Image Mining
2013

OPTICAL IMAGE MATCHING TECHNIQUES

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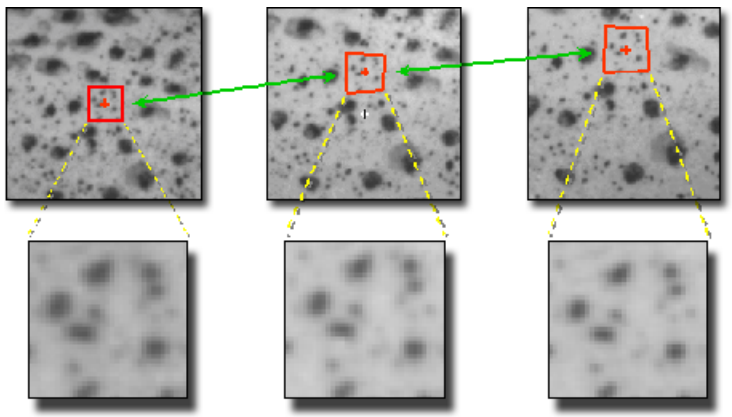
ROADMAP

- Objectives and Applications
- Image Matching Techniques
- Geometric modelling
- Some examples

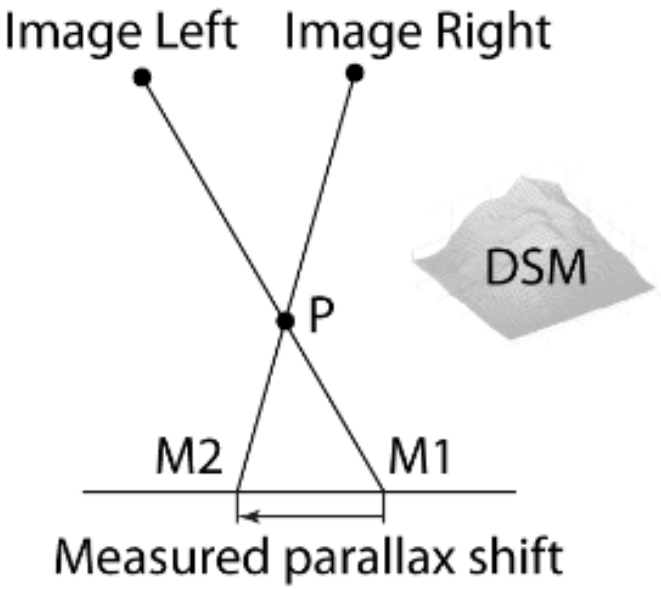
OBJECTIVES OF IMAGE MATCHING TECHNIQUES

- Image alignment / co-registration

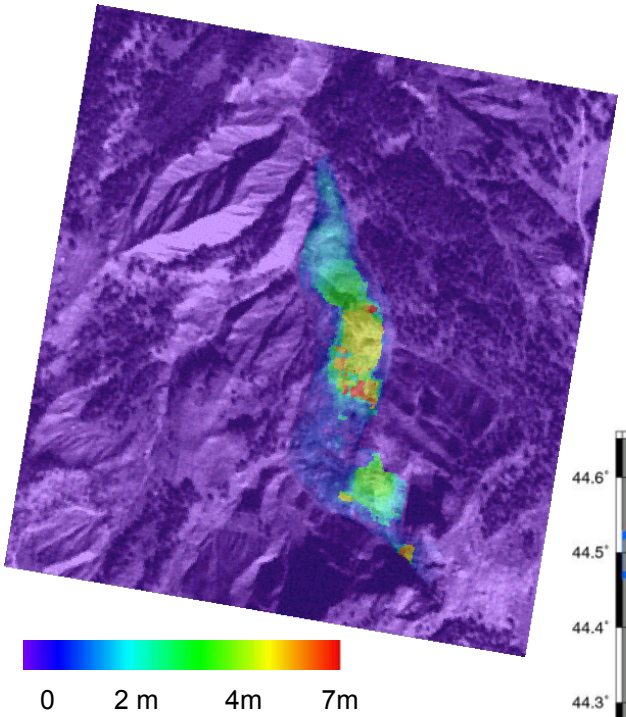


- Reconstructing motion between two or more dates

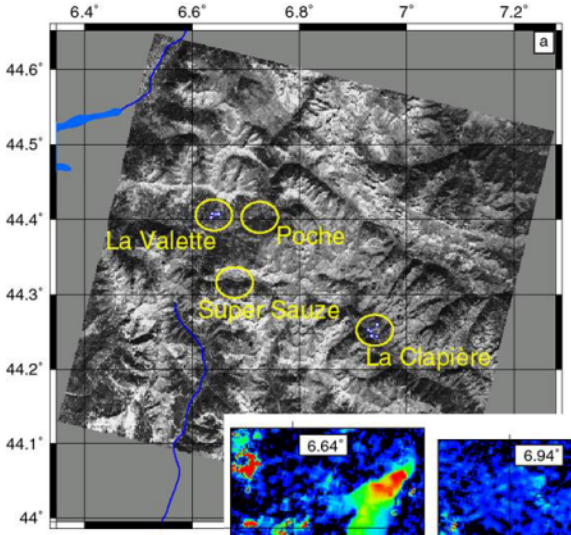
- Reconstructing of the depth or elevation of a surface from two or more images

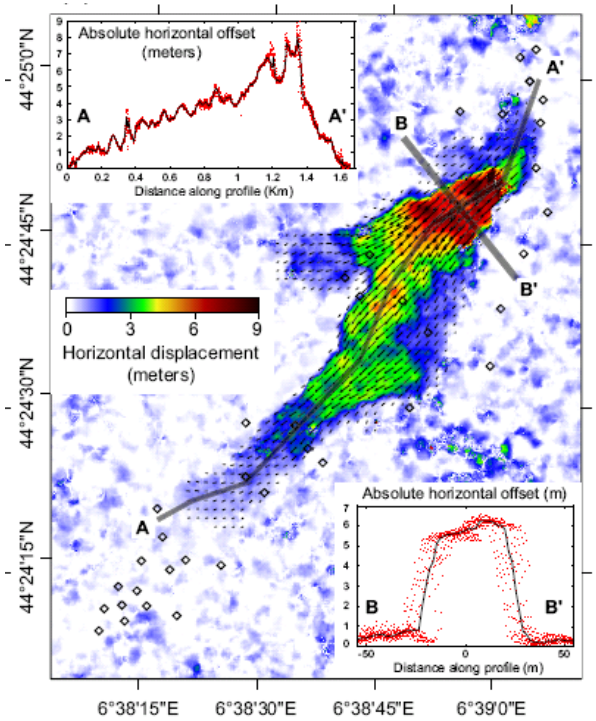


APPLICATIONS ON SATTELITE IMAGES

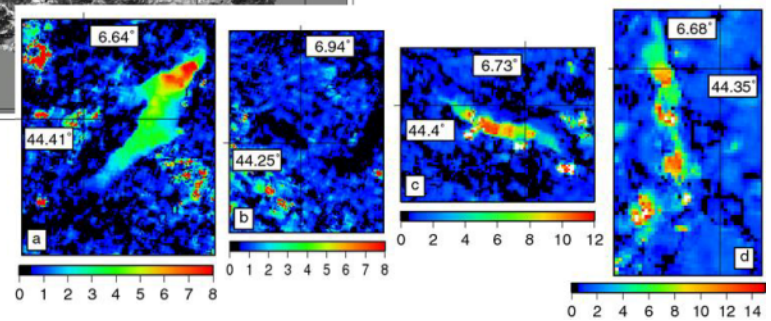


Delacourt, Allemand and Thomas (2006, unpublished)



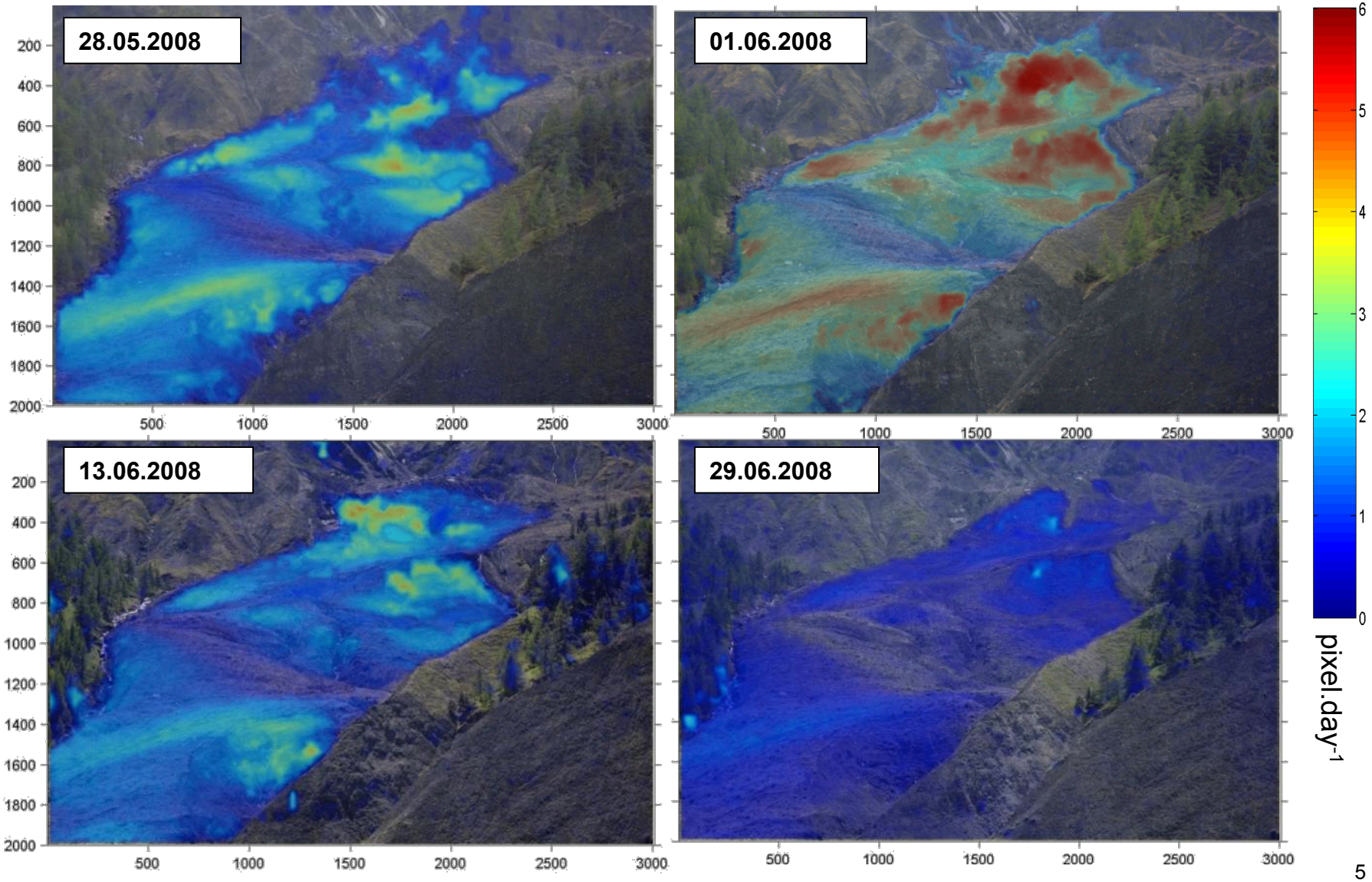


Le Prince et al. (2008)

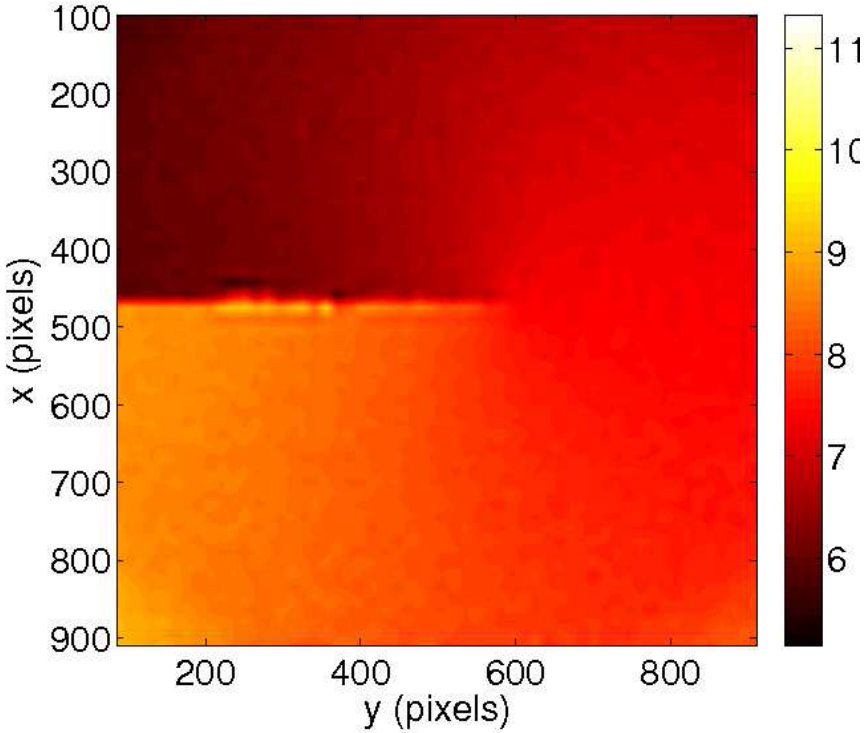


Correlation of SPOT5 imagery
South French Alps (2003-2004)
(Delacourt et al., 2006)

APPLICATIONS ON TERRESTRIAL IMAGES

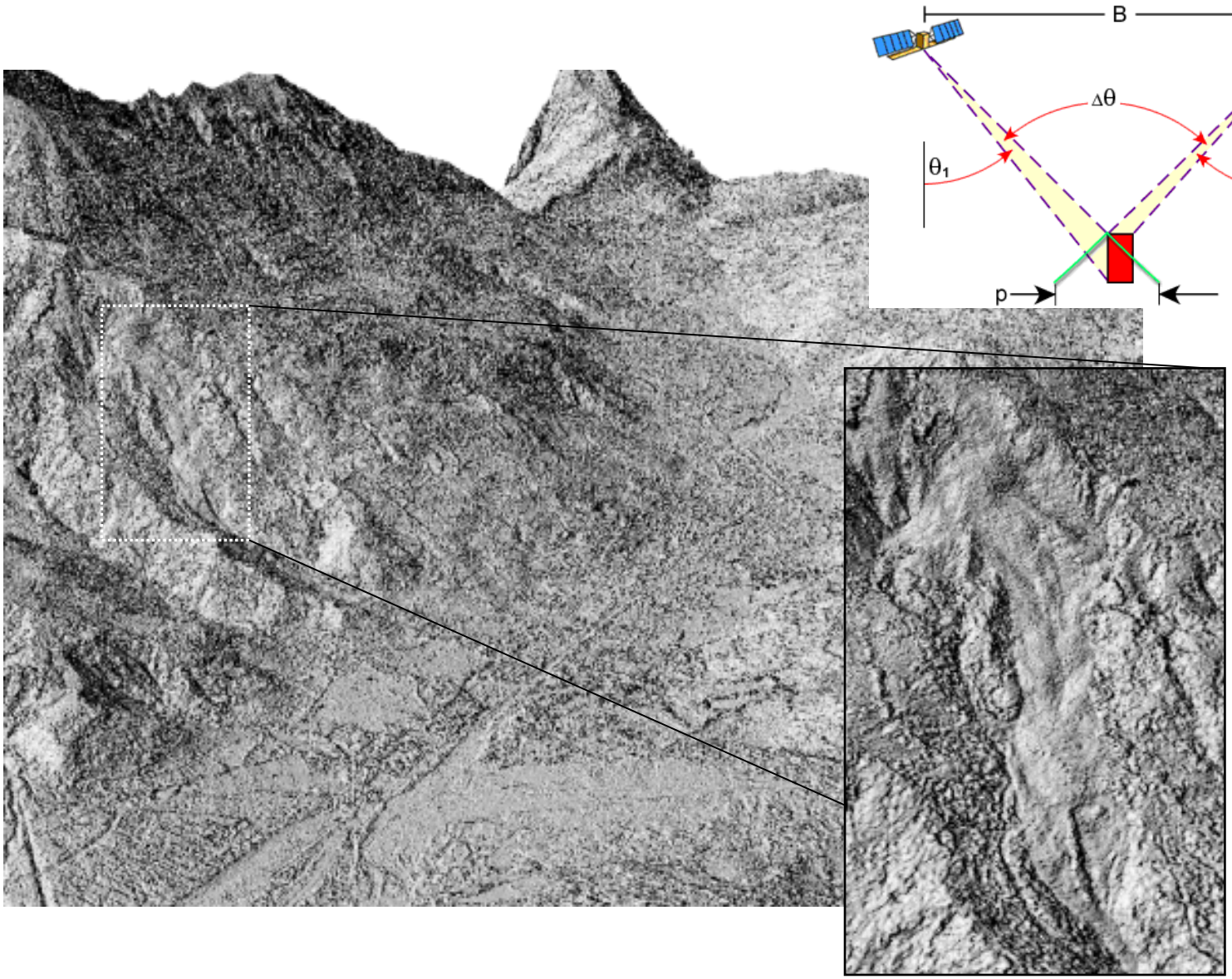


APPLICATIONS FOR LABORATORY TESTS

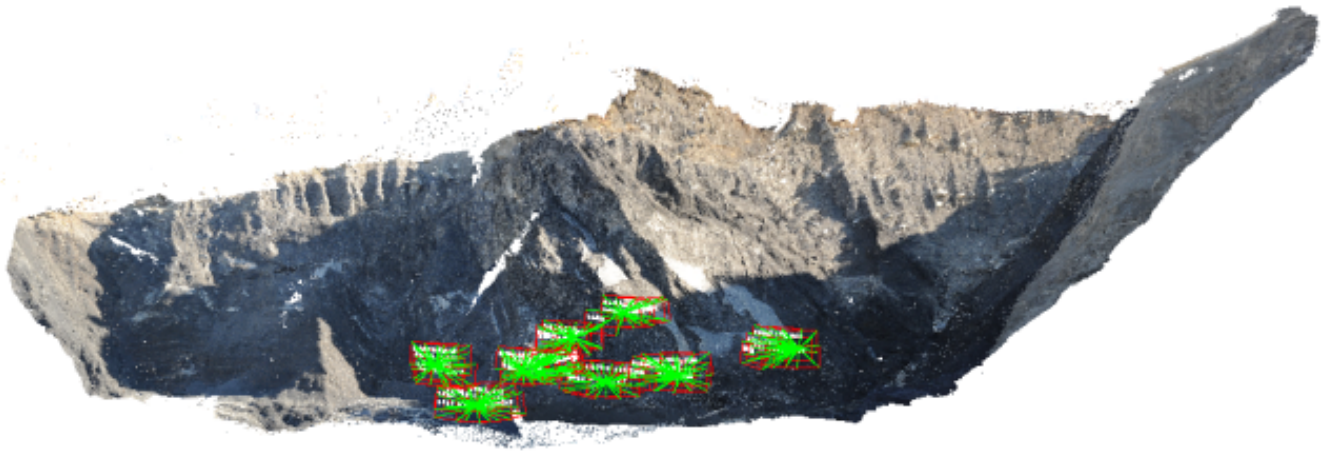


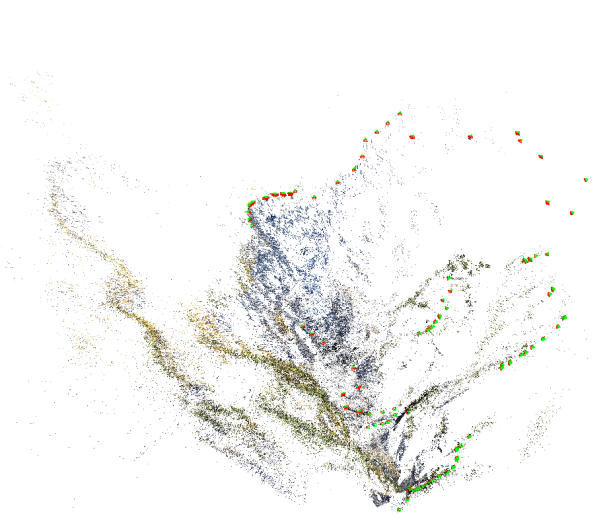
Mathieu et al. 2011

SATTELITE STEREOPHOTOGRAMMETRY



TERRESTRIAL PHOTOGRAMMETRY





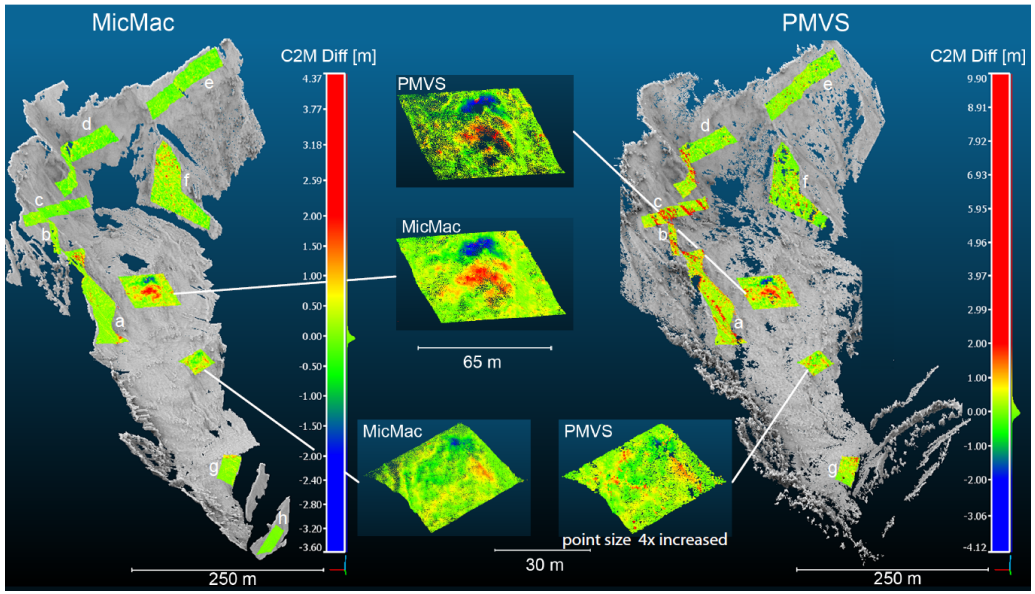


IMAGE MATCHING TECHNIQUES

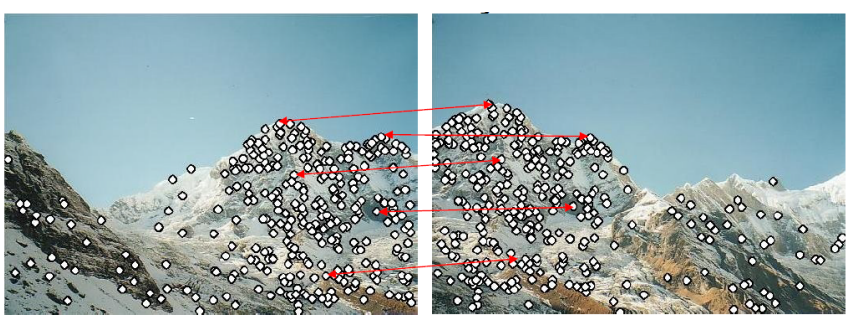
Feature based vs. patch based

- Harris corner detector (Harris and Stephens 1988
- SIFT (Lowe 2004)
- FAST (Rosten and Drummond 2006)
- DAISY (Tola et al. 2010)
- BRIEF (Calonder et. al. 2012)
- ORB (Rublee et al. 2011)
- BRISK (Leutenegger et al. 2011)

…

- Matching Costs
  - Squared differences
  - Normalized Cross-Correlation
  - Mutual Information
  - CENSUS
  - Rank matching
  - Fourier domain
- Different pre-filtering algorithms
- Hierarchical vs. non-hierarchical

…



Brown and Lowe 2003

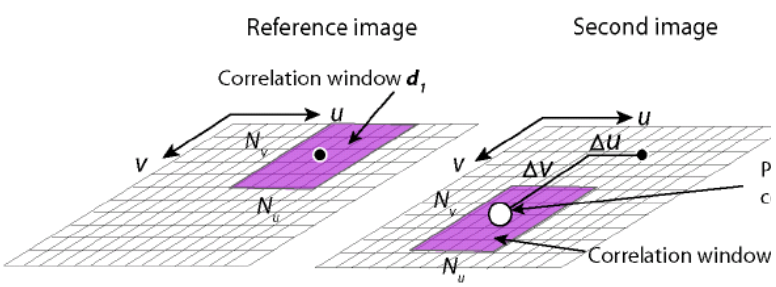
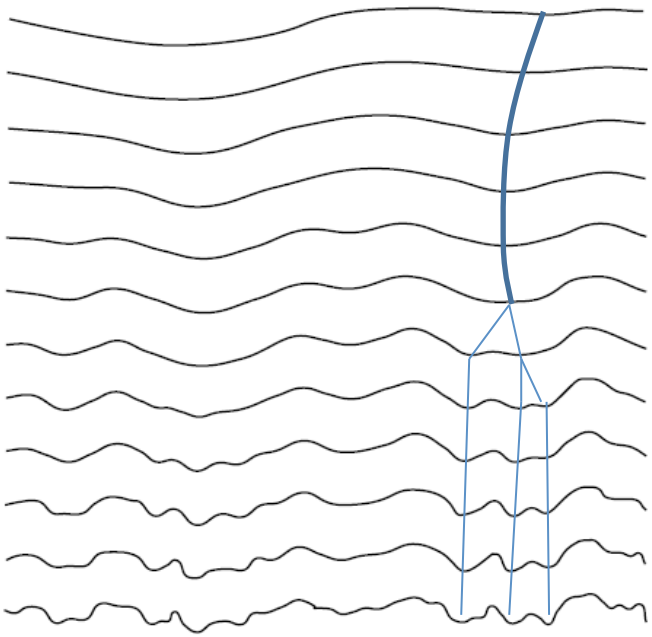


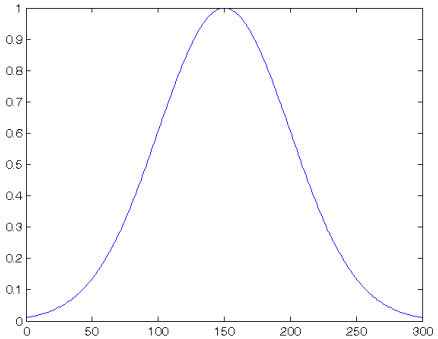
IMAGE MATCHING TECHNIQUES

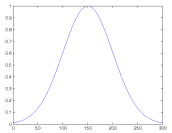
SIFT – Scale invariant feature targets

- Feature detection



Scale, Gaussian Smoothing



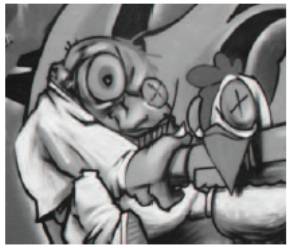


When smoothing a signal iteratively some features are persistent among a number of scales

Witkin 1983

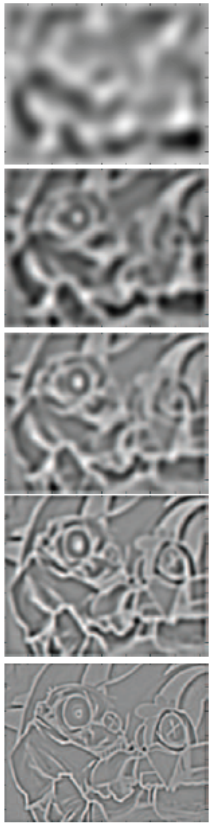
SIFT – Scale invariant feature targets

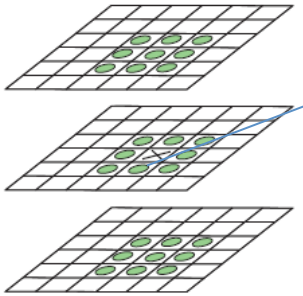
- Feature detection

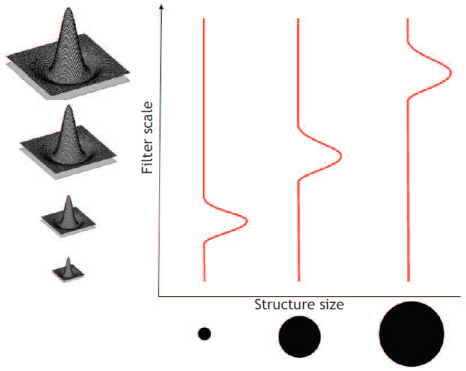


$$L_{xx}(\sigma) + L_{yy}(\sigma) \rightarrow$$

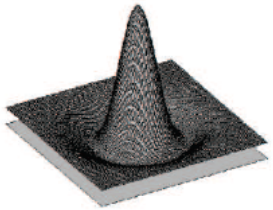
σ^5, σ^4, σ^3, σ^2, σ







The feature point is “salient” if is the maximum or minimum of all 27 pixel values



0	−1	0
−1	4	−1
0	−1	0

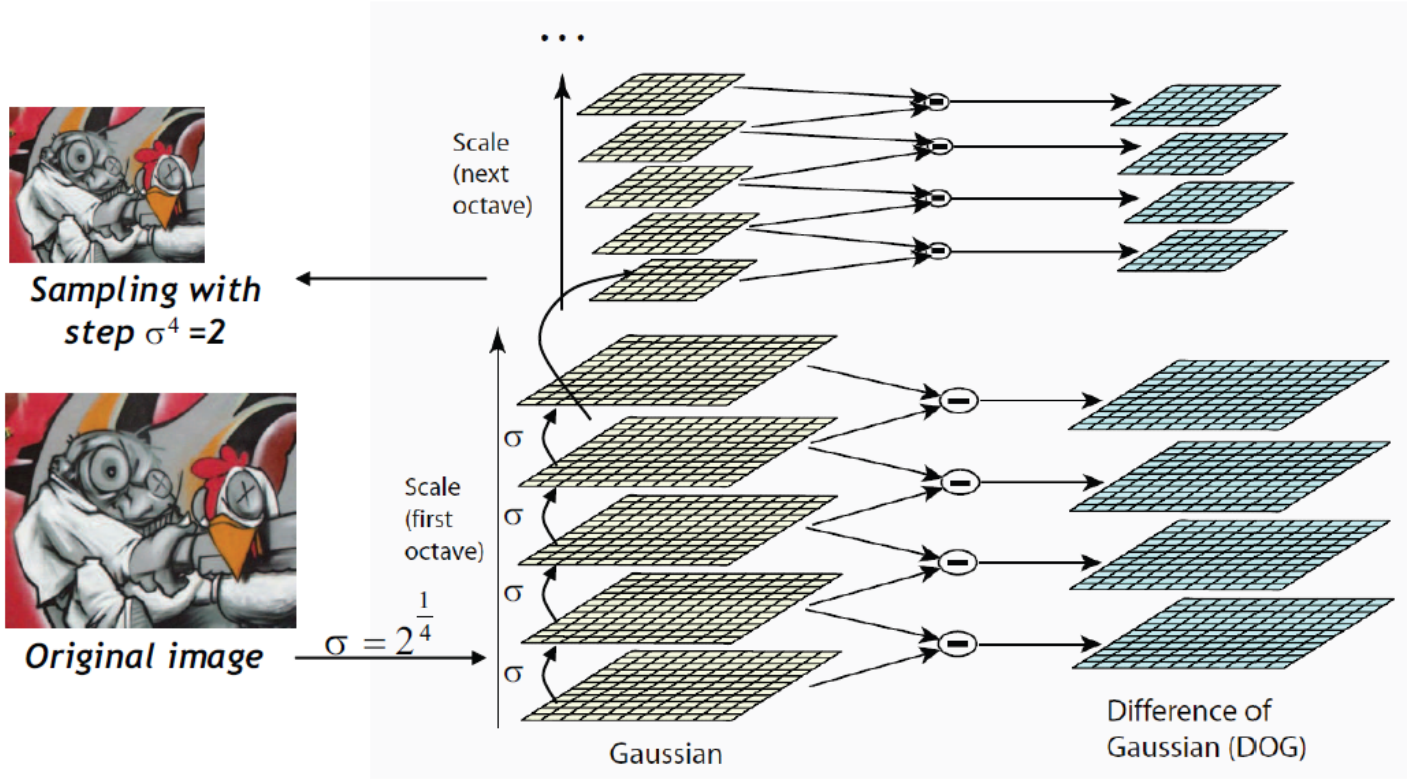
−1	−1	−1
−1	8	−1
−1	−1	−1

Laplacian-of-Gaussian (LoG)

Grauman and Leibe 2011

SIFT – Scale invariant feature targets

- Feature detection



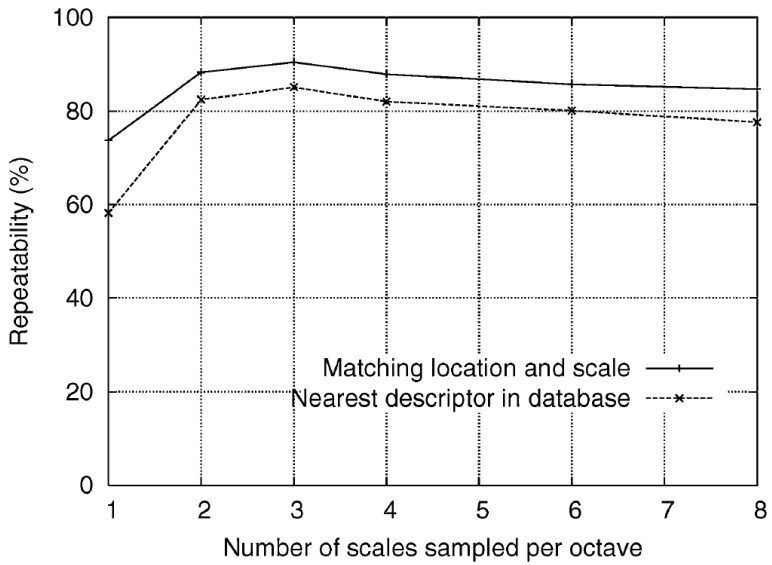
Difference-of-Gaussian (DoG) provides a good approximation LoG and can be efficiently computed

Grauman and Leibe 2011

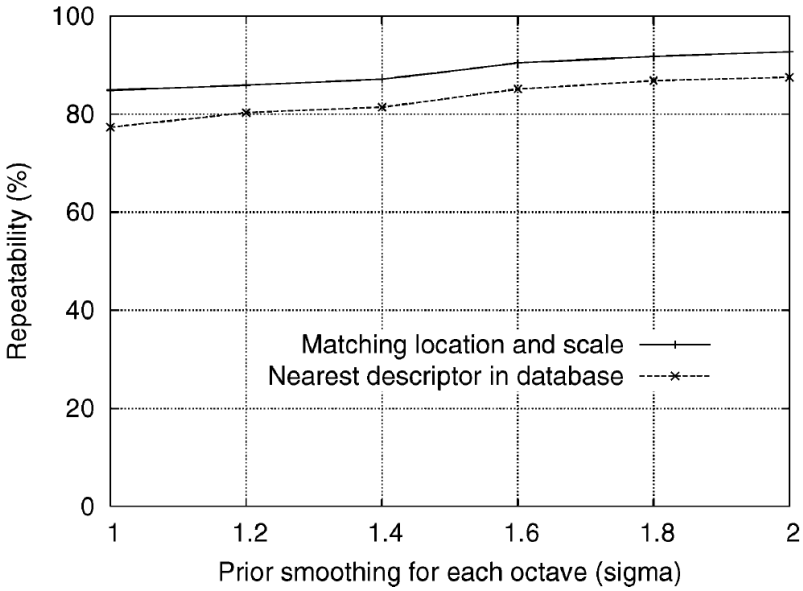
SIFT – Scale invariant feature targets

- Feature detection

How many scales should be used?



Prior smoothing improves stability



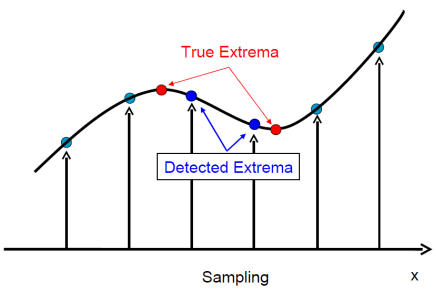
- Construction of octaves starts from an upsampled version of the original image
- Roughly log2(min(width,height) = number of octaves

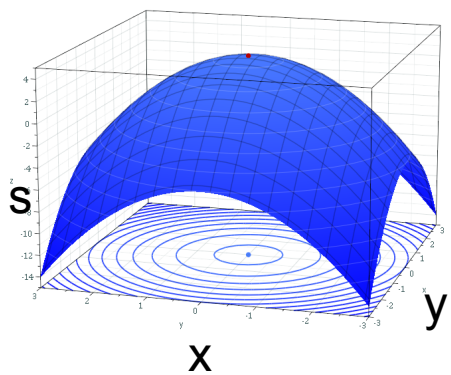
Lowe 2004

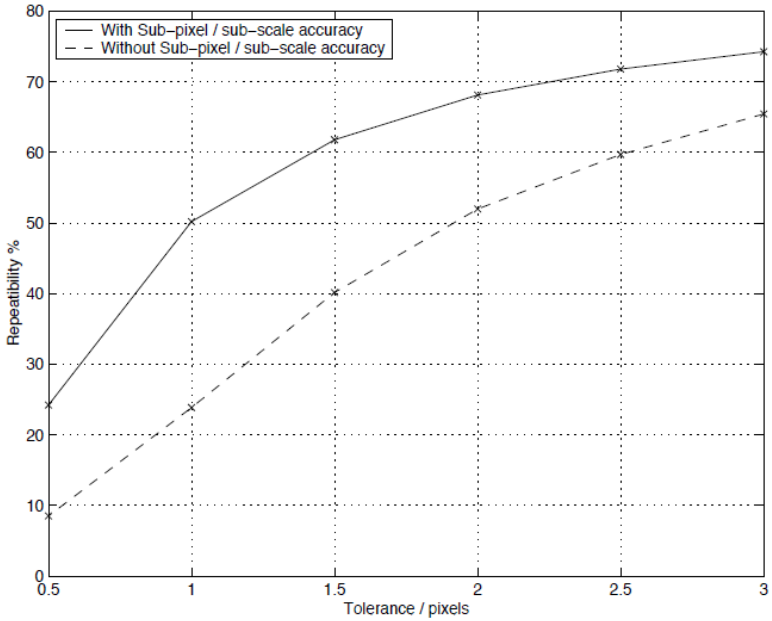
IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

- Feature detection
  - outlier rejection in areas with low contrast
  - sub-pixel accuracy
  - Rejection of edges where gradient in one direction is relatively low







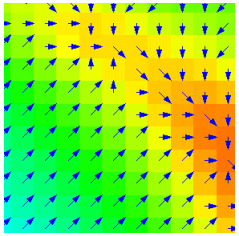
$$\mathbf{x} = (x, y, s)^T$$

$$L(\mathbf{x}) = L + \frac{\partial L}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 L}{\partial \mathbf{x}^2}\mathbf{x}$$

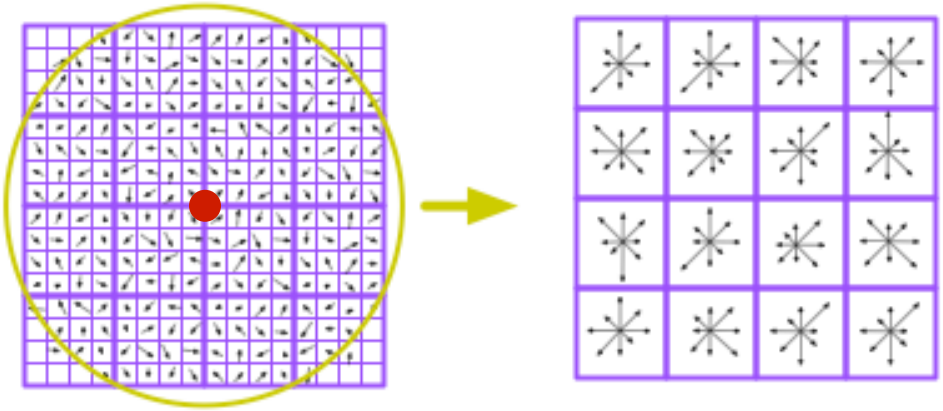
Brown and Lowe 2002

SIFT – Scale invariant feature targets

- Feature description
  - Gradient magnitude and orientation



Similar to computing slope and flow direction in terrain analyses



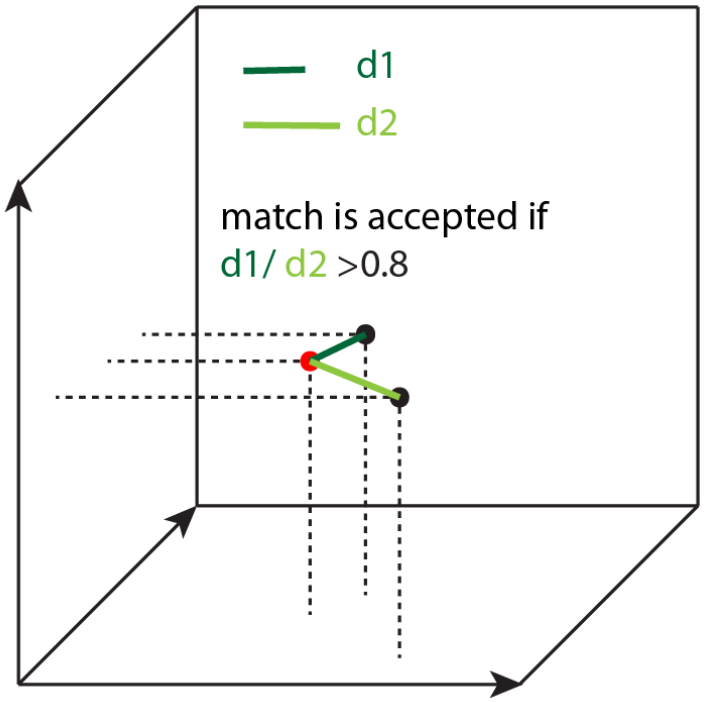
Resulting feature vector is 4x4x8 = 124 features
(additionally very large gradients are removed + normalization)

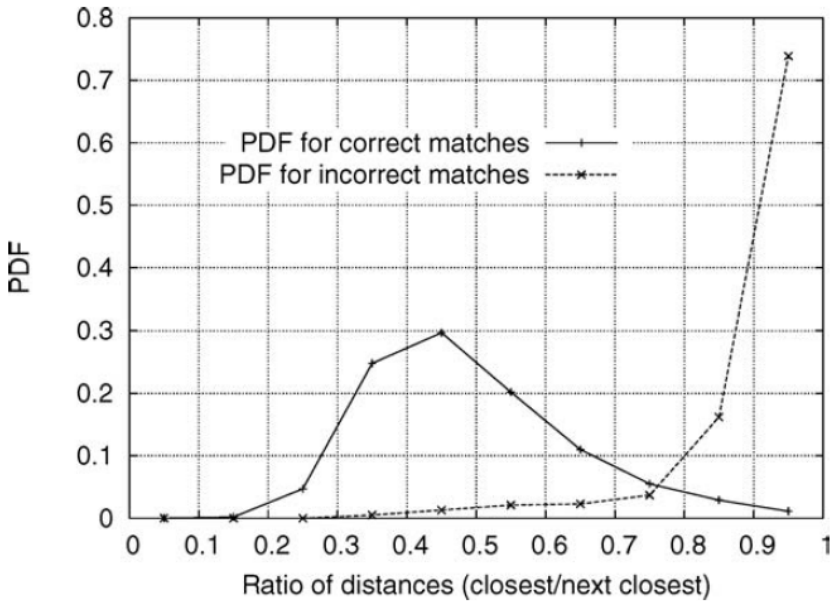
- Use the octave and scale of the keypoint
- Compute orientation and gradients for each pixel in 16 × 16 neighborhood
- Histograms with 8 bins (360°/8)
- Orientations are weighted by distance to interest point and gradient magnitude

IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

- Feature matching
  - Efficient nearest neighbor with rejection of weak matches





Lowe 2004

SIFT – Scale invariant feature targets

- Does it work?
  - Very robust to illumination changes, rotation, scaling and moderate affine transformations
  - Many applications in image matching, object recognition, etc.
  - Faster and open-source implementation are available
  - Many enhancement have been proposed but the algorithm remains state of the art

Distinctive image features from **scale-invariant keypoints**
DG Lowe - International journal of computer vision, 2004 - Springer
... Page 5. **Distinctive Image Features** from **Scale-Invariant Keypoints** 95 Figure 1. For each octave of scale space, the initial **image** is repeatedly convolved with Gaussians to produce the set of scale space **images** shown on the left. ...
Cité 20257 fois Autres articles Les 236 versions Citer

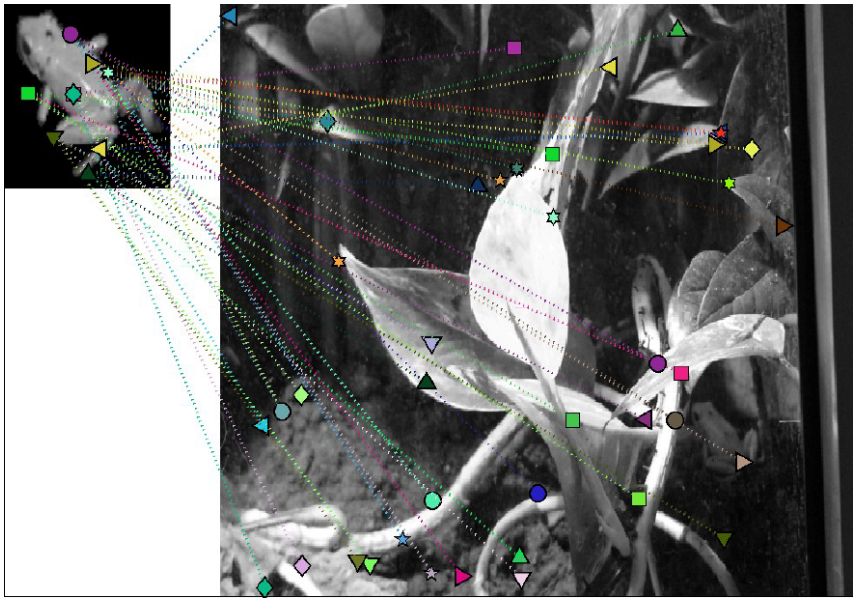
IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

- Limitations?

Very strong illumination changes

Non-rigid deformation and view-angle changes > 20 degree

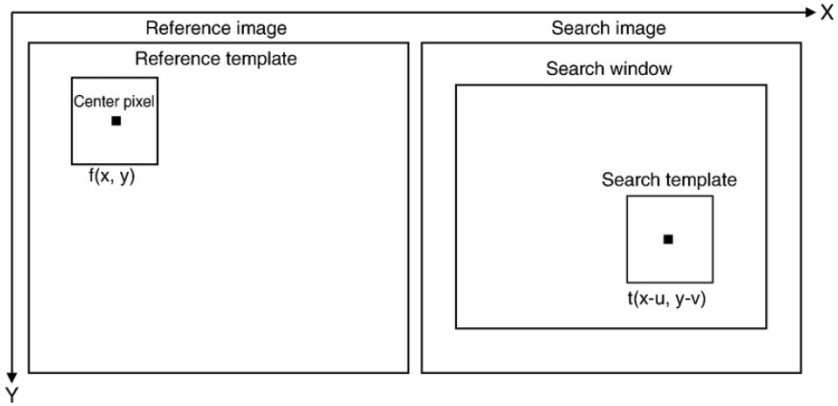


Ofir Pele

IMAGE MATCHING TECHNIQUES

Patch-based image correlation

Statistical correlation vs. Fourier domain

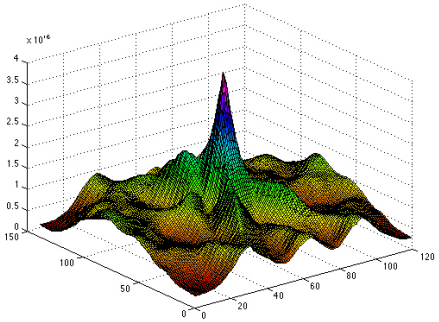


Window size

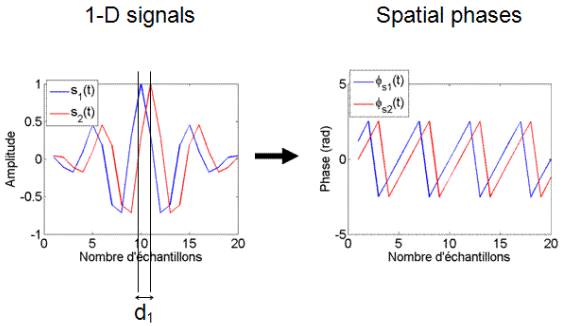
Search window size

Step size

A shift in the image corresponds to a change of the phase in the Fourier domain



Correlation peak indicates the new position



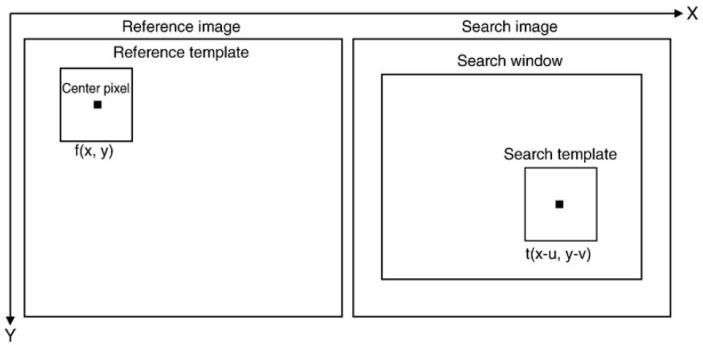
Debella-Gilo & Andreas Kääb 2011

IMAGE MATCHING TECHNIQUES

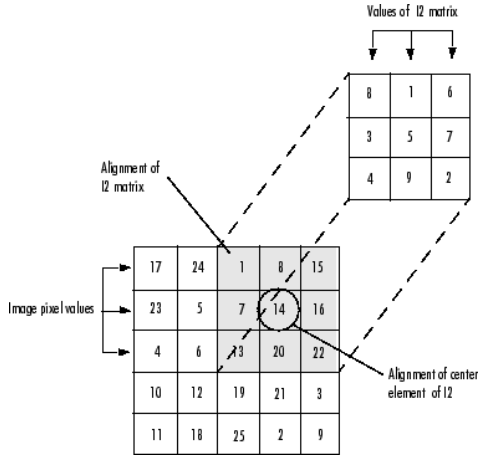
Statistical correlation

Cost functions to evaluate similarity of image patches

- Squared differences (easy computation)
- Normalized Cross-Correlation (common standard)
- Mutual Information (Robust)
- CENSUS (Robust)
- Rank matching (Robust)



Normalized Cross-Correlation



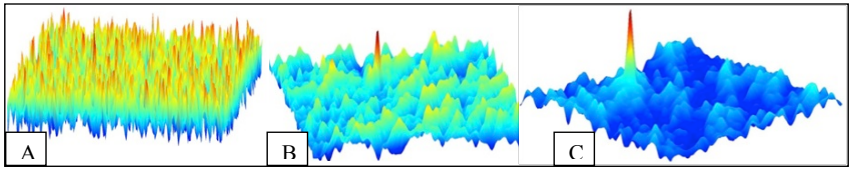

```
I1 <- c(1,8,15,7,14,16,13,20,22)
I2 <- c(8,1,6,3,5,7,4,9,2)
A = sum(I1*I2)
# 585
B = sqrt(sum(I1^2) * sum(I2^2))
# 724.9414
NCC = A/B
# 0.8069618
```

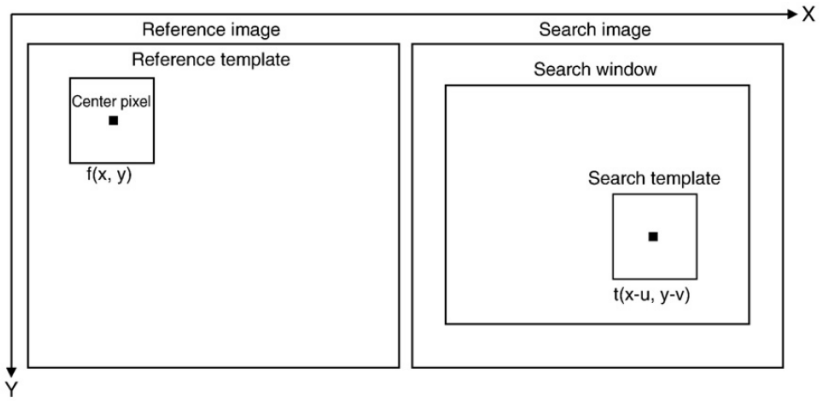
Normalization accounts for variable illumination and scaling of the DN values

IMAGE MATCHING TECHNIQUES

Normalized Cross-Correlation

Window size?
- Sufficiently large to be robust
- Sufficiently small to capture local differences





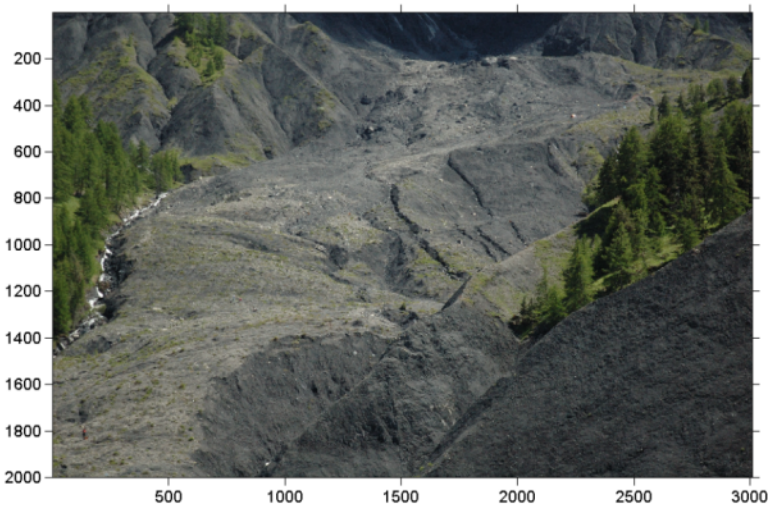
Search window size?
- Sufficiently large to capture maximum displacement
- Larger search space increases the probability of false matches and computation time

Step size?
- Often 1 pixel
- Equal to window size is a good choice to obtain independent measurements

IMAGE MATCHING TECHNIQUES

Hierarchical normalized Cross-Correlation

- Resolves most window size questions
- Even more robust if applied to high pass-filtered derivate of the image



Sobel filter

$$\mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A}$$

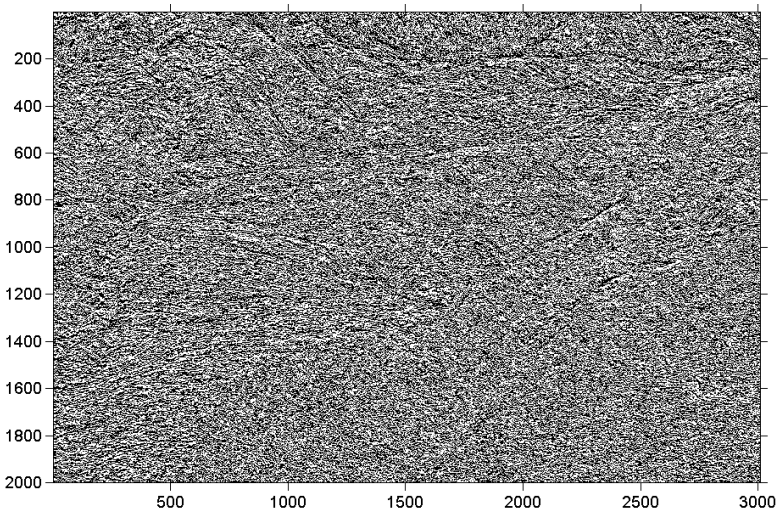


IMAGE MATCHING TECHNIQUES

Hierarchical normalized Cross-Correlation

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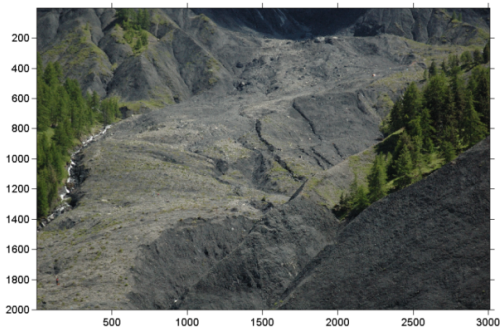


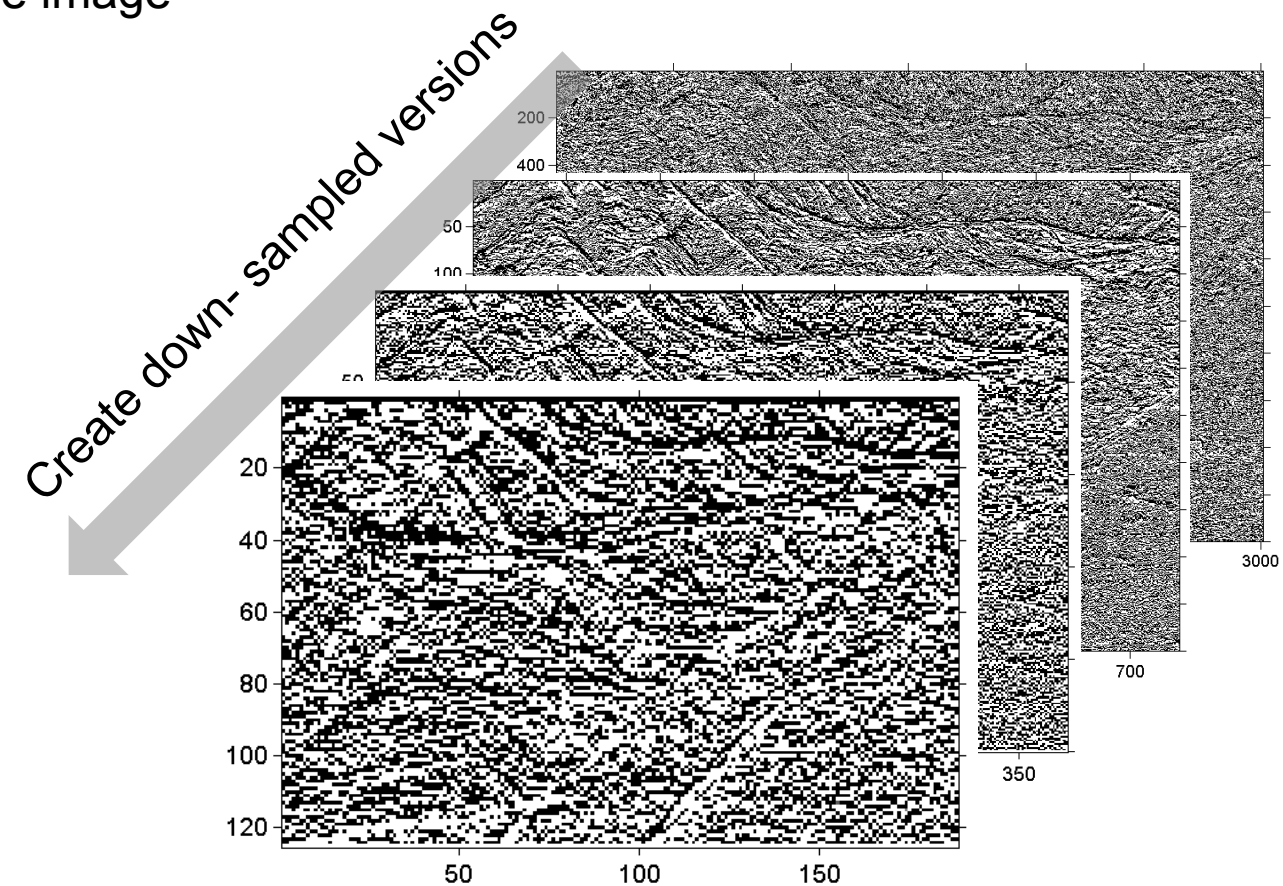


IMAGE MATCHING TECHNIQUES

HNCC

Reference image t=1

$$\Phi(u,v) = \frac{\sum_{x,y}[f(x,y)-\overline{f}_{u,v}][t(x-u,y-v)-\bar{t}]}{\left\{\sum_{x,y}[f(x,y)-\overline{f_{u,v}}]^2 \sum_{x,y}(t(x-u,y-v)-\bar{t})^2\right\}^{0.5}}$$

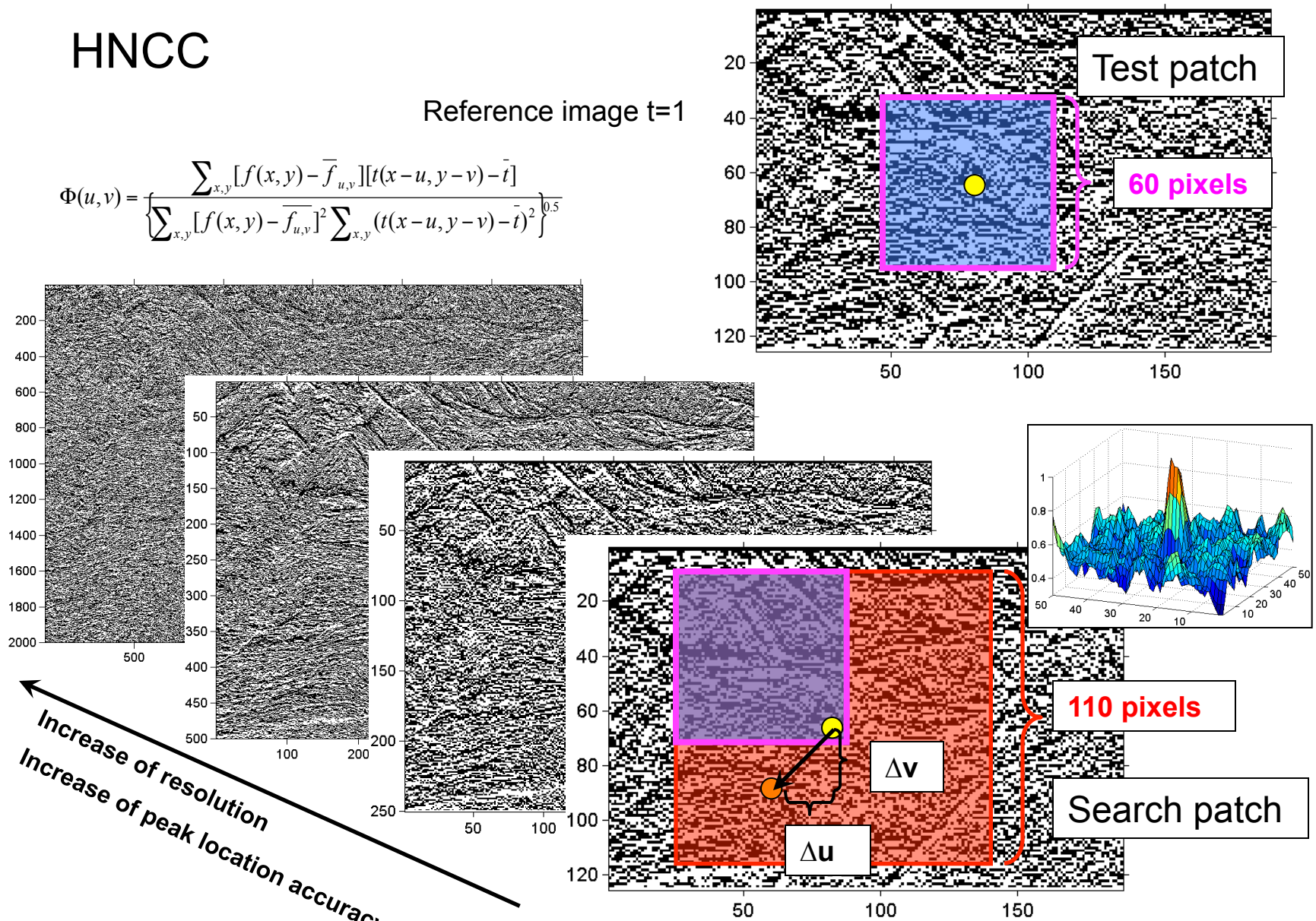


IMAGE MATCHING TECHNIQUES

HNCC

Reference image t=1

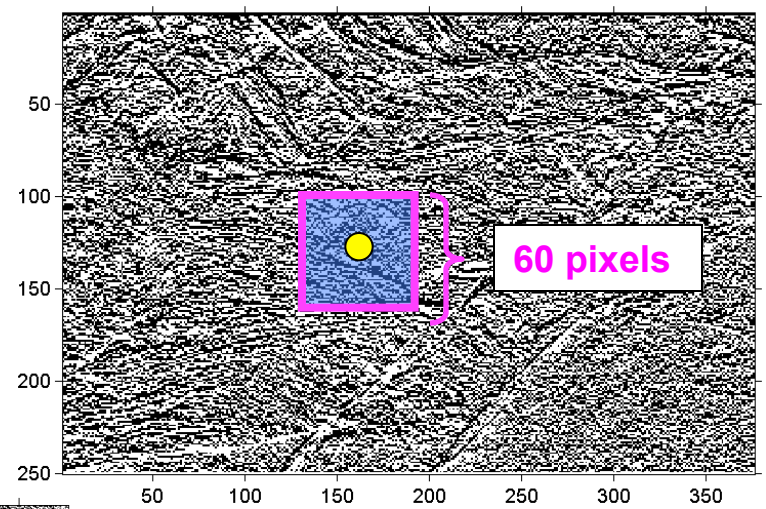
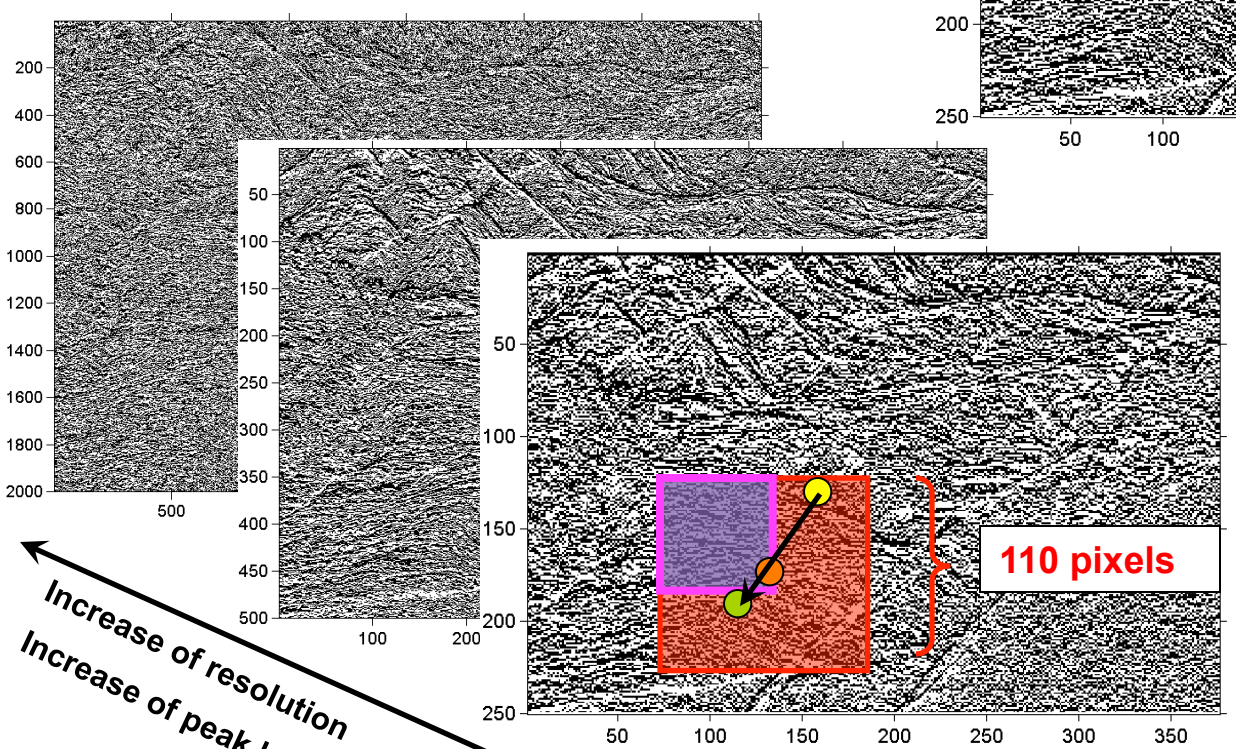
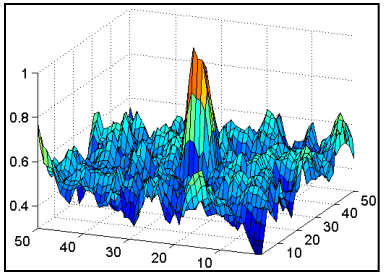


Image t=2





Increase of resolution

Increase of peak location accuracy

IMAGE MATCHING TECHNIQUES

HNCC

Reference image t=1

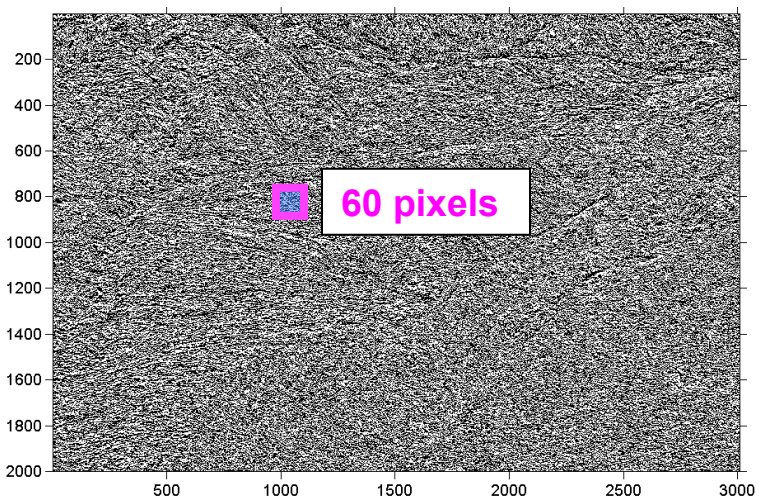
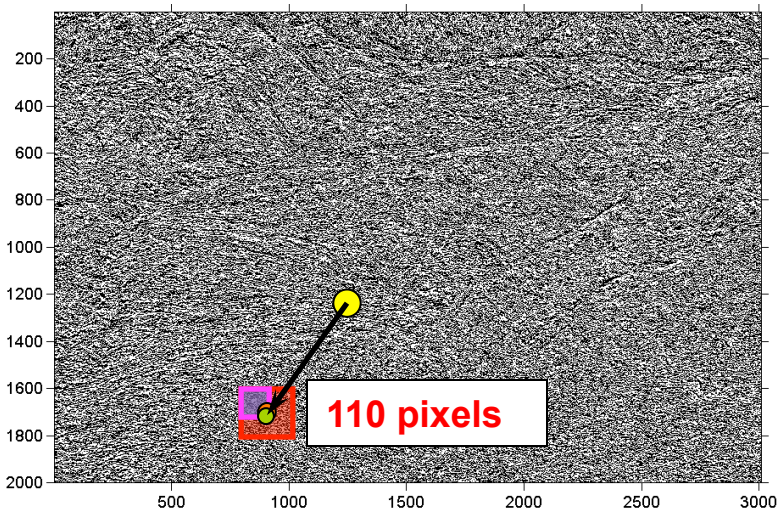
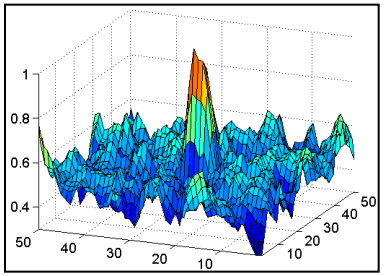


Image t=2



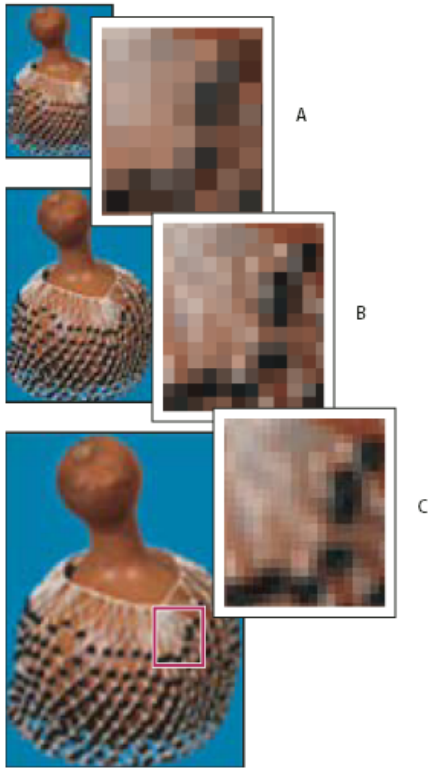


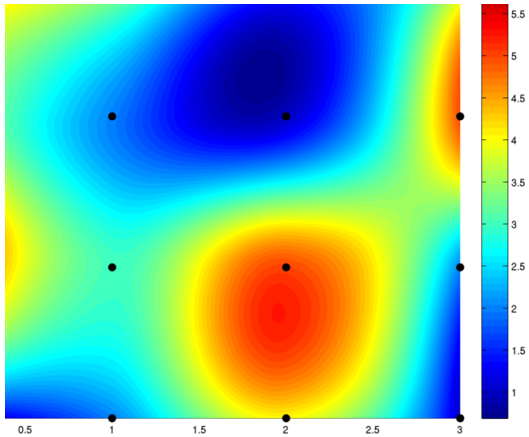
Robust estimation of displacement with pixel precision

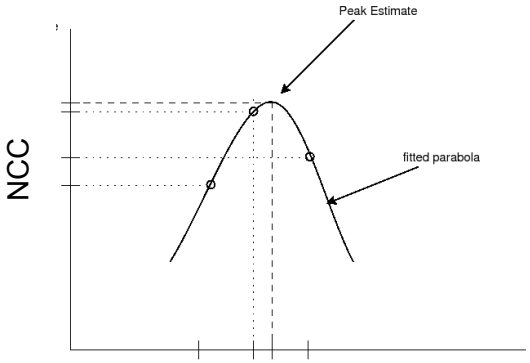
IMAGE MATCHING TECHNIQUES

HNCC – Subpixel precision

Interpolate image vs. interpolate correlation surface vs. peak fitting







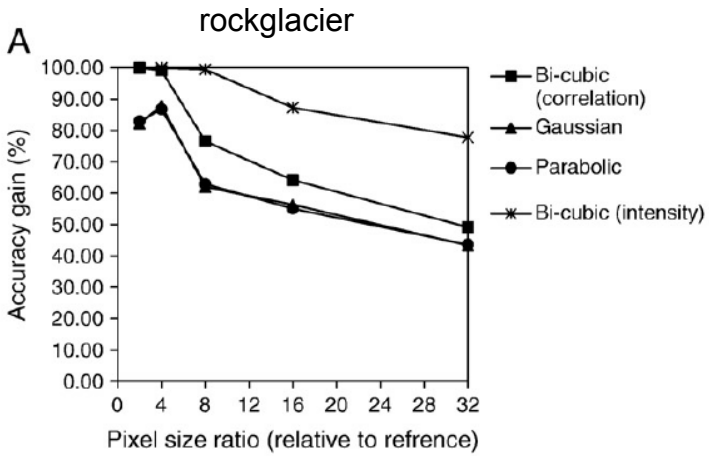
HNCC – Subpixel precision

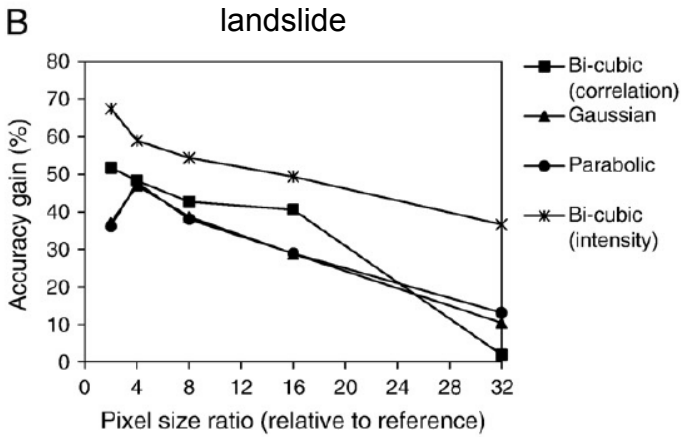
Interpolate image vs. interpolate correlation surface vs. peak fitting

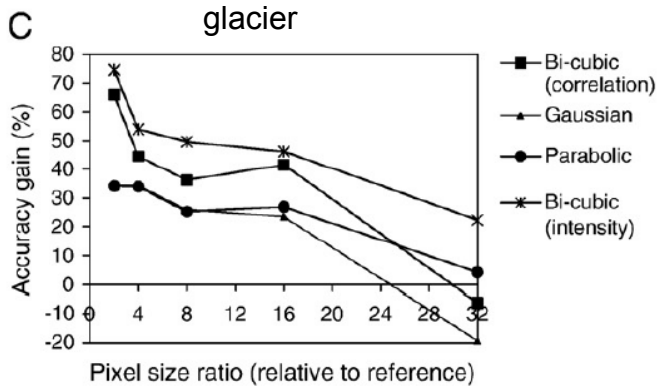
Bicubic intensity

Bi-cubic (correlation)

Parabolic
or Gaussian







Reference is the original image at full resolution

Image interpolation with a bi-cubic scheme results as the most precise
… but also significantly increases the computational costs!!!

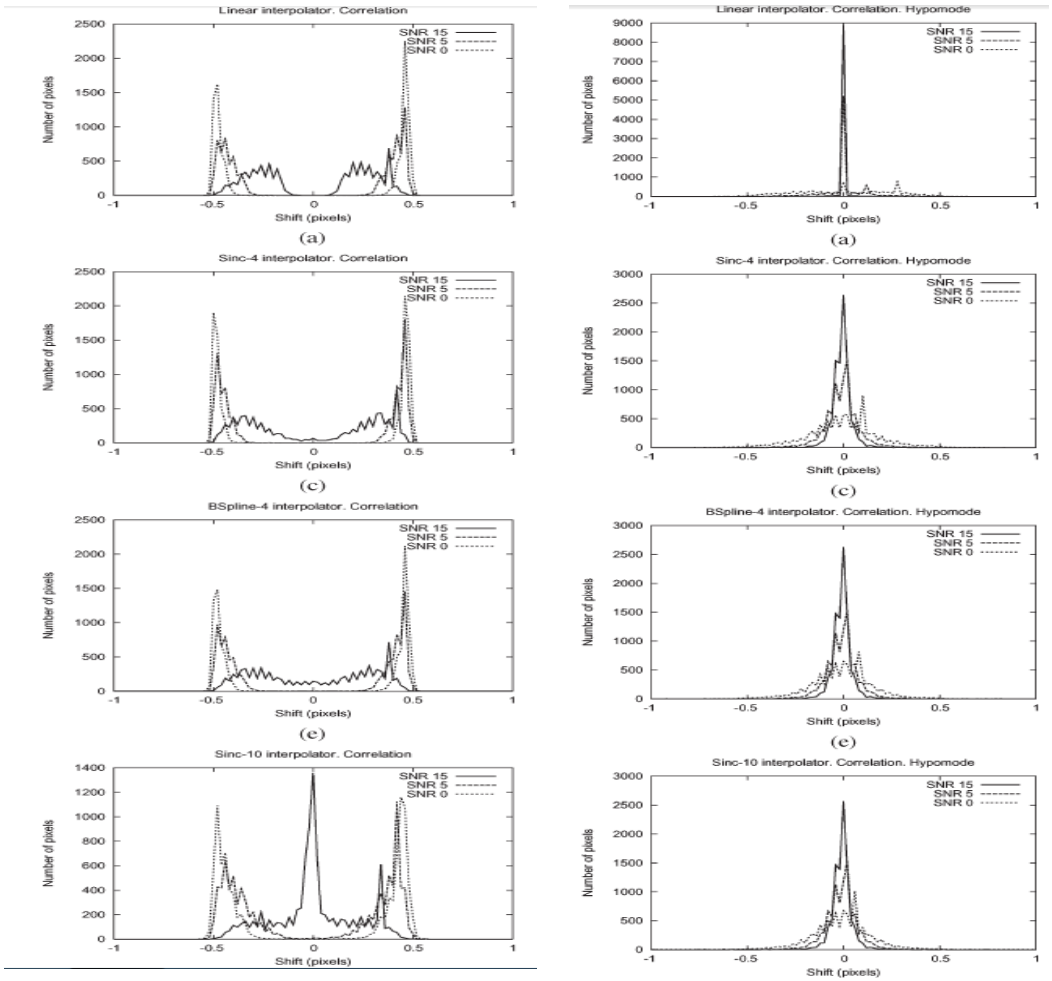
Debella-Gilo and Kääb 2011

IMAGE MATCHING TECHNIQUES

Histograms of measured shifts under zero-shift using different interpolator

Matching on interpolated images

Matching on interpolated images after low-pass filtering



Interpolated image should be smoothed with a low-pass filter before correlation

> Reduces aliasing effects significantly

Inglada et al. 2007

GEOMETRIC MODELLING

Satellite photogrammetry

R. Binet

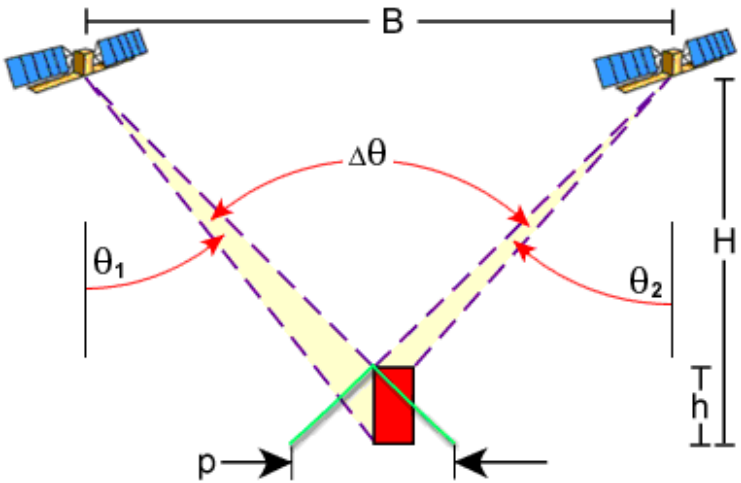
GEOMETRIC MODELLING

Satellite photogrammetry

R. Binet

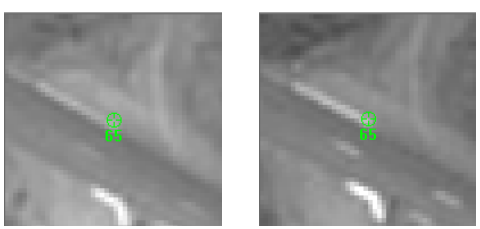
GEOMETRIC MODELLING

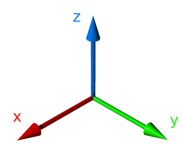
Satellite photogrammetry



- Rigorous sensor model
- Rational functional model

➢ Typically not sufficiently precise to apply photogrammetric techniques directly
➢ Homologous points (tie points) between the images can resolve relative bias
➢ But GCPs are required to resolve for scaling and absolute bias





$$l + A_0 + A_1 l + A_2 s = \frac{F_1(U,V,W)}{F_2(U,V,W)}$$

$$s + B_0 + B_1 l + B_2 s = \frac{F_3(U,V,W)}{F_4(U,V,W)}.$$

Tie point extraction → GCPs → Bundle Adjustment

GEOMETRIC MODELLING

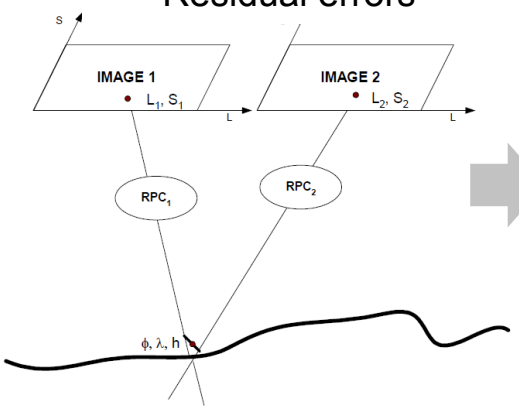
Satellite photogrammetry

- Bundle adjustment with Rational Functional Sensor Models

$$l = \frac{F_1(U,V,W)}{F_2(U,V,W)}$$
$$s = \frac{F_3(U,V,W)}{F_4(U,V,W)}$$

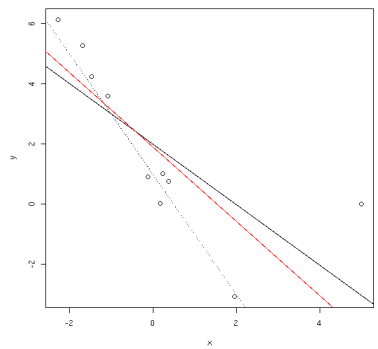
U,V,W …coordinates in ground space
l , s … line, row coordinates in image space
$F_{1,2,3,4}$ … rational functions with 80 coefficients

Residual errors



Grodecki et al. 2004

Iterative least square



Adjustment parameters

$$l + A_0 + A_1 l + A_2 s = \frac{F_1(U,V,W)}{F_2(U,V,W)}$$
$$s + B_0 + B_1 l + B_2 s = \frac{F_3(U,V,W)}{F_4(U,V,W)}$$

Shift → Rot → Affine

RPC Bundle Adjustment Solution	No. of GCPs (Number of Checkpoints)	RMS of l, s Image Residuals (pixels)	RMS Value of Ground Checkpoint Discrepancies. Units are Meters and Pixels		
			Latitude (along track)	Longitude (across track)	Height
Spatial Intersection	None (110)	-	2.9	1.2	4.0
Shift: A_0, B_0	2 (108)	0.24	0.67	0.29	0.70
Shift: A_0, B_0	1 at 1,200 m (109)	0.24	0.60	0.29	0.87
Drift: A_0, B_0, A_1, B_1	6 (104)	0.21	0.68	0.26	0.72
Affine: $A_0 - B_2$	9 (101)	0.20	0.59	0.25	0.78
Shift: A_0, B_0	*110 (sigma = 2 m)*	*0.24*	*0.54*	*0.26*	*0.54*

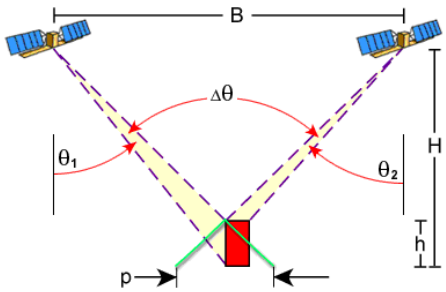
Fraser and Hanley 2005

Tie point extraction → GCPs → Bundle Adjustment

GEOMETRIC MODELLING

Satellite photogrammetry

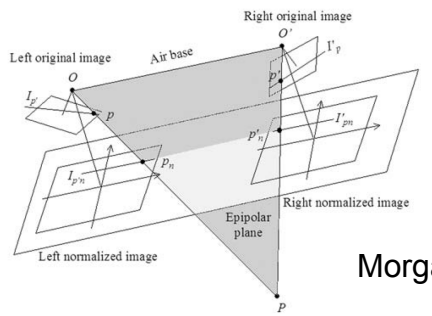
- DSM extraction



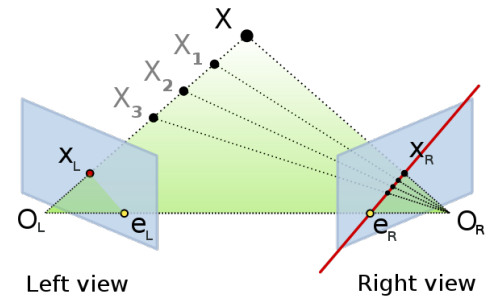
$$l + A_0 + A_1 l + A_2 s = \frac{F_1(U,V,W)}{F_2(U,V,W)}$$

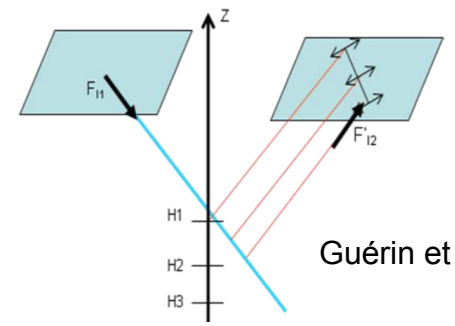
$$s + B_0 + B_1 l + B_2 s = \frac{F_3(U,V,W)}{F_4(U,V,W)}$$

Epipolar resampling (homologous points are in the same rows)



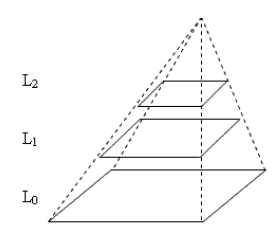
Morgan et al. 2006

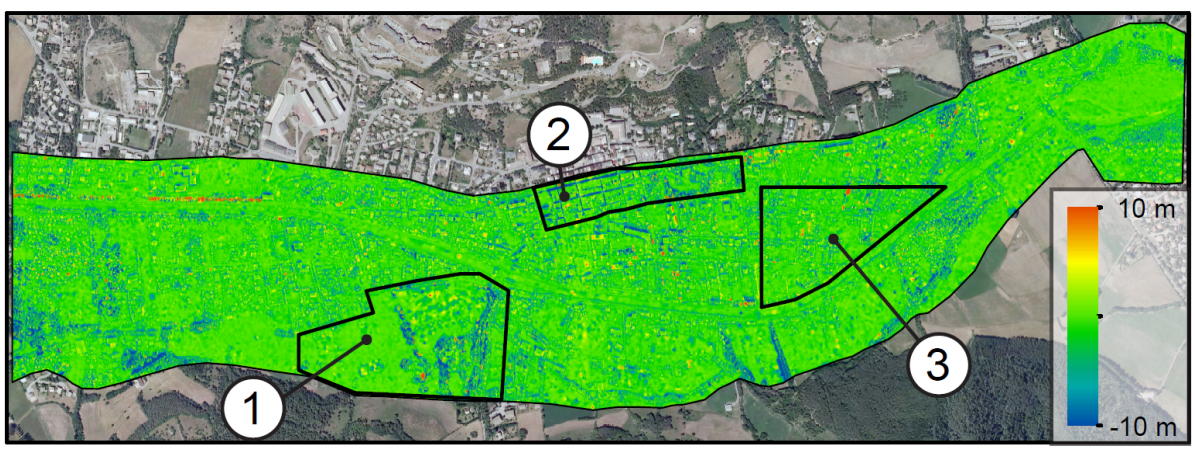




Guérin et al. 2012

Hierarchical Image Correlation

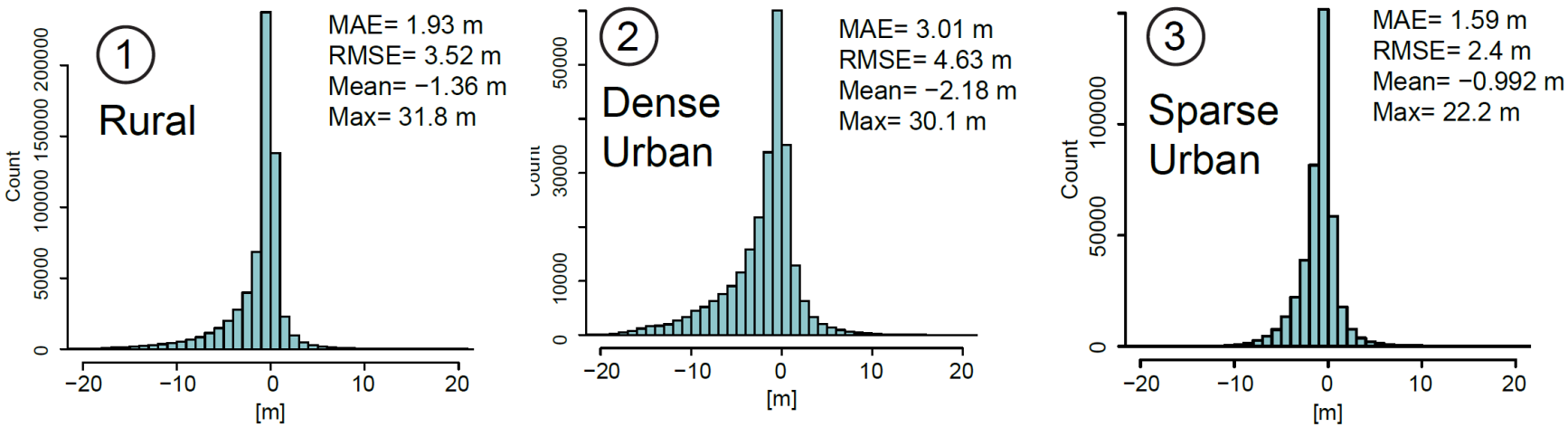


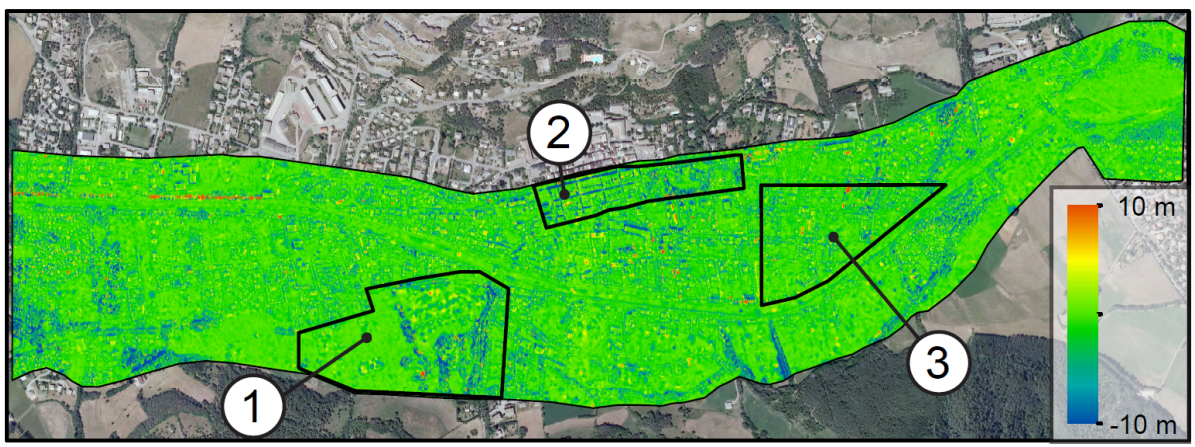


GEOMETRIC MODELLING

Satellite photogrammetry

- Accuracy?





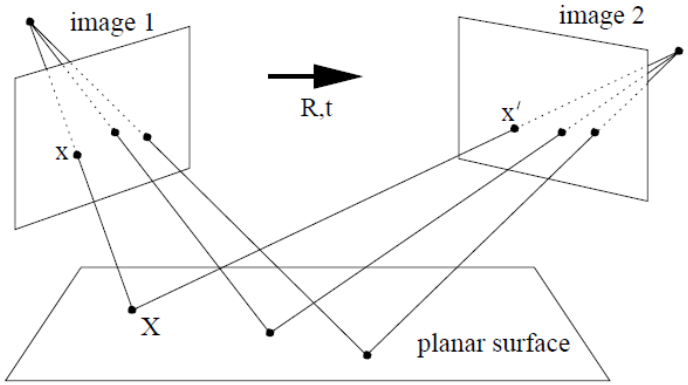
open source ???

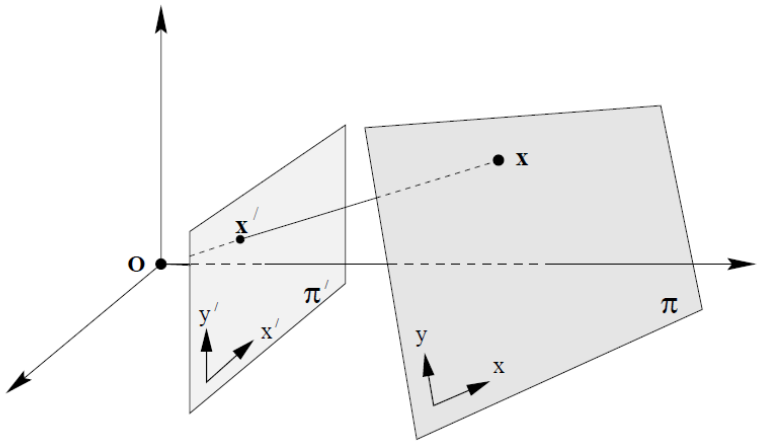
- Tie point detection
- Hierarchical Image Correlation
- RPF Bundle Adjustment

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Projective transformation / Homography





$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \qquad \begin{matrix} x \\ y \\ 1 \end{matrix}$$

$$\mathbf{x}' = \mathbf{H}\mathbf{x}$$

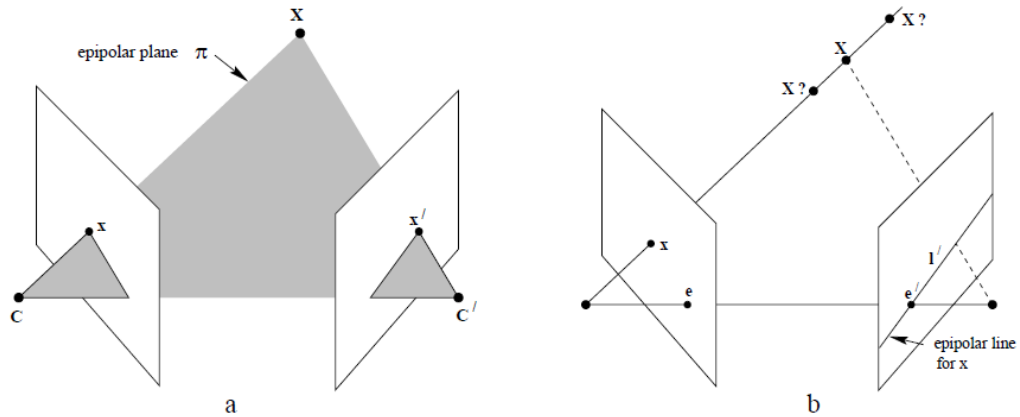
- H is defined up to scale > 8 degrees of freedom
- At least four point correspondences are needed to solve H for the projective transformation between two planes

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Epipolar geometry and the Fundamental Matrix



- For each point in one each image there is an epipolar line in the second image

$$\mathbf{x} \mapsto \mathbf{l}'$$

$\mathbf{l}' = \mathbf{F}\mathbf{x}$ is the epipolar line corresponding to $\mathbf{x}$.

$\mathbf{l} = \mathbf{F}^\mathsf{T}\mathbf{x}'$ is the epipolar line corresponding to $\mathbf{x}'$

$$\mathbf{x}'^\mathsf{T}\mathbf{F}\mathbf{x} = 0$$

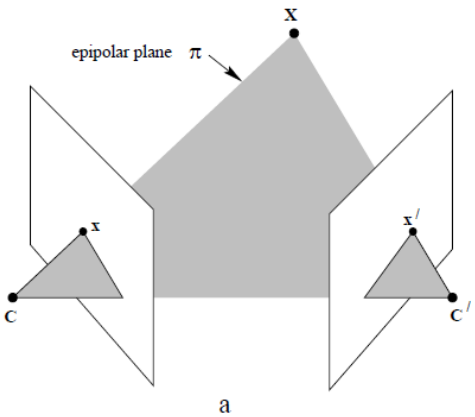
- F is a 3×3 matrix with 8 independent ratios (defined up to scaling)
- F also satisfies det F = 0 which removes one degree of freedom
- not full rank (since an epipolar line cannot be mapped to one point)
- F depends on the cameras not the world coordinate system

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the Fundamental Matrix



- Given at least 8 independent (not collinear) point correspondences $\mathbf{x} \leftrightarrow \mathbf{x}'$ $\quad \mathbf{x}'^{\mathsf{T}}\mathbf{F}\mathbf{x} = 0$

- In the linear form

$$x'xf_{11} + x'yf_{12} + x'f_{13} + y'xf_{21} + y'yf_{22} + y'f_{23} + xf_{31} + yf_{32} + f_{33} = 0$$

- We get n linear equations where n is the number of point correspondences

$$\mathtt{A}\mathbf{f} = \begin{bmatrix} x'_1x_1 & x'_1y_1 & x'_1 & y'_1x_1 & y'_1y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \\ x'_nx_n & x'_ny_n & x'_n & y'_nx_n & y'_ny_n & y'_n & x_n & y_n & 1 \end{bmatrix} \mathbf{f} = \mathbf{0}$$

- Minimize $\|\mathtt{A}\mathbf{f}\|$ (least square)

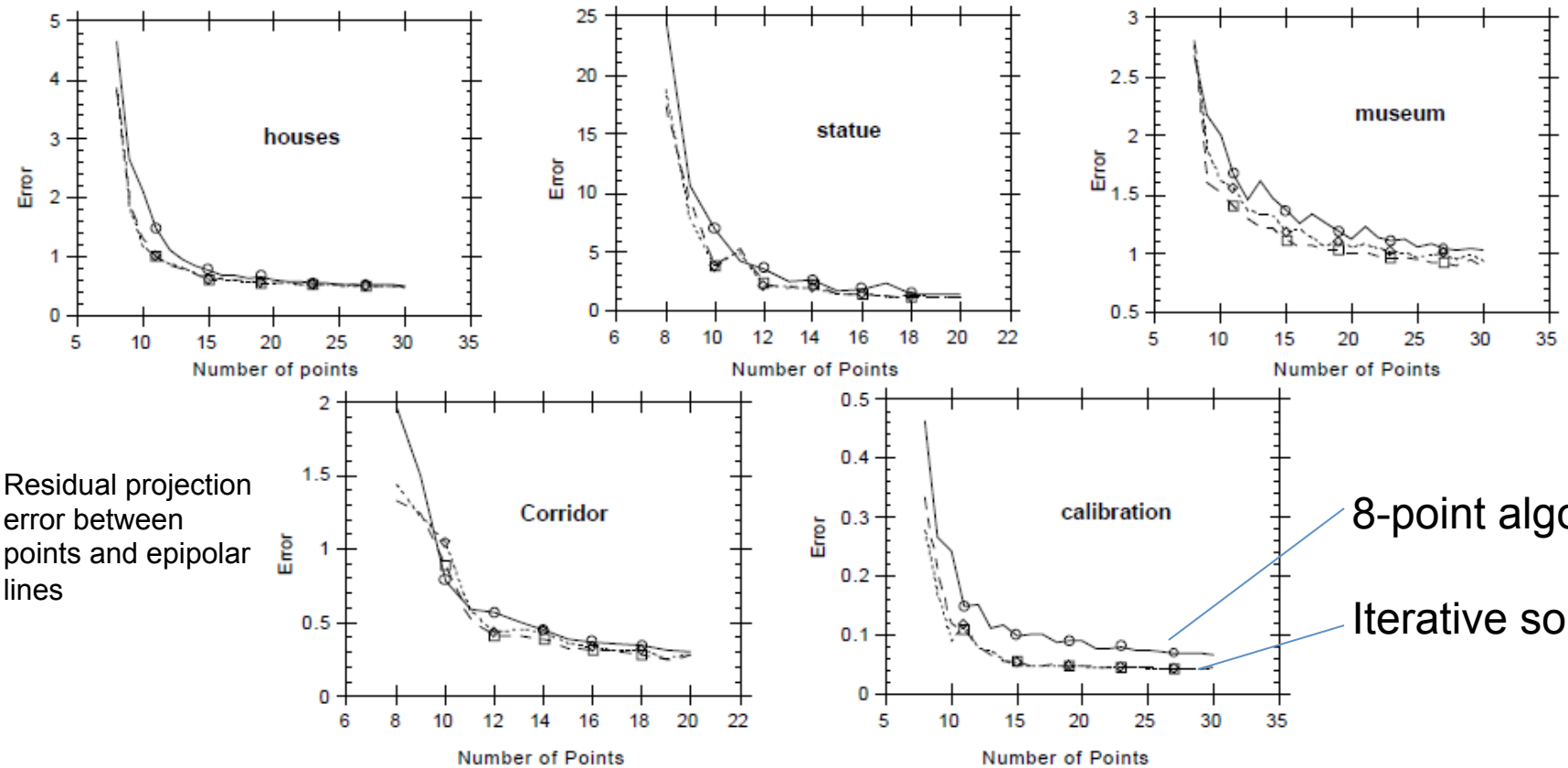
$$\|\mathbf{f}\| = 1$$

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the Fundamental Matrix



Residual projection error between points and epipolar lines

8-point algorithm

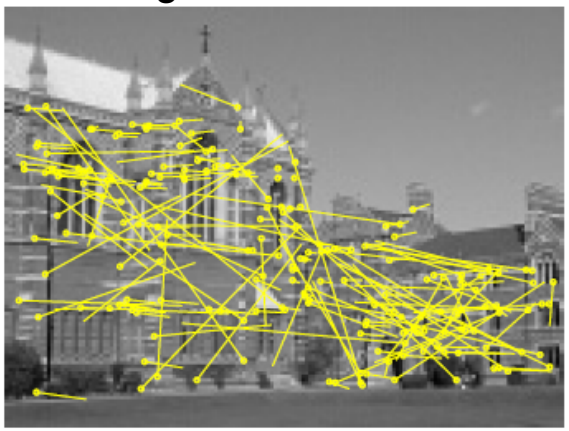
Iterative solutions

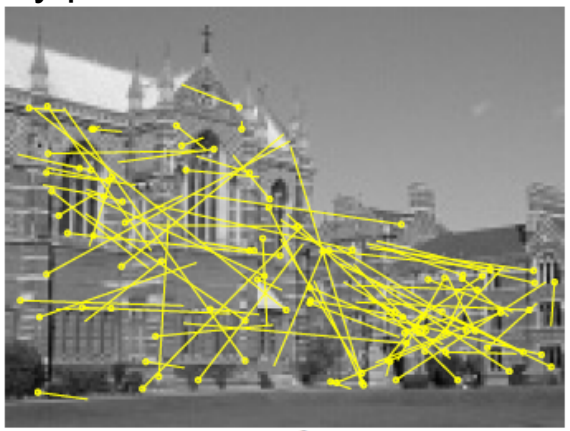
Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the Fundamental Matrix with noisy point matches





RANSAC robust estimation: Repeat for *N* point correspondences

(a) Select a random sample of 7 correspondences and compute F

(b) Calculate the residual projection distances $d\perp$ for all matching points

(c) Compute the number of inliers consistent with F

(d) If there are three real solutions for F the number of inliers is computed

Choose the F with the largest number of inliers.

Non-linear estimation: re-estimate F from all correspondences (Levenberg–Marquardt algorithm)

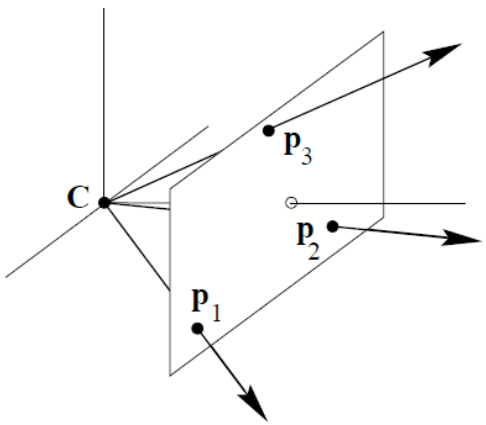
Guided matching: Further interest point correspondences are now determined using the estimated F

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the camera matrix



- Camera model where the mapping between image space and world space is linear
- Can be extracted from the fundamental matrix

$$P_2 = [[\mathbf{e}_2]_\times F \quad \mathbf{e}_2]$$

$$\mathtt{P} = \begin{bmatrix} 3.53553\,e{+}2 & 3.39645\,e{+}2 & 2.77744\,e{+}2 & -1.44946\,e{+}6 \\ -1.03528\,e{+}2 & 2.33212\,e{+}1 & 4.59607\,e{+}2 & -6.32525\,e{+}5 \\ 7.07107\,e{-}1 & -3.53553\,e{-}1 & 6.12372\,e{-}1 & -9.18559\,e{+}2 \end{bmatrix}$$

$$\mathtt{P} = \mathtt{K}[\mathtt{R} \mid \mathbf{t}] \qquad \mathtt{K} = \begin{bmatrix} \alpha_x & & x_0 \\ & \alpha_y & y_0 \\ & & 1 \end{bmatrix}$$

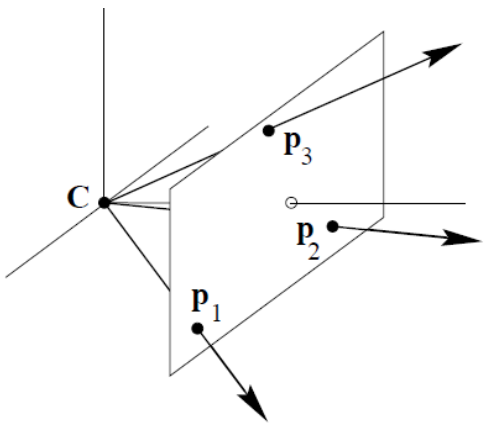
Where ax and ay are the focal length in pixel
x0 and y0 are the principal point coordinates

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the camera matrix



- Camera model where the mapping between image space and world space is linear
- Can be extracted from the fundamental matrix

$$P_2 = [[\mathbf{e}_2]_\times F \quad \mathbf{e}_2]$$

$$\mathtt{P} = \begin{bmatrix} 3.53553\,e{+}2 & 3.39645\,e{+}2 & 2.77744\,e{+}2 & -1.44946\,e{+}6 \\ -1.03528\,e{+}2 & 2.33212\,e{+}1 & 4.59607\,e{+}2 & -6.32525\,e{+}5 \\ 7.07107\,e{-}1 & -3.53553\,e{-}1 & 6.12372\,e{-}1 & -9.18559\,e{+}2 \end{bmatrix}$$

$$\mathtt{P} = \mathtt{K}[\mathtt{R} \mid \mathbf{t}] \qquad \mathtt{K} = \begin{bmatrix} \alpha_x & & x_0 \\ & \alpha_y & y_0 \\ & & 1 \end{bmatrix}$$

Where ax and ay are the focal length in pixel
x0 and y0 are the principal point coordinates

	f_y	f_x/f_y	skew	x_0	y_0	residual
algebraic	1633.4	1.0	0.0	371.21	293.63	0.601
geometric	1637.2	1.0	0.0	371.32	293.69	0.601

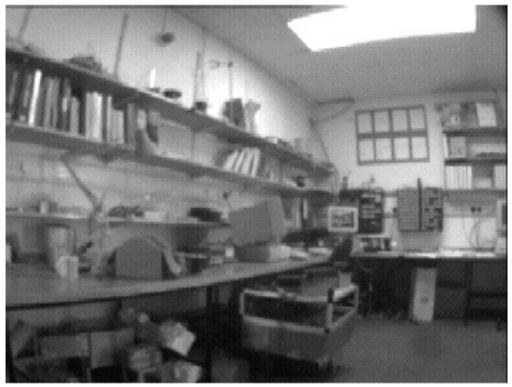
Relative high residual because lens distortion is not considered

Hartley and Zisserman 2004

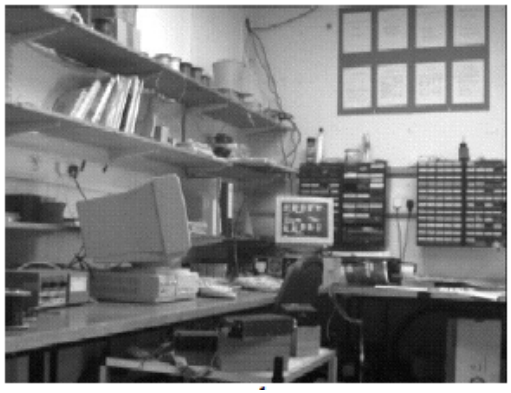
GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

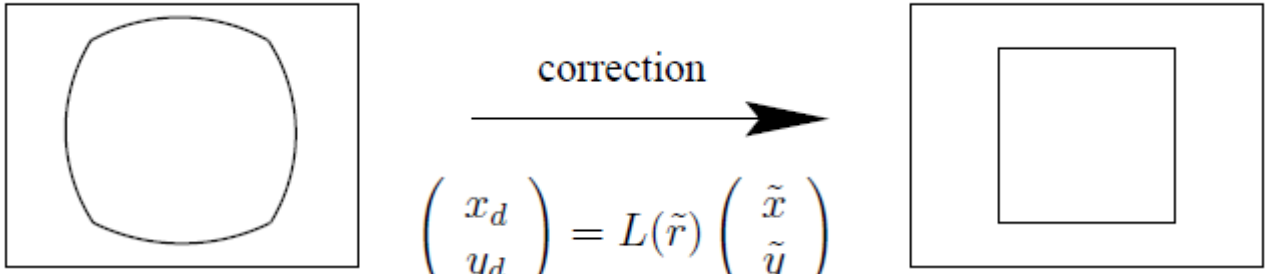
- Lens distortion



radial distortion



linear image



$$\begin{pmatrix} x_d \\ y_d \end{pmatrix} = L(\tilde{r}) \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$$

actual image position

ideal image position

$\tilde{r}$ is the radial distance $\sqrt{\tilde{x}^2 + \tilde{y}^2}$ from the centre for radial distortion.

$L(\tilde{r})$ is a distortion factor, which is a function of the radius $\tilde{r}$ only.

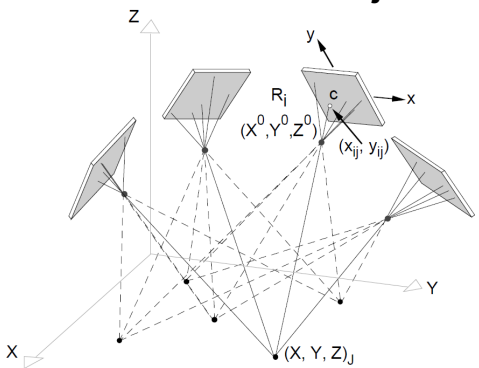
- Lens parameters can be determined from a single image imposing constraints from parallel lines
- More commonly done during bundle adjustment as 'final' step of the reconstruction

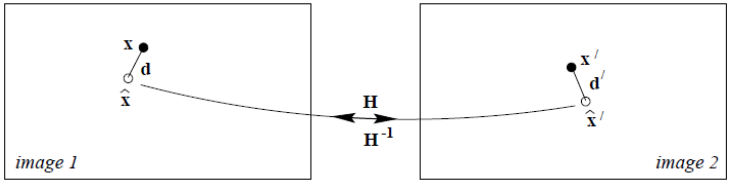
Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Bundle adjustment and auto-calibration





$$\min_{\mathbf{a}_j, \mathbf{b}_i} \sum_{i=1}^{n} \sum_{j=1}^{m} v_{ij}\, d(\mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i), \mathbf{x}_{ij})^2,$$

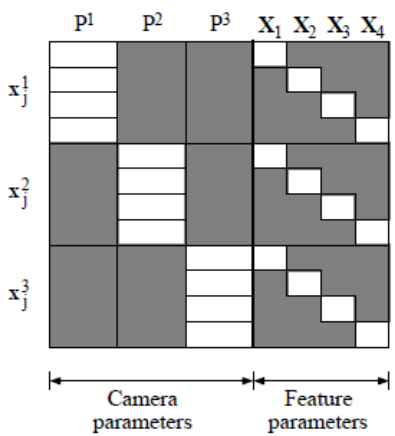
n 3d points seen in m images

v_{ij} 0/1 … point visible in image j or not

$\mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i)$ Projected position for point i in image j

$\mathbf{x}_{ij}$ Observed position for point i in image j

Organized in a Jacobian



Sparse Levenberg – Marquardt

Joint optimization of **internal** and **external** camera parameters

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Bundle adjustment and auto-calibration – Recommendations

  - Take pictures with sufficient motion
  - Use priors (Size of the sensor, Principal point, Focal length) to enable better convergence
  - If you don’t have exact values use a range to constrain the solution

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Further concepts
  - Lens models

RadialExtended a model with radial distorsion (as specified in 13.2.2); in this model there are 10 degrees of freedom: 1 for focal length , 2 for principal point, 2 for distorsion center , 5 for coefficients of radial distorsion (r^3, r^5 ... r^{11});

RadialBasic a "subset" of previous model: radial distorsion with limited degrees of freedom ; adapted when there is a risk of divergence of `RadialExtended`; in this model there are 5 degrees of freedom : 1 for focal length , 2 for principal point and distorsion center[3] , 2 for coefficients of radial distorsion (r^3 and r^5);

Fraser a radial model, with decentric and affine parameters (as specified in 13.2.3); there are 12 degrees of freedom: 1 for focal length , 2 for principal point, 2 for distorsion center , 3 for coefficients of radial distorsion (r^3, r^5 r^7), 2 for decentric parameters, 2 for affine parameters; the

FraserBasic same as previous with for principal point and distorsion center constrained to have the same value (so 10 degree of freedom);

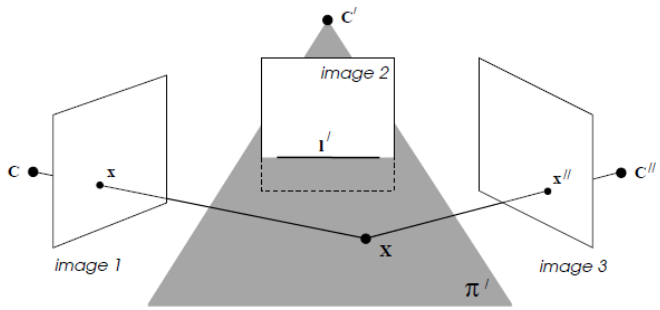
FishEyeEqui a model adapted for diagonal fisheyes equilinear (with *atan* physicall model completed with polynomial parameters, as specified in 13.3.4); there are 14 degrees of freedom: 1 for focal length , 2 for principal point, 2 for distorsion center , 5 for coefficients of radial distorsion (r^3, r^5 r^7), 2 for decentric parameters, 2 for affine parameters; by default the ray defining the usefull

Pierrot-Deseilligny et. al. 2013

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Trifocal Tensor



- The fundamental matrix for 3-view geometry
- 18 degrees of freedom

- Essential matrix

$$\hat{\mathbf{x}}'^{\mathsf{T}}\mathbf{E}\hat{\mathbf{x}} = 0$$

$$\mathbf{E} = \mathbf{K}'^{\mathsf{T}}\mathbf{F}\mathbf{K}$$

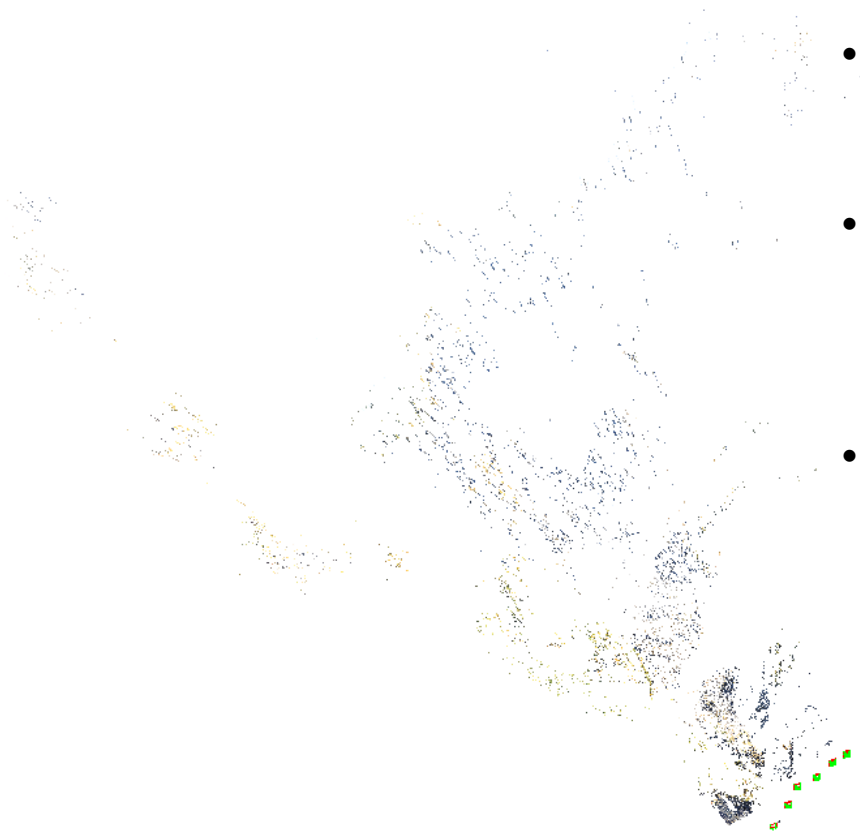
- Defines projective transformation like the fundamental matrix F but assuming that all images have the same known calibration
- Only 5 degrees of freedom

Hartley and Zisserman 2004

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Example of a sparse point cloud

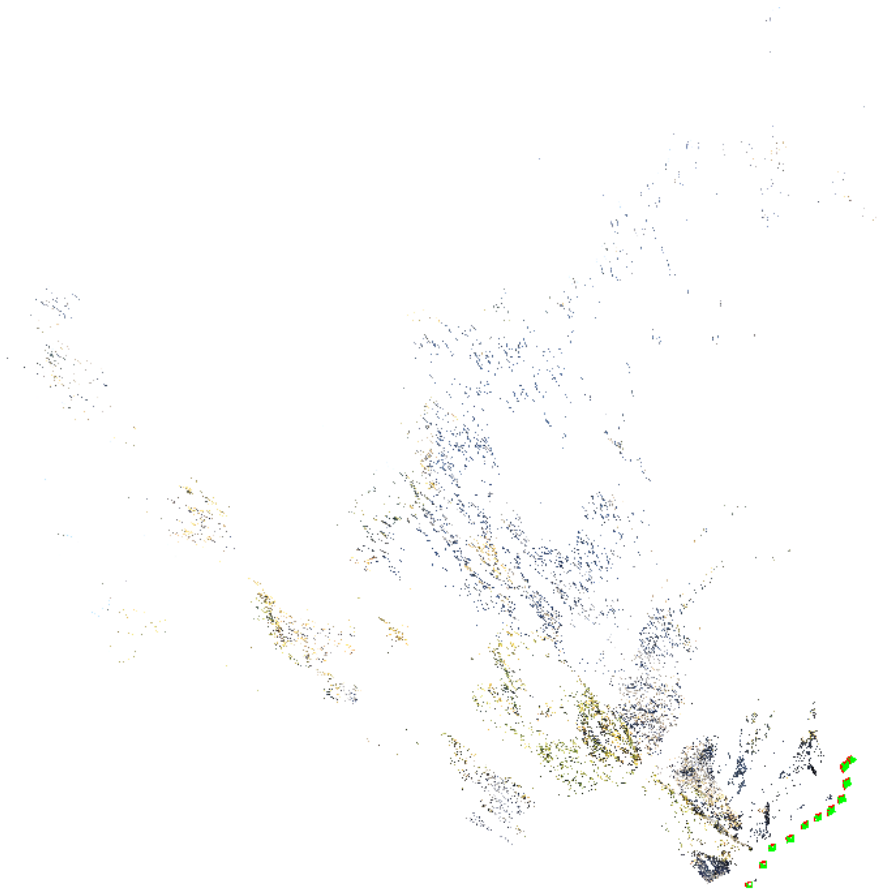


- Apero (Open Source project hosted at IGN)
- Starting from ~10 views for initial auto-calibration (Fraser lens model)
- Keep lens model frozen when adding all further images

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

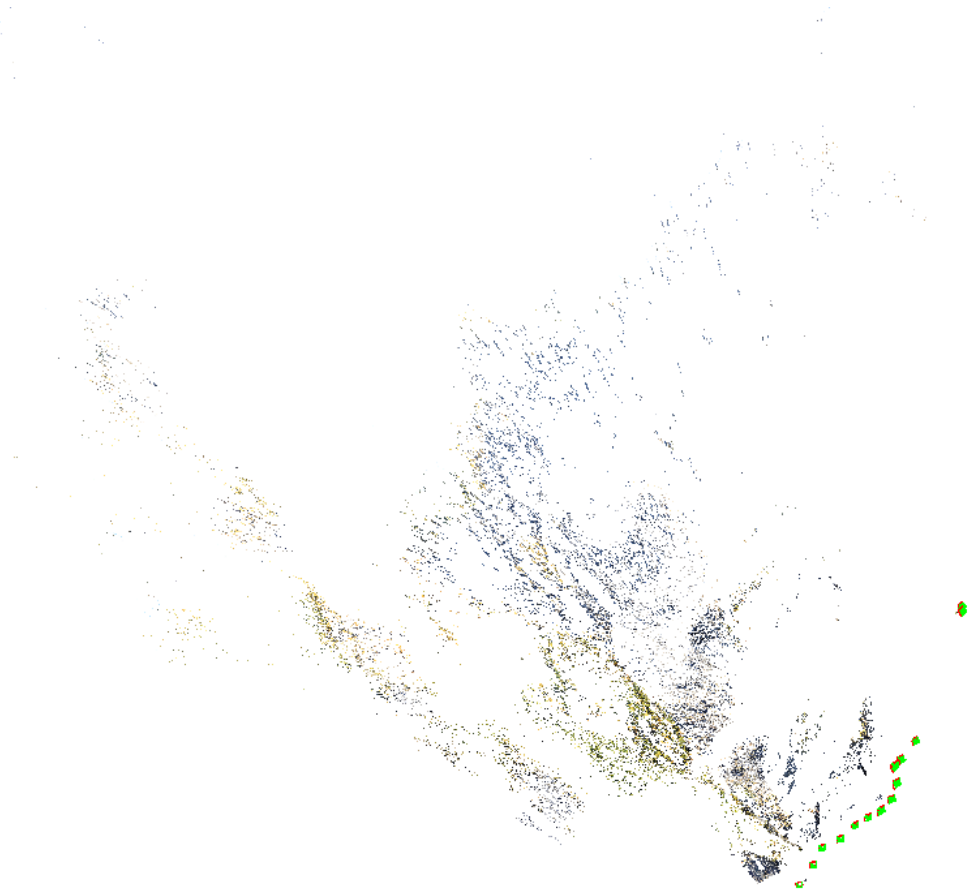
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

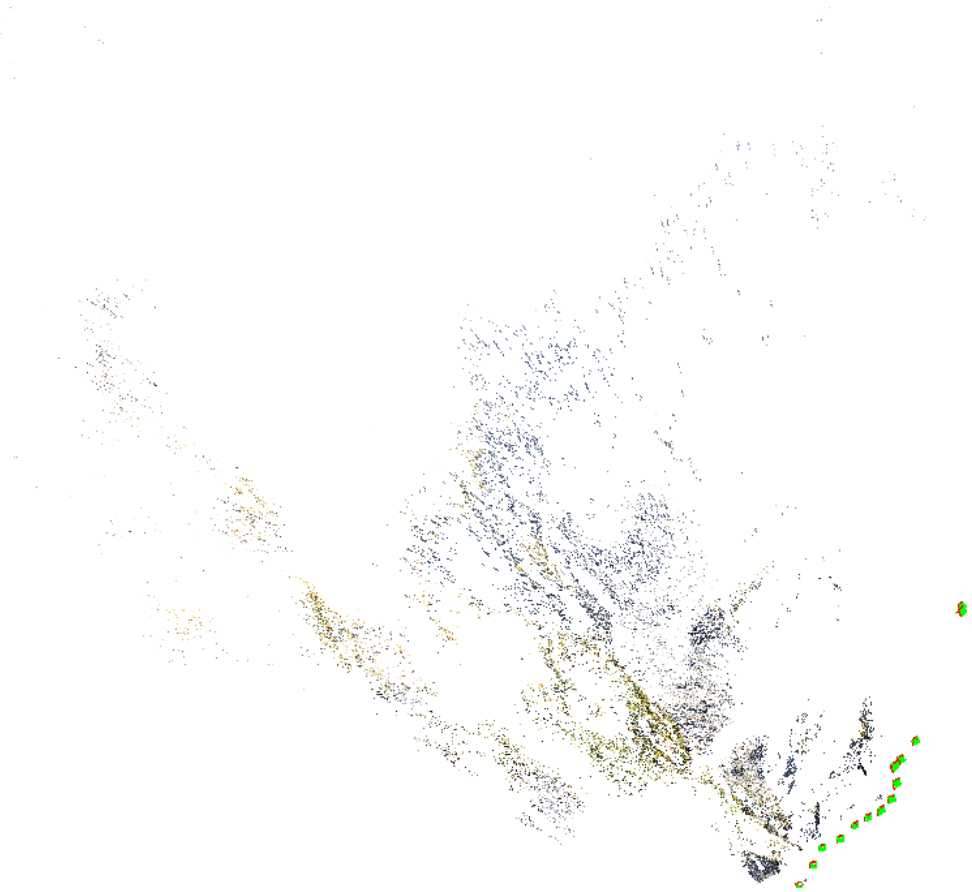
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

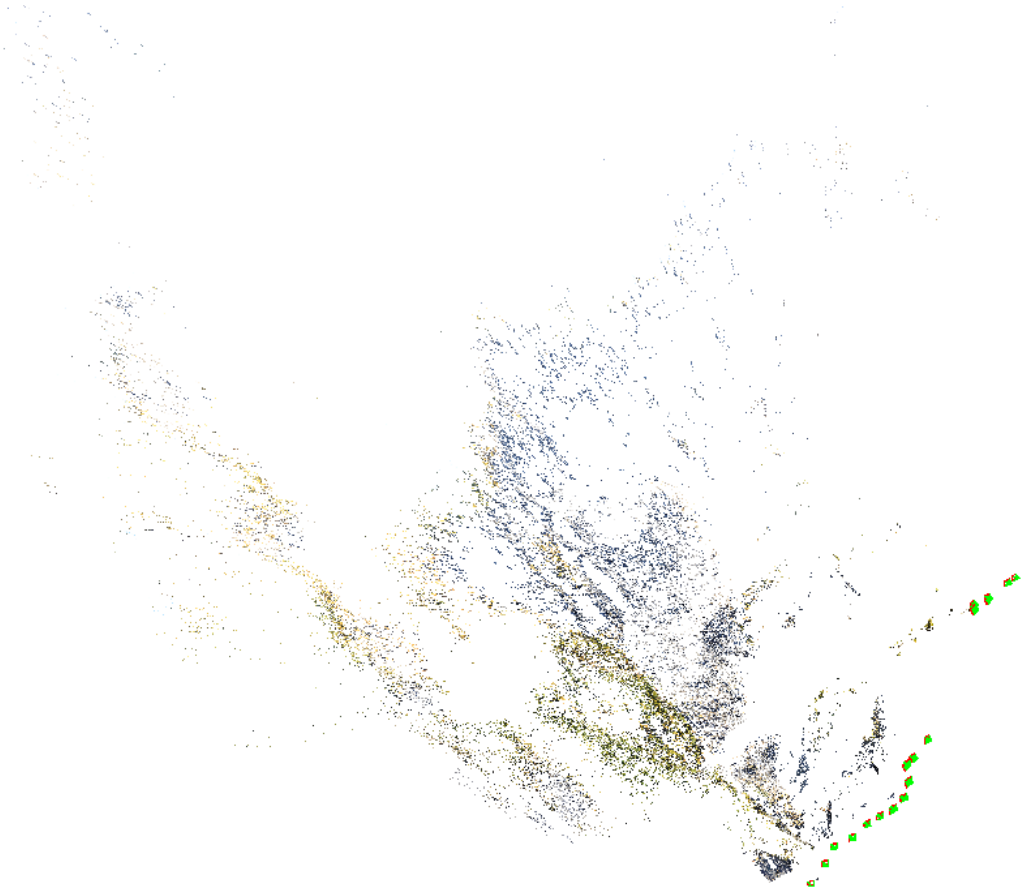
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

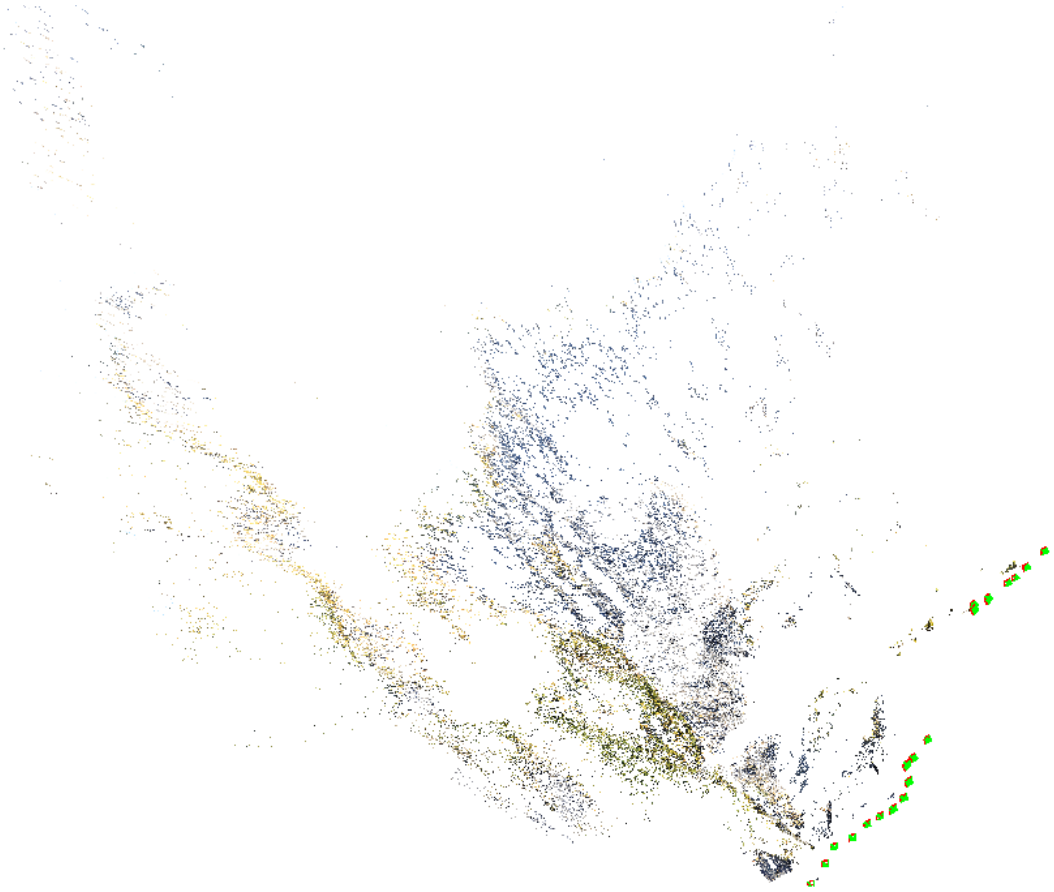
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

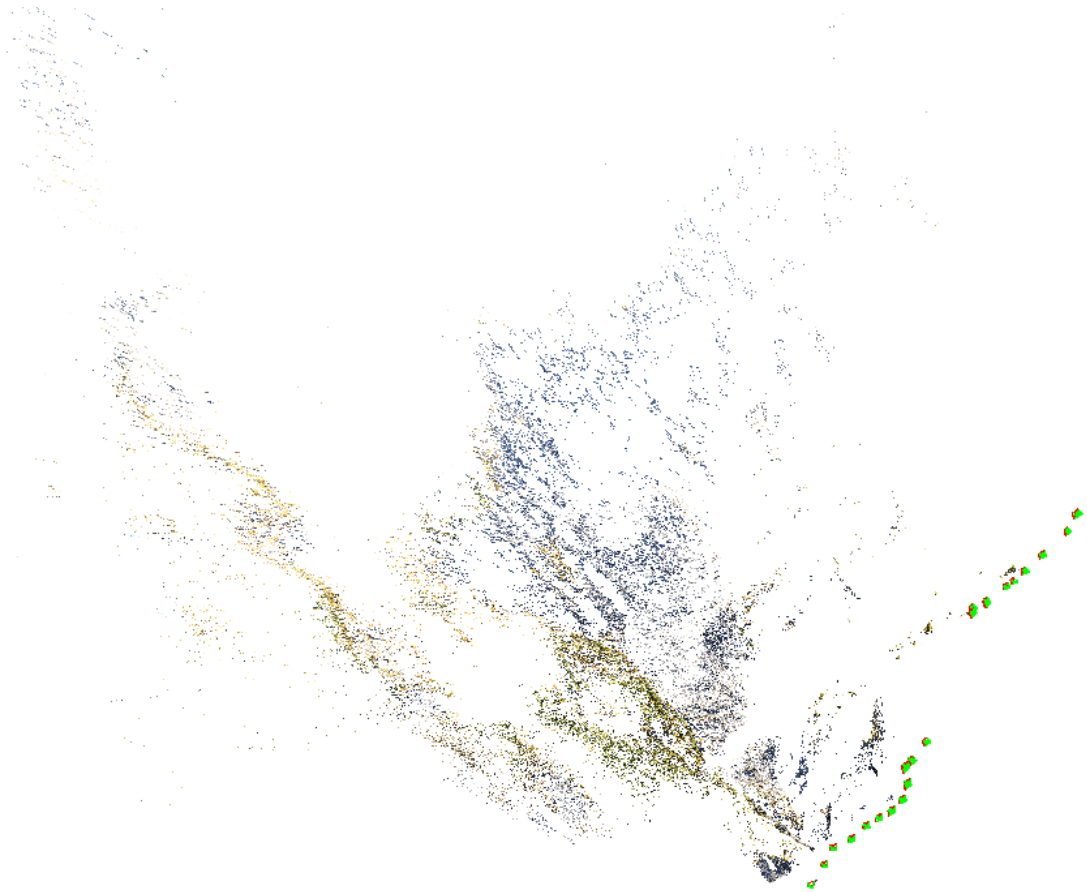
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

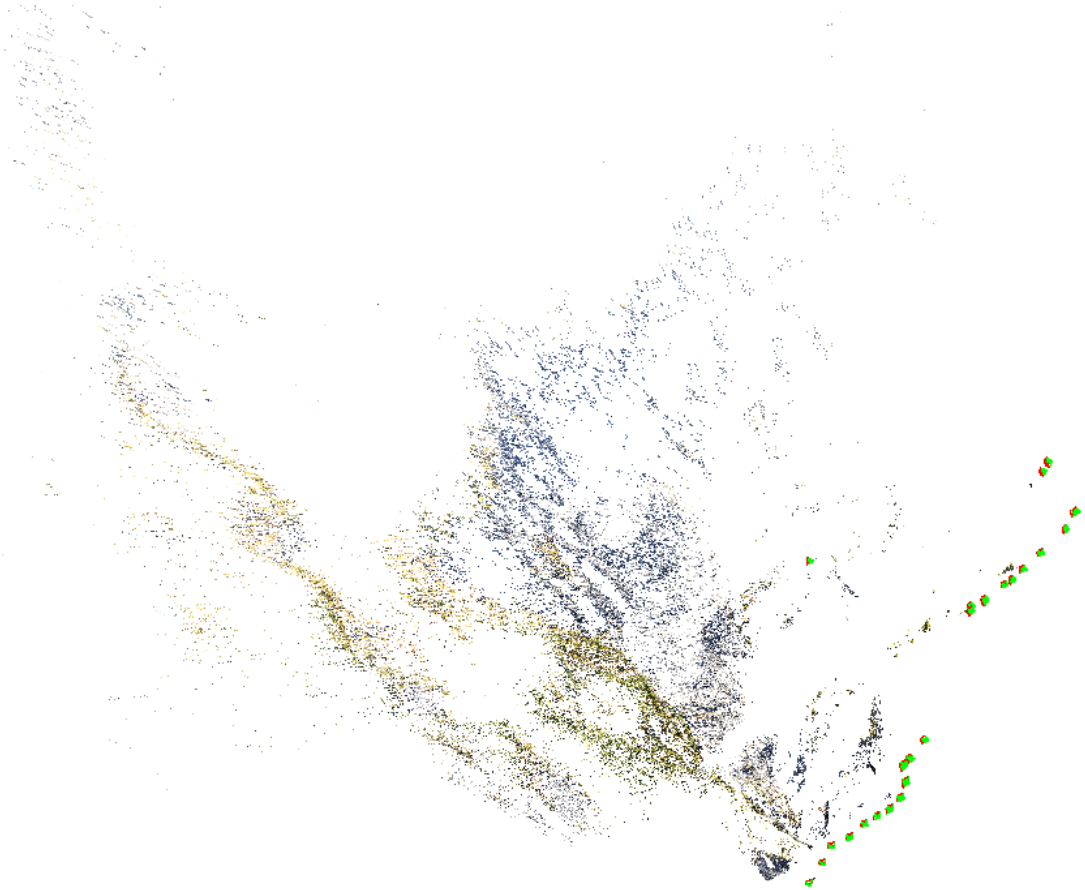
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

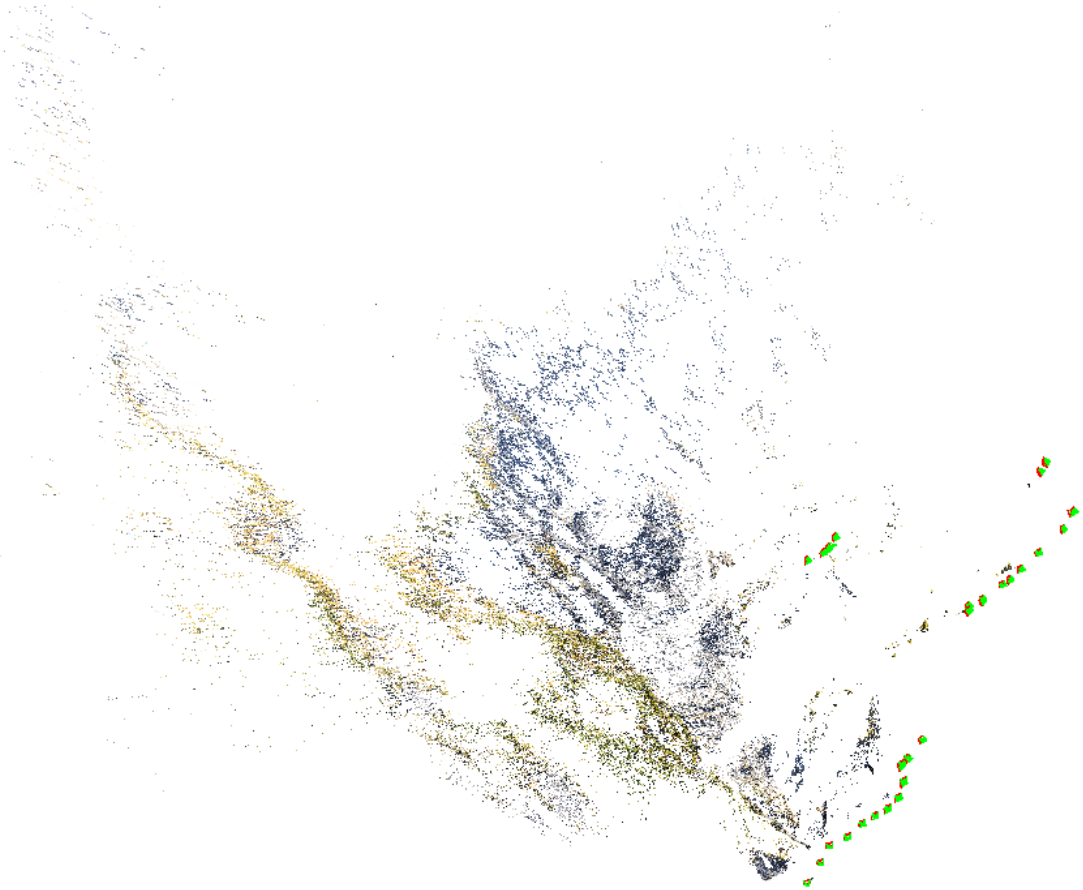
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

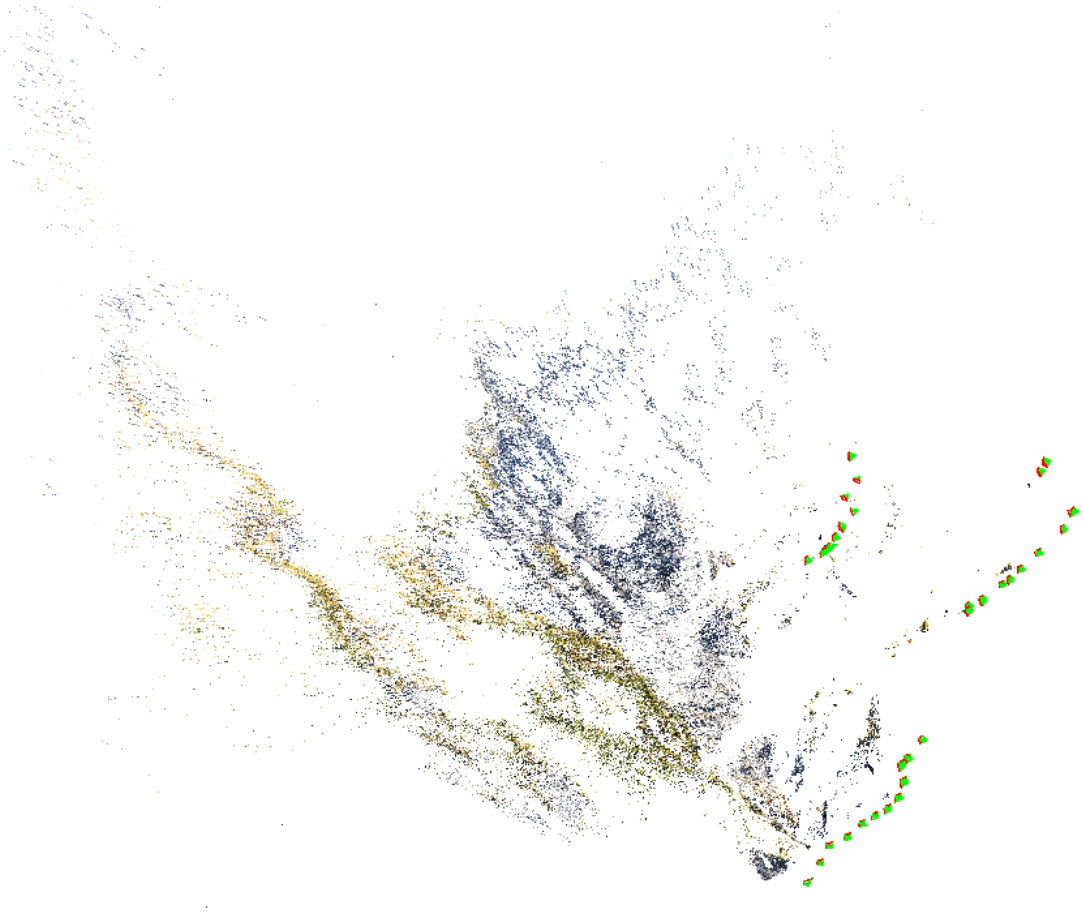
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

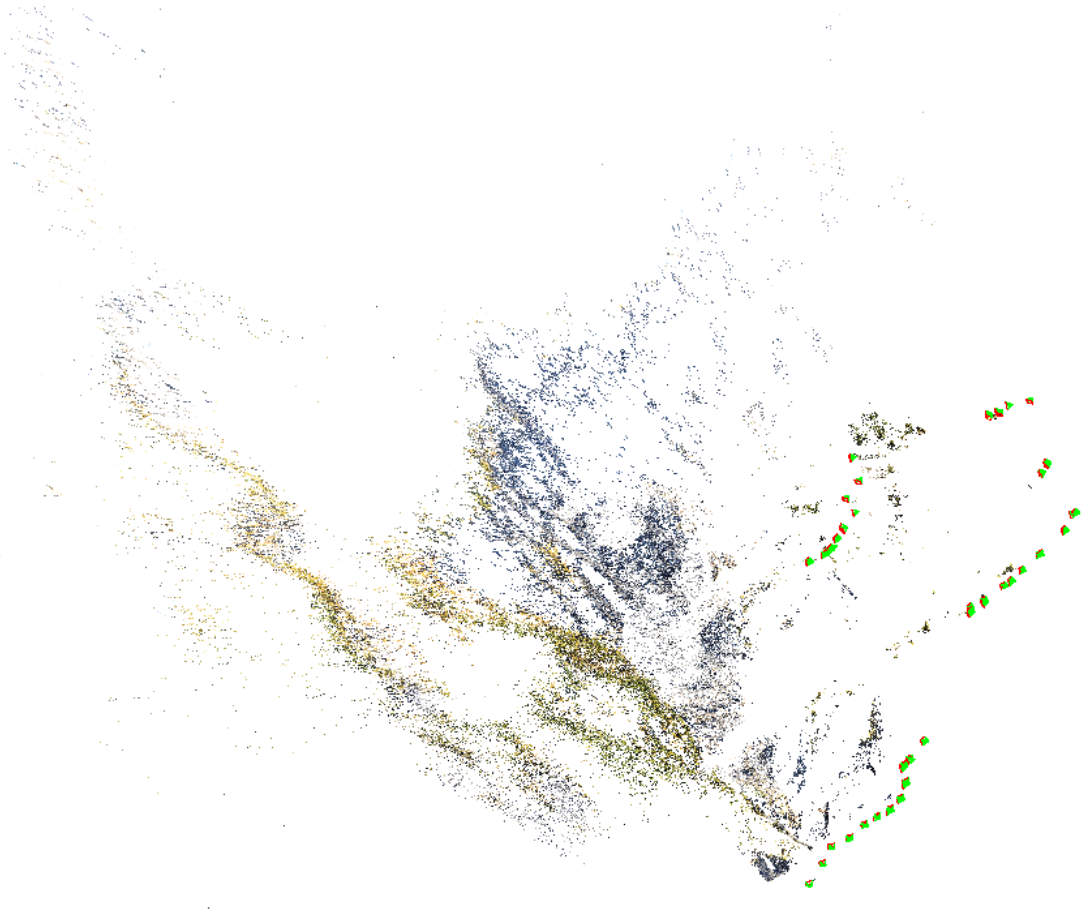
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

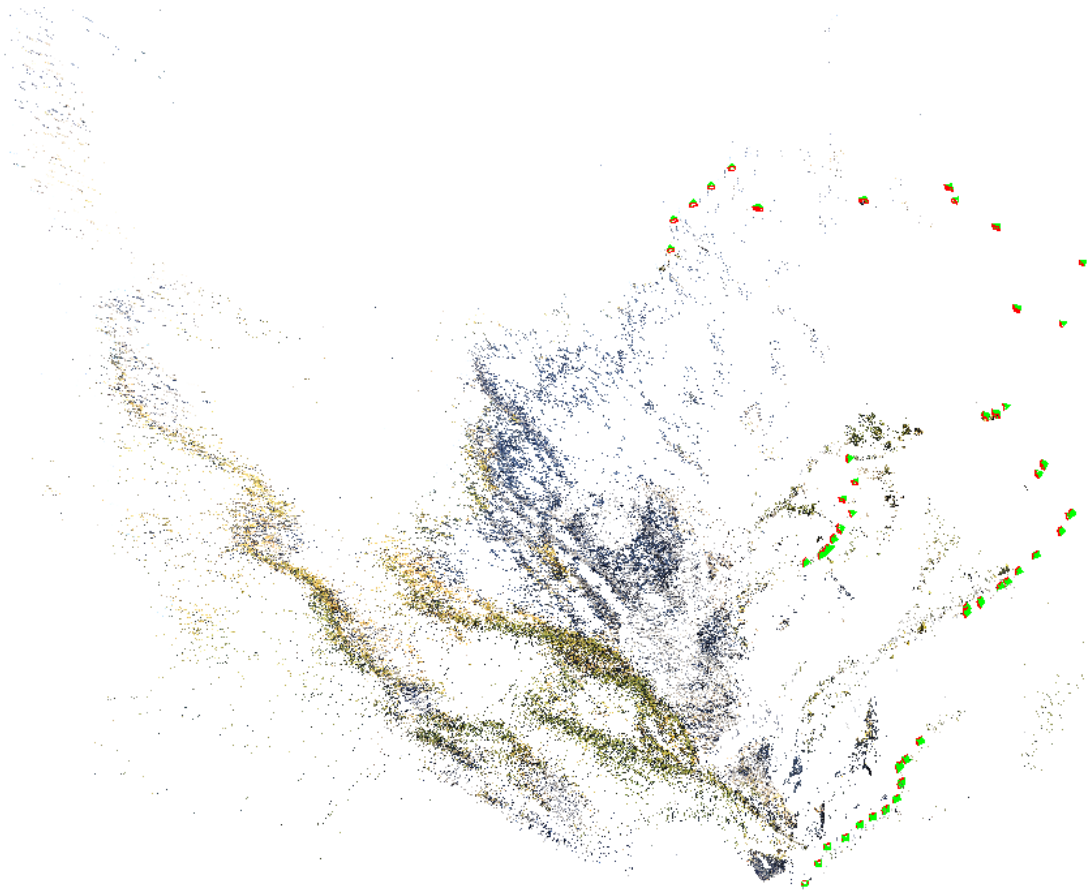
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

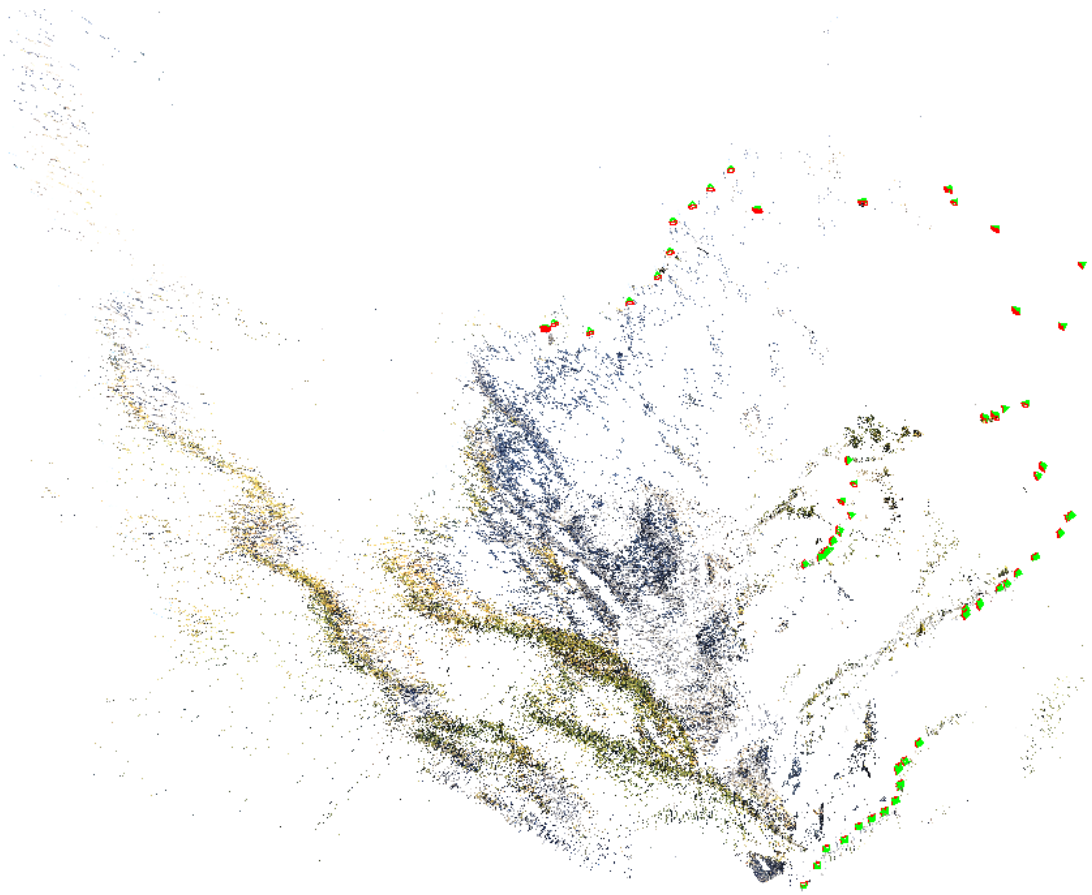
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

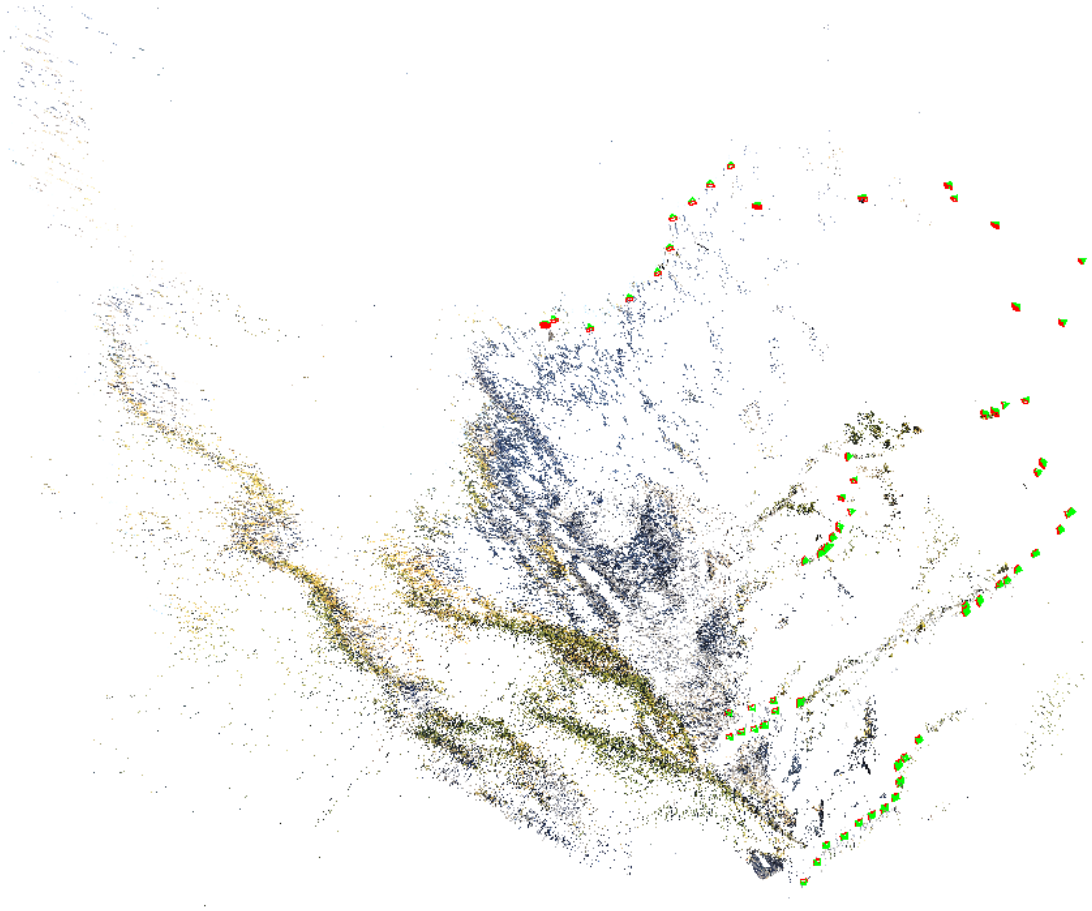
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

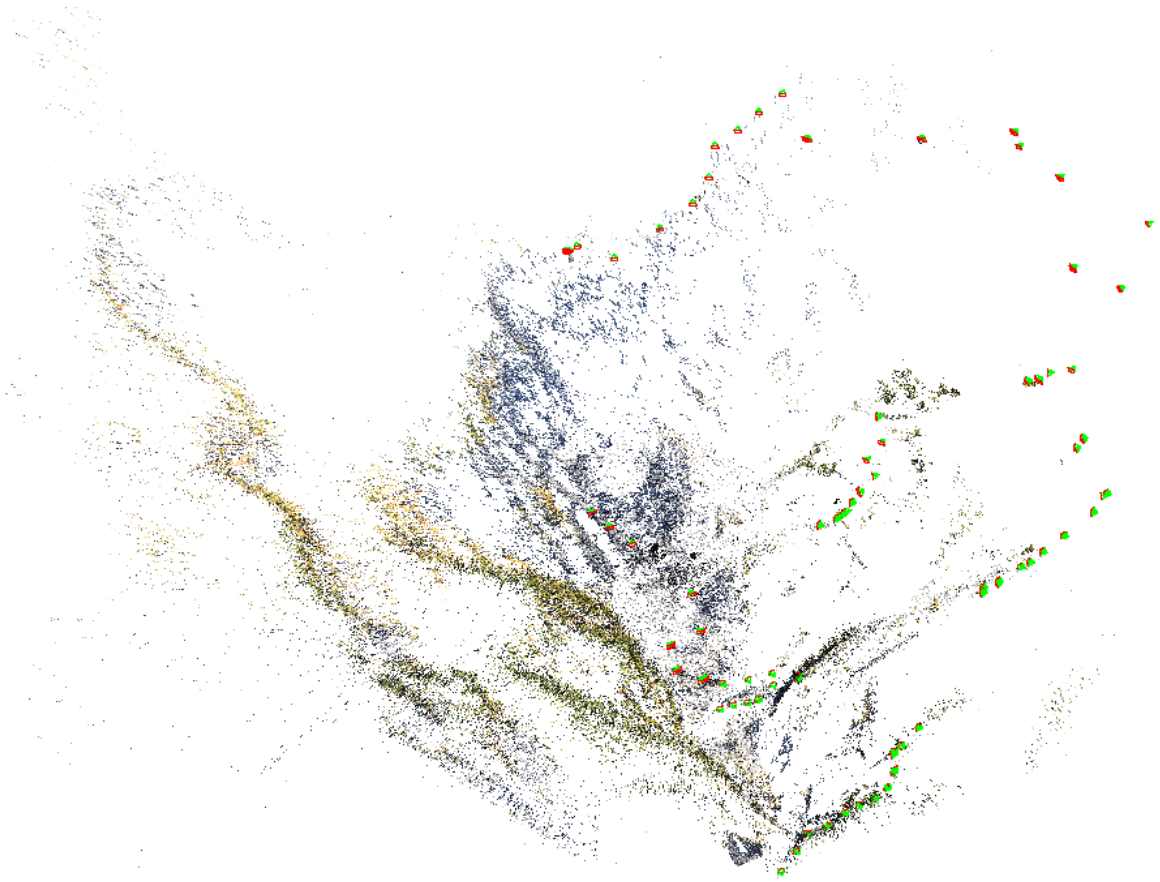
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

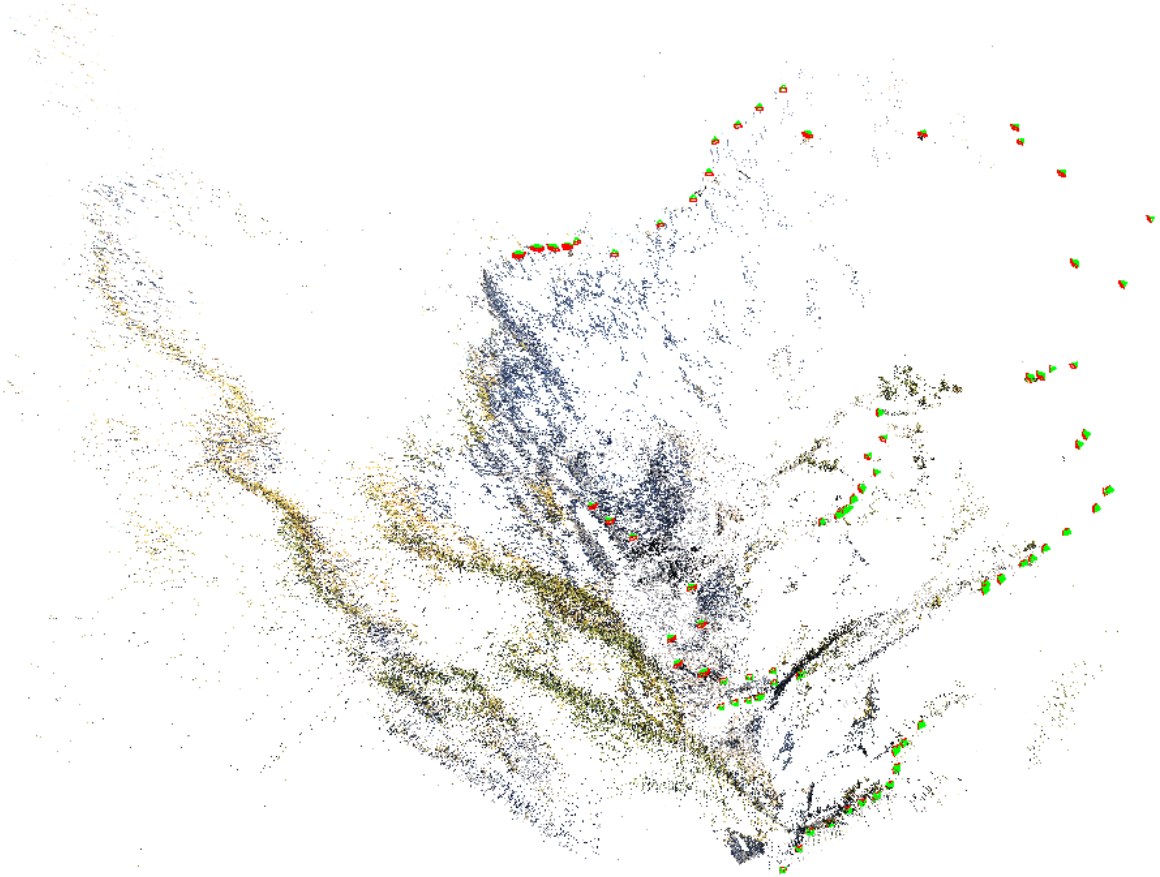
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

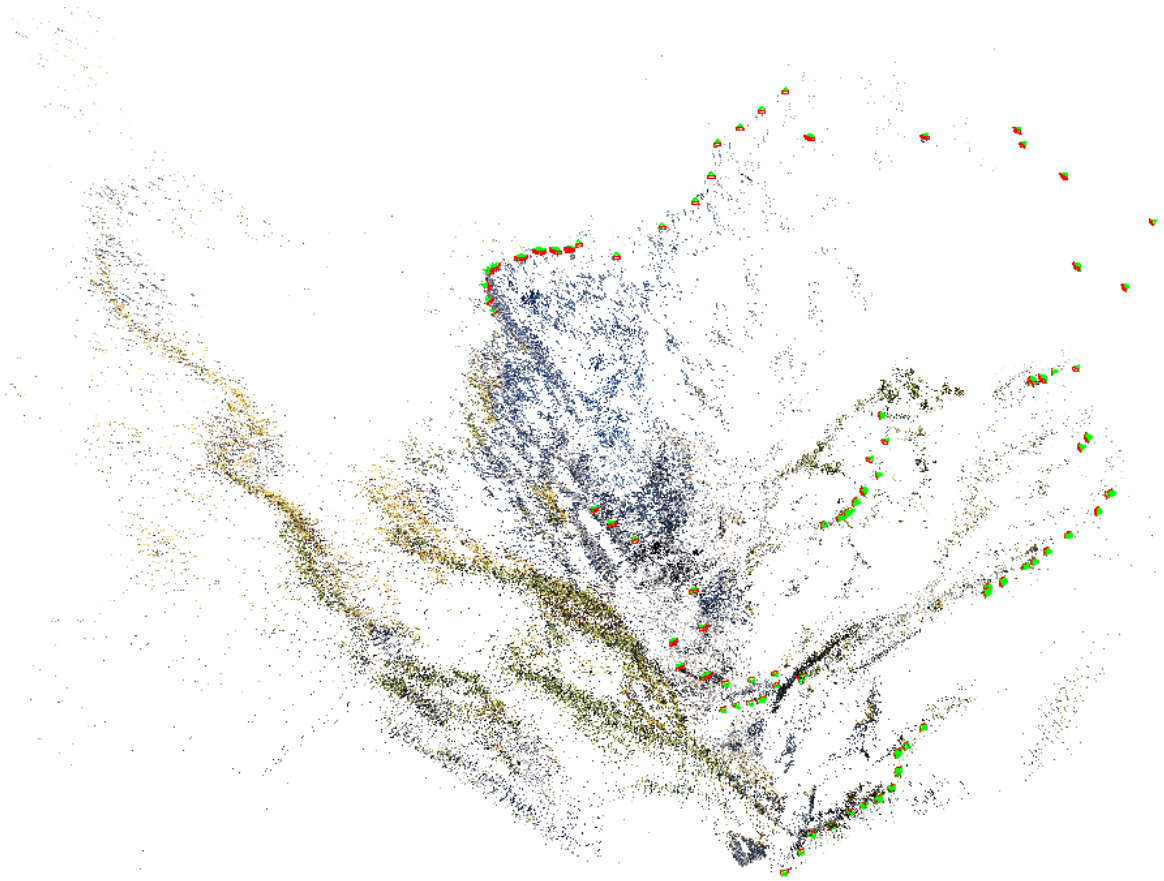
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

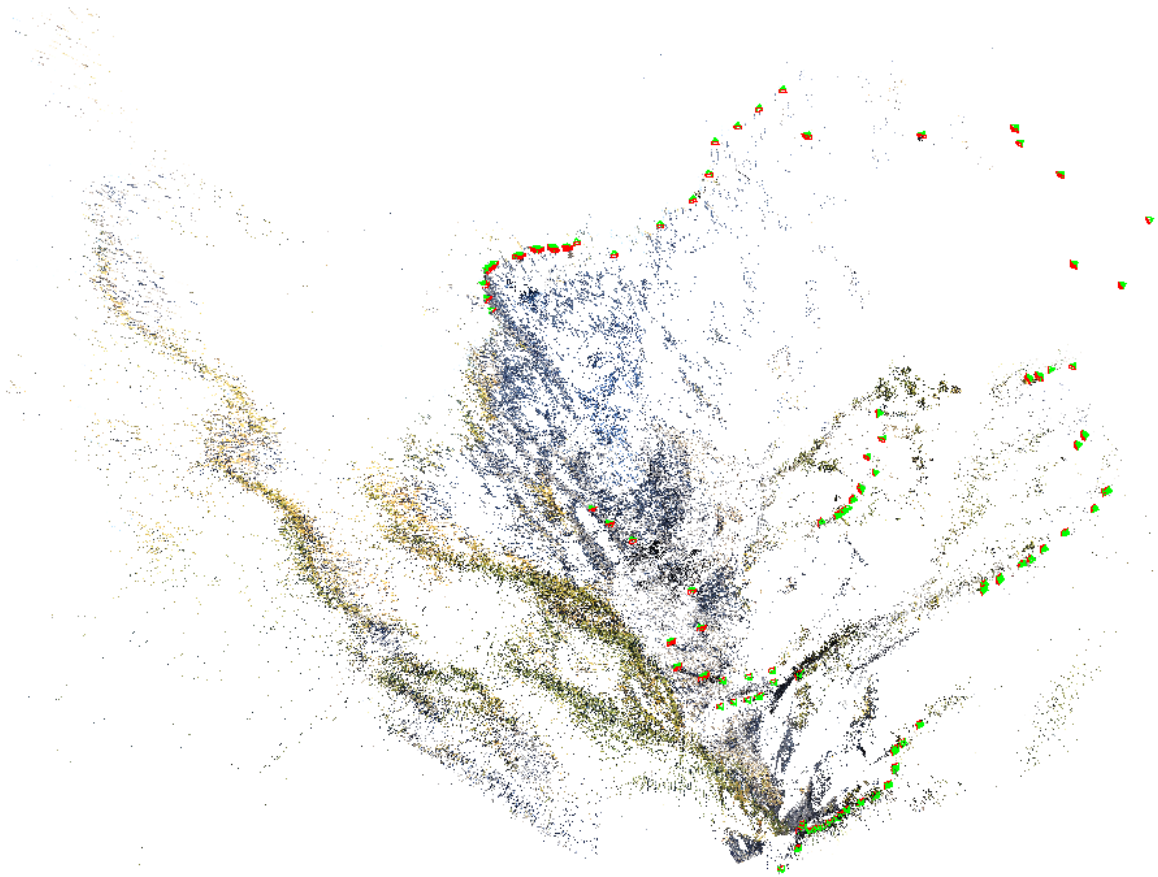
- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Example



GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Meshlab

GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Dense matching
  - Obtain a dense point cloud by refining the sparse correspondence model
  - Many different techniques
    - PMVS (Furukawa and Ponce 2008)
    - MicMac (Pierrot-Deseilligny et al. 20xx)
    - Semi Global Matching (Hirschmueller 2008)
  - Evaluation framework http://vision.middlebury.edu/mview/eval/

Multi-View Stereo | Evaluation • Datasets • Submit • Code

Acc. Threshold: 90%
Comp. Threshold: 1.25 mm

Data in new window ☐ Open Data Window
Data: View 1 and Ground Truth Image Size Small

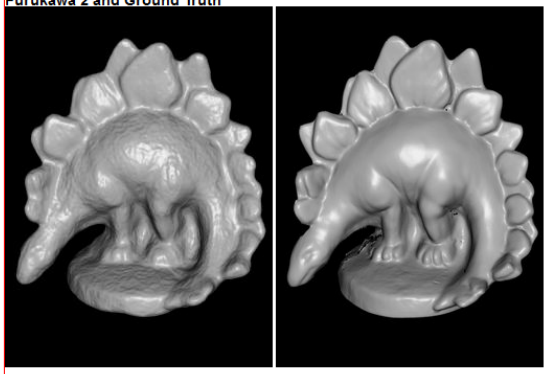
Tip: Mousing over any portion of a method's row will show its reference

Sort By	Temple Full 312 views Acc [mm]	Temple Full 312 views Comp [%]	Temple Ring 47 views Acc [mm]	Temple Ring 47 views Comp [%]	Temple Sparse 16 views Acc [mm]	Temple Sparse 16 views Comp [%]	Dino Full 363 views Acc [mm]	Dino Full 363 views Comp [%]	Dino Ring 48 views Acc [mm]	Dino Ring 48 views Comp [%]	Dino Sparse 16 views Acc [mm]	Dino Sparse 16 views Comp [%]
Furukawa 2	0.54	99.3	0.55	99.1	0.62	99.2	0.32	99.9	0.33	99.6	0.42	99.2
Furukawa 3	0.49	99.6	0.47	99.6	0.63	99.3	0.33	99.8	0.28	99.8	0.37	99.2
Schroers	0.57	99.1	0.64	96.4	2.12	62.9	0.33	99.7	0.33	99.7	0.54	98.6
Guillemaut	0.43	99.0	0.71	97.6	0.86	96.2	0.35	100	0.58	99.5	0.68	98.0
GCPR-3	0.52	96.2	0.76	94.9	0.97	77.1	0.41	95.3	0.47	94.9	0.56	83.6
Vogiatzis	1.07	90.7	0.76	96.2	2.77	79.4	0.42	99.0	0.49	96.7	1.18	90.8
Habbecke	0.66	98.0					0.43	99.7				
Goesele 2007	0.42	98.2					0.46	96.7				
Lambert3	0.48	99.7					0.48	99.4				
Hernandez	0.36	99.7	0.52	99.5	0.75	95.3	0.49	99.6	0.45	97.9	0.6	98.5
Furukawa	0.65	98.7	0.58	98.5	0.82	94.3	0.52	99.2	0.42	98.8	0.58	96.9
Zach2	0.51	98.8	0.56	99.0			0.55	98.7	0.51	99.1		
Generalized-SSD	0.53	99.4	0.81	95.8			0.55	98.1	0.6	96.0		
Goesele	0.42	98.0	0.61	86.2	0.87	56.6	0.56	80.0	0.46	57.8	0.56	26.0
Hongxing	0.83	95.7	0.79	96.3	0.97	93.9	0.62	96.3	0.5	99.1	0.52	98.4
Lambert	0.55	99.7					0.76	99.0				
Hornung	0.58	98.7					0.79	95.1				
Jancosek-3DIM09	0.65	85.8	0.7	78.9	0.59	74.9	0.91	73.8	0.71	76.6	0.66	74.9
Auclair			0.86	96.2	1.03	92.5			0.62	96.7	0.74	96.8
Beljan	0.79	92.2										

Reference: M. Habbecke and L. Kobbelt. A surface-growing approach to multi-view stereo reconstruction. CVPR 2007.

Normalized Time (H:M:S): 3:44:00

Furukawa 2 and Ground Truth



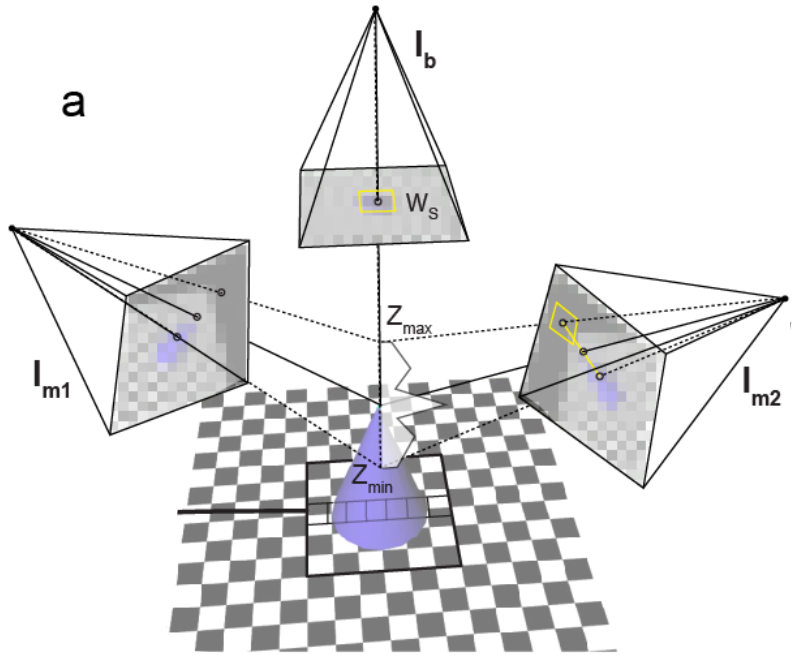
GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- MicMac: **M**ulti **I**mage **C**orrespondances par **M**ethodes **A**utomatiques de **C**orrelation
  - Developement started at IGN Paris in 2005 by Marc-Pierrot-Deseilligny
  - Open Source project under CeCILL-B license (adaptation to the French law of the L-GPL license)
  - C++ and XML
  - Versatile library
    - Tapioca – Homologous point detection
    - Tapas/Apero – Pose estimation and lens calibration
    - Malt/MicMac – Dense correlation
    - Tarama – Rectification
    - …further for integration GPS, GCPs, etc.…
  - Initially developed for aerial surveys but now very specialized in MVP
  - Current team Jeremy Belveaux, Gerald Choqueux, Matthieu Deveau, Luc Girod
  - Active community of users and contributing developers (French and International): http://forum-micmac.forumprod.com/
  - Source code under:
    - hg clone https://geoportail.forge.ign.fr/hg/culture3d
      login culture3d
      pswd culture3d
  - Binary for windows are available but Linux version is more stable/up-to-date

GEOMETRIC MODELLING

MicMac



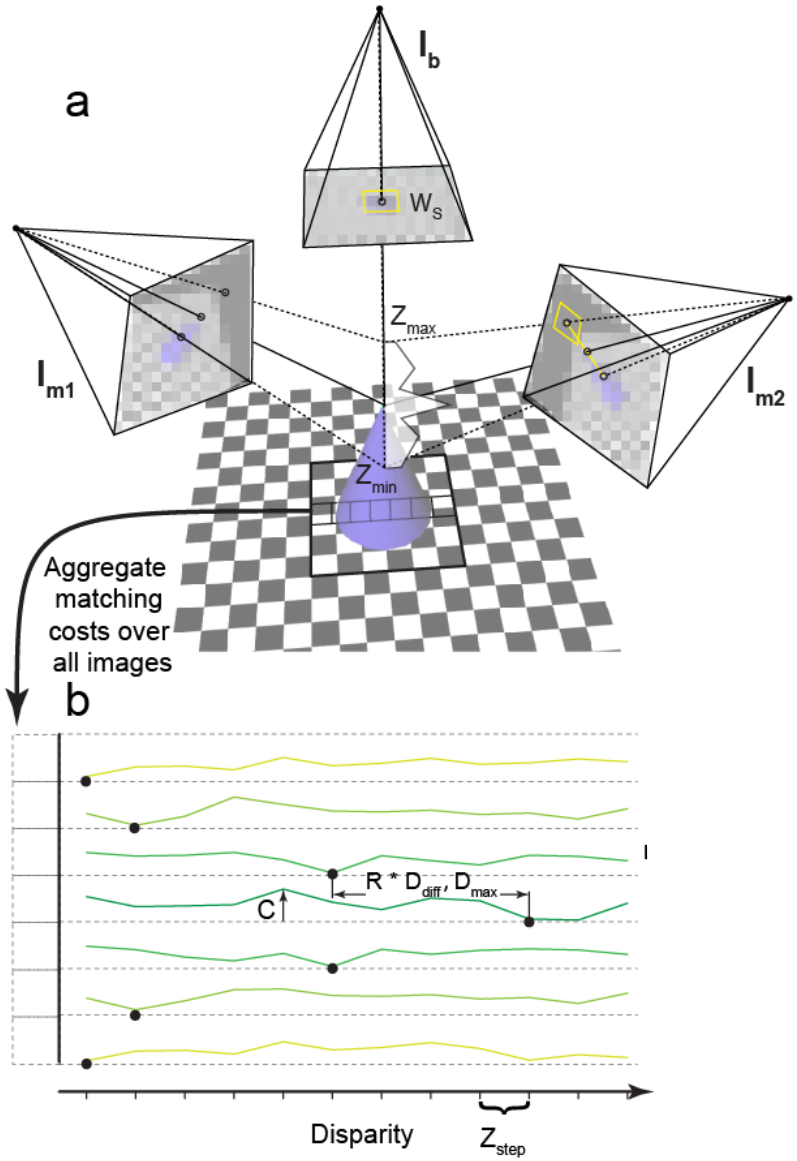
Modified after Cox and Roy 1998

- All camera parameters are estimated
- A base image is selected (I_b)
- Starting from a down sampled image and take a patch from I_b and project it in the matching images I_m according to the epipolar constraints
  - Further constraints from prior knowledge on the min and max depth (Z_{min}, Z_{max})
- Compute matching costs
  - Mean NCC
    - over all image combinations
    - or only with the base image

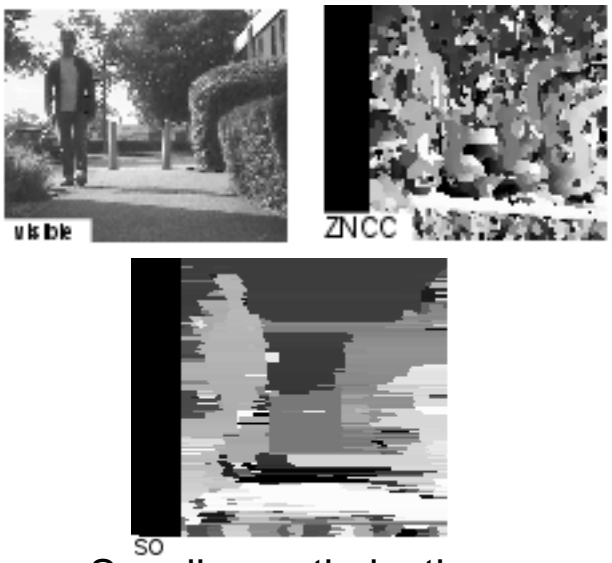
$$Corr^S(U_1, \ldots, U_N) = \frac{2}{N * (N-1)} \sum_{1 \leq i < j \leq N} Corr(U_i, U_j)$$

GEOMETRIC MODELLING

MicMac



- Max score / Min Cost (C) is prone to produce many outliers
- A smoothness term is ($R*D_{diff}$) is used to avoid unlikely solutions
  - R defines the strength of the regularization
  - Dmax define maximum disparity difference

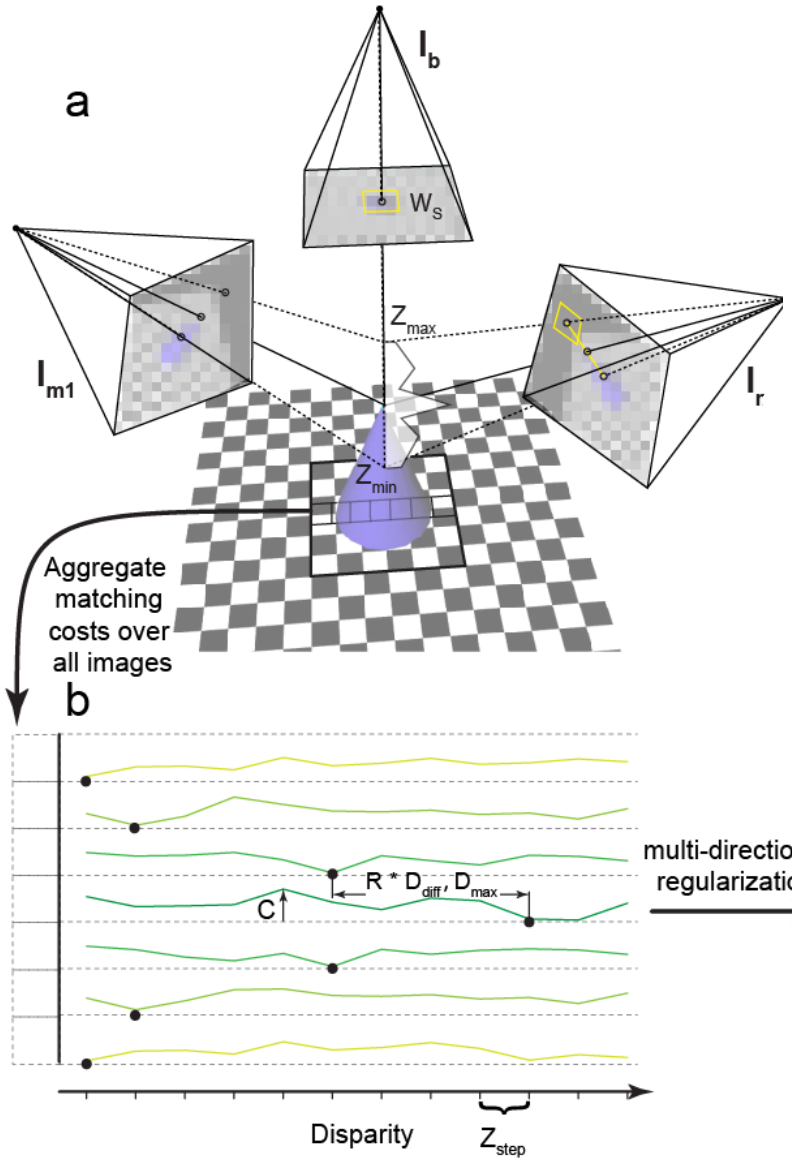


Scanline optimization

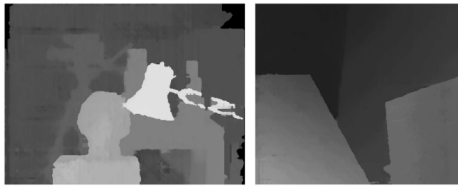
http://public.cranfield.ac.uk/c5354/demos/crossstereo/

GEOMETRIC MODELLING

MicMac



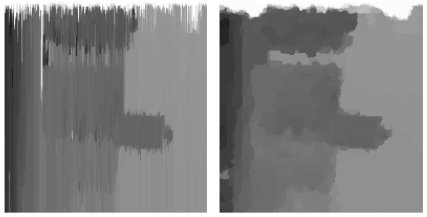
Semi-Global Matching



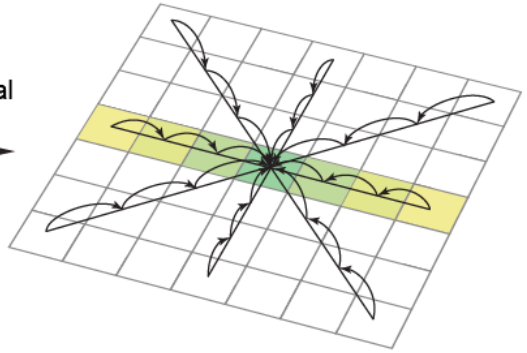
Hirschmueller 2008

Scanline optimization

Max-flow



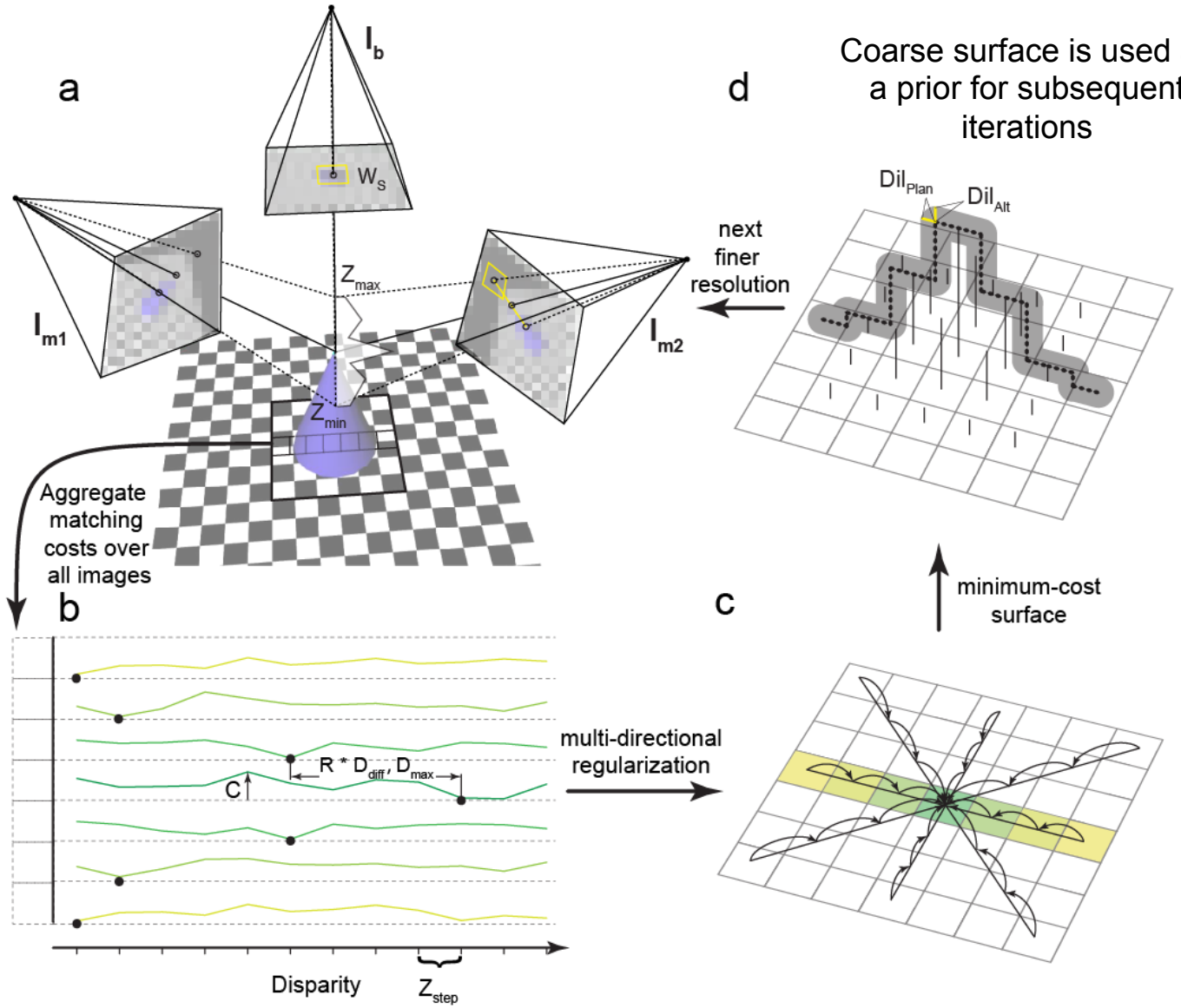
Cox and Roy 1998



Similar to Semi-Global Matching

GEOMETRIC MODELLING

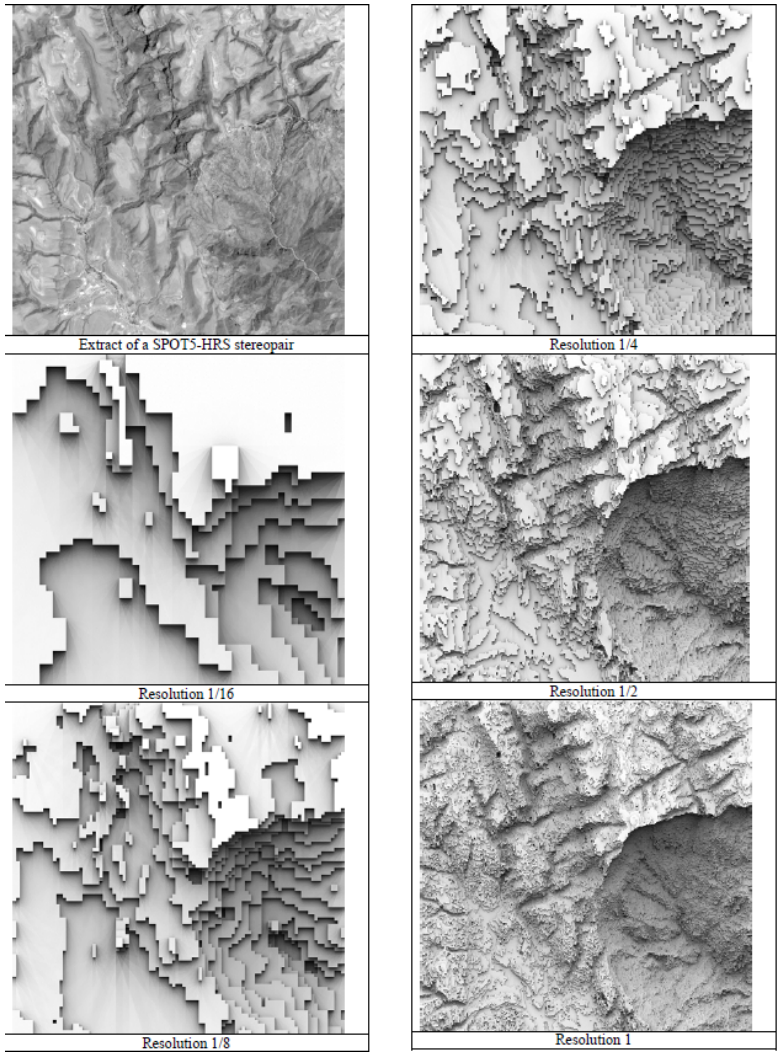
MicMac



Coarse surface is used as a prior for subsequent iterations

GEOMETRIC MODELLING

MicMac – Coarse to fine



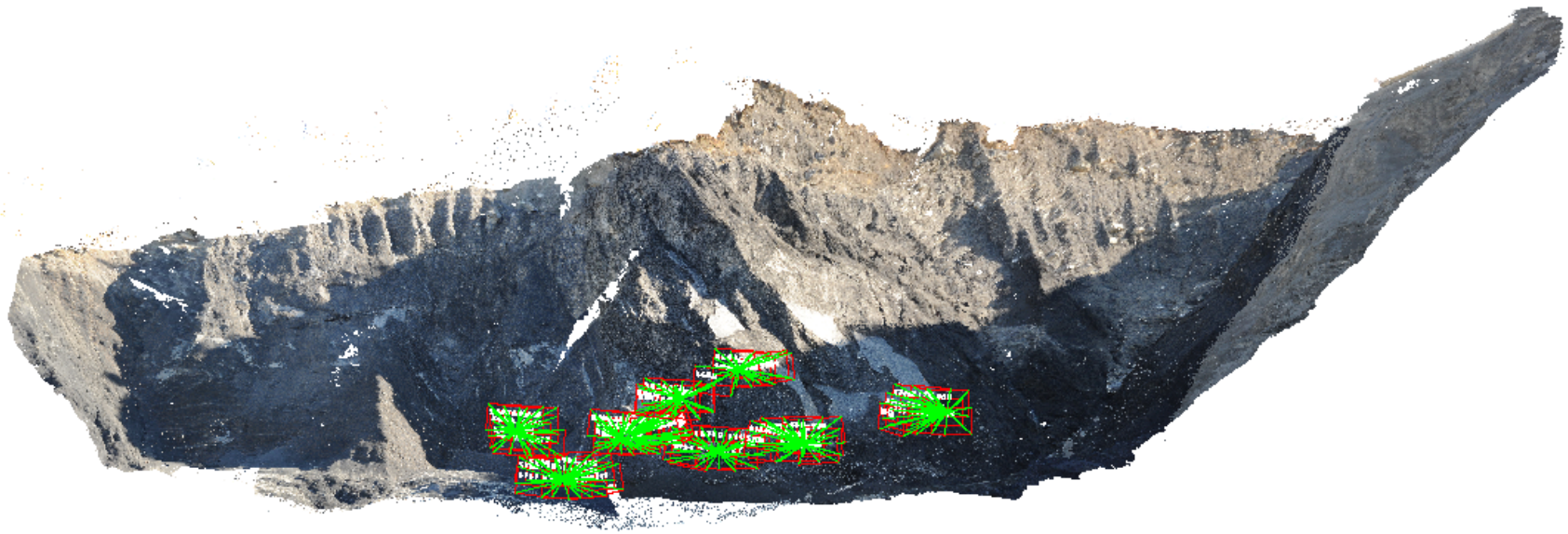
Pierrot-Deseilligny and Paparoditis 2006

GEOMETRIC MODELLING

MicMac – Examples on landslides

- Scarp Super Sauze October 2011

- 84 images
- ~ 10 Mio points



GEOMETRIC MODELLING

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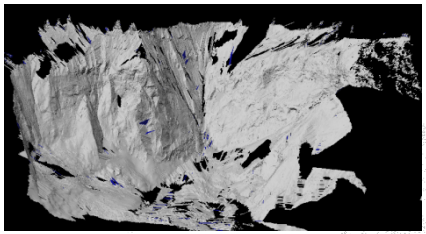
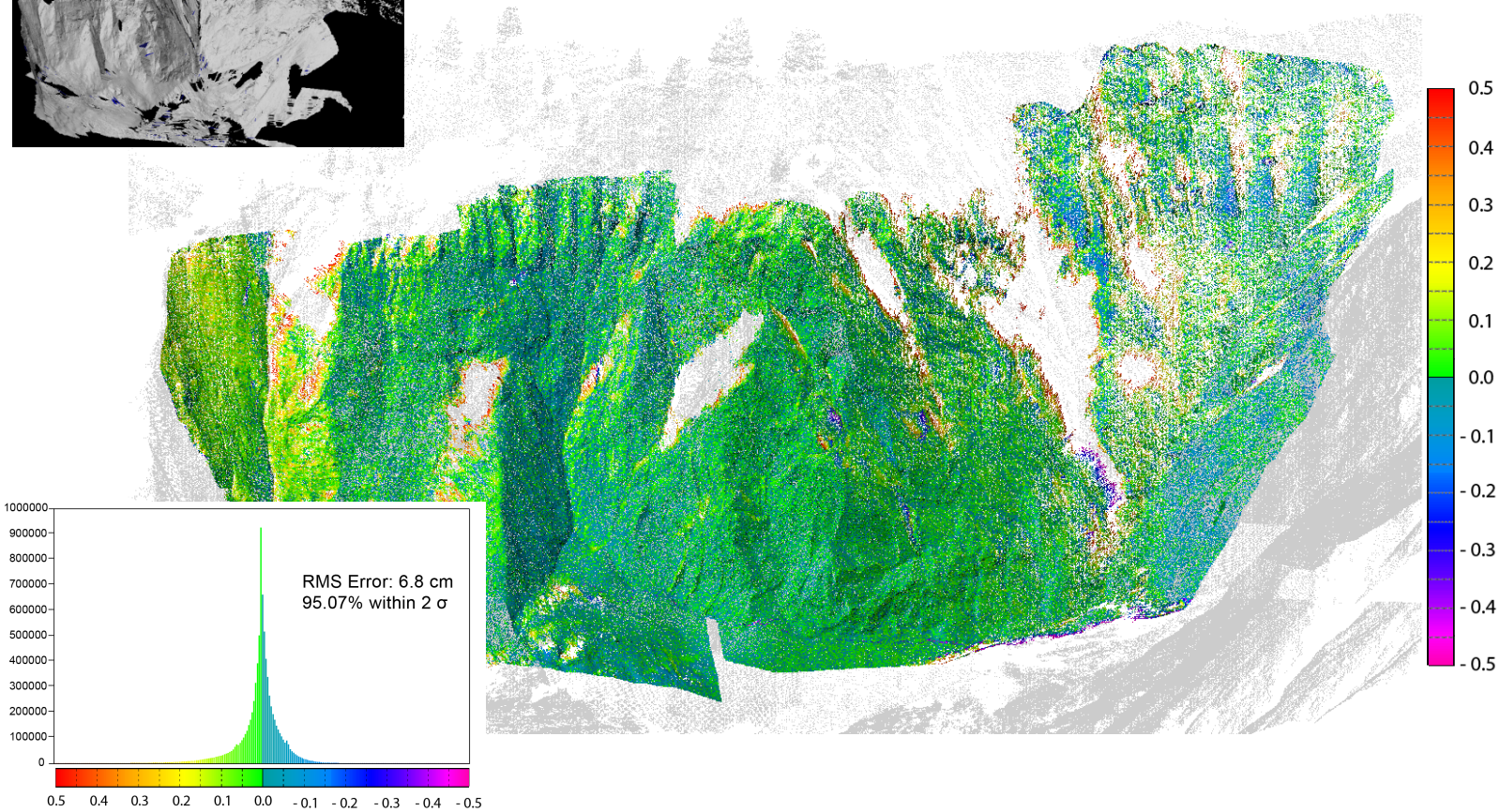


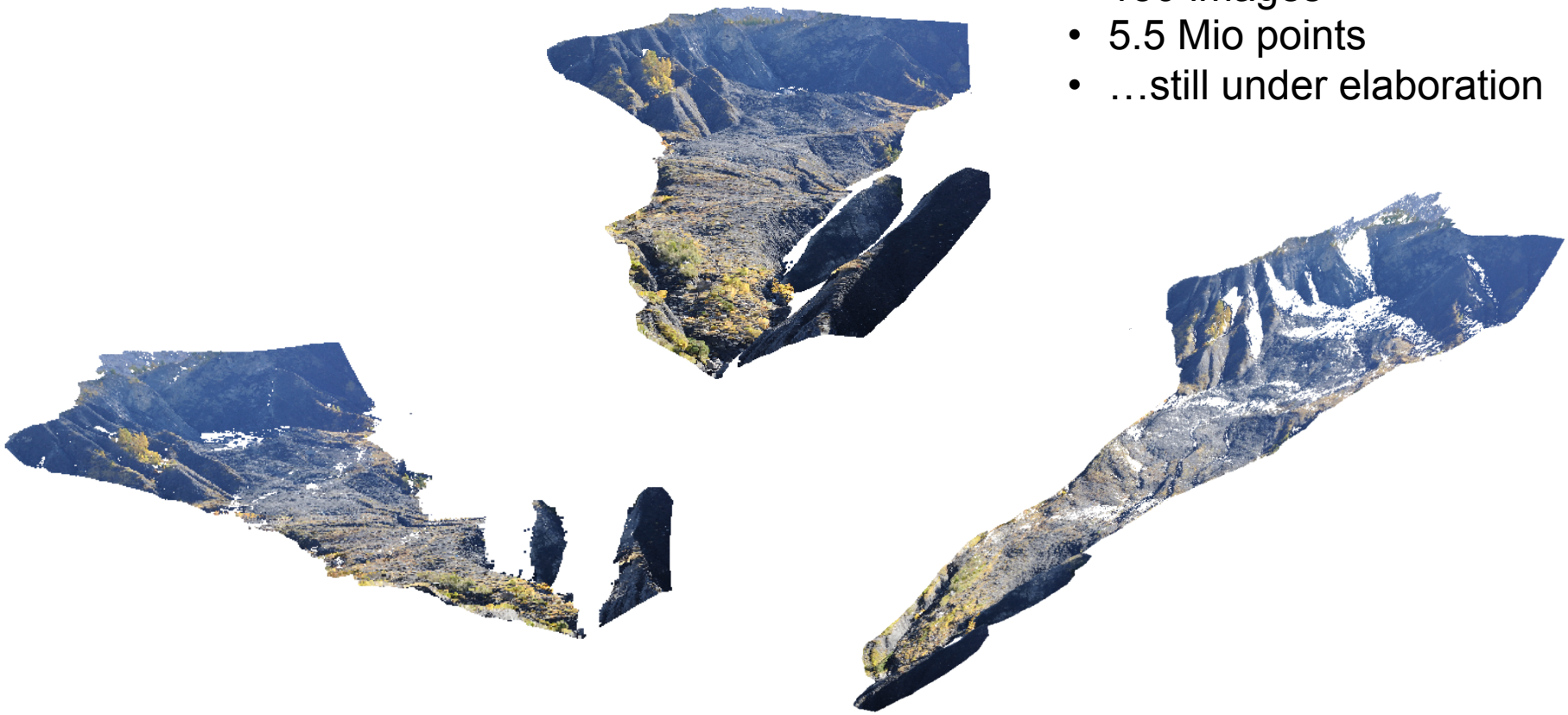


GEOMETRIC MODELLING

MicMac – Examples on landslides

- Global model

- 150 images
- 5.5 Mio points
- …still under elaboration



GEOMETRIC MODELLING

MicMac – Examples on landslides

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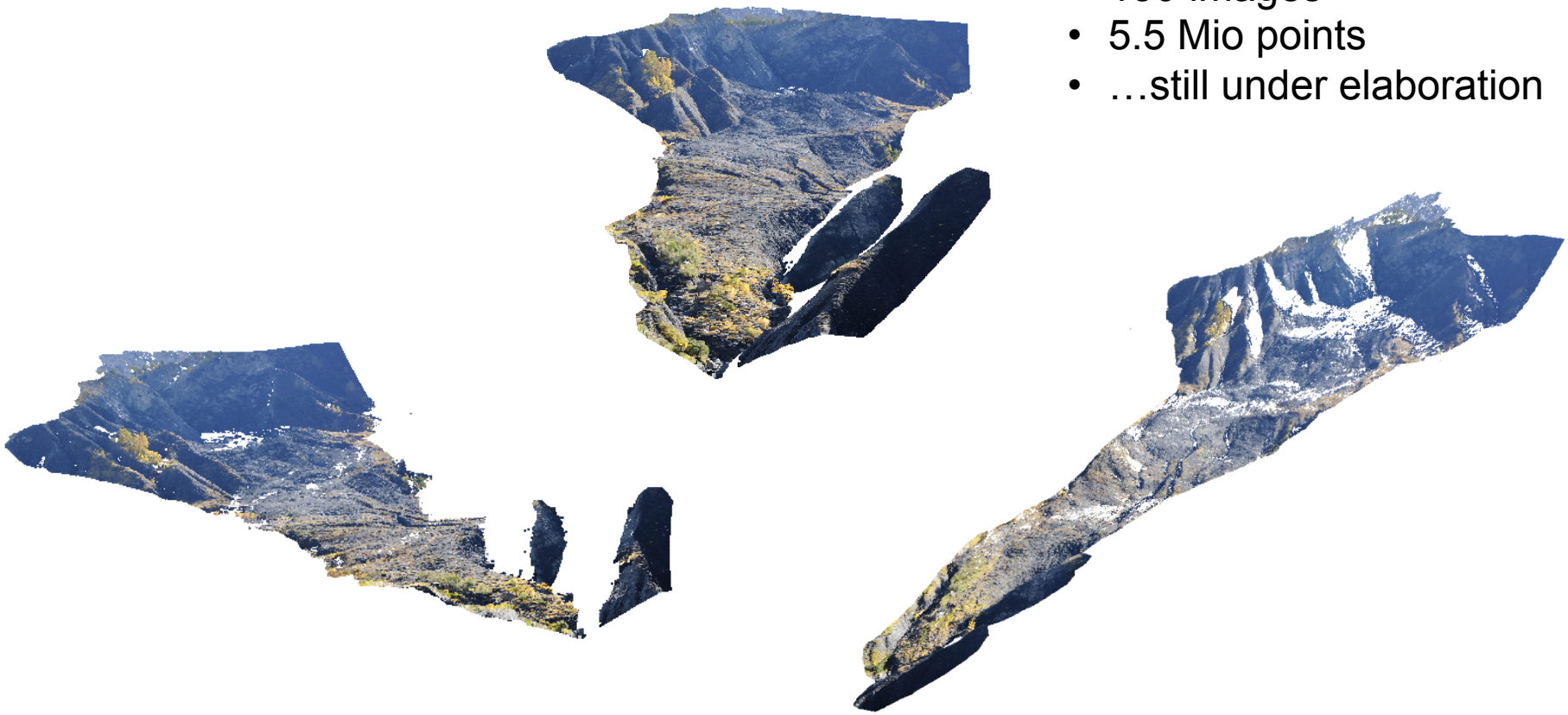
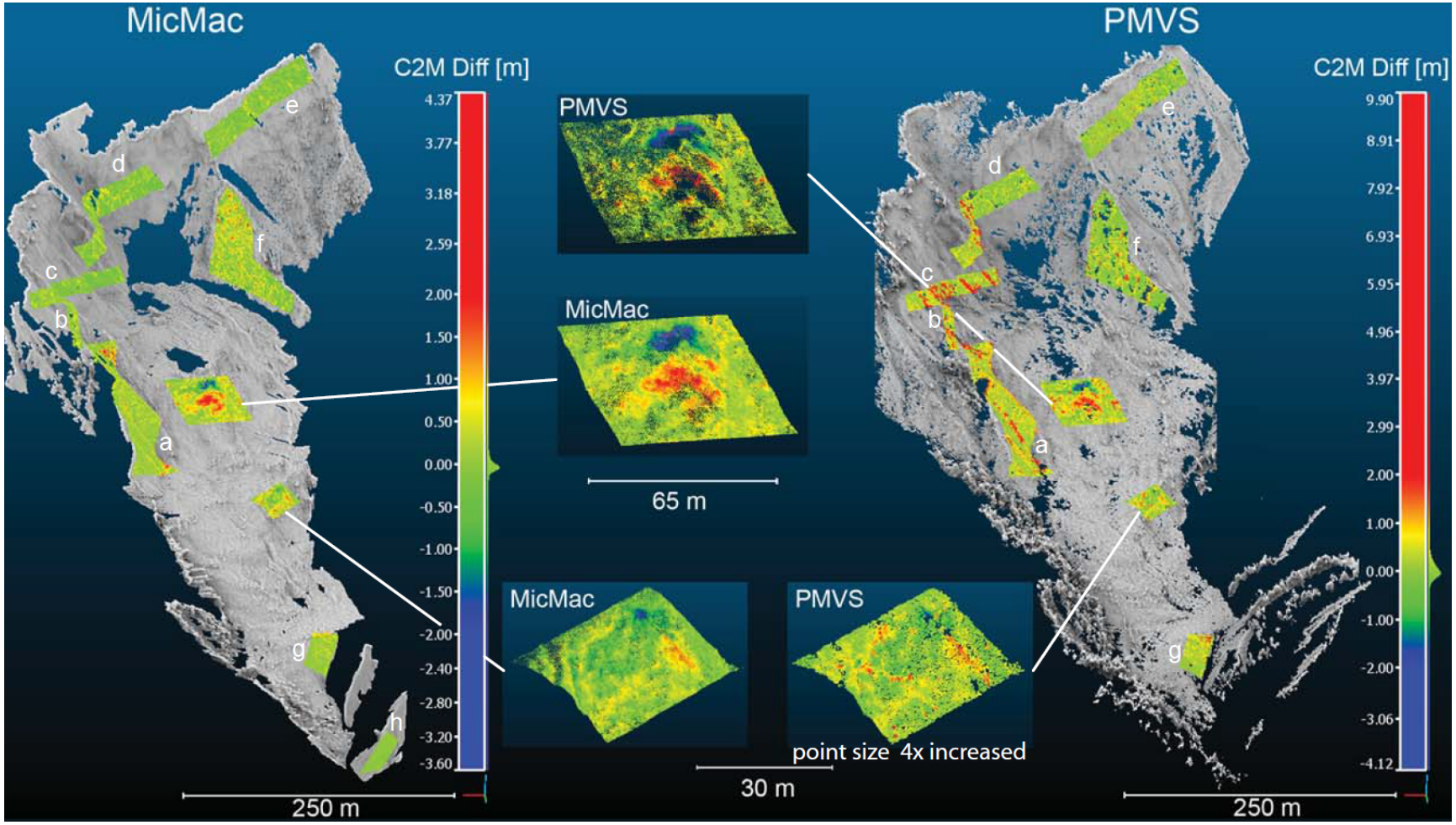
- 5.5 Mio points
- …still under elaboration



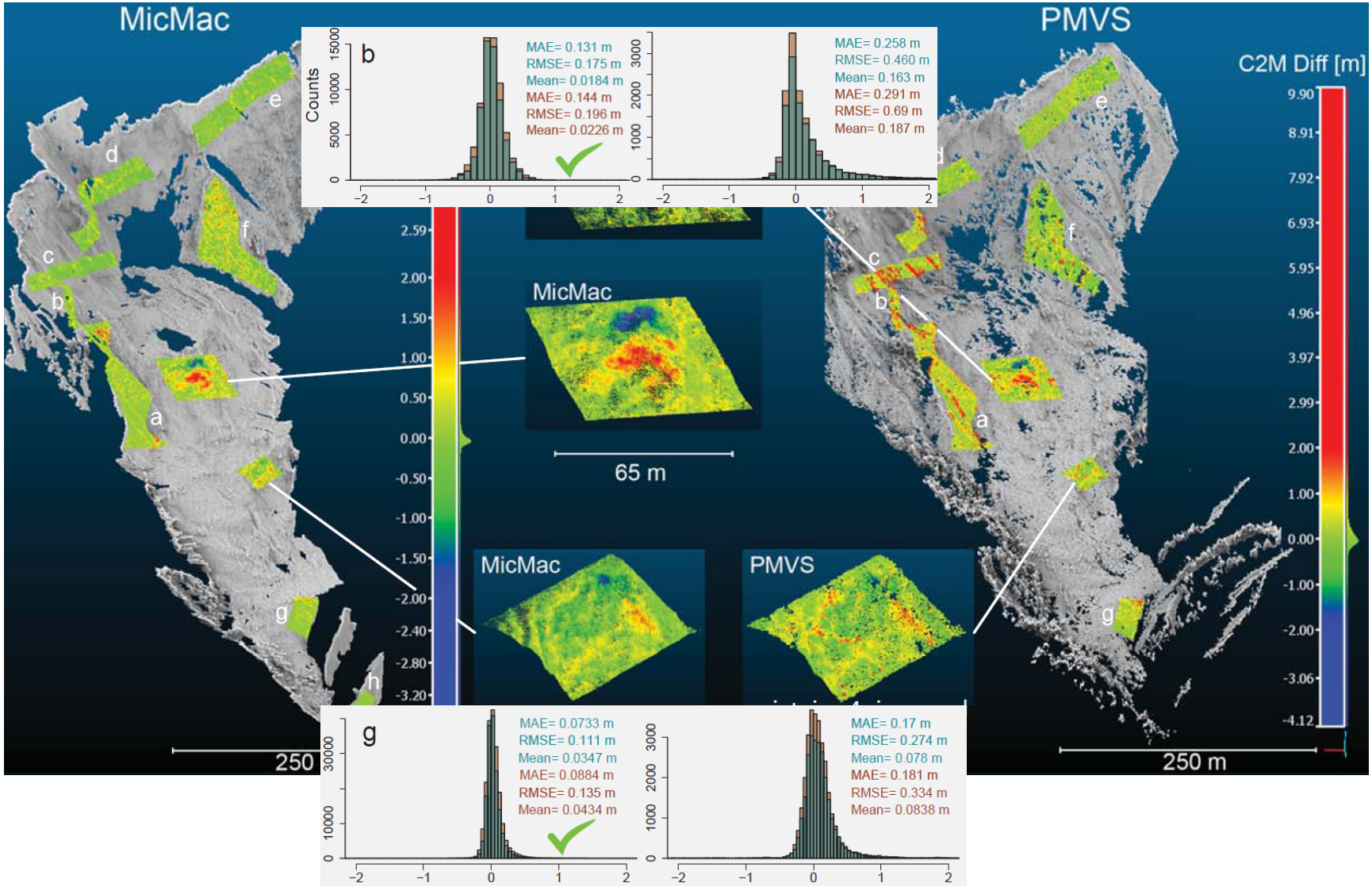
GEOMETRIC MODELLING

MicMac – Examples on landslides



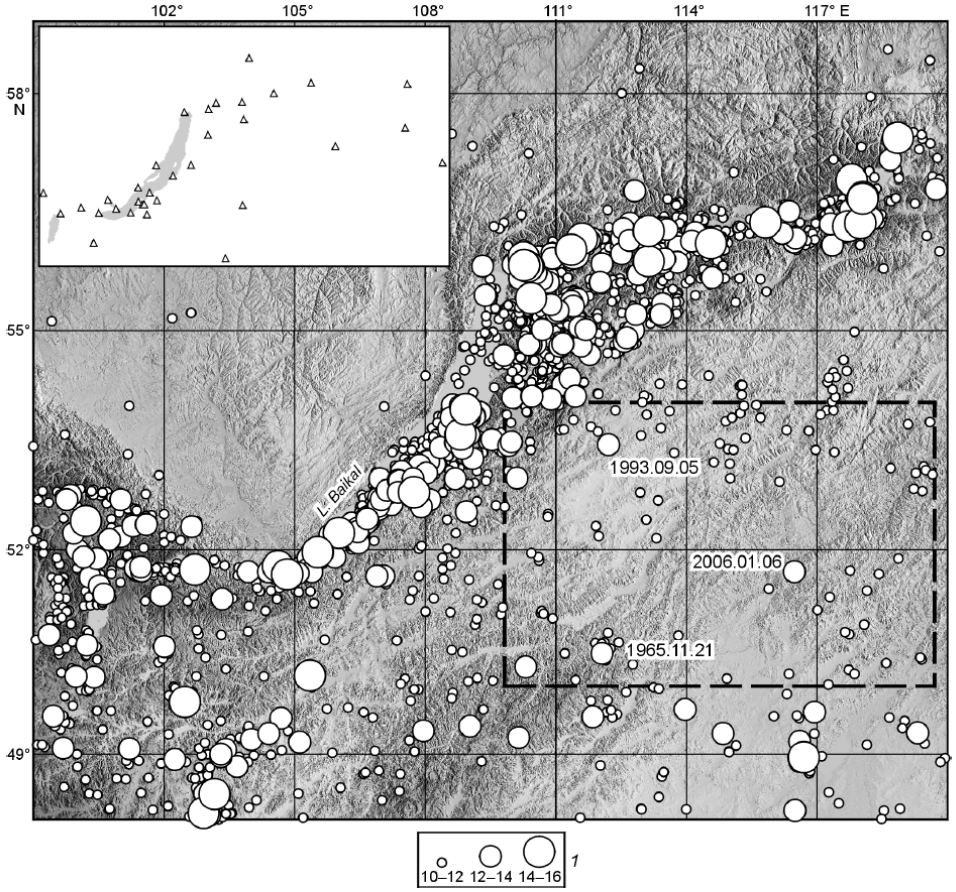
GEOMETRIC MODELLING

MicMac – Examples on landslidesc



MICMAC EXAMPLES

Gulya earthquake 2006 (?)



THANKS FOR YOUR ATTENTION

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