

Spectral Monte Carlo Image Denoising

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JCAD 2023

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

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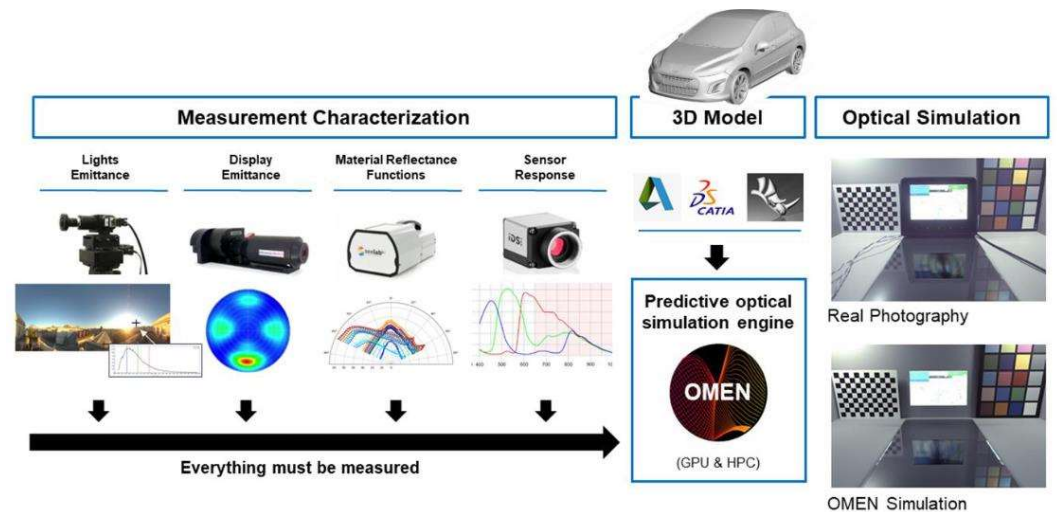
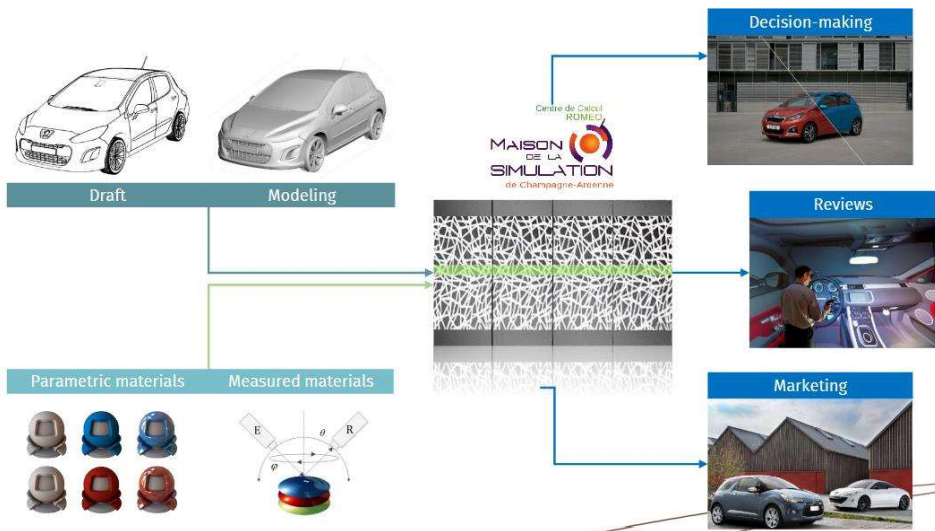
UVR United Visual
Researchers

SUMMARY

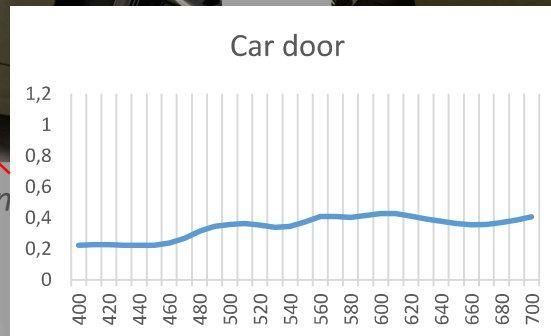
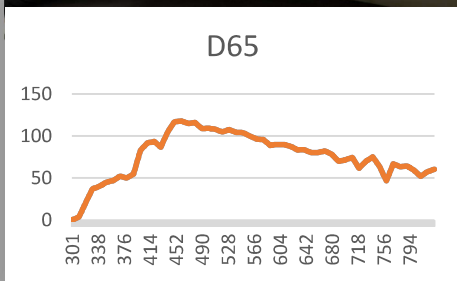
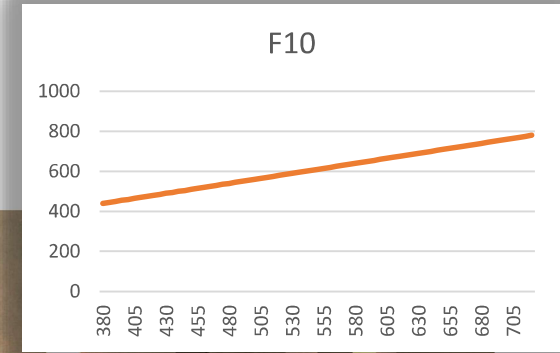
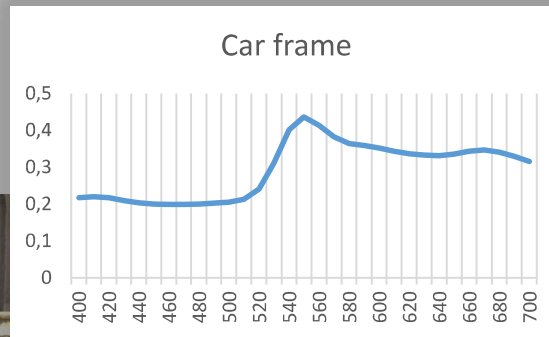
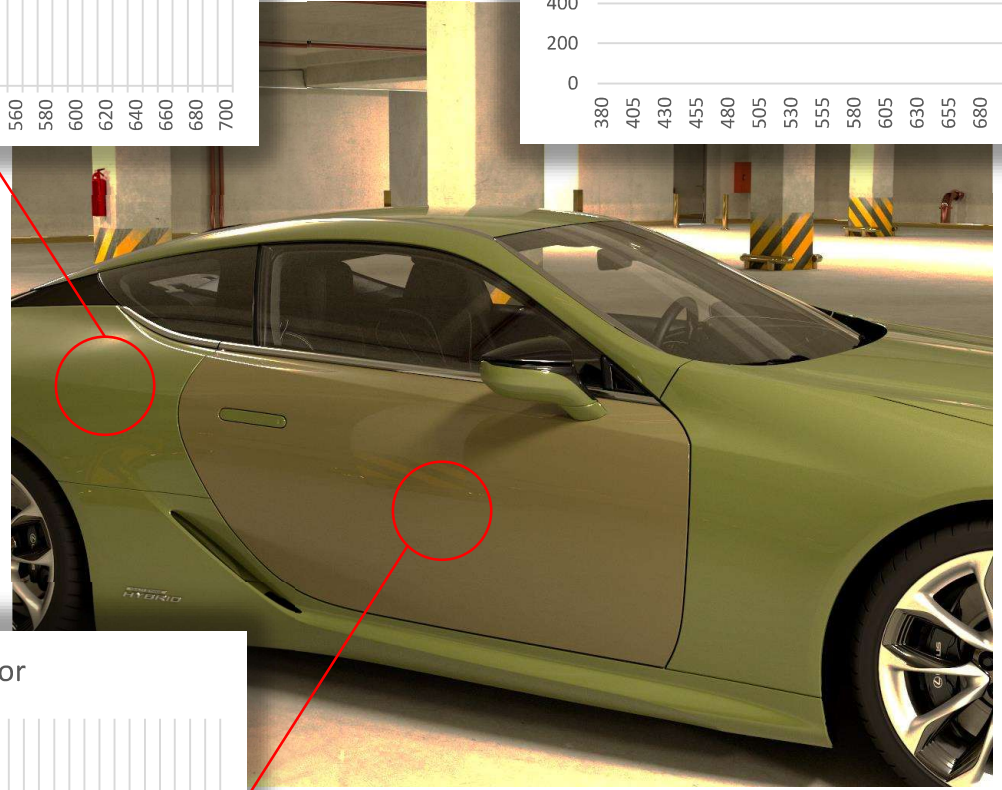
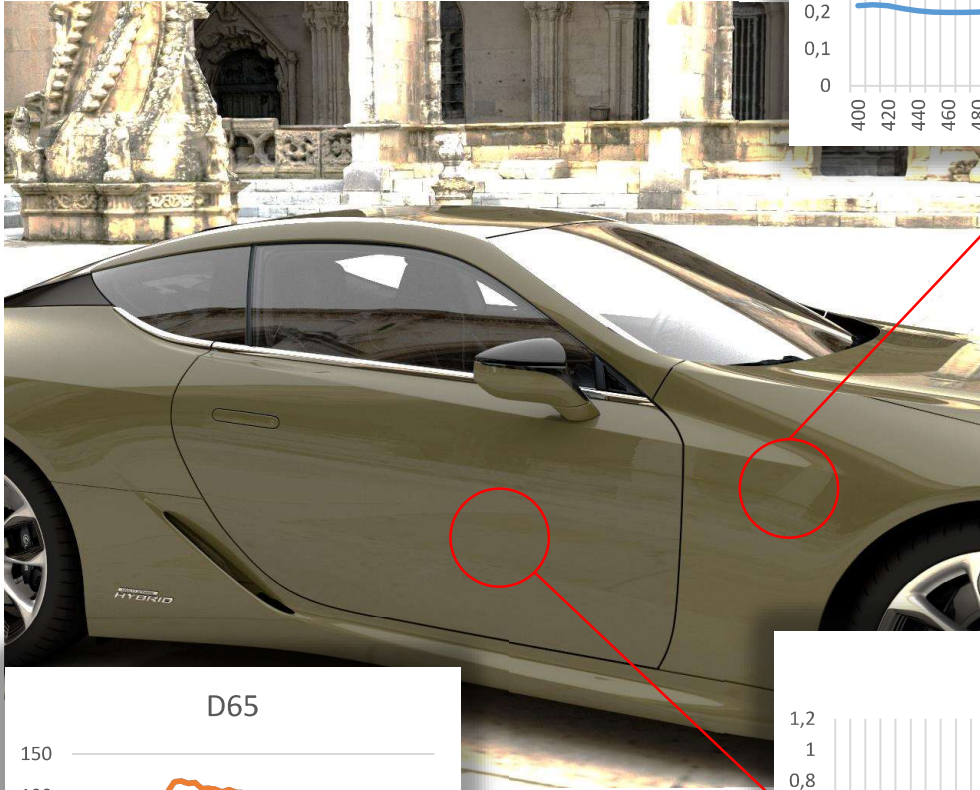
- General context
- Previous works
- Contributions and results
- Conclusion

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

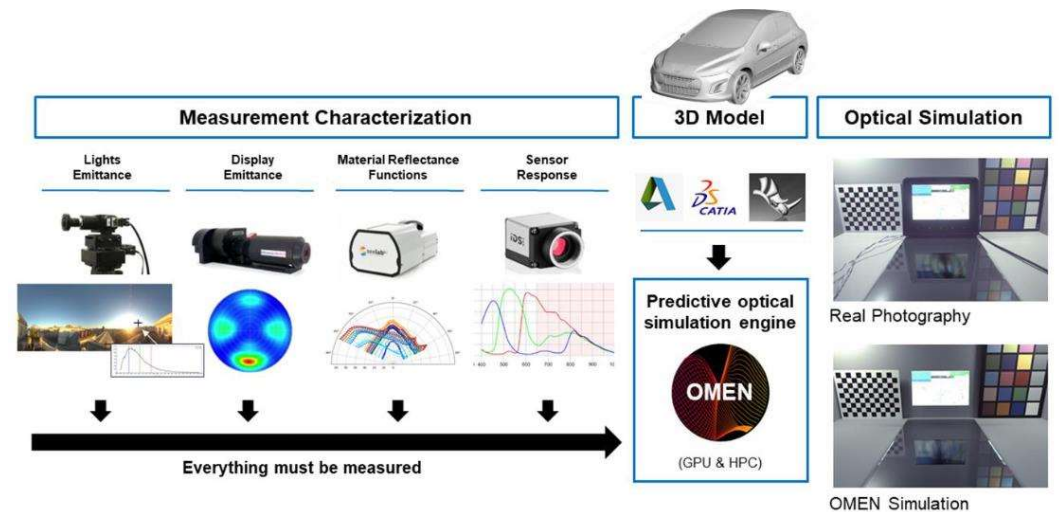
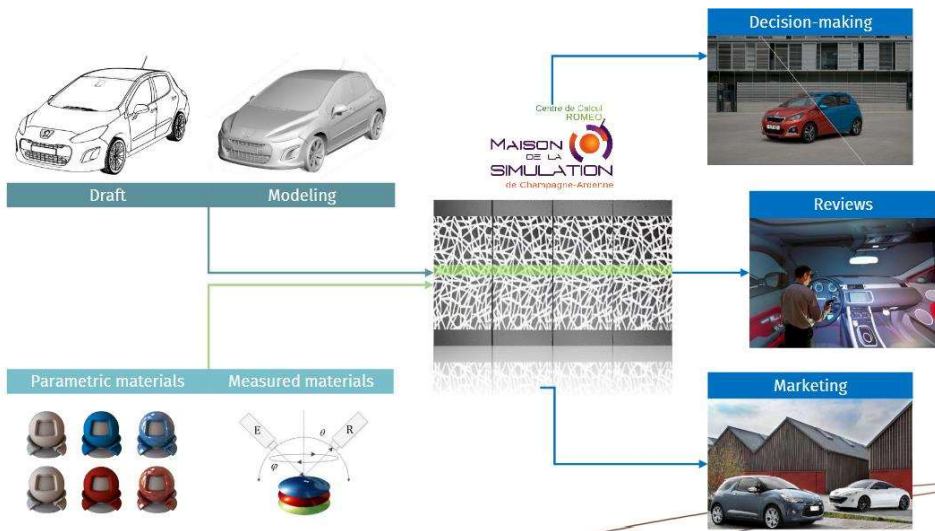


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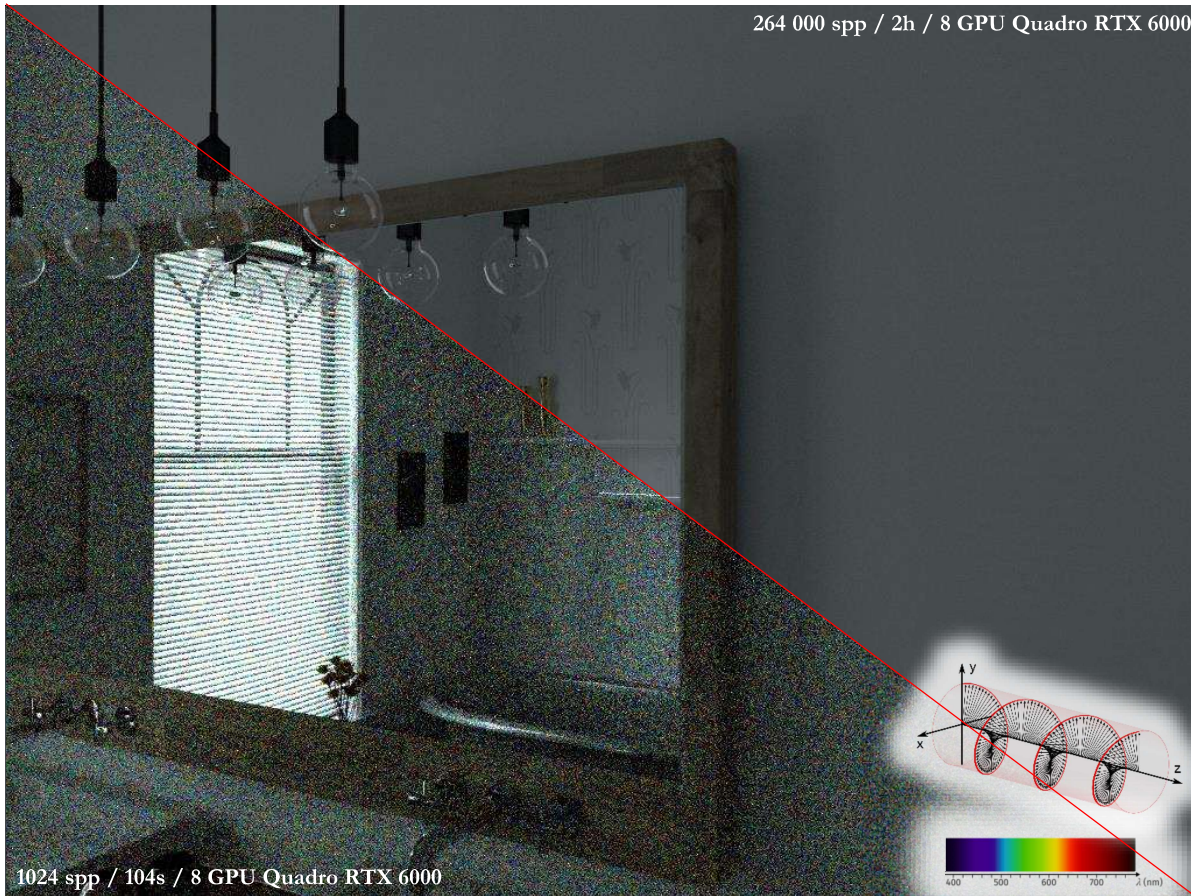
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GENERAL CONTEXT

- 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

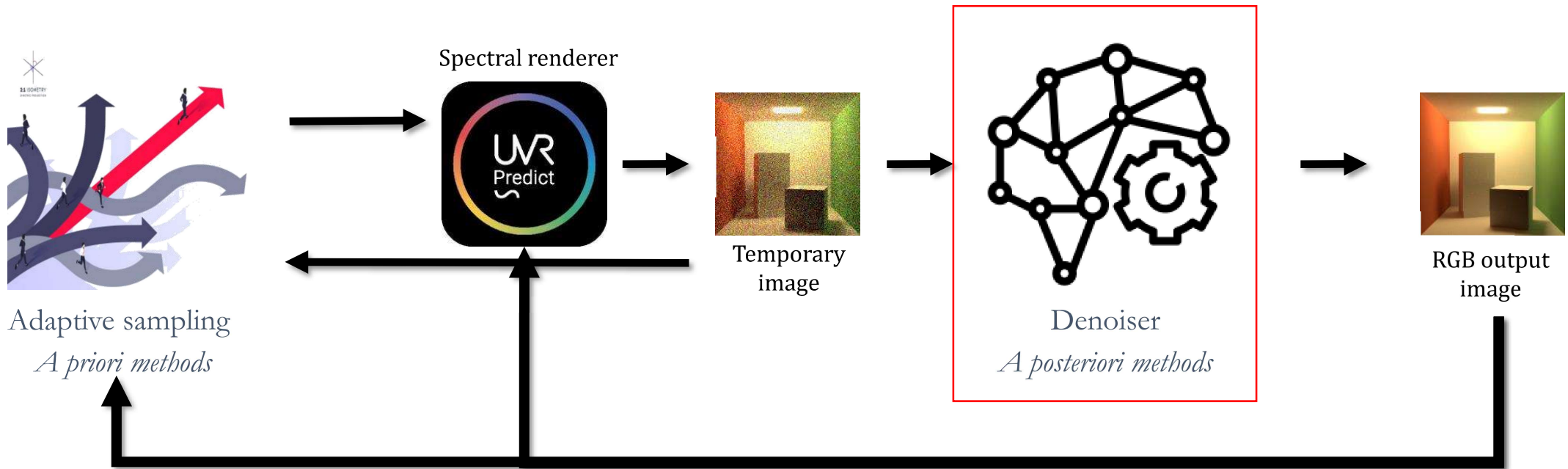
- Resolution based Monte Carlo approach

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

- 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)

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

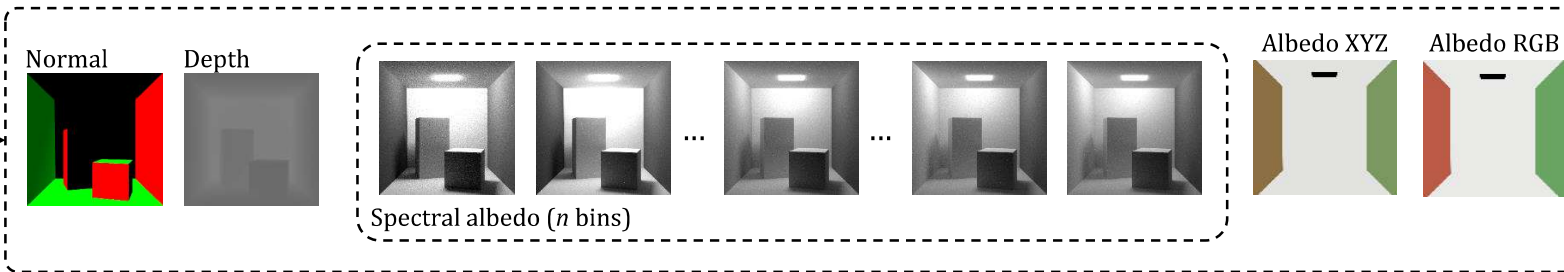
CIE-1931



XYZ output image

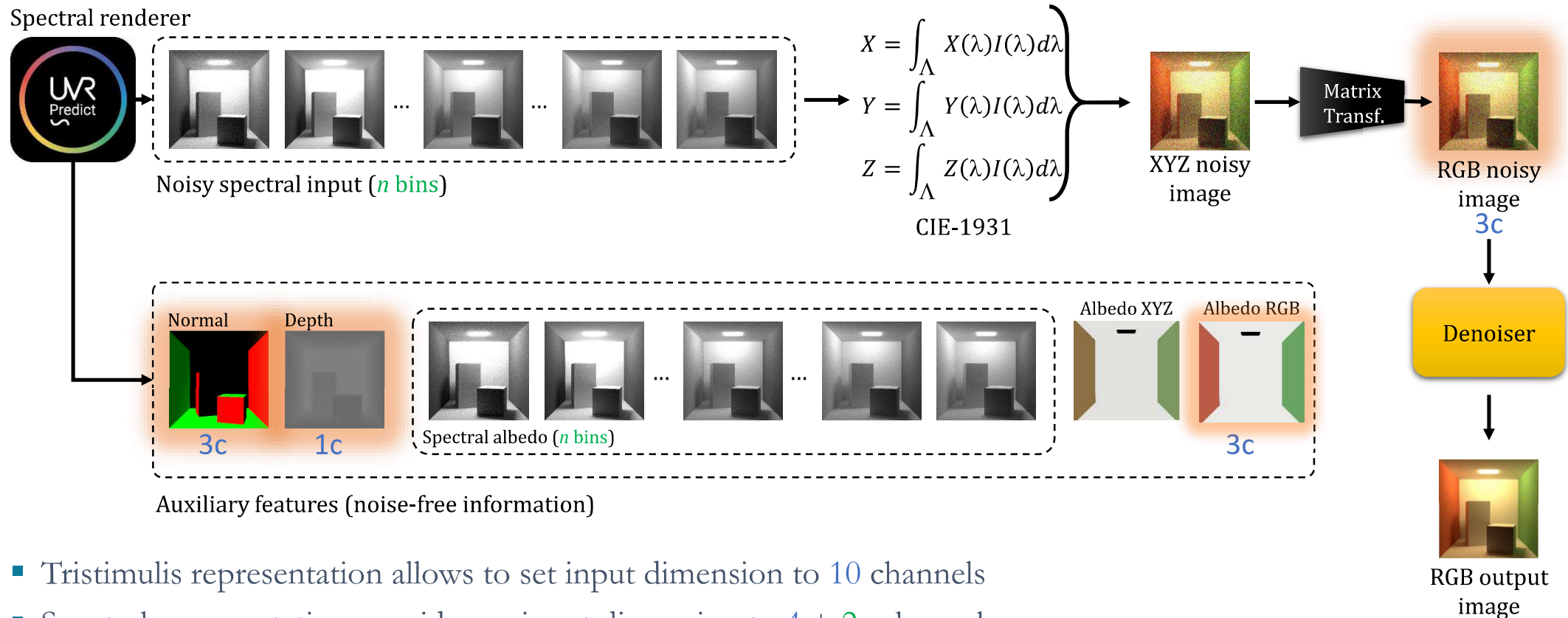


RGB output image



Auxiliary features (noise-free information)

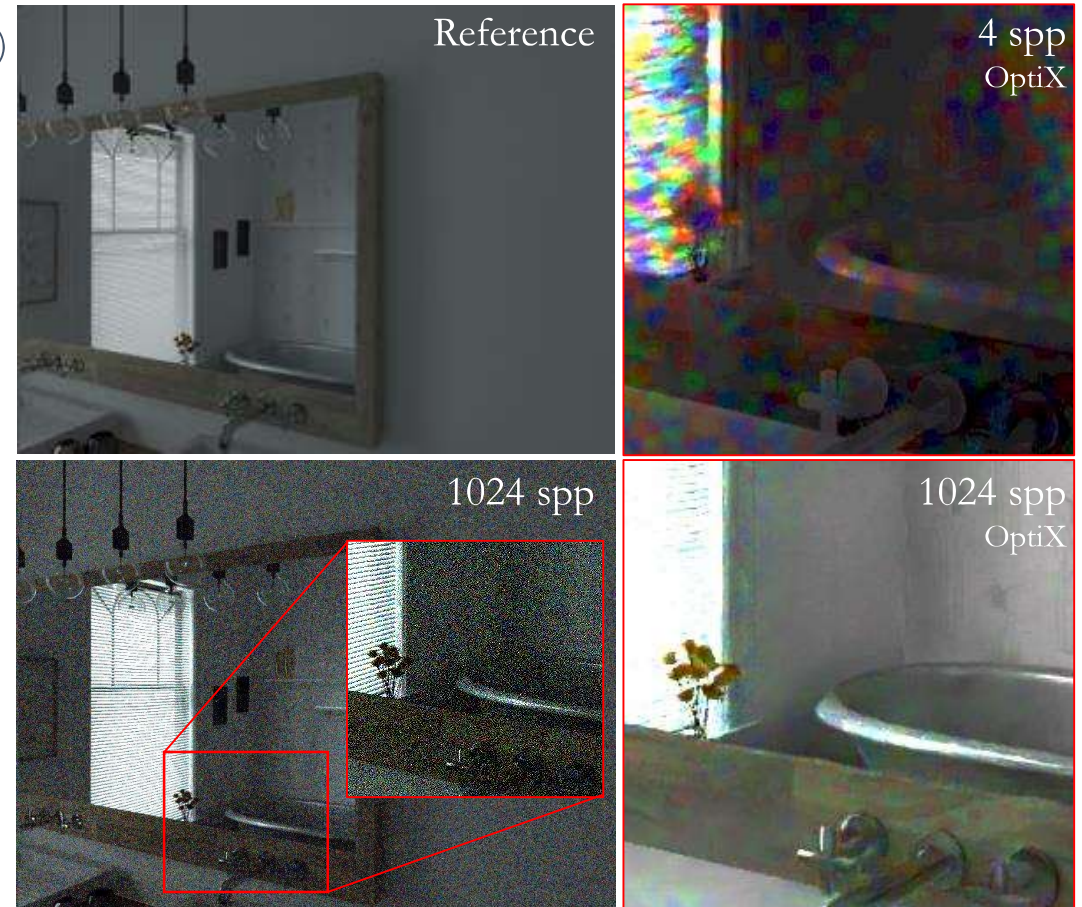
STATE OF THE ART - DENOISING



- 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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 CHRISTOPH SCHIED, NVIDIA and Karlsruhe Institute of Technology
 MARCO SALVI, NVIDIA
 AARON LEFJOHN, NVIDIA
 DEREK NONOVICZEZHAI, McGill University
 TIAGO ALLA, NVIDIA

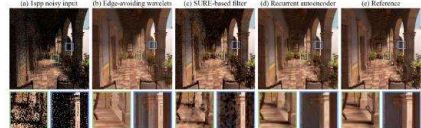


Fig. 1. Left to right (a) noisy image generated using path-traced global illumination with one indirect scene reflection and 1 sample/pixel. (b) edge-weighting weights that [Zhou et al., 2017] use at 200. (c) SIEM-based filter [Li et al., 2012]. (d) 124. (e) Reference path-traced image with 4000 samples/pixel.

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. Motivated by recent advances in image denoising with deep convolutional networks, we propose a variant of these networks tailored to the characteristics of noisy Monte Carlo rendering. We attend to weak longer pixel neighborhoods, we reduce noise artifacts, while also preserving temporal coherence by means of an auxiliary recurrent layer. The primary concern is the additional reconstruction in the presence of noise to drastically improve temporal stability for sequences of specially sampled image frames. Our method also has the desirable property of automatically adjusting to varying noise levels and auxiliary control inputs, such as depth and normals. The above 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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[Chaitanya et al. 2017]

Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings

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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 3* (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 input and the output. In this paper, we propose a novel method that is more robust to a large set of different renderers, but they are not required to be fast and that still have denoising ability. To address this problem, we propose a novel, supervised learning approach that allows for training kernels for more complex and generalizable features. A deep convolutional neural network (CNN) denoising layer, in use as an end-to-end system, 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, lower-level prediction network which uses the CNN to estimate the local weighting kernels 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; Ray tracing.

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

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[Bako et al. 2017]

Direct prediction
 ~1-4 spp*
 Loss details

Kernel prediction
 ~64-128 spp*
 Details reconstructed

spp* = 1 sample in RGB

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Yang X, Wang D, He W et al. DEDMC: 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)

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

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Abstract In this paper, we present DEDMC, 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 insensitive by gradients (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 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 integral, over all the ray paths between light sources and every point on image sensors. Monte Carlo (MC) raytracing¹ 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^{2,3,4} 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
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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, VnA Research, Vietnam and Vrije University, Vietnam
 TOSHIBA HACHISUKA, The University of Tokyo, Japan
 ROCHANG MOON, Georgia Institute of Science and Technology, South Korea

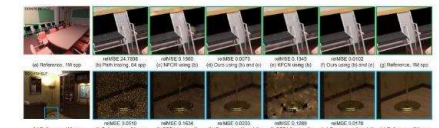


Fig. 1. Our framework allows us to combine two different types of images, independent pixel estimates (i.e., path-traced images) and correlated pixel estimates (i.e., denoised images), and reduce remaining errors (red marks) or systematic errors (as noticeable warped final color histogram (NOI) [Baker 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 combining some form of correlation among pixels. While these existing methods reduce noise, they are known to still suffer from certain specific residual noise or systematic errors. Our proposed unified framework that reduces noise remaining errors of rendered image 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 also enables the two images to be used combination freely. We extend our combination kernel, as 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 advantage of our unified framework can be naturally viewed as the error of existing methods while treating them as black boxes.

CCS Concepts: • Computing methodologies — Ray tracing

Additional Key Words and Phrases: Combinations kernel; Monte Carlo Ray Tracing

ACM Reference Format: Jonghee Back, Binh-Sun Hua, Toshiba Hachisuka, and Rochang Moon. 2020. Deep Combiner for Independent and Correlated Pixel Estimates. ACM Trans. Graph., 39(4), Article . October 2020, 12 pages. DOI: <https://doi.org/10.1145/3456789>

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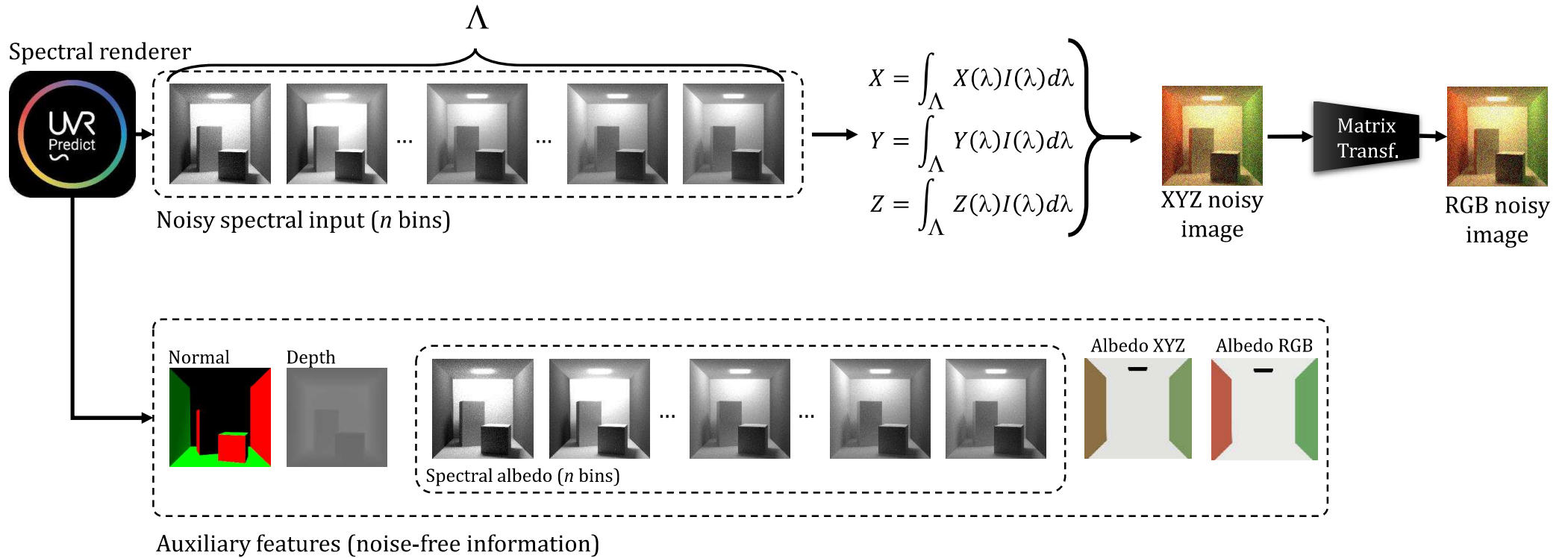
ACM Transactions on Graphics, Vol. 39, No. 4, Article . Publication date: October 2020.

[Back et al. 2020]

Kernel prediction
 independent of spp*
 Improve diffuse details reconstruction

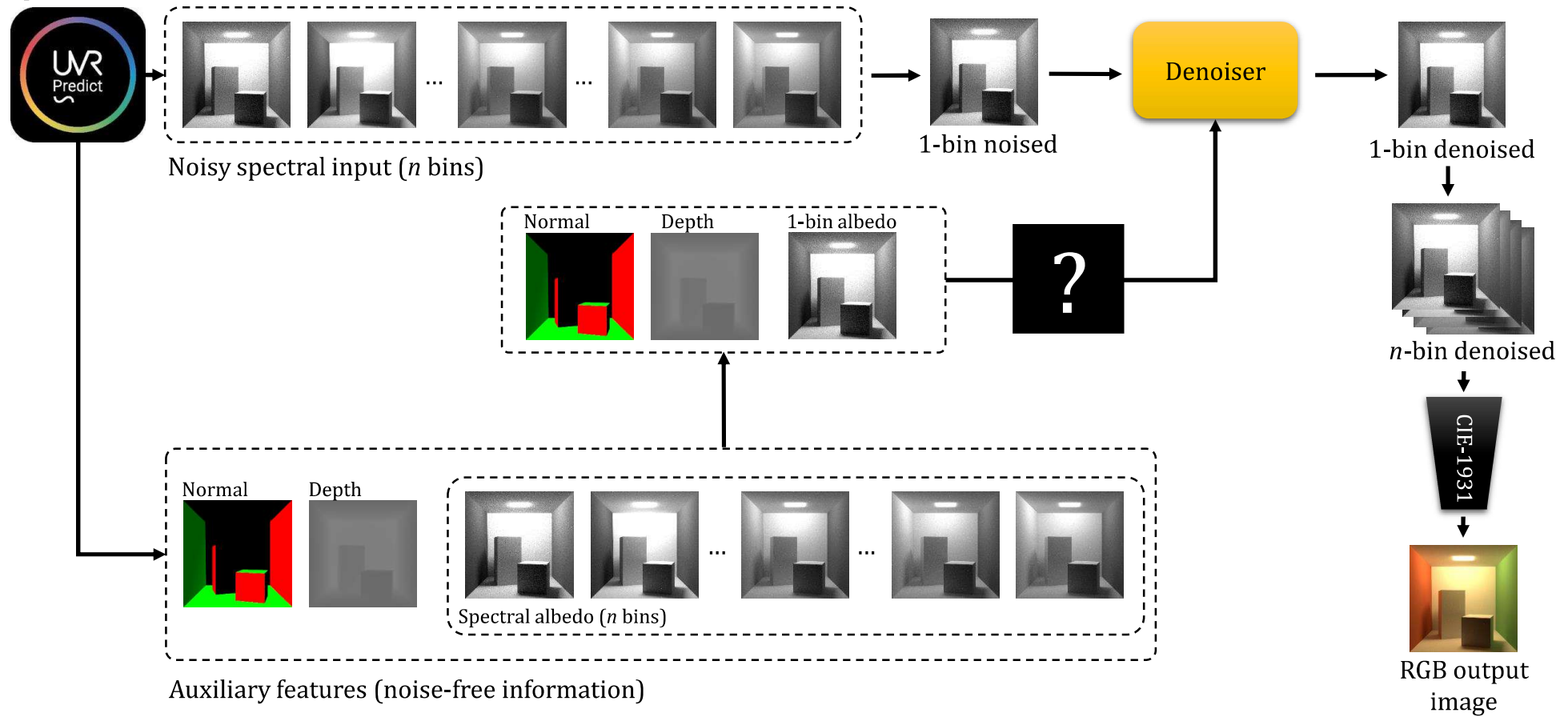
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DATA MANAGING



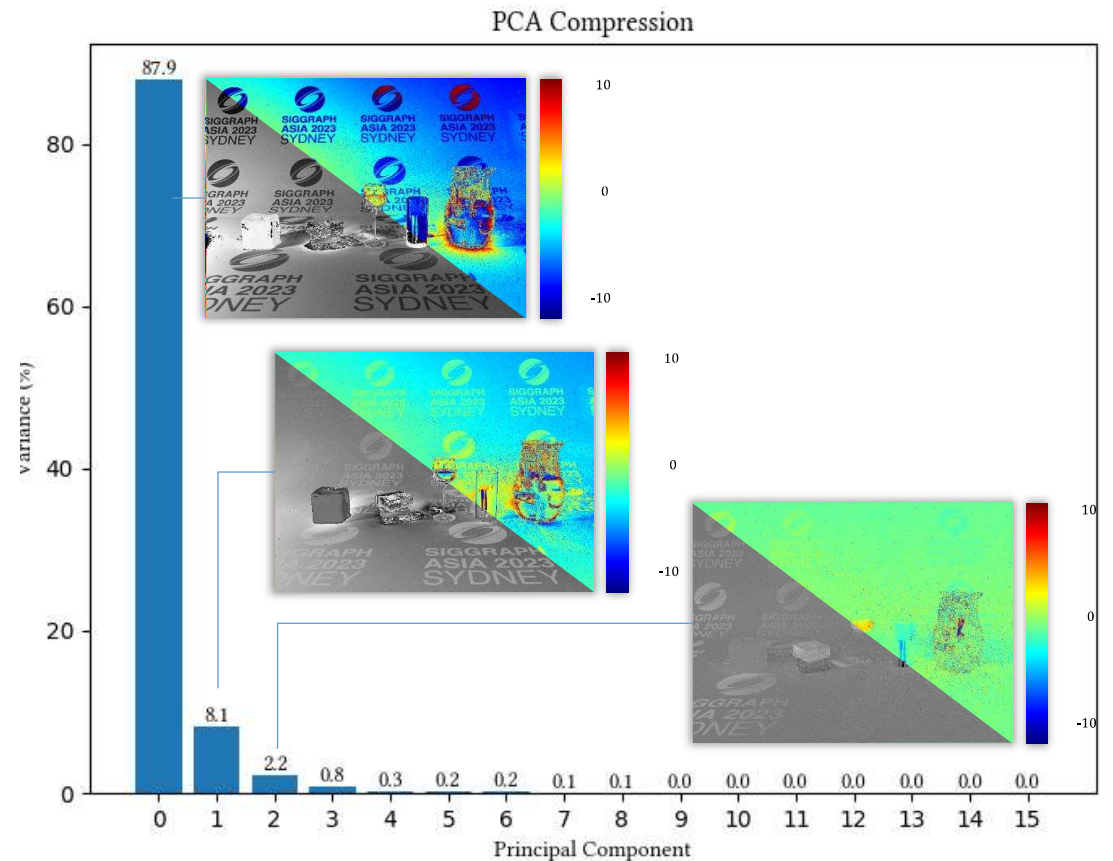
DATA MANAGING

Spectral renderer

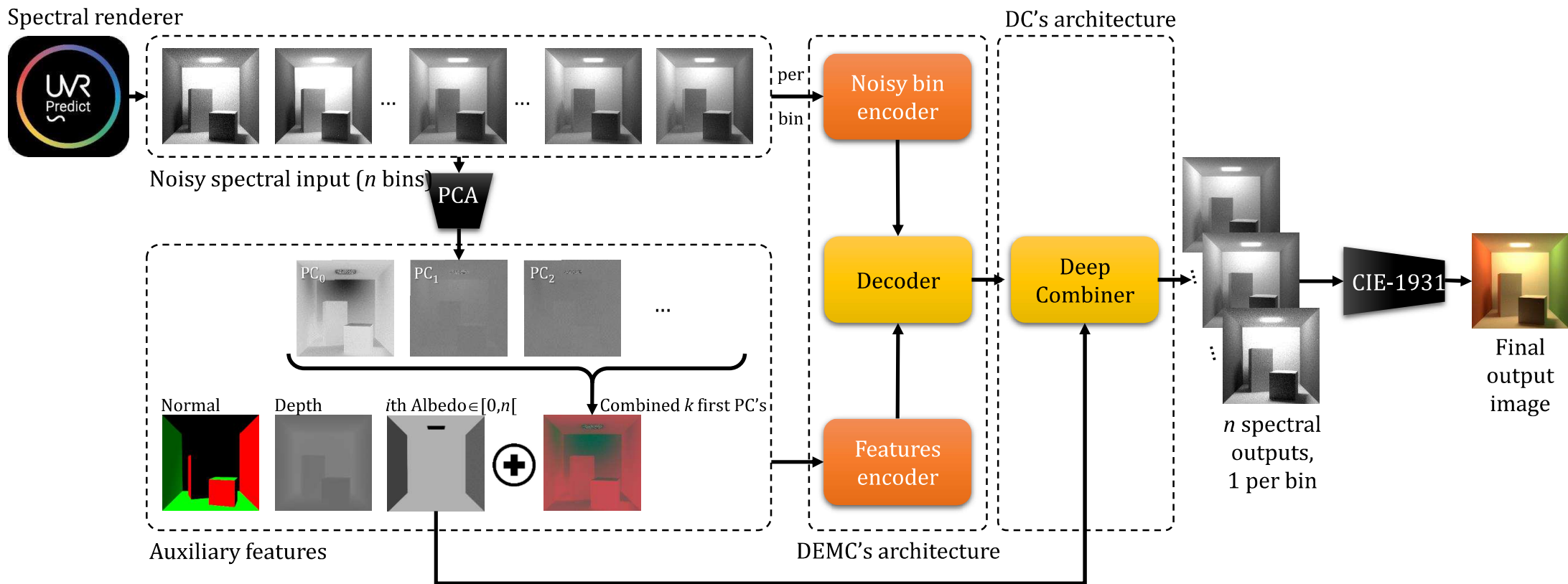


SPECTRAL COMPRESSION

- 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

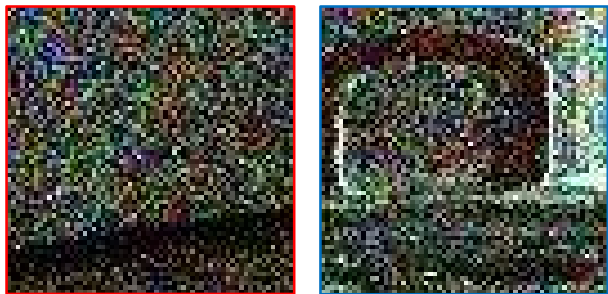


TRAINING INFORMATION

- 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

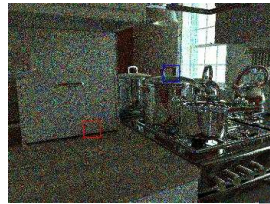


SPP: 1024
Time: 89 s on 1 GPU
RelMSE: 0.70

1 M
≈ 36 h on 4 GPUs
GT

1024
89.16 s on 1 GPU
0.0313

RESULTS

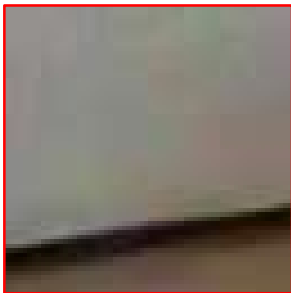
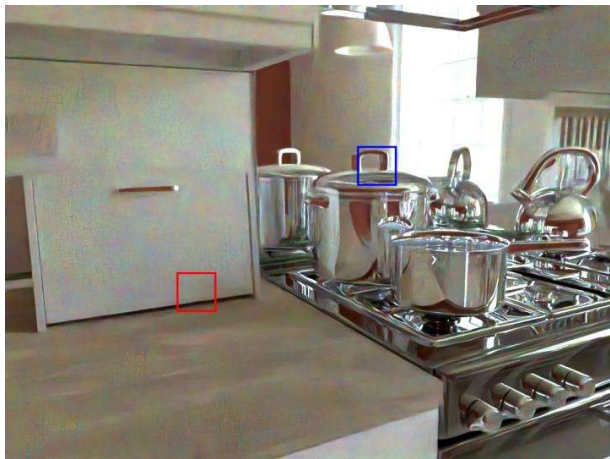


Noisy image
1024 SPP

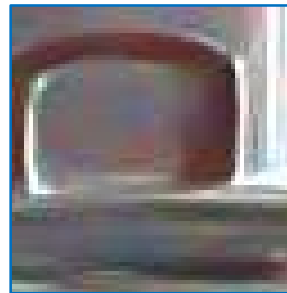
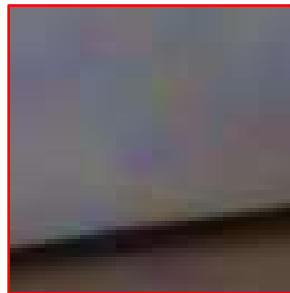


Reference image
1M SPP

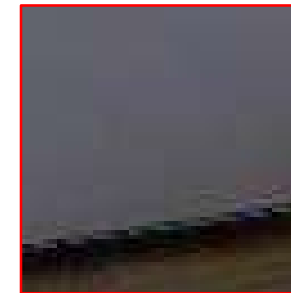
Intel



OptiX



Ours



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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