LISIC - Webinar

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

Context

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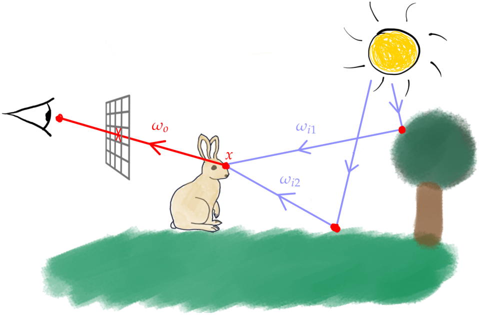

$$L_o(x, \omega_o) = L_e(x, \omega_o) + \int_{\Omega} L_i(x, \omega_i) \cdot f_r(x, \omega_i \rightarrow \omega_o) \cdot \cos\theta_i d\omega_i \qquad (1)$$

Photorealistic image synthesis

- Global illumination rendering
- Monte Carlo

Context: noise in photorealistic image

(a) After 1 sample

(b) After 20 samples

(c) After 10, 000 samples

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(a) After 1 sample

(b) After 20 samples

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Question:

How can human perceive this MC noise ?

Dataset

Dataset creation: need of human data

Problem of photorealistic image synthesis rendering

- No-reference context during rendering
- Unavailable models for noise perception in MC generated images
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Use these perceptual thresholds into a perceptual noise model

Perception: definition

Just-Noticeable Difference (JND)

Noise can be viewed as a perceptible difference into image

20 samples

1000 samples

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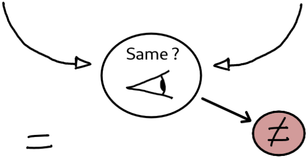

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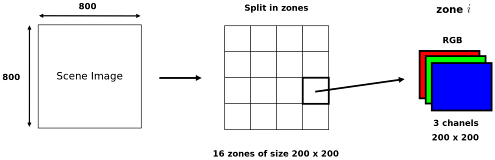
Our way of getting perceptual subjective thresholds



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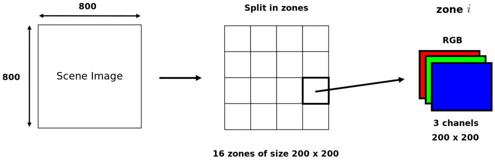

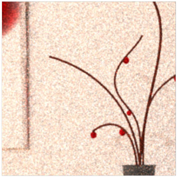

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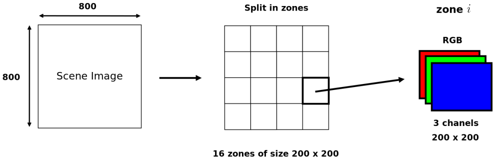

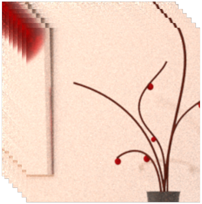

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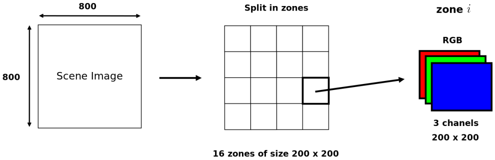

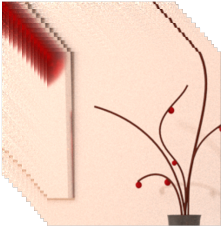

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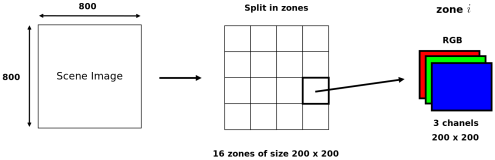

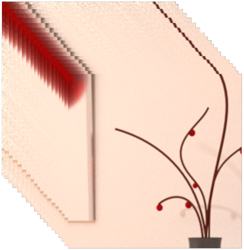

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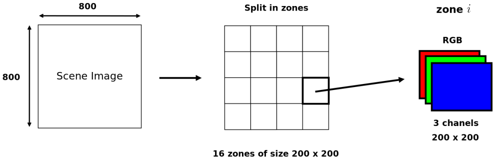

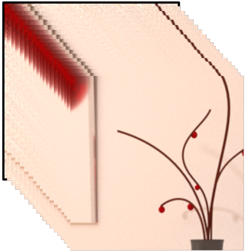

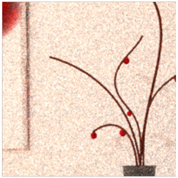

20 samples

3000 samples (reference)

Dataset creation: collect human subjective threshold

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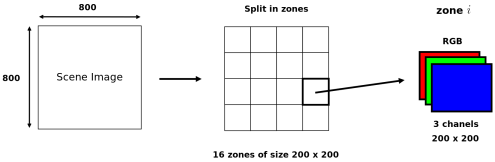

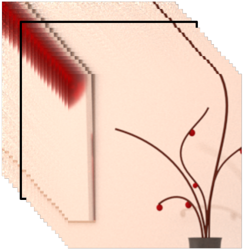

220 samples

3000 samples (reference)

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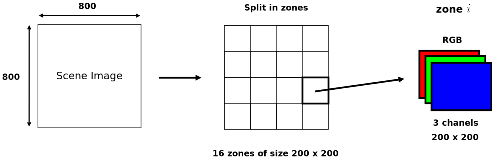

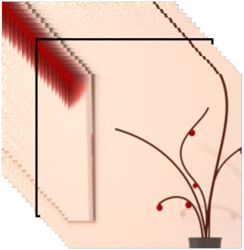

500 samples

3000 samples (reference)

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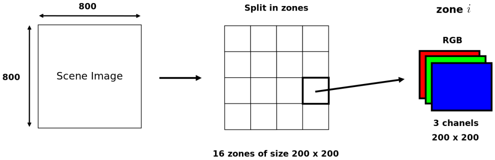

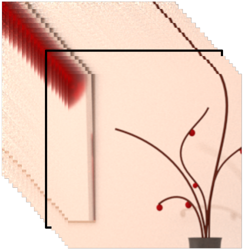

900 samples

3000 samples (reference)

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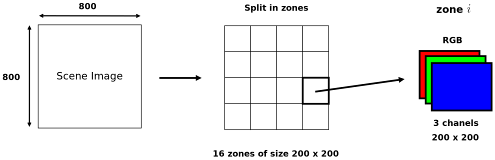

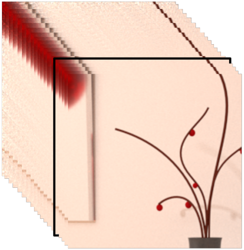

1400 samples

3000 samples (reference)

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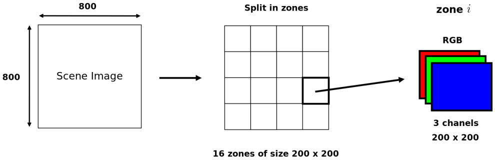

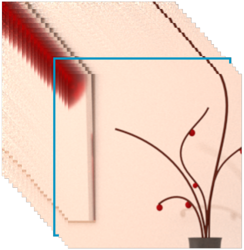

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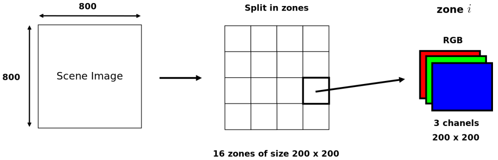

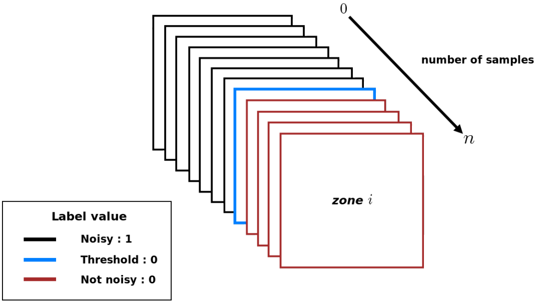

Dataset creation: overview

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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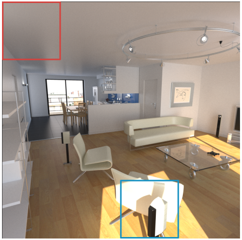
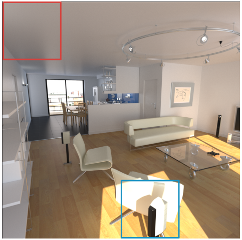


(b) Human reference



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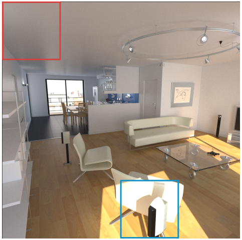
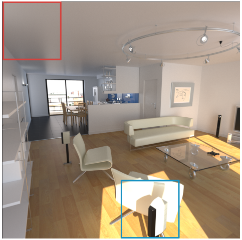


(b) Human reference
SSIM: 0.70 (< 0.95)



(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.

Build of new dataset

Previous dataset

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

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New dataset

- 40 viewpoints with $10,000$ images of 1 sample (HD images)
- only **pbrt-v3** renderer
- use of **path-tracing**
- available soon

Build of new dataset

Why saving image of 1 sample ?

- generate $\binom{10000}{k}$ images of k samples from pool of $10,000$ samples

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- **posterior** study of samples **distribution**
- use of deep learning approach (RNN, GAN, Autoencoder...)

Build of new dataset

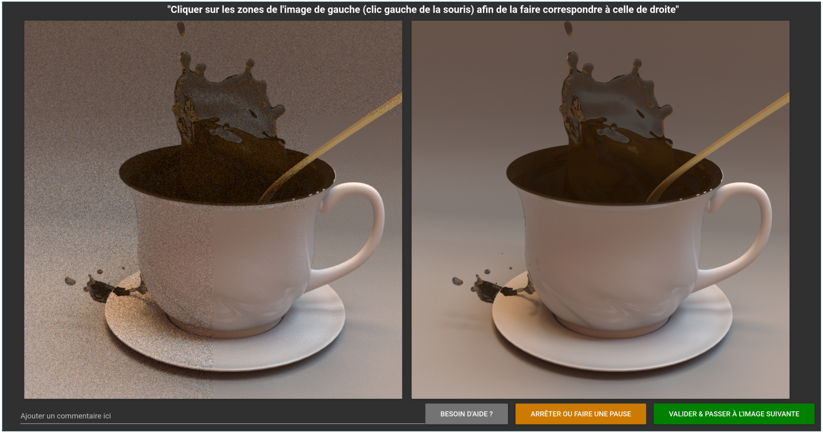

Figure 5: SIN3D web application

Expected model

Binary classification

- Model which labels image as **noisy** or **not** (**converged** or **not**)
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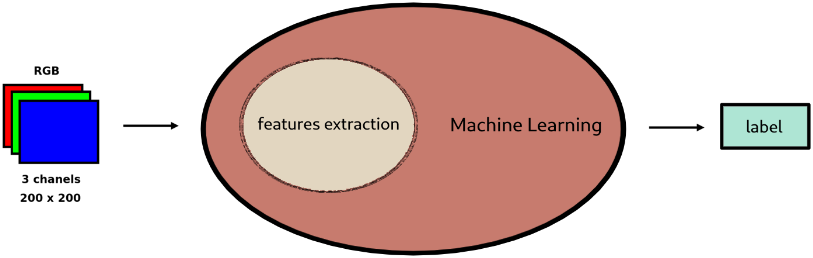
Common pipeline used



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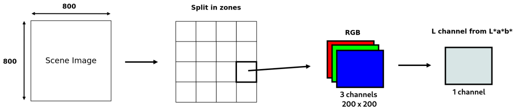
- **save** computation time
- target more complex parts of the scene

Noise detection

SVD attributes



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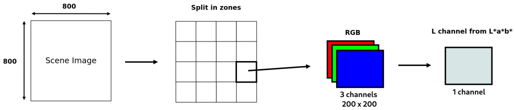
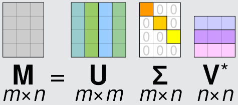


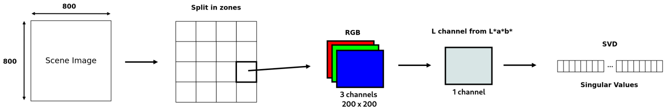
Singular Value Decomposition



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.

SVD attributes



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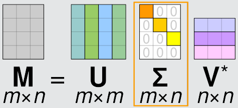

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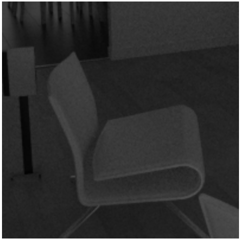
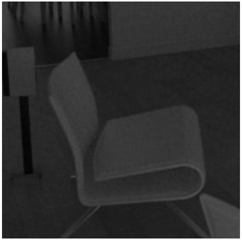
SVD attributes

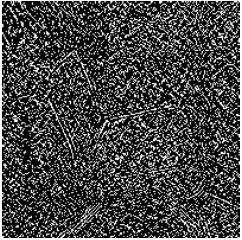
Possibility to decompose image using SVD into structure dependent and non-dependent images (Wang et al. 2013).



(a) L chanel (500 samples)

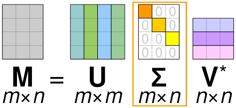


(b) SVD reconstruction (0, 50)



(c) SVD reconstruction (50, 200)

SVD-Entropy and RNN



Shannon entropy of singular values can be defined as SVD-Entropy (O.Alter, P.O.Brown, and D.Bolstein 2000):

$$H_{SVD} = -\frac{1}{\log(O)} \sum_{i=1}^{O} \overline{\sigma}_i \log(\overline{\sigma}_i) \qquad (2)$$

where :

$$\overline{\sigma}_i = \sigma_i^2 / \sum_{p=1}^{O} \sigma_p^2 \qquad (3)$$

SVD-Entropy

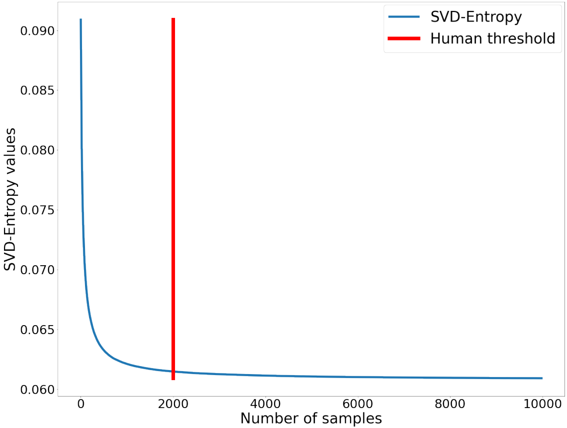
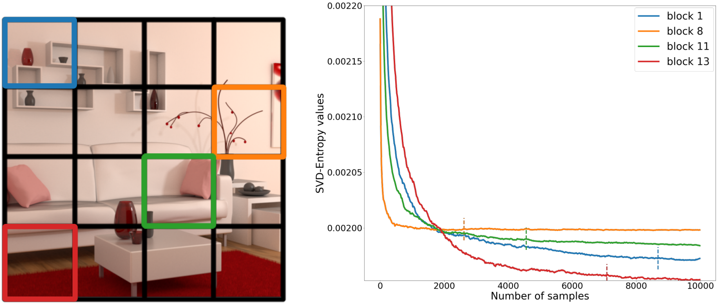


Figure 7: H_{SVD} evolution during over Kitchen image.

SVD-Entropy



(a) Selected blocks indications

(b) Normalized H_{SVD} evolution overview for the 4 selected blocks

Figure 8: Overview of the evolution of H_{SVD} for the *Living room 3* image.

SVD-Entropy and RNN

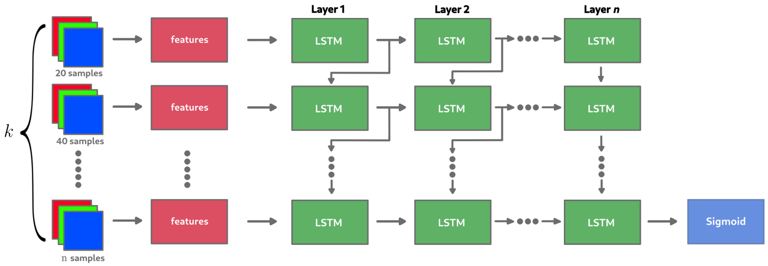


Figure 9: Recurrent neural network with different samples images level as input

SVD-Entropy and RNN

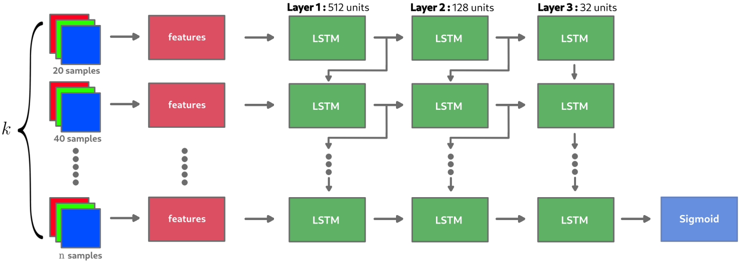


Figure 10: Recurrent neural network with different samples images level as input

SVD-Entropy and RNN

Parameters studied:

- The size of the sequence of RNN with $k \in [3, 4, ..., 10]$;
- $m \in [4, 25, 100, 400]$ (number of sub-blocks cut out within the block). Sub-blocks are respectively of size 100×100, 40×40, 20×20 and 10×10 ;
- Batch size: $b_s \in [64, 128]$;
- Samples sequence step: $n \in [20, 40, 80]$;
- Input normalization: *bnorm* or *snorm* ;
- The value extracted from a sub-block $F \in [H_{SVD}, H^1_{SVD}, H^2_{SVD}]$.

where:

$$H^1_{SVD} = -\frac{1}{\log(\frac{O}{4})} \sum_{i=0}^{O/4} \overline{\sigma}_i \log_2 \overline{\sigma}_i \qquad H^2_{SVD} = -\frac{1}{\log(O - \frac{O}{4})} \sum_{i=O/4}^{O} \overline{\sigma}_i \log_2 \overline{\sigma}_i$$

SVD-Entropy and RNN

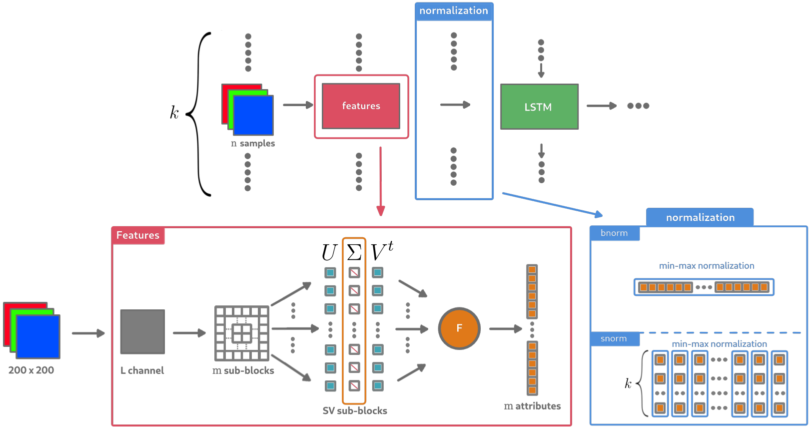


Figure 11: Pipeline for SVD-Entropy and RNN

SVD-Entropy and RNN

Fixed parameters:

- **RNN:** LSTM (512) / LSTM (128) / LSTM (32) / Sigmoid (1) ;
- Dropout for each LSTM layers set to 40% ;
- Recurrent activation function: *Hard Sigmoid* (input, forget, and output gates);
- Activation function: *Sigmoid* (hidden state and output hidden state);
- Balanced samples weights when propagating binary crossentropy loss.

Dataset specifications

Around 300.000 samples (depending of k) obtained from the 40 viewpoints. 12 blocks used as train data set, the 4 others as testing data set part. Same dataset (train / test) is used for each run (parameters combination).

SVD-Entropy and RNN

Comparisons metrics:

- Accuracy: fraction of predictions model got right;
- AUC ROC: Area Under Curve of receiver operating characteristic curve.

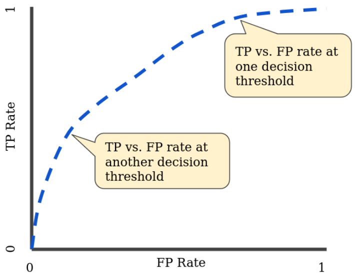


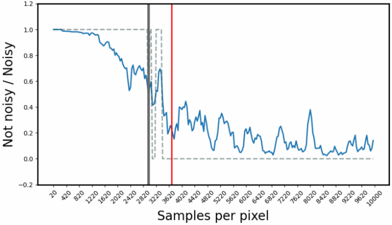
Figure 12: AUC ROC for regression logistic model

SVD-Entropy and RNN

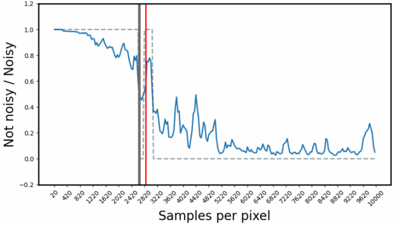
k	m	F	b_s	$bnorm$	$snorm$	n **step**	**Acc Train**	**Acc Test**	**AUC Train**	**AUC Test**
8	100	H_{SVD}	128	0	1	40	84.58 %	82.74 %	84.44 %	82.55 %
5	100	H_{SVD}	128	0	1	80	83.78 %	82.87 %	83.32 %	82.47 %
6	100	H_{SVD}	64	0	1	40	84.18 %	82.61 %	84.01 %	82.45 %
7	100	H_{SVD}	64	0	1	40	84.62 %	82.79 %	84.24 %	82.44 %
7	100	H_{SVD}	128	0	1	40	84.65 %	82.75 %	84.36 %	82.42 %
7	100	H_{SVD}	64	0	1	80	83.67 %	82.36 %	83.70 %	82.38 %
5	100	H_{SVD}	64	0	1	80	83.61 %	82.17 %	83.85 %	82.27 %
9	100	H_{SVD}	64	0	1	40	83.46 %	81.99 %	83.84 %	82.21 %
10	100	H_{SVD}	128	0	1	40	84.52 %	82.58 %	84.20 %	82.16 %

Table 1: 10 best parameters combinations results for RNN model

SVD-Entropy and RNN



(a) Block 5 on Arc sphere viewpoint

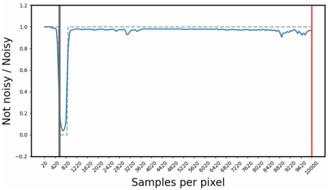


(b) Block 8 on Arc sphere viewpoint

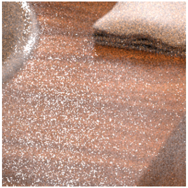
Prediction fluctuation

To overcome this problem and to make thresholds prediction more robust, it was proposed to consider that a block is no longer noisy after **3 successive noiseless** predictions.

SVD-Entropy and RNN



(a) Predictions over the block 10 of *Bathroom* viewpoint



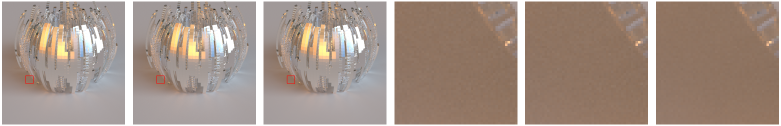
(b) Still noisy block 10 with 500 samples

(c) Reference block 10 with $10,000$ samples

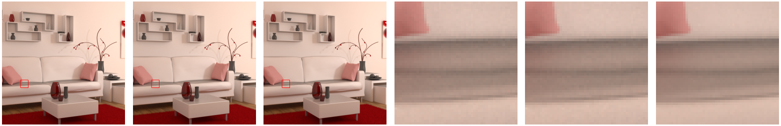
Critical prediction

The block targeted here from the bathroom point of view is still noisy up to $10,000$ samples and seems to contain a significant light reflection.

SVD-Entropy and RNN



SSIM : 0.9840 SSIM : 0.9775 SSIM : 1.0 SSIM : 0.9776 SSIM : 0.9780 SSIM : 1.0



SSIM : 0.9830 SSIM : 0.9903 SSIM : 1.0 SSIM : 0.9927 SSIM : 0.9921 SSIM : 1.0

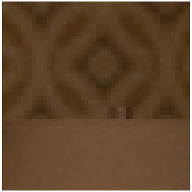
SSIM : 0.9880 SSIM : 0.9604 SSIM : 1.0 SSIM : 0.9878 SSIM : 0.9650 SSIM : 1.0

RNN - H_{SVD} Human Reference RNN - H_{SVD} Human Reference

SVD-Entropy and RNN

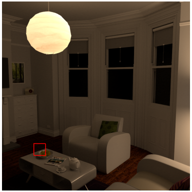
SSIM : 0.9898

SSIM : 1.0

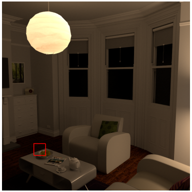


SSIM : 0.9833

SSIM : 1.0

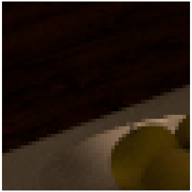


SSIM : 0.9845



SSIM : 1.0

SSIM : 0.9806



SSIM : 1.0

RNN - H_{SVD}	Reference	RNN - H_{SVD}	Reference

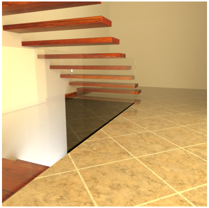
SVD-Entropy and RNN

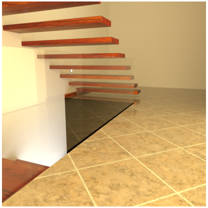
San miguel

10000	8220	6540	10000
9460	8500	8420	10000
6620	8540	10000	10000
9380	6620	10000	9620

Staircase 2

3180	2820	4860	7300
3180	3820	5900	9460
5620	3660	2260	2820
2500	2220	1780	2020





Point of view | Predicted thresholds | H_{SVD} RNN prediction | 10, 000 samples

Conclusion

Conclusion

- Generic method to establish a perceptual stopping criterion
- Some critical cases (lack of data for better generalisation ?)
- Data are available in `https://prise3d.univ-littoral.fr`

Conclusion

Future works:

- MDPI Entropy journal : SVD-Entropy and RNN (submitted) ;
- Use of HDR images for same experiment and make comparisons ;
- Application of *Median Of meaNs* in rendering. Conference or graphics-oriented journal (in progress) ;
- Features selection optimisation : Conference or journal oriented in machine learning / optimisation ;
- Image database : human thresholds, images generated with 1 sample (RAWLS) and images in PNG formats.

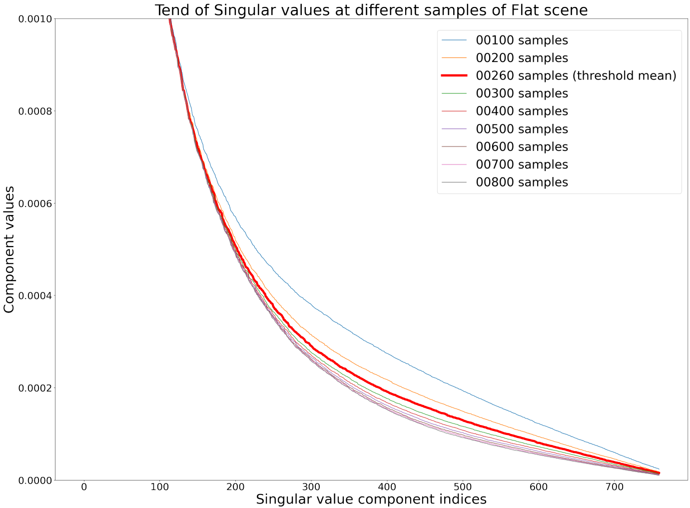
Conclusion

In continuity :

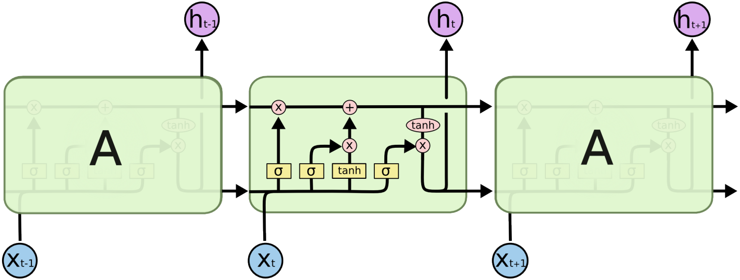
- Improve deep learning works (GAN for denoising) ;
- Create new base with 3D images (stereoscopic).

Thanks for your attention!

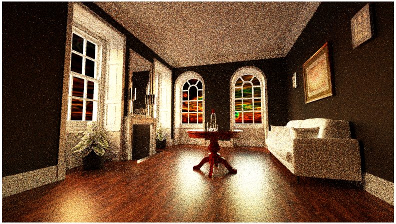
Backup: use of singular values



Backup: LSTM cells



Backup: distribution analysis



(a) Variance

(b) Standard deviation

(c) Skewness

(d) Kurtosis