THIN DETAILS MEET LARGE-SCALE 3D-RECONSTRUCTION

Photometric Stereo for Cultural Heritage

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Digitizing two cultural heritage masterpieces

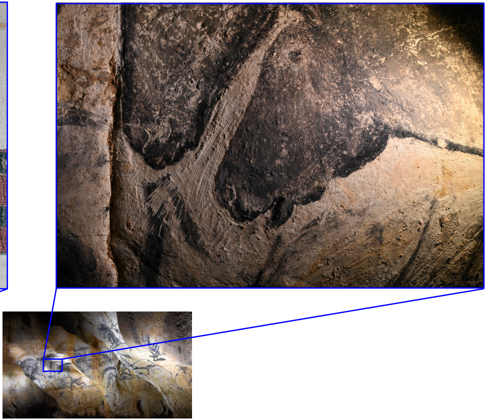
The Bayeux tapestry
XIth century, 70 m long

The Chauvet cave
36,000 years ago, 500 m long

Aim of the project

Develop AI tools for helping the 3D-digitization of these fragile, large-scale artifacts

When thin details meet large-scale



The artworks are large-scale, yet exhibit extremely thin details:

- Wool strings on a linen canvas
- Engravings on limestone

Challenge: digitize both the low and high geometric frequencies, while not deteriorating the artifacts

Outline

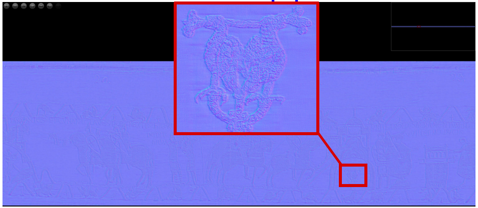
1. Case of the Bayeux tapestry

2. Case of the Chauvet cave

3D-digitization of the Bayeux tapestry

RBG panorama

Normal map panorama

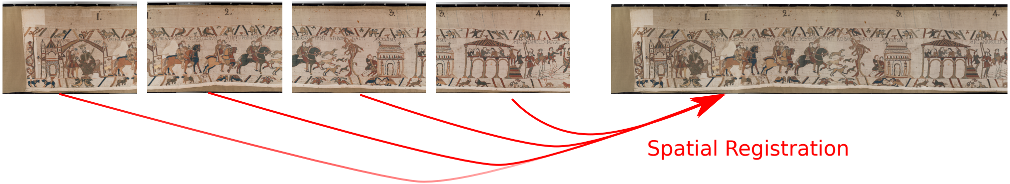


Goal: construct a 2.5D panorama of this 70 m-long medieval wool and linen *embrodery*, telling the conquest of England by William, Duke of Normandy, in 1066

- An RGB panorama is already available: `https://www.bayeuxmuseum.com/en/the-bayeux-tapestry/discover-the-bayeux-tapestry/explore-online/`
- Can we convert it to 3D?

Redon et al., *3D surface Approximation of the Entire Bayeux Tapestry for Improved Pedagogical Access*, Proc. ICCV 2023 workshop on e-heritage

From an RGB panorama to a 2.5D one



High-resolution ($480,000 \times 6,000\ px$) RGB panorama, created from 86 images acquired in 2017 by La Fabrique de patrimoines en Normandie

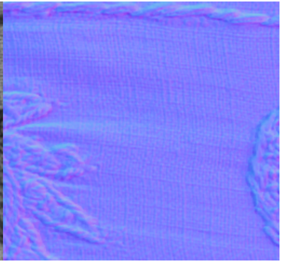
Proposed strategy for 3D-digitization

1. Store the RGB spatial registration parameters
2. Turn each RGB image to 2.5D using deep learning
3. Apply the same spatial registration to the 2.5D images

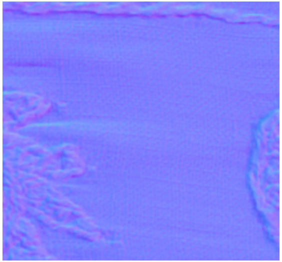
Deep image-to-geometry learning

Input image

Ground truth normal map



Estimated normal map



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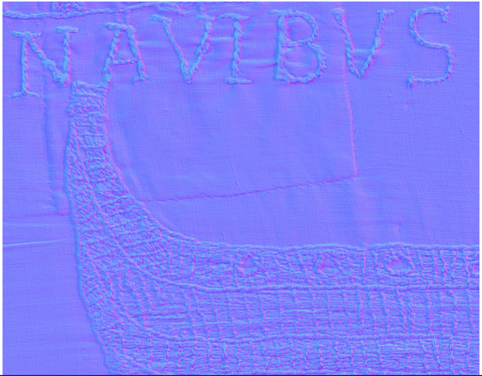
Ground truth geometry acquisition campaign

3D-reconstruction of 12 scenes, based on photometric stereo:

Left: three input images, taken from the same viewing angle but varying lighting

Right: output high-resolution mesh (5M triangles)

Ground truth geometry acquisition campaign



We have $\approx$ 30 couples (RGB,normals) of size $3000\,\text{px}^2$

$\rightarrow$ Thousands of $128\,\text{px}^2$ patches for learning the mapping RGB $\mapsto$ geometry

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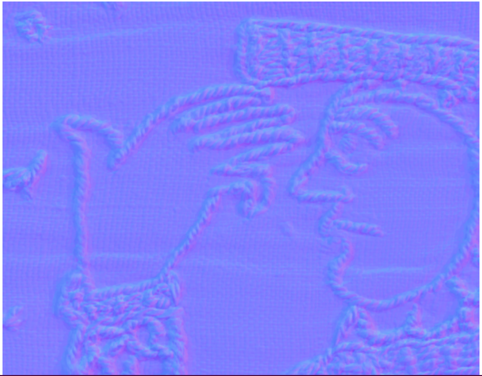

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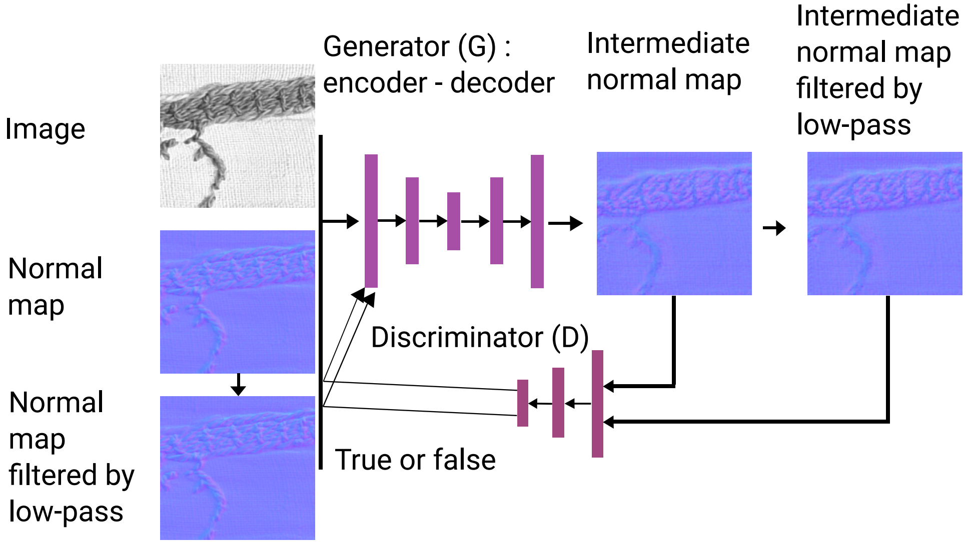
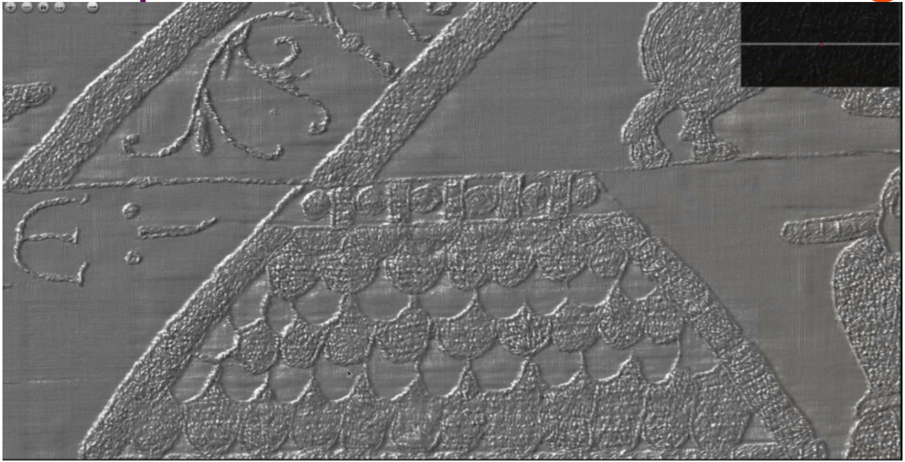


Geometric panorama



https://redonmarjorie.github.io/projects/BayeuxPanorama.html

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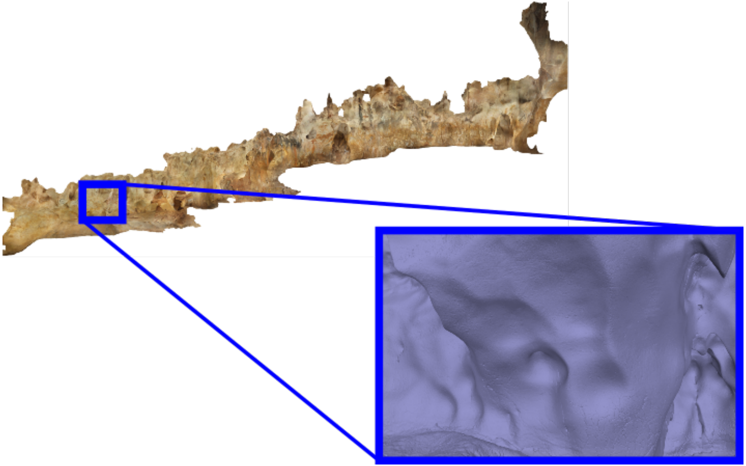
2. Case of the Chauvet cave

Case of the Chauvet-Pont-d’Arc cave

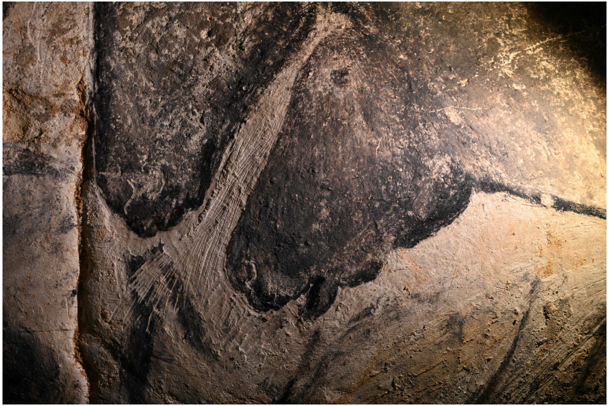
“Panneau des chevaux” (Chauvet-Pont-d’Arc cave, Ardèche, France)

Photogrammetry in Chauvet



3D model of the Chauvet cave. Thin details are not reconstructed

Needs for photometric stereo



Zoom on the "Panneau des chevaux"

Needs

- Precision: capturing digitized tracings, fine engravings, etc.
- Separate the relief from the color: analysis of the antero-posteriority

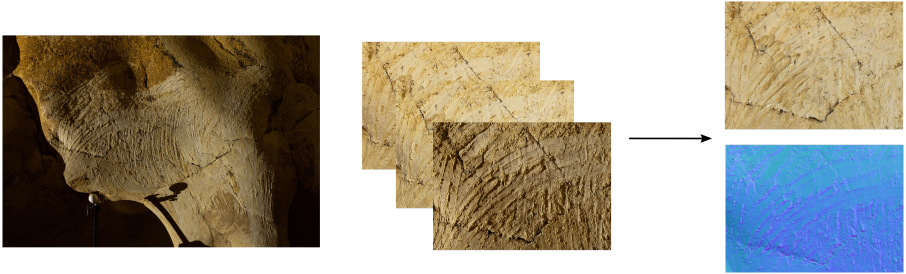
Photometric methods

- Have a pixel-size precision
- Separate light, geometry and color

Classic photometric stereo case

Lighting calibration with a sphere

- Matte or glossy sphere placed in the scene
- Algorithm adapted to each type of sphere
- Sphere can be manually defined

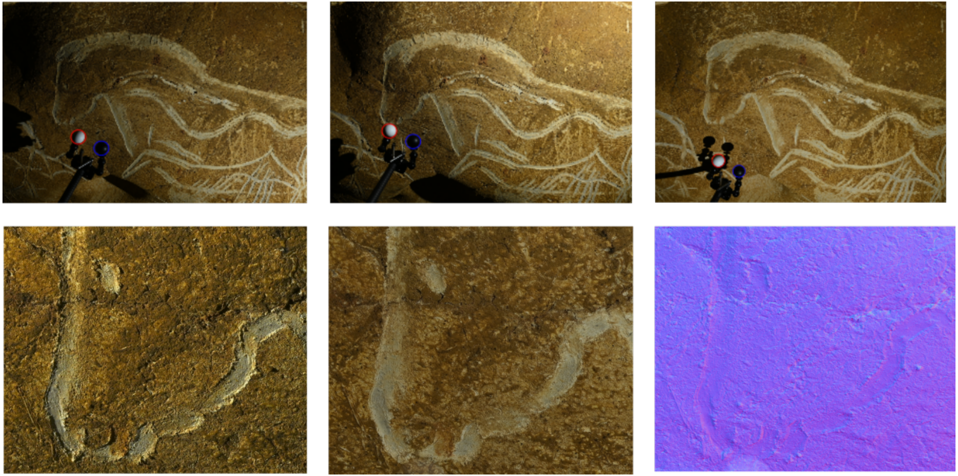


PS on the “Panneau des mammouths raclés”. From left to right: one of the 13 pictures, zoom on three pictures and results of PS (albedo and normal map)

Accessibility constraints in the Chauvet cave

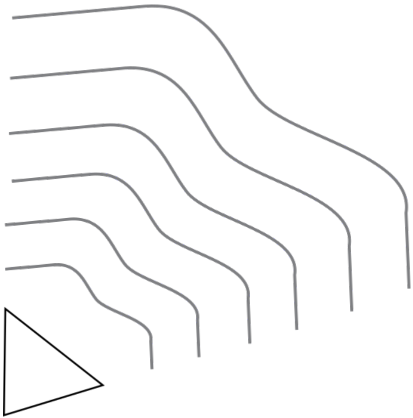
- Spheres are positioned at the end of a pole
- Position of the sphere in the image differs from one image to another
- Automatic detection with DETR network

Automatic neural lighting calibration



Top: three pictures (out of 16) with calibration spheres on a pole
Bottom: zoom on a picture, albedo and normal map

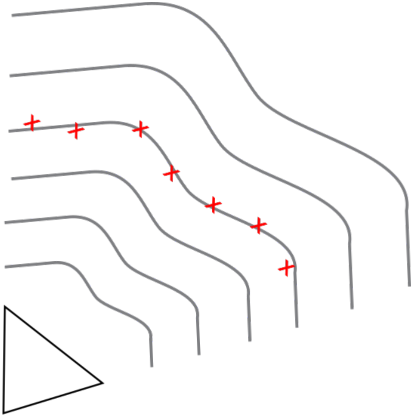
Combining photogrammetry and photometric stereo



Ongoing work

- Depth deduced from normals, up to a scale factor

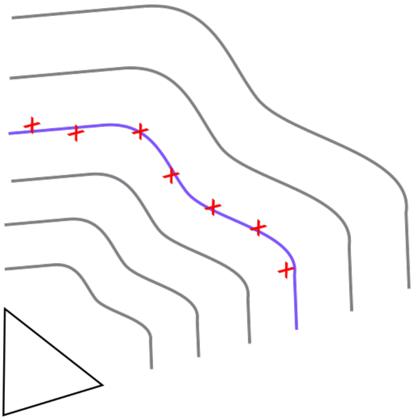
Combining photogrammetry and photometric stereo



Ongoing work

- ▶ Depth deduced from normals, up to a scale factor
- ▶ Idea: use the photogrammetric cloud to determine the right scale

Combining photogrammetry and photometric stereo



Ongoing work

- Depth deduced from normals, up to a scale factor
- Idea: use the photogrammetric cloud to determine the right scale

Thank you

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https://alicevision.org/labcom-alicia/
https://redonmarjorie.github.io/projects/BayeuxPanorama.html