GT Rendu 2020

Toward a noise perception model for photorealistic image synthesis

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Team: IMAP (Images et Apprentissage)

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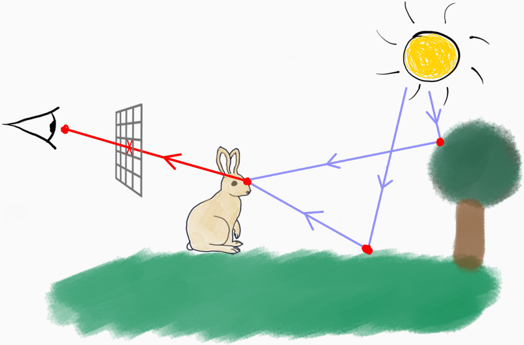
* ANR support : project ANR-17-CE38-0009
Univ. Littoral Côte d'Opale, LISIC, F-62100 Calais, France

Agenda

1. Context
2. Noise
3. Perception
4. Relative & current works
5. Conclusion

Context

Context



Photorealistic image synthesis

- Global illumination rendering
- Monte Carlo

Context: noise in photorealistic image

(a) After 1 sample

(b) After 20 samples

(c) After 10000 samples

Context: ways to tackle the noise problem in rendering

How to improve the rendered image ?

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How to improve the rendered image ?

- by improving the path-tracing strategies
  1. **Integrator:** Bidirectional path-tracing (*Lafortune and Willems 1993*), Metropolis light transport (*Veach and Guibas 1997*)
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How can humans perceived the photorealistic rendering generated noise ?

Noise

Noise: overview

- Capture $\rightarrow$ a lot of noise perception models
  - **Full-reference:** SSIM (Carnec, Le Callet, and Barba 2003)
  - **No-reference:** BRISQUE (Mittal, Moorthy, and Bovik 2012)
  - ...

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Objective

Build a noise perception model for computer graphics

Perception

Perception: definition

Just-Noticeable Difference (JND)

Noise can be viewed as a perceptible difference into image

20 samples

1000 samples

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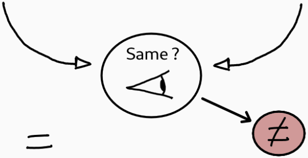
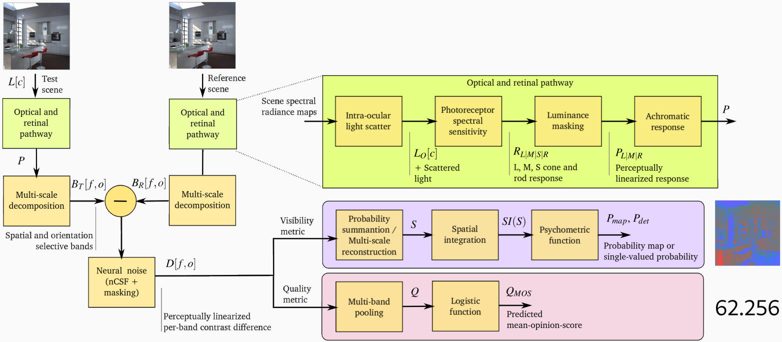


Perception: Visual Difference Predictor

HDR-VDP: a calibrated method for objective quality prediction (*Narwaria et al. 2015*)



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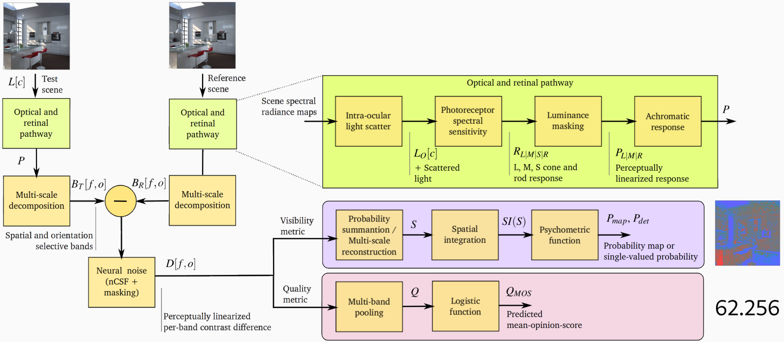

Problem

- complex model, with a lot of parameters (room luminance, screen luminance...).
- model which requires **reference** which is not available in computer graphics.

Relative & current works

1. How to build a such model ?
2. Previous & current team works
3. Deep Learning approaches

1. **How to build a such model ?**

2. Previous & current team works

3. Deep Learning approaches

Dataset creation: need of human data

Problem of photorealistic image synthesis rendering

- No-reference context during rendering
- No human perceptual reference data

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A solution

Collect human subjective perceptual threshold during rendering as ground truth

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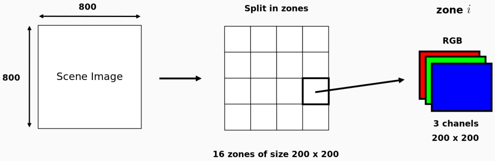
Build a model

Use these perceptual thresholds into a perceptual noise model

Our way of getting perceptual subjective thresholds



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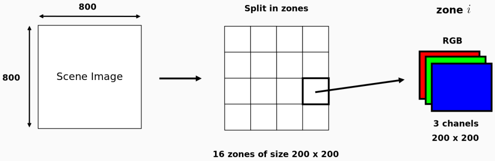

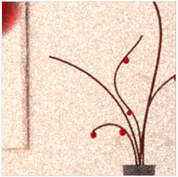

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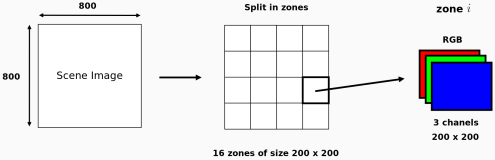

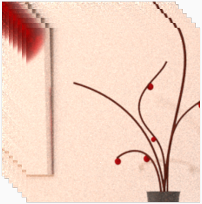

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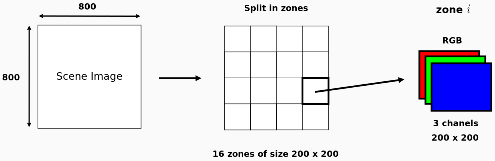

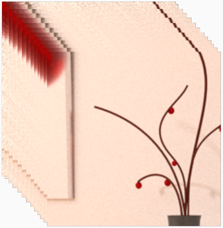

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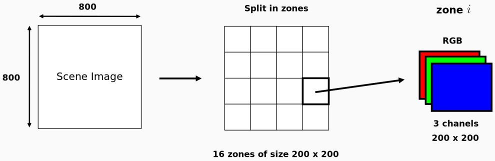

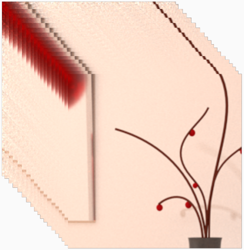

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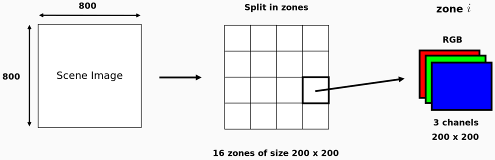

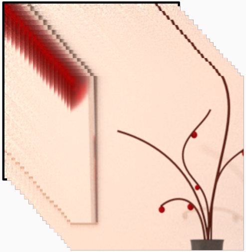

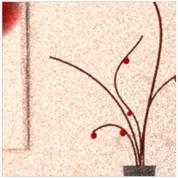

20 samples

3000 samples (reference)

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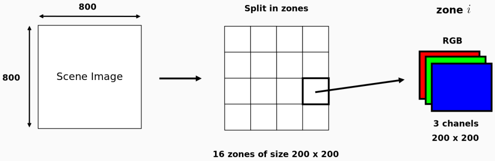

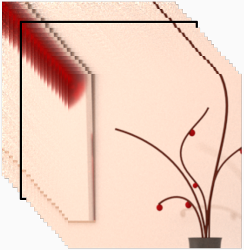

220 samples

3000 samples (reference)

Dataset creation: collect human subjective threshold

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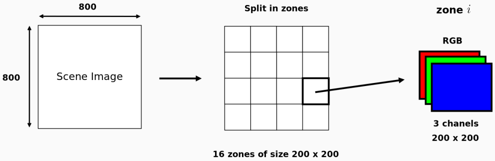

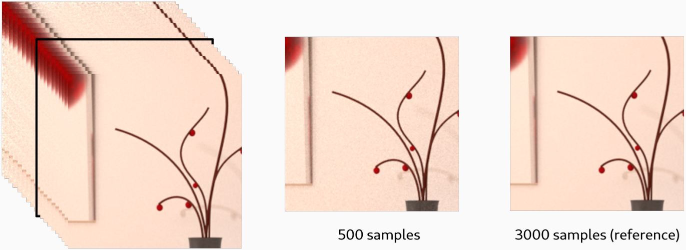

500 samples

3000 samples (reference)

Dataset creation: collect human subjective threshold

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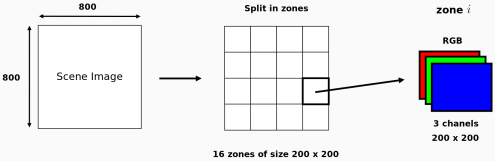

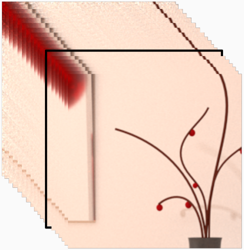

900 samples

3000 samples (reference)

Dataset creation: collect human subjective threshold

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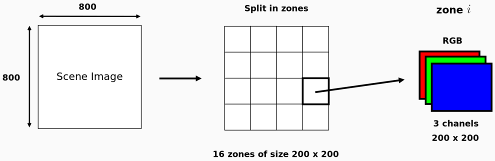

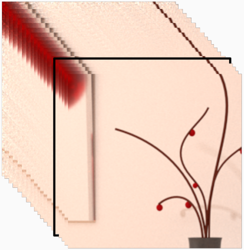

1400 samples

3000 samples (reference)

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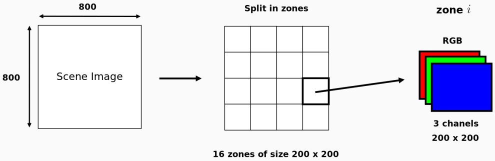

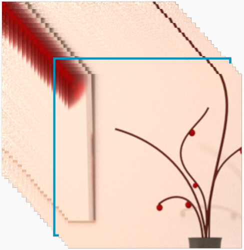

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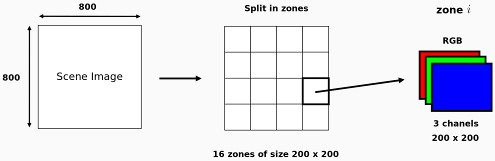

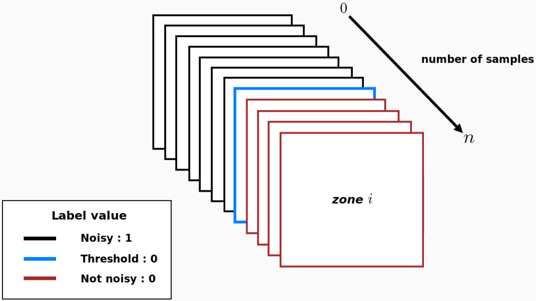

Dataset creation: overview

313	312	274	271
310	301	308	235
248	292	222	240
211	151	139	177

(a) Human thresholds (Mean Opinion Score)

(b) Human reference

(c) After 900 samples

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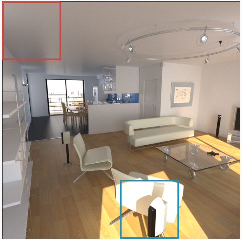
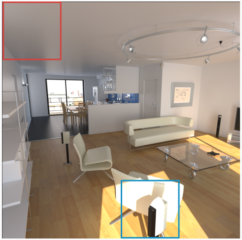


(b) Human reference



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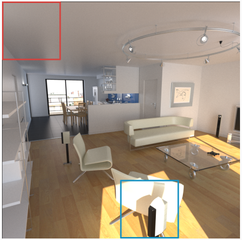
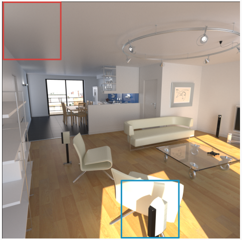


(b) Human reference
SSIM: 0.70 (< 0.95)



(c) After 900 samples
SSIM: 1

Structural Similarity Index (SSIM)

SSIM metric quantifies the visibility of errors between a distorted image and a reference image using a variety of known properties of the human visual system.

Database creation: expected model

Binary classification

- Model which labels image as **noisy** or **not** (**converged** or **not**)
- Supervised learning

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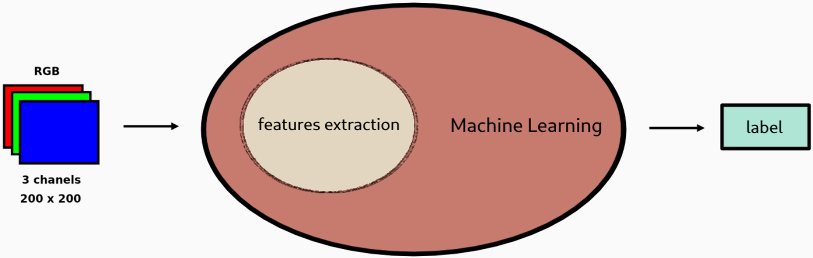
Common pipeline used



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- **stopping criterion** during rendering based on sub-blocks of rendered image
- **save** computation time
- target more complex parts of the scene

1. How to build a such model ?
2. **Previous & current team works**
3. Deep Learning approaches

Perception model for synthesis images:

- Image noise detection in global illumination methods based on FRVM (*J. Constantin, A. Bigand, et al. 2015*)
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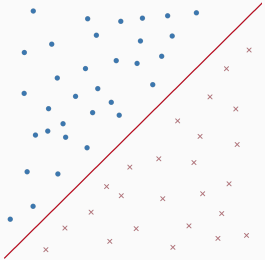
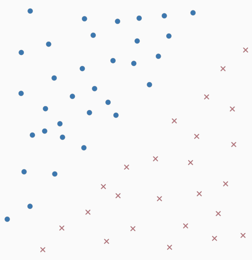
Support Vector Machine (SVM):



(a) Linear classifier model



(b) SVM classifier model

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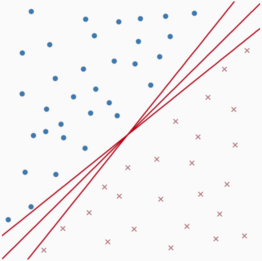

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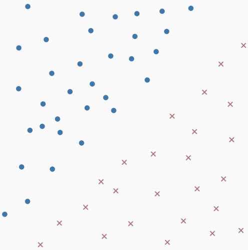

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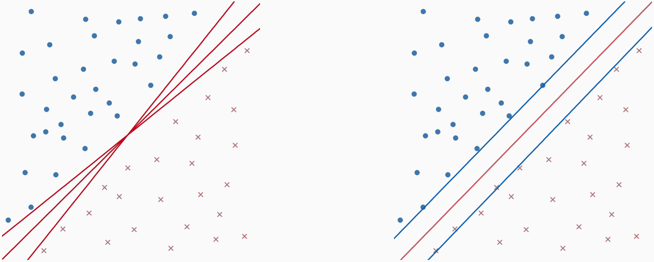

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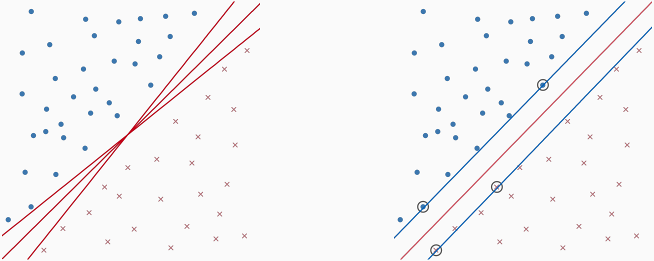

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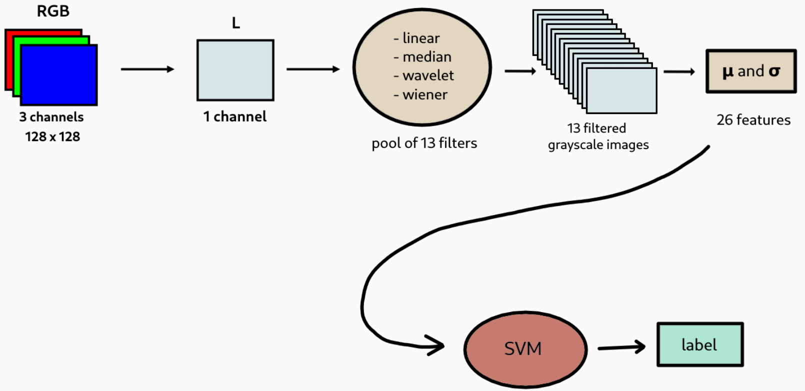

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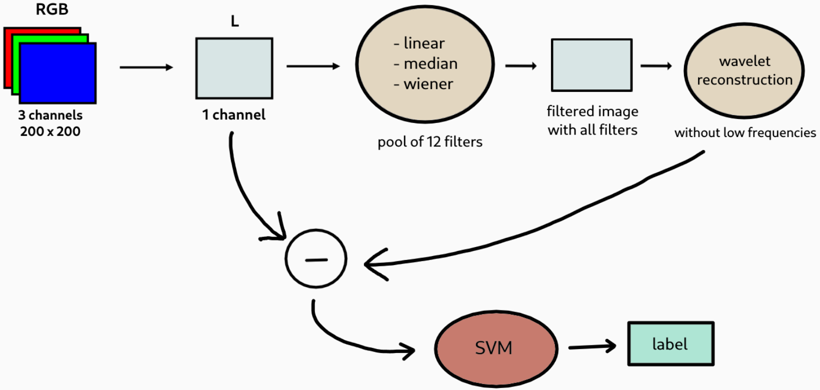

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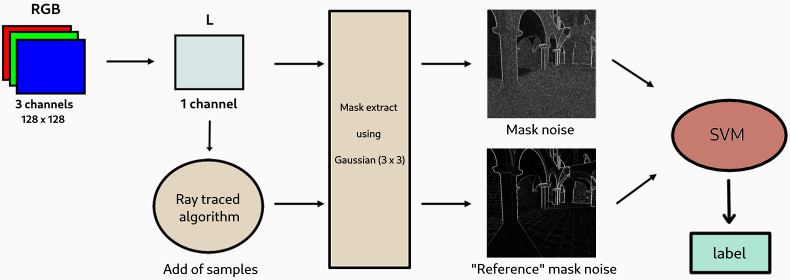
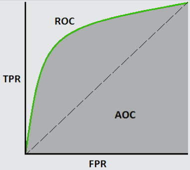


Team works: previously

Model	features	zones	Accuracy Train	Accuracy Test	AUC ROC Train	AUC ROC Test
SVM	(J. Constantin 2015)	12	0.9592	**0.8756**	0.9677	**0.8755**

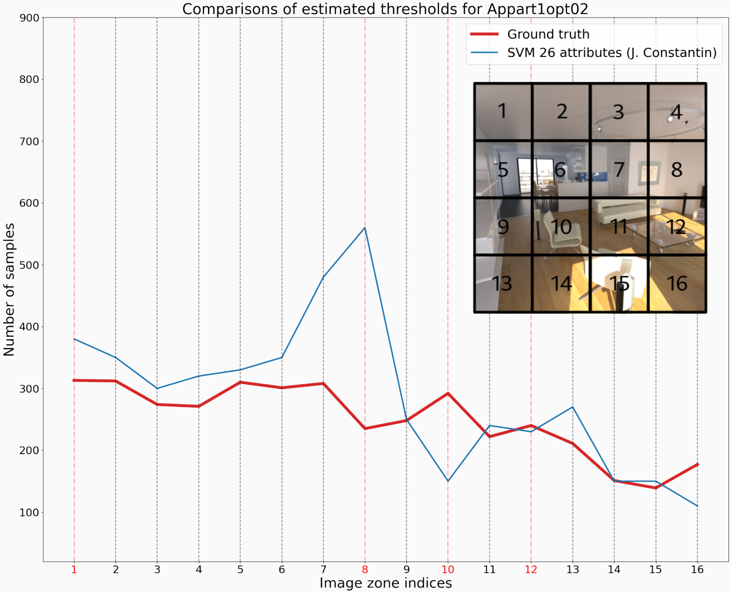
Training parameters

- Use of 4 viewpoints from 3 scenes (same renderer)
- 12 zones used from training / 4 for testing
- ROC is a probability curve and AUC represents degree or measure of separability



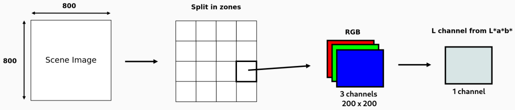
- $TPR = \frac{TP}{TP+FN}$
- $FPR = \frac{FP}{TN+FP}$

Team works: previously



LISIC ANR

Team works: use of singular values



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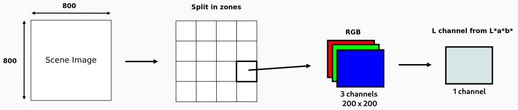
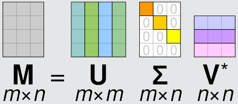


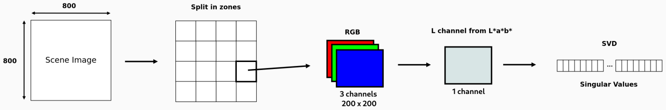
Singular Value Decomposition



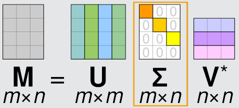
where:

- M is an $m \times n$ real or complex matrix
- U is an $m \times m$ real or complex unitary matrix.
- Σ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal.
- V is an $n \times n$ real or complex unitary matrix.

Team works: use of singular values



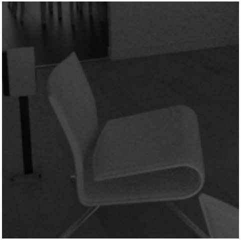
Singular Value decomposition



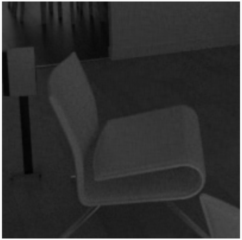
where:

- M is an $m \times n$ real or complex matrix
- U is an $m \times m$ real or complex unitary matrix.
- Σ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal.
- V is an $n \times n$ real or complex unitary matrix.

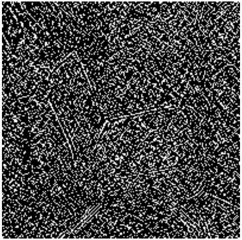
Possibility to decompose image using SVD into structure dependent and non-dependent images (Wang et al. 2013).



(a) L chanel (500 samples)

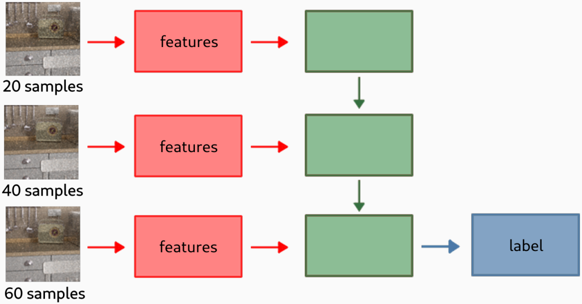


(b) SVD reconstruction (0, 50)



(c) SVD reconstruction (50, 200)

Team works: Recurrent Neural Networks



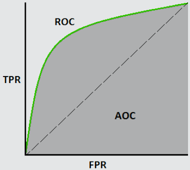
Input and parameters

- Σ singular values from SVD
- Window size of 5

Model	features	zones	Accuracy Train	Accuracy Test	AUC ROC Train	AUC ROC Test
SVM	(J. Constantin 2015)	12	0.9592	0.8756	0.9677	0.8755
RNN	Singular values [0, 200[	12	0.9404	**0.8966**	0.9249	**0.8859**

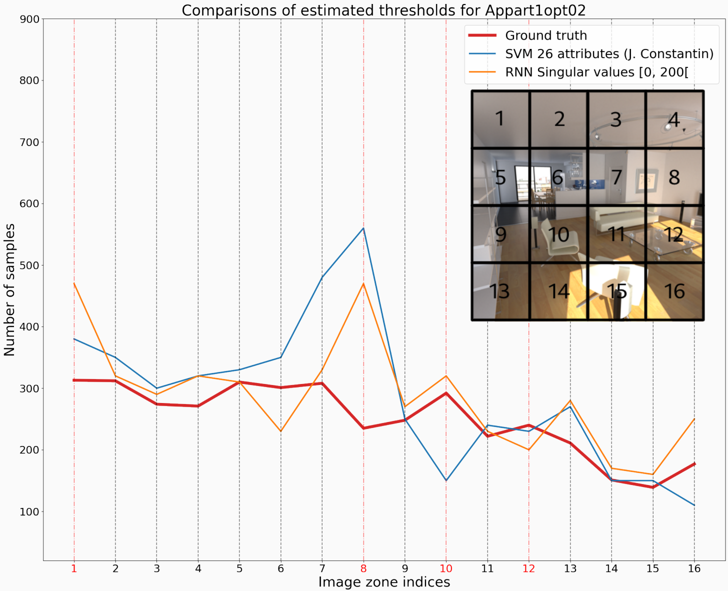
Training parameters

- Use of 4 viewpoints from 3 scenes (same renderer)
- 12 zones used from training / 4 for testing
- ROC is a probability curve and AUC represents degree or measure of separability



- $TPR = \frac{TP}{TP+FN}$
- $FPR = \frac{FP}{TN+FP}$

Team works: Recurrent Neural Networks



Team works: conclusion

Encountered problems:

- difficulty to generalize using dataset
- scene structure gives strong influence for model performance
- need more data to fit well

Relative & current works

1. How to build a such model ?
2. Previous & current team works
3. **Deep Learning approaches**

DL approaches: build of new dataset

Previous dataset

- 9 viewpoints from scenes
- different renderers (maxwell, igloo, cycle...)
- hence, different algorithms

Previous dataset

- 9 viewpoints from scenes
- different renderers (maxwell, igloo, cycle...)
- hence, different algorithms

New dataset

- 40 viewpoints with 10000 images of 1 sample
- only **pbrt-v3** renderer
- use of **path-tracing**
- available soon

DL approach: build of new dataset

Why saving image of 1 sample ?

- generate $\binom{10000}{k}$ images of k samples from pool of 10000 samples

DL approach: build of new dataset

Why saving image of 1 sample ?

- generate $\binom{10000}{k}$ images of k samples from pool of 10000 samples
  $\Rightarrow \binom{10000}{20} \approx 4.3\mathrm{e}61$

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- **posterior** study of samples **distribution**

DL approach: build of new dataset

Why saving image of 1 sample ?

- generate $\binom{10000}{k}$ images of k samples from pool of 10000 samples
  $\Rightarrow \binom{10000}{20} \approx 4.3\mathrm{e}61$
- **posterior** study of samples **distribution**
- use of deep learning approach (RNN, GAN, Autoencoder...)

Conclusion

Conclusion

Presented works:

- Singular values vector seems to fit well using RNN
- Lack of data and need of new dataset
- Enable posterior samples study using this new dataset

Perspectives

Improve dataset:

- check convergence of all generated scenes
- use of web experiment (SIN3D) app to collect human thresholds

Perspectives

Improve dataset:

- check convergence of all generated scenes
- use of web experiment (SIN3D) app to collect human thresholds

Use of Deep Learning:

- exploit new dataset with CNN / RNN
  - using preprocessed images
  - features based only
- samples distribution study
- denoising approaches

Thanks for your attention

Resources:

- **Scene files:** `https://gogs.univ-littoral.fr/Prise3D/p3d_pbrt-scenes.git`

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Backup: SIN3D calibration

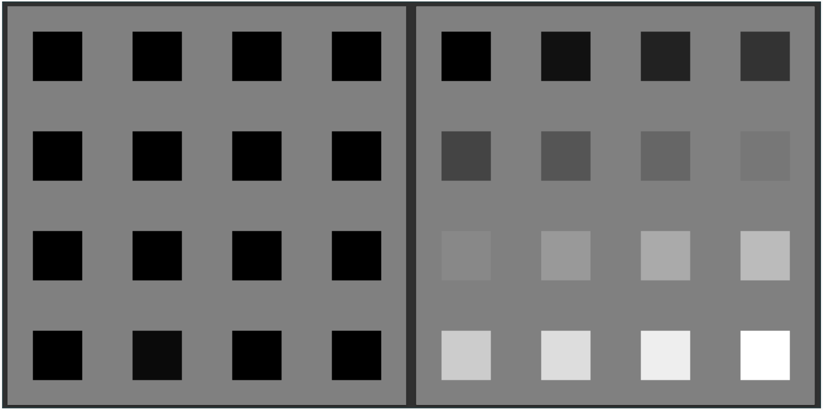


Figure 10: Calibration scene

Backup: SIN3D overview

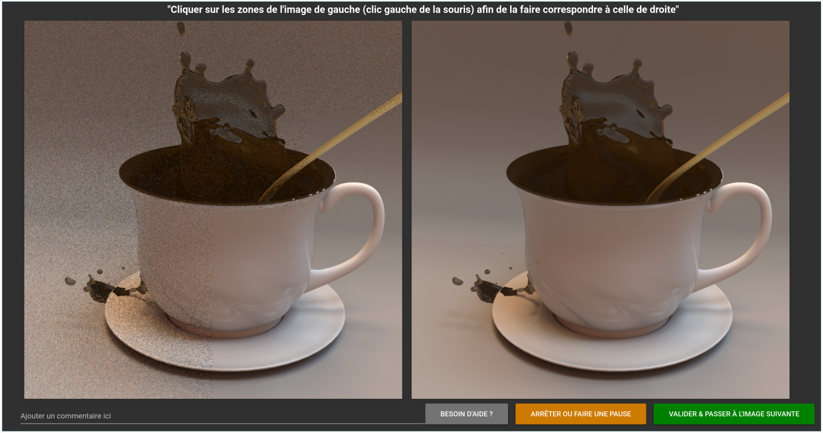
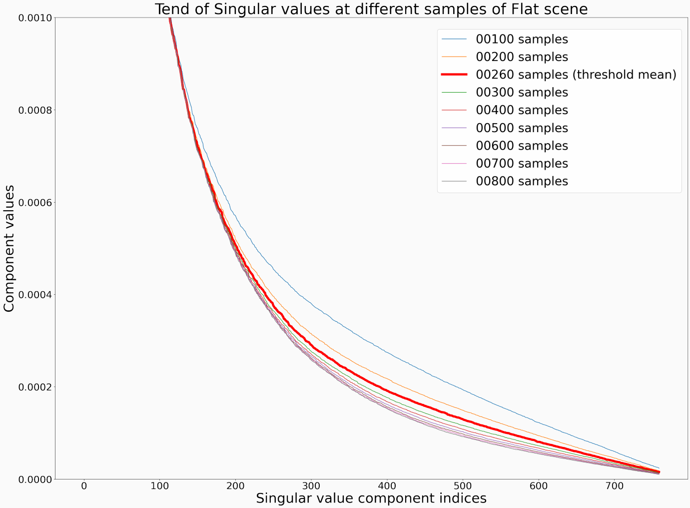
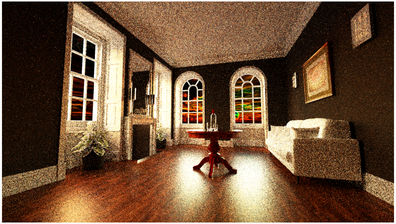


Figure 11: User interface

Backup: use of singular values



Backup: distribution analysis



(a) Variance

(b) Standard deviation

(c) Skewness

(d) Kurtosis

Backup: RAWLS

New dataset:

- Use of new image format: **RAWLS** for *RAW Light Simulation*

Python package:

rawls https://prise-3d.github.io/rawls