Generalized Shortest Path-based Superpixels for Accurate Segmentation of Spherical Images

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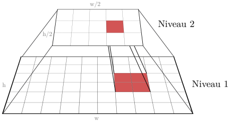
Large data → high computational times → Dimension reduction

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



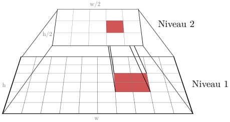

Image


Decomposition into blocks


Average colors

Large data → high computational times → Dimension reduction

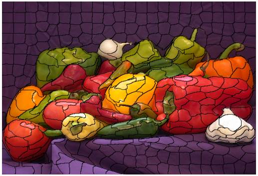
- Regular multi-resolution:
  Decompose the image into regular blocks
- Superpixels (since [Ren and Malik, 2003]):
  Local grouping of pixels with homogeneous colors




Image


Decomposition into blocks


Average colors


Decomposition into superpixels


Average colors

Many applications:

- Semantic segmentation:
  [Tighe and Lazebnik, 2010], [Wang and Yushkevich, 2013], [Mostajabi et al., 2015], ...
- Optical flow estimation:
  [Menze and Geiger, 2015], ...
- Style transfer:
  [Liu et al., 2017], ...

←

Many superpixel algorithms:

- 2D standard images:
  SLIC [Achanta et al., 2012], LSC [Chen et al., 2017], SNIC Achanta and Süsstrunk [2017], SCALP [Giraud et al., 2018], ...
- Videos:
  [Reso et al., 2013], ...
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- Spherical/Omnidirectional applications: [Zhang et al., 2019], [Yang et al., 2020], ...

Equirectangular image

Projected spherical image

Only one dedicated superpixel algorithm suffering from significant limitations [Zhao et al., 2018]

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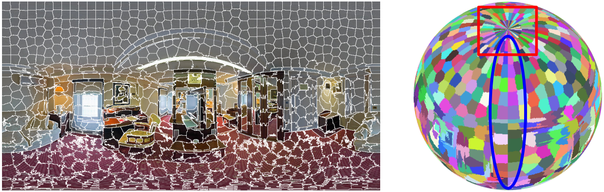

Standard 2D planar superpixels using [Chen et al., 2017]

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Equirectangular image

Projected spherical image

Spherical superpixels using **the proposed SphSPS method**

1 Introduction

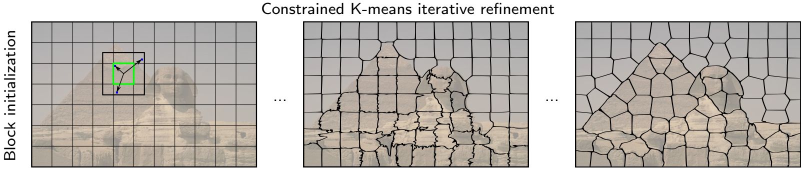
2 Spherical SLIC Superpixels (SphSLIC)

3 Proposed Spherical Shortest Path-based Superpixels (SphSPS)

4 Results

Spherical SLIC Superpixels [Zhao et al., 2018]

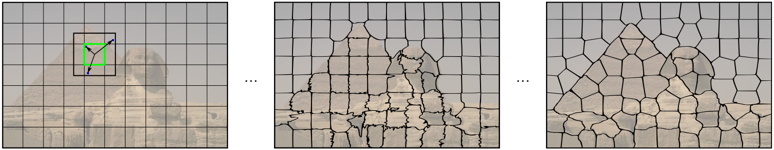
- SLIC: Simple Linear Iterative Clustering [Achanta et al., 2012]

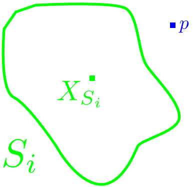


- SLIC: Simple Linear Iterative Clustering [Achanta et al., 2012]

Constrained K-means iterative refinement

Block initialization





$C_p = [l_p, a_p, b_p]$ color in the CIELab space

$X_p = [x_p, y_p]$ position

C_{S_i}, X_{S_i} average on pixels $\in S_i$

Distance between a pixel p and a superpixel S_k:

$$D_{\text{SLIC}}(p, S_i) = d_{\text{color}}(C_p, C_{S_i}) + d_{\text{spatial}}(X_p, X_{S_i})$$

Adaptation to spherical geometry: SphSLIC [Zhao et al., 2018]

- Search area: Regular in the acquisition (spherical) space

- Spatial distance $d_{\text{spatial}}(X_p, X_{S_i}) = \|X_p - X_{S_i}\|_2^2$ on spherical coordinates X^a:

$$X^a = \begin{bmatrix} x^a = \sin(\frac{y\pi}{h})\cos(\frac{2x\pi}{w}) \\ y^a = \sin(\frac{y\pi}{h})\sin(\frac{2x\pi}{w}) \\ z^a = \cos(\frac{y\pi}{h}) \end{bmatrix} \leftrightarrow X = \begin{bmatrix} x = \lfloor \frac{\text{arctan2}(y^a, x^a)w}{2\pi} \rfloor \\ y = \lfloor \frac{\text{arccos}(z^a)h}{\pi} \rfloor \end{bmatrix}$$

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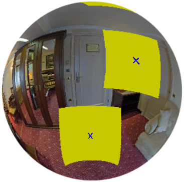

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$\rightarrow$ Standard SLIC limitations:

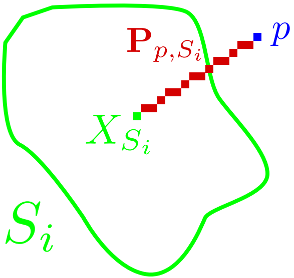
- Poor robustness to noise
- Potential irregular shapes
- Low contour adherence performances

Shortest Path-based Distance:

SCALP (Superpixels with Contour Adherence using Linear Path) [Giraud et al., 2018]

- Color distance of each pixel in linear path $\mathbf{P}_{p,S_i}$ to the barycenter of the superpixel

  $\rightarrow$ Robustness to noise + regular shapes



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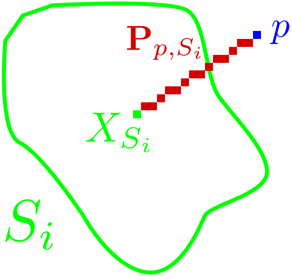
- Maximum of contour map intensity on $\mathbf{P}_{p,S_i}$

  $\rightarrow$ Respect of object contours



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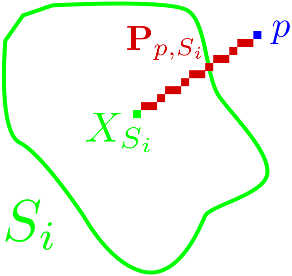


Shortest Path-based distance:

$$D_{\mathsf{SPS}}(p, S_i) = \left(d_{\mathsf{color}}(C_p, C_{S_i}, \mathbf{P}_{p,S_i}) + d_{\mathsf{spatial}}(X_p, X_{S_i})\right) d_{\mathsf{contour}}(\mathbf{P}_{p,S_i})$$

Generalized Shortest Path:

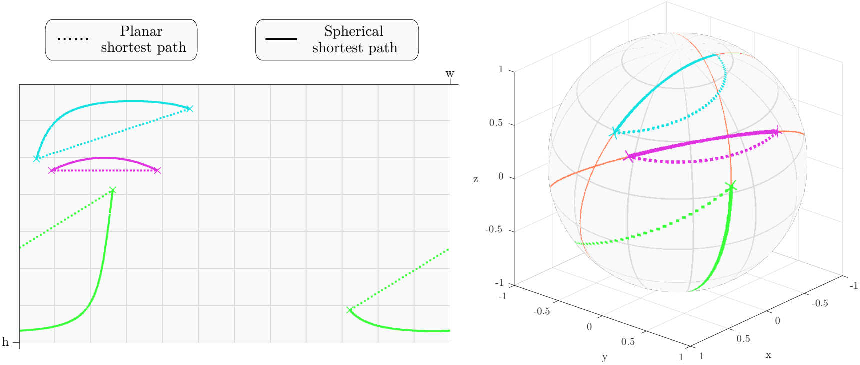
$$\mathbf{P}_{p,S_i} = \mathbf{P}^a_{p,S_i} \ \overrightarrow{\text{proj}} \ \{\mathbb{N}^2\}$$

$\mathbf{P}_{p,S_i}$ Path in planar space

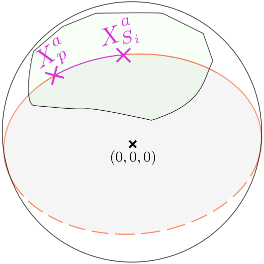
$\mathbf{P}^a_{p,S_i}$ Shortest Path in acquisition space

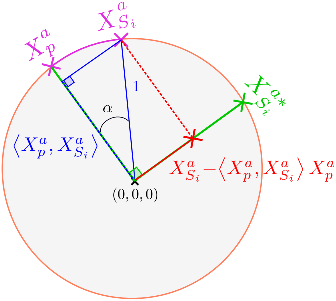
- Spherical acquisition space:

  The shortest path $\mathbf{P}^a_{p,S_i}$ follows the geodesic along the *great circle*



- Fast discrete implementation: Sampling of N points along the great circle





Coordinate system within the great circle:

$$X_{S_i}^{a}{}^* = \frac{X_{S_i}^a - \left\langle X_p^a, X_{S_i}^a \right\rangle X_p^a}{\left\| X_{S_i}^a - \left\langle X_p^a, X_{S_i}^a \right\rangle X_p^a \right\|_2}$$

$\rightarrow$

Radius sampling:

$$\mathbf{P}_{p,S_i}^a = \cos(\alpha_{\mathbf{N}}) X_p^a + \sin(\alpha_{\mathbf{N}}) X_{S_i}^{a*}$$

with $\alpha_{\mathbf{N}} = \frac{[0, N-1]}{N-1} \alpha \in \mathbb{R}^N$

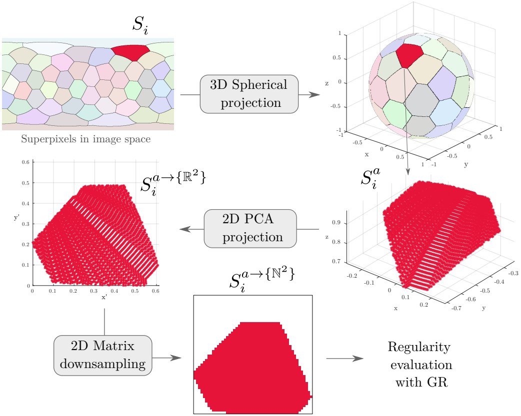
- Recursive optimization using path redundancy:
  $\rightarrow$ The processing time of SphSPS reduces to 0.7s (for 1024×512 images)

- **Generalized Global Regularity metric (G-GR)**:

  → Extension of robust Global Regularity using 2D convex hull [Giraud et al., 2017]

For each superpixel shape S_i:

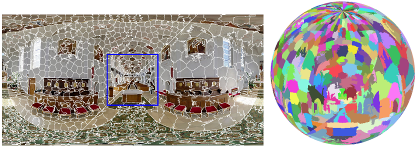
1. Spherical projection on $\mathbb{R}^3$
2. 2D PCA projection on $\mathbb{R}^2$
3. Downsampling for dense discretization on $\mathbb{N}^2$
4. Measure of the Global Regularity (GR) with [Giraud et al., 2017]



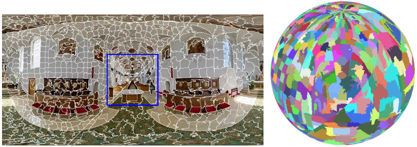
Results - Qualitative comparison

- Comparison for different scales on equirectangular images:

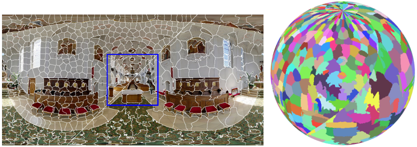
Planar methods



LSC [Chen et al., 2017]

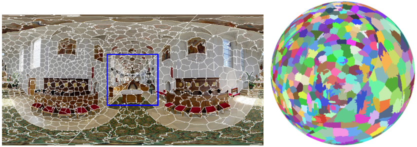


SNIC [Achanta and Süsstrunk, 2017]

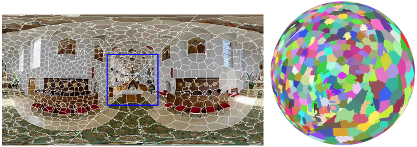


SCALP [Giraud et al., 2018]

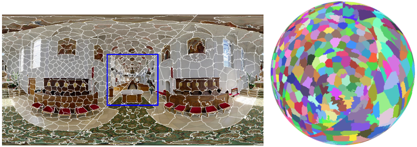
Spherical methods



SphSLIC-Euc [Zhao et al., 2018]



SphSLIC-Cos Zhao et al. [2018]



SphSPS

Results - Qualitative comparison

- Comparison for different scales on equirectangular images:


LSC


SNIC


SCALP


SphSLIC-Cos


SphSLIC-Euc


SphSPS

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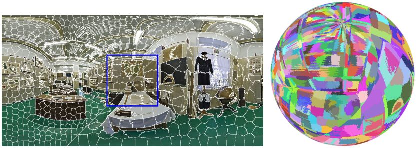

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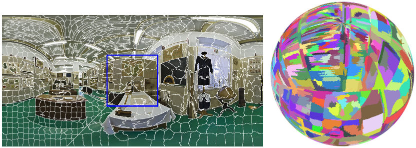

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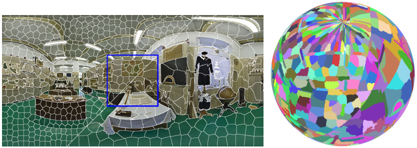

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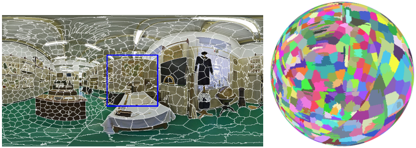

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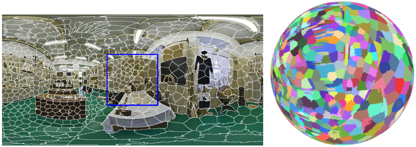

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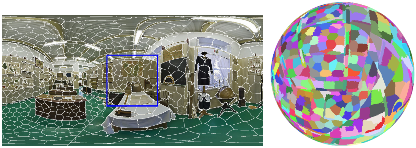

SphSPS

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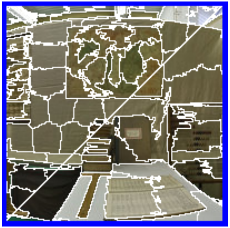

LSC

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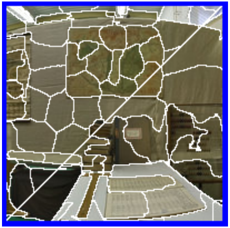
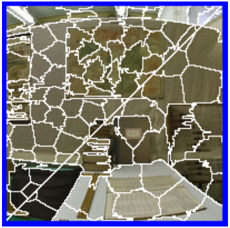
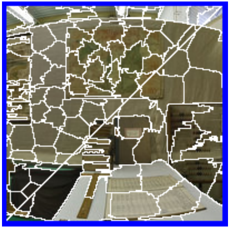


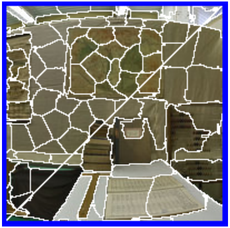
SCALP



SphSLIC-Cos

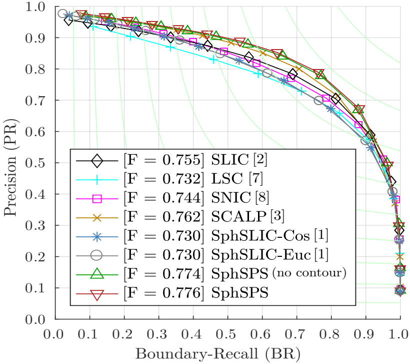


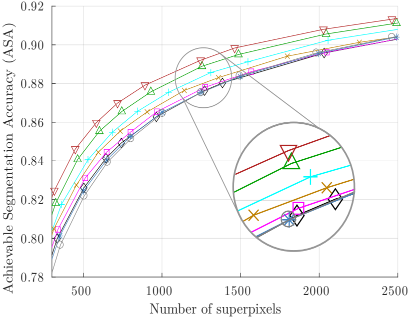
SphSLIC-Euc



SphSPS

- **Dataset**: Standard *Panorama Segmentation Dataset* (PSD) [Zhao et al., 2018]
  75 equirectangular images of 1024×512 pixels with ground truth segmentation
- **Metrics**:
  - Contour detection: Precision-Recall curves with F-measure (F)
  - Object segmentation: Achievable Segmentation Accuracy (ASA)





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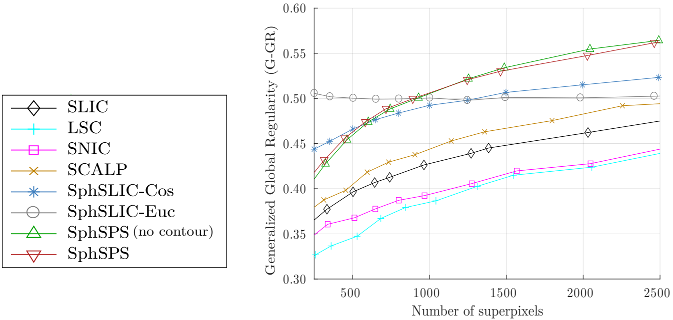

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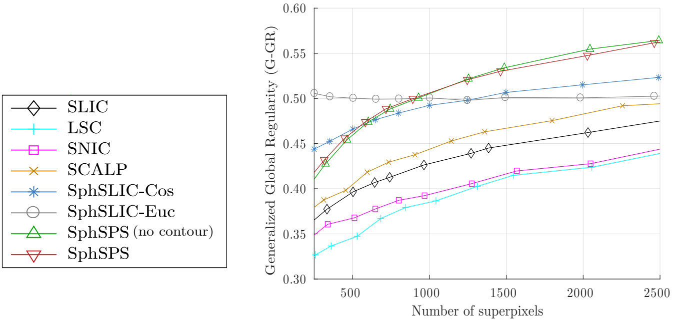

→ SphSPS has the best accuracy and regularity in the spherical space

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Source code available at:

`https://github.com/rgiraud/sphsps`

Check other superpixel works at:

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

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