

# Improving the Progressive Denoising of MC Rendered Images in low SPPs

(From “Progressive Denoising of MC Rendered Images”, A. Firmino et al, EG 2022)

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CS482 Final Project Presentation

Team 3  
Jaehyun Ha



# Background: Noises in MC-Rendering @ low SPP

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**16 Samples Per Pixel**



**1024 Samples Per Pixel**

# Background: Denoising in MC-Rendering

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**16 Samples Per Pixel**



**16 Samples Per Pixel *Denoised***  
*(By Intel OIDN)*

# Background: Denoisers do the things too much!

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***1024 Samples Per Pixel **Denoised*****

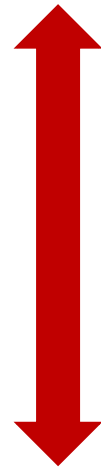


***1024 Samples Per Pixel***

# Problem: Existing deep-learning based denoisers for MCR

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***“Can produce smooth images using a low sample count”***



***How to overcome the problem?***

***“Biased and do not converge to ground truth as SPP increase”***

# Recap: Progressive Denoising

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- Blend denoised & original images based on variance of non-denoised pixels
- Produce optimal per-pixel mix parameter (which takes the best pixels of each image)



***Input 1: Rendered***



***Input 2: Denoised***



***Per-pixel mixing param***

# Limitations : Progressive denoising

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- Progressive denoising shows limitations at very low sample counts



**Figure 13:** *Limitation of our method at very low sample counts, 2spp in this example, arising from insufficiently accurate sample variance estimates.*

# Motivation

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## *“Improving progressive denoising at low SPPs”*

### Strengths

**Apply denoising only  
when it's beneficial**

**Better Quality @ High SPPs**

### Our workarounds

**Acceptable performance  
@ Low SPPs**

**“Consistent, versatile denoiser in all SPP ranges”**



# Approaches

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## **Adaptive Sampling based approach:**

- Can expect better quality in low SPPs
- Cannot guarantee if the implementation will be feasible

## **Widening kernel based approach**

- Easy to implement
- Weak impact & cannot guarantee the quality

# Approaches (1) : Mounting of Adaptive sampling

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- **Adaptive Sampling**: Optimizing technique in MC rendering which allocates more samples to the areas of the suspicious part of the image

*How to apply?*



*Un-denoised image  
with low SPP*

*Variance : 0!*



*Denoising decision*

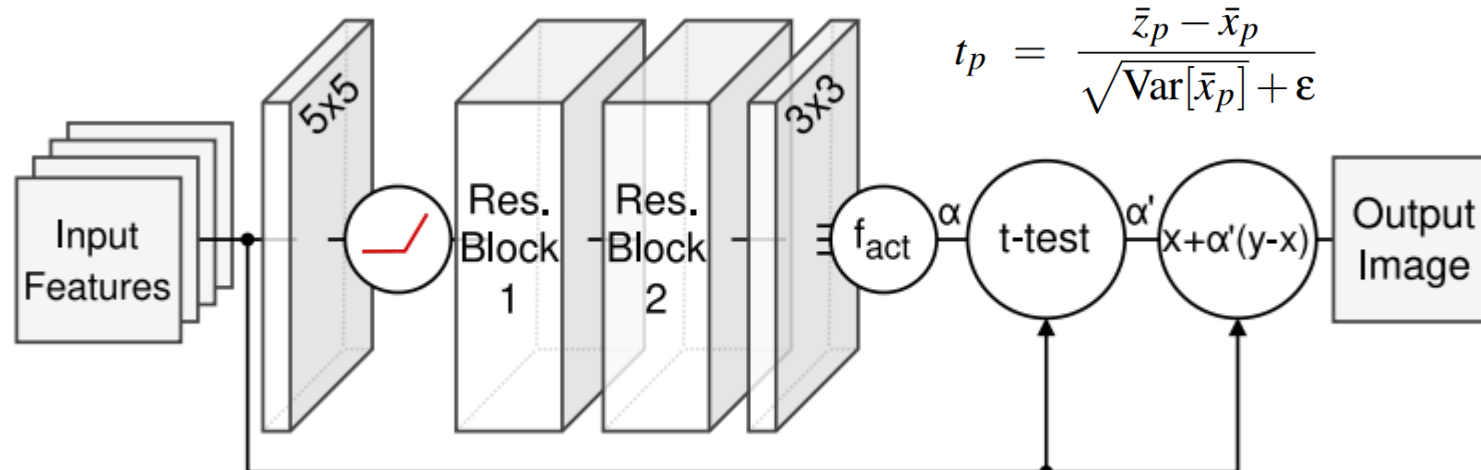
Pre-denoising step  
If (variance too low):  
*More samples (~32)!*

*Variance: XX (>0)*

# Approaches (1) : Mounting of Adaptive sampling

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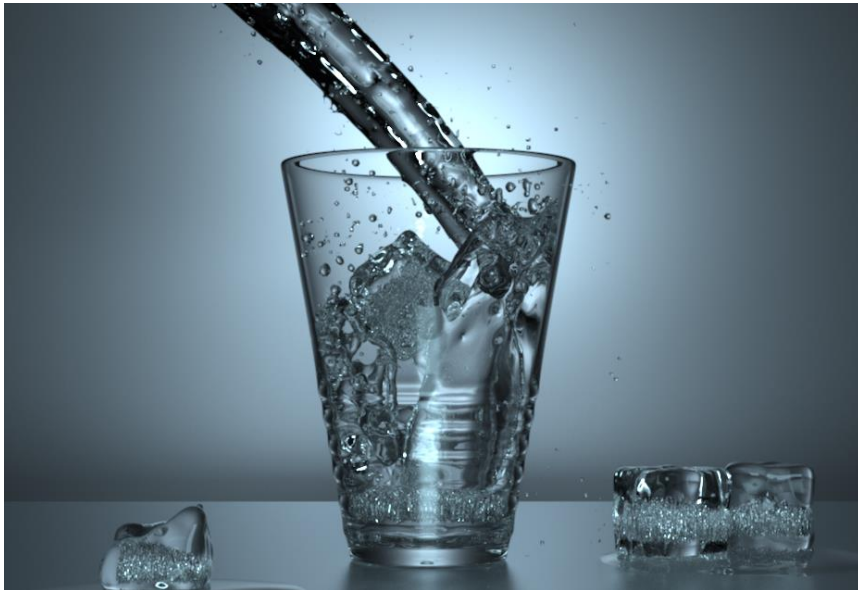
- **Adaptive Sampling** requires implementing another neural network for allocating extra samples on top of existing denoiser
- **Intensive training time**: > 10 hours of training each model with RTX 3090



# Approaches (2) : Estimate from widen neighbourhood

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- Original paper uses **11-by-11** size neighbourhood to estimate the radiance & variance of pixel
- Check if different kernel size options can give better results while it does not give performance degradance



# Approaches (2) : Estimate from widen neighbourhood

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*GW: Glass-of-Water Scene (2 spp),  
BR: Bathroom scene (2spp, High variance)*

	Pro-den (11x11, paper)	Pro-den (19x19, <b>ours</b> )	Pro-den (27x27, <b>ours</b> )	OIDN	MCR
RMSE - GW	0.7832	<b>0.7689</b>	0.7867	0.7722	3.6853
RMSE - BR	1.2612	1.2566	1.2553	<b>1.2480</b>	9.2901
Training Time	14h 38m	15h 05m	15h 03m	-	-

# Approaches (2) : Estimate from widen neighbourhood

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Evaluation – comparison with Ground Truth / MC rendering



***Ground Truth***



***Ours (2spp prog-denoised, 19\*19)***

# Approaches (2) : Estimate from widen neighbourhood

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Evaluation – comparison with Ground Truth / MC rendering



*MC rendering (2 spp)*



*Ours (2spp prog-denoised, 19\*19)*

# Approaches (2) : Estimate from widen neighbourhood

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Evaluation – comparison with existing denoiser (OIDN)



**OIDN**



***Ours (2spp prog-denoised, 19\*19)***



# Conclusion

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## Main goal:

- Improving the quality of progressive denoising @ low sample counts
- Implementing the consistent, versatile denoiser at all SPP ranges.

## Our approach:

- Applying adaptive sampling to progressive denoising
- Widening the kernel size for estimations

# Results & Limitations

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## 1. Adaptive Sampling based approach takes too much time:

- If the training process takes this long, investigating methods for reducing the training time would also be a novel work

## 2. Widening kernel size needs a good compromise

- Widening the kernel size for computing the radiance values is helpful depends on the scenes

# Roles

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## Jaehyun Ha

- Coordinates the entire project
- Check if widening kernel-based approach works
- Check whether adaptive sampling methods can be applied on top of progressive denoising
- Making slides
- Review the literatures
- ...

# Thank You

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