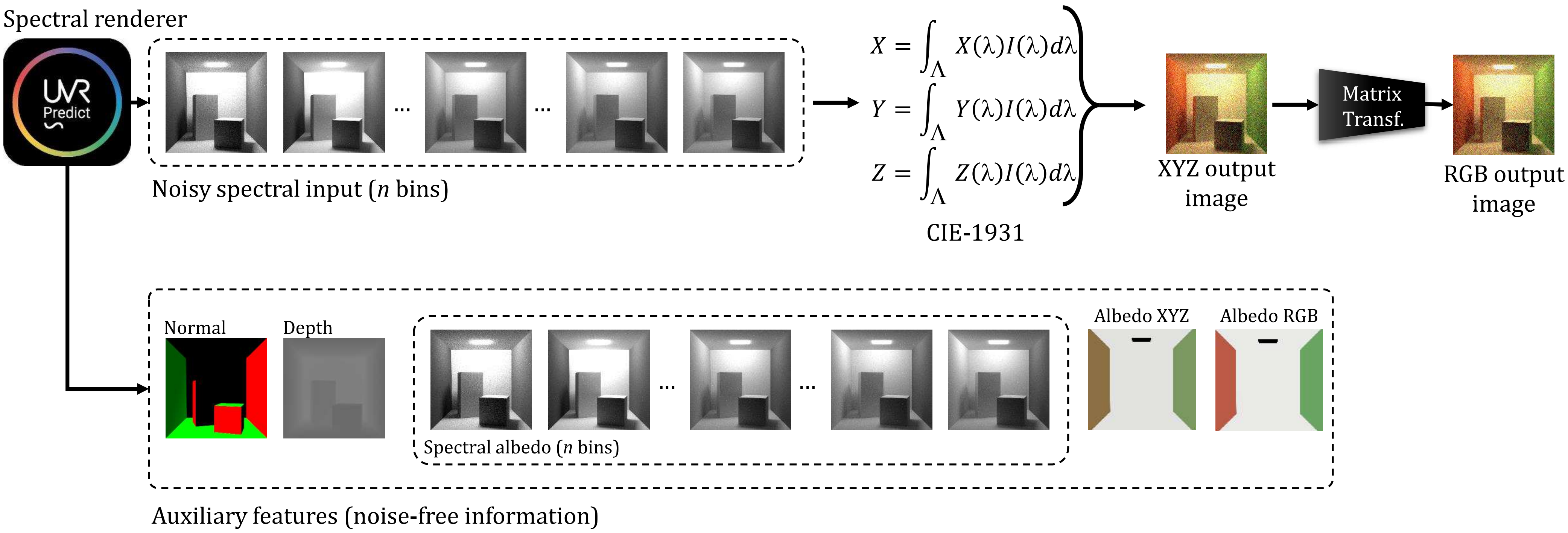
- Approximate the solution from a number of sample

OUR GOAL

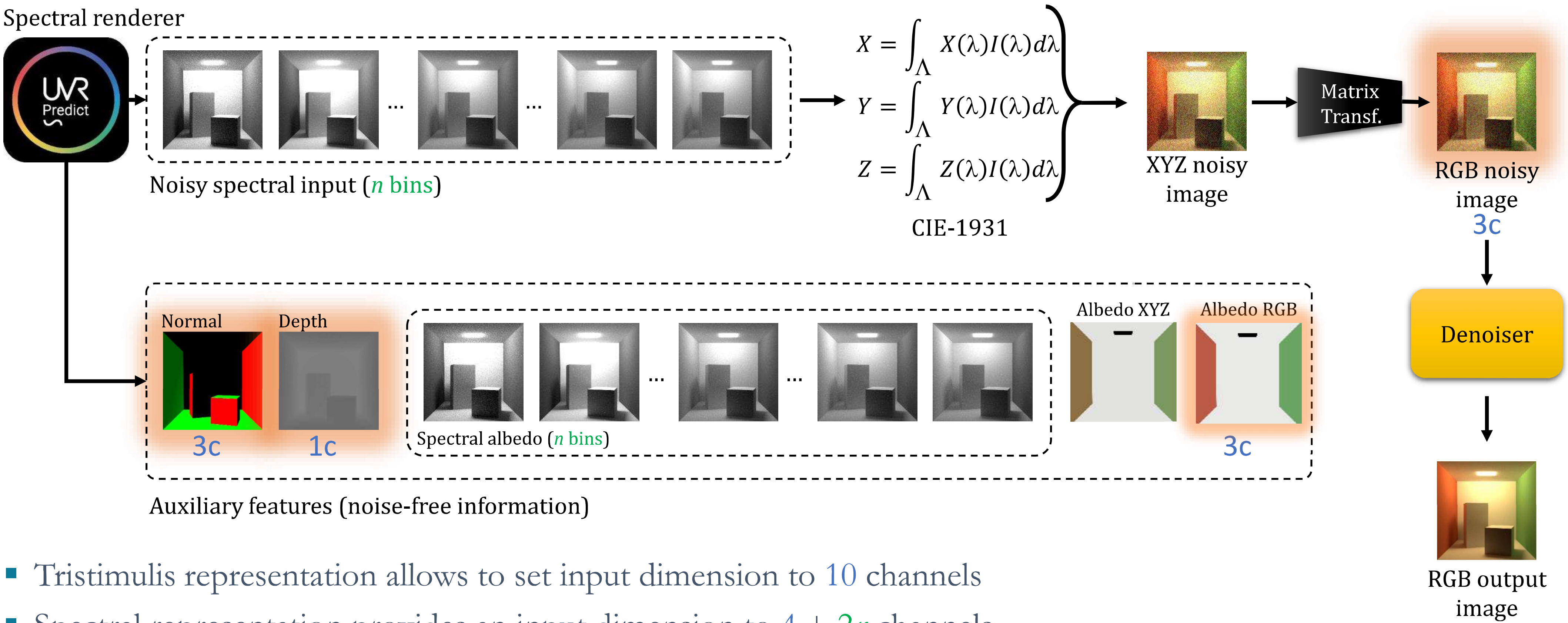
Conventional pipeline
LUCE's pipeline



Available data from Spectral Monte Carlo Rendering



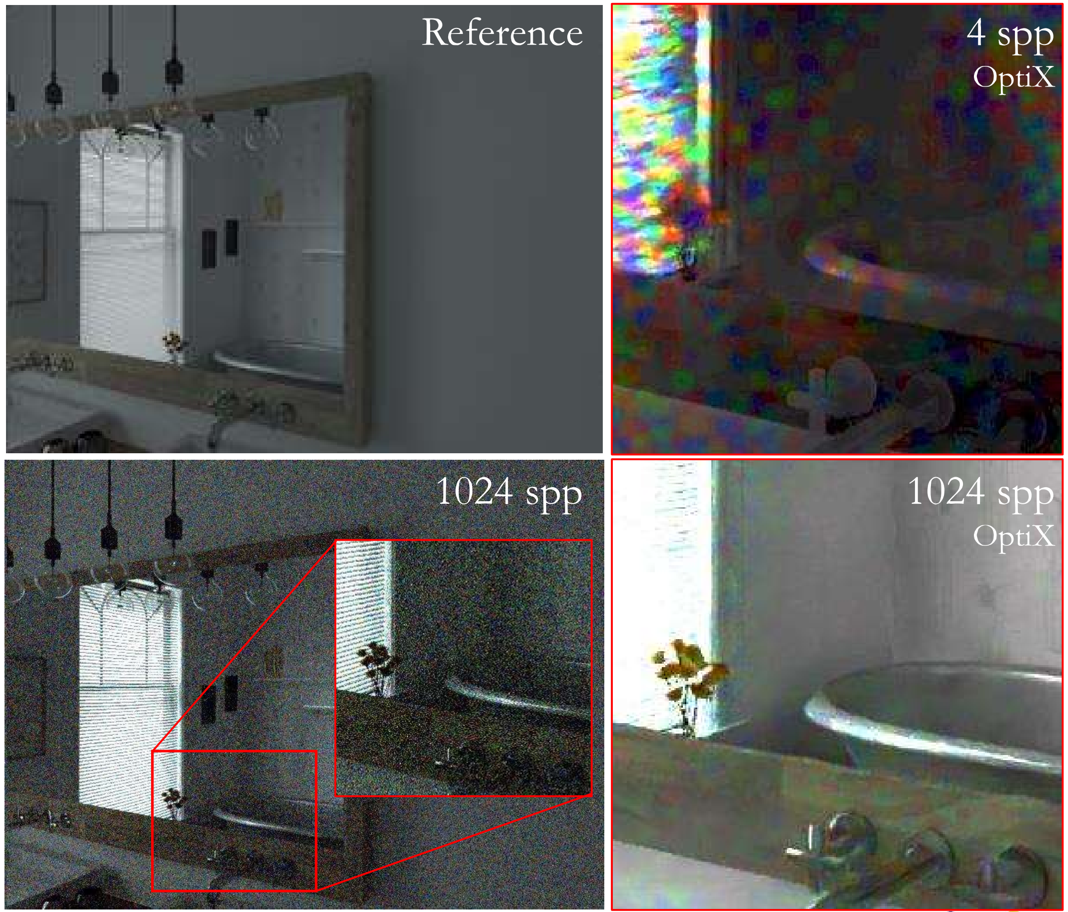
State of the art - Denoising



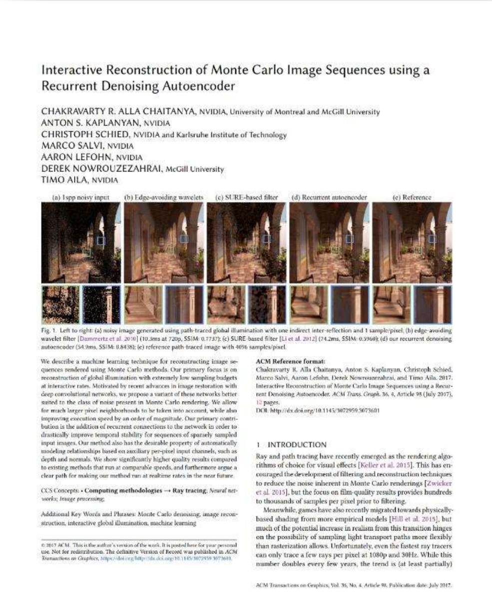
- Tristimulis representation allows to set input dimension to 10 channels
- Spectral representation provides an input dimension to $4 + 2n$ channels

State of the art – Off-the-shell denoiser

- Denoise the tristimulis representation (RGB, XYZ…)
  - NVIDIA OptiX denoiser
  - Intel Open Image Denoiser (IOID)
- Apply denoiser with a well sample rate
- Limits
  - Compress all spectrum information into 3 dimensions
  - Bring chromatic aberration
- Questions
  - Has off-the-shell denoiser train on spectral rendering?
  - Do spectral denoisers exist?



State of the art – Monte Carlo Denoising

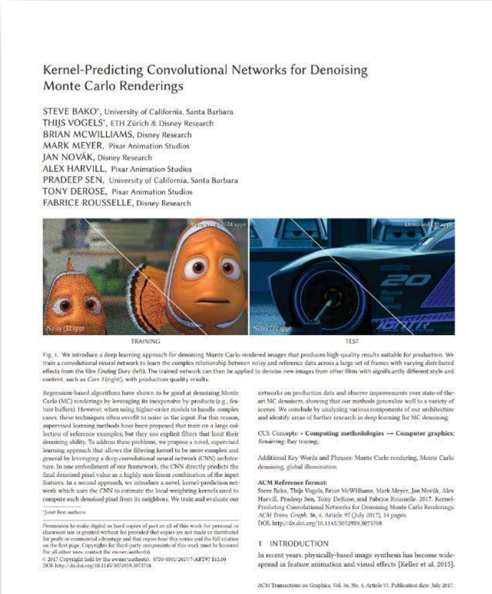

Interactive Reconstruction of Monte Carlo Image Sequences using a Recurrent Denoising Autoencoder

[Chaitanya et al. 2017]

Direct prediction

~1-4 spp*

Loss details

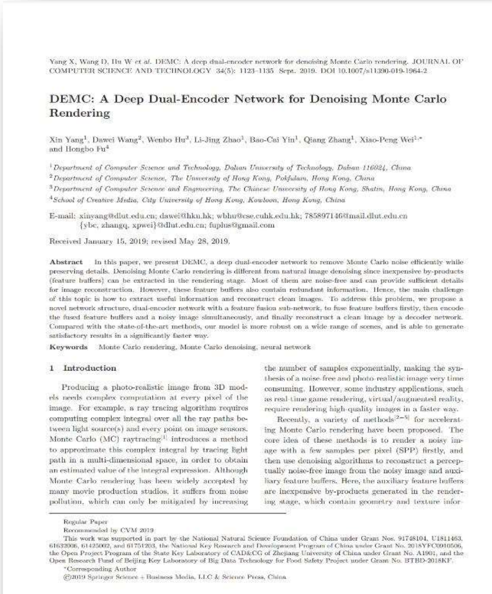

Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings

[Bako et al. 2017]

Kernel prediction

~64-128 spp*

Details reconstructed


DEMC: A Deep Dual-Encoder Network for Denoising Monte Carlo Rendering

[Yang et al. 2019]

Direct prediction

~1-4 spp*

Reduce artifact induce by auxilairy features

Less of diffuse details lost


Deep Combiner for Independent and Correlated Pixel Estimates

[Back et al. 2020]

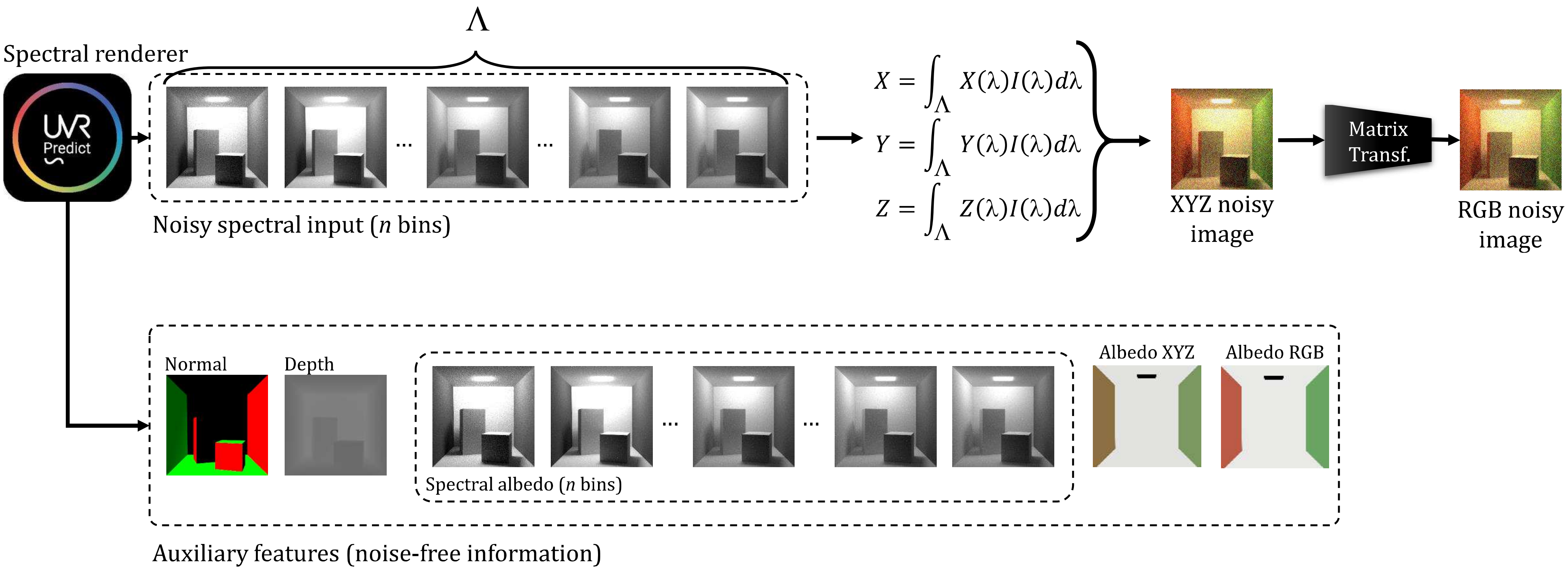
Kernel prediction

independent of spp*

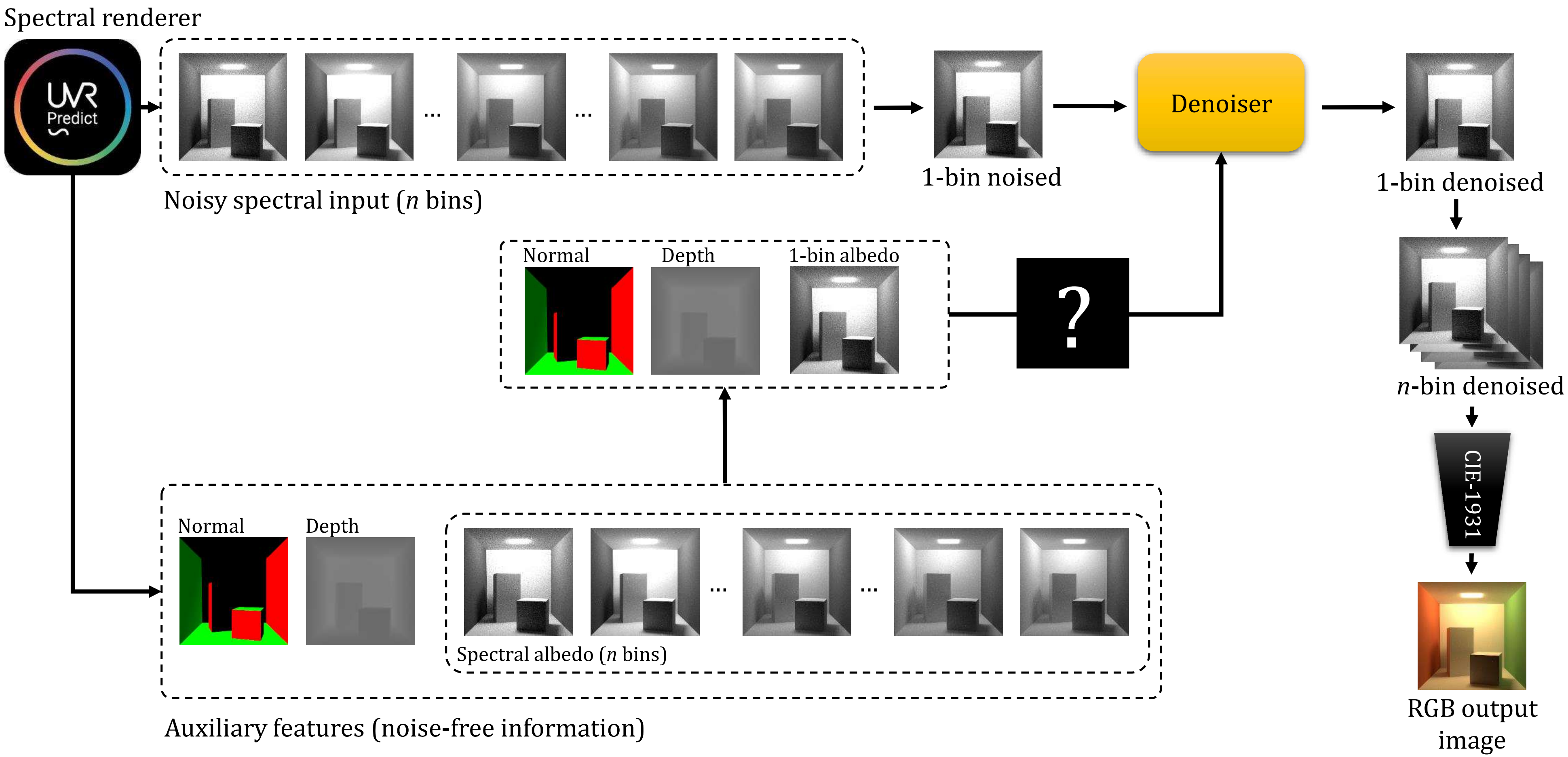
Improve diffuse details reconstruction

spp* = 1 sample in RGB

DATA MANAGING



Data managing



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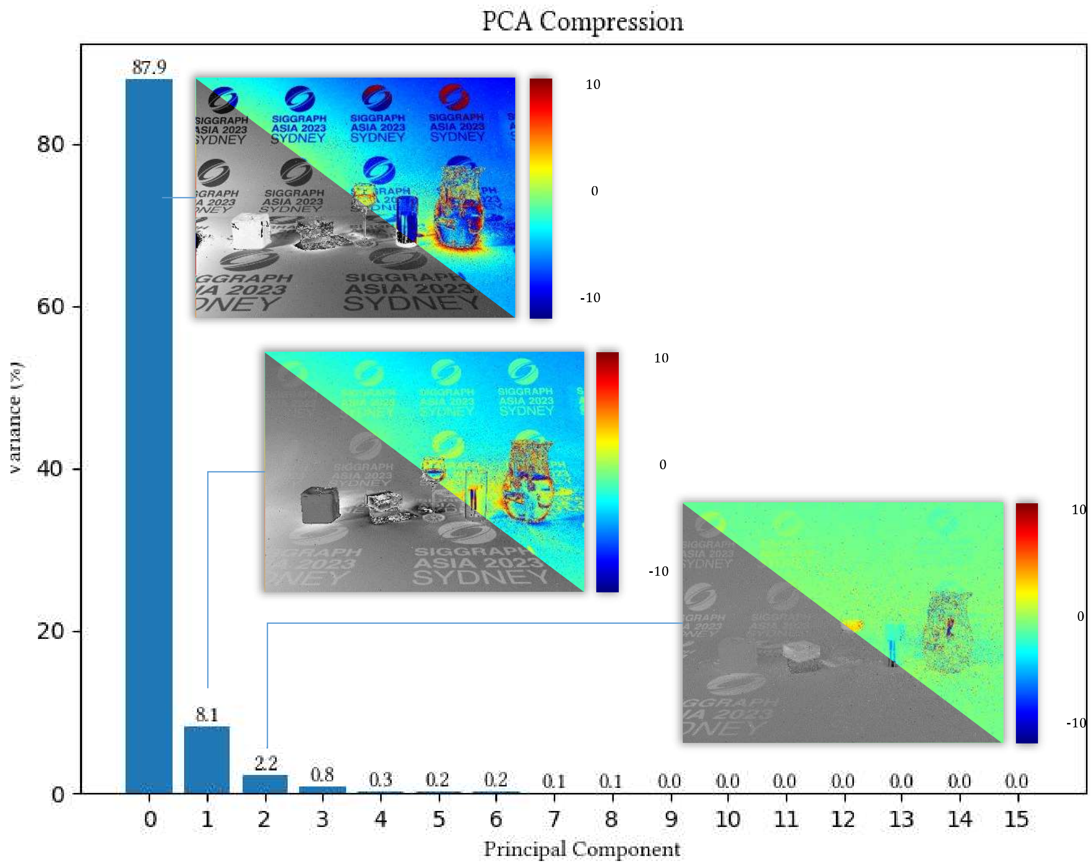
Spectral compression

- Aim to provide full light spectrum information
  - With fixed set input dimension

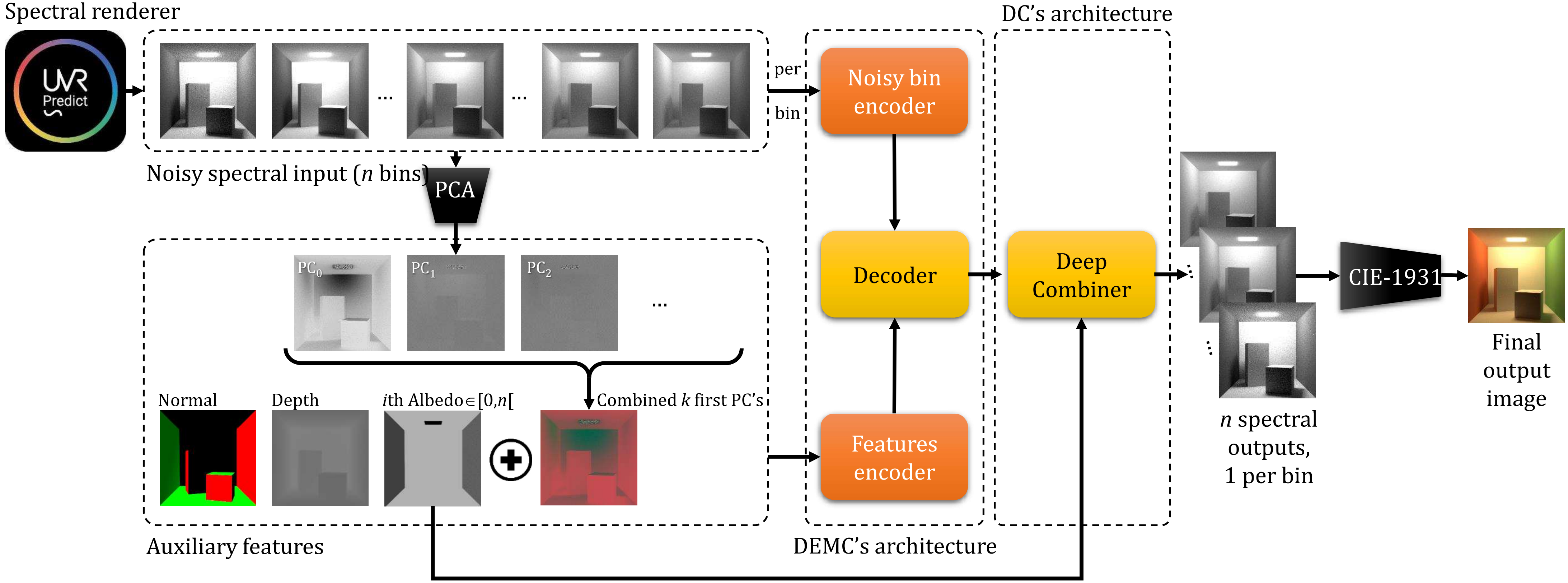
- Tri-chromatic representation
  - Set to 3 dimensions
  - Provide a displayable information
  - Change the nature of data representation

- PCA
  - No truncate spectral information
  - Compress without data lost

  - The 3 first PC represent 98.2% of initial information



Our contribution



Training information

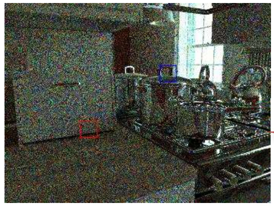
- Loss function: SMAPE
- Dataset
  - 5500 image peers (4554 for training, 946 for testing)
  - 23 scenes (22 points of views)
  - Resolution of image's crop 128×128
- Training parameters (for each network)
  - Epochs : 5000
  - Learning rate : 10^{-4}
  - Optimizer : Adam
- Training time: ~3 days
- 4 GPU Nvidia Tesla P100 (16 Go VRAM)

Results

Noisy image | Reference image | Denoised image with our method

SPP:	1024	1 M	1024
Time:	89 s on 1 GPU	≈ 36 h on 4 GPUs	89.16 s on 1 GPU
RelMSE:	0.70	GT	0.0313

Results



Noisy image
1024 SPP

Reference image
1M SPP

Intel | OptiX | Ours

RelMSE: 0.176 | 0,205 | 0.0313

Conclusion & Future works

- Contributions
  - First spectral denoiser
    - based on the spectral bins processing
    - Tailoring input, auxiliary and output features to favorize spectral information
  - Out-perform off-the-shell denoiser (with RelMSE measure)
  - Submitted to Eurographics 2024

- Future works
  - Improve border reconstruction
  - Improve albedo computation to reduce artifacts

Thanks for your attention!

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