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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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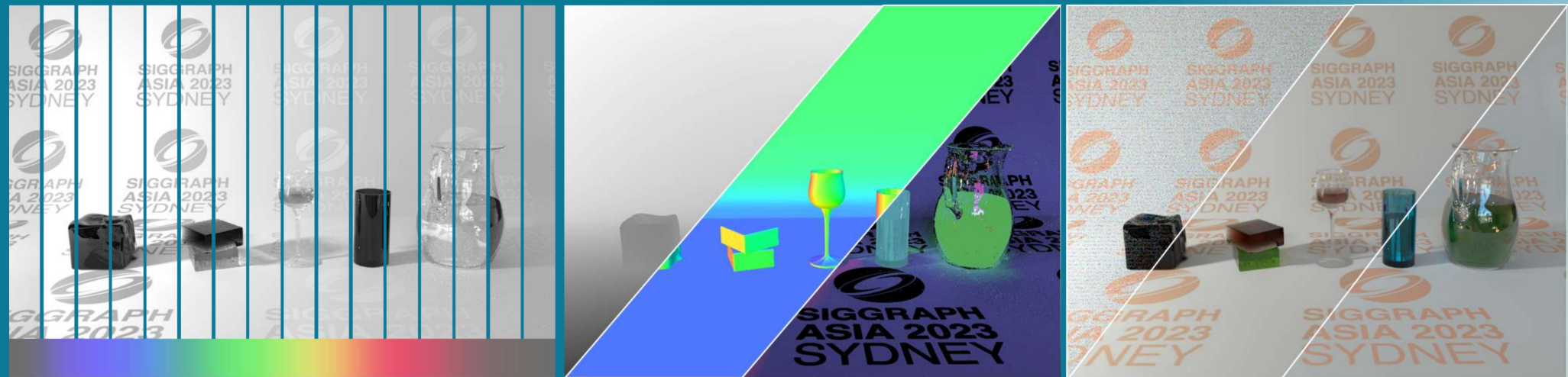
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Submitted on 1 Oct 2024

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Spectral Monte Carlo Image Denoising

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LICIIS
LRC
DIGIT

JCAD 2023

anr[®] LUCE
Light-transport Simulation
and Machine Learning

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CHAMPAGNE-ARDENNE

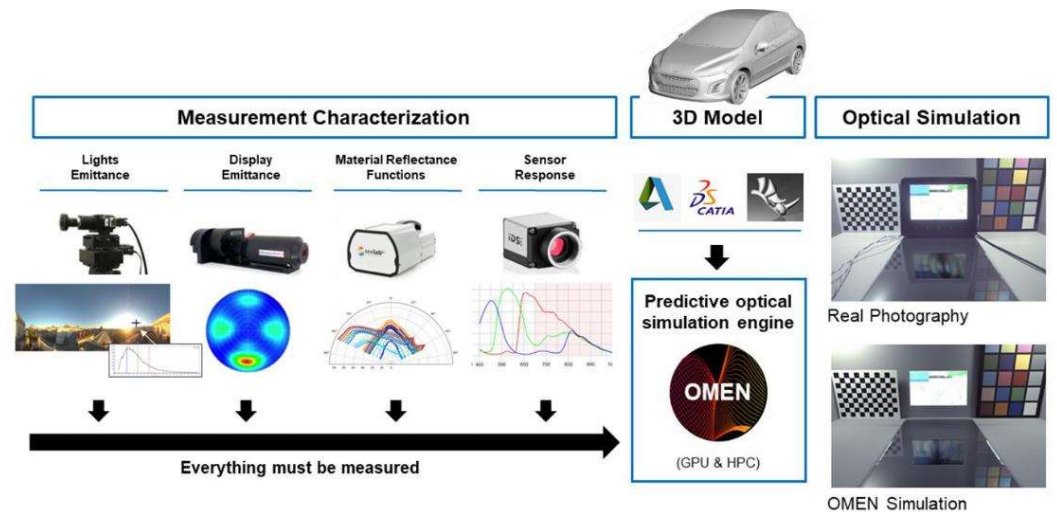
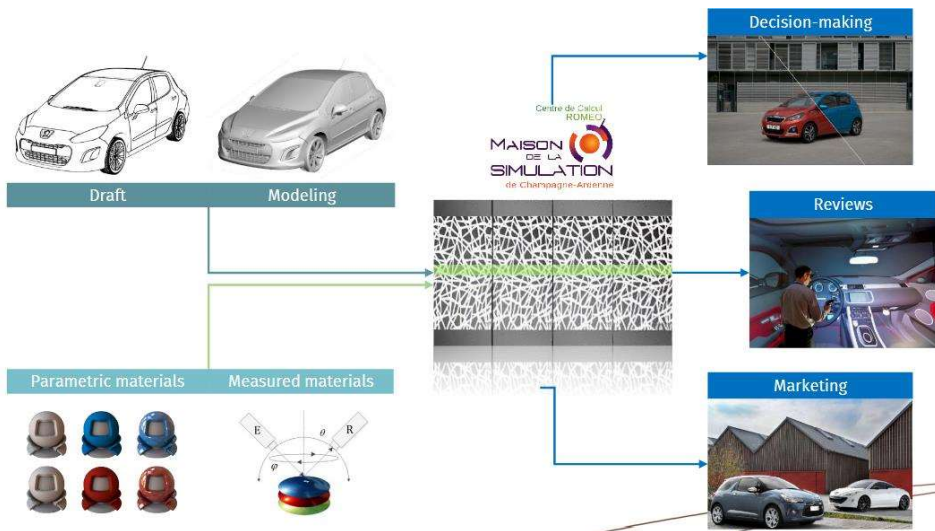
UVR United Visual
Researchers

SUMMARY

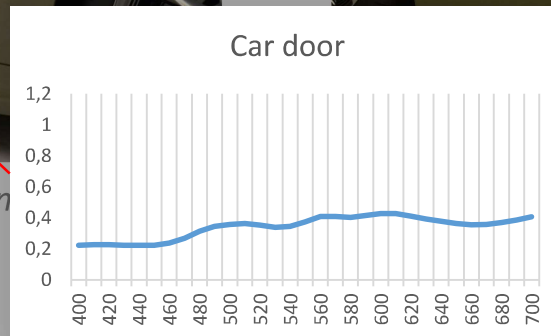
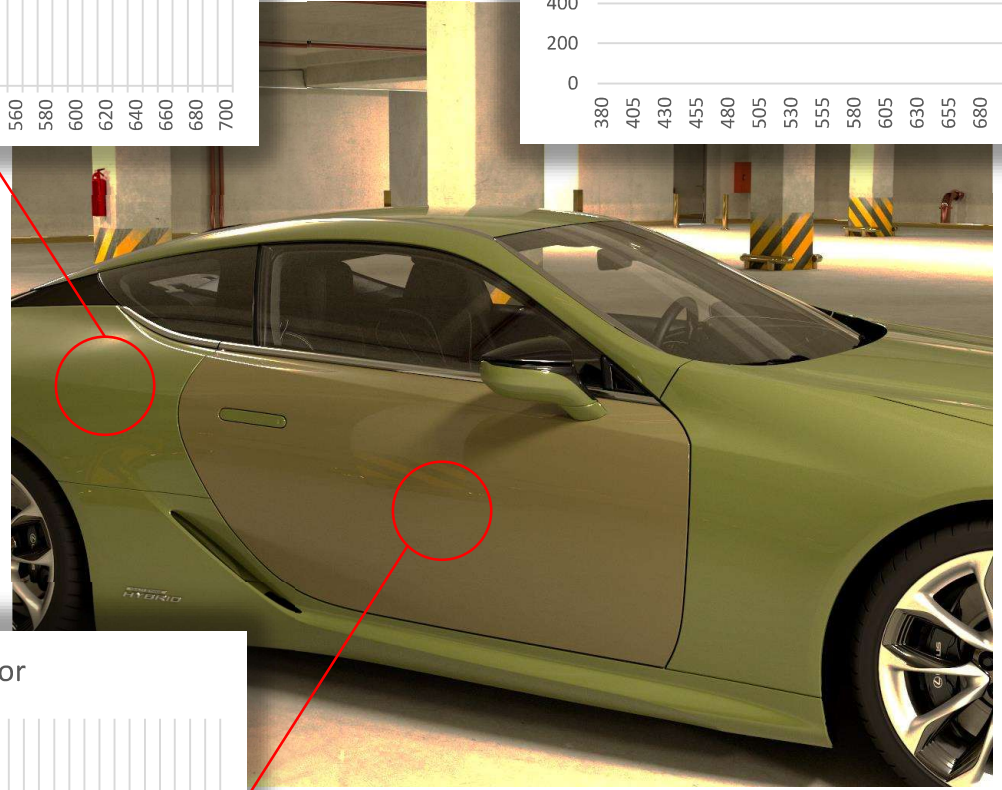
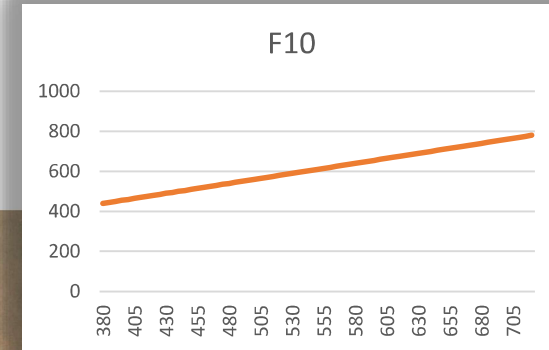
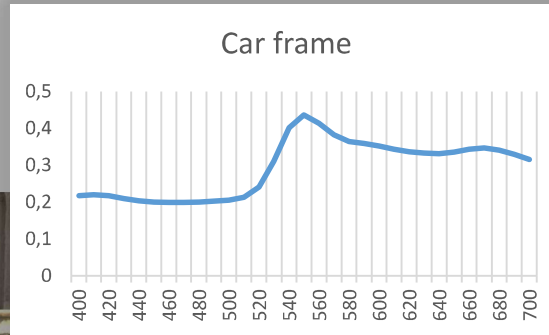
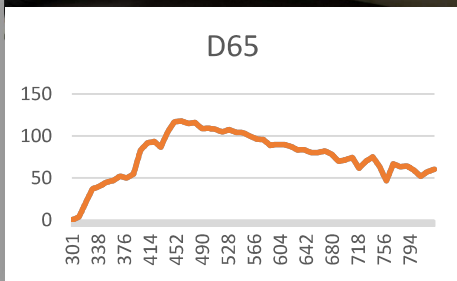
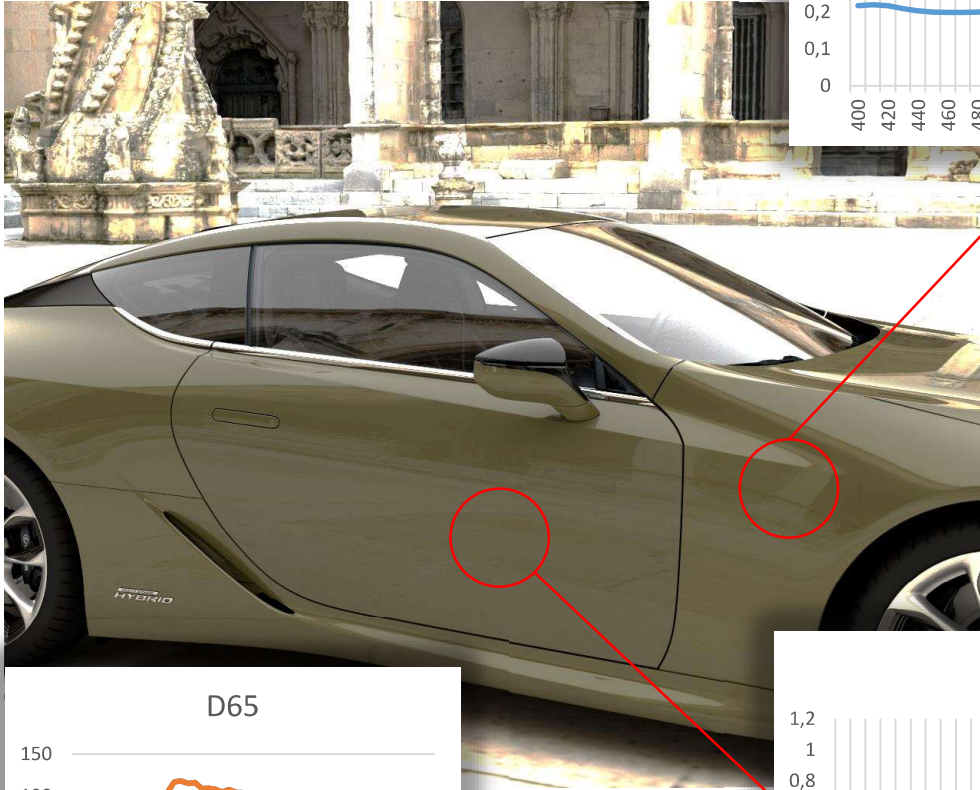
- General context
- Previous works
- Contributions and results
- Conclusion

GENERAL CONTEXT

- Predictive visualisation – in interactive time – of complex materials for industry (CA²O)
 - 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

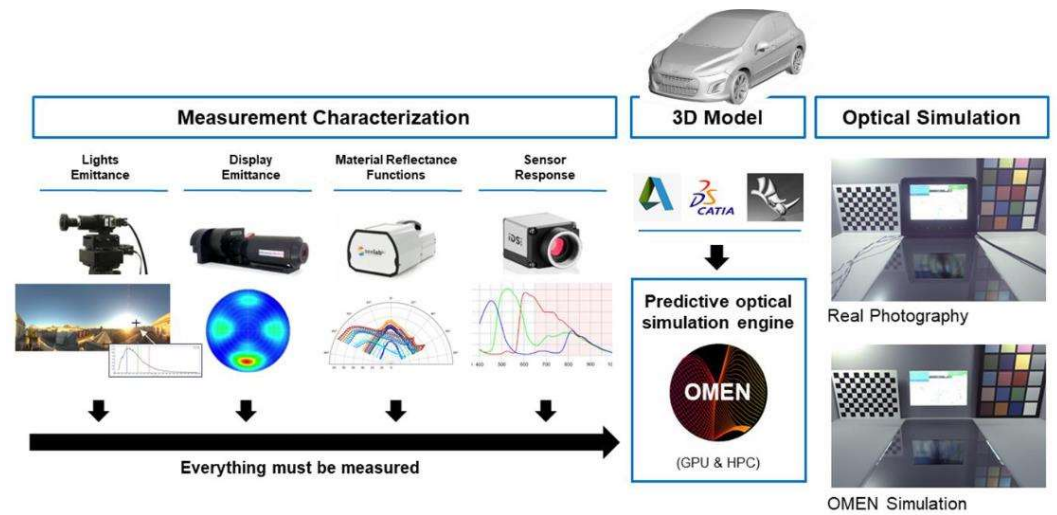
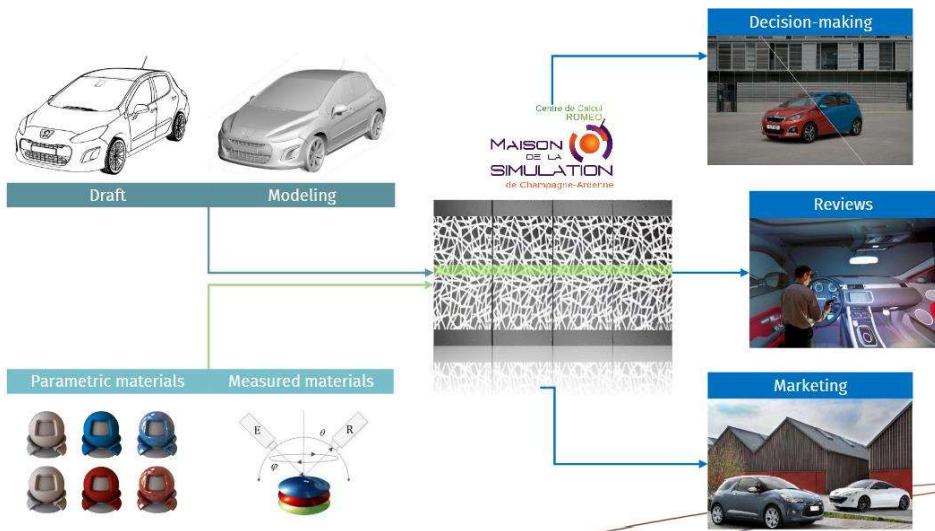


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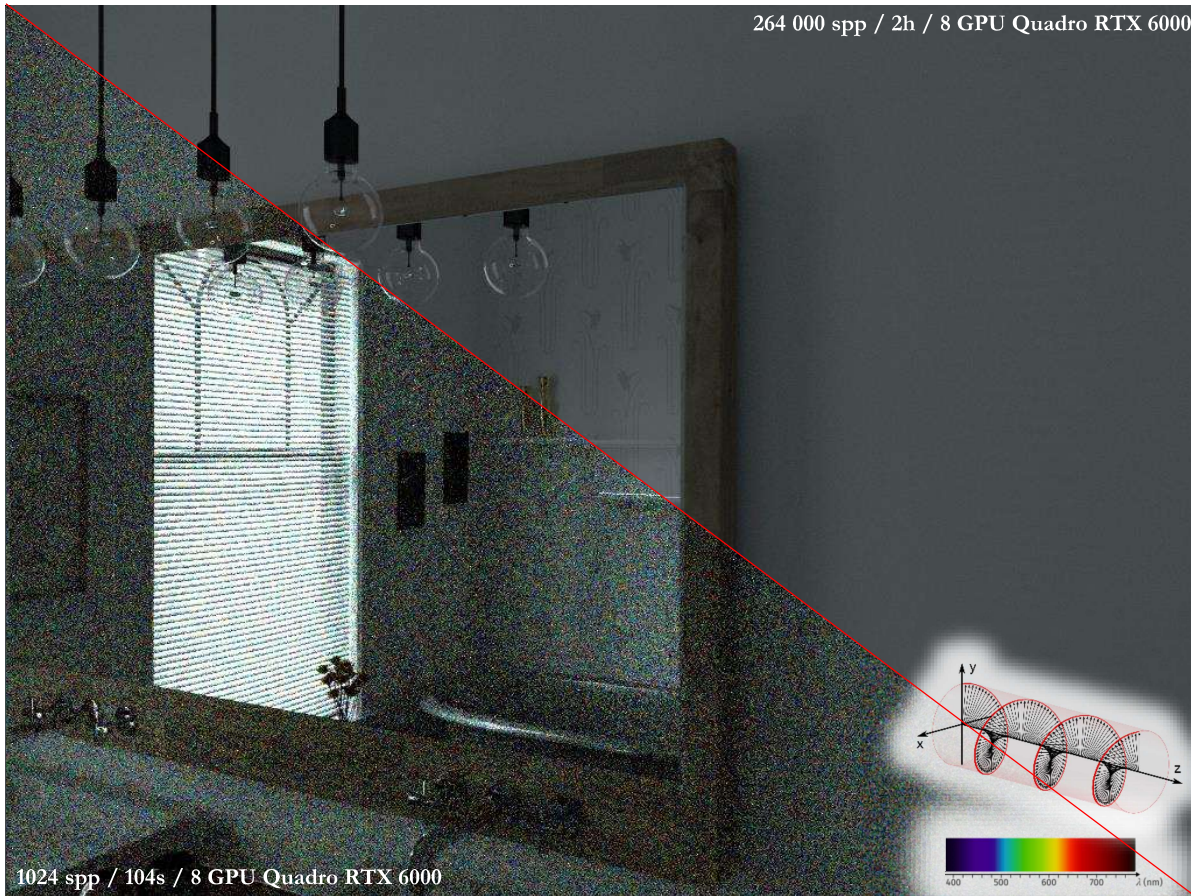
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GENERAL CONTEXT

- Predictive visualisation – in interactive time – of complex materials for industry (CA²O)
 - 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

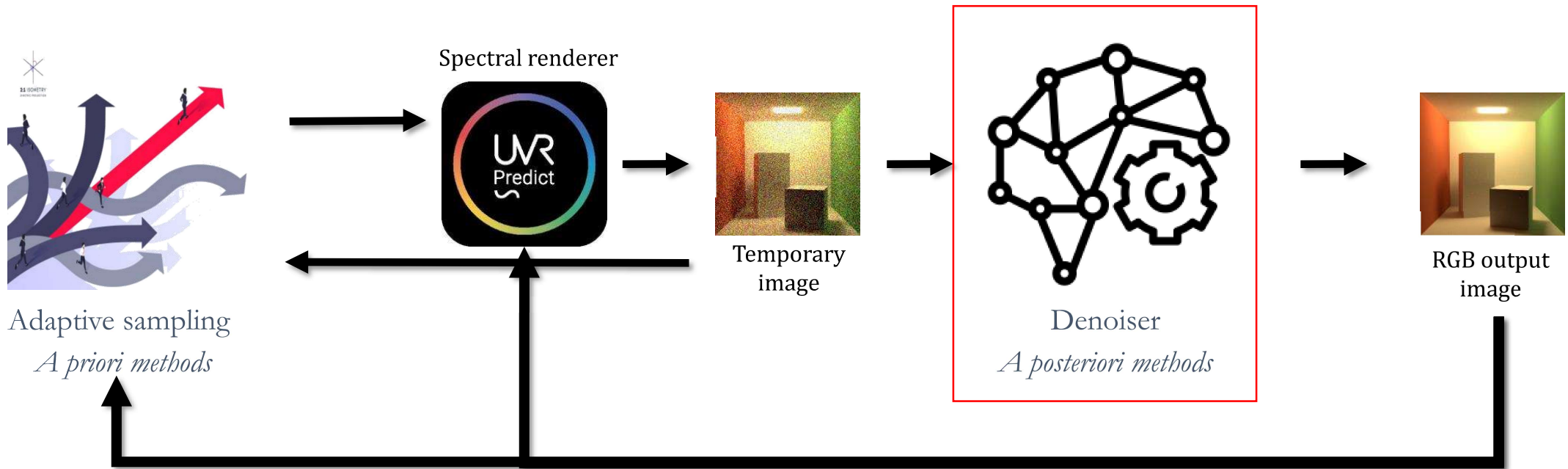
- Resolution based Monte Carlo approach

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

- Approximate the solution from a number of sample

OUR GOAL

Converting a pipeline



AVAILABLE DATA FROM SPECTRAL MONTE CARLO RENDERING

Spectral renderer



Noisy spectral input (n bins)

$$\begin{aligned}
 X &= \int_{\Lambda} X(\lambda)I(\lambda)d\lambda \\
 Y &= \int_{\Lambda} Y(\lambda)I(\lambda)d\lambda \\
 Z &= \int_{\Lambda} Z(\lambda)I(\lambda)d\lambda
 \end{aligned}$$

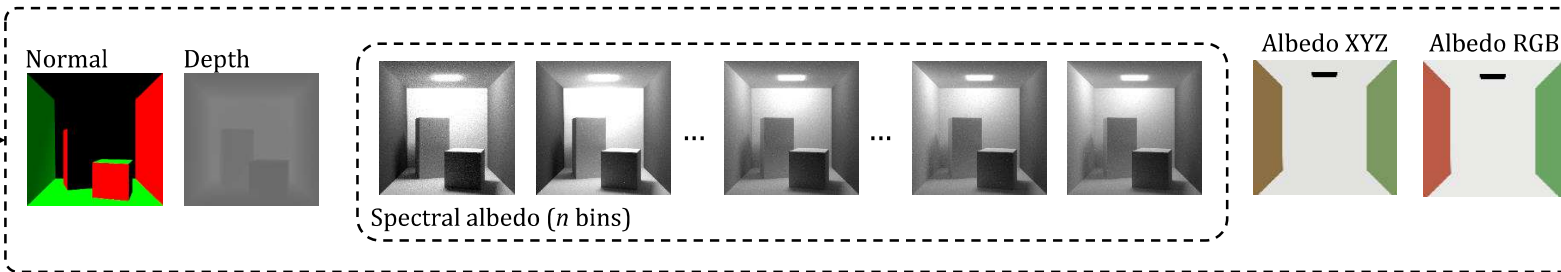
CIE-1931



XYZ output image

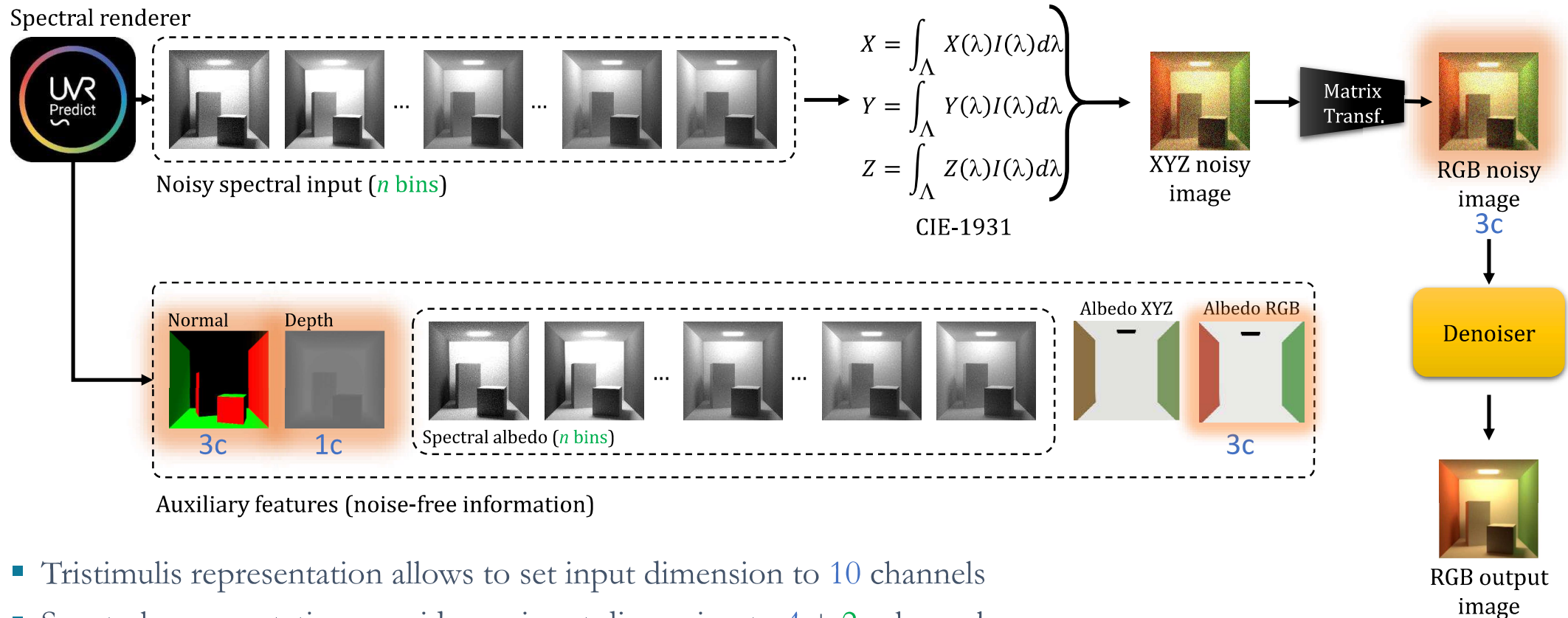


RGB output image



Auxiliary features (noise-free information)

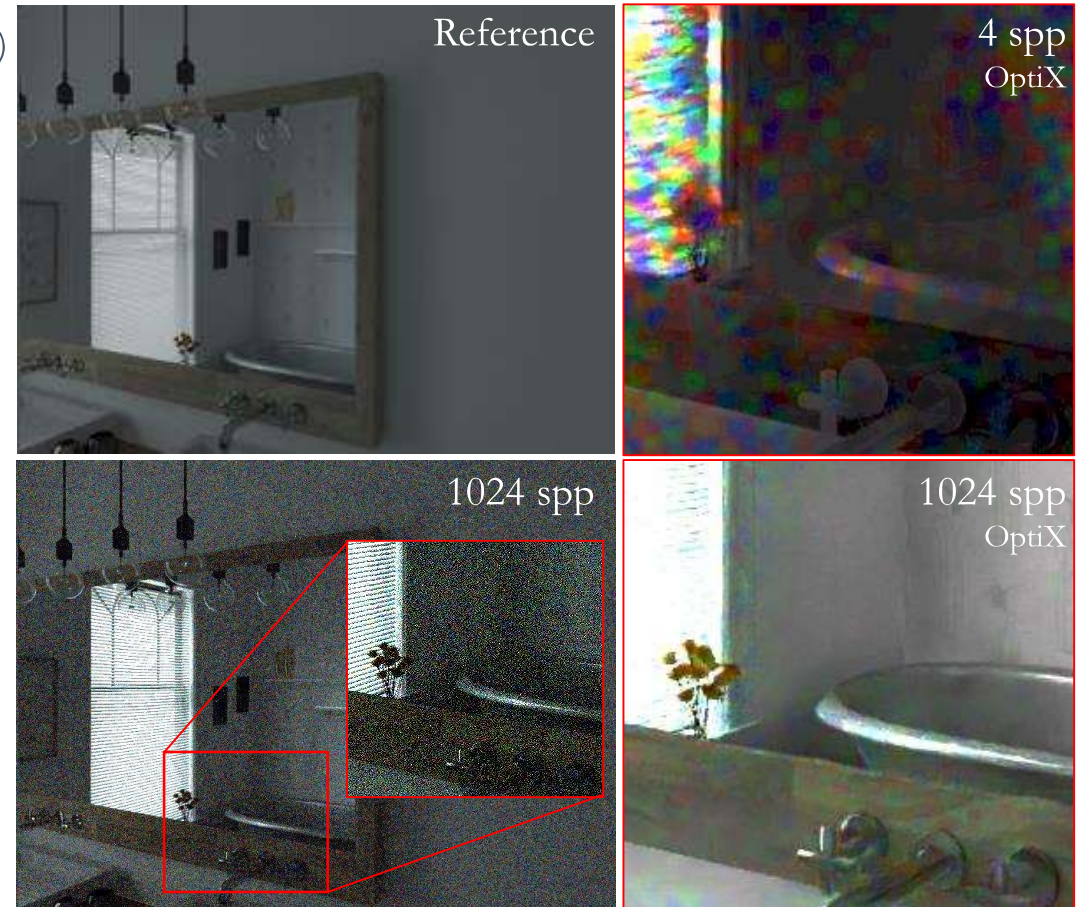
STATE OF THE ART - DENOISING



- 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

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 ANTON S. KAPLANIAN, NVIDIA
 CHRISTOPH SCHIED, NVIDIA and Karlsruhe Institute of Technology
 MARCO SALVI, NVIDIA
 AARON LEFONN, NVIDIA
 DEREK NONOVROZZEZHAI, McGill University
 TIAGO ALA, NVIDIA

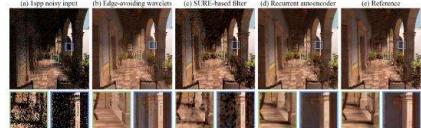


Fig. 1. Left to right (a) noisy image generated using path traced global illumination with one indirect ray collection and 1 sample/pxel, (b) edge-weighted Laplacian filter [Zhou et al., 2015] (1/16 at 256, SSIM 0.7725), (c) SRCNN based filter [Li et al., 2015] (1/16, SSIM 0.9298), (d) our recurrent denoising autoencoder (1/4 timesteps, SSIM 0.8408), (e) reference path traced image with 4096 samples/pxel.

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 re-use of history information with deep convolutional networks, we propose a variant of these networks based on the idea of denoising by re-use of history information. We allow the weak learner prior neighborhood, by hidden state context, while also progressively refining the state of output. The primary focus behind the additional recurrent connection is the person to be able to dynamically improve temporal stability for sequences of randomly sampled input images. Our method also has the desirable property of automatically adjusting values based on auxiliary context input channels, such as depth and normals, to allow 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 runtime rates in the user frame.

ACM Reference format:
 Chaitanya R. Alla Chaitanya, Anton S. Kaplanian, Christoph Schied, Marco Salvi, Aaron Lefonn, Derek Nonovrozzezhai, and Tiago Ala, 2017. Interactive Reconstruction of Monte Carlo Image Sequences using a Recurrent Denoising Autoencoder. ACM Trans. Comput. Sci., 4, Article 94 (Oct. 2017), 12 pages.
 DOI: <https://doi.org/10.1145/3120735.3120736>

1 INTRODUCTION
 Ray and path tracing have recently emerged as the rendering algorithms of choice for visual effects [Baker et al., 2013]. This has encouraged the development of filtering and denoising techniques to reduce the noise inherent in Monte Carlo rendering [Dreier et al., 2012], but the focus on this quality results provides bandwidth to thousands of samples per pixel prior to filtering.
 Meanwhile, users have also recently engaged in physically-based shading from more empirical methods [Li et al., 2015], but much of the practical increase in realism from this transition hinges on the possibility of sampling light transport paths more flexibly than radiance-driven alternatives. Unfortunately, even the fastest ray tracers can only trace a few rays per pixel at 1080p and 30FPS. While this number doubles every few years, the trend is (at best partially)

[Chaitanya et al. 2017]

Direct prediction
 ~1-4 spp*
 Loss details

Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings

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 THIJS VOGELS², ETH Zürich & Disney Research
 BRIAN MCWILLIAMS, Disney Research
 MARK MEYER, Pixar Animation Studios
 JAN NOVÁK, Disney Research
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 TONY DEUSSE¹, Pixar Animation Studios
 FABRICE ROUSSELLE, Disney Research



Fig. 1. We introduce 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 *Car: The Hub* (right), with production quality results.

Regression based algorithms have shown to be good at denoising Monte Carlo (MC) renderings by learning to integrate by gradient or, for the better. However, while state-of-the-art models can handle complex scenes, they often struggle to denoise noisy data in the input. For this reason, supervised learning methods have been proposed that train on a large set of denoising examples that they can exploit from the fact that denoising is an ill-posed problem, we propose a novel, supervised learning approach that allows filtering benefits to more complex and general by leveraging a deep convolutional neural network (CNN) denoising. In our end-to-end deep framework, the CNN directly predicts the final denoised pixel value as a highly non-linear combination of the input features. In a second approach, we introduce a novel, learnable prediction network which uses the CNN to estimate the final denoising kernel used to compute each denoised pixel from its neighbors. We train and evaluate our system on two scenes.

CCS Concepts: Computing methodologies → Computer graphics; Learning by tracing.

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

ACM Reference format:
 Steve Bako, Thijs Vogels, Brian McWilliams, Mark Merritt, Jan Novák, Alex Harville, Pradeep Sen, Tony Deusse, and Fabrice Rouselle, 2017. Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings. ACM Trans. Comp. Sci., 4, Article 97 (July 2017), 14 pages.
 DOI: <https://doi.org/10.1145/3120735.3120738>

1 INTRODUCTION
 In recent years, physically-based image synthesis has become widespread in feature animation and visual effects [Richter et al., 2015].

[Bako et al. 2017]

Kernel prediction
 ~64-128 spp*
 Details reconstructed

18 octobre 2023

JCAD 2023

Yang X, Wang D, He W et al. DDMC: 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](https://doi.org/10.1007/s11390-019-1064-2)

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

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Abstract. In this paper, we present DDMC, 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 its non-regular 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, some 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 fuse feature buffers flexibly, then encode the fused 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 complex complex integrals over all the ray paths between light sources and every point on image sensors. Monte Carlo (MC) ray tracing¹ 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, still require real-time, require rendering high-quality images in a faster way. Recently, a variety of methods^{2,3,4,5,6,7} 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

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^{*}Corresponding Author.
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[Yang et al. 2019]

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

Deep Combiner for Independent and Correlated Pixel Estimates

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 BINH-SUN HUA, VnAI Research, Vietnam and Vrije Universiteit, Vietnam
 TOSHIYA HACHISUKA, The University of Tokyo, Japan
 ROCHANG MOON, Georgia Institute of Science and Technology, South Korea

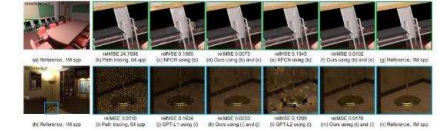


Fig. 1. Our framework allows us to combine two different types of images, independent pixel estimates (i.e., path traced images) and correlated pixel estimates (i.e., denoised images), and reduce remaining errors (red marks) or systematic errors (as noticeable vertical lines) from Color Regression Network [Baker et al., 2015], Kernel Predicting Convolutional Network (KPCNN) [Bako et al., 2017], and Gradient domain Path Tracing with L1 and L2 regularization (GPFL and GPFL2) [Wattanasit et al., 2015]. The numbers are the relative mean square error (RMSE) [Bonneville et al., 2015].

Monte Carlo integration is an efficient method to solve high-dimensional integral on light transport simulation, but it typically produces noisy images due to its stochastic nature. Many existing methods, such as image denoising and gradient domain reconstruction, aim to mitigate this noise by combining some form of correlation among pixels. While these methods reduce noise, they are prone to still suffer from either local specific redaction noise or systematic errors. We propose a unified framework that reduces noise remaining errors. Our framework takes a pair of images, one with 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 line combines the two images to avoid combination error. We avoid combination error by a weighting function with a deep neural network that reduces 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 problem is that independent pixel estimates can be unreliable while the correlation methods while treating them as black boxes.

ACM Reference format:
 Jonghee Back, Binh-Sun Hua, Toshiya Hachisuka, and Rochang Moon, 2020. Deep Combiner for Independent and Correlated Pixel Estimates. *ACM Trans. Comput. Sci.*, Article 202 (December 2020), 12 pages. <https://doi.org/10.1145/3424885.3424747>

1 INTRODUCTION
 Monte Carlo (MC) rendering [Kajiya 1986] has been recognized as a powerful tool for light transport simulation, which has been widely adopted in production rendering recently [Piper 2013]. MC rendering can simulate a variety of lighting effects by randomly sampling light paths and averaging their contributions in every pixel. Pixel estimates in MC rendering are typically independent of each other. The main problem is that independent pixel estimates, which also stems from its random nature. In general, a large number of samples (often a considerable amount of computation time) are needed to reduce such noise to an unacceptable level.
 A popular class of noise reduction methods in MC rendering is image super-resolution [Overland et al., 2009; Sun and Plaza 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; Cho et al., 2019; Xia 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

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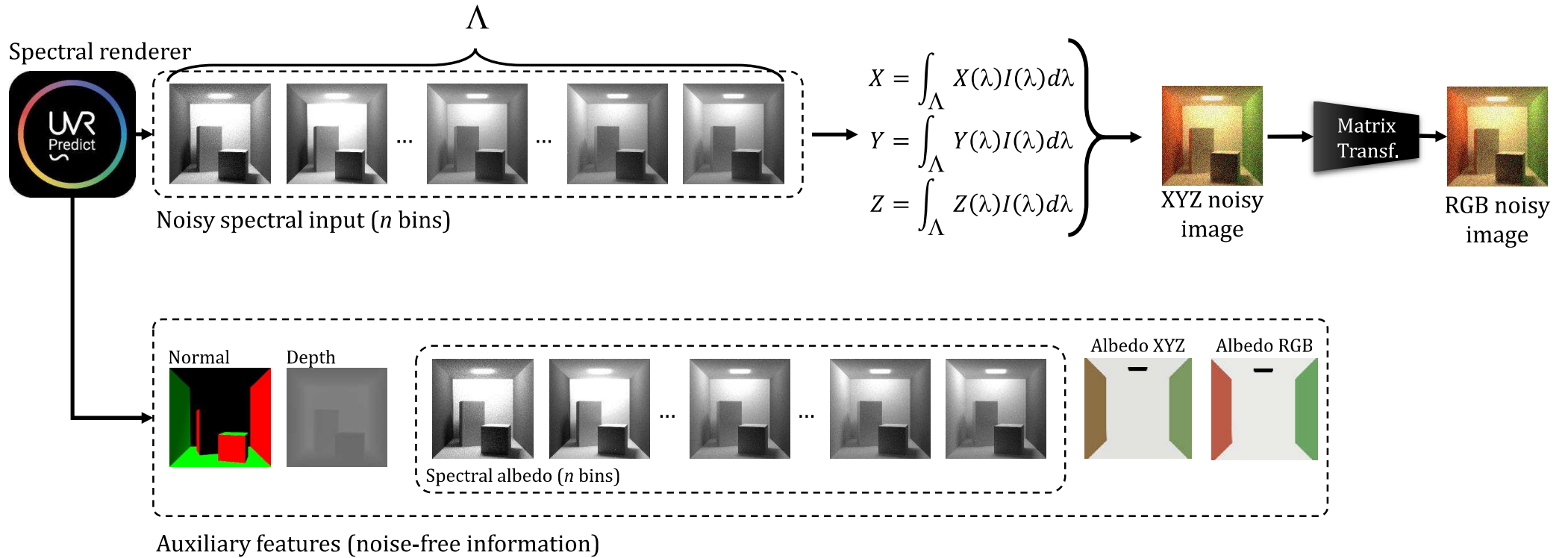
[Back et al. 2020]

Kernel prediction
 independent of spp*
 Improve diffuse details reconstruction

11

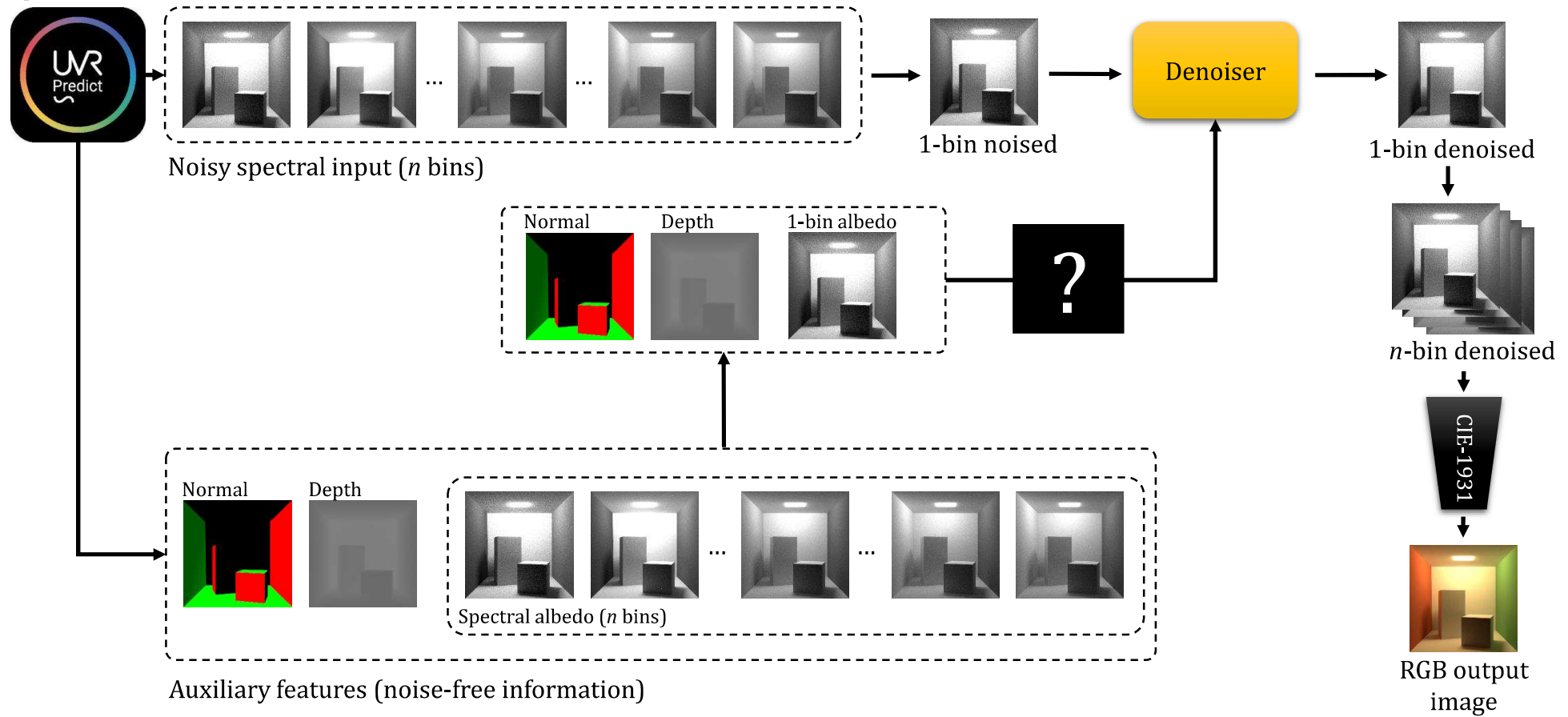


DATA MANAGING



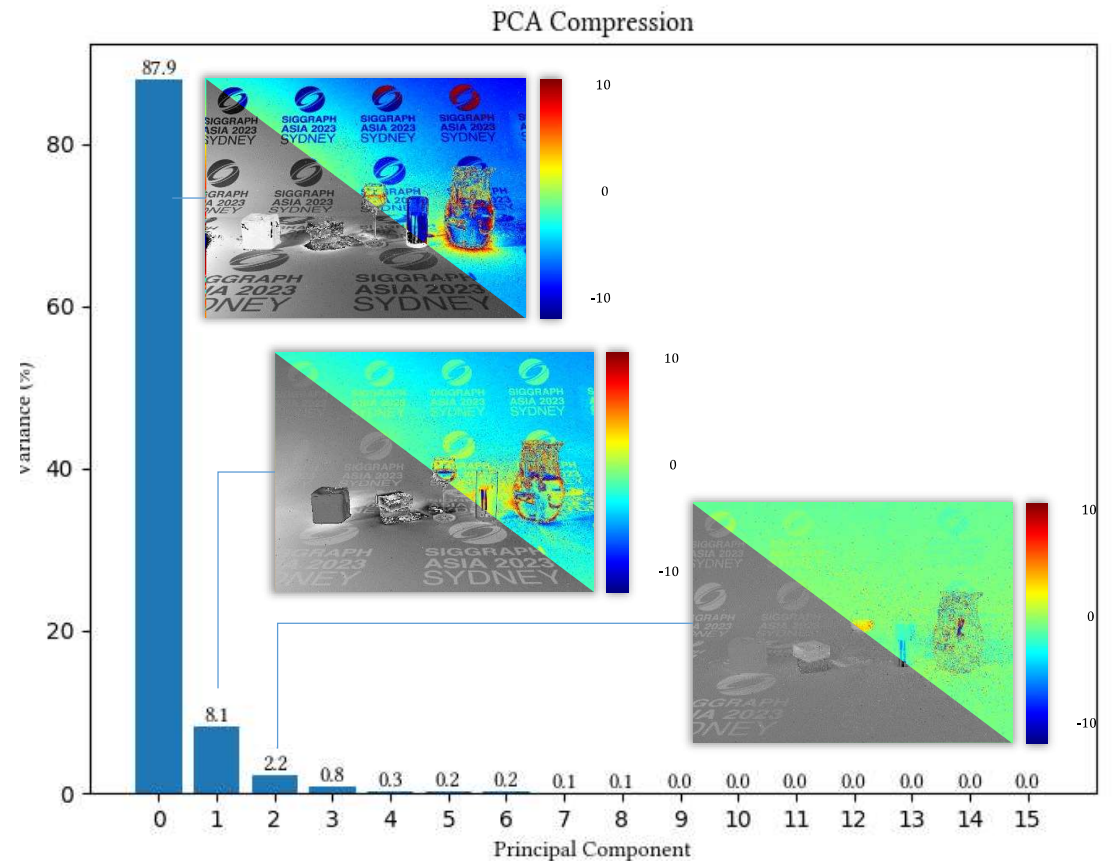
DATA MANAGING

Spectral renderer

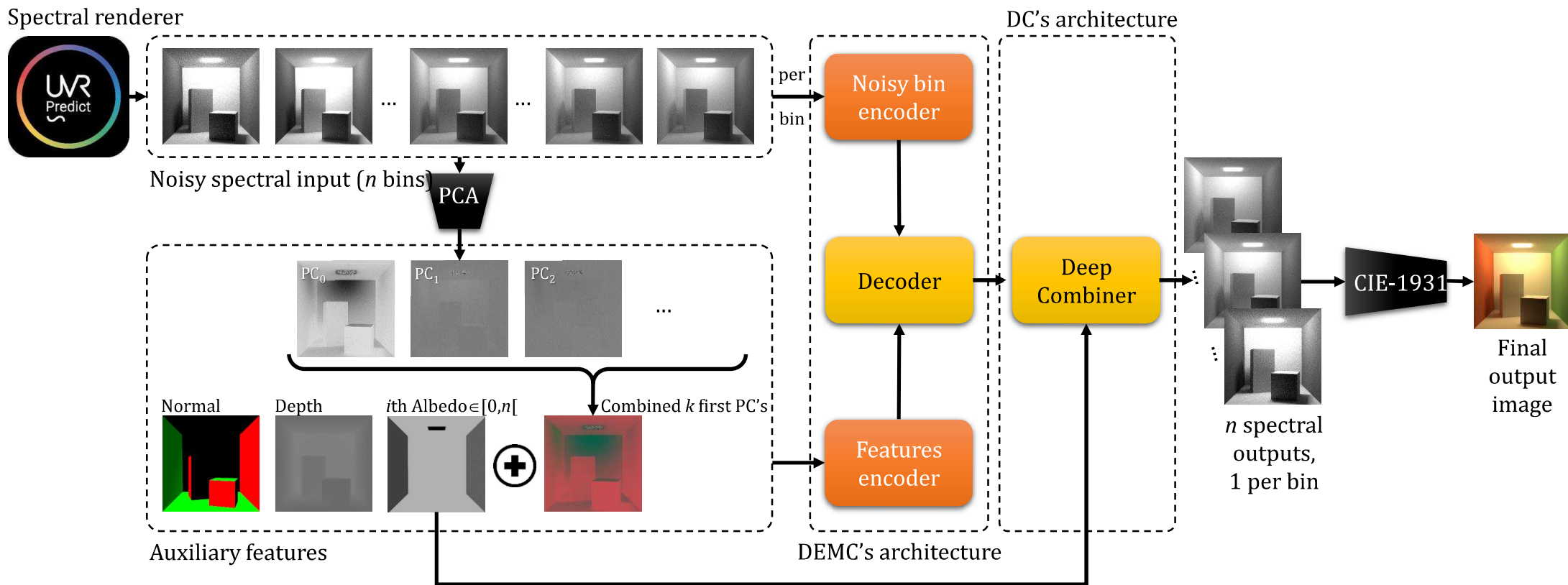


SPECTRAL COMPRESSION

- 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

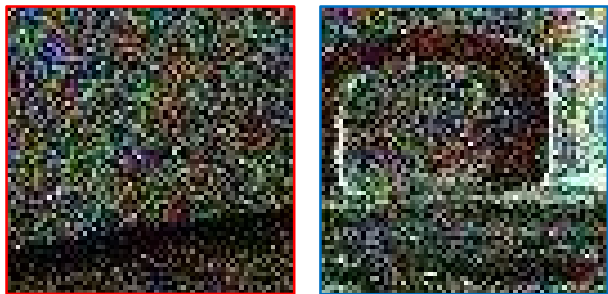
Noisy image



Reference image

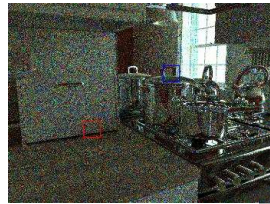


Denoised image with our method



SPP:	1024	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

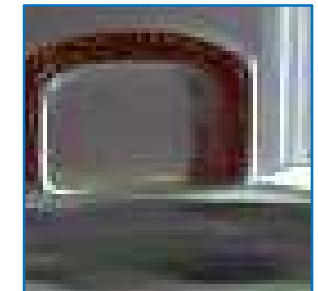
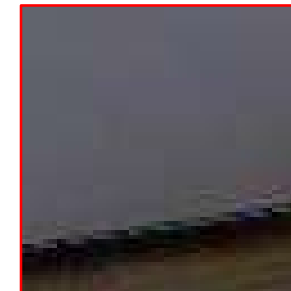
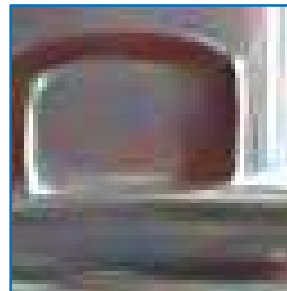
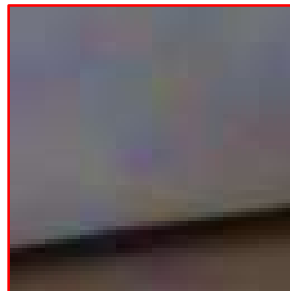
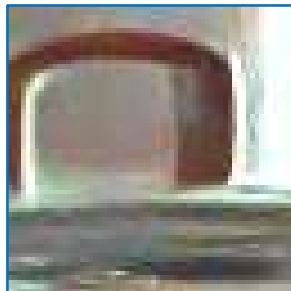
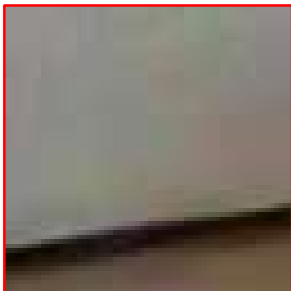


Reference image
1M SPP

Intel

OptiX

Ours



ReIMSE: 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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