# Automated 3D reconstruction from satellite images SIAM IS18 Minitutorial 

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## Overview

- This is a hands-on course on satellite image processing
- Objective: go from satellite images to a 3D model

- Plan and logistics

1. Basics of satellite images

- First on-line exercise with Jupyter at https://gfacciol.github.io/IS18/

2. Stereovision with satellite images

- Second on-line exercise with Jupyter Notebook

3. Triangulation and digital elevation model generation

- Third on-line exercise with Jupyter

4. 3D from collections of images

## Speakers



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Carlo de Franchis


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Thank:

- Mila Nikolova, Fiorella Sgallari, and all the organizers
- Jean-Michel Morel and all our colleagues at ENS Paris-Saclay and Master2 MVA
- Katherine Scott for the inspiring "Python from Space" notebooks

Acknowledge:


## Towards a daily cover of the Earth

## Increasing resolution

- 2008: RapidEye, 5 satellites ( 5 m )
- 2008: GeoEye (0.4m)
- 2011: Pleiades, 2 satellites ( 0.7 m )
- 2013: SkySat, 5 satellites (1m)

- 2015: Sentinel-2, 2 satellites ( 10 m )
- 2017: Planet Labs Flock-1, $150 \mu$-satellites (3-5m)

Port-au-Prince in 2012 (after the 2011 quake)

- 2018: Satellogic, $5 \mu$-satellites (1m), ~300 planned


## Need for automatic analysis

- Automatic event detection, ignoring radiometric changes
- Independence of acquisition geometry
- Use historical data

and in 2013


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Elevations in 2012 (after the 2011 quake)


Elevations in 2013

## Towards a daily cover of the Earth

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Need for automatic analysis

- Automatic event detection, ignoring radiometric changes


Difference between the 2012 and 2013 elevations (Demolished, Built)

- Independence of acquisition geometry
- Use historical data


## What a time to be alive!

Traditionally, newcomers to remote sensing should pay a high cost (in terms of knowledge) to work with satellite images.

- access to images
- file formats
- cartographic standards
- projection models
- specialized software
- etc...


A short Sentinel 2 time series
Today this is no longer true:

```
import tsd # timeseries downloader
aoi = {'coordinates': [[[2.306, 48.831], [2.306, 48.869],
    [2.376, 48.869], [2.376, 48.831]]], 'type': 'Polygon'}
tsd.get_sentinel2(aoi, out_dir='paris') # download data from ESA
```


## Why 3D digital models?

They are an essential tool for:

- large-scale measurements:
- snow height on glaciers [Berthier et al. 2014]
- forests evolution [Gumbricht 2012]
- assessment after natural disasters [Yésou et al. 2015]
- change detection [Chaabouni-Chouayakh et al. 2010]
- cartography (orthorectification) [Leprince et al. 2007]
- more generally, image comparison


Bassies (Pyrénées), 2015-03-11
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Bassies (Pyrénées), 2014-10-26
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## 3D models and orthorectification



## Stereovision core idea: parallax is proportional to height



Images: AirbusDS Pleiades

3D reconstruction from image pairs

General principle:

- find corresponding pixels
- intersect the back-projected 3D lines

Need a camera model, and its parameters.


3D reconstruction from image pairs


## Satellite Stereo Pipeline (S2P)

- Modular 3D stereo pipeline for satellite images
- Developed at ENS Paris-Saclay and CNES
- Open source: https://github.com/MISS3D/s2p
- Currently used by CNES in production


An automatic and modular stereo pipeline for pushbroom images,
C. de Franchis, E. Meinhardt-Llopis, J. Michel, J.-M. Morel, G. Facciolo. ISPRS Annals, 2014.

## Section 1. Coordinate Systems and Geometric Modeling

Satellite images $==$ big data

## Put a camera in space

- altitude: 400 to 700 km
- acquire very large images $40000 \times 40000$ pixels

footprint of an entire image

a small crop


## Geographic and projected reference systems

Geographic: describe 3D points relative to a reference ellipsoid using latitude, longitude, and altitude


The reference ellipsoid:


Projected: transform the elliptical earth into a flat surface

- Mercator: preserves shapes but not size

- Universal Transverse Mercator: uses easting and northing



## The Linear Pushbroom Camera

Similar to a pinhole camera, but:

- only one line of pixel sensors in the focal plane,
- the camera center moves at constant speed.

Internal parameters:

- focal length: $f$,
- position of the principal point: $y_{0}$,
- size of the pixel sensors: $w$,
- dwell time: $\delta_{t}$.

[Gupta and Hartley 1997] R. Gupta and R. Hartley. Linear pushbroom cameras. TPAMI, 1997.


## Geometric relationship between image and space

- Given a complete set of parameters, and an image point $\mathbf{x}$, what is the back-projected ray?



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- Where does it intersect the Earth surface?



## Geometric relationship between image and space

- Given a complete set of parameters, and an image point $\mathbf{x}$, what is the back-projected ray?
- Where does it intersect the Earth surface?
- Express this line in a coordinate system which rotates with the Earth.



## Geometric relationship between image and space

$$
\left[\begin{array}{ccc}
c_{\tau+\lambda_{0}} & -s_{\tau+\lambda_{0}} & 0 \\
s_{\tau+\lambda_{0}} & c_{\tau+\lambda_{0}} & 0 \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & c_{i-\frac{\pi}{2}} & -s_{i-\frac{\pi}{2}} \\
0 & s_{i-\frac{\pi}{2}} & c_{i-\frac{\pi}{2}}
\end{array}\right]\left[\begin{array}{ccc}
c_{-\alpha_{t}-\frac{\pi}{2}} & 0 & s_{-\alpha_{t}-\frac{\pi}{2}} \\
0 & 1 & 0 \\
-s_{-\alpha_{t}-\frac{\pi}{2}} & 0 & c_{-\alpha_{t}-\frac{\pi}{2}}
\end{array}\right]\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & c_{\varphi} & -s_{\varphi} \\
0 & s_{\varphi} & c_{\varphi}
\end{array}\right]\left[\begin{array}{ccc}
c_{\psi} & 0 & s_{\psi} \\
0 & 1 & 0 \\
-s_{\psi} & 0 & c_{\psi}
\end{array}\right]\left[\begin{array}{ccc}
c_{\omega} & -s_{\omega} & 0 \\
s_{\omega} & c_{\omega} & 0 \\
0 & 0 & 1
\end{array}\right]\left(\begin{array}{c}
0 \\
w\left(y-y_{0}\right) \\
f
\end{array}\right)
$$



Image formation model

## Localization function:

$$
\begin{aligned}
L: \mathbf{R}^{2} \times \mathbf{R} & \rightarrow[-\pi, \pi] \times\left[-\frac{\pi}{2}, \frac{\pi}{2}\right] \\
(\mathbf{x}, h) & \mapsto(\lambda, \theta)
\end{aligned}
$$



## The Rational Polynomial Camera Model

- A true camera model is difficult to implement
- For end-users, image vendors provide a very close approximation of the localization function $L$, given as a Rational Polynomial Functions with degree 3.
- Its inverse, with respect to $\mathbf{x}$, is given as well.


Localization of a point on a non-elliptical earth

Find the coordinates of an image point on the globe


## Shuttle Radar Topography Mission (SRTM)

SRTM provides a near-global high-resolution digital topographic database of Earth

- Acquired in the year 2000
- Resolution 30 m



## Section 2. Epipolar Rectification and Stereo Matching

## Baseline 3D reconstruction algorithm



## Baseline 3D reconstruction algorithm



## Epipolar rectification: what is it?

Process of resampling the images in such a way that depth variations cause apparent motion in the horizontal direction only.


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## Pinhole cameras

- $\mathbf{C}, \mathbf{C}^{\prime}$ and x define a plane, called the epipolar plane.
- Its intersection with the second image is the epipolar line of $\mathbf{x}$, denoted by epi ${ }^{\mathrm{x}}$.
- All the $\mathrm{x}^{\prime} \in$ epi $^{\mathrm{x}}$ share the same epipolar plane, hence the same
 epipolar line in the first image.

Conclusion: there is a one-to-one correspondence between epipolar lines.

## Pushbroom cameras

- Satellite cameras are not pinhole, but pushbroom.
- As the camera center moves, the epipolar plane becomes a doubly ruled surface, namely a hyperbolic paraboloid.
- Epipolar lines become curves, still denoted by epi ${ }^{\mathrm{x}}$.
- All the $\mathrm{x}^{\prime} \in \mathrm{epi}^{\mathrm{x}}$ have a different epipolar surface, hence a different epipolar line in the first image.
Conclusion: there is no one-to-one correspondence between epipolar curves.



## Epipolar rectification: why?

Why epipolar rectification:

- speed: reduces the exploration from 2D to 1D
- robustness: reduces the risks for false matches
- compatibility: allows to use standard stereo-matching algorithms


It is just an intermediate step. Then it could be done locally. What if you try to approximate locally the pushbroom camera model with a pinhole camera model?

## RPC approximation

Let $P: \mathbb{R}^{3} \rightarrow \mathbb{R}^{2}$ be the RPC projection function. The first order Taylor approximation of $P$ around point $X_{0}$ is

$$
\begin{align*}
P(X) & =P\left(X_{0}\right)+\nabla P\left(X_{0}\right)\left(X-X_{0}\right) \\
& =\nabla P\left(X_{0}\right) X+T \tag{1}
\end{align*}
$$

with $T=P\left(X_{0}\right)-\nabla P\left(X_{0}\right) X_{0}$ and $\nabla P\left(X_{0}\right)$ the jacobian matrix.
This can be rewritten using homogeneous coordinates as

$$
P(X)=\underbrace{\left[\begin{array}{cc}
\nabla P\left(X_{0}\right) & T  \tag{2}\\
0 & 1
\end{array}\right]}_{\text {matrix of size }(3,4)}\left[\begin{array}{c}
X \\
1
\end{array}\right]
$$

This is the projection function of an affine camera! [Hartley and Zisserman 2004]

## Epipolar rectification: how?

In general:

1. Find keypoint matches $\mathbf{x}_{i} \leftrightarrow \mathbf{x}_{i}^{\prime}$ with SIFT [Lowe 2004, Rey Otero 2014]
2. Estimate the fundamental matrix F [Hartley and Zisserman 2004] with RANSAC.

$$
\mathbf{x}_{i}^{\prime \top} \mathrm{Fx}_{i}=0
$$

## Epipolar rectification: how?

What is the fundamental matrix?
The fundamental matrix is the algebraic representation of epipolar geometry. [Hartley and Zisserman 2004]
The fundamental matrix $F$ of a pair of cameras is a $3 \times 3$ matrix of rank 2 such that any pair of corresponding points $\mathbf{x}_{i} \leftrightarrow \mathbf{x}_{i}^{\prime}$ verify the equation

$$
\mathbf{x}_{i}^{\prime \top} \mathrm{F} \mathbf{x}_{i}=0 .
$$

The fundamental matrix song:
https://youtu.be/DgGV3182NTk


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$$
\mathbf{x}_{i}^{\prime \top} \mathrm{F} \mathbf{x}_{i}=0
$$

3. Estimate resampling homographies H and $\mathrm{H}^{\prime}$ [Loop Zhang 1999]

$$
F=H^{\prime \top}\left[\begin{array}{ccc}
0 & 0 & 0 \\
0 & 0 & -1 \\
0 & 1 & 0
\end{array}\right] H
$$

## Epipolar rectification: how?

If you know the two camera matrices A and B :

1. Compute the fundamental matrix F [Hartley and Zisserman 2004]

$$
\mathrm{F}_{j i}=(-1)^{i+j} \operatorname{det}\left[\begin{array}{c}
\sim \mathbf{a}^{i}  \tag{3}\\
\sim \mathbf{b}^{j}
\end{array}\right]
$$

where $\sim \mathbf{a}^{i}$ denotes the matrix obtained from A by omitting the row $\mathbf{a}^{i}$. This formula expresses directly each entry of F in terms of determinants computed from the entries of $A$ and $B$.
2. Estimate resampling homographies $H$ and $H^{\prime}$ [Loop Zhang 1999]

$$
\mathrm{F}=\mathrm{H}^{\prime \top}\left[\begin{array}{ccc}
0 & 0 & 0 \\
0 & 0 & -1 \\
0 & 1 & 0
\end{array}\right] \mathrm{H}
$$

## Epipolar rectification: how?

If the two cameras are affine, then:

- The fundamental matrix has a special form:

$$
\mathrm{F}=\left[\begin{array}{lll}
0 & 0 & a  \tag{4}\\
0 & 0 & b \\
c & d & e
\end{array}\right]
$$

This expresses the fact that the epipolar lines are bundles of parallel lines.

- The rectification can be achieved with just a similarity (composition of rotation, zoom and translation).


Figure courtesy of Hartley and Zisserman, 2004

## Epipolar rectification: how?

Two similarities that transform the epipolar lines in a set of matching horizontal lines can be computed directly from F.

$$
\mathrm{S}_{1}=\left[\begin{array}{c|c}
z \mathrm{R}_{1} & 0  \tag{5}\\
& t \\
\hline 0 & 0
\end{array} 1 . \quad \mathrm{S}_{2}=\left[\begin{array}{c|c}
\frac{1}{z} \mathrm{R}_{2} & 0 \\
\hline 0 & 0
\end{array}\right]\right.
$$

where $z=\sqrt{\frac{r}{s}}, t=\frac{e}{2 \sqrt{r s}}$ with $r=\sqrt{a^{2}+b^{2}}, s=\sqrt{c^{2}+d^{2}}$ and the two rotations $R_{1}$ and $R_{2}$ are given by

$$
\mathrm{R}_{1}=\frac{1}{\sqrt{a^{2}+b^{2}}}\left[\begin{array}{cc}
b & -a  \tag{6}\\
a & b
\end{array}\right] \quad \mathrm{R}_{2}=\frac{1}{\sqrt{c^{2}+d^{2}}}\left[\begin{array}{cc}
-d & c \\
-c & -d
\end{array}\right]
$$

## Epipolar rectification: conclusion

We have a blind way to rectify pushbroom images using a $1^{\text {st }}$ order Taylor approximation of their RPC camera model. How accurate is the approximation?

The are several ways to measure it:

1. Estimate the projection approximation error of a single camera:

- estimate $\max \|P(X)-A X\|$ for $X$ varying in a neighborhood of $X_{0}$
- evaluate the $2^{\text {nd }}$ order term of the Taylor approximation

2. Estimate the rectification approximation error of two cameras:
2.1 compute the fundamental matrix F of their affine approximations
2.2 measure how well $F$ fits the exact projections of some 3 D points

## Epipolar rectification: results



To evaluate the method, measure the epipolar error:

$$
\max _{i \in\{1, \ldots, n\}} \max \left\{d\left(\mathbf{x}_{i}^{\prime}, \mathbf{F x}_{i}\right), d\left(\mathbf{x}_{i}, \mathbf{F}^{\top} \mathbf{x}_{i}^{\prime}\right)\right\},
$$

where $d\left(\mathbf{x}^{\prime}, \mathrm{F}^{\top} \mathbf{x}\right)$ is the vertical disparity:


$$
d\left(\mathbf{x}^{\prime}, \mathbf{F} \mathbf{x}\right)=\frac{\left|\mathbf{x}^{\prime \top} \mathbf{F} \mathbf{x}\right|}{\sqrt{\left(\mathrm{F}_{1}^{\top} \mathbf{x}\right)^{2}+\left(\mathrm{F}_{2}^{\top} \mathbf{x}\right)^{2}}}
$$

## Epipolar rectification: results



## Conclusion:

- After epipolar rectification, the maximal error w.r.t true camera model (RPC) is only 0.05 pixel!
- Working with small areas of interest (e.g. $500 \times 500$ meters) permits to do the
 usual epipolar rectification with enough accuracy for stereo matching.

Epipolar rectification: in practice


Epipolar rectification: in practice

rectified from the RPC's affine approximation

Epipolar rectification: in practice

rectified from the RPC's affine approximation

It's still moving vertically, isn't it?

The relative pointing error

Due to attitude measurement inaccuracies, the RPC functions may contain an error of a few pixels.

Given two corresponding points $\mathrm{x} \leftrightarrow \mathrm{x}^{\prime}$,
 the epipolar curve

$$
\operatorname{epi}_{u v}^{\mathrm{x}}: h \mapsto P_{v}\left(L_{u}(\mathbf{x}, h), h\right)
$$

may not pass through $\mathrm{x}^{\prime}$.


## The relative pointing error: why?

The camera parameters are measured on board. What's their accuracy?

- internals: carefully calibrated (in-flight commissioning)
- orbit parameters: cm accuracy with DORIS (GPS) intruments
- attitude coefficients: a few tens of $\mu \mathrm{rad} X$


$$
a \varepsilon \approx 700 \mathrm{~km} \times 50 \mu \mathrm{rad}=35 \mathrm{~m}
$$

[de Lussy et al. 2012] Pléiades HR in flight geometrical calibration: location and mapping of the focal plane

## Effect of attitude errors

The effect of a yaw error is negligible with respect to the effect of an error on roll or pitch.

$$
a \varepsilon \gg \frac{D}{2} \varepsilon
$$

- $a$ : flying altitude

- D: swath width

Thus the effect of attitude errors is mostly a constant image shift.

## On small areas of interest

- epipolar curves are approximated by a bundle of parallel lines
- the effect of pointing error is approximated by a constant offset

Hence, given a set of keypoint matches (obtained with SIFT [Lowe 2004]), the error can be corrected with a vertical translation of the rectified images:

$$
t^{\star}=\underset{t}{\arg \min } \frac{1}{N} \sum_{i=1}^{N}\left|y_{i}^{\prime}-y_{i}+t\right|
$$



Effect of pointing error before correction
where $y_{i}$ and $y_{i}^{\prime}$ are the vertical coordinates of the keypoints in the rectified images.
[Lowe 2004]David G. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, IJCV 2004

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Local correction of the relative pointing error


## Robust stereo matching

Stereo matching computes correspondences between a pair of images (easier if they are rectified). We use SGM [Hirschmüller'05] to approximately minimize

$$
E(\mathrm{D})=\sum_{\mathbf{p} \in \mathcal{V}} C_{\mathbf{p}}\left(\mathrm{D}_{\mathbf{p}}\right)+\sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{E}} V\left(\mathrm{D}_{\mathbf{p}}, \mathrm{D}_{\mathbf{q}}\right)
$$

Critical ingredients for remote sensing applications:

- matching cost: robustness to illumination changes (e.g. Census Transform [Zabih \& Woodfill '94])
- disparity post-processing: removal of spurious matches (left-right, speckle)


Left and Right images


SGM+Census Disparity


Filtered Disparity

## Section 3. Triangulation and Digital Elevation Models

Disparity Charts vs. Elevation Maps : they are not the same!


Scheme of the whole pipeline (for one image pair)

Four steps to convert a pair of images to a DEM:


## Match triangulation

Input: a point correspondence between two satellite images
Output: a 3D point
Algorithm: (triangulation)

1. Let $L_{A}, L_{B}, P_{A}, P_{B}$ be the localization and projection functions of each image
2. Let $p, q$ be a corresponding pair of points between $A$ and $B$
3. Solve the system of equations $\left\{\begin{array}{l}p=P_{A}(x, y, h) \\ q=P_{B}(x, y, h)\end{array} \quad\right.$ or $P_{B}\left(L_{A}(p, h), h\right)=q$.

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## Tricks:

1. In either case, the system is over-determined. You have to find a minimum-error solution.
2. Since the calibration functions are very smooth, you can linearize them and the system becomes linear (with a single unknown $h$, to be found by least squares).

## Solving the triangulation equation

Given the a matching pair $\mathbf{p} \sim \mathbf{q}$, find $h$ such that

$$
P_{B}\left(L_{A}(\mathbf{p}, h), h\right)=\mathbf{q}
$$

## Observations:

1. Two equations and one unknown: overdetermined!
2. "Define" the solution as $h=\arg \min \left\|P_{B}\left(L_{A}(\mathbf{p}, h), h\right)-\mathbf{q}\right\|^{2}$
3. The functions $P_{B}$ and $Q_{A}$ are rational functions $\mathbf{R}^{3} \rightarrow \mathbf{R}^{2}$ of degree 3 (80 coefficients each)
4. Very well-posed problem: Newton's method converges in 2 iterations.

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4. Very well-posed problem: Newton's method converges in 2 iterations.
5. Still better: solve the linearized system $\mathrm{d} P_{B} \cdot \mathrm{~d} L_{A}\left(\begin{array}{c}p_{1} \\ p_{2} \\ h\end{array}\right)=\binom{q_{1}}{q_{2}}$ which has the form $\binom{a_{1}}{a_{2}} h=\binom{b_{1}}{b_{2}}$, whose Moore-Penrose solution is $h=\frac{b \cdot a}{\|a\|^{2}}$

## Dense stereo

Input: two satellite images
Output: a 3D point cloud Algorithm:

1. compute a dense field of correspondences
2. triangulate each correspondence


Input pair


Pixel correspondences


3D point cloud

## Creation of a raster DEM

DEM = "Digital Elevation Model" an image whose pixel values represent heights
Input: a 3D point cloud
Input: a geographic grid
Output: a raster image (DEM) Algorithm:

1. average all the 3D points that fall in each cell of the grid


3D point cloud


DEM

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3D point cloud


DEM

fancy DEM rendering

## 3D modeling form collections of multi-date images

## 3D modeling form collections of multi-date images

Challenge: Exploit the growing collection of satellite images

- from different satellites
- at different dates
- in different conditions


Input: multiple views


Output: 3D reconstruction

Images: WorldView3 from the MVS benchmark dataset of [Bosch et al 2016]

## IARPA MVS challenge dataset

47 Worldview3 images of Buenos Aires taken over 14 months


Baseline choice


The first and last images are very different, but consecutive images have a low $b / h$, thus are rather easy to match.

## Slanted views



Images: WorldView3 from the MVS benchmark dataset of [Bosch et al 2016]

Multi-date issue: vegetation changes


Multi-date pair, taken from a similar point of view.
Notice that the trees are different.

Multi-date issue: radiometric changes


Multi-date pair, taken from a similar point of view. One image is taken in winter (dark image, long shadows) and the other is taken in summer (brighter image, shorter shadows).

## Multi-view stereo strategies

1. Traditional bundle adjustment + multi-view. Images can have very different appearances: different radiometry, changes, new structures.

- needs tie points (not stable in multi-date)
- solve large optimization problem with all the images

2. Fusion of 3D models from stereo pairs.

Compute models independently and combine them as 3D point clouds/meshes.

- uses geometry (more stable than tie points) to align
- can incorporate new data without overhead
- fusion uses statistical validation

Rationale: images may change but geometry does not

## Our approach: choosing the good stereo pairs

The quality of 3D models from multi-date pairs varies wildly! Our solution aggregates models computed from well-chosen pairs.


Automatic 3D Reconstruction from Multi-Date Satellite Images,
G. Facciolo, C. de Franchis, and E. Meinhardt, Earth Vision CVPRW, 2017
(Winning solution of the 2016 IARPA challenge)

## Algorithm overview

1. Select only the "best" pairs

- Maximum incidence angle $\theta_{\max }<40^{\circ}$
- Angle between the views $\alpha \in[5,45]^{\circ}$
- Temporal proximity

2. Stereo matching of selected pairs

- Use S2P Satellite Stereo Pipeline
- Triangulate and project


## 3. Alignment and fusion

- Align surface models by correlation (corrects bias)
- Aggregate by taking the heigh of the lower k-medians cluster at each pixel (removes seasonal vegetation)


## Justifications

Pair selection strategy is obtained by studying all the 2162 stereo pairs.


## Fusion criterion


median of 700 pairs

median of 50 pairs

k-medians of 50 pairs

Fusion results


## Conclusion



Goal of this tutorial: Get a free entrance to the community of satellite imaging.
Techniques learned:

- Use Taylor theorem to approximate all your functions to order 1
- Basic linear algebra
- Convert between different geodetic coordinate systems
- Think globally, process your images locally

Basis of this tutorial: Our MsC course on satellite imaging at the ENS Paris-Saclay

