

# ANR Prise 3D

**Thesis :** Noise detection in stereoscopic synthesis images  
using machine learning

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LISIC - Imap

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## Noise in synthesis images

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# Output overview



(a) After 50 samples



(b) After 300 samples



(c) After 1200 samples

**Figure 1:** Preview of the images obtained by the Maxwell rendering engine of the Cuisine01 (D) scene at different generation times

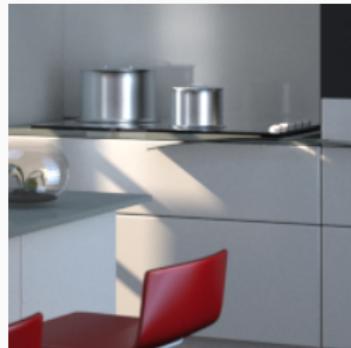
## Sub image overview



(a) After 50 samples



(b) After 300 samples



(c) After 1200 samples

**Figure 2:** Preview of the sub images obtained by the Maxwell render engine of the Cuisine01 (D) scene at different generation times

## Noise overview

As we can see after 50 minutes of generation, a perceptual noise is generated due to the Monte-Carlo (stochastic) process.

## Problematic

- How to detect this **perceptual** noise ?

# Problematic

- How to detect this **perceptual** noise ?
- How to **quantify** it ?

## Image quality

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# Image quality metrics

Image quality assessment (IQA) metrics can be divided in three categories :

- Full reference (FR) metrics

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- Reduced reference (RR) metrics
- No reference (NR) metrics

# Image quality metrics

- Full reference :
  - Peak Signal to Noise Ratio (PSNR)
  - Structural Similarity Index Metrix (SSIM) [Wang et al., 2004]
  - Multi-Scale SSIM (MS-SSIM) [Wang et al., 2003]
  - ...
- No-reference :
  - Blind Image Quality Index (BIQI) [Moorthy and Bovik, 2010]
  - Blind Referenceless Image Spatial Quality Evaluator (BRISQUE) [Mittal et al., 2012]
  - Perception-based Image QULITY Evaluator (PIQUE) [N. et al., 2015]
  - ...

## Image quality metrics Databases

Database of natural images are available with distortions applied on these images.

A **subjective** score is then associated to these images.

- TID2008
- LIVE
- CSIQ
- ...

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### Model objective

Correlate as well as possible with the subjective scores.

## Image quality metrics Databases

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A **subjective** score is then associated to these images.

- TID2008
- LIVE
- CSIQ
- ...

### Synthesis images database

Currently in the literature, there is no database that identifies the noise present into synthesis images.

# Database

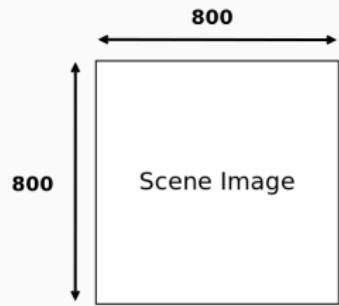
---

# Scenes

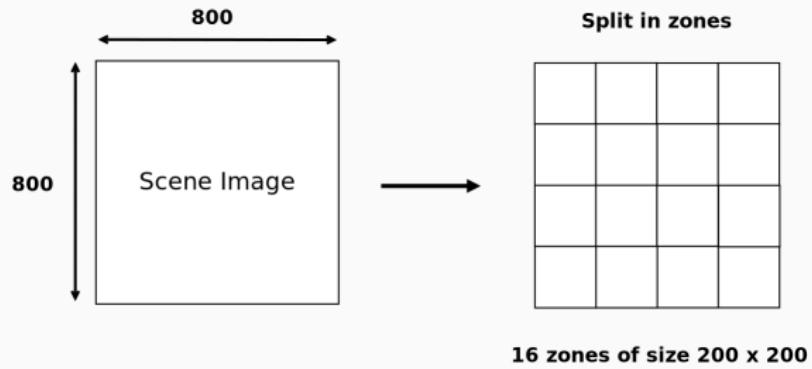
ID	Scene	Indices (samples)	Step	Images
A	Appart02	20 → 900	10	89
D	Cuisine01	20 → 1200	10	119
G	SdbCentre	20 → 950	10	94
H	SdbDroite	20 → 950	10	94

**Table 1:** Reduced database information

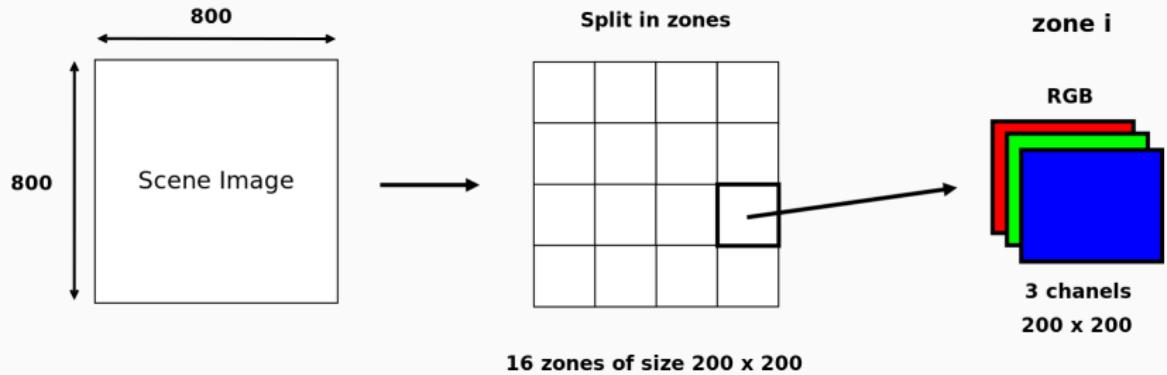
# Database explanations



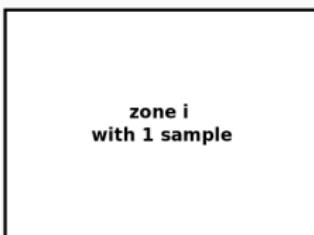
# Database explanations



# Database explanations

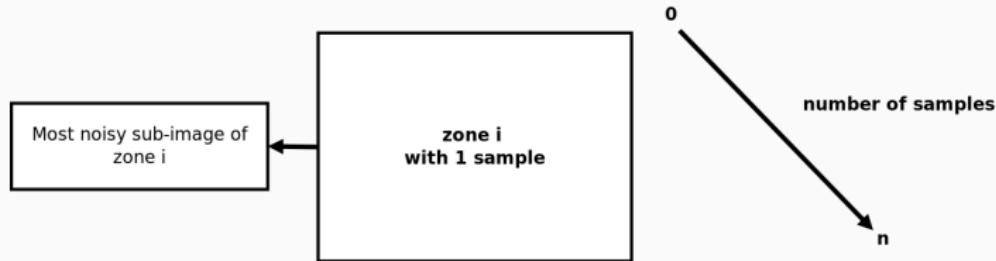


# Subjective perceptual threshold

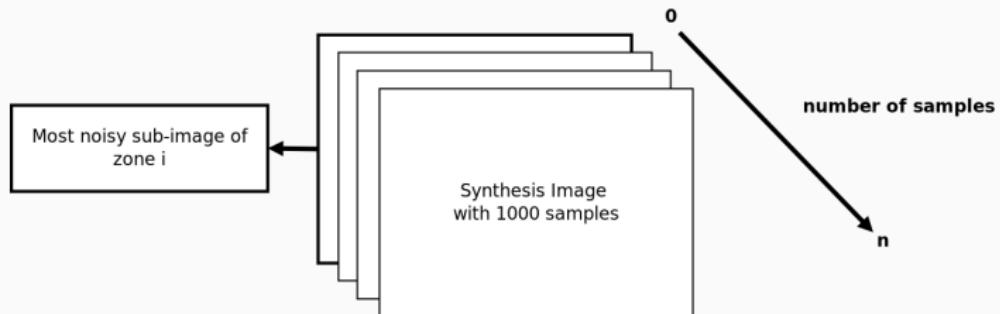


**zone i  
with 1 sample**

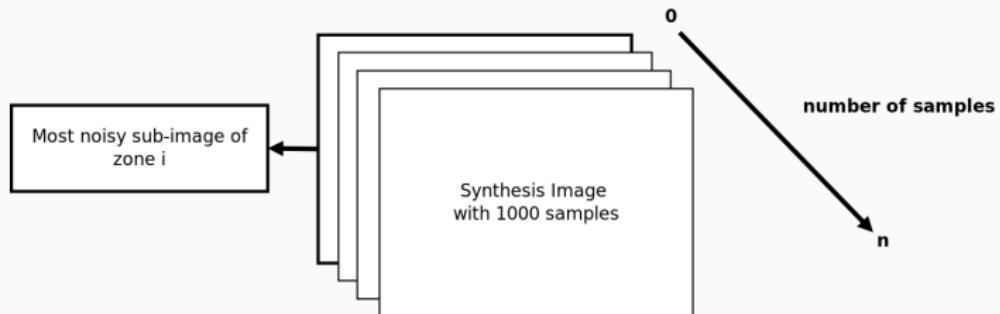
# Subjective perceptual threshold



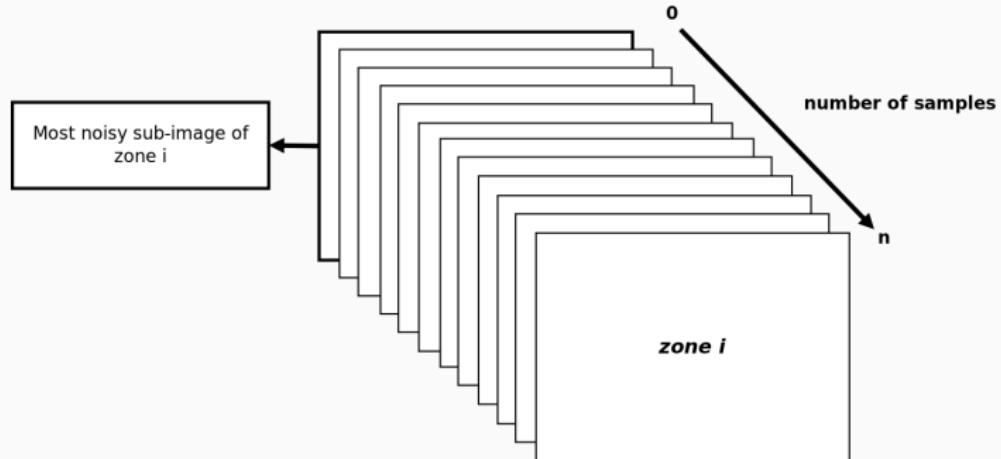
# Subjective perceptual threshold



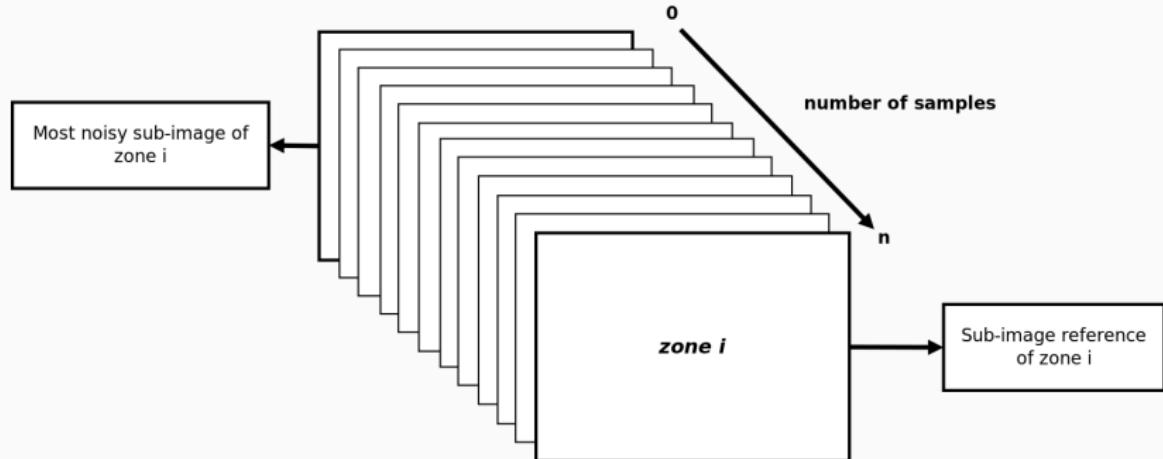
# Subjective perceptual threshold



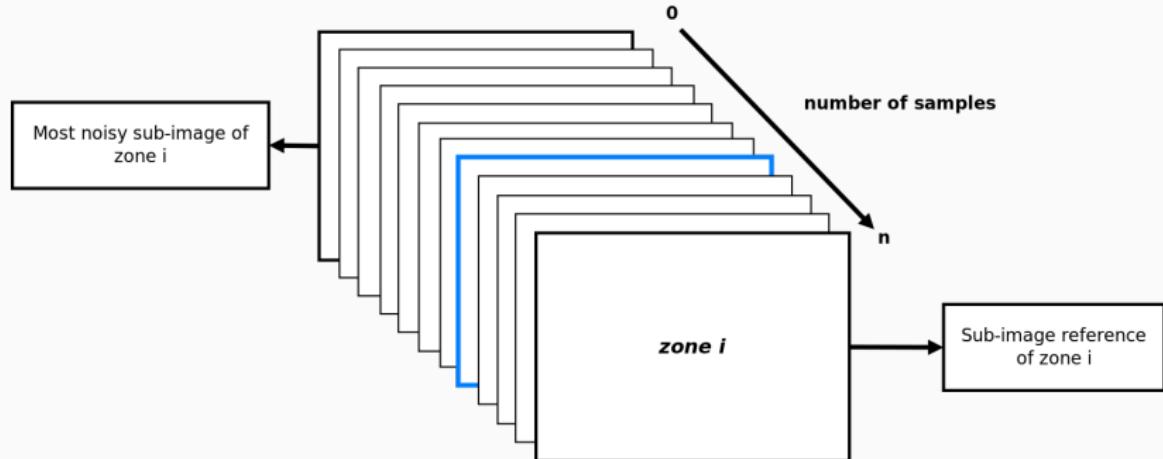
# Subjective perceptual threshold



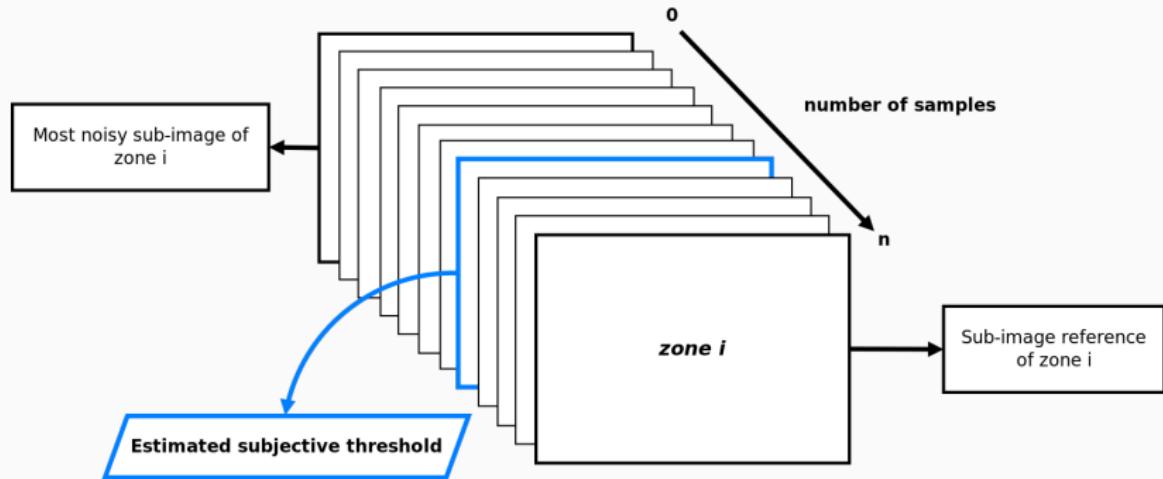
# Subjective perceptual threshold



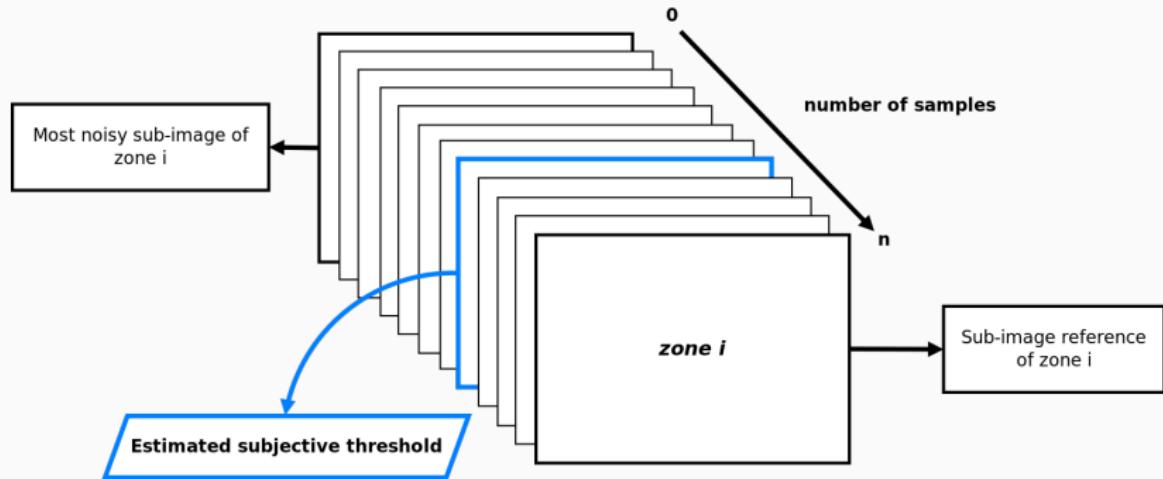
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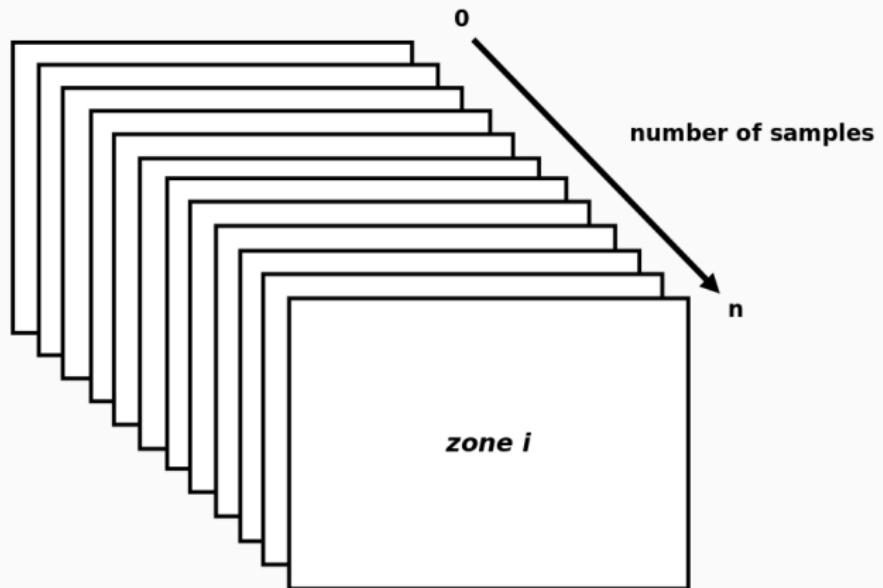
# Subjective perceptual threshold



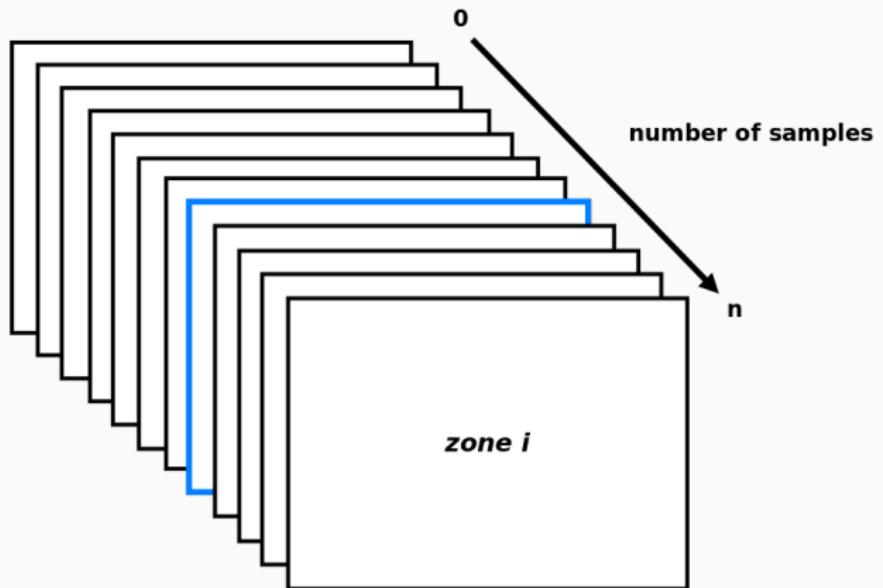
## Information

The final threshold for a zone is the **mean** of all subjective thresholds obtained.

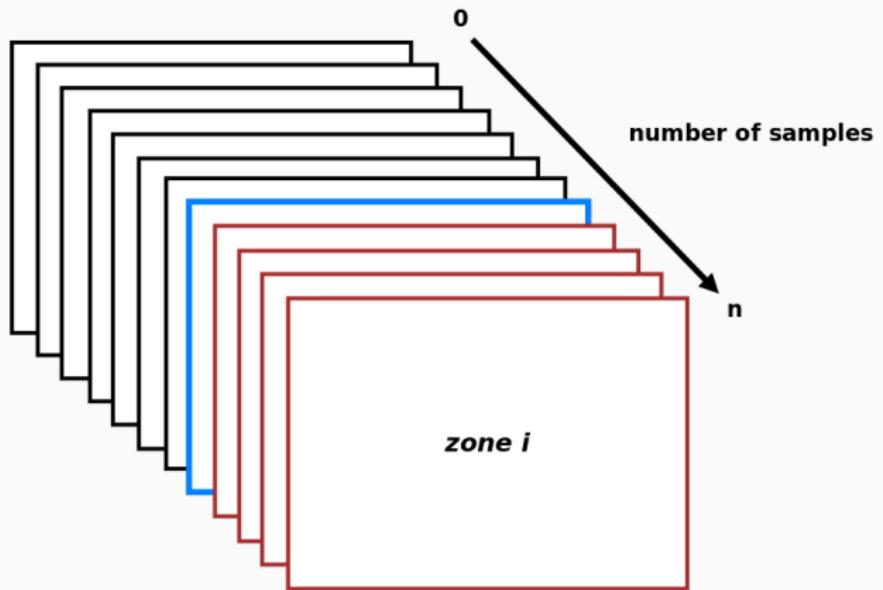
## How sub-images are classified ?



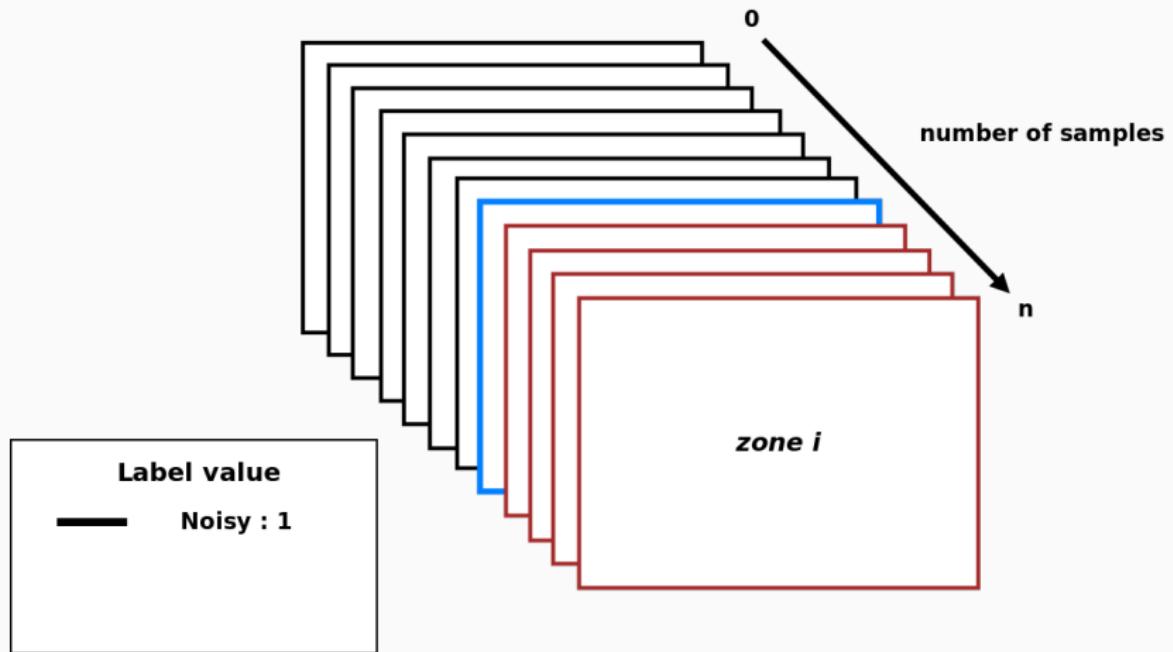
## How sub-images are classified ?



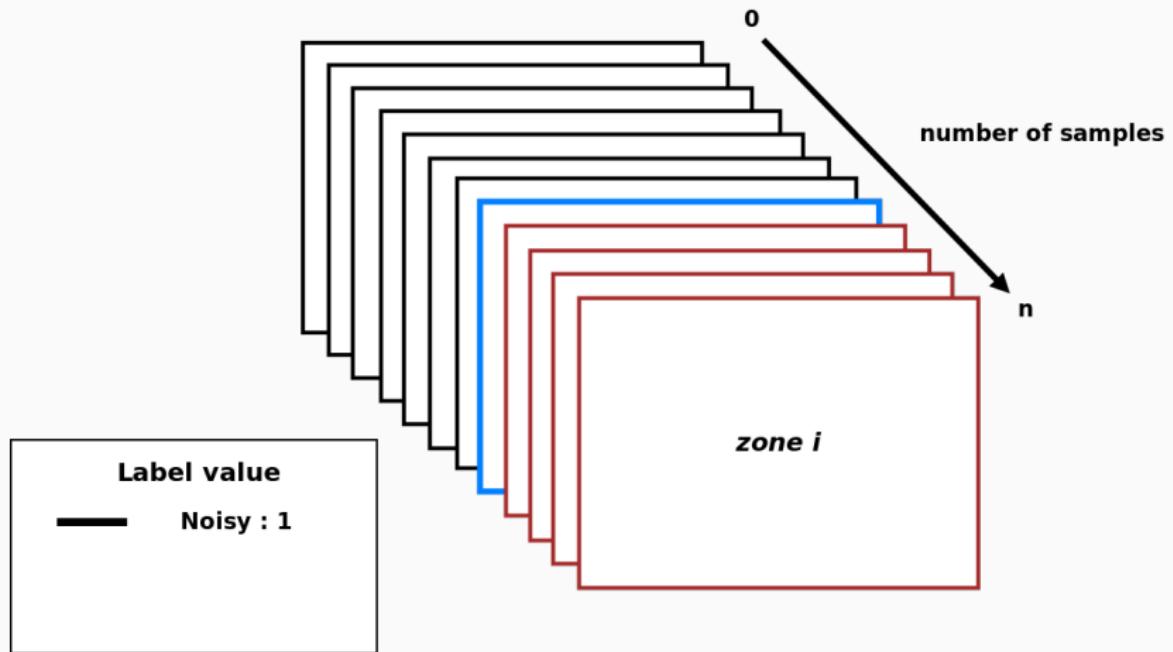
## How sub-images are classified ?



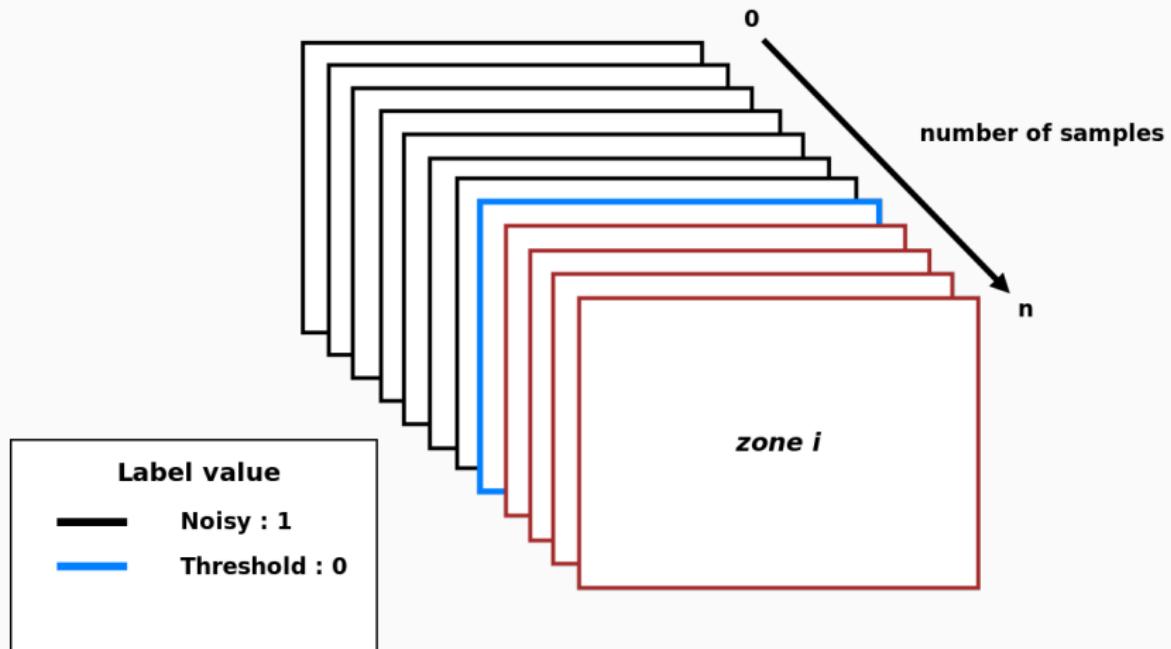
# How sub-images are classified ?



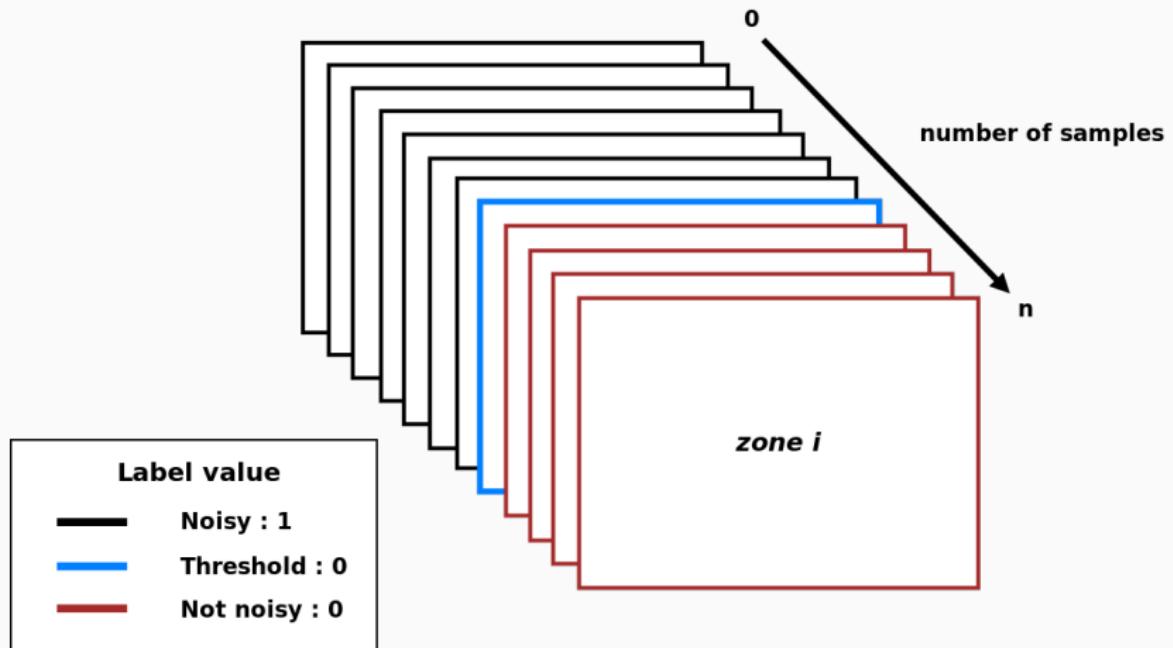
# How sub-images are classified ?



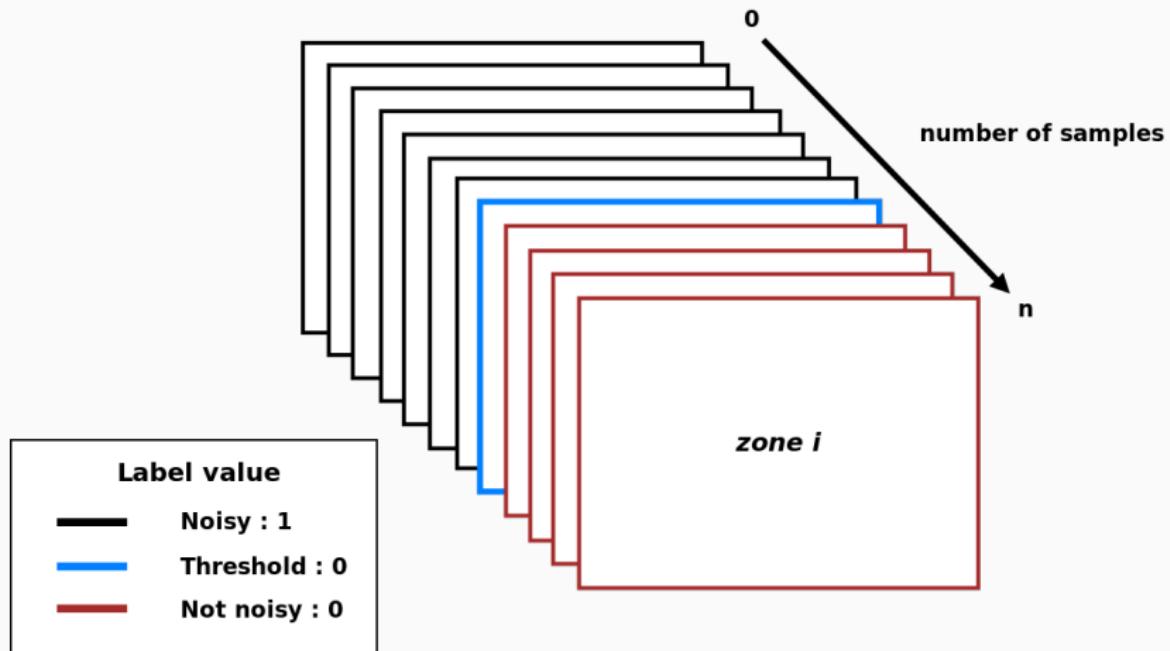
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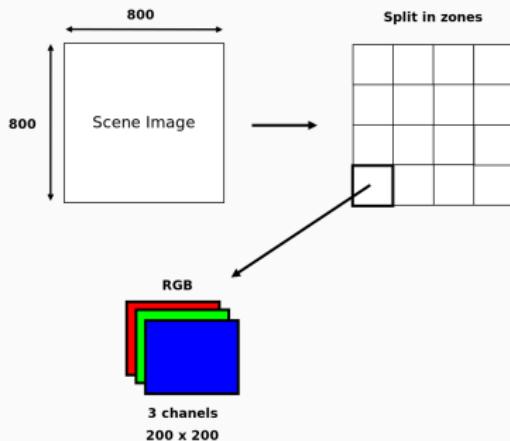
## Label attribution

For each zone, a **label** value (0 or 1) is associated to the sub-image obtained at  $n$  samples during the generation.

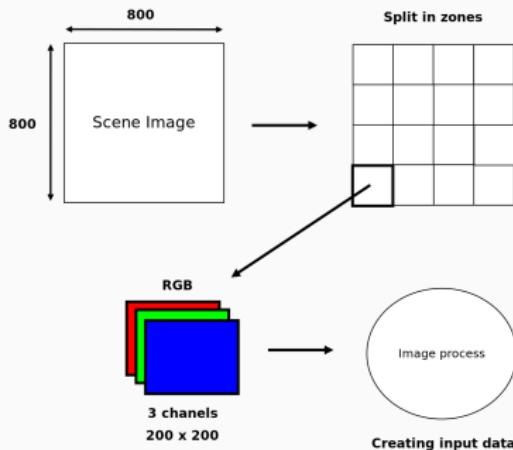
## **Current works**

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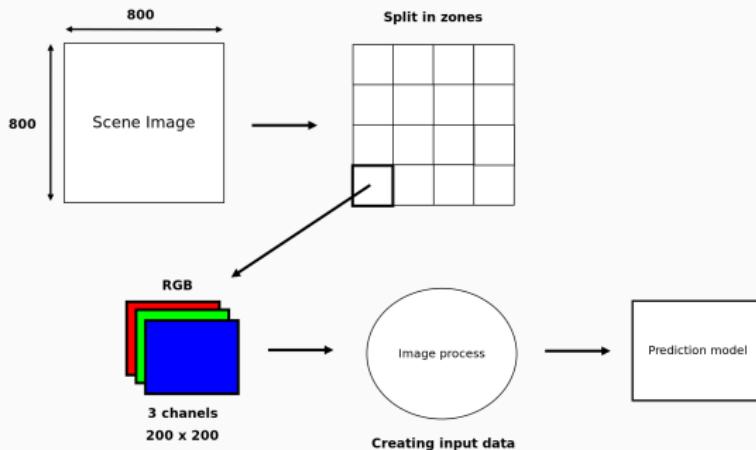
# What we need ?



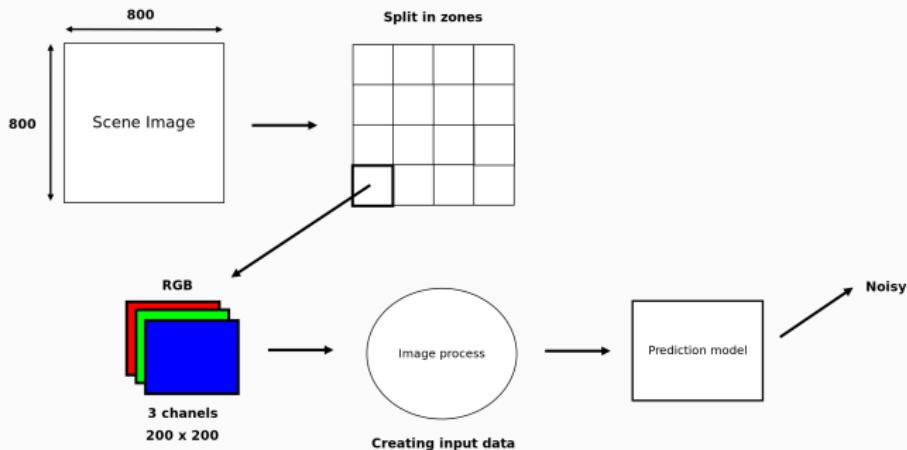
# What we need ?



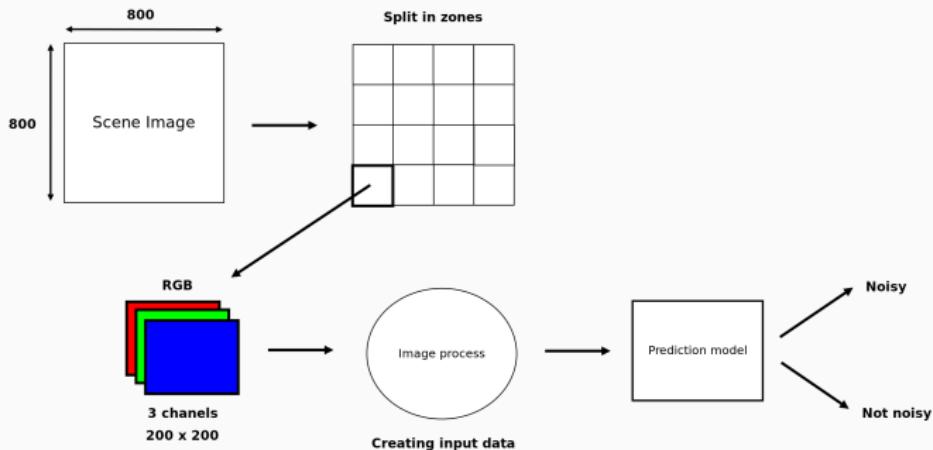
# What we need ?



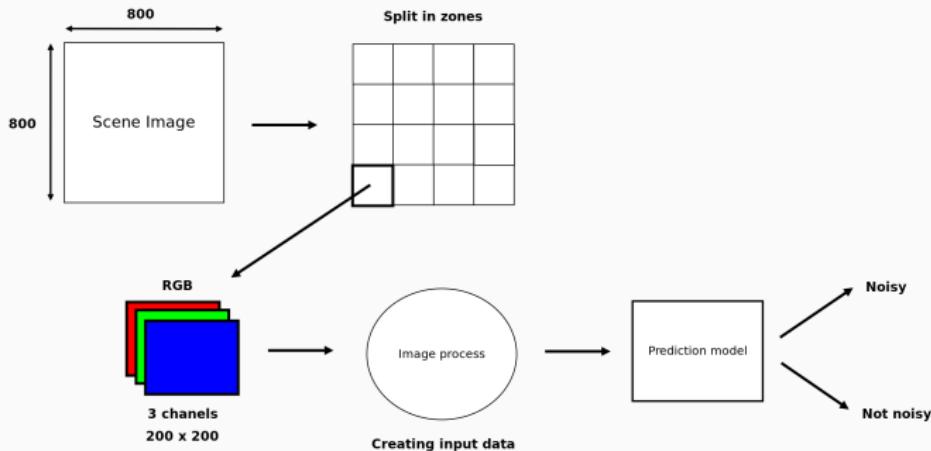
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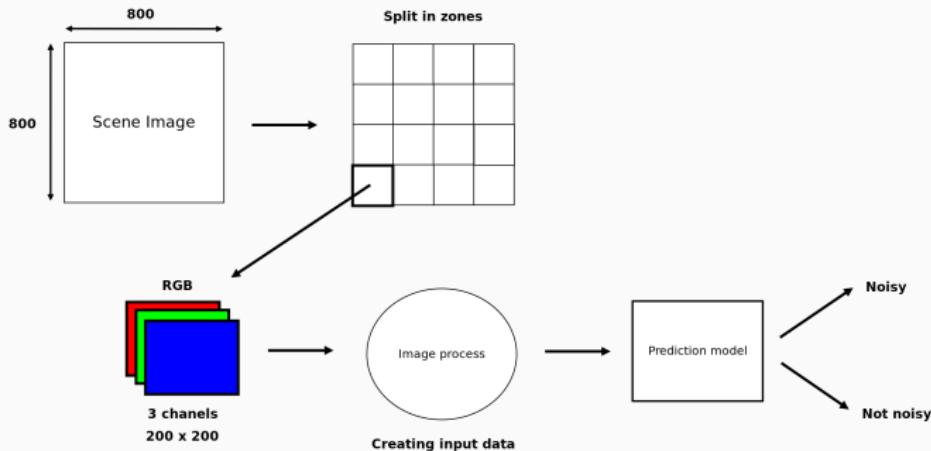


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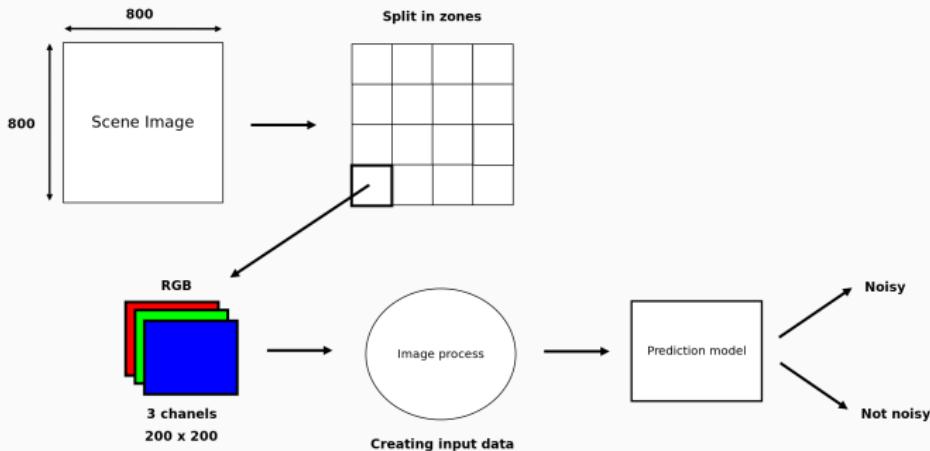
- What kind of data model wants in order to classify as well as possible sub-images

# What we need ?



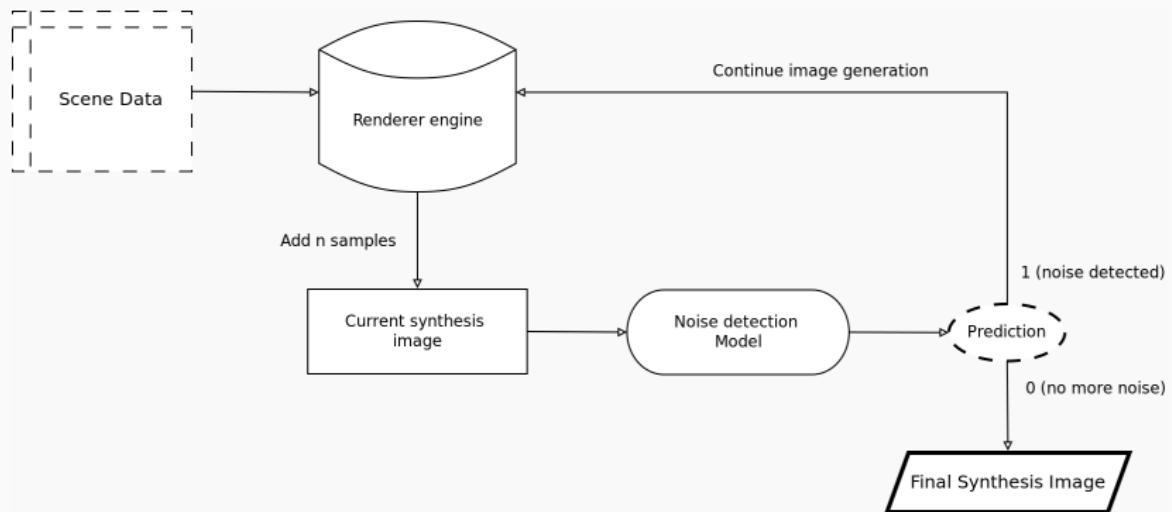
- What kind of data model wants in order to classify as well as possible sub-images
- The whole sub-image or reduced information ?

# What we need ?

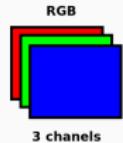


- What kind of data model wants in order to classify as well as possible sub-images
- The whole sub-image or reduced information ?
- What kind of data well described the perceived noise in image ?

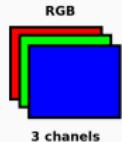
# Expected model interactions



# Reduction of canals

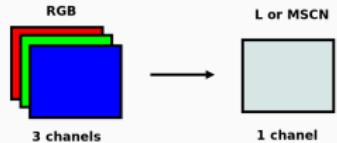


# Reduction of canals

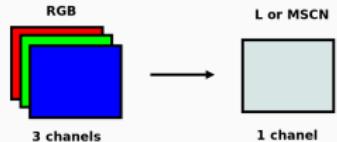


- Using **L** (luminance) canal from L\*a\*b transformation.
- Using the Mean Substracted Contrast Normalized (MSCN, see Eq. 3) matrix.

# Pool of final features



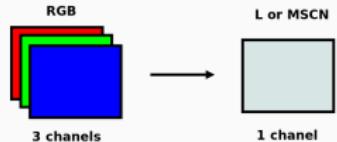
# Pool of final features



## Hypothesis

Low bits values from images perhaps keep information about noise

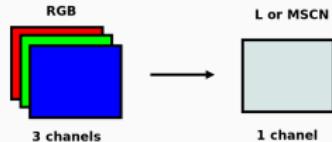
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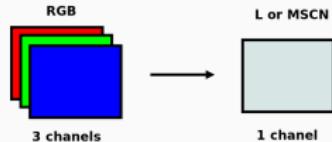
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Low bits values from images perhaps keep information about noise

### low\_bits\_3



# Pool of final features



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Low bits values from images perhaps keep information about noise

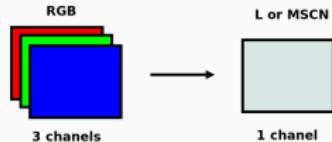
### low\_bits\_3



### low\_bits\_4\_shifted\_2



# Pool of final features



## Hypothesis

Low bits values from images perhaps keep information about noise

### low\_bits\_3



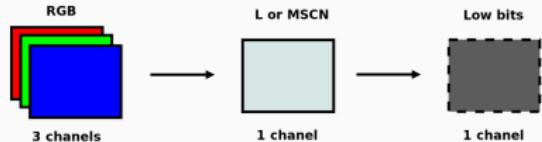
### low\_bits\_4\_shifted\_2



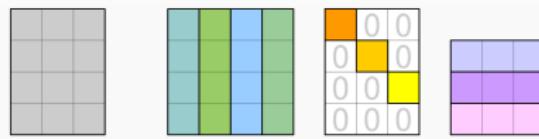
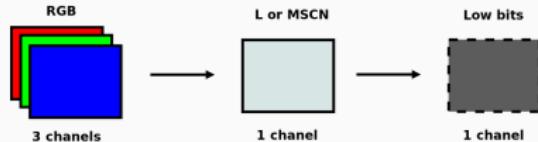
$$F = \{lab, mscn, low\_bits\_4\_shifted\_2\} + [low\_bits\_i]$$

with  $i \in [2, 6]$  and  $|F| = 8$

# Dimension reduction using SVD

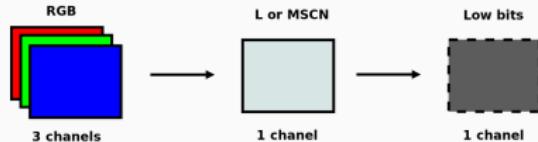


# Dimension reduction using SVD



$$M_{m \times n} = U_{m \times m} \Sigma_{m \times n} V^*_{n \times n}$$

# Dimension reduction using SVD



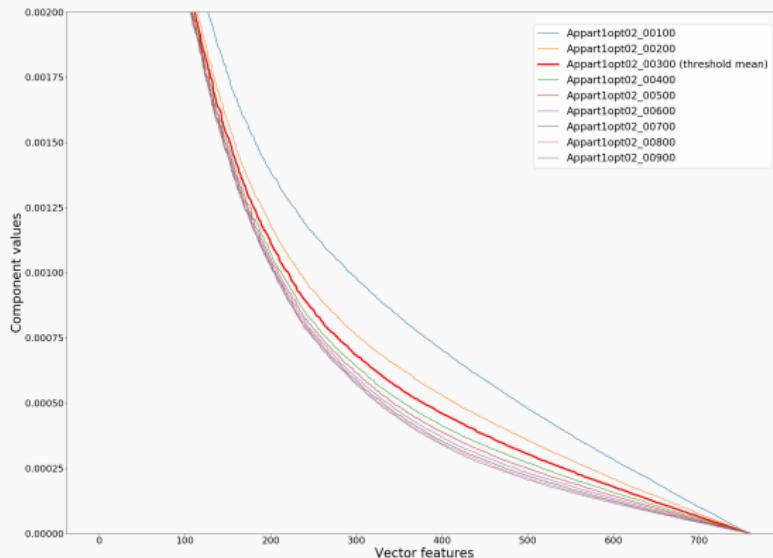
The diagram shows the Singular Value Decomposition (SVD) of a matrix  $M$  into three components:

$$M_{m \times n} = U_{m \times m} \Sigma_{m \times n} V^*_{n \times n}$$

Each component is represented by a grid of colored squares:

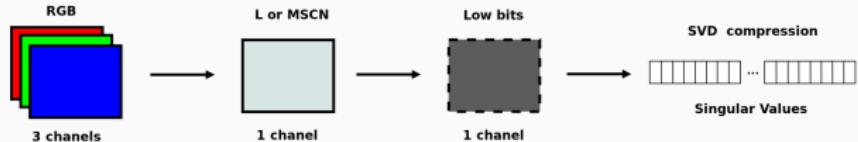
- $M$ : A gray  $m \times n$  grid.
- $U$ : A vertical stack of colored  $m \times m$  squares (blue, green, blue, green).
- $\Sigma$ : A  $m \times n$  grid with a red border, containing colored squares (orange, yellow, yellow, orange) at the top-left and zeros elsewhere.
- $V^*$ : A horizontal stack of colored  $n \times n$  squares (purple, pink, purple, pink).

# Why the use of SV vector ?

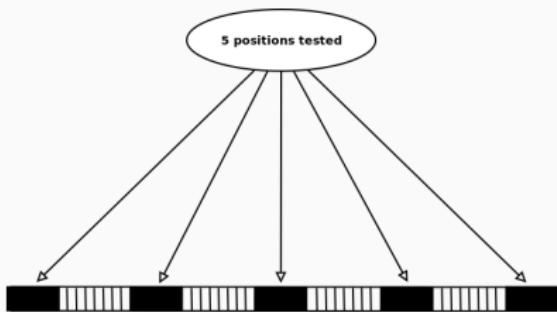
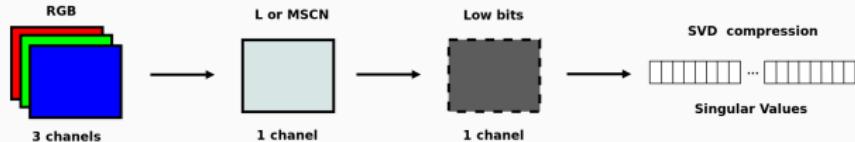


**Figure 3:** Singular values vector obtained from images of Appart02 (A) scene with L channel

# Another reduction



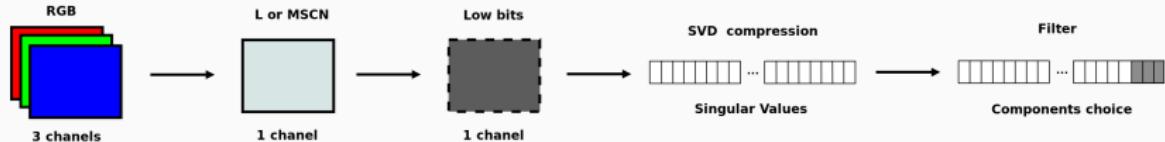
# Another reduction



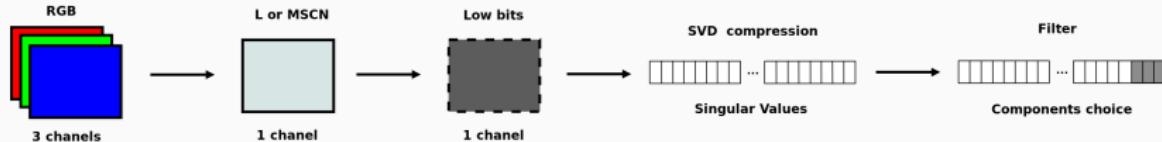
- Positions set,  $P$  with  $|P| = 5$
- Potential sub-vectors size,

$$N = [4, 8, 16, 26, 32, 40]$$

# Other parameters : normalization



## Other parameters : normalization

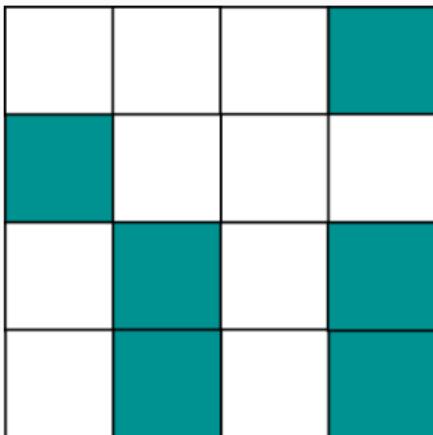
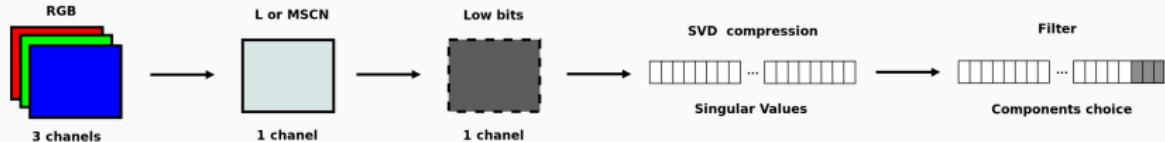


$$K = [svd, svdn, svdne]$$

where

- svd : no normalization
- svdn : sub-vector is normalized itself
- svdne : sub-vector is normalized depending the **min** and **max** sub-vectors interval values from the whole dataset

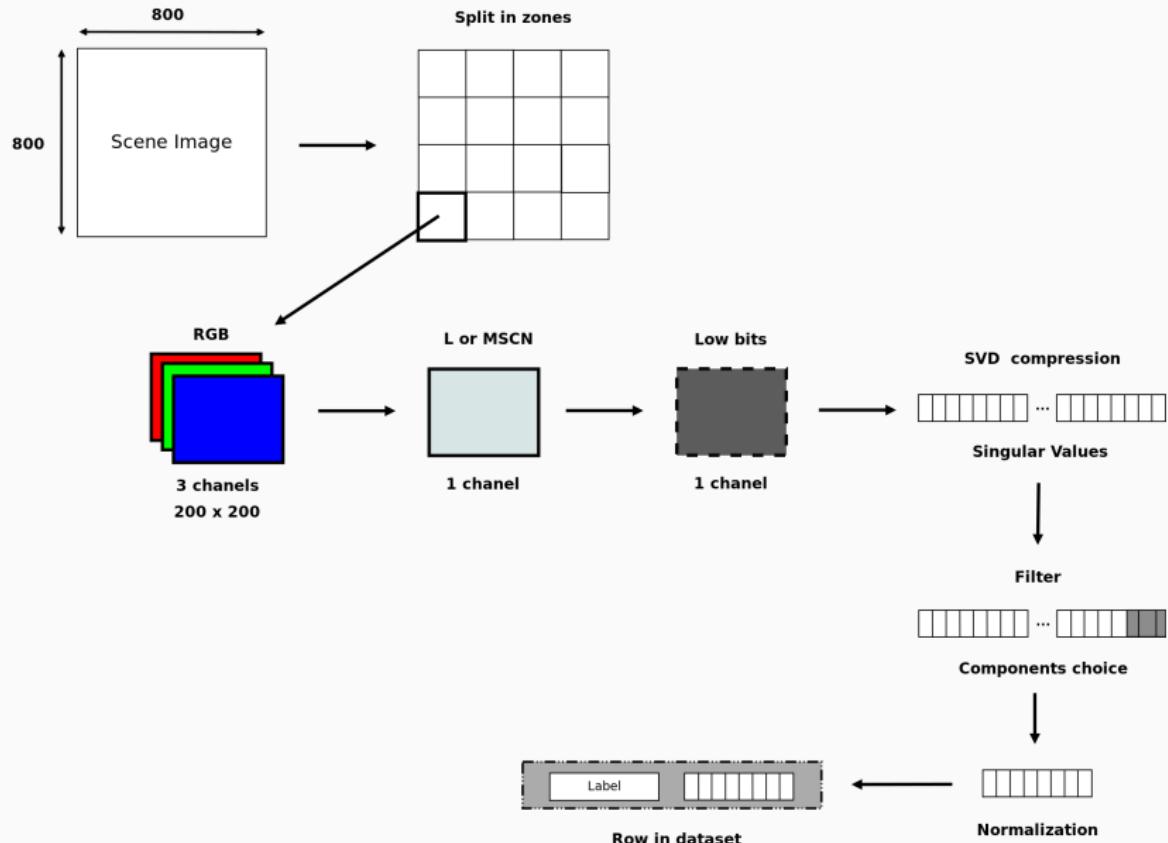
## Other parameters : training data



Zones are selected randomly with

$$Z = [4, 6, 8, 10, 12]$$

# Final features as model input



# Kind of models

We define 3 model architectures to fit as well as possible final features :

- M1 : **Support Vector Machine**
- M2 : **Ensemble\_model** (3 sub-models)
- M3 : **Ensemble\_model\_v2** (5 sub-models)

## Ensemble models configurations

These ensemble models are in fact **voting classifier** with principle of fair voting and regulated on *soft*.

## Parameters : total combinations

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Finally using all these parameters, we have a lot of combinations :

$$\begin{aligned}r &= 3 \times |F| \times |P| \times |N| \times |K| \times |Z| \\&= 3 \times 8 \times 5 \times 6 \times 3 \times 5 \\&= 10800\end{aligned}$$

# Build of specific dataset

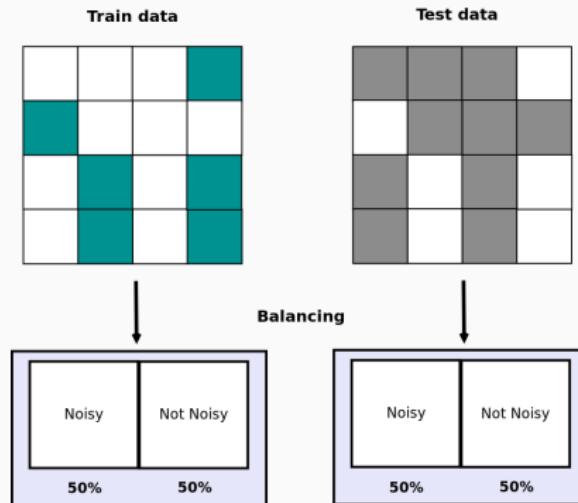
**Train data**


# Build of specific dataset

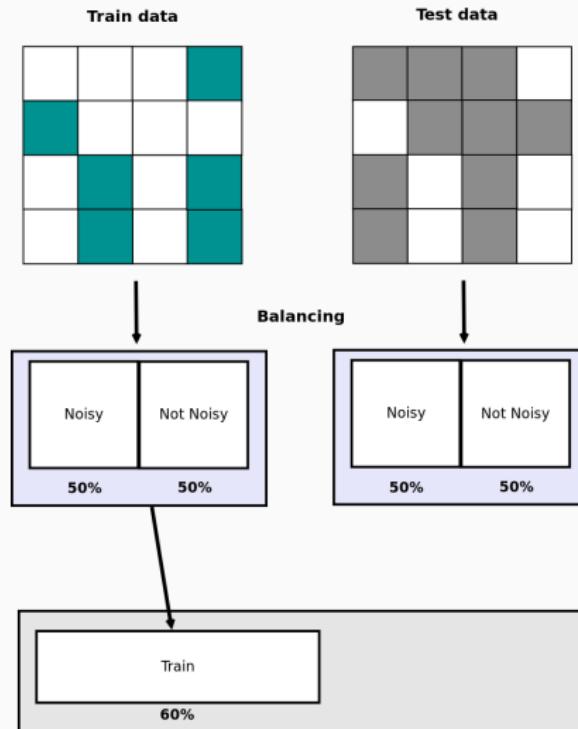
Train data


Test data

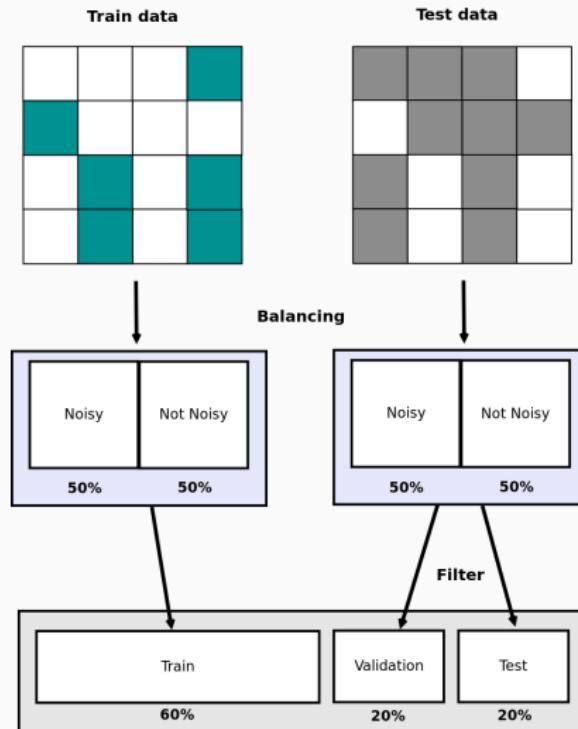

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## How to compare model ?

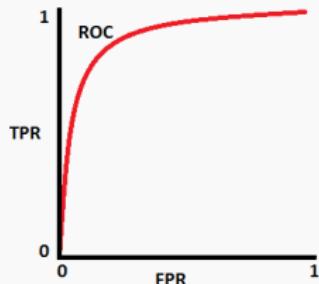
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The Area Under The Curve Receiver Operating Characteristics score is used to compare these models based on **test** dataset.

## How to compare model ?

The Area Under The Curve Receiver Operating Characteristics score is used to compare these models based on **test** dataset.

**AUC - ROC** score is a performance measurement for classification problem. It tells how much model is capable of distinguishing between classes.

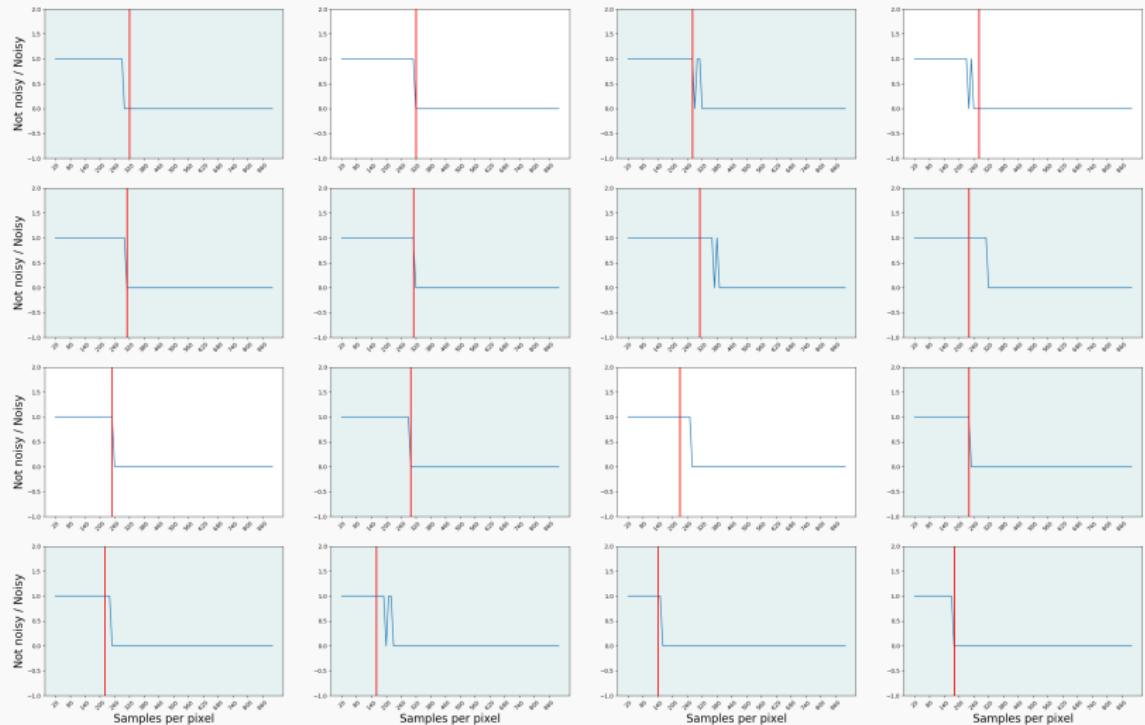


# First results

Model	feature	size	interval	zones	ROC Train	ROC Val	ROC Test
M3	lab (svd)	40	[80, 120[	12	0.9418	0.9023	0.9219
M2	lab (svd)	32	[84, 116[	4	0.9158	0.8724	0.9153
M2	lab (svd)	40	[80, 120[	12	0.9629	0.9049	0.9145
M2	lab (svdne)	26	[87, 113[	6	0.9337	0.8763	0.9089
M3	low_bits_2 (svd)	40	[0, 40[	12	0.9567	0.8417	0.9081

**Table 2:** The 5 best models found based on AUC ROC score

# Simulation from best model



**Figure 4:** Simulation of each zone obtained on scene Appart02 (A)

# Simulation from best model



**Figure 5:** Simulation of each zone obtained on scene SdbDroite (H)

# Other approaches

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## Features

- Statistics approach, use of statistics from sub-block
  - Mean, Median, Percentile at 25%, Percentile at 75%, Variance, Area under curve

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- Use of correlation matrix from SV

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- Statistics approach, use of statistics from sub-block
  - Mean, Median, Percentile at 25%, Percentile at 75%, Variance, Area under curve
- Use of MSCN statistics
- Use of correlation matrix from SV
- Use of correlation between SV and labels

# Other approaches

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## Model

- Use of Deep Learning approach as model

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- Statistics approach, use of statistics from sub-block
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- Use of MSCN statistics
- Use of correlation matrix from SV
- Use of correlation between SV and labels

## Model

- Use of Deep Learning approach as model

## Remark

All of these approaches seems to give same results as before.. Hence, **overfitting** or bad approximation.

## Conclusion

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Difficult to have a model which **generalizes** for each scene but why ?

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Difficult to have a model which **generalizes** for each scene but why ?

- Scene seems to have each own components to describe the noise
- Difficult to find the best components from data

# Conclusion

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Difficult to have a model which **generalizes** for each scene but why ?

- Scene seems to have each own components to describe the noise
- Difficult to find the best components from data

Solution :

- Find a way to choose components depending of the scene ?
- Use of work of André and Rémi : SV entropy

## Noise detection

- Study of Singular Values behaviors from few noises
- Use of Generative Adversarial Network model
- Use of Transfer learning (Alexnet, Resnet, ...)
- Work with University of Lille 3
- Tackle the **stereoscopic** aspect

## Noise detection

- Study of Singular Values behaviors from few noises
- Use of Generative Adversarial Network model
- Use of Transfer learning (Alexnet, Resnet, ...)
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- Tackle the **stereoscopic** aspect

## Denoising

- Use of Deep Learning approaches (autoencoder and others...) to denoise images
- Create custom denoiser for synthesis images

# Development

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Developments are centralized into the *IPFML* python package  
[\(<https://github.com/jbuisine/IPFML>\).](https://github.com/jbuisine/IPFML)



**Questions?**

## References i

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## Backup slides (PSNR)

$$PSNR = 10 \times \log_{10} \left( \frac{d^2}{MSE} \right) \quad (1)$$

where  $d$  is the signal dynamics (the maximum possible value for a pixel). In the standard case of an image where the components of a pixel are encoded on 8 bits,  $d = 255$  and  $MSE$  (see Eq. 2) is the mean square error between the 2 images.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (I_o(i,j) - I_r(i,j))^2 \quad (2)$$

where  $I_o$  is the distorted image and  $I_r$  the reference image, both of size  $m \times n$

## Backup slides (MSCN)

To calculate the MSCN matrix, we must first convert our RGB image to a grayscale image. The MSCN will extract Natural Structure Scene (NSS) information from this grayscale image. An operation is applied to the luminance image  $I(i,j)$  to produce :

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \quad (3)$$

where  $i \in 1, 2 \dots M, j \in 1, 2 \dots N$  are spatial indices,  $M, N$  are respectively the height and width of the image,  $C$  is constant, which is set to 1 to avoid instability

## Backup slides (MSCN)

and where,

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j) \quad (4)$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} (I_{k,l}(i,j) - \mu(i,j))^2} \quad (5)$$

In (4) and (5)  $w = \{w_{k,l} | k = -K, \dots, K, l = -L, \dots, L\}$  is a circularly symmetrical 2D Gaussian weighting function sampled at 3 standard deviations ( $K = L = 3$ ) and recalculated at unit volume. Then, the transformed luminance values of (3) are called Mean Subtracted Contrast Normalized (MSCN) coefficients.

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- **Ensemble\_model\_v2**, composed of :
  - SVM with same configuration as previous model
  - Random Forest with 100 estimators
  - Logistic Regression with *liblinear* kernel
  - KNeighbors Classifier
  - Gradient Boosting Classifier with 100 estimators and learn step set to 1.0.