OPTICAL IMAGE MATCHING TECHNIQUES

ANDRE STUMPF
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 SATELLITE IMAGES

Correlation of SPOT5 imagery
(Delacourt et al., 2006)

Delacourt, Allemand and Thomas (2006, unpublished)

Le Prince et al. (2008)
APPLICATIONS ON TERRESTRIAL IMAGES

28.05.2008

01.06.2008

13.06.2008

29.06.2008
APPLICATIONS FOR LABORATORY TESTS

Mathieu et al. 2011
SATTELITE STEREOPHOTOGRAMMETRY
TERRESTRIAL PHOTOGRAMMETRY
IMAGE MATCHING TECHNIQUES

Feature based vs. patch based

Feature 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)

Patch based:
- 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

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

Witkin 1983
IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

- Feature detection

\[ L_{xx}(\sigma) + L_{yy}(\sigma) \rightarrow \sigma^3 \]

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

Laplacian-of-Gaussian (LoG)

Grauman and Leibe 2011
IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

- Feature detection

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

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 $\log_2(\min(\text{width}, \text{height})) = \text{number of octaves}$

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
    - 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

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

SIFT – Scale invariant feature targets

• Feature matching
  
o Efficient nearest neighbor with rejection of weak matches

\[
\text{match is accepted if } \frac{d1}{d2} > 0.8
\]

Lowe 2004
IMAGE MATCHING TECHNIQUES

SIFT – Scale invariant feature targets

• Does it work?

  o Very robust to illumination changes, rotation, scaling and moderate affine transformations
  o Many applications in image matching, object recognition, etc.
  o Faster and open-source implementation are available
  o 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

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

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

\[
I_1 <- c(1,8,15,7,14,16,13,20,22) \\
I_2 <- c(8,1,6,3,5,7,4,9,2) \\
A = sum(I_1*I_2) \\
# 585 \\
B = sqrt(sum(I_1^2) * sum(I_2^2)) \\
# 724.9414 \\
NCC = A/B \\
# 0.8069618
\]

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
Hierarchical normalized Cross-Correlation

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

\[
G_y = \begin{bmatrix}
+1 & +2 & +1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{bmatrix} \ast A
\]

\[
G_x = \begin{bmatrix}
+1 & 0 & -1 \\
+2 & 0 & -2 \\
+1 & 0 & -1
\end{bmatrix} \ast A
\]
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
HNCC

Reference image t=1

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

Increase of resolution
Increase of peak location accuracy

Search patch

Test patch

60 pixels

110 pixels
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
IMAGE MATCHING TECHNIQUES

HNCC – Subpixel precision

Interpolate image vs. interpolate correlation surface vs. peak fitting

Bicubic intensity

Bi-cubic (correlation)

Parabolic or Gaussian

Debella-Gilo and Kääb 2011
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
GEOMETRIC MODELLING

Satellite photogrammetry
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

\[
\begin{align*}
I + A_0 + A_1I + A_2s &= \frac{F_1(U,V,W)}{F_2(U,V,W)} \\
S + B_0 + B_1I + B_2s &= \frac{F_3(U,V,W)}{F_4(U,V,W)}
\end{align*}
\]
GEOMETRIC MODELLING

Satellite photogrammetry

- Bundle adjustment with Rational Functional Sensor Models

\[
\begin{align*}
I &= \frac{F_1(U, V, W)}{F_2(U, V, W)} \\
S &= \frac{F_3(U, V, W)}{F_4(U, V, W)}
\end{align*}
\]

- \( U, V, W \) ... coordinates in ground space
- \( I, S \) ... line, row coordinates in image space
- \( F_{1,2,3,4} \) ... rational functions with 80 coefficients

Fraser and Hanley 2005

Grodecki et al. 2004

Iterative least square

Adjustment parameters

Fraser and Hanley 2005
GEOMETRIC MODELLING

Satellite photogrammetry

- DSM extraction

Epipolar resampling (homologous points are in the same rows)

\[ I + A_0 + A_1 I + A_2 d = F_1(U, V, W) \]
\[ s + B_0 + B_1 I + B_2 d = F_2(U, V, W) \]
\[ F_3(U, V, W), F_4(U, V, W) \]

Morgan et al. 2006

Guérin et al. 2012

Hierarchical Image Correlation
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Satellite photogrammetry

• Accuracy?

1. Rural
   - MAE = 1.93 m
   - RMSE = 3.52 m
   - Mean = -1.36 m
   - Max = 31.8 m

2. Dense Urban
   - MAE = 3.01 m
   - RMSE = 4.63 m
   - Mean = -2.18 m
   - Max = 30.1 m

3. Sparse Urban
   - MAE = 1.59 m
   - RMSE = 2.4 m
   - Mean = -0.992 m
   - Max = 22.2 m

• Tie point detection
• Hierarchical Image Correlation
• RPF Bundle Adjustment
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Multi-View Terrestrial Photogrammetry

- Projective transformation / Homography

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

- \( H \) 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
Multi-View Terrestrial Photogrammetry

- Epipolar geometry and the Fundamental Matrix

\[ I' = Fx \] is the epipolar line corresponding to \( x \).

\[ l = F^T x' \] is the epipolar line corresponding to \( x' \).

- \( F \) is a 3×3 matrix with 8 independent ratios (defined up to scaling)
- \( F \) also satisfies \( \text{det} F = 0 \) 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
Multi-View Terrestrial Photogrammetry

- Estimating the Fundamental Matrix

  - Given at least 8 independent (not collinear) point correspondences

    $$x \leftrightarrow x', \quad x'^{T}Fx = 0$$

  - In the linear form

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

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

    $$A_{f} = \begin{bmatrix} x'_{1}x_{1} & x'_{1}y_{1} & x'_{1} & y'_{1}x_{1} & y'_{1}y_{1} & y'_{1} & x_{1} & y_{1} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x'_{n}x_{n} & x'_{n}y_{n} & x'_{n} & y'_{n}x_{n} & y'_{n}y_{n} & y'_{n} & x_{n} & y_{n} & 1 \end{bmatrix} \quad f = 0$$

  - Minimize $$\|A_{f}\|$$ (least square)

    $$\|f\| = 1$$

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
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 \( F \)
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

\[
P_2 = [e_2] \times F \ e_2
\]

\[
P = \begin{bmatrix}
3.53553 \times 10^2 & 3.39645 \times 10^2 & 2.7744 \times 10^2 & -1.14946 \times 10^6 \\
-1.03528 \times 10^2 & 2.33212 \times 10^2 & 4.59607 \times 10^2 & -6.32525 \times 10^5 \\
7.07107 \times 10^{-1} & -3.53553 \times 10^{-1} & 6.12372 \times 10^{-1} & -9.18859 \times 10^2
\end{bmatrix}
\]

\[
P = K[R \ | \ t] \quad K = \begin{bmatrix}
\alpha_x & x_0 \\
\alpha_y & y_0 \\
1 & 1
\end{bmatrix}
\]

Where \(ax\) and \(ay\) are the focal length in pixel
\(x_0\) and \(y_0\) are the principal point coordinates

Hartley and Zisserman 2004
GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Estimating the camera matrix

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\]

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-1.03528 \text{e}+2 & 2.33212 \text{e}+1 & 4.59607 \text{e}+2 & -6.32525 \text{e}+5 \\
7.07107 \text{e}+1 & -3.53553 \text{e}+1 & 6.12372 \text{e}+1 & -9.18559 \text{e}+2 \\
\end{bmatrix}
\]

\[
P = K[R \mid t]
\]

\[
K = \begin{bmatrix}
\alpha_x & x_0 \\
\alpha_y & y_0 \\
0 & 1
\end{bmatrix}
\]

Where \( ax \) and \( ay \) are the focal length in pixel
\( x_0 \) and \( y_0 \) are the principal point coordinates

Relative high residual because lens distortion is not considered

<table>
<thead>
<tr>
<th></th>
<th>( f_y )</th>
<th>( f_x/f_y )</th>
<th>skew</th>
<th>( x_0 )</th>
<th>( y_0 )</th>
<th>residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>algebraic</td>
<td>1633.4</td>
<td>1.0</td>
<td>0.0</td>
<td>371.21</td>
<td>293.63</td>
<td>0.601</td>
</tr>
<tr>
<td>geometric</td>
<td>1637.2</td>
<td>1.0</td>
<td>0.0</td>
<td>371.32</td>
<td>293.69</td>
<td>0.601</td>
</tr>
</tbody>
</table>

Hartley and Zisserman 2004
Multi-View Terrestrial Photogrammetry

- Lens distortion

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.

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

\( \tilde{r} \) 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.

Hartley and Zisserman 2004
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- Bundle adjustment and auto-calibration

\[
\min_{a_j, b_i} \sum_{i=1}^{n} \sum_{j=1}^{m} v_{ij} d(Q(a_j, b_i), x_{ij})^2;
\]

\( n \) 3d points seen in \( m \) images

\( U_{ij} \) 0/1 … point visible in image \( j \) or not

\( Q(a_j, b_i) \) Projected position for point \( i \) in image \( j \)

\( x_{ij} \) 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
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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
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- Further concepts
  - Lens models

**RadialExtended** a model with radial distortion (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 distortion center, 5 for coefficients of radial distortion ($r^3$, $r^5 \ldots r^{11}$);

**RadialBasic** a "subset" of previous model: radial distortion 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 distortion center, 2 for coefficients of radial distortion ($r^3$ and $r^5$);

**Fraser** a radial model, with decenteric 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 distortion center, 3 for coefficients of radial distortion ($r^3$, $r^5$ $r^7$), 2 for decenteric parameters, 2 for affine parameters; the **FraserBasic** same as previous with for principal point and distortion center constrained to have the same value (so 10 degree of freedom);

**FishEyeEqui** a model adapted for diagonal fisheyes equilinear (with $atan$ physical 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 distortion center, 5 for coefficients of radial distortion ($r^3$, $r^5$ $r^7$), 2 for decenteric parameters, 2 for affine parameters; by default the ray defining the usefull
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Multi-View Terrestrial Photogrammetry

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

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

\[ \hat{x}'^T E \hat{x} = 0 \]
\[ E = K'^T F K \]
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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
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Multi-View Terrestrial Photogrammetry

- Example

Hartley and Zisserman 2004
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Multi-View Terrestrial Photogrammetry

- Example
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Multi-View Terrestrial Photogrammetry

• Example
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GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

• Example
GEOMETRIC MODELLING

Multi-View Terrestrial Photogrammetry

- Example
Multi-View Terrestrial Photogrammetry

- Meshlab
• 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/
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Multi-View Terrestrial Photogrammetry

- **MicMac**: Multi Image Correspondances par Methodes Automatiques de Correlation
  - Development 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
  - Source code under:
    - hg clone [https://geoportail.forge.ign.fr/hg/culture3d](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
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 ($Z_{\text{min}}, Z_{\text{max}}$)
Compute matching costs
  - Mean NCC
    - over all image combinations
    - or only with the base image

Modified after Cox and Roy 1998
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MicMac

- Max score / Min Cost (C) is prone to produce many outliers

- A smoothness term is \((R \cdot D_{\text{diff}})\) 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
Scanline optimization
Max-flow

Cox and Roy 1998
Hirschmueller 2008

Similar to Semi-Global Matching
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MicMac

Coarse surface is used as a prior for subsequent iterations

Aggregate matching costs over all images

minimum-cost surface

next finer resolution

multi-directional regularization

Disparity $Z_{\text{step}}$
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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

MicMac – Examples on landslides

- Scarp Super Sauze October 2011
- 84 images
- ~ 10 Mio points

RMS Error: 6.8 cm
95.07% within 2 σ
GEOMETRIC MODELLING

MicMac – Examples on landslides

• Global model

• 150 images
• 5.5 Mio points
• …still under elaboration
GEOMETRIC MODELLING

MicMac – Examples on landslides

- Global model

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

MicMac – Examples on landslides

[Image of geometric modelling example]
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MicMac – Examples on landslides
MICMAC EXAMPLES

Gulya earthquake 2006 (?)
THANKS FOR YOUR ATTENTION

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