Texture-Aware Superpixel Segmentation
(Superpixels adaptés localement aux textures)

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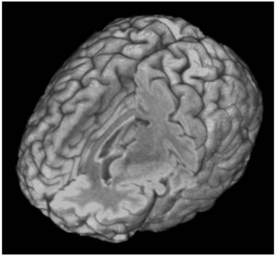
Introduction

Large data $\rightarrow$ high computational times

Image HD



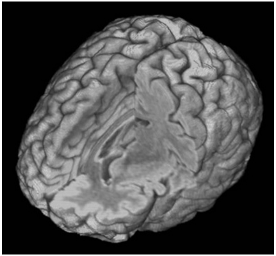
Volume 3D

Video

Introduction

Large data $\rightarrow$ high computational times $\rightarrow$ Dimension reduction

Image HD

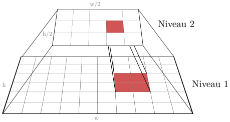


Volume 3D

Video

Large data → high computational times → Dimension reduction

- Regular multi-resolution:
  Decompose the image into regular blocks



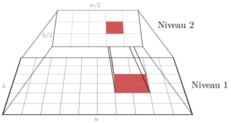

Image


Decomposition into blocks


Average colors

Large data → high computational times → Dimension reduction

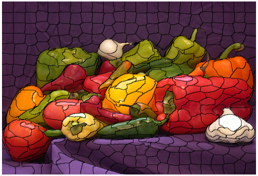
- Regular multi-resolution:
  Decompose the image into regular blocks
- Superpixels (since [Ren and Malik, 2003]):
  Local grouping of pixels with homogeneous colors




Image


Decomposition into blocks


Average colors


Decomposition into superpixels


Average colors

Desired properties of superpixel methods:

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- Limited parameter settings ✓

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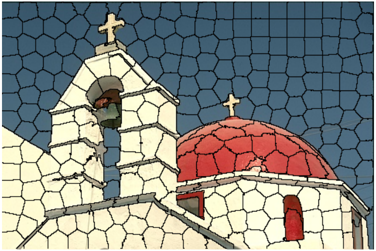

[Chen et al., 2017]

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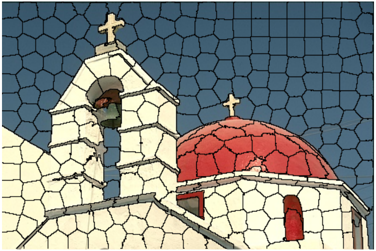
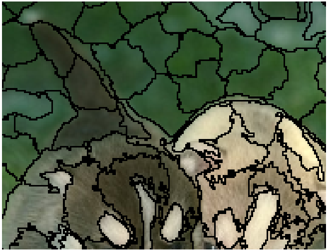


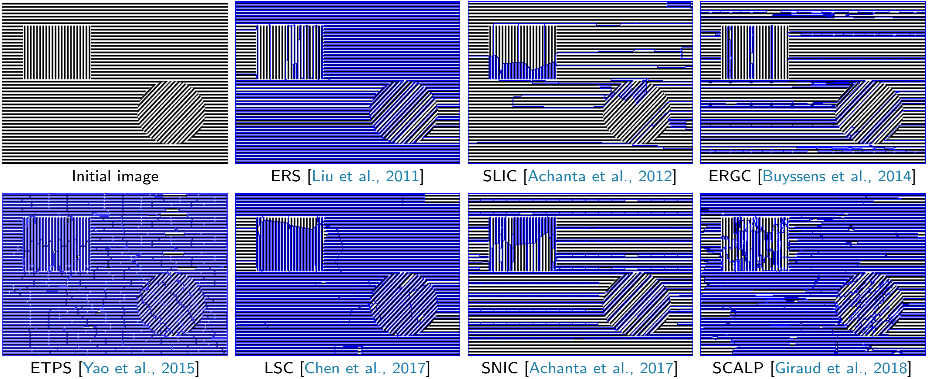
[Chen et al., 2017]



[Chen et al., 2017]

→ Irregular borders on textured regions

What about textured images?



→ All state-of-the-art methods severely fail at clustering textures

Robustness of state-of-the-art methods

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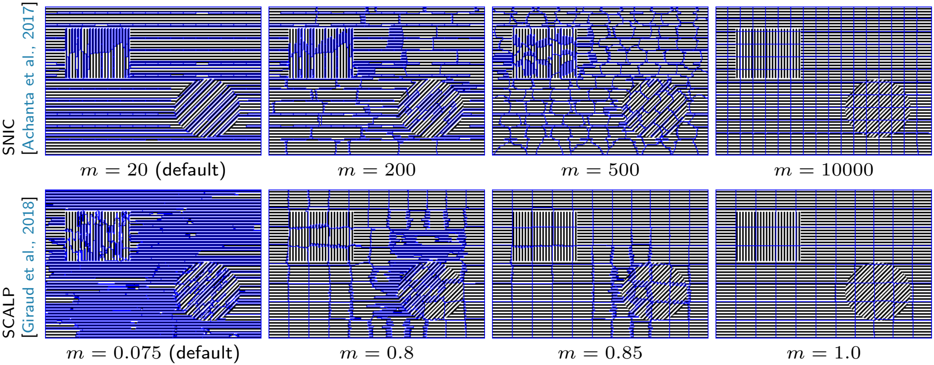

→ Even with manual regularity tuning, no explicit consideration of texture information

Robustness of state-of-the-art methods

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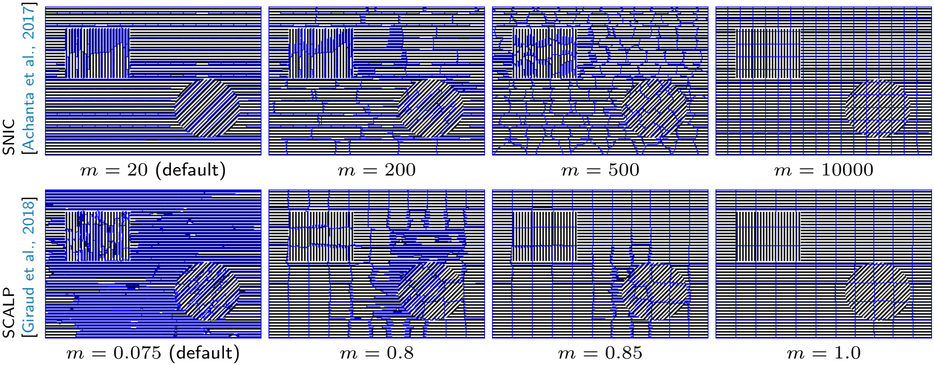
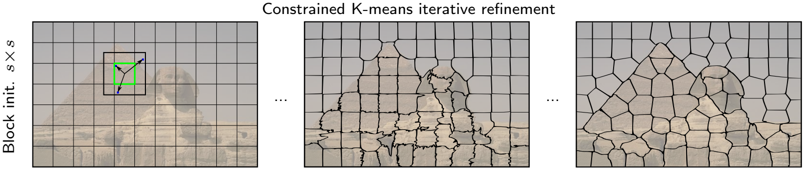


→ Even with manual regularity tuning, no explicit consideration of texture information

→ TASP: Texture-Aware SuperPixel segmentation method

Simple Linear Iterative Clustering (SLIC) [Achanta et al., 2012]



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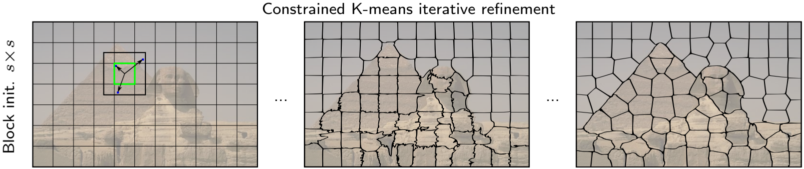
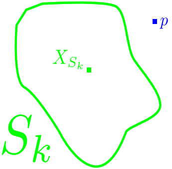


Distance between a pixel p and a superpixel S_k:

$$D(p, S_k) = d_{\text{color}}(F_p, F_{S_k}) + d_{\text{spatial}}(X_p, X_{S_k})m$$



$F_p = [l_p, a_p, b_p]$ color in the CIELab space
$X_p = [x_p, y_p]$ position
F_{S_k}, X_{S_k} average on pixels $\in S_k$
m regularity parameter

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Limitations:

- Global regularity parameter $\rightarrow$ irregular borders with low m / inaccurate borders with high m.
- Only local pixel color considered $\rightarrow$ not robust to texture.

$m = 10$

$m = 60$

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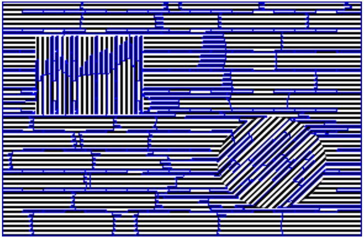
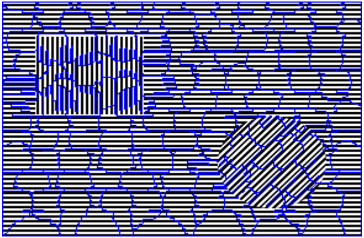


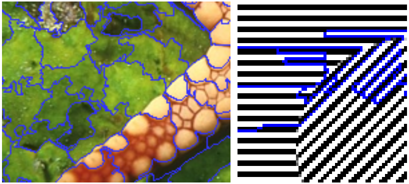
$m = 200$



$m = 500$

The TASP method

- Automatic adaptation of the regularity parameter:



SLIC [Achanta et al., 2012]

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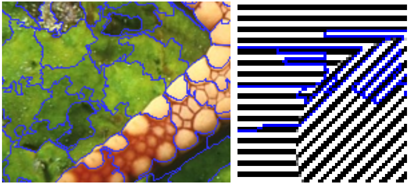

SLIC [Achanta et al., 2012]

Ponderation with feature variance within superpixels:

$$m_k = m \exp\left(\frac{\sigma(F_{p \in S_k})}{\beta}\right)$$

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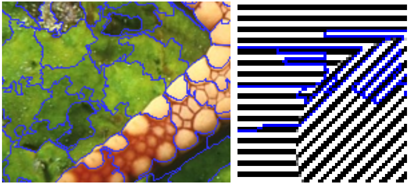

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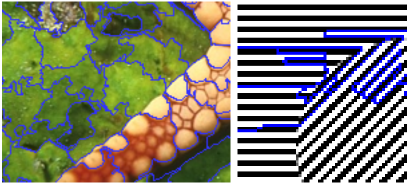

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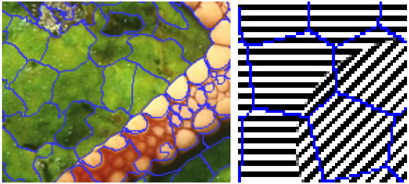

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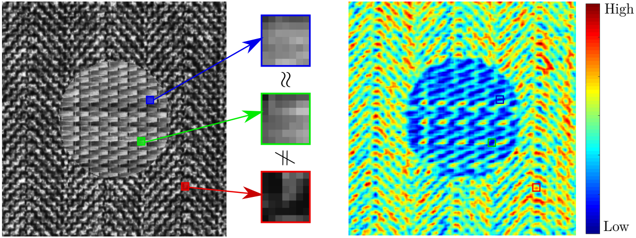
  $\rightarrow$ *Patch-based distance?*

  No complex texture classification approach
  Remains in the same feature space than pixel to superpixel distances



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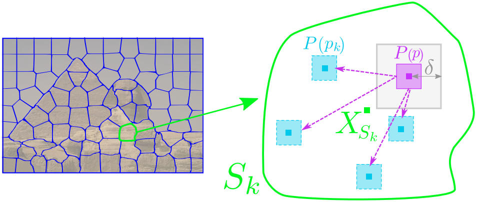
  Ability to find only similar texture patterns
  Fast selection of N similar patches with PatchMatch [Barnes et al., 2009]



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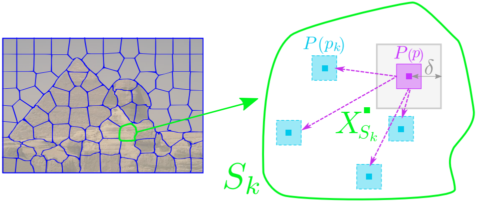

Texture homogeneity term:

$$d_{\text{texture}}(p, S_k) = \frac{1}{N} \sum_{p_k \in \mathcal{K}_p} \frac{1}{n} \| F_{P(p)} - F_{P(p_k)}) \|_2$$

The TASP method

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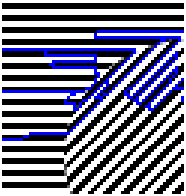

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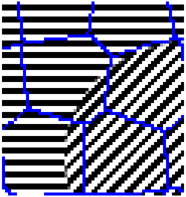

TASP w/ d_{texture}

d_{texture} does not guarantee texture unicity within superpixels

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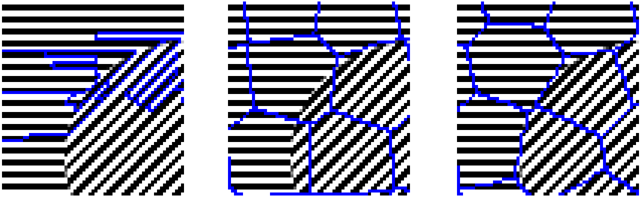

SLIC [Achanta et al., 2012] | TASP w/ d_{texture} | TASP w/ $d_{\text{texture}} + d_{\text{unicity}}$

d_{texture} does not guarantee texture unicity within superpixels

$\rightarrow$ d_{unicity} forces the selection of patches p_k close to the superpixel barycenter:

Spatial distance on selected patches:

$$d_{\text{unicity}}(p, S_k) = 2.\frac{1}{N}\sum_{p_k \in \mathcal{K}_p}\left(1 - \exp\left(-\frac{\|X_{p_k} - X_{S_k}\|_2^2}{s^2}\right)\right)$$

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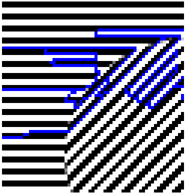

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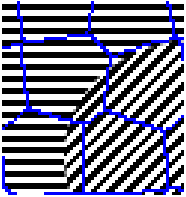

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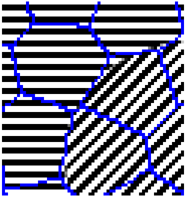

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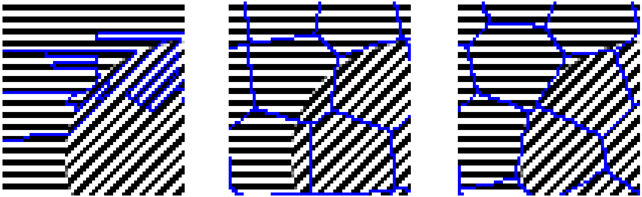

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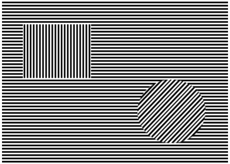
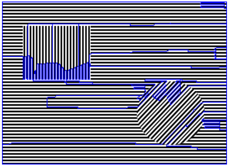
Final TASP clustering distance:

$$D(p, S_k) = d_{\text{color}}(F_p, F_{S_k}) + d_{\text{spatial}}(X_p, X_{S_k})m_k + d_{\text{texture}}(p, S_k) + d_{\text{unicity}}(p, S_k)m_k$$

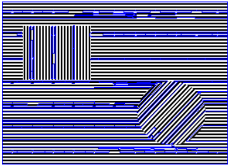
On a very textured synthetic image:



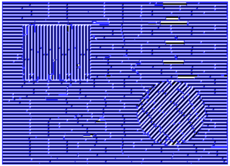
Initial image



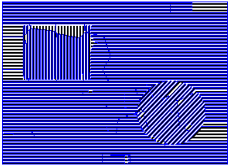
SLIC [Achanta et al., 2012]



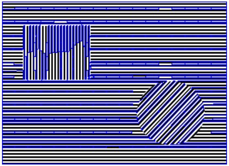
ERGC [Buyssens et al., 2014]



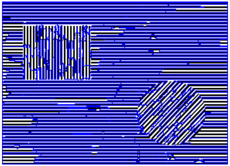
ETPS [Yao et al., 2015]



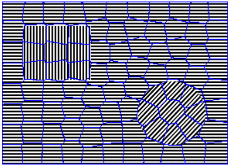
LSC [Chen et al., 2017]



SNIC [Achanta et al., 2017]



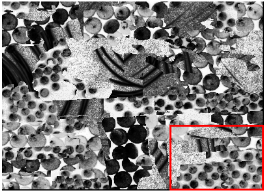
SCALP [Giraud et al., 2018]

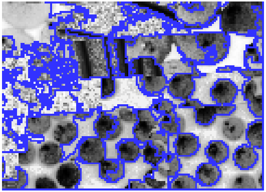


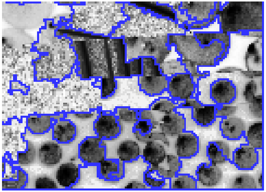
TASP

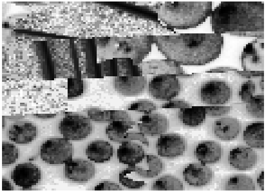
mix-Stripes: dataset of 10 images of size 300×400 with synthetic stripe textures

On a composite natural texture image:


Initial image


LSC [Chen et al., 2017]


SNIC [Achanta et al., 2017]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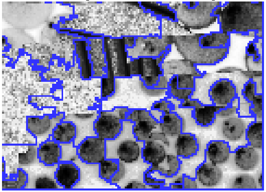
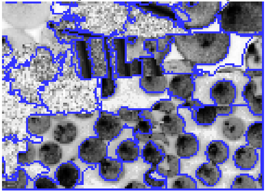
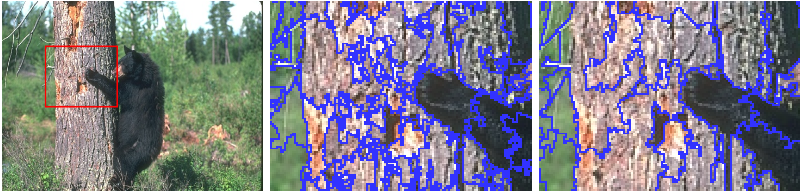

SCALP [Giraud et al., 2018]

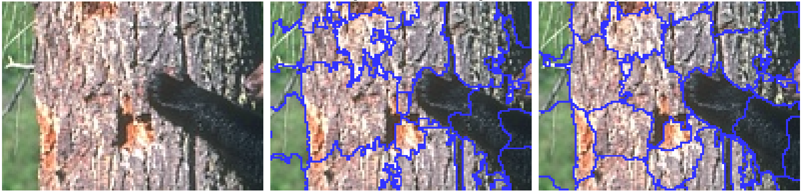

TASP

mix-Brodatz: dataset of 100 images of size 300×400 with natural textures [Brodatz, 1966]

On a natural color image:



Initial image | LSC [Chen et al., 2017] | SNIC [Achanta et al., 2017]



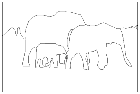
Initial image | SCALP [Giraud et al., 2018] | TASP

BSD: dataset of 200 natural color images of size 321×481 [Martin et al., 2001]

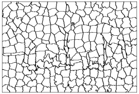
Standard metrics:

- Superposition with several objects: ASA
- Contour detection: F-measure

Image



Manual segmentation



Superpixels

	mix-Stripes (synthetic textures)		*mix-Brodatz* (natural textures)		*BSD* (natural color)	
Method	ASA	F	ASA	F	ASA	F
SLIC [Achanta et al., 2012]	0.7256	<u>0.4048</u>	0.7784	0.4607	0.9445	0.4706
ERGC [Buyssens et al., 2014]	0.6107	0.3717	0.7796	0.4677	0.9477	0.4571
ETPS [Yao et al., 2015]	<u>0.7769</u>	0.2953	0.7568	0.4354	0.9433	0.4710
LSC [Chen et al., 2017]	0.6979	0.3156	0.7908	0.4552	<u>0.9503</u>	0.4421
SNIC [Achanta et al., 2017]	0.6659	0.3529	0.7662	<u>0.4815</u>	0.9410	0.4617
SCALP [Giraud et al., 2018]	0.7307	0.3290	<u>0.7977</u>	0.4759	0.9499	<u>0.4914</u>
TASP	**0.8706**	**0.4232**	**0.8139**	**0.4824**	**0.9503**	**0.4992**

$\rightarrow$ Best performances on the three data types with the same parameters

Conclusion

Summary of contributions

- Superpixel method robust to texture
- Generic patch-based texture homogeneity term
- No need for manual regularity setting
- Accurate results on both texture and natural color datasets

Work in progress / Research perspectives

- Improvement of computational time (EUSIPCO 2019)
- Use of advanced texture descriptors
- Application to real data (3D medical, satellite, etc.)

Texture-Aware Superpixel Segmentation
(Superpixels adaptés localement aux textures)

Thank you for your attention

Reference paper

[R. Giraud et al., *Texture-Aware Superpixel Segmentation*, ICIP 2019]

Check for source codes at

http://rgiraud.vvv.enseirb-matmeca.fr

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