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## Spectral Monte Carlo Image Denoising

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

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Mathieu Noizet, Robin Rouphael, Stéphanie Prévost, Hervé Deleau, Luiz Angelo Steffenel, et al.. Spectral Monte Carlo Image Denoising. Journée Calcul et données, Sep 2023, Reims (51), France. hal-04716991

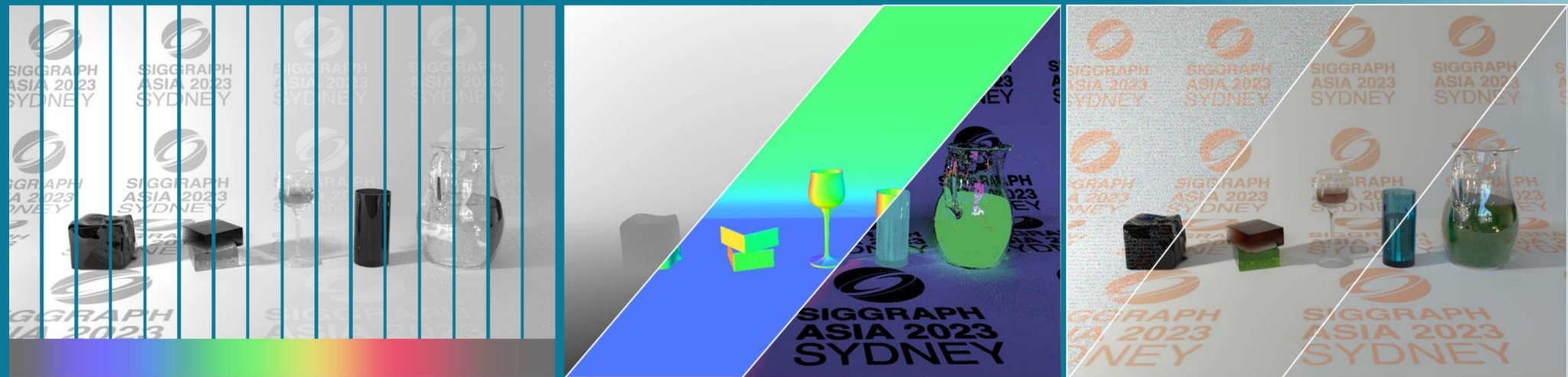
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Submitted on 1 Oct 2024

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# Spectral Monte Carlo Image Denoising

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LICIIS  
LRC  
DIGIT

JCAD 2023

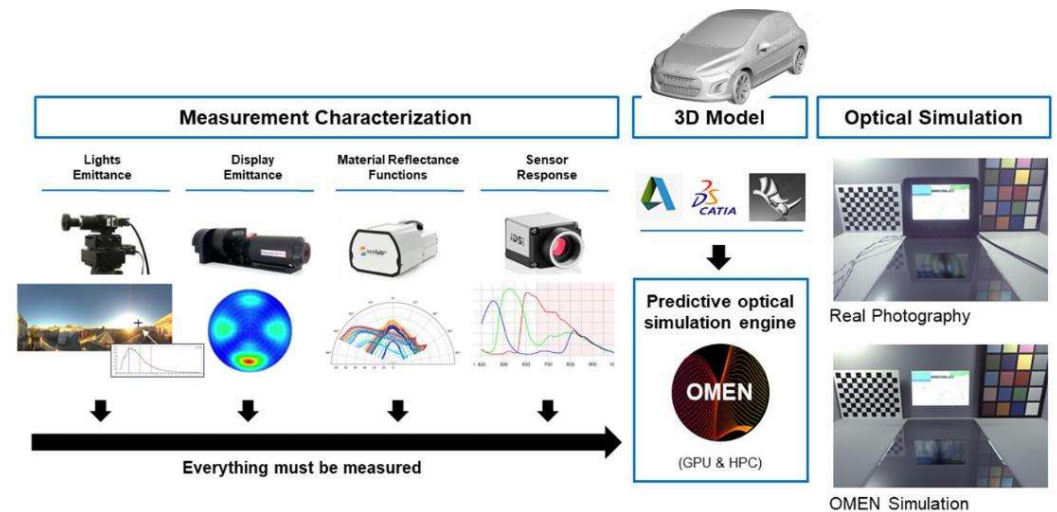
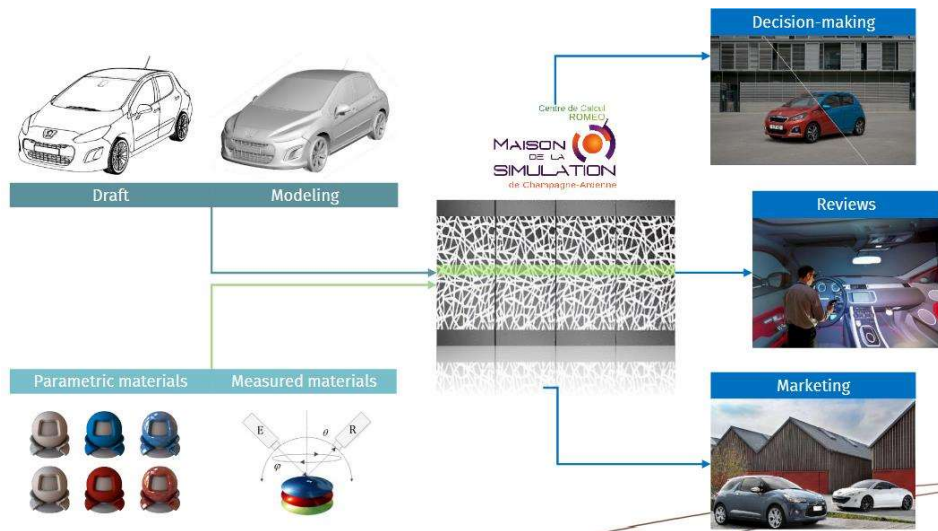


# SUMMARY

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

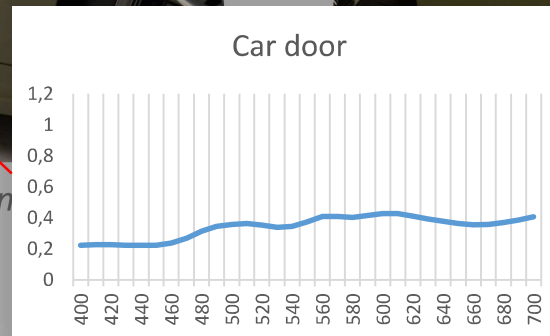
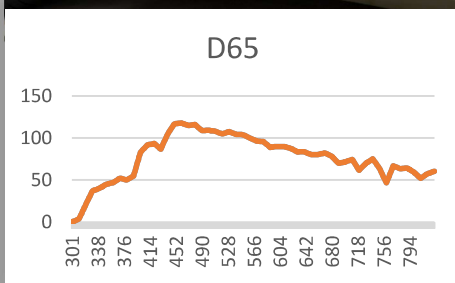
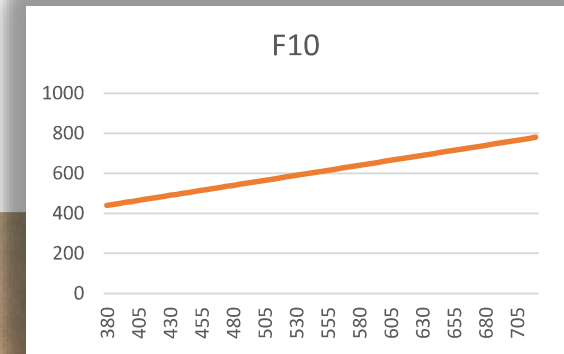
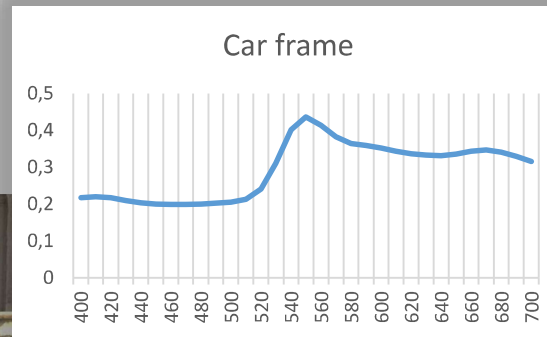
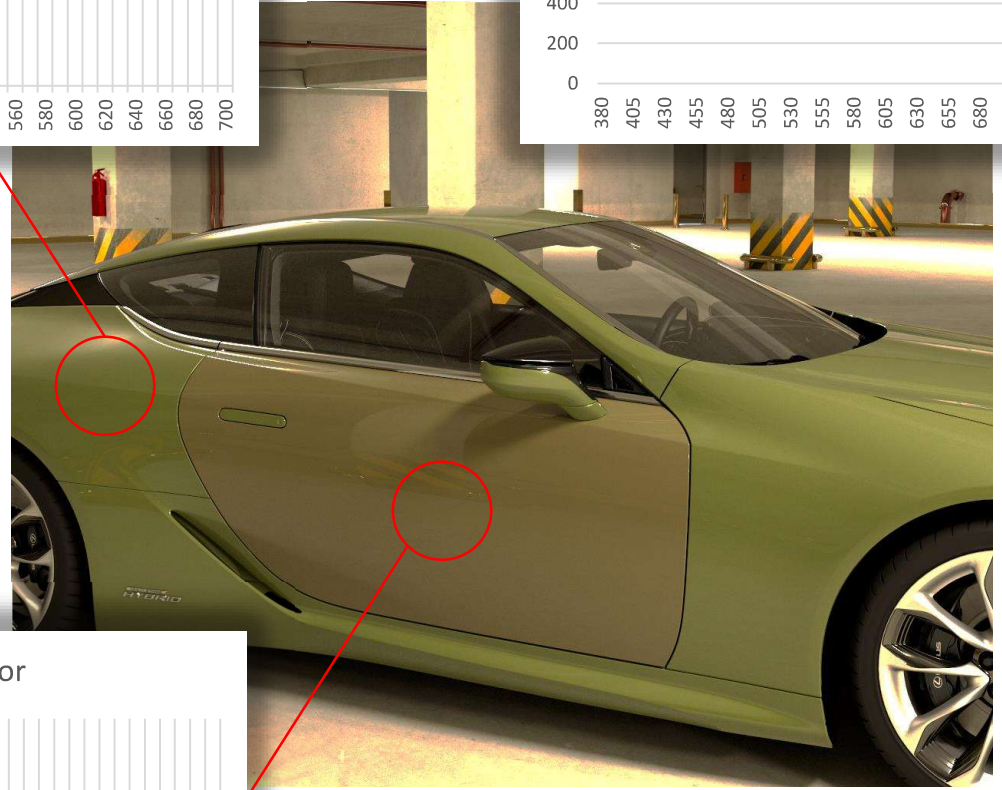
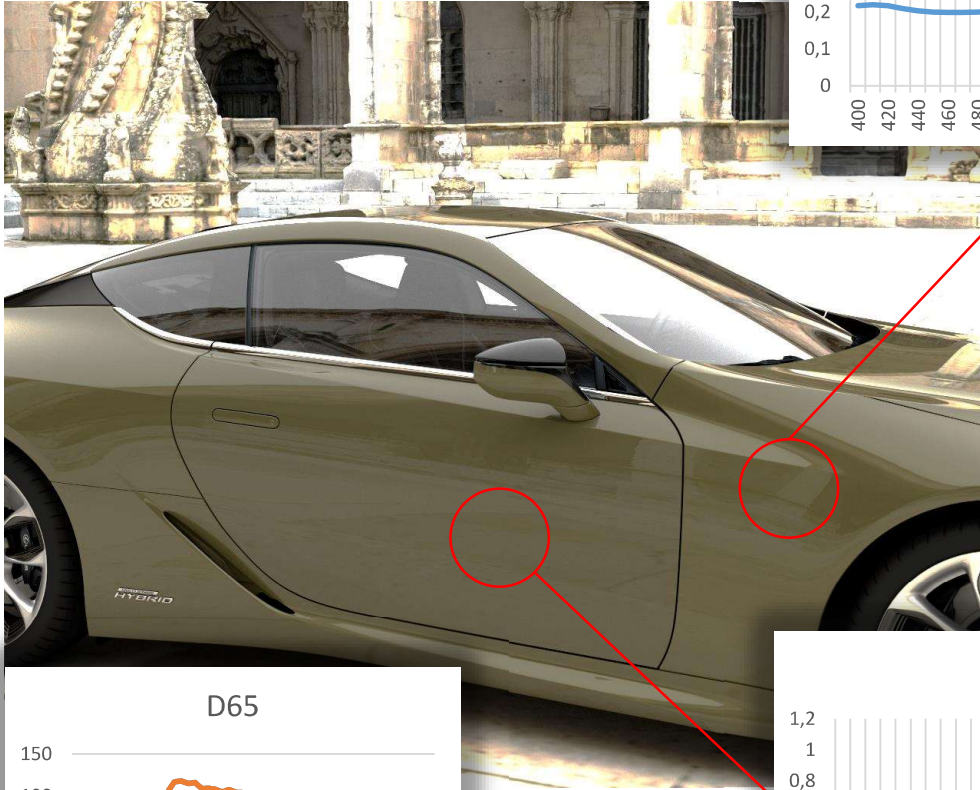
# GENERAL CONTEXT

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





# METARISM

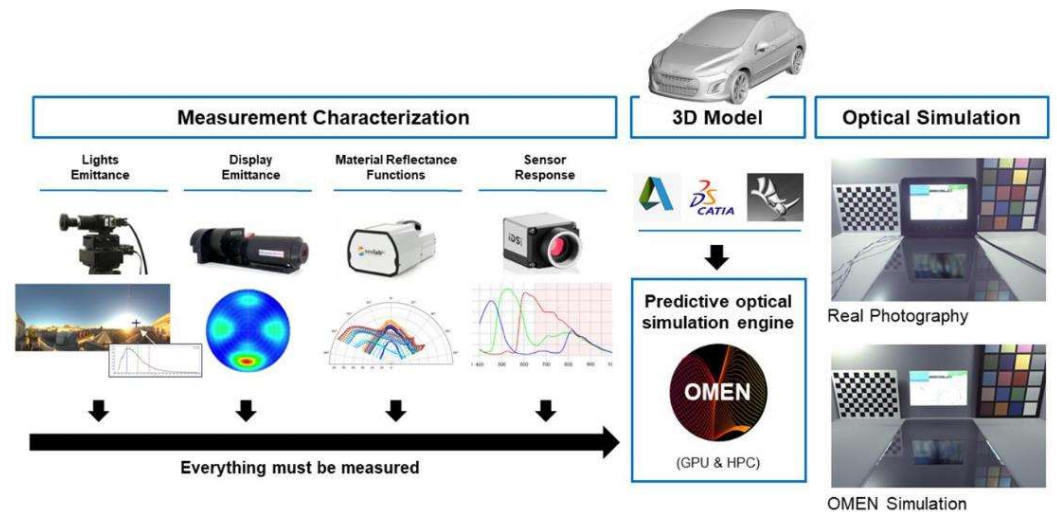
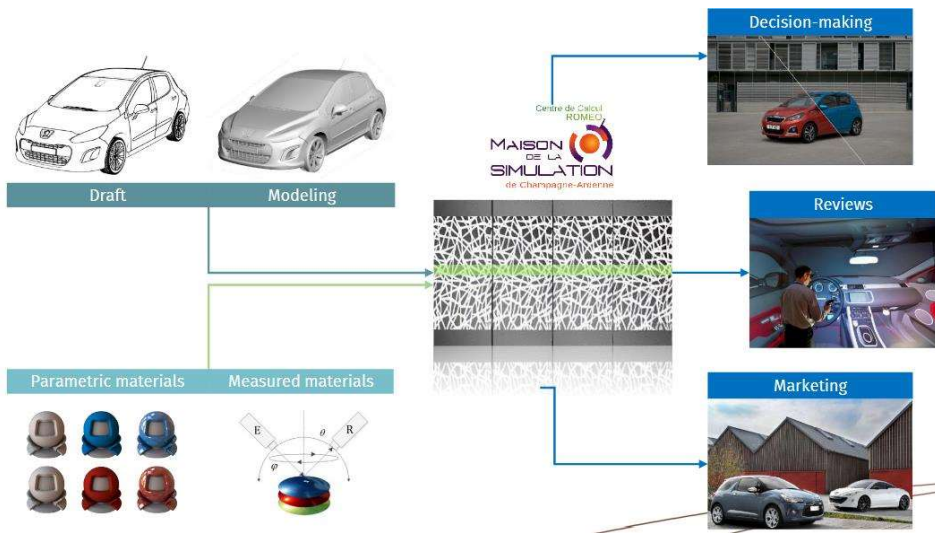


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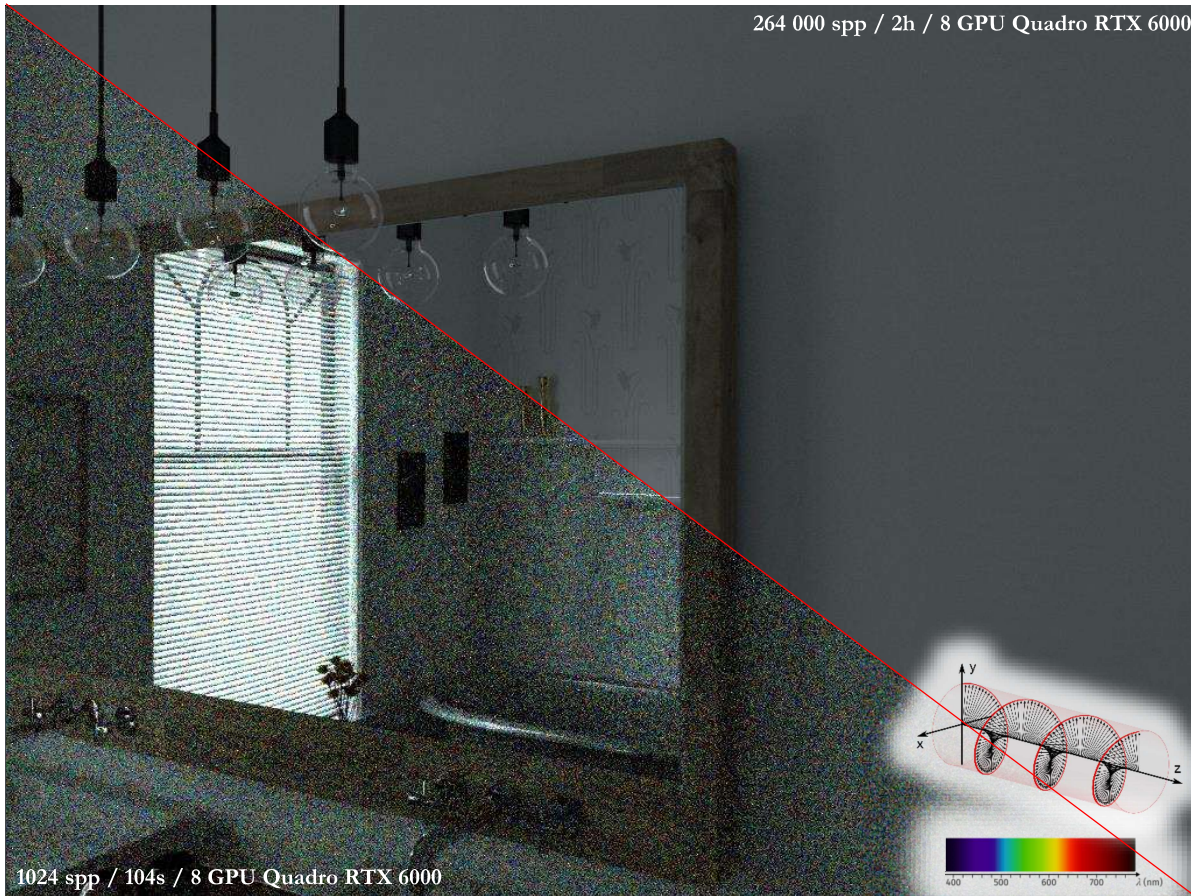
# GENERAL CONTEXT

- Predictive visualisation – in interactive time – of complex materials for industry (CA<sup>2</sup>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



1024 spp / 104s / 8 GPU Quadro RTX 6000

Rendering by UVR Predict Engine

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- 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

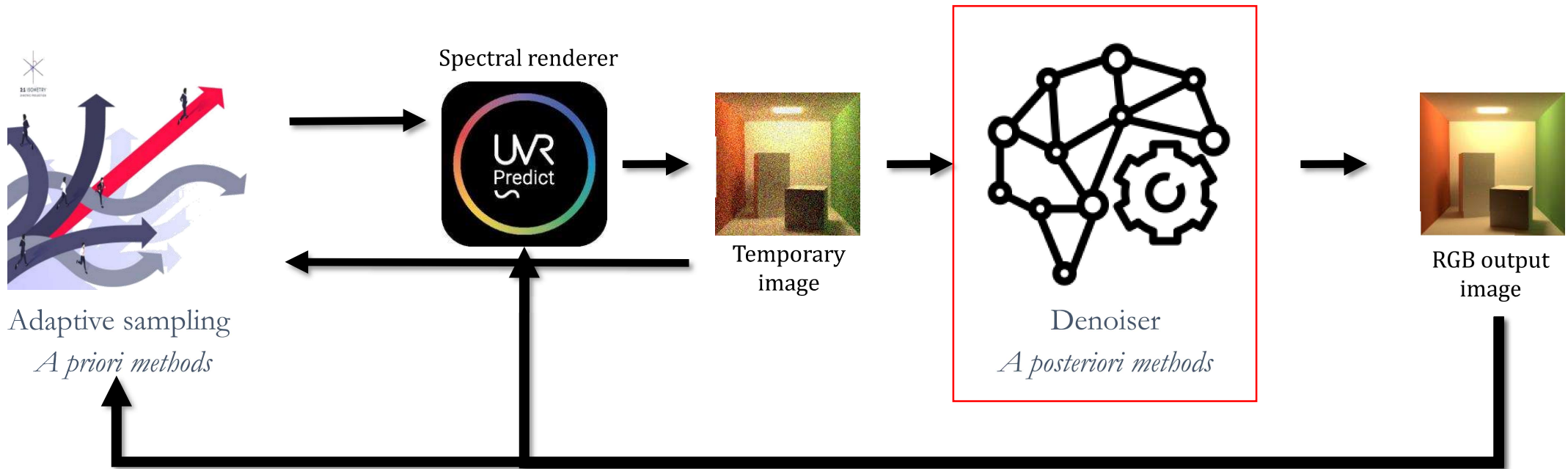
- Resolution based Monte Carlo approach

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

- Approximate the solution from a number of sample

# OUR GOAL

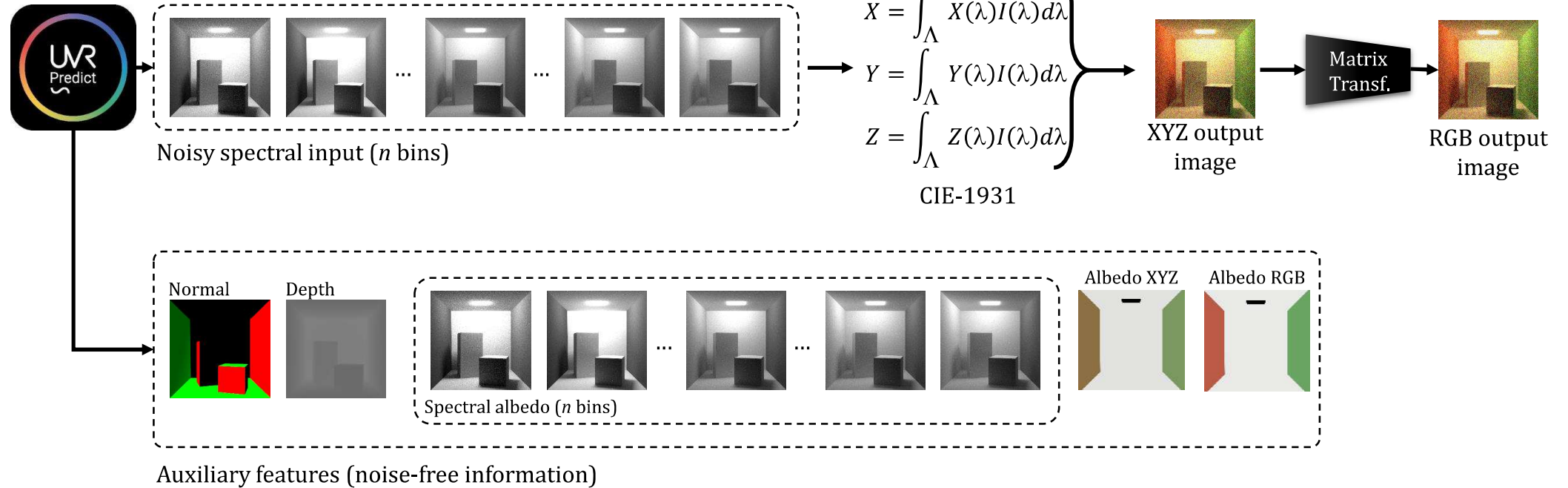
Converting a pipeline



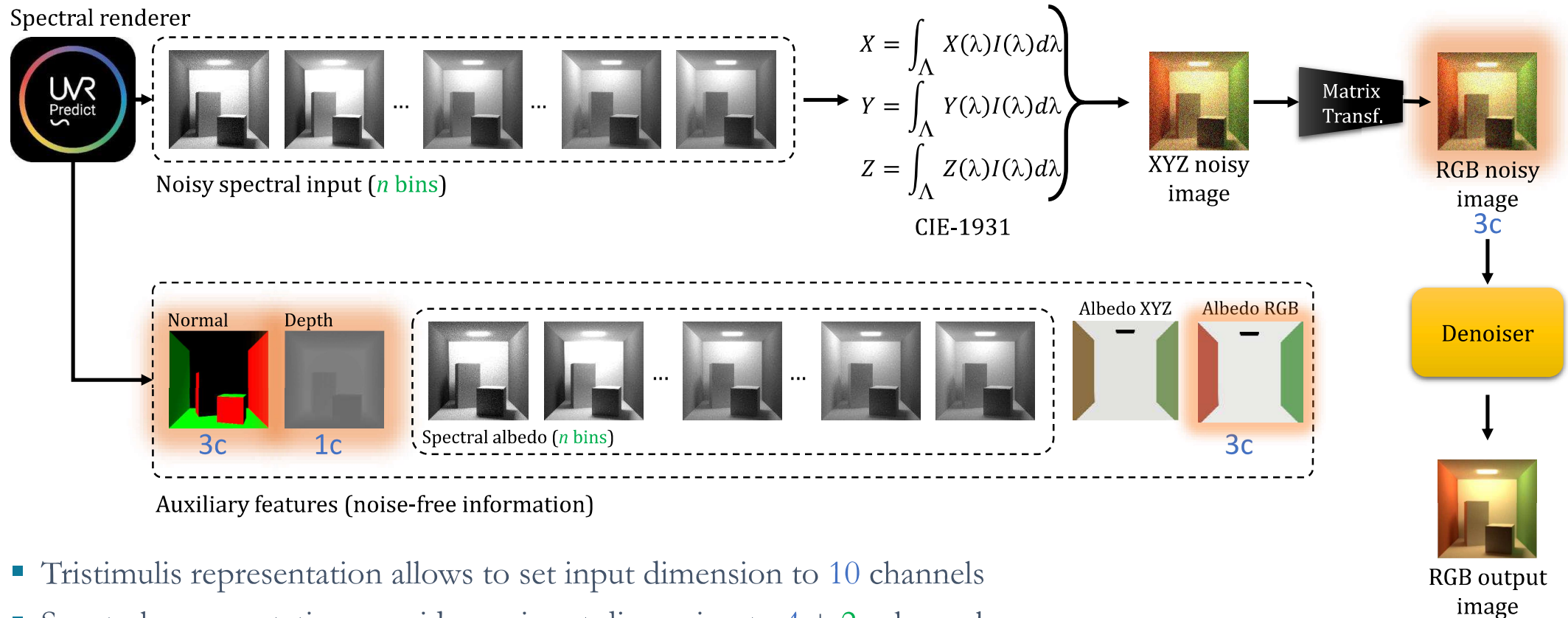


# AVAILABLE DATA FROM SPECTRAL MONTE CARLO RENDERING

Spectral renderer



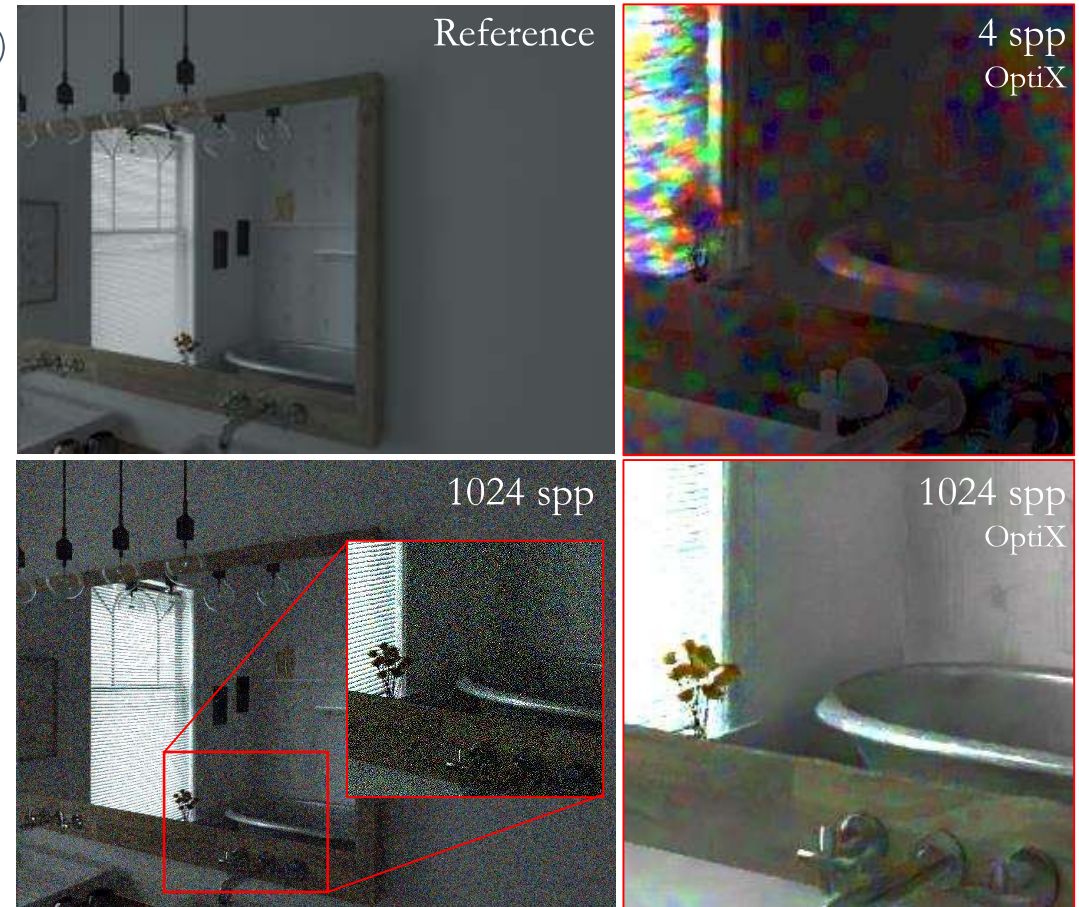
# STATE OF THE ART - DENOISING



- Tristimulus 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 tristimulus 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

CHAKRAVARTY R. ALLA CHAITANYA, NVIDIA, University of Montreal and McGill University  
 ANTON S. KAPLANIAN, NVIDIA  
 CHRISTOPH SCHIED, NVIDIA and Karlsruhe Institute of Technology  
 MARCO SALVI, NVIDIA  
 AARON LEFJOHN, NVIDIA  
 DEREK NONOVICZEZHAI, McGill University  
 TIAGO ALLA, NVIDIA

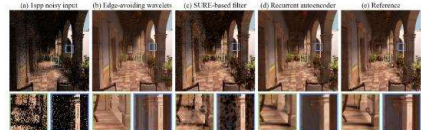


Fig. 1. Left to right (a) noisy image generated using path-traced global illumination with one indirect scene reflection and 1 sample/pixel. (b) edge-weighting method [Zhang et al., 2017] (100 steps, SSIM 0.8276). (c) SIEM-based filter [Li et al., 2021] (100 steps, SSIM 0.9296). (d) our recurrent denoising autoencoder (50 steps, SSIM 0.8408). (e) reference path-traced image with 4096 samples/pixel.

We describe a machine learning technique for reconstructing image sequences rendered using Monte Carlo methods. Our primary focus is on reconstruction of global illumination with extremely low sampling budgets at interactive rates, obtained by reusing information from image-reconstruction with deep convolutional networks, we propose a variant of these networks based on weak-layer prior neighborhoods, to be taken into account, while also incorporating temporal consistency in the process by using a recurrent denoising autoencoder. Our method also has the desirable property of automatically increasing temporal stability for sequences of images, such as depth and normals, as these significantly higher quality results compared to existing methods that are at comparable speeds, and furthermore expose a clear path for making our method work at real-time rates in the near future.

CCS Concepts: • Computing methodologies — Ray tracing; Neural networks; Image processing.

Additional Key Words and Phrases: Monte Carlo denoising; image reconstruction; interactive global illumination; machine learning

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ACM Transactions on Graphics, Vol. 42, No. 4, Article . Publication date: July 2023.

## Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings

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 THIAS VOGELS<sup>2</sup>, ETH Zurich & Disney Research  
 BRIAN MCWILLIAMS<sup>3</sup>, Disney Research  
 MARK MEYER<sup>4</sup>, Pixar Animation Studios  
 JAN NOVÁK<sup>5</sup>, Disney Research  
 ALEX HARVILL<sup>6</sup>, Pixar Animation Studios  
 PRADEEP SEN<sup>7</sup>, University of California, Santa Barbara  
 TONY DEUSE<sup>8</sup>, Pixar Animation Studios  
 FABRICE ROUSSELLE<sup>9</sup>, Disney Research

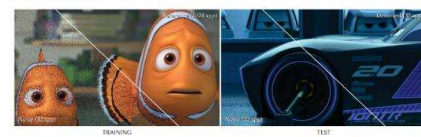


Fig. 1. We consider a deep learning approach for denoising Monte Carlo-rendered images that produces high-quality results suitable for production. We train a convolutional neural network to learn the complex relationship between noisy and reference data across a large set of frames with varying distributed effects from the film *Finding Dory* (left). The trained network can then be applied to denoise new images from other films with significantly different style and content, such as *Cars* (right), with production-quality results.

Regression-based algorithms have shown to be good at denoising Monte Carlo (MC) renderings by leveraging the invariance by gradient of the feature buffers. However, while state-of-the-art methods in handle complex scenes, there is a significant gap between the quality of the results and the quality of the reference images. In this paper, we propose a novel network structure, dual-encoder network with a feature buffer sub-network, to learn feature buffers flexibly, then encode the feature buffers using a noisy image simultaneously, and finally reconstruct a clean image by a decoder network. Compared with the state-of-the-art methods, our model is more robust on a wide range of scenes, and is able to generate satisfactory results in a significantly faster way.

CCS Concepts: • Computing methodologies — Computer graphics; Learning by training.

Additional Key Words and Phrases: Monte Carlo rendering; Monte Carlo denoising; global illumination

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[Chaitanya et al. 2017]

[Bako et al. 2017]

[Yang et al. 2019]

[Back et al. 2020]

Direct prediction  
 ~1-4 spp\*  
 Loss details

Kernel prediction  
 ~64-128 spp\*  
 Details reconstructed

Direct prediction  
 ~1-4 spp\*  
 Reduce artifact induce by auxiliary features  
 Less of diffuse details lost

Kernel prediction  
 independent of spp\*  
 Improve diffuse details reconstruction

spp\* = 1 sample in RGB

18 octobre 2023

JCAD 2023

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Yang X, Wang D, He W et al. DEEM: A deep dual-encoder network for denoising Monte Carlo rendering. JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY 34(5): 1123–1135, Sept. 2019. DOI: 10.1007/s11390-019-1064-2

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

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Received January 15, 2019; revised May 28, 2019.

**Abstract** In this paper, we present DEEM, a deep dual-encoder network to remove Monte Carlo noise efficiently while preserving details. Denoising Monte Carlo rendering is different from natural image denoising since uncorrelated pixel features (feature buffers) can be extracted in the rendering stage. Most of them are noise-free and can provide sufficient details for image reconstruction. However, these feature buffers also contain redundant information. Hence, the main challenge of this topic is how to extract useful information and reconstruct clean images. To address this problem, we propose a novel network structure, dual-encoder network with a feature buffer sub-network, to learn feature buffers flexibly, then encode the feature buffers using a noisy image simultaneously, and finally reconstruct a clean image by a decoder network. Compared with the state-of-the-art methods, our model is more robust on a wide range of scenes, and is able to generate satisfactory results in a significantly faster way.

**Keywords** Monte Carlo rendering, Monte Carlo denoising, neural network

### 1 Introduction

Producing a photorealistic image from 3D models needs complex computations at every pixel of the image. For example, a ray tracing algorithm requires computing complex integrals over all the ray paths between light sources and every point on image sensors. Monte Carlo (MC) raytracing<sup>1</sup> introduces a method to approximate this complex integral by tracing light paths in a multi-dimensional space, in order to obtain an estimated value of the integral expression. Although Monte Carlo rendering has been widely accepted by many movie production studios, it suffers from noise pollution, which can only be mitigated by increasing

the number of samples exponentially, making the synthesis of a noise-free and photo-realistic image very time-consuming. However, some industry applications, such as real-time game rendering, virtual augmented reality, require rendering high-quality images in a faster way. Recently, a variety of methods<sup>2,3,4</sup> for accelerating Monte Carlo rendering have been proposed. The core idea of these methods is to render a noisy image with a few samples per pixel (SPP) flexibly, and then use denoising algorithms to reconstruct a perceptually indistinguishable image from the noisy image and auxiliary feature buffers. Here, the auxiliary feature buffers are inexpensive by-products generated in the rendering stage, which contain geometry and texture information

Regular Paper  
 Received by JCVI 2019.  
 This work was supported in part by the National Natural Science Foundation of China under Grant No. 91781404, U1811403, 61876116, 61876116, and 61771201. We thank the National Key Research and Development Program of China under Grant No. 2019YFC0801000, the Open Project Program of the State Key Laboratory of CAD&GP of Zhejiang University of China under Grant No. A1901, and the Open Research Fund of Beijing Key Laboratory of Digital Technology for Food Safety Project under Grant No. YF2019-0101P.  
 \*Corresponding Author.  
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## Deep Combiner for Independent and Correlated Pixel Estimates

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 BINH-SUN HUA, VnA Research, Vietnam and VnUniversity, Vietnam  
 TOSHIBA HACHISUKA, The University of Tokyo, Japan  
 ROCHANG MOON, Georgia Institute of Science and Technology, South Korea

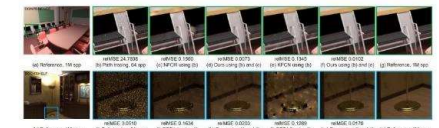


Fig. 1. Our framework allows us to combine two different types of images, independent pixel estimates (i.e., path-traced images) and correlated pixel estimates (i.e., denoised images), and reduce remaining errors (red marks) or systematic errors of the existing methods such as Nonlocaly-weighted Fast Color Regression (NCFR) [Baker et al. 2013], Kernel-Predicting Convolutional Network (KPCN) [Bako et al. 2017], and Gradient-domain Path Tracing with L1 and L2 reconstruction (GPL) and GPL2 [Battar et al. 2015]. The numbers are the relative mean square error (RMSE) [Battar et al. 2015].

Monte Carlo integration is an efficient method to solve high-dimensional integral in light transport simulation, but it typically produces noisy results due to its stochastic nature. Many existing methods, such as image denoising and gradient-domain reconstruction, aim to mitigate this noise by introducing some form of correlation among pixels. While these existing methods reduce noise, they are known to still suffer from local specific residual noise or systematic errors. We propose a unified framework that reduces noise remaining errors of independent pixel estimates, and uses independent estimates, and the other with the corresponding correlated estimates. Correlated pixels are generated by noise-reducing methods such as denoising and gradient-domain rendering. Our framework also enables the two-stage pipeline-based combination. We extend our combination kernel, as a weighting function with a deep neural network-based learning, to the correlation among pixel estimates. To improve the robustness of our framework for noise, we additionally propose an extension to handle multiple image buffers. The main advantage of our method framework can be naturally used to the case of multiple noisy pixel estimates, which also stems from its random nature. In general, a large number of samples is often a considerable amount of computation time are needed to reduce such noise in an unacceptable level.

A popular class of noise reduction methods in MC rendering is image-space denoising [Overholt et al. 2009; Sun and Durkin 2012]. Its main advantage is that it can handle different types of random noise generated by complex lighting effects without suffering from the complexity of light transport. Learning-based denoising [Bako et al. 2017; Chaitanya et al. 2017; Ghahramani et al. 2019; Xu et al. 2019] has achieved an impressive level of noise reduction recently. The denoising process typically introduces correlation among pixels.

CCS Concepts: • Computing methodologies — Ray tracing

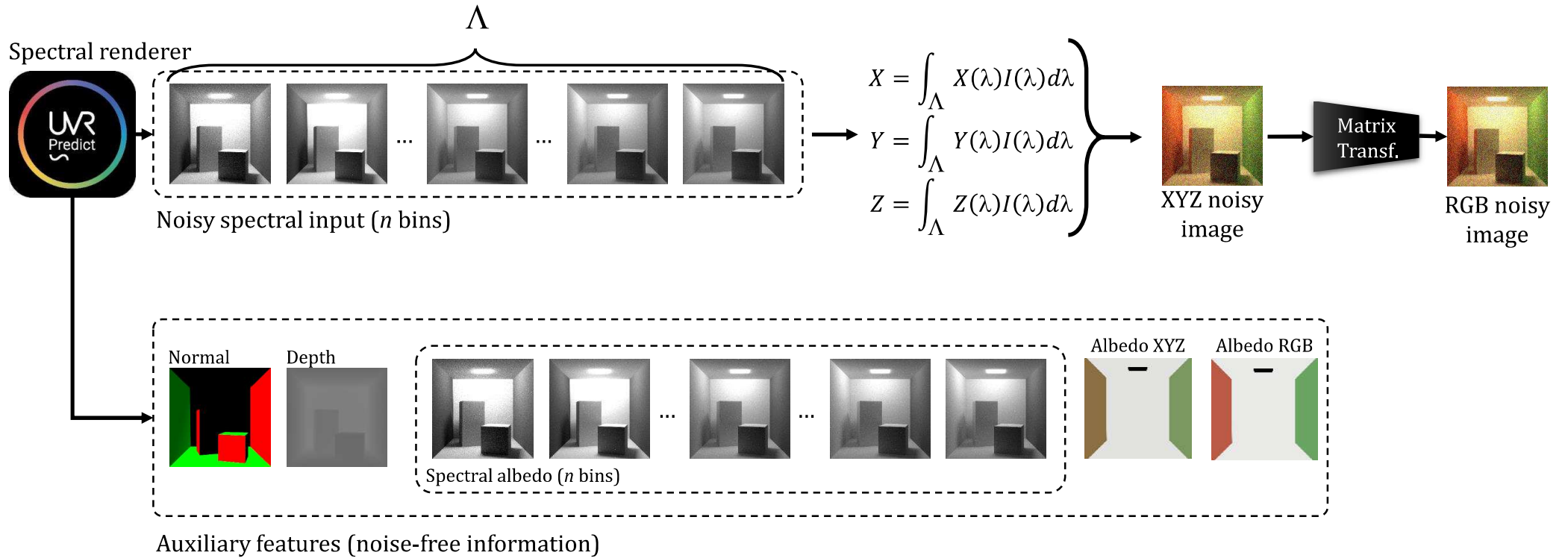
Additional Key Words and Phrases: Monte Carlo rendering; Monte Carlo denoising; global illumination

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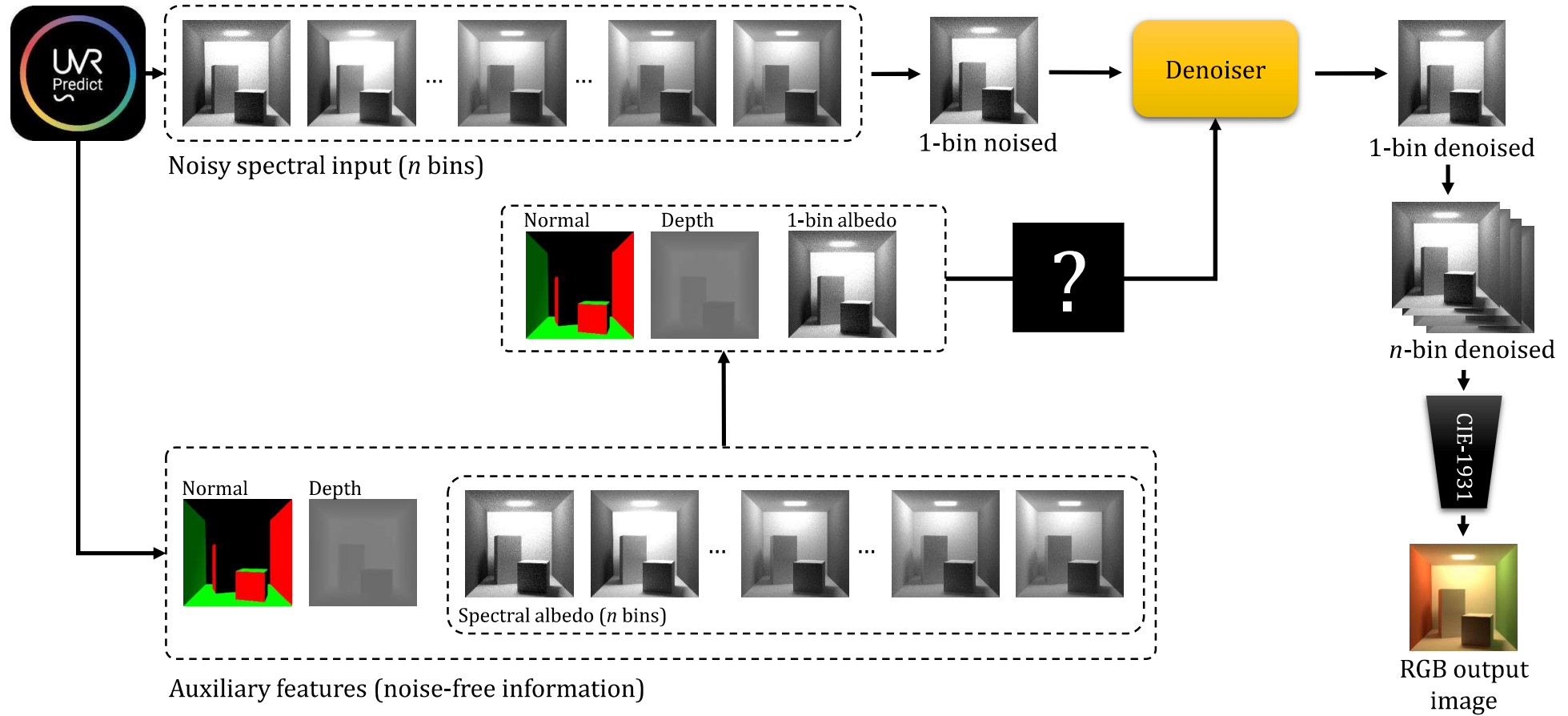


# DATA MANAGING



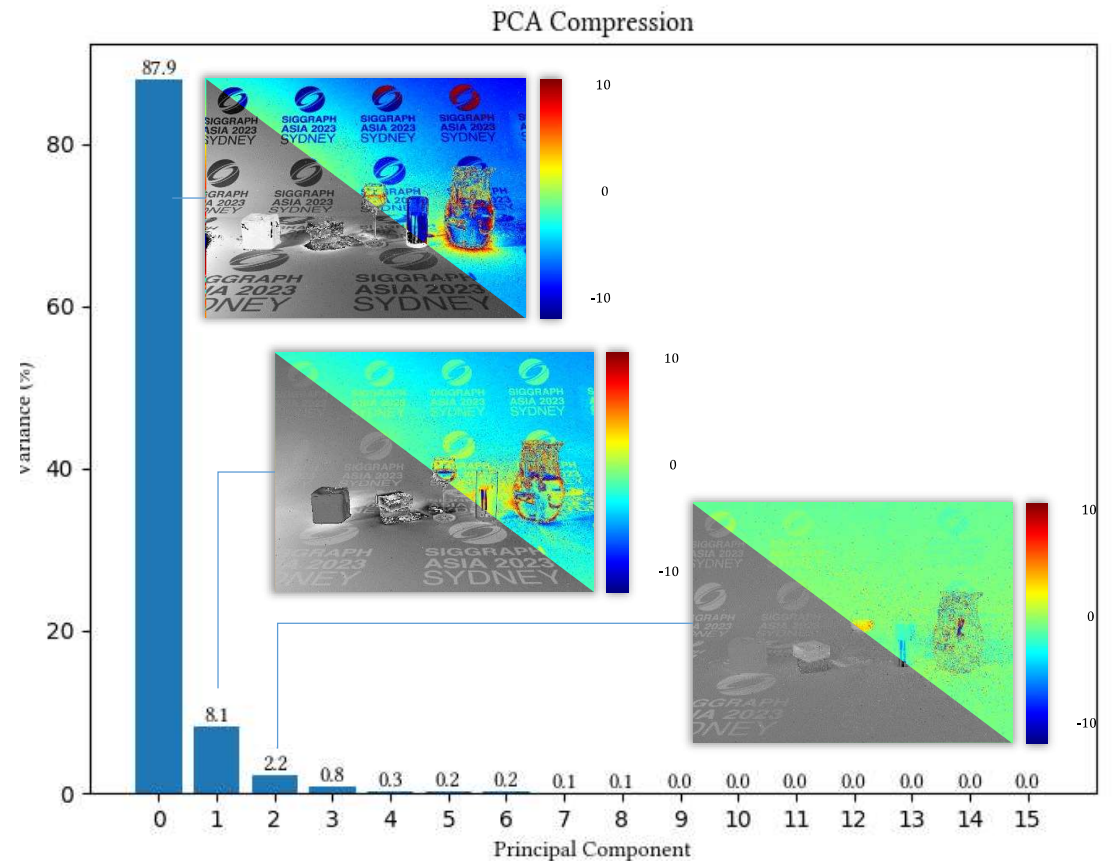
# DATA MANAGING

Spectral renderer

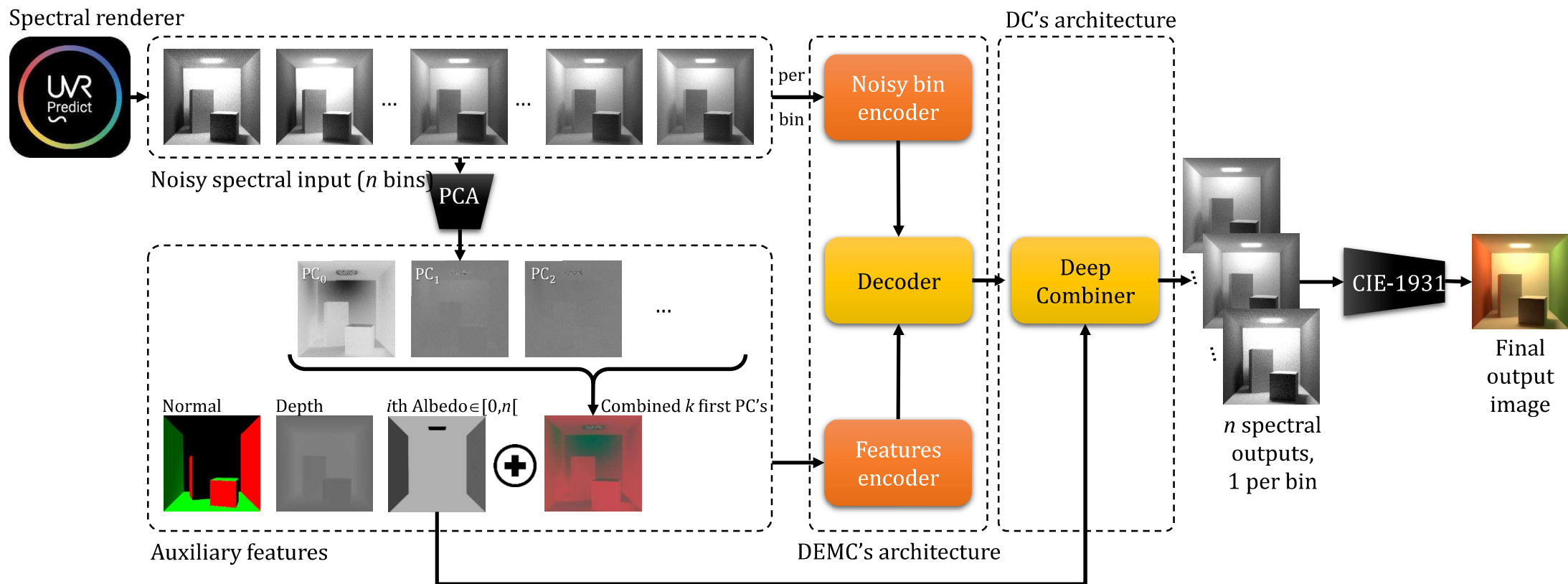


# SPECTRAL COMPRESSION

- 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

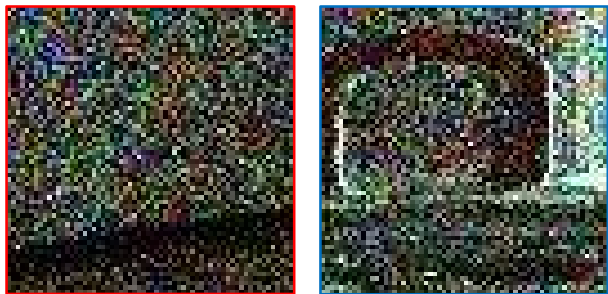
Noisy image



Reference image



Denoised image with our method



SPP: 1024  
Time: 89 s on 1 GPU  
RelMSE: 0.70

1 M  
≈ 36 h on 4 GPUs  
GT

1024  
89.16 s on 1 GPU  
0.0313

# RESULTS



Noisy image  
1024 SPP

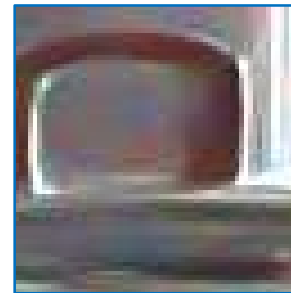
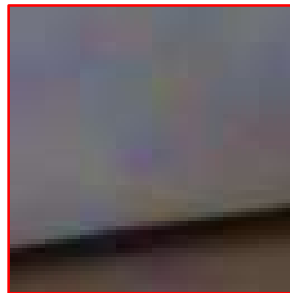


Reference image  
1M SPP

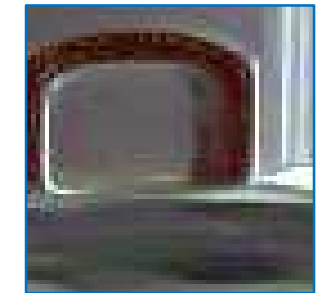
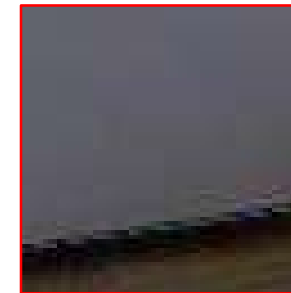
Intel



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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