

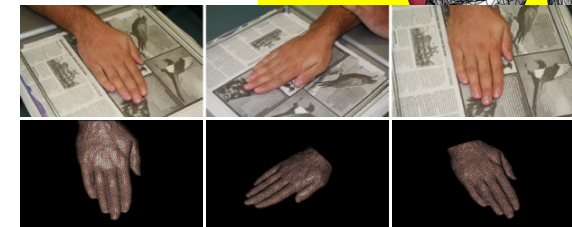
Multi-View 3D-Reconstruction

Slobodan Ilic

Computer Aided Medical Procedures (CAMP)
Technische Universität München, Germany

3D Models

- ⤴ “Digital copy” of real object
- ⤴ Allows us to
 - Inspect details of object
 - Measure properties
 - Reproduce in different material
- ⤴ Many applications
 - Cultural heritage preservation
 - Computer games and movies
 - City modelling
 - E-commerce
 - 3d object recognition/scene analysis



Applications: cultural heritage

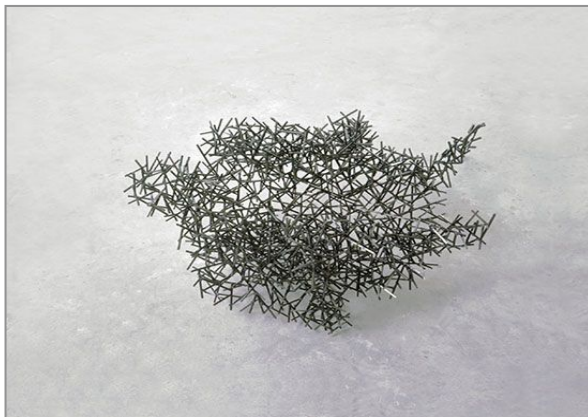
SCULPTEUR European project



Applications: art



Block Works Precipitate III 2004
Mild steel blocks 80 x 46 x 66 cm



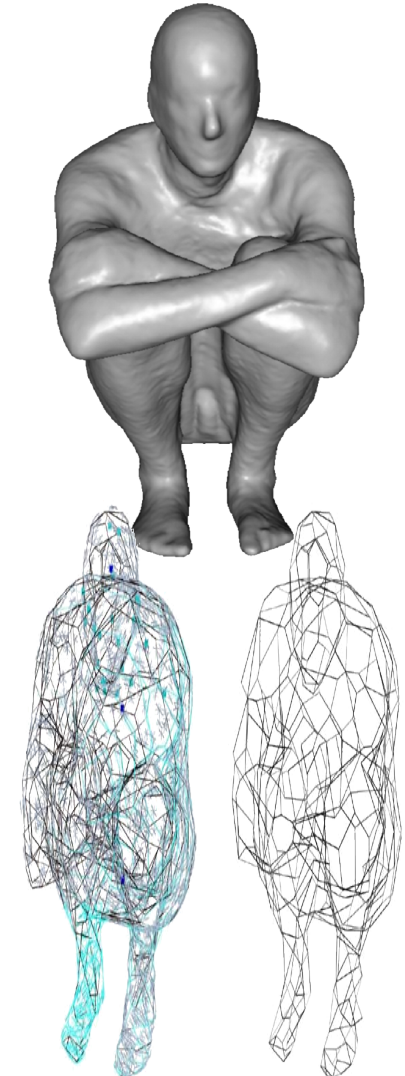
Domain Series Domain VIII Crouching
1999 *Mild steel bar 81 x 59 x 63 cm*



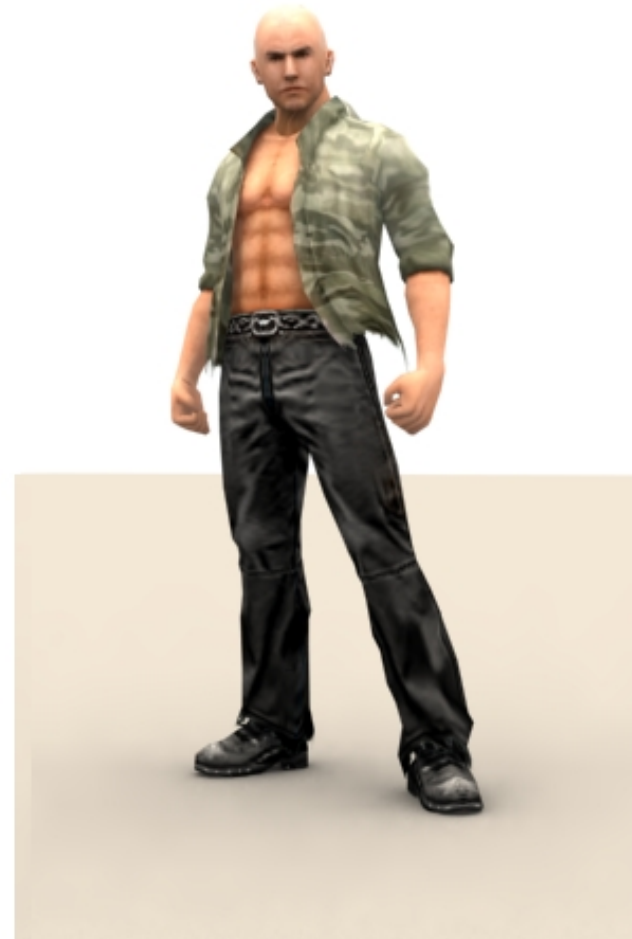
Applications: structure engineering



BODY / SPACE / FRAME, Antony Gormley, Lelystad, Holland



Applications: computer games



Applications: 3D indexation

3D models indexing results with method aMRG

| | | | | |
|-------------------------|---------------------------|--|--|--|
| | | | | |
| 0 : deesse0 0.000000 | 1 : deesse5 0.092800 | | | |
| | | | | |
| 5 : deesse2 0.211000 | 6 : ARCHI3203 0.236800 | | | |

3
915

?

?

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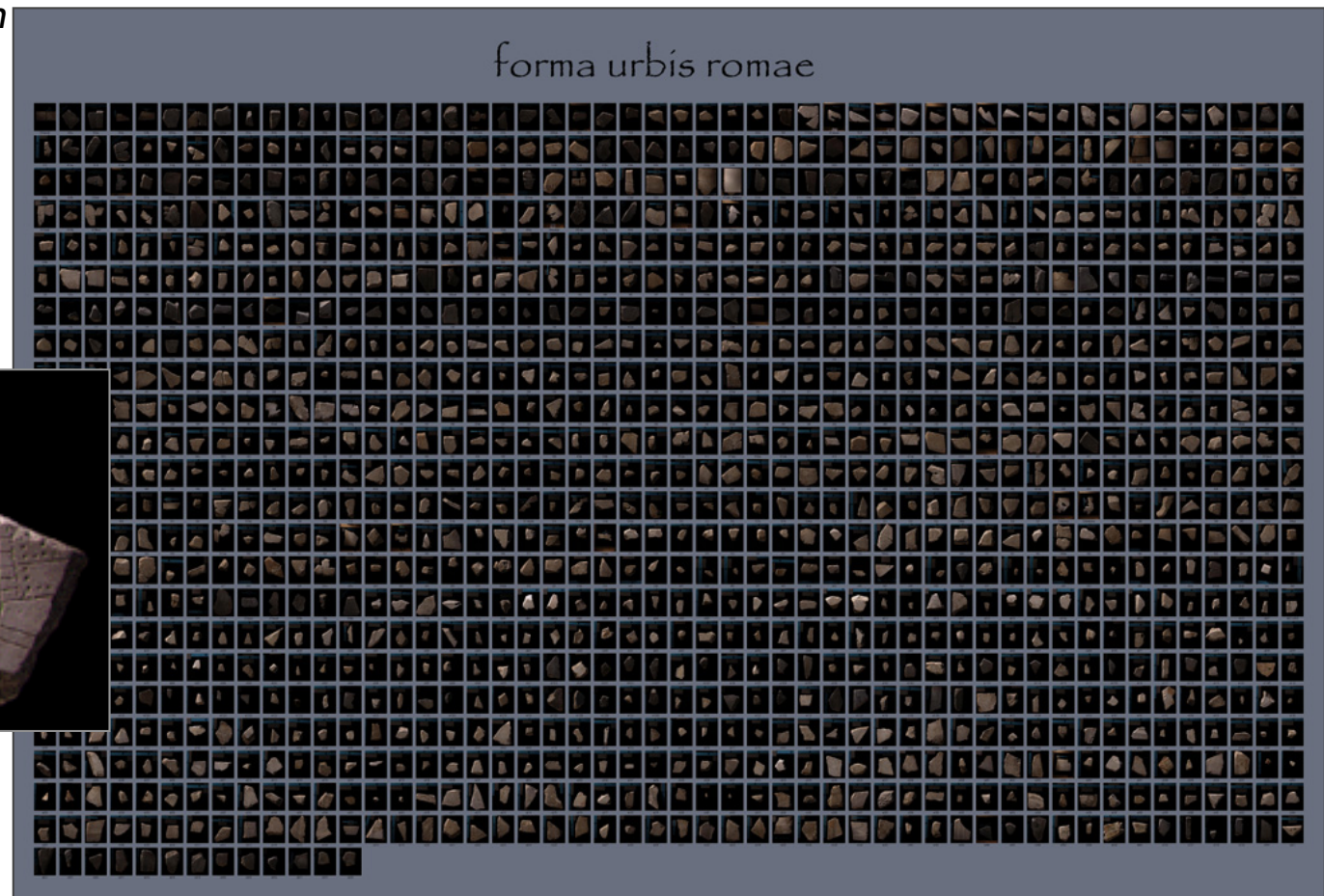
Applications: archaeology

✦ “forma urbis romae” project

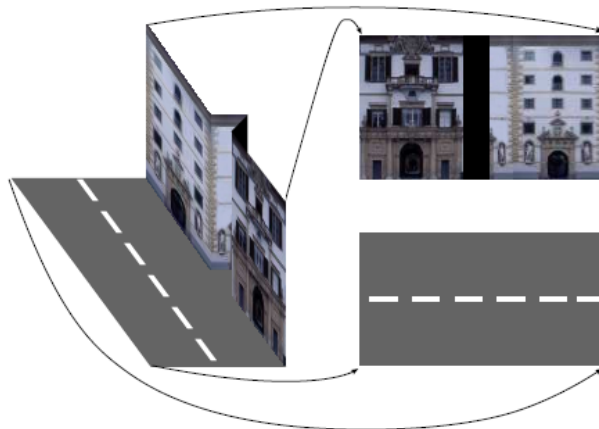
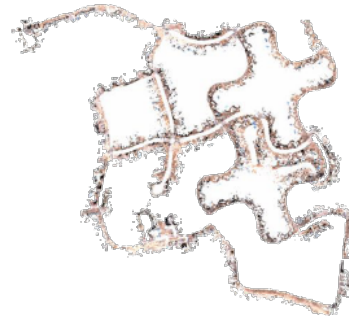
Fragments of the City: Stanford's Digital Forma Urbis Romae Project

David Koller, Jennifer Trimble, Tina Najbjerg, Natasha Gelfand, Marc Levoy

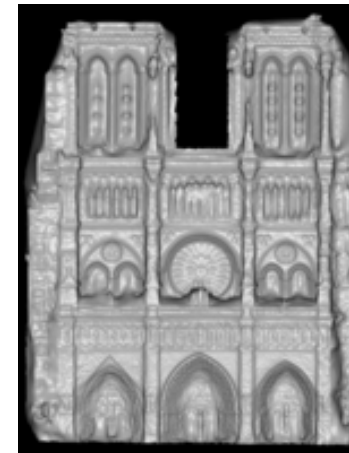
*Proc. Third Williams Symposium
on Classical Architecture,
Journal of Roman Archaeology
supplement, 2006.*



Applications: large scale modelling



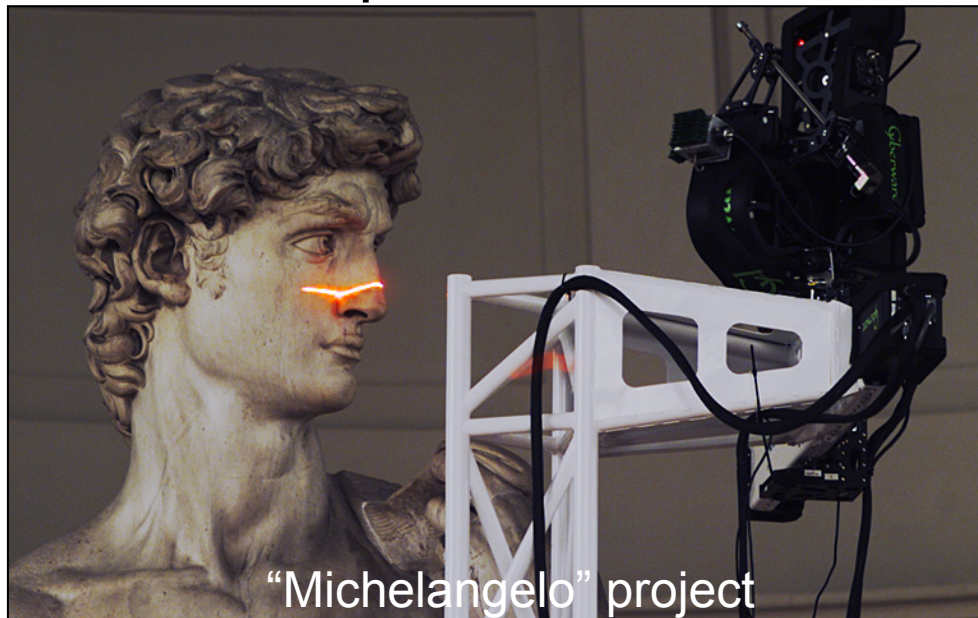
[Cornelis08]



[Goesele07]

Scanning technologies

- ✦ Laser scanner, coordinate measuring machine
 - Very accurate
 - Very Expensive
 - Complicated to use



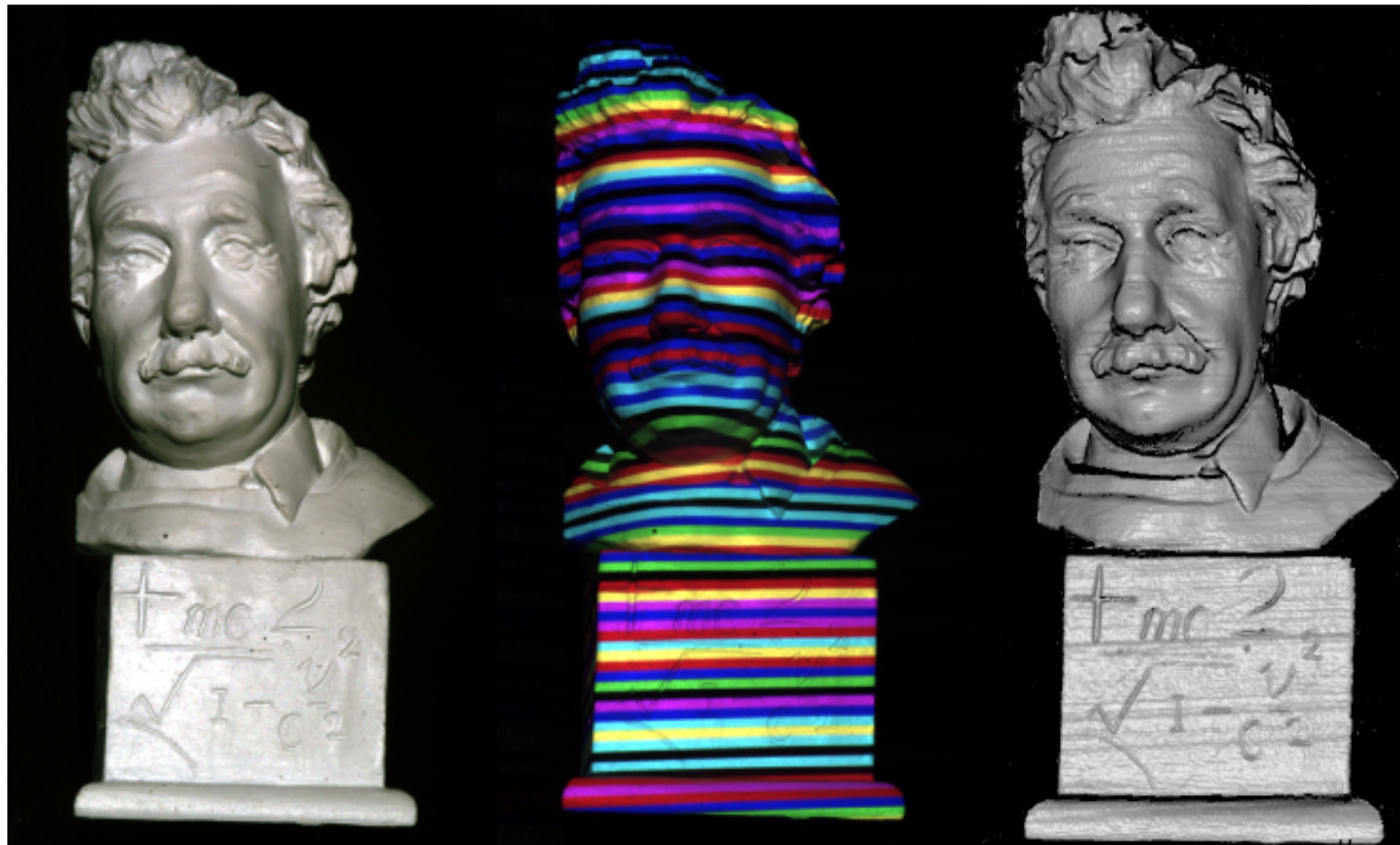
Minolta



Contura CMM

Scanning technologies

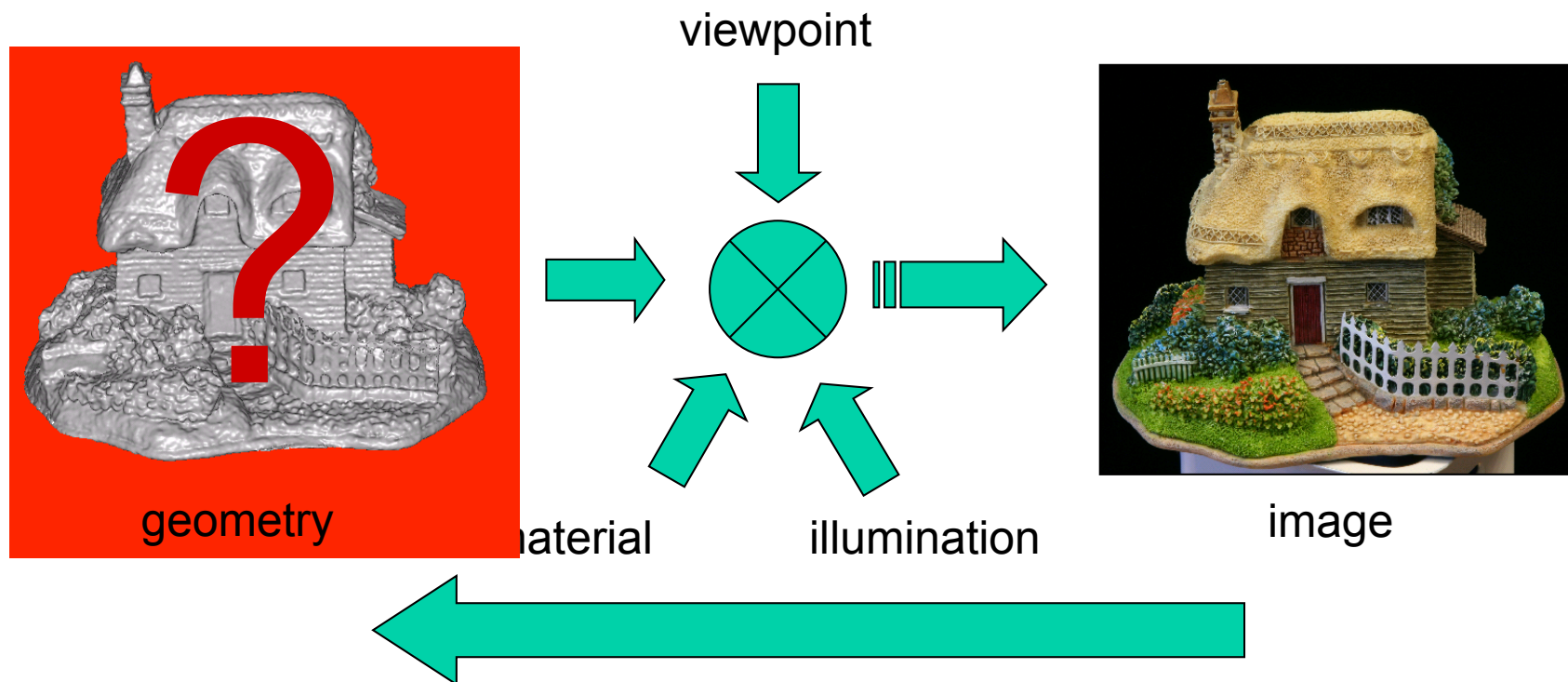
Structured light



[Zhang02]

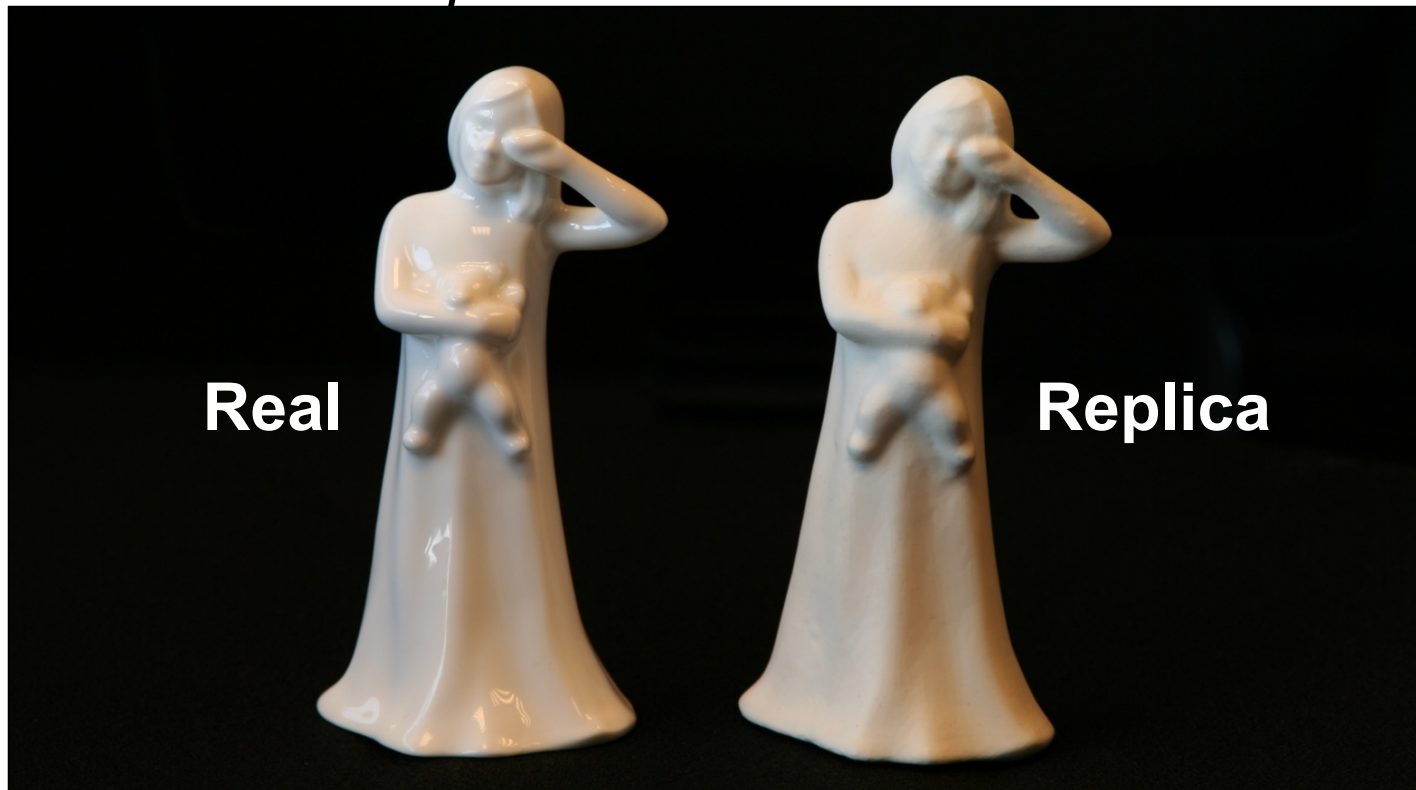
3D shape from photographs

“Estimate a 3d shape that would generate the input photographs given the same material, viewpoints and illumination”



3d shape from photographs

“Estimate a 3d shape that would generate the input photographs given the same material, viewpoints and illumination”



3d shape from photographs

Appearance strongly depends on the material and lighting



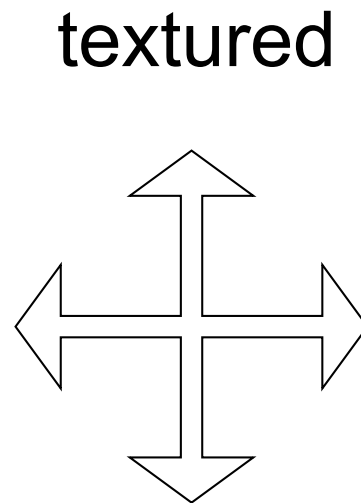
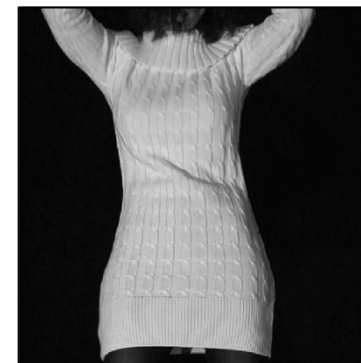
rigid



deforming



textureless



3d shape from photographs

Appearance strongly depends on the material and lighting



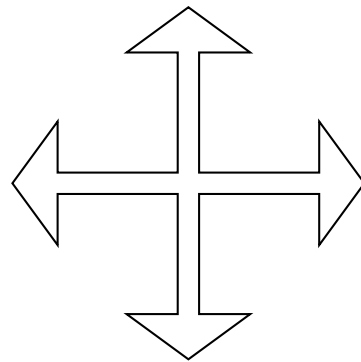
No single algorithm exists dealing with **any** type of scene



rigid



textured



deforming

textureless



3D shape from photographs

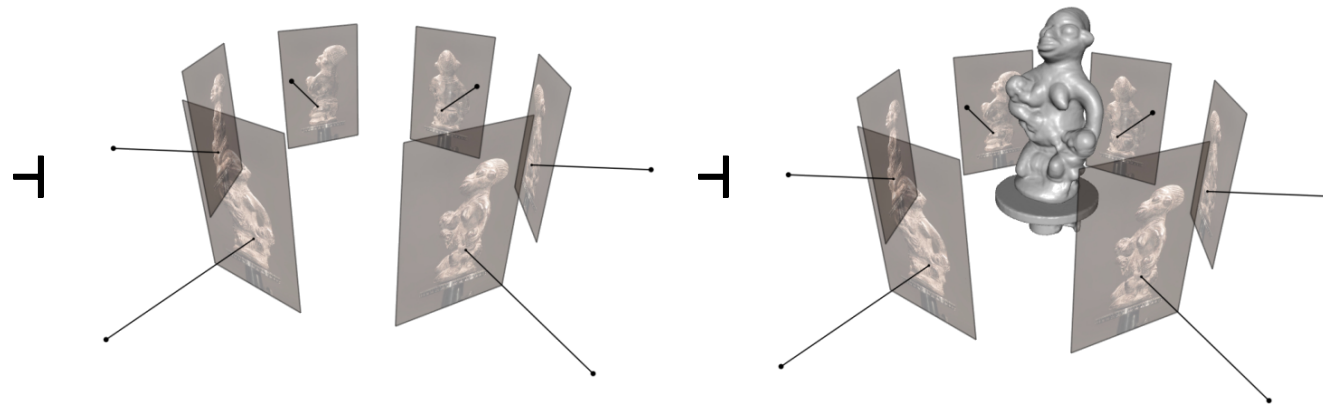
Photograph based 3d reconstruction is:

- ✓ practical
- ✓ fast
- ✓ non-intrusive
- ✓ low cost
- ✓ Easily deployable outdoors
- ✗ “low” accuracy
- ✗ Results depend on material properties

Multi-view reconstruction pipeline



Image acquisition



Camera pose

3d reconstruction

Image acquisition

- ⌘ **Studio conditions**

controlled environment



- ⌘ **Uncontrolled environment**

hand-held

unknown illumination



- ⌘ **Internet**

Unknown content



- **Video**

small motion between frames

huge amount of data



Studio image acquisition



Outdoor image acquisition



Internet image acquisition



colosseum Search SafeSearch moderate

Page 3 of about 1,290,000 results (0.05 seconds) [Advanced search](#)



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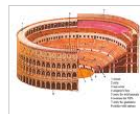
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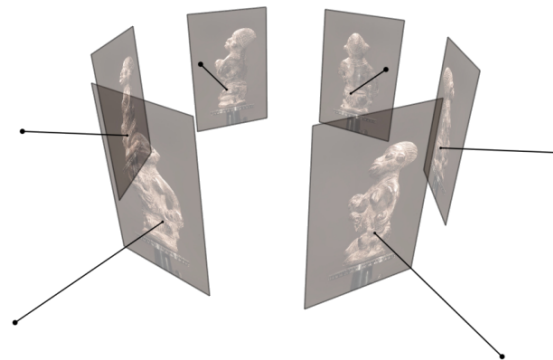
Video image acquisition



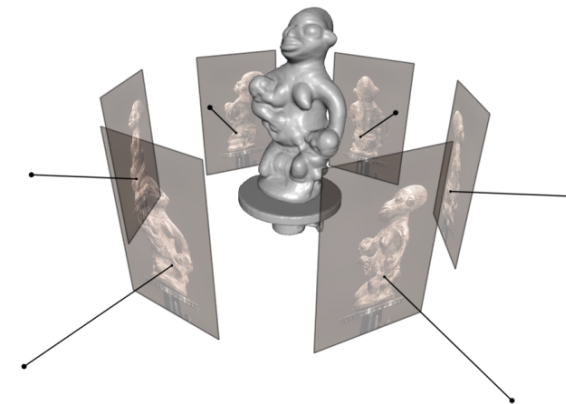
Multi-view reconstruction pipeline



Image acquisition



Camera pose



3d reconstruction

Camera pose

- Robotic arm

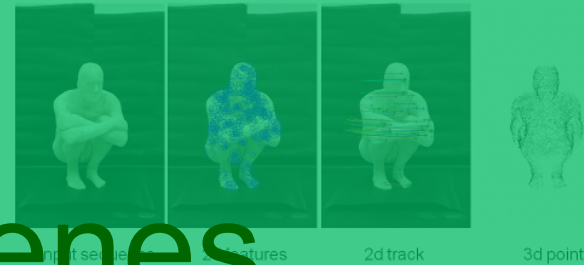


Small Scenes

- Fiduciary markers



- Structure-from-Motion



Large scenes

- SfM from unorganized photographs



Robotic arm

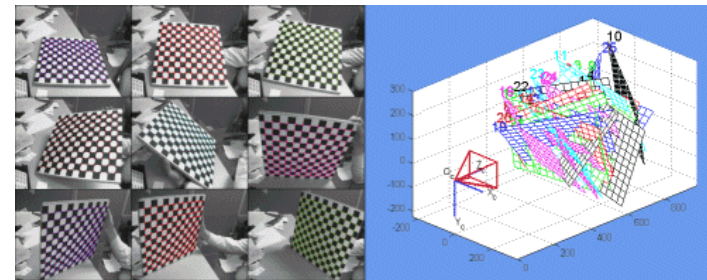


Fiduciary markers

- ARToolkit

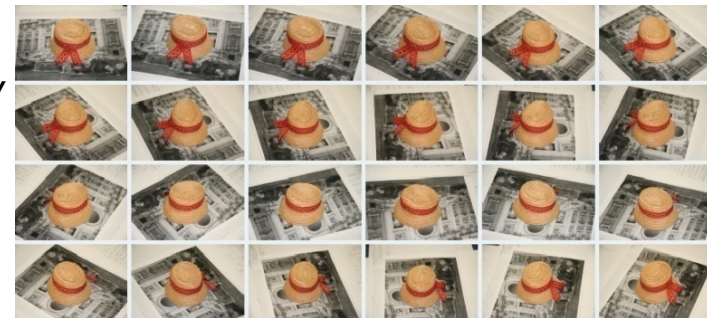


- Bouguet's MATLAB Toolbox



www.vision.caltech.edu/bouguetj/calib_doc/

- Robust planar patterns



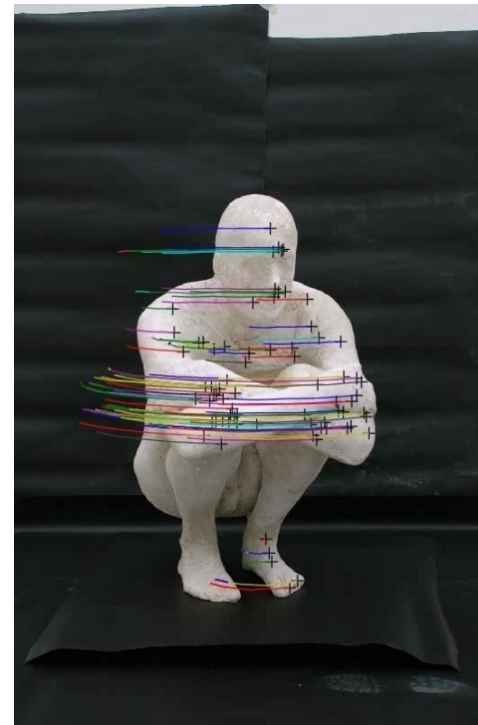
Structure from motion



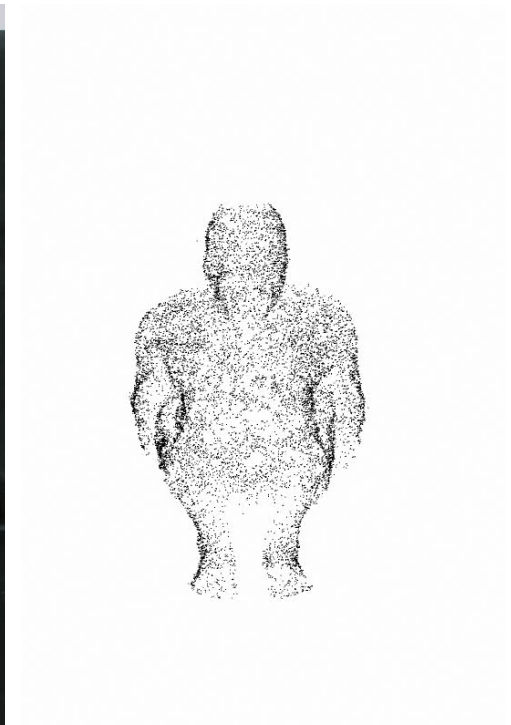
Input sequence



2d features



2d track



3d points

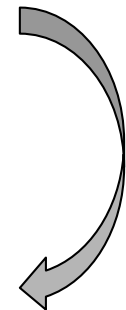
Motion estimation result



Structure-from-Motion from unordered image collections

[Brown05, Snavely06, Agarwal09]

- Image clustering
- Pose initialization
- Bundle-adjustment

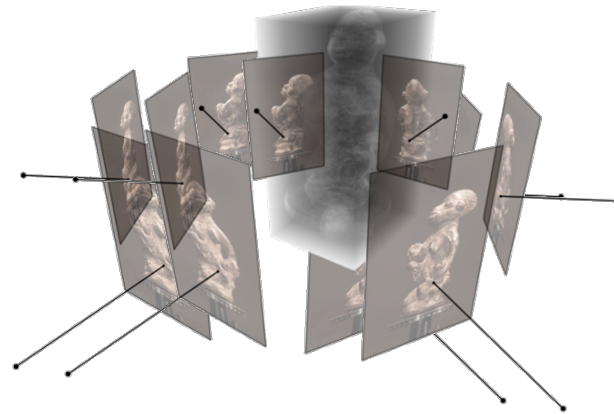


phototour.cs.washington.edu/bundler

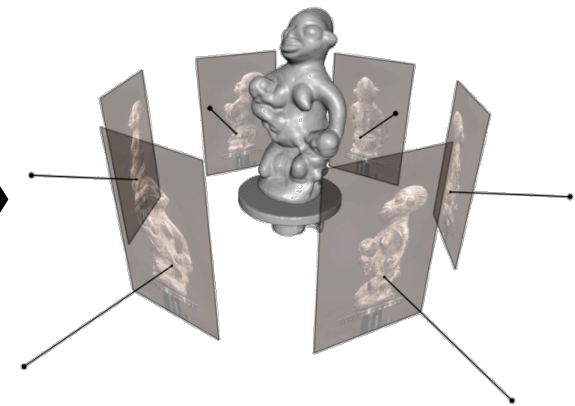
Multi-view reconstruction pipeline



Image acquisition,
camera pose



Camera pose or
photo-consistency
from images

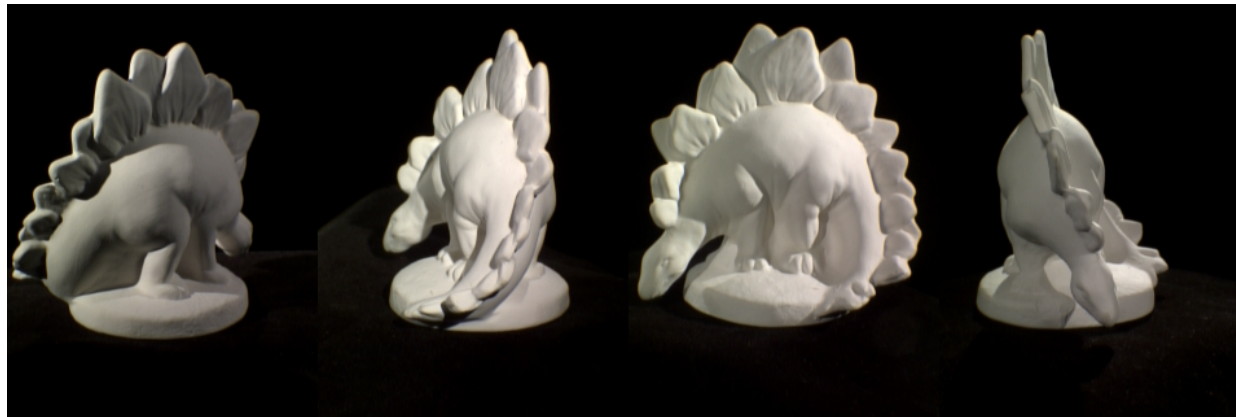


3d reconstruction from
3d photo-consistency

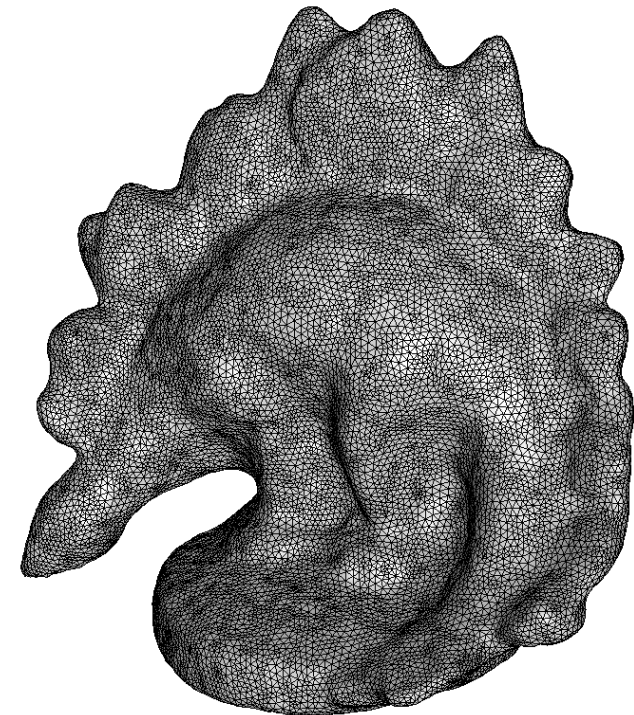
3d reconstruction = 3d segmentation

Problem Statement

Given several calibrated views of an object ...

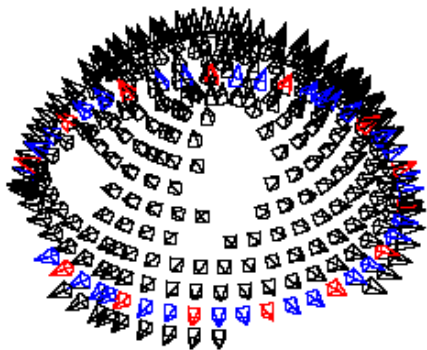


...how can we automatically build a 3D model of it ?



The Middlebury datasets

- Provides two datasets: “Temple” and “Dino”
 - Images corrected for radial distortion.
 - Camera calibration (intrinsics & extrinsics)
- Three versions for each dataset
 - Full hemisphere (> 300 images)
 - Ring (48 images)
 - Sparse Ring (16 images)
- They keep **Ground Truth** to evaluate results.



Multi-View Stereo Evaluation • Datasets • Submit • Code

Acc. Threshold: 90% Data in new window Open Data Window

Comp. Threshold: 1.25 mm Data: View 1 and Ground Truth Image Size: Small

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

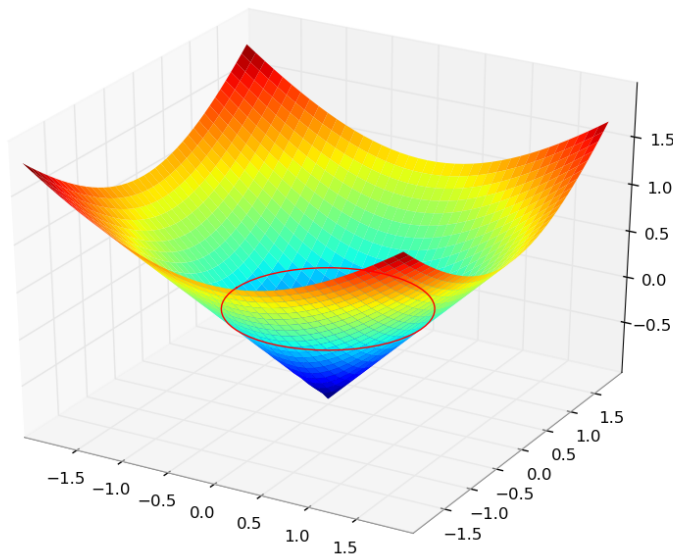
| Sort By | Temple Full 312 views | | Temple Ring 47 views | | Temple Sparse 16 views | | Dino Full 383 views | | Dino Ring 48 views | | Dino Sparse 16 views | |
|--------------------|--------------------------|------|-------------------------|------|---------------------------|------|------------------------|------|-----------------------|------|-------------------------|------|
| | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp |
| | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] |
| Auclair | | | 0.86 | 96.2 | 1.03 | 92.5 | | | 0.62 | 96.7 | 0.74 | 96.8 |
| Bradley | | | 0.57 | 98.1 | 0.48 | 93.7 | | | 0.39 | 97.6 | 0.38 | 94.7 |
| Campbell | 0.41 | 99.9 | 0.48 | 99.4 | 0.53 | 98.6 | | | | | | |
| Chang | | | 0.54 | 99.0 | 0.73 | 94.5 | | | 0.51 | 94.6 | 0.66 | 89.9 |
| Continuous Probab | | | 1.89 | 92.1 | | | | | 2.61 | 91.4 | | |
| Delauoy | | | | | 0.73 | 95.9 | | | | | 0.89 | 93.9 |
| Deng | | | 0.54 | 98.5 | | | | | | | 0.43 | 97.8 |
| ECCV_216 | | | 0.53 | 99.5 | 0.72 | 96.8 | | | 0.46 | 99.5 | 0.42 | 97.8 |
| 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 |
| 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 |
| Gargallo | | | 0.88 | 84.3 | 1.05 | 81.9 | | | 0.6 | 92.9 | 0.76 | 90.7 |
| 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 |
| Goesele 2007 | 0.42 | 98.2 | | | | | 0.46 | 96.7 | | | | |
| Guillemaut | 0.43 | 99.0 | 0.71 | 97.6 | 0.86 | 96.2 | 0.35 | 100 | 0.58 | 99.5 | 0.68 | 98.0 |
| Habbecke | 0.66 | 98.0 | | | | | 0.43 | 99.7 | | | | |
| 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 |
| 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 |
| 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 |
| JancosekCVWW | | | | | | | | | 0.79 | 95.9 | | |
| Kolev | | | 0.79 | 96.0 | | | | | 0.53 | 96.9 | | |
| Kolev2 | | | 0.72 | 97.8 | 1.04 | 91.8 | | | 0.43 | 99.4 | 0.53 | 98.3 |
| Kolev3 | | | 0.7 | 98.3 | 0.97 | 92.7 | | | 0.42 | 99.5 | 0.48 | 98.6 |
| Kolmogorov | | | 1.86 | 90.4 | | | | | 2.81 | 86.0 | | |
| Kun Li | | | | | 0.81 | 92.1 | | | | | 0.47 | 97.4 |
| Ladikos | | | | | | | | | | | 0.89 | 95.0 |
| Lambert | 0.55 | 99.7 | | | | | 0.76 | 99.0 | | | | |
| Lambert3 | 0.48 | 99.7 | | | | | 0.48 | 99.4 | | | | |
| Li | | | 0.64 | 98.2 | | | | | 0.43 | 99.7 | | |
| Liu | | | | | 0.96 | 89.6 | | | | | 0.59 | 98.3 |
| Liu2 | | | | | 0.65 | 96.9 | | | | | 0.51 | 98.7 |
| Massively Parallel | 0.79 | 92.2 | | | | | | | | | | |
| Merrell Confidence | | | 0.83 | 88.0 | | | | | 0.84 | 83.1 | | |
| Merrell Stability | | | 0.76 | 85.2 | | | | | 0.73 | 73.1 | | |
| NIPS_829 | | | | | 2.83 | 81.3 | | | | | 1.07 | 91.0 |
| Pons | | | 0.6 | 99.5 | 0.9 | 95.4 | | | 0.55 | 99.0 | 0.71 | 97.7 |
| Sinha | | | 0.79 | 94.9 | | | | | 0.69 | 97.2 | | |
| Song | | | 0.61 | 98.3 | | | | | 0.38 | 99.4 | 0.54 | 95.5 |
| Sormann | | | 0.69 | 97.2 | | | | | 0.81 | 95.2 | | |
| Stark | | | | | 1.97 | 87.7 | | | | | 1.01 | 90.7 |

Representing Shape

Implicit

Represent the surface as the 0 level-set of a scalar function f :

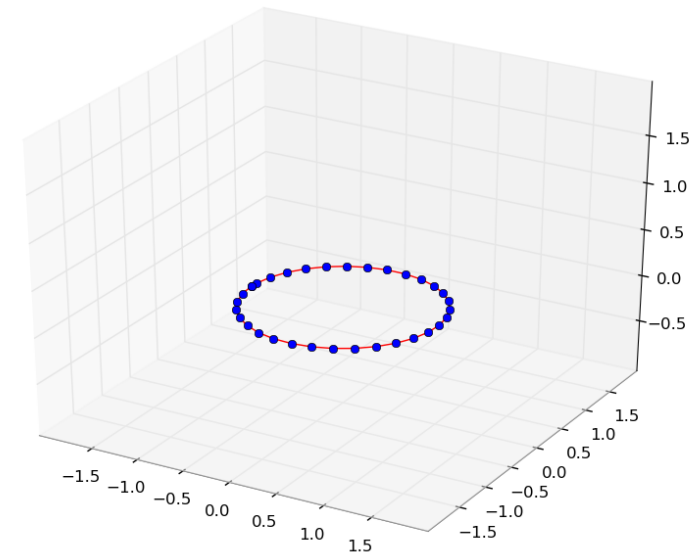
$f(x) = 0$ surface
 $f(x) > 0$ inside
 $f(x) < 0$ outside



Explicit

Discretize the interface itself with a mesh:

$M = (V, T)$
 V are the vertices
 T are the triangles



Representing Shape

Implicit

- heavy in memory.

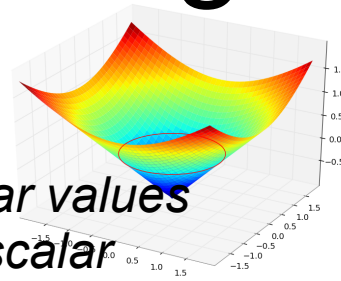
*In 2D: hold $N_x * N_y$ scalar values*

*In 3D: hold $N_x * N_y * N_z$ scalar values*

- possible refinements:

- *octrees*

- uniformity of sampling.



Explicit

- lightweight representation.

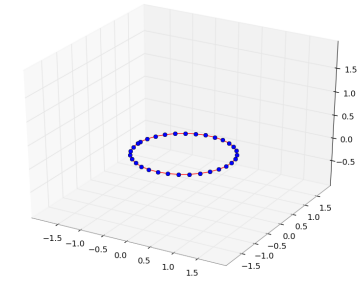
- easy to render on the GPU.

- versatile:

* adaptive sampling

* open meshes

* non manifoldness



Dealing with moving interfaces (in time or iterations of an algorithm)

- *Eulerian* point of view.

- handles naturally changes of topology.

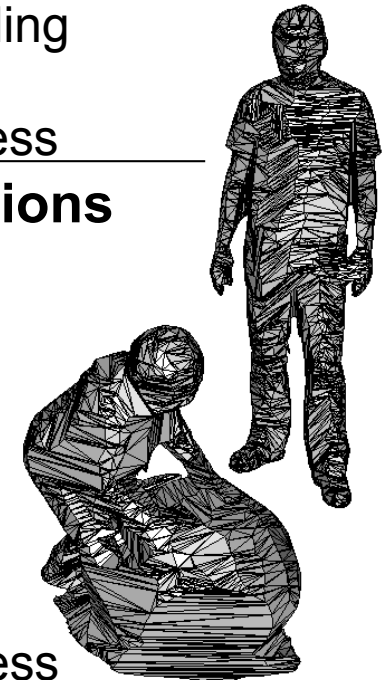
- Can maintain point correspondence.

(Lagrangian)

- difficult to preserve correct sampling.

* non uniformity

* non manifoldness

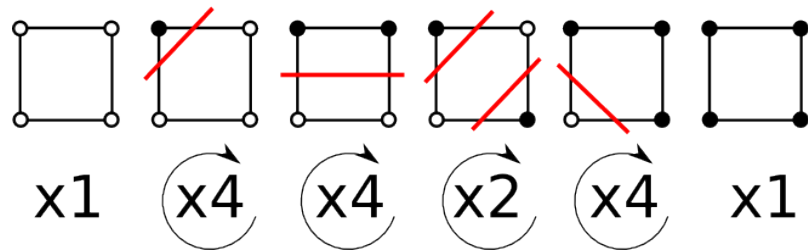


From Implicit Surfaces to Meshes

The main idea:

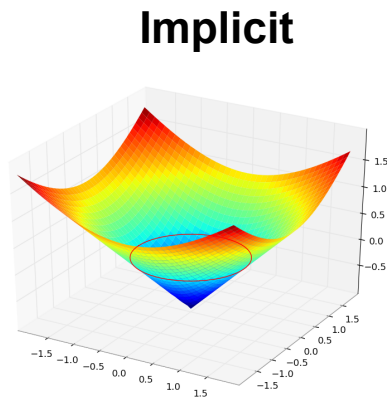
- From a given implicit surface create a triangular mesh that approximates this surface
- Compute normals of the mesh surface at each vertex of created triangles
- Use marching cubes algorithm

Marching Cubes Algorithm



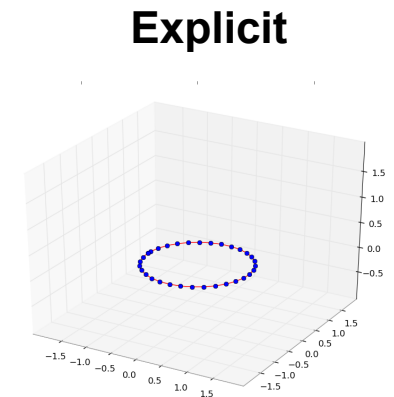
2D Marching cubes: 16 cases
 3D Marching cubes: 256 cases

- Assign zero to vertices outside the surface
- Assign one to vertices inside the surface
- Surface intersects squares/cubes at places where the surface passes, i.e. between vertices that are inside and outside the implicit surface



Marching Cubes

Voxelization



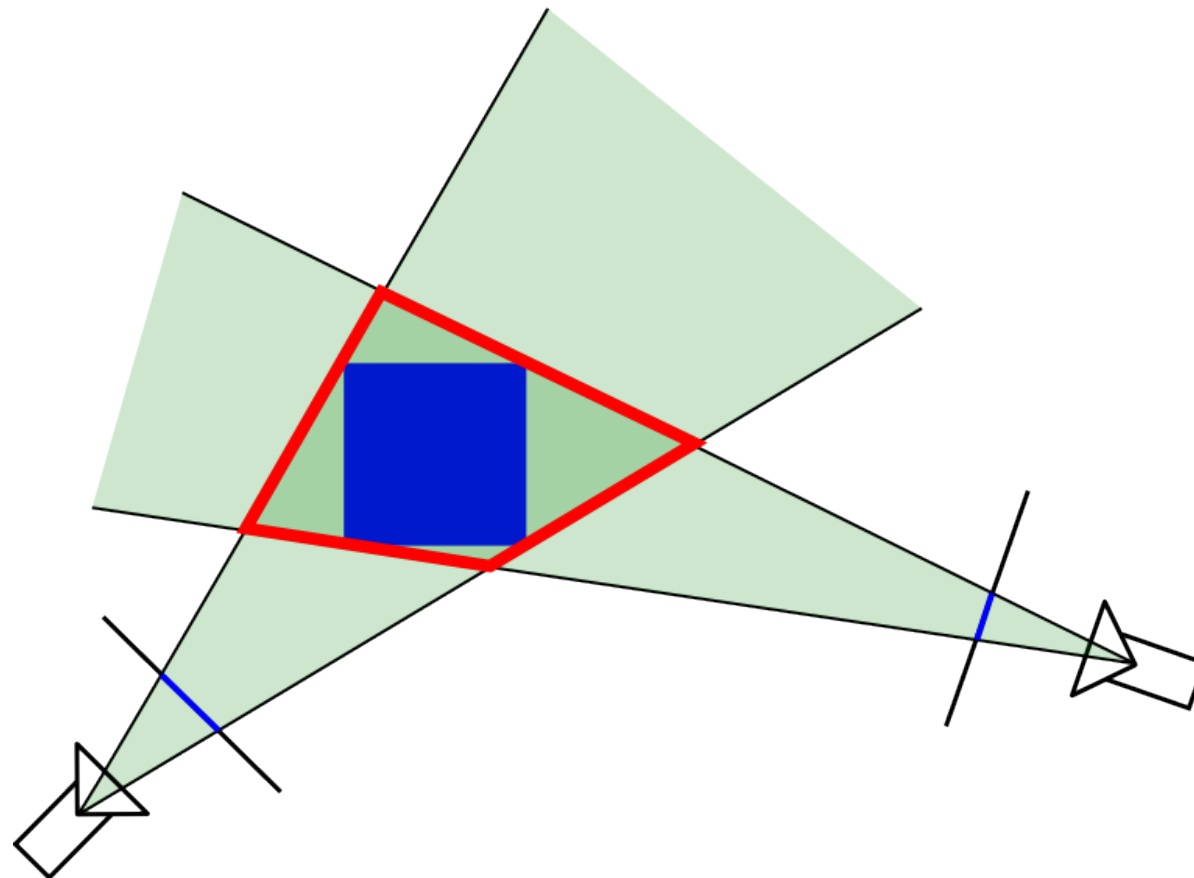


Reconstruction I

Shape From Silhouette

SFS - Principle

The visual hull is the shape maximally consistent with the silhouettes

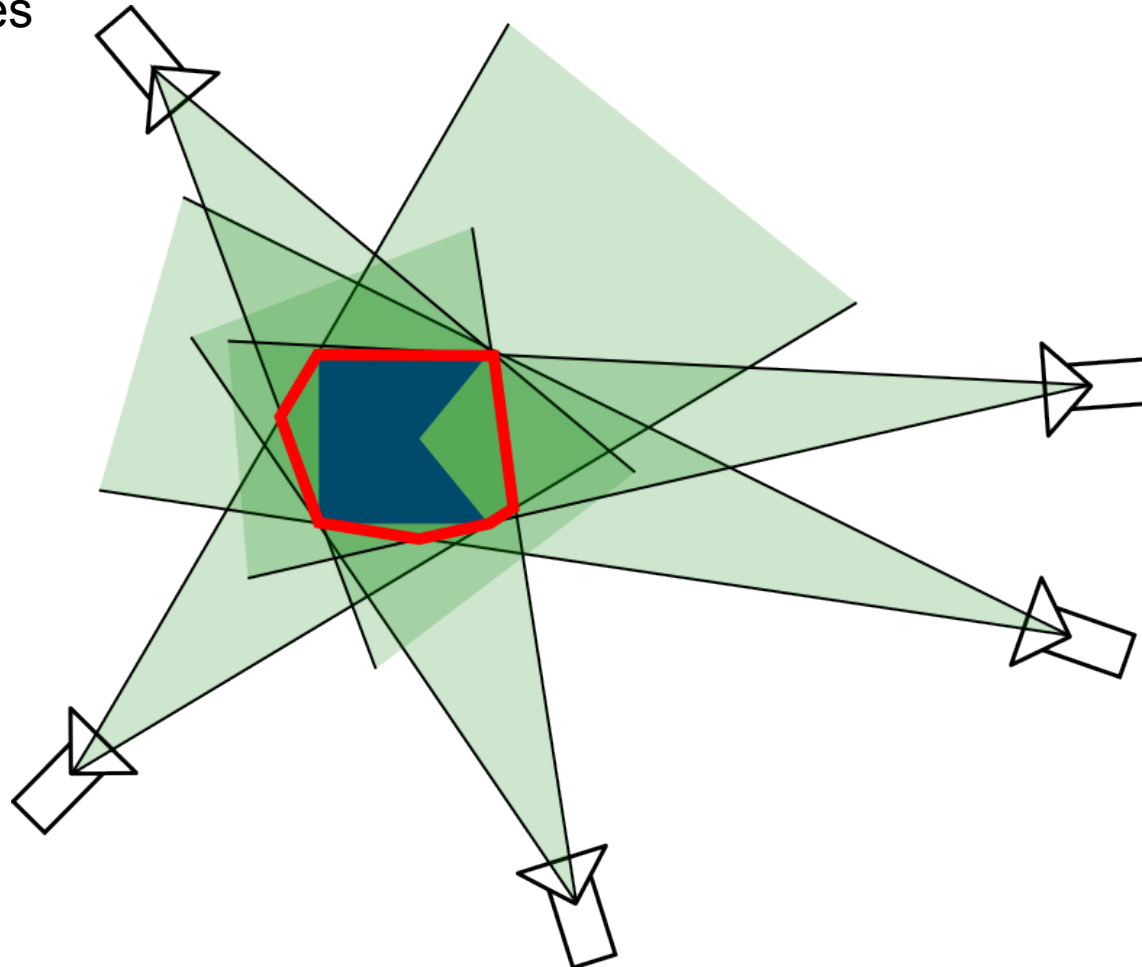


SFS

Does it converge to the true shape as we add more and more cameras ?

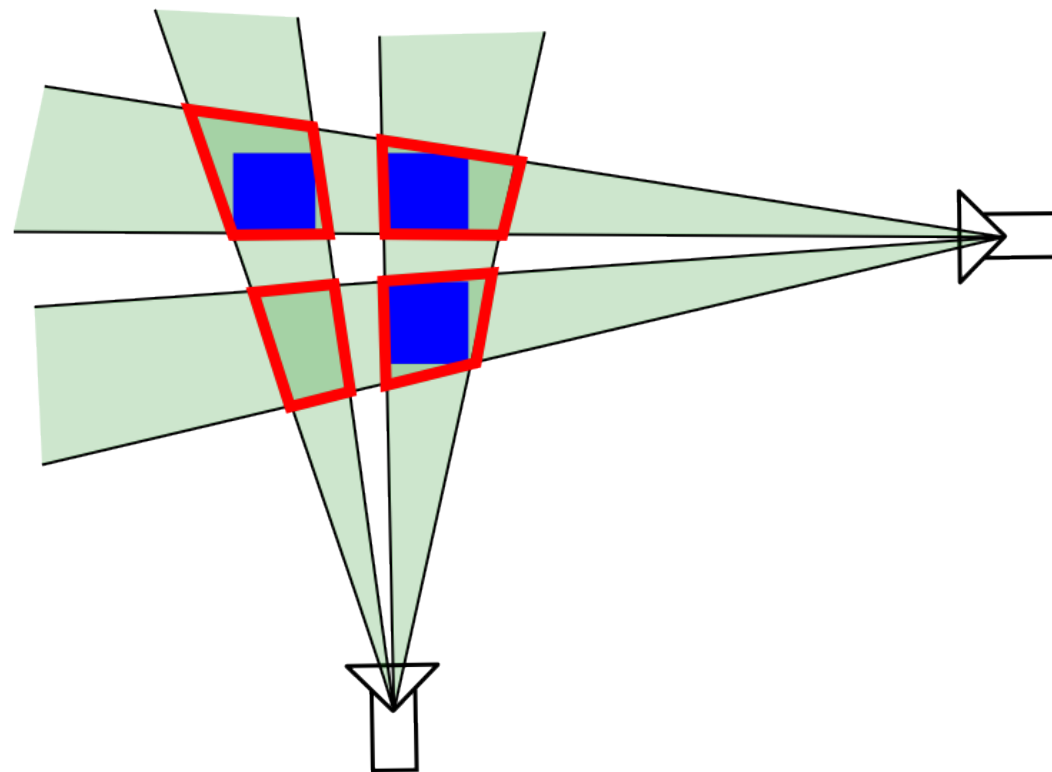
SFS - concavities

The visual hull cannot capture concavities not visible in the silhouettes



SFS – concavities

This can lead to severe reconstruction artifacts such as erroneous additional connected components.

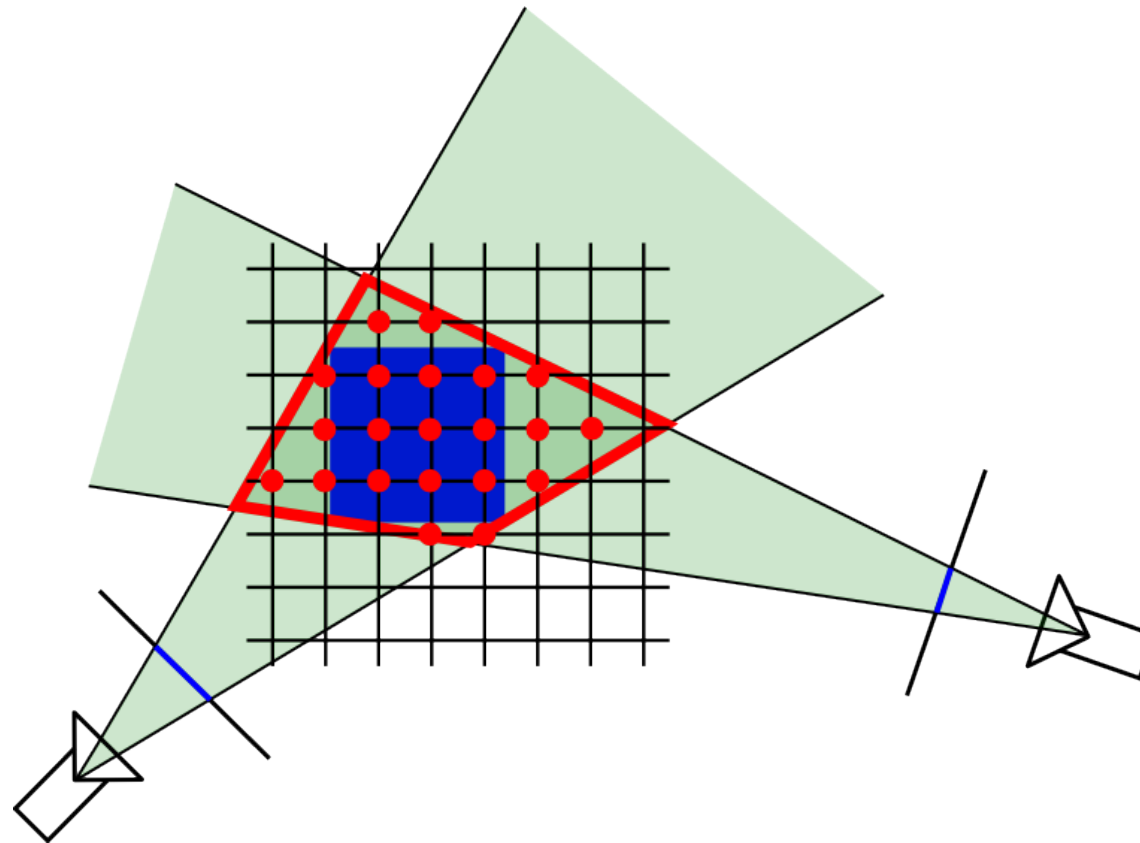


SFS – silhouette errors

All the previous slides were considering perfect silhouettes.

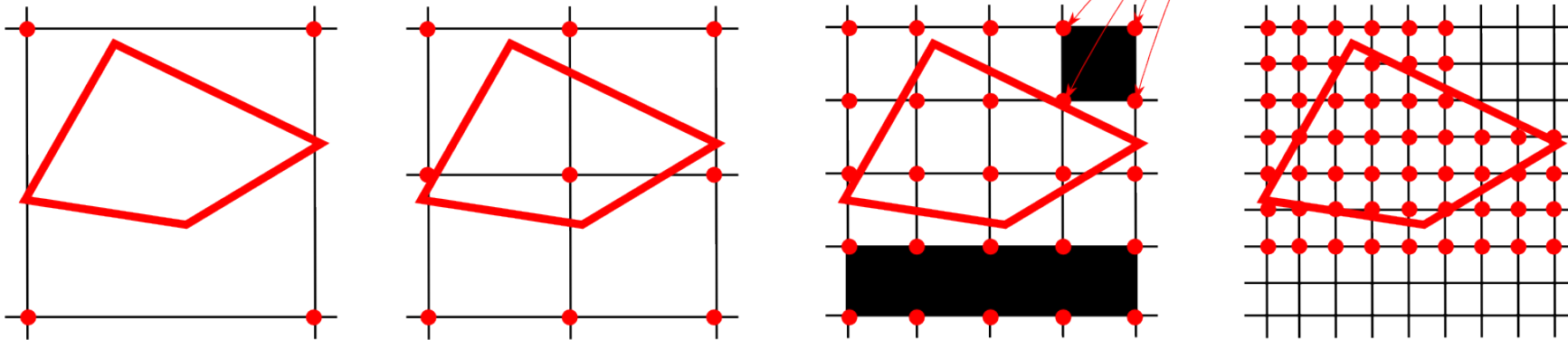
SFS – Volumetric Approach

- Define the scene's bounding box and discretize it.
- Evaluate for each voxel: “am I in the object ?”



SFS – Octree speed up

In the integral images of each camera,
these 4 points gave the same value.
→ do not check next level



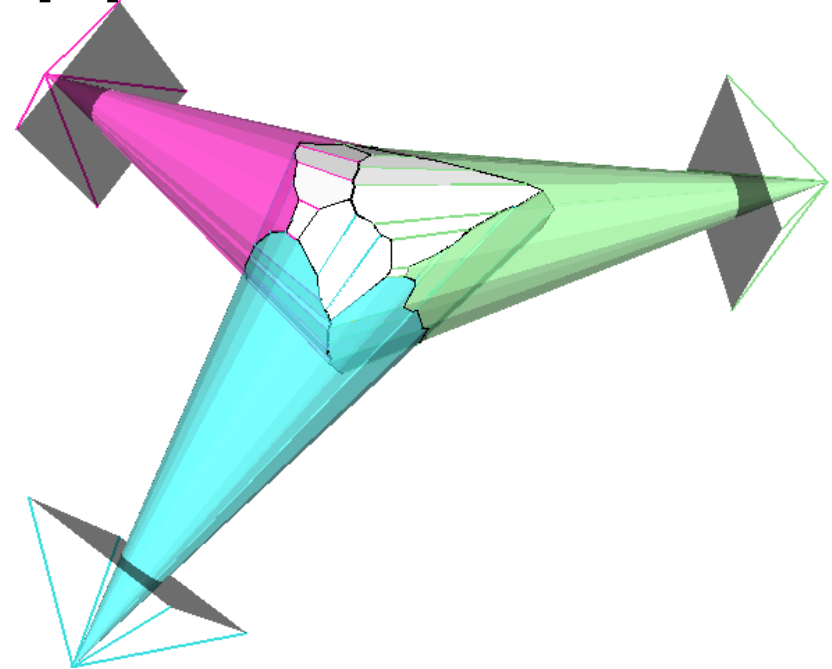
SFS – Polyhedral Approach

PROS :

- silhouettes are backprojected to cones which are intersected in 3D.
- Good performance in real-time systems
- Does not suffer from discretization artifacts. The precision is only limited by the resolution of silhouette images.

CONS :

- Involved implementation.
- Problematic when silhouettes contain errors
- Does not scale very well with the number of images.
- Gives non uniformly sampled geometry



SFS - Summary

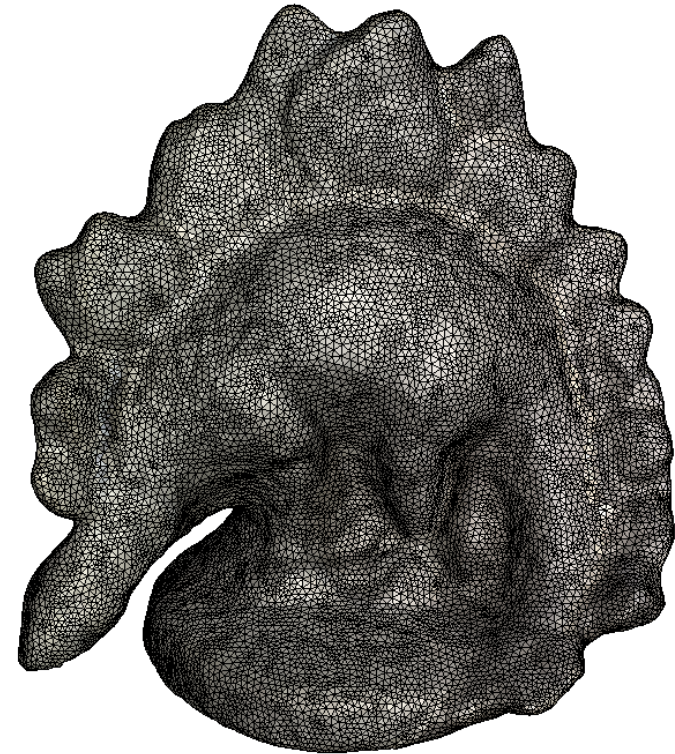
PROS:

- Only silhouette images are required
- No need for correspondences or texture
- Robust
- Efficient and easy to implement

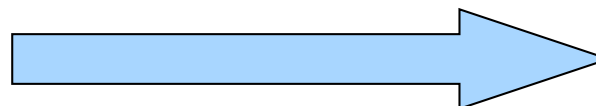
CONS:

- Cannot recover concavities not seen in the silhouette images
- Artifacts for complex scenes and low number of cameras
- Needs calibrated input images
- Silhouettes have to be available (difficult outside of controlled studio environments)

Beyond the Visual Hull



Visual Hull



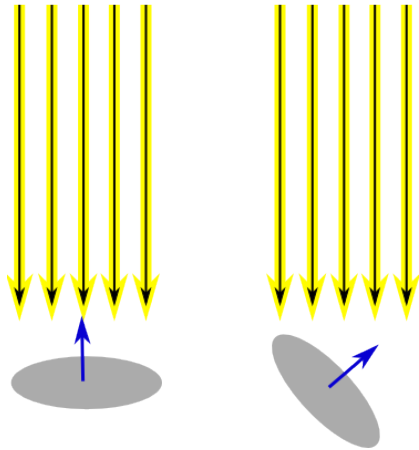
Photoconsistent surface



Reconstruction II

Photoconsistency

Lambertian assumption



- Far away light source
- small piece of surface

Question 1:

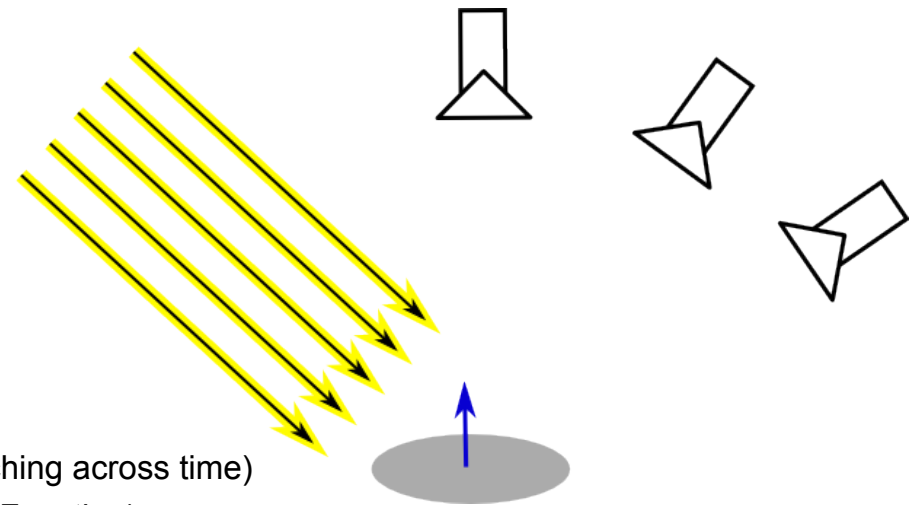
- How much light power does it receive ? (Surface **Irradiance**)
→ proportional to $\cos(\text{incident ray, normal})$

Question 2:

- How much light power gets reflected ? Where ?

The Lambertian model (roughly) says:

- All these cameras are going to see the same color, no matter where they are looking from. (i.e the surface elements equally reflects in all directions)



Are not modeled:

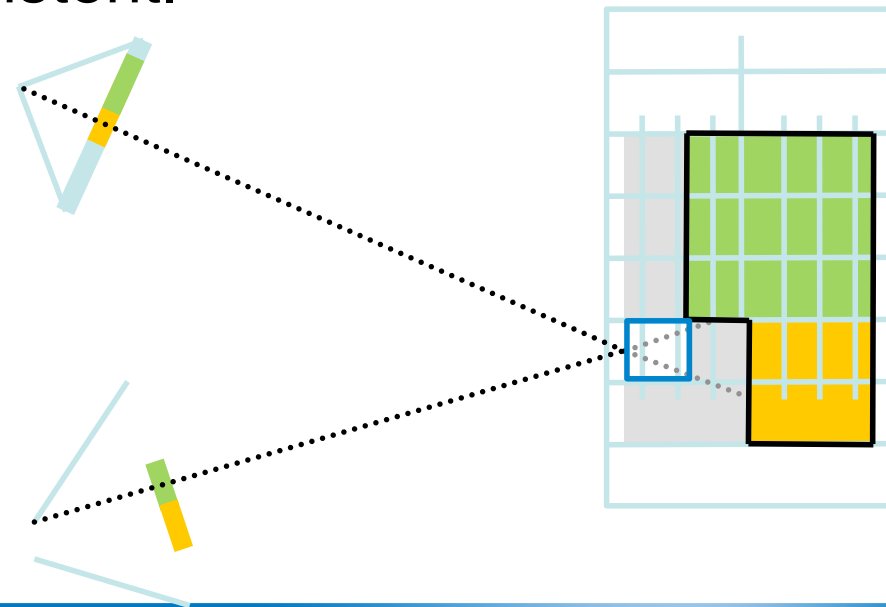
- Specularities (lat. "Speculum" - mirror)
- Cast shadows, ambient occlusion (important when matching across time)
- More complex BRDF (Bidirectional Reflectance Distribution Function)

Space Carving

One of the earliest methods.

- Initialize a volume with a superset of the true scene
- Repeat until convergence :
 - Project a surface voxel into all images in which it is visible.
 - Remove if not photoconsistent.

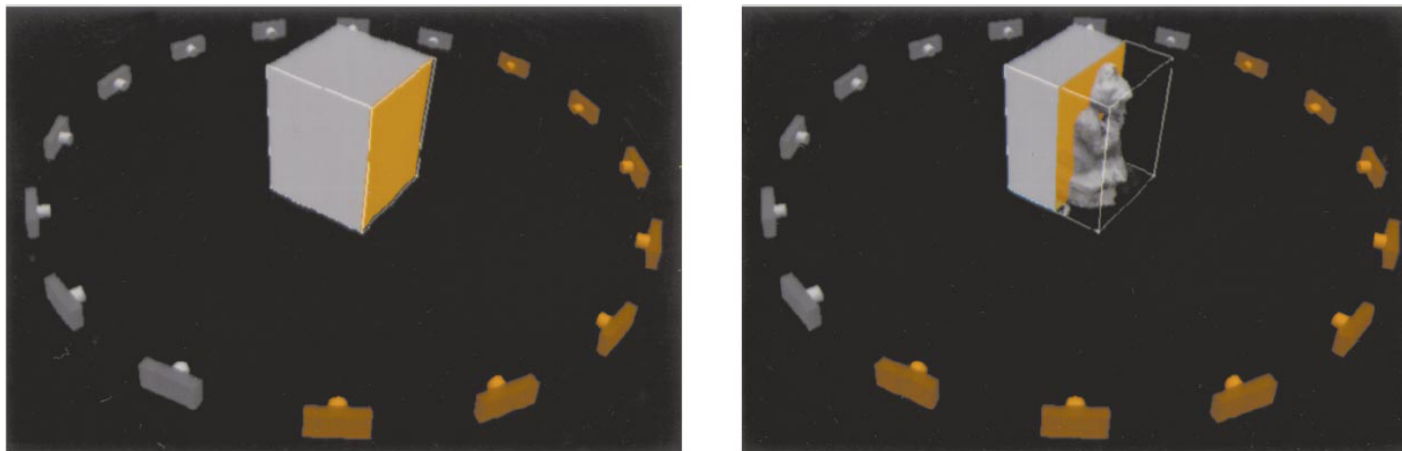
The photoconsistent surface is called the **photo hull** and is the tightest possible bound on the true scene



Space Carving

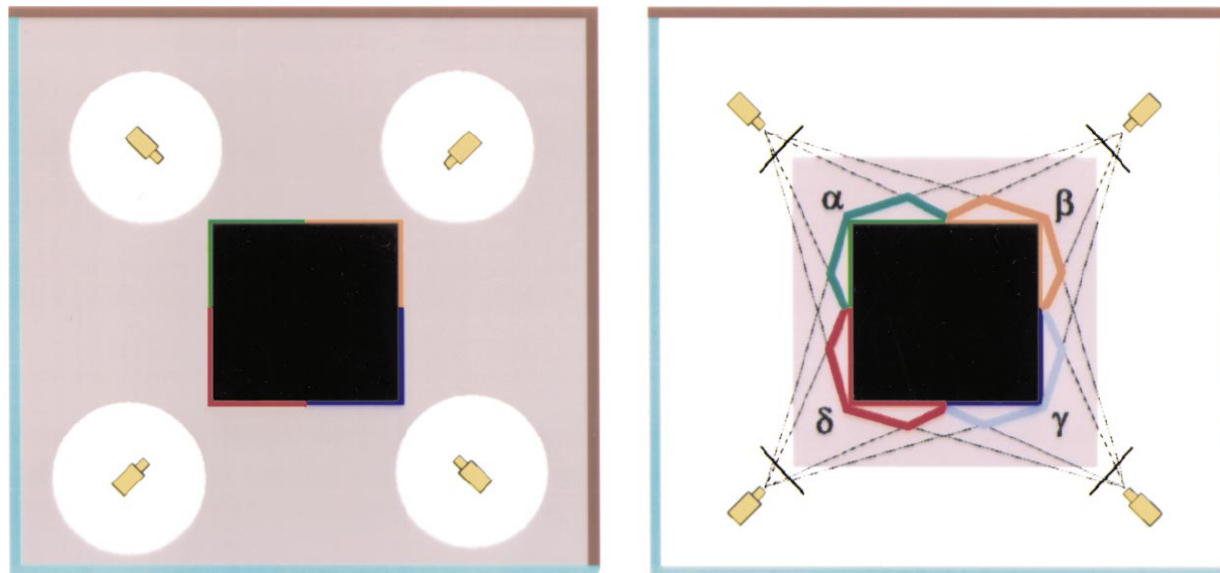
Problem: occlusions

- The photoconsistency is only evaluated in the views in which a voxel is visible
- When a voxel is deleted new voxels become visible and the visibility has to be updated
- This is efficiently done using a multi-pass plane-sweep algorithm.
Scene is swept with a plane in each of the six principle directions and only cameras on one side of the plane are considered



Space Carving - Limitations

- The photohull is only guaranteed to be the tightest superset of the true reconstruction.
- If a voxel is wrongly removed it can lead to the removal of other correct parts of the object.
- The choice of the photoconsistency measure is critical.



Space Carving: Limitations

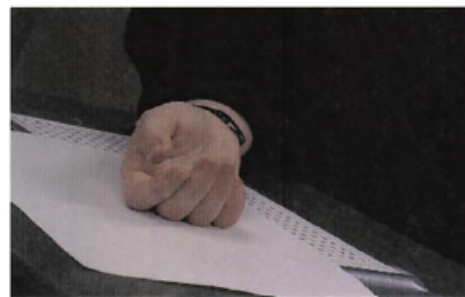
- Needs calibrated input images
- Problematic for non-lambertian objects
- No regularization (e.g. smoothing)

- The Photo Hull is only a superset of the true shape
- Greedy approach
 - Removed voxels cannot be re-added to the reconstruction
- Accuracy limited by voxel resolution
 - Voxels should be small
 - Discretization artifacts

Space Carving: Results



Space Carving: Results



(a)



(b)



(c)



(d)



(e)



(f)

Photo-consistency of a 3d point

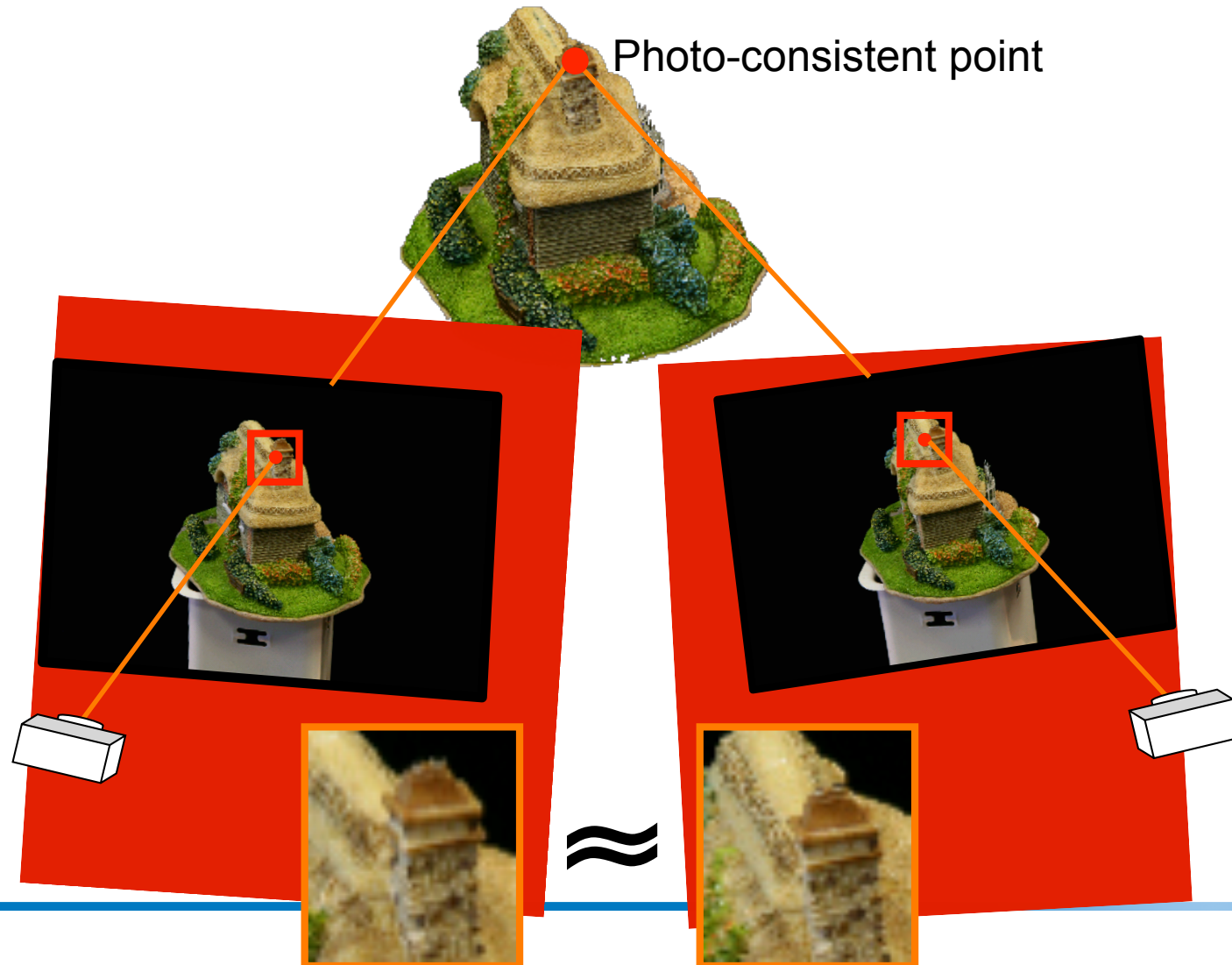


Photo-consistency of a 3d point

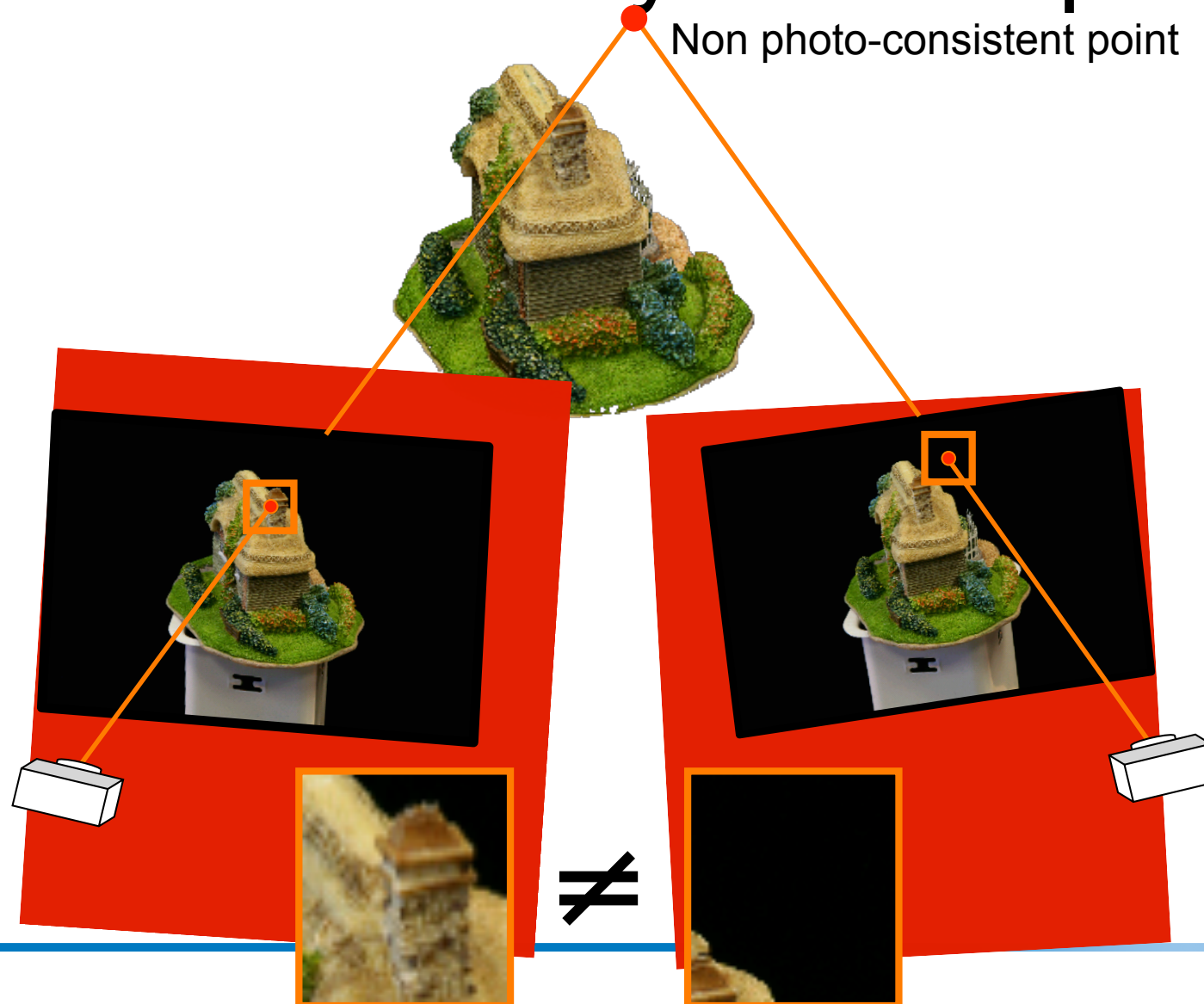
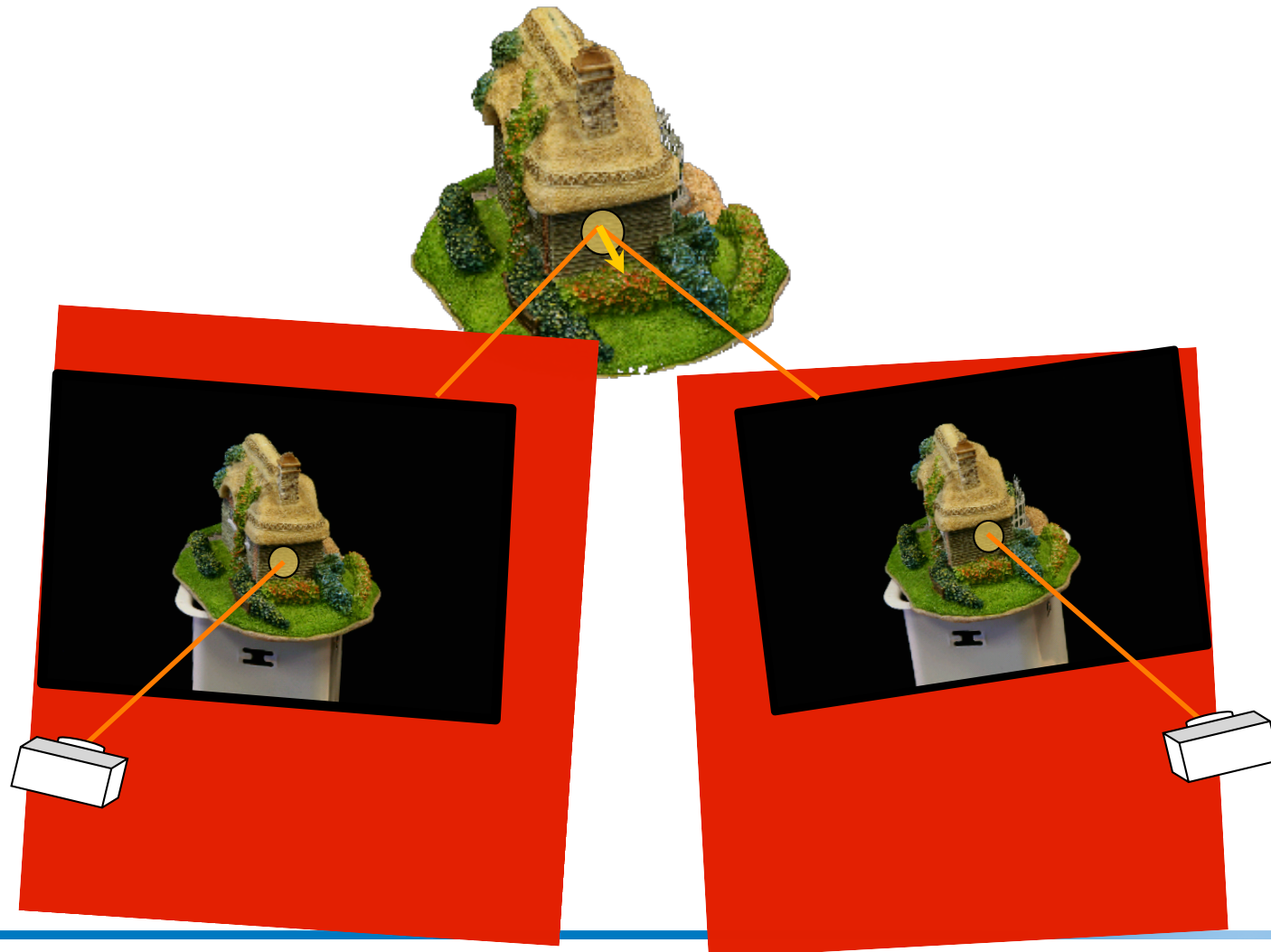
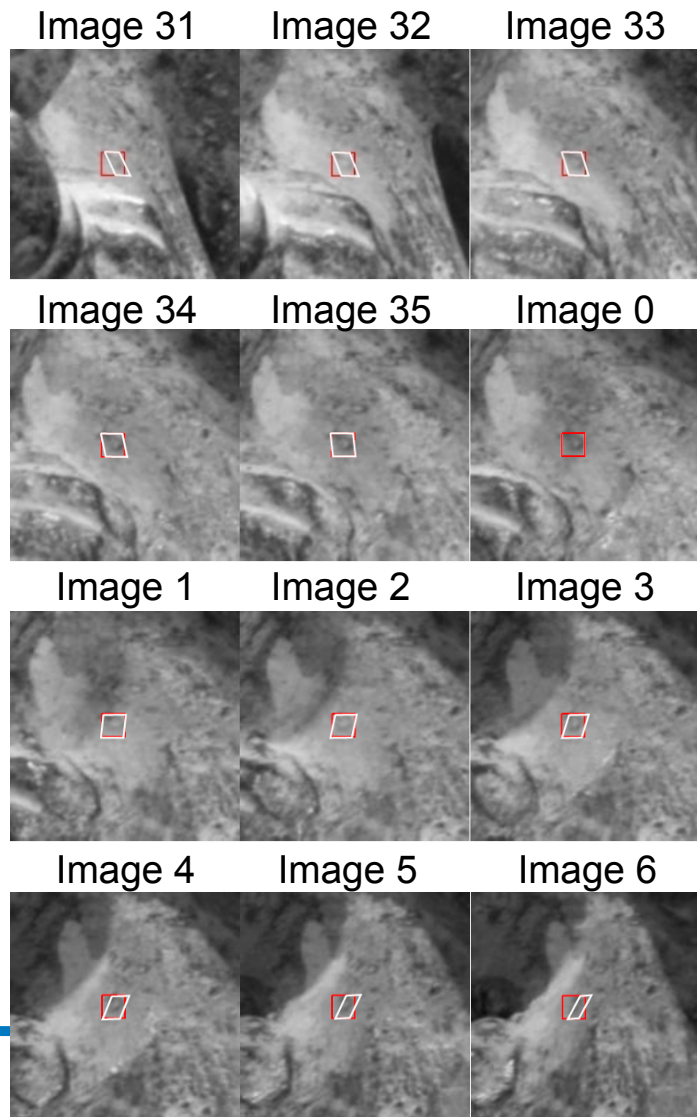


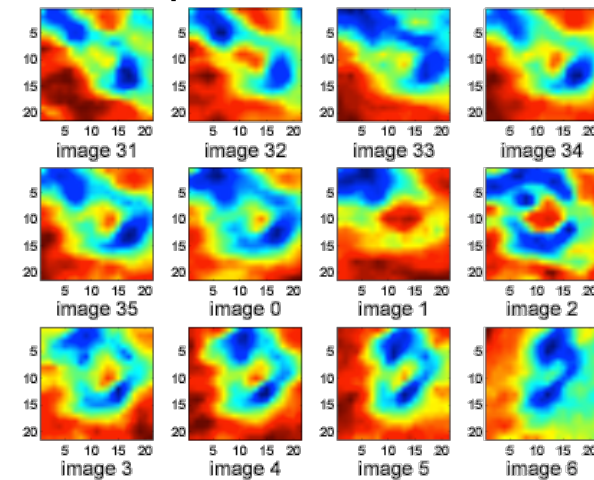
Photo-consistency of a 3d patch



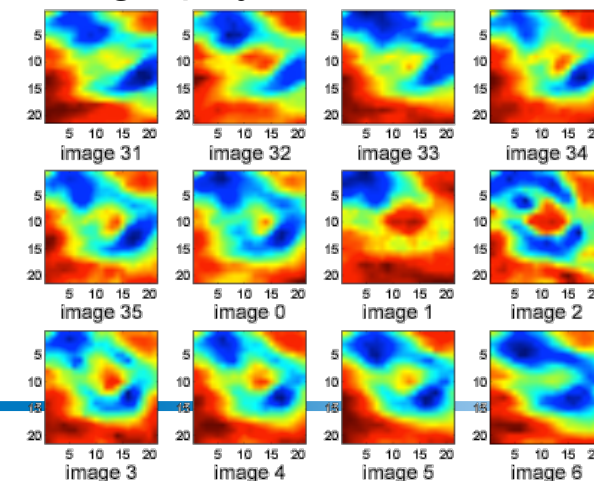
Window comparison: Normalized Cross Correlation



square window

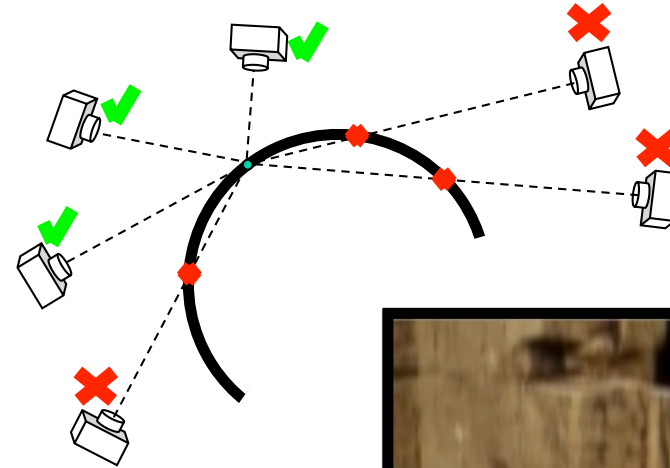


homography-based window



Challenges of photo-consistency

- Camera visibility



- Failure of comparison metric

- repeated texture
- lack of texture
- specularities



Multi-view stereo algorithms

Comparison and evaluation:

A Comparison and Evaluation of Multi-View Stereo Reconstruction Algorithms,
S. Seitz et al., CVPR 2006, vol. 1, pages 519-526.

Quick history of algorithms:

Representing stereo data with the Delaunay triangulation,
O. Faugeras et al., Artificial Intelligence, 44(1-2):41-87, 1990.

A multiple-baseline stereo,
M. Okutomi and T. Kanade, TPAMI, 15(4):353-363, 1993.

Object-centered surface reconstruction: Combining multi-image stereo and shading,
P. Fua, Y. Leclerc, International Journal of Computer Vision, vol. 16:35-56, 1995.

A portable three-dimensional digitizer,
Y. Matsumoto et al., Int. Conf. on Recent Advances in 3D Imaging and Modeling, 197-205, 1997

Photorealistic Scene Reconstruction by Voxel Coloring,
S. M. Seitz and C. R. Dyer, CVPR., 1067-1073, 1997.

Variational principles, surface evolution, PDE's, level set methods and the stereo problem,
O. Faugeras and R. Keriven, IEEE Trans. on Image Processing, 7(3):336-344, 1998.

Multi-view stereo algorithms

Comparison and evaluation:

A Comparison and Evaluation of Multi-View Stereo Reconstruction Algorithms,
S. Seitz et al., CVPR 2006, vol. 1, pages 519-526.

<http://vision.middlebury.edu/mview/>

Recently many new algorithms

Very good accuracy & completeness

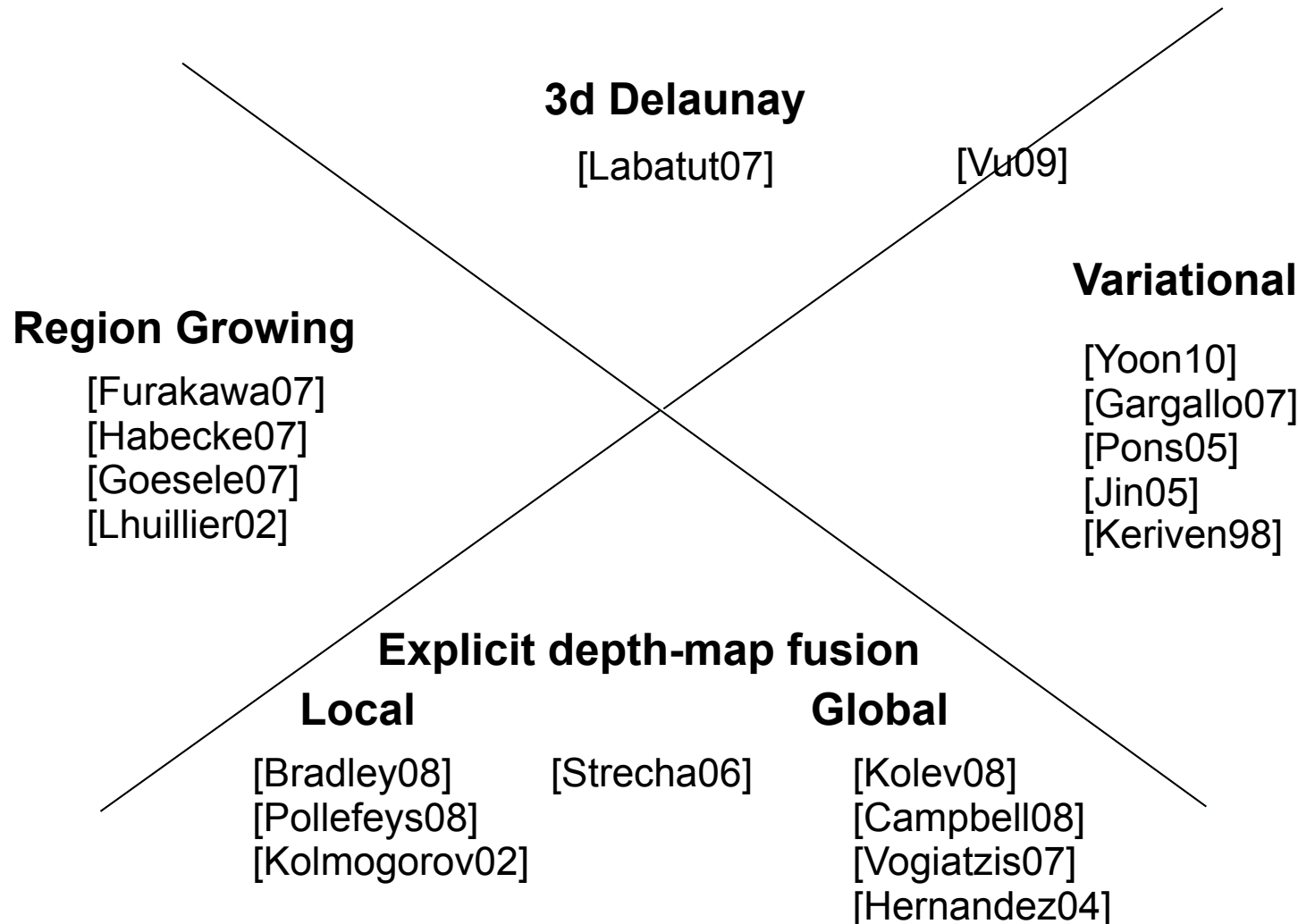
Almost all deal with small number of images (~100)
main exception [Pollefeys08]

Offline algorithms, no feedback

| Sort By | Temple Full 312 views | | Temple Ring 47 views | | Temple Sparse 16 views | | Dino Full 363 views | | Dino Ring 48 views | | Dino Sparse 16 views | |
|--------------------|--------------------------|------|-------------------------|------|---------------------------|------|------------------------|------|-----------------------|------|-------------------------|------|
| | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp | Acc | Comp |
| | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] | [mm] | [%] |
| 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 |
| Campbell | 0.41 | 99.9 | 0.48 | 99.4 | | | 0.53 | 98.6 | | | | |
| 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 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 |
| Zaharescu | | | 0.55 | 99.2 | 0.78 | 95.8 | | | 0.42 | 98.6 | 0.45 | 99.2 |
| Zach2 | 0.51 | 98.8 | 0.56 | 99.0 | | | 0.55 | 98.7 | 0.51 | 99.1 | | |
| SurfEvolution | | | 0.56 | 98.9 | 0.78 | 96.8 | | | 0.56 | 97.7 | 0.66 | 97.6 |
| Bradley | | | 0.57 | 98.1 | 0.48 | 93.7 | | | 0.39 | 97.6 | 0.38 | 94.7 |
| Zach | | | 0.58 | 99.0 | | | | | 0.67 | 98.0 | | |
| 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 |
| Pons | | | 0.6 | 99.5 | 0.9 | 95.4 | | | 0.55 | 99.0 | 0.71 | 97.7 |
| 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 |
| Zaharescu2 | | | 0.62 | 98.5 | | | | | 0.5 | 98.5 | | |
| Vogiatzis2 | 0.5 | 98.4 | 0.64 | 99.2 | 0.69 | 96.9 | | | | | | |
| Sormann | | | 0.69 | 97.2 | | | | | 0.81 | 95.2 | | |
| ICCV_1500 | 0.65 | 85.8 | 0.7 | 78.9 | 0.59 | 74.9 | 0.91 | 73.8 | 0.71 | 76.6 | 0.66 | 74.9 |
| Kolev2 | | | 0.72 | 97.8 | 1.04 | 91.8 | | | 0.43 | 99.4 | 0.53 | 98.3 |
| Surfel Cut | | | 0.73 | 97.5 | | | | | 0.69 | 98.7 | | |
| Merrell Stability | | | 0.76 | 85.2 | | | | | 0.73 | 73.1 | | |
| 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 |
| Kolev | | | 0.79 | 96.0 | | | | | 0.53 | 96.9 | | |
| Sinha | | | 0.79 | 94.9 | | | | | 0.69 | 97.2 | | |
| Merrell Confidence | | | 0.83 | 88.0 | | | | | 0.84 | 83.1 | | |
| Auclair | | | 0.86 | 96.2 | 1.03 | 92.5 | | | 0.62 | 96.7 | 0.74 | 96.8 |
| Strecha | | | 0.86 | 97.6 | 1.05 | 94.1 | | | 1.21 | 92.4 | 1.41 | 91.5 |
| Gargallo | | | 0.88 | 84.3 | 1.05 | 81.9 | | | 0.6 | 92.9 | 0.76 | 90.7 |
| Tran | | | 1.12 | 92.3 | 1.53 | 85.4 | | | 1.12 | 92.0 | 1.26 | 89.3 |
| Kolmogorov | | | 1.86 | 90.4 | | | | | 2.81 | 86.0 | | |
| Continuous Probab | | | 1.89 | 92.1 | | | | | 2.61 | 91.4 | | |
| 3DIM_155 | 0.55 | 99.7 | | | | | 0.76 | 99.0 | | | | |
| Delaunoy | | | | | 0.73 | 95.9 | | | | | 0.89 | 93.9 |
| Goesele 2007 | 0.42 | 98.2 | | | | | 0.46 | 96.7 | | | | |
| Habbecke | 0.66 | 98.0 | | | | | 0.43 | 99.7 | | | | |
| Hornung | 0.58 | 98.7 | | | | | 0.79 | 95.1 | | | | |
| JancosekCVWW | | | | | | | | | 0.79 | 95.9 | | |
| Ladikos | | | | | | | | | | | 0.89 | 95.0 |
| Liu | | | | | 0.96 | 89.6 | | | | | 0.59 | 98.3 |
| Liu2 | | | | | 0.65 | 96.9 | | | | | 0.51 | 98.7 |
| Massively Parallel | 0.79 | 92.2 | | | | | | | | | | |
| Starck | | | | | 1.27 | 87.7 | | | | | 1.01 | 90.7 |

Different approaches*

*Disclaimer: classifying 3d algorithms is **challenging**



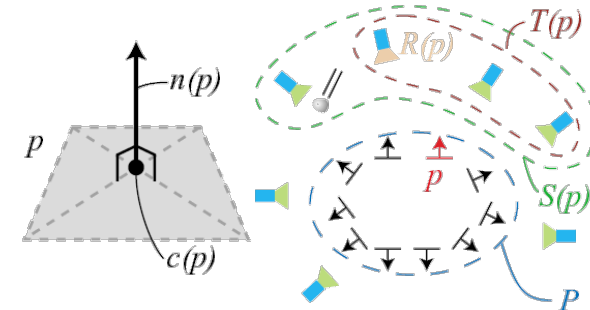
Best flexible algorithms

| | Region growing | Depth-map fusion |
|---------|---|--|
| summary | Starts from a cloud of 3d points, and grows small flat patches maximizing photo-consistency | Fuses a set of depth-maps computed using occlusion-robust photo-consistency |
| pros | Provides best overall results due to a plane-based photo-consistency | Elegant pipeline Plug-n-play blocks Easily parallelizable |
| cons | Many tunable parameters, i.e., difficult to tune to get the optimal results | Photo-consistency metric is simple and not optimal. The metric suffers when images are not well textured or low resolution |

Overview: region growing

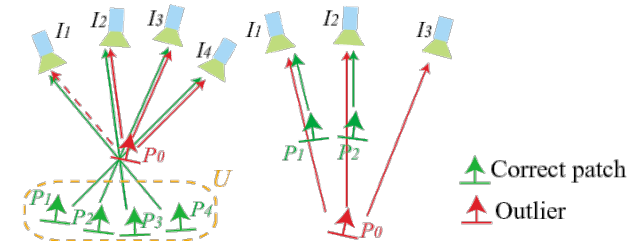
1. Fitting step

A local surface patch is fitted, iterating visibility



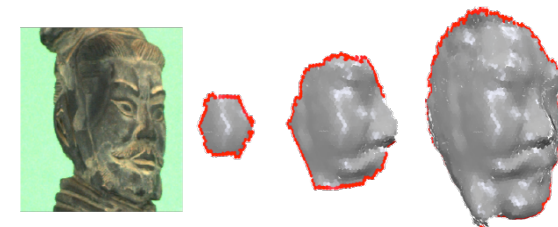
2. Filter step

Visibility is explicitly enforced



3. Expand step

Successful patches are used to initialise active boundary



Overview: depth-map fusion

- 1. Compute depth hypotheses**
- 2. Volumetrically fuse depth-maps**
- 3. Extract 3d surface**

