Quality-driven autonomous scanning of complex objects

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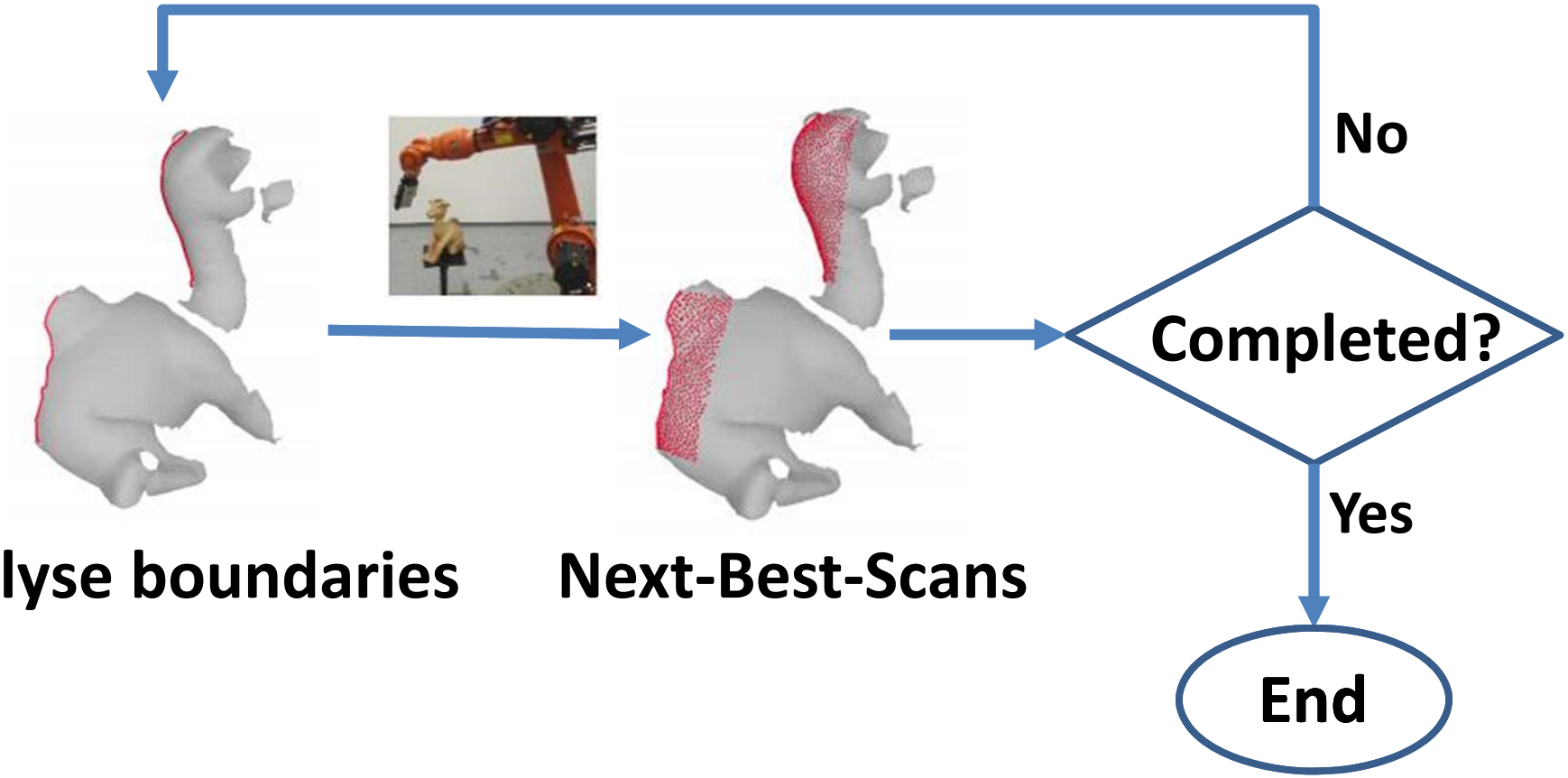
Introduction

https://www.youtube.com/watch?v=BLX4LbiUtSQ

Next Best View Problem

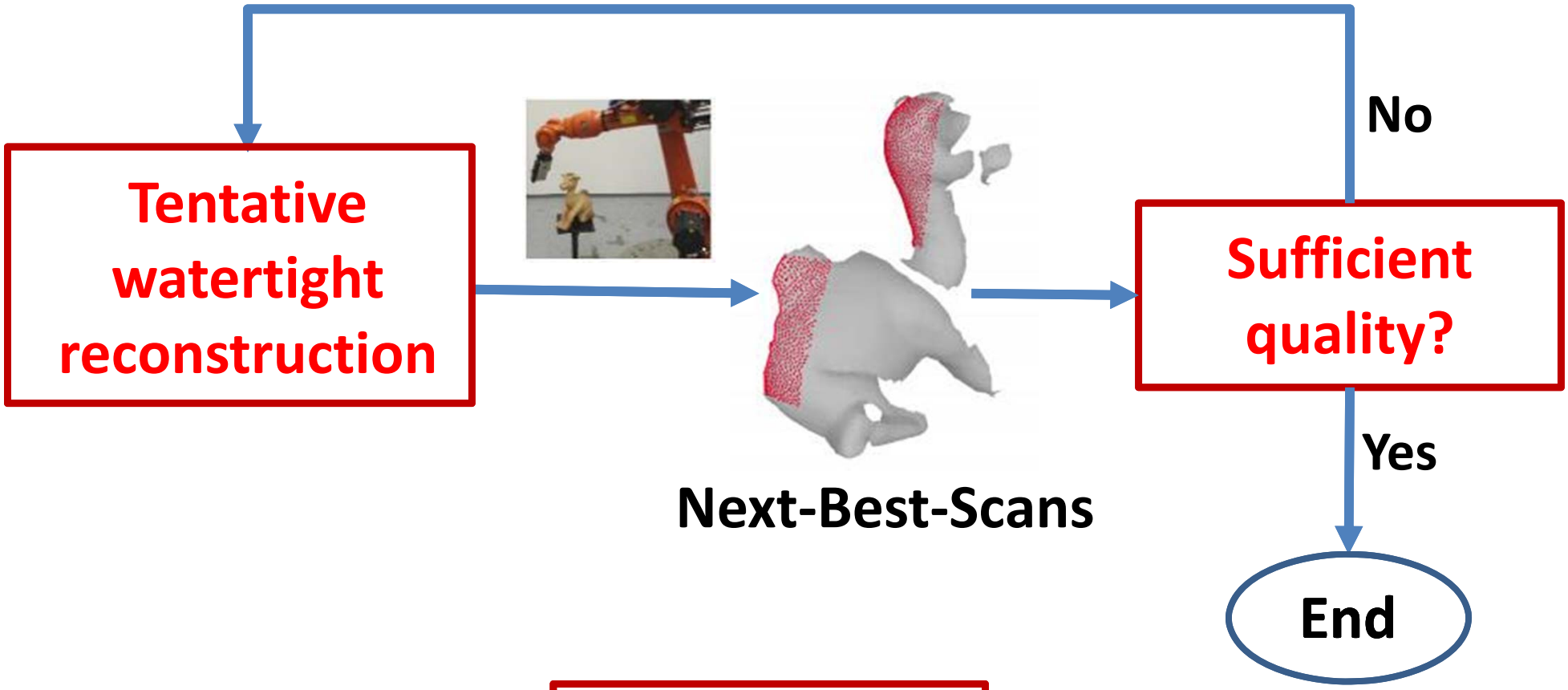
- **Next sensor position to maximize information gain [Connolly 1985]**
- **Unknown object**
- **NBV computed on-the-fly**

Related Work



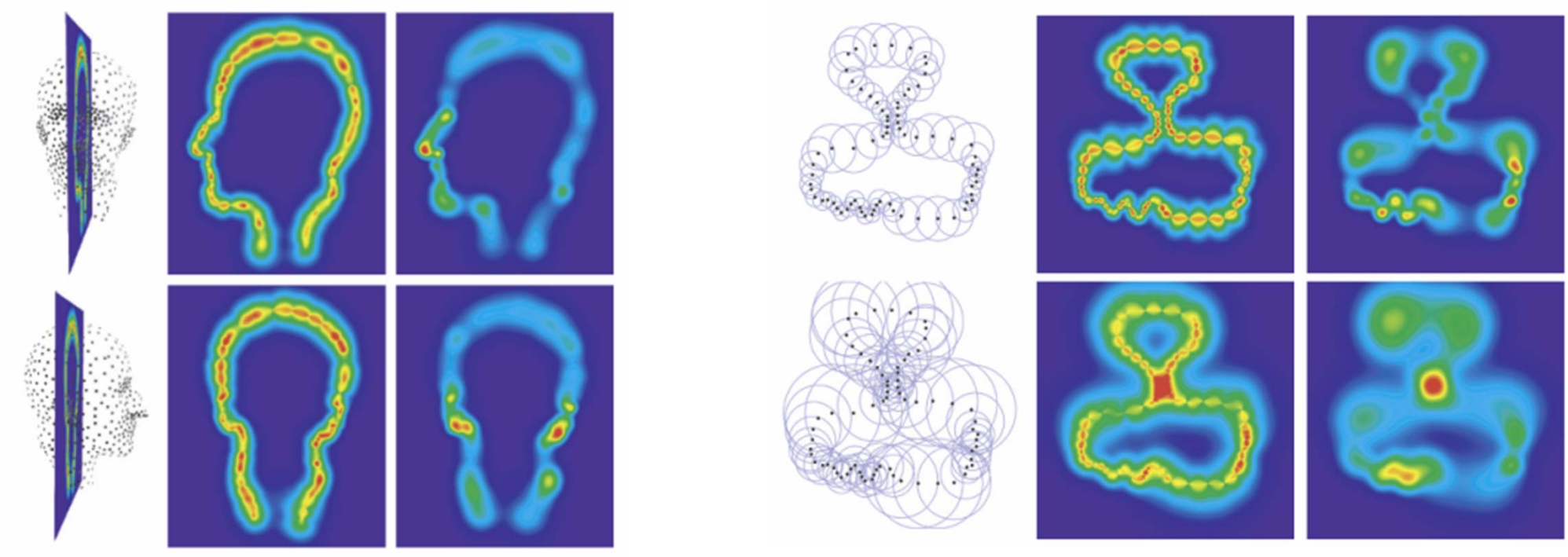
[Kriegel et al. 2013]
(state-of-the-art)

Related Work



Our approach

Related Work

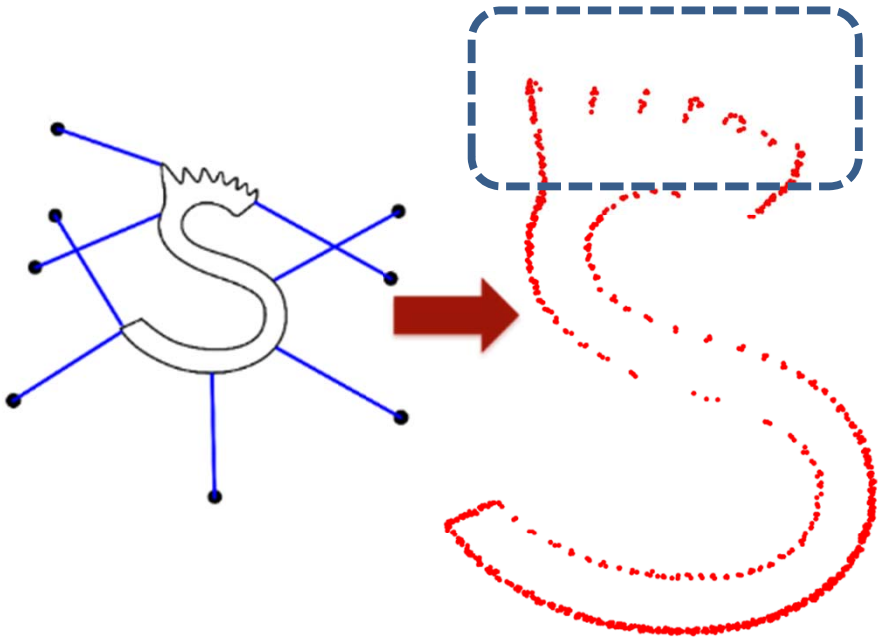


[Pauly et al. 2004]

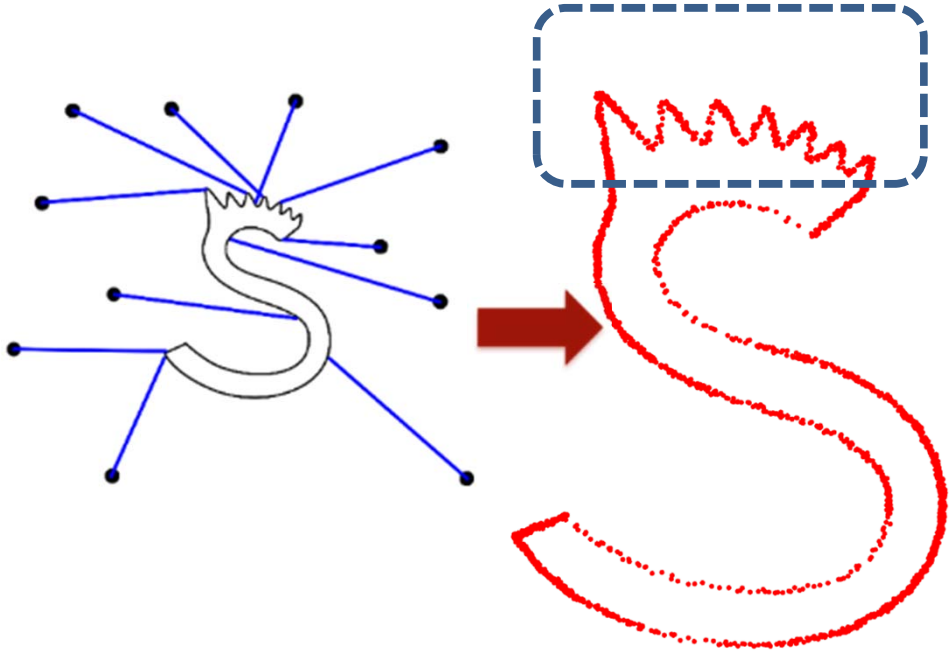
Focus on density, regularity and curvature

Do not account for geometric completeness and topology

Related Work

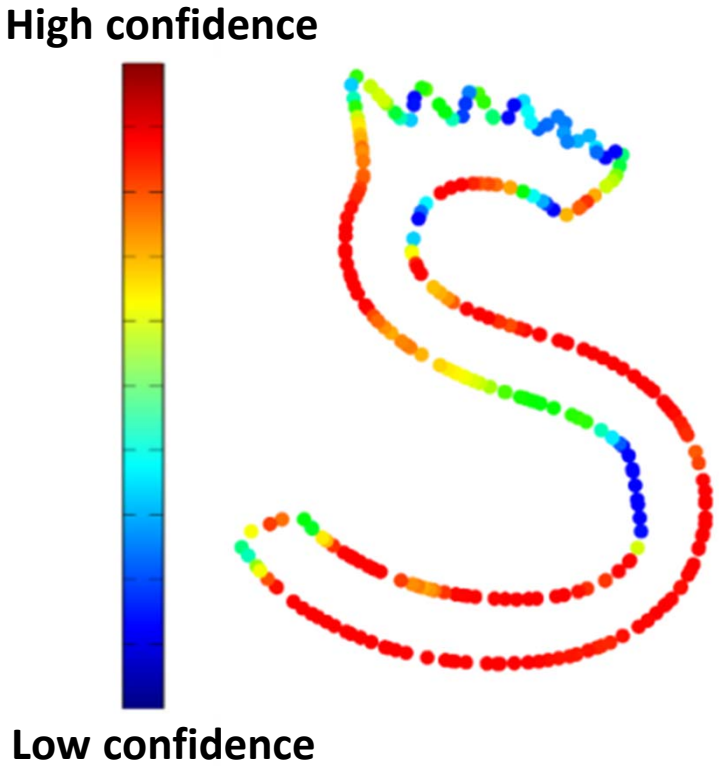


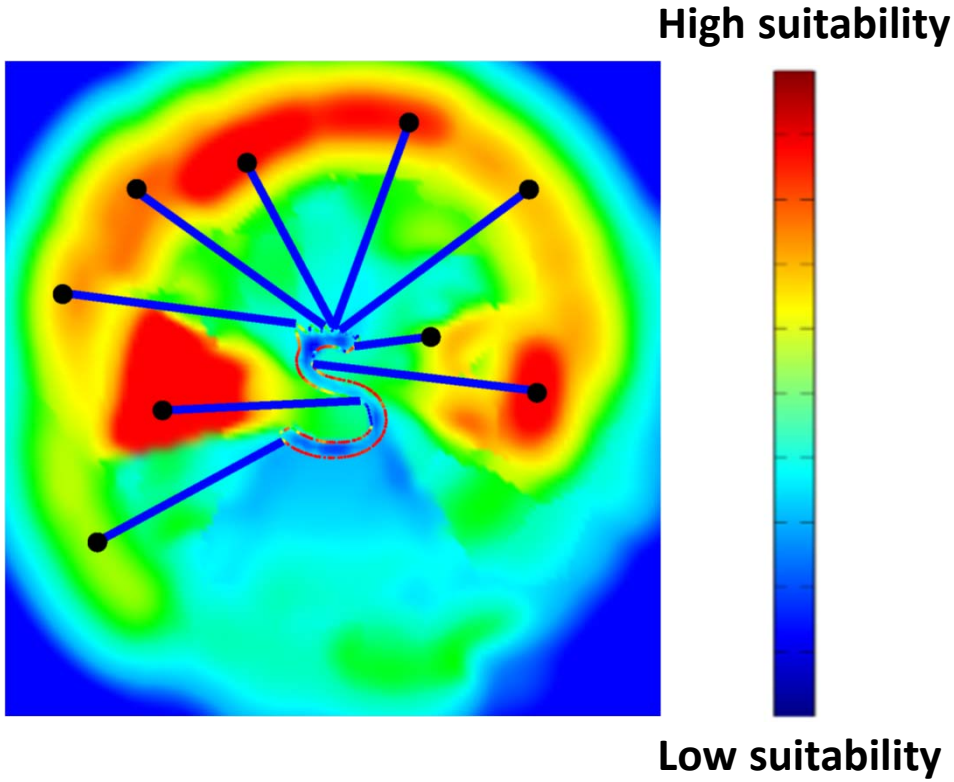
Conventional NBV method:
Boundary-driven



Our method:
Quality-driven

Key Idea

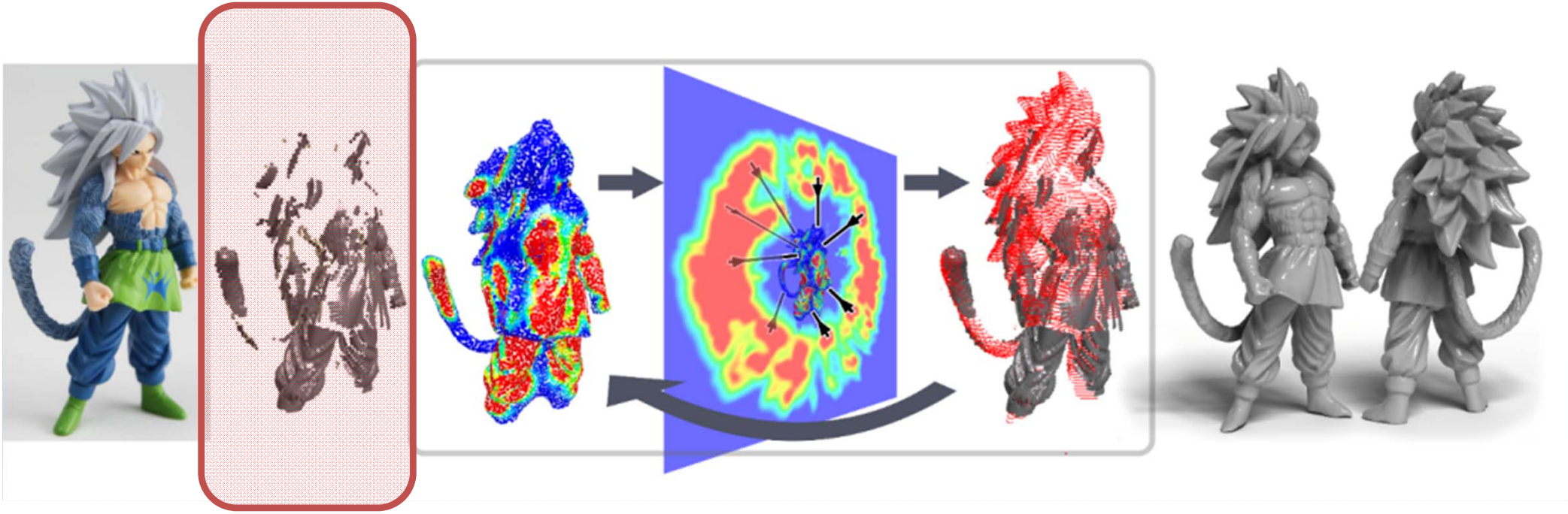




Tentative watertight surface confidence map

Ambient viewing field next-best-scans

Algorithm Overview

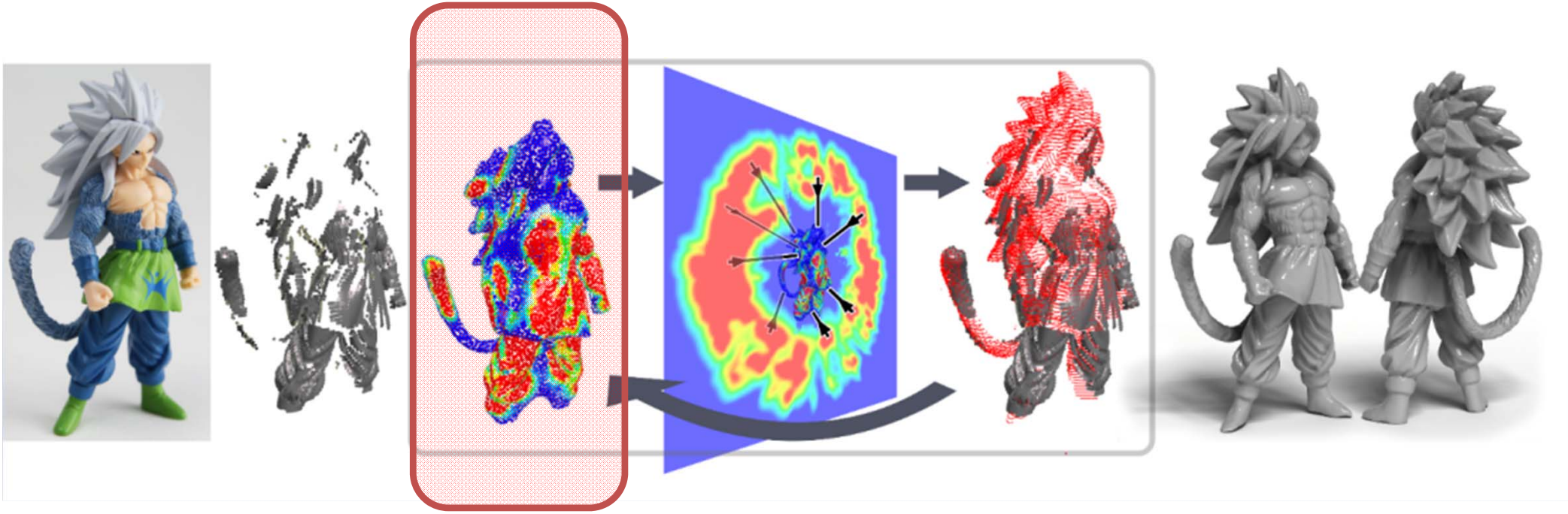


Initial scan

Initial Blind Scan

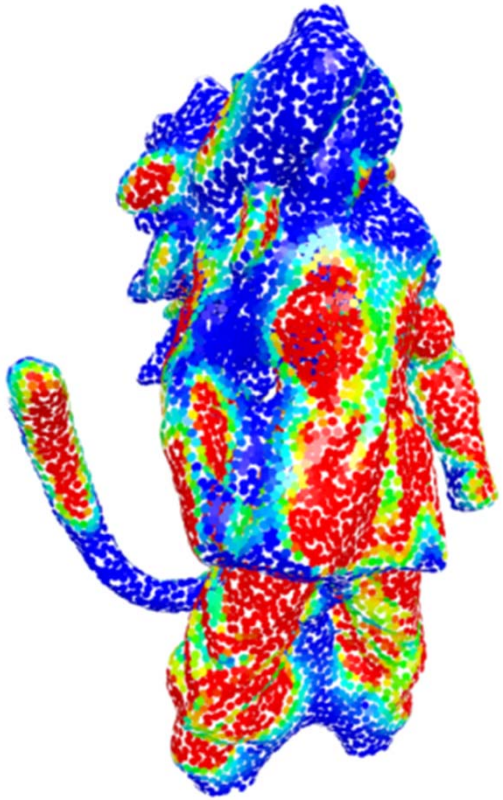
Start with an initial blind, all-around scanning

Algorithm Overview



Confidence map of iso-surface

Confidence Map



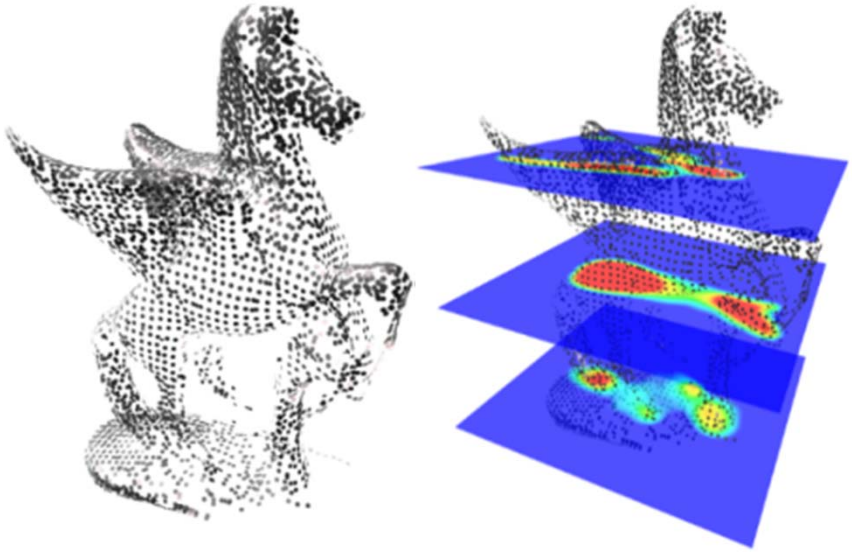
Confidence map of iso-points

$$f(s_k) = f_g(s_k, n_k)\, f_s(s_k, n_k)$$

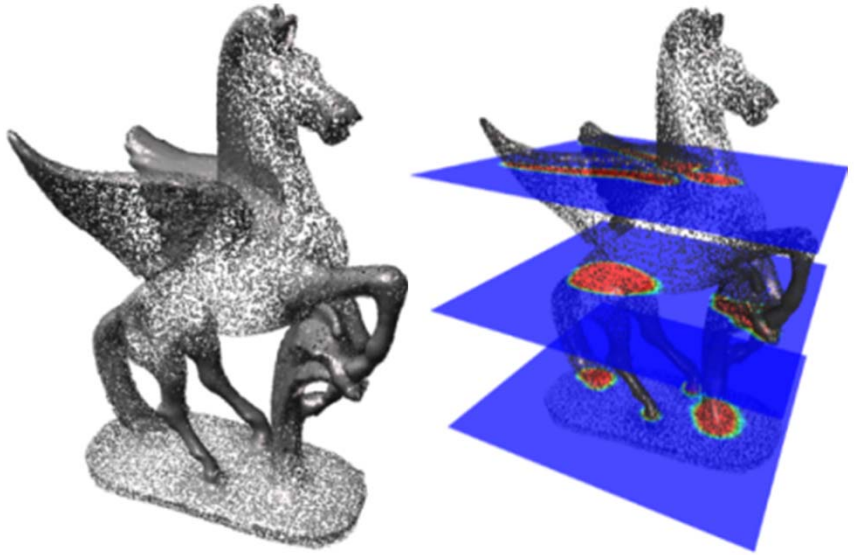
Confidence **Completeness** **Smoothness**

Completeness Confidence

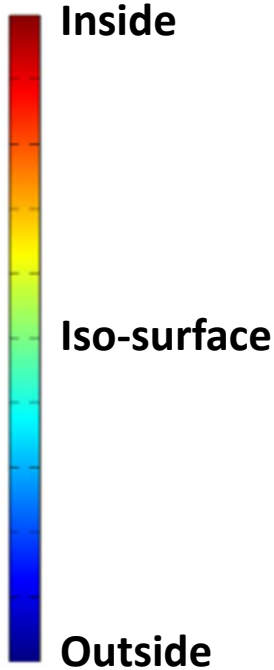
Directional gradient of the Poisson scalar field



Poisson Scalar field of incomplete point cloud



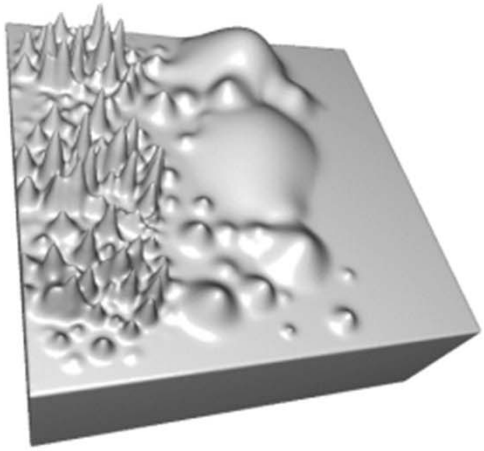
Poisson Scalar field of completed point cloud



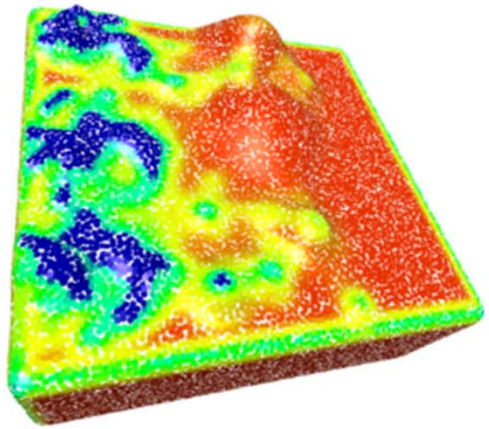
Smoothness Confidence

Bilateral weighted sum: $f_s(s_k, \mathbf{n}_k) = \sum_{j \in \Omega_k} \theta(\|s_k - q_j\|)\, \phi(\mathbf{n}_k, q_j - s_k)$

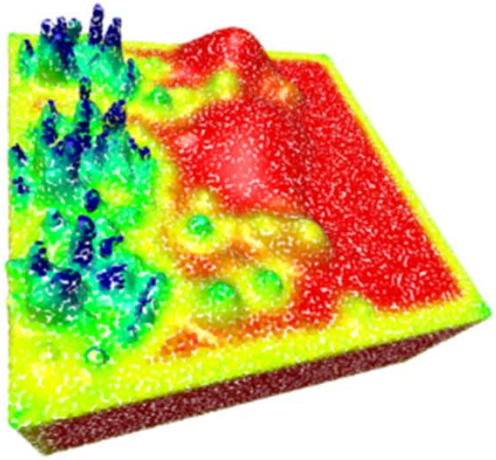
Density **Curvature**



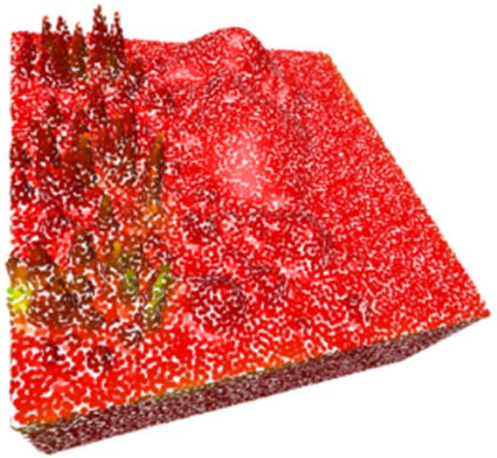
A synthetic model



One scan



Five scans



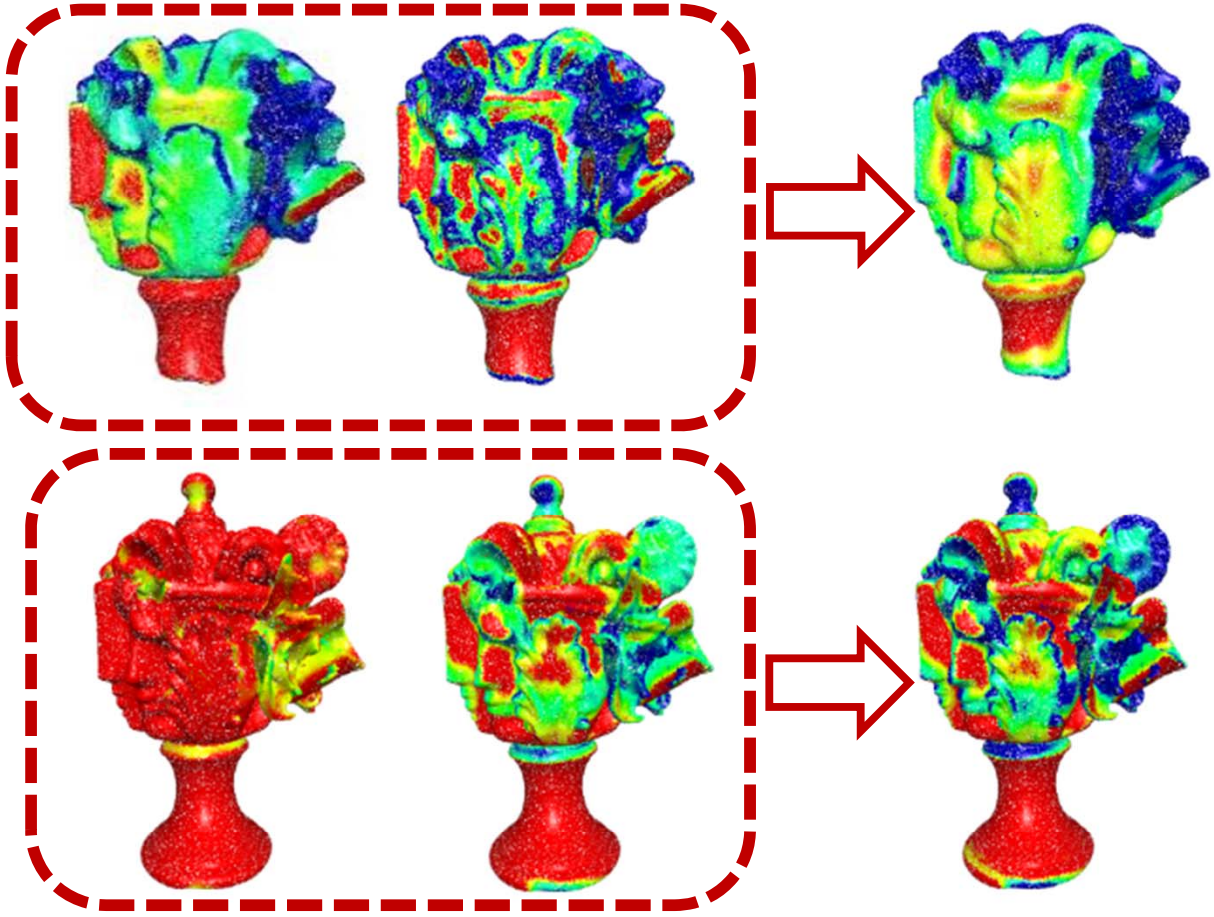
Ten scans

Combination: $f(s_k) = f_g(s_k, n_k) f_s(s_k, n_k)$

Artwork

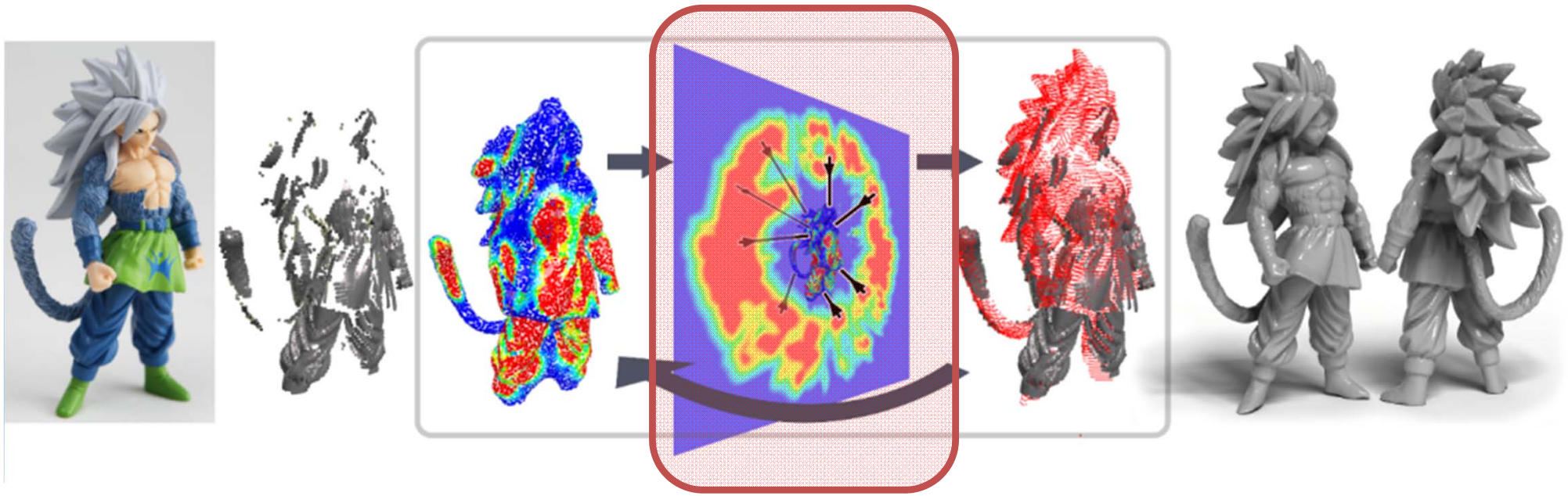
Initial scanning

After 4 scan iterations



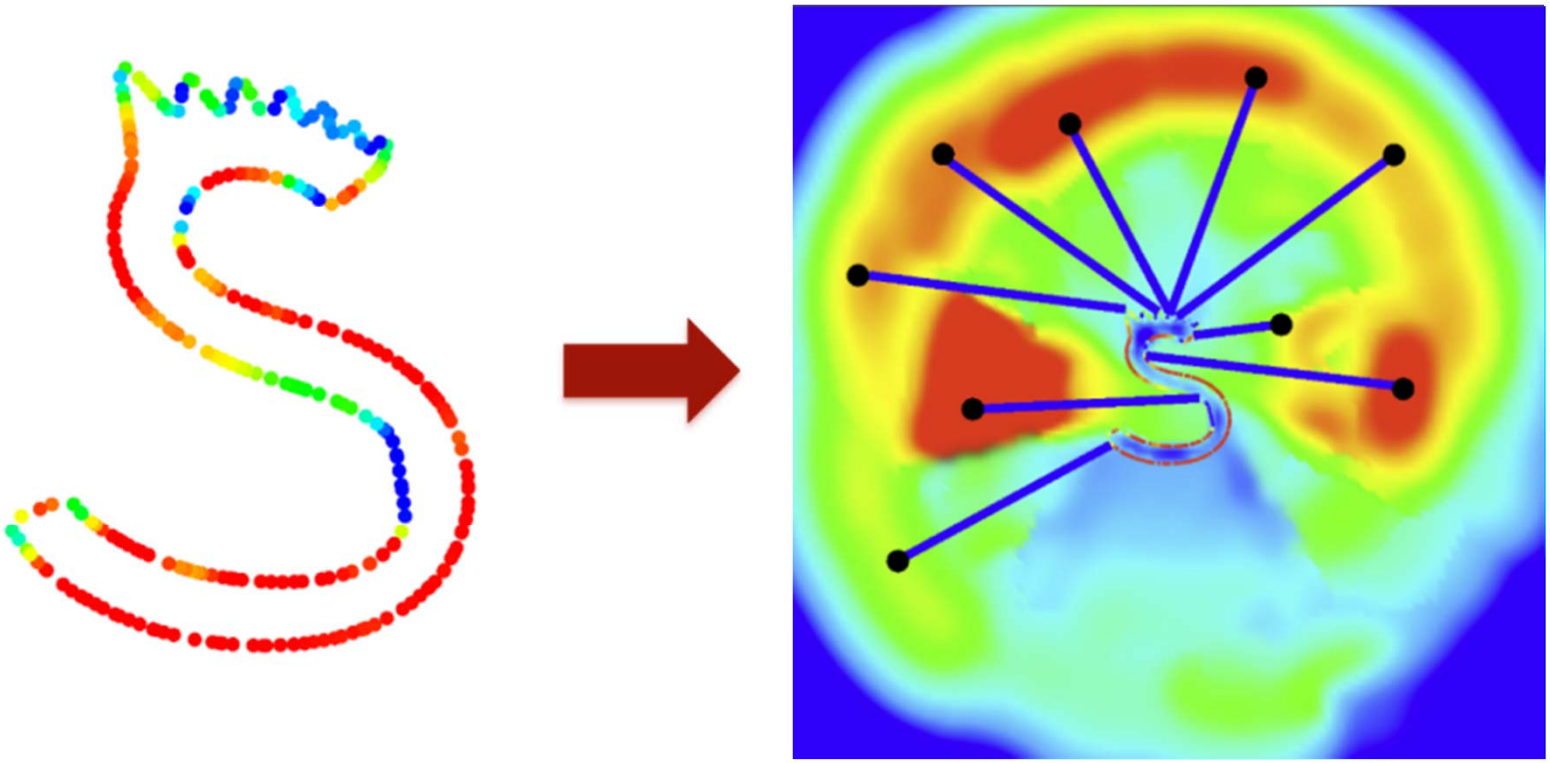
Completeness Smoothness Confidence

Algorithm Overview



View selection using Ambient viewing field

Next Best View Selection



Iso-points **Ambient viewing field**

Search in 5D space

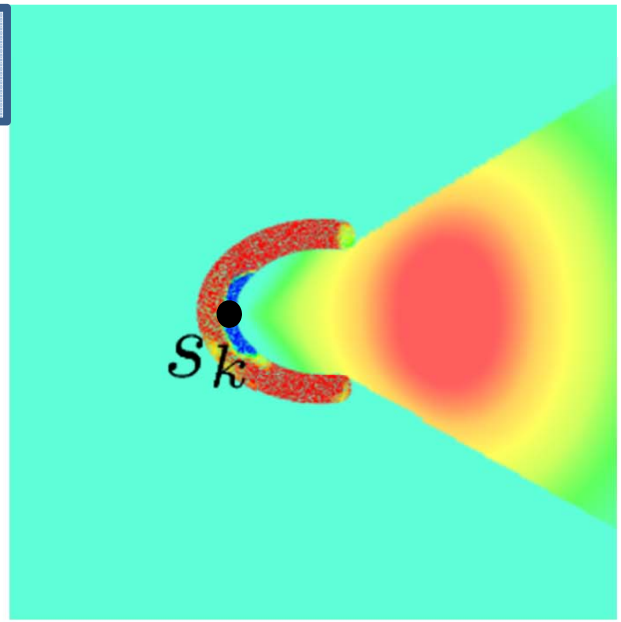
Viewing Vector Field Generation

Confidence score

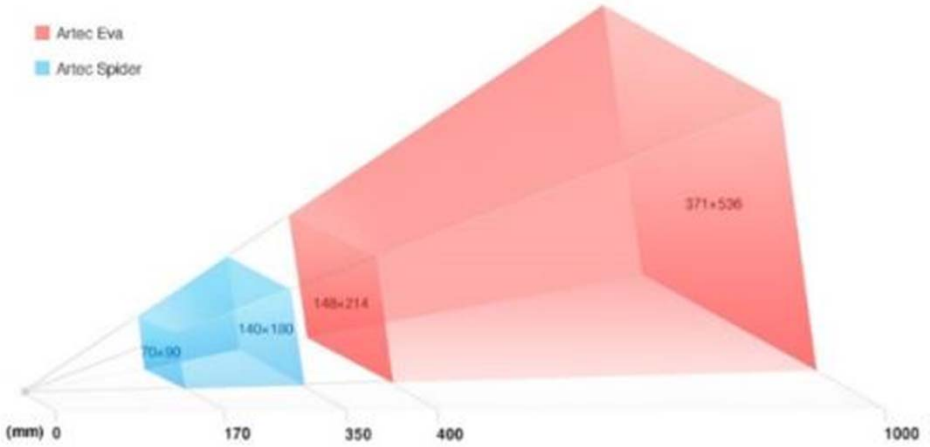
NBV score: $g(v_i) = \max_{s_k}\{w(v_i, s_k)(1 - f(s_k))\}$

$$w(v_i, s_k) = w_d(s_k, v_i)w_o(s_k, v_i)w_v(s_k, v_i)$$

Distance **Orientation** **Visibility**

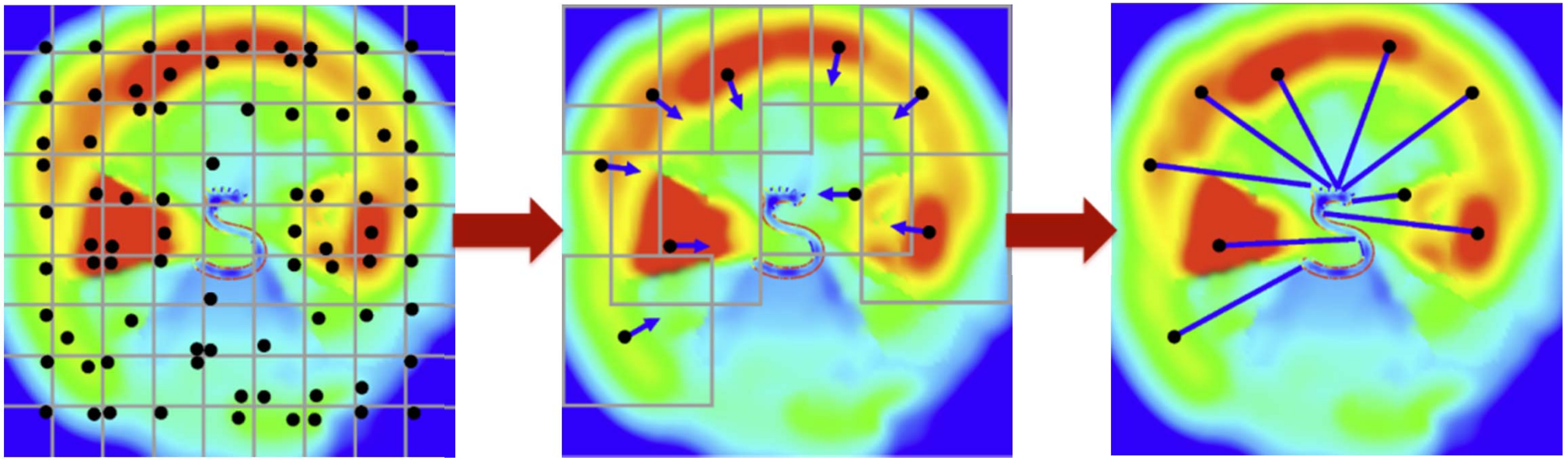


Confidence propagation on s_k



Scanner specification

Field-guided View Selection



Local maxima

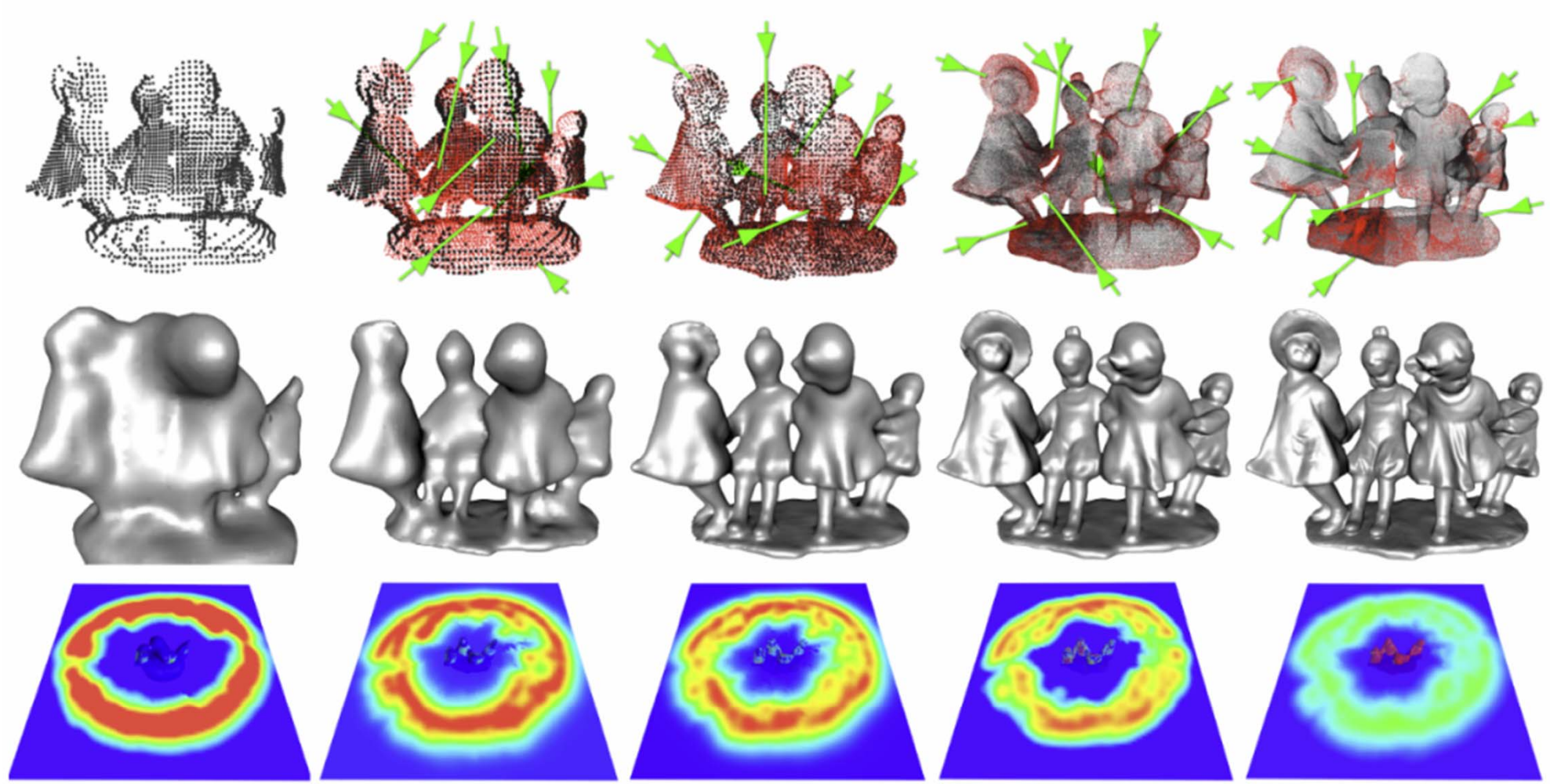
Non-adjacent maxima

(Optimal positions)

Next-Best-Views

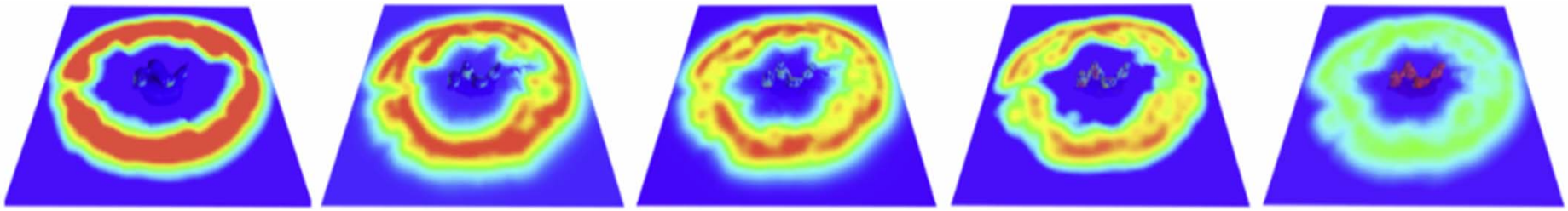
(Optimal directions)

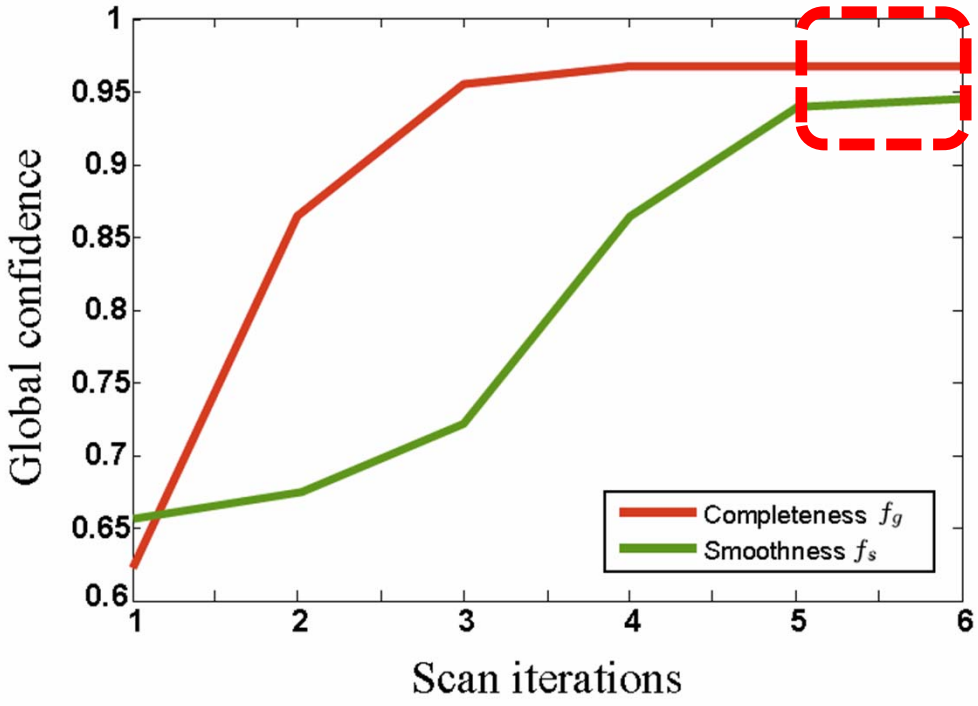
Ambient Viewing Field in 3D

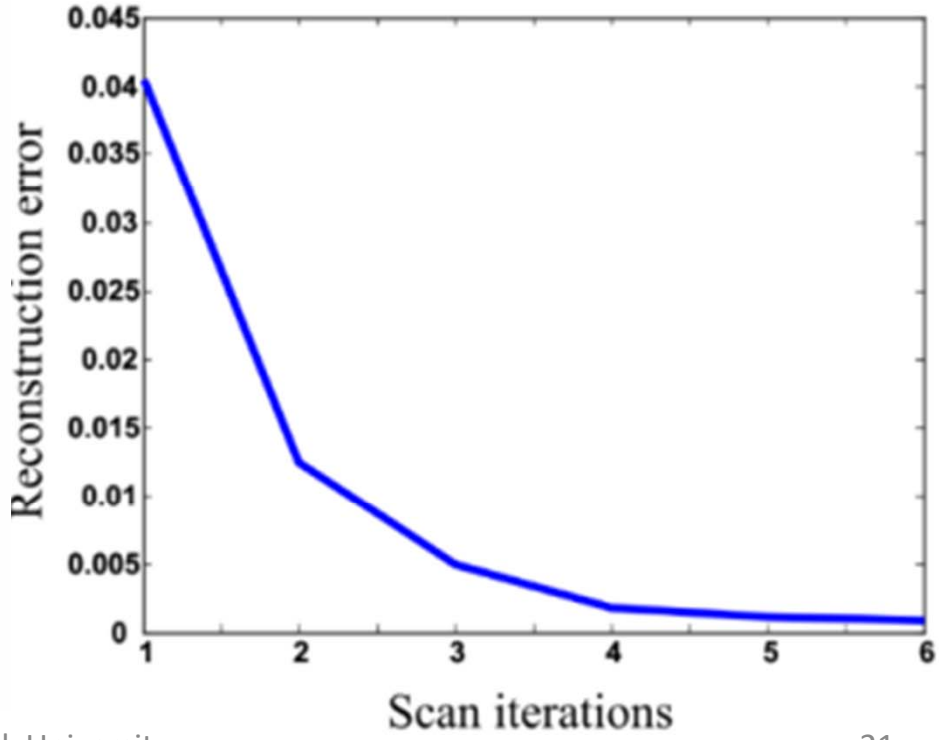


More scans

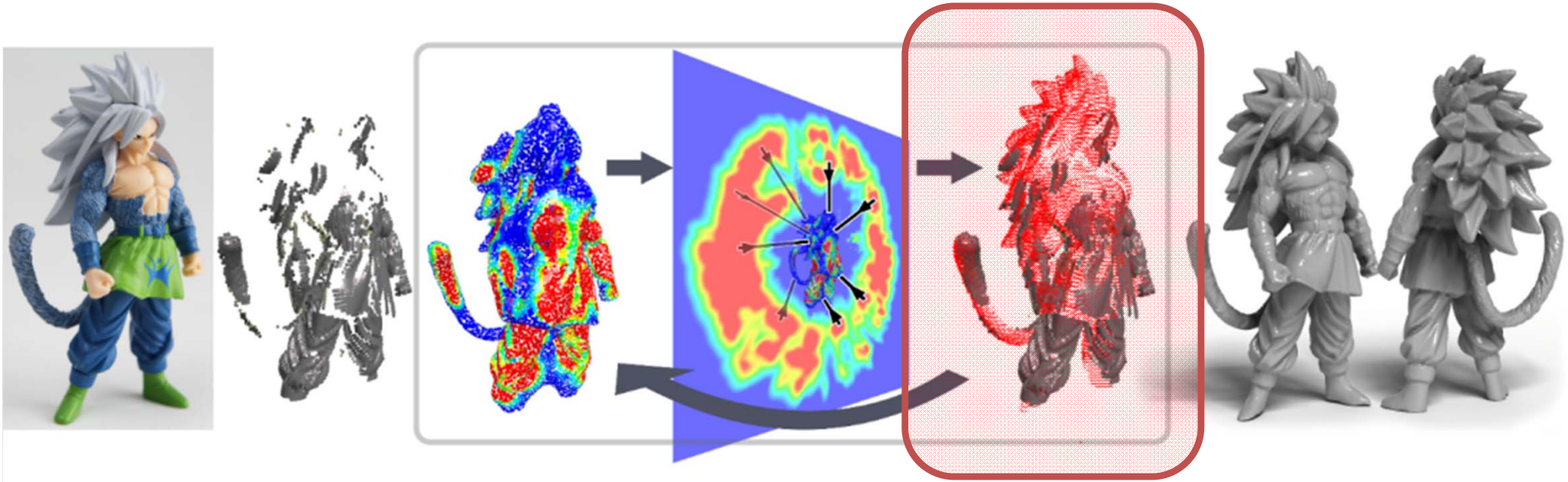
Ambient Viewing Field in 3D





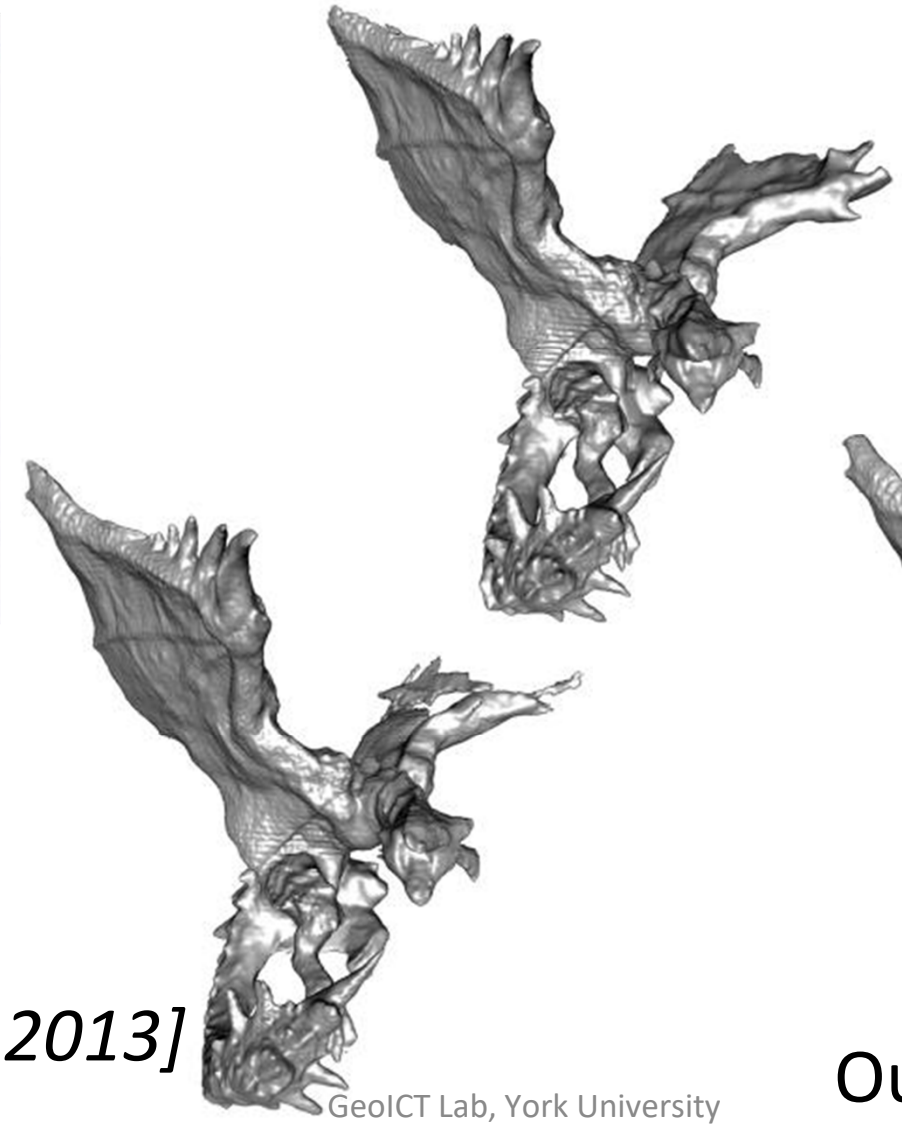


Algorithm Overview



Scan at NBVs till converge

Result Evaluation

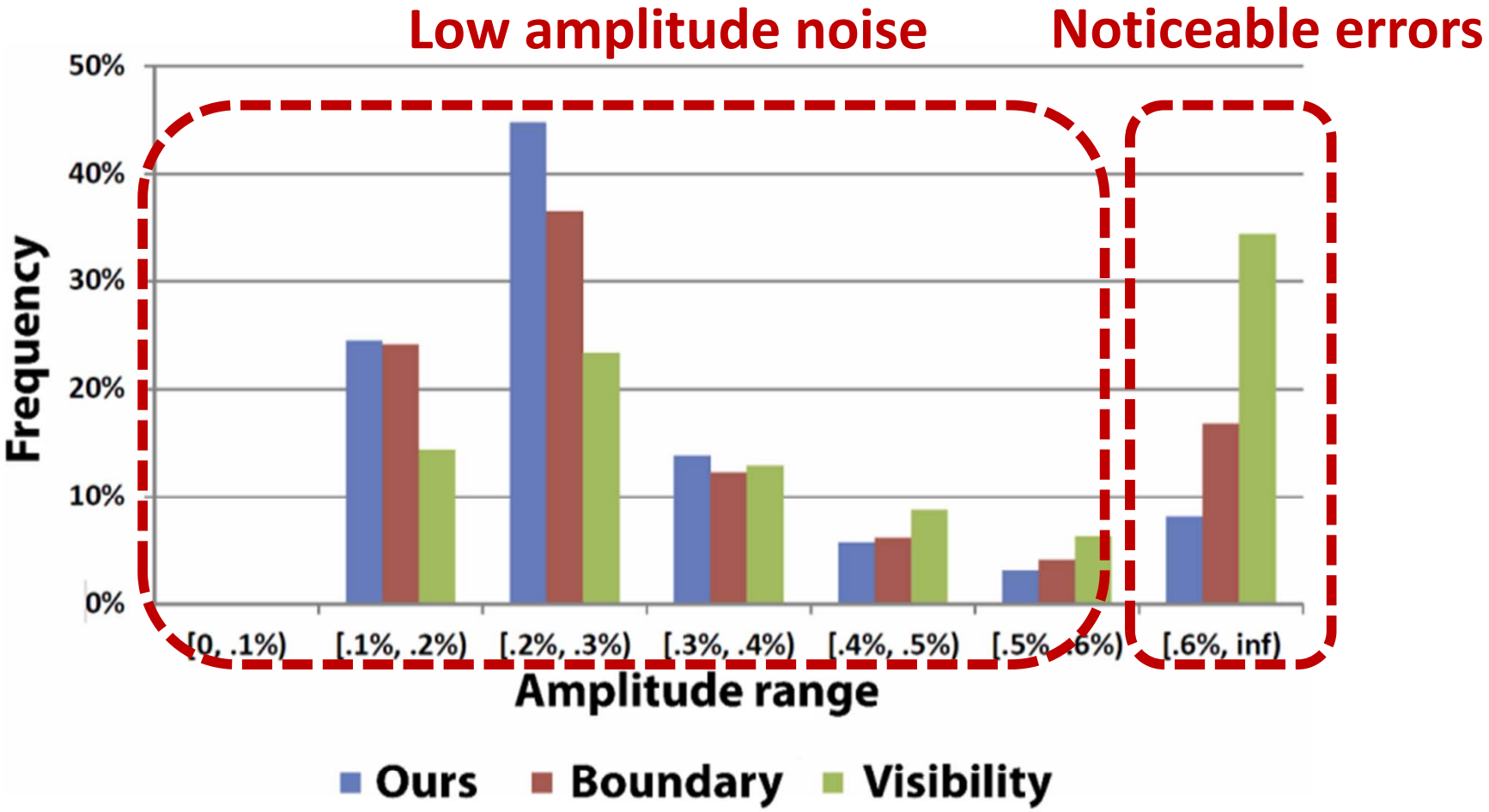


Boundary
[Kriegel et al. 2013]

Visibility
[Khalfaoui et al. 2013]

Ours

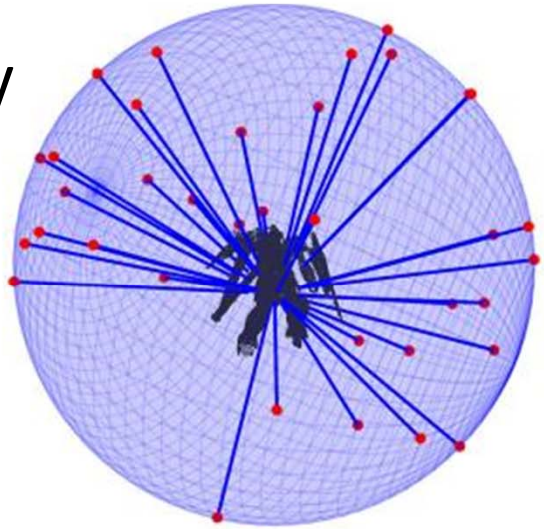
Quantitative Evaluation



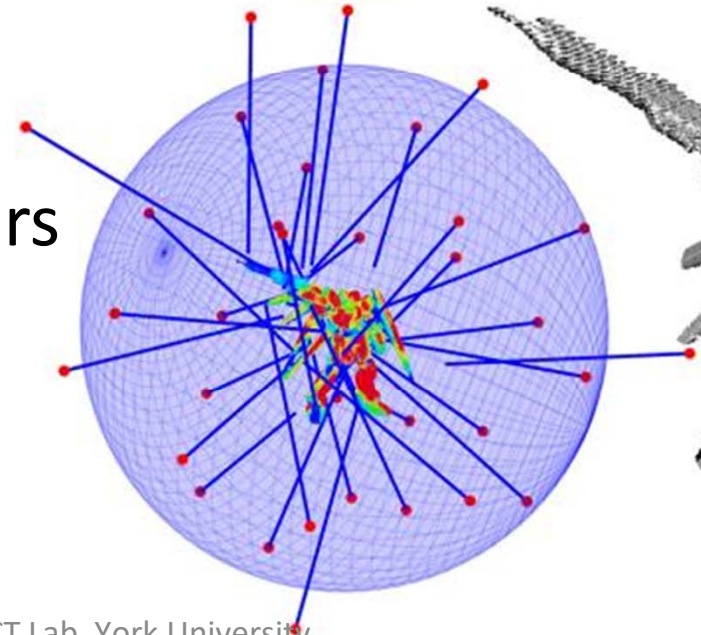
Quantitative error evaluation

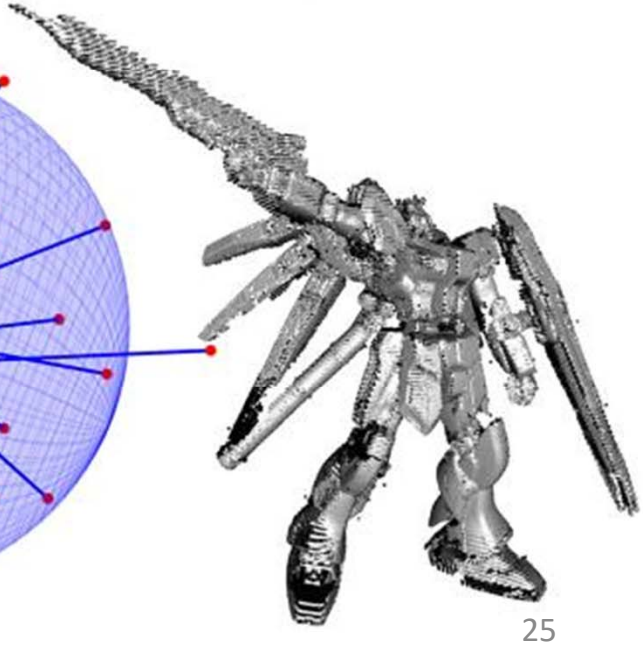
More Comparison

Sphere-based NBV
[V´asquez-G´omez et al. 2009]

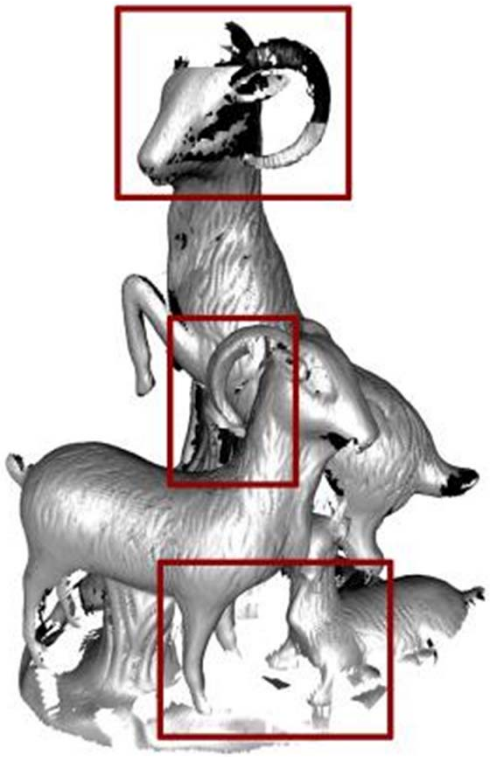


Ours

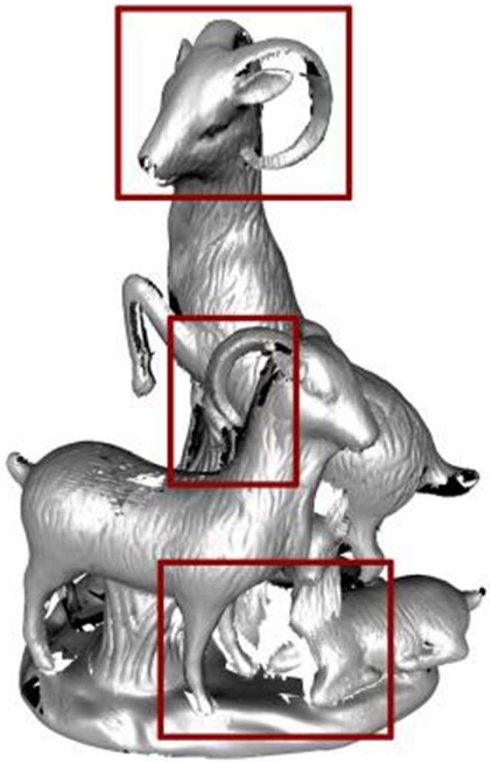




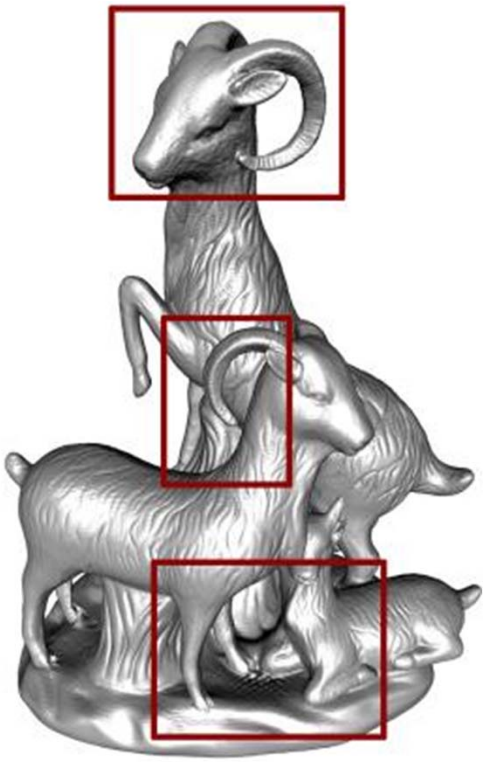
Confidence Measure Selection



Local curvature

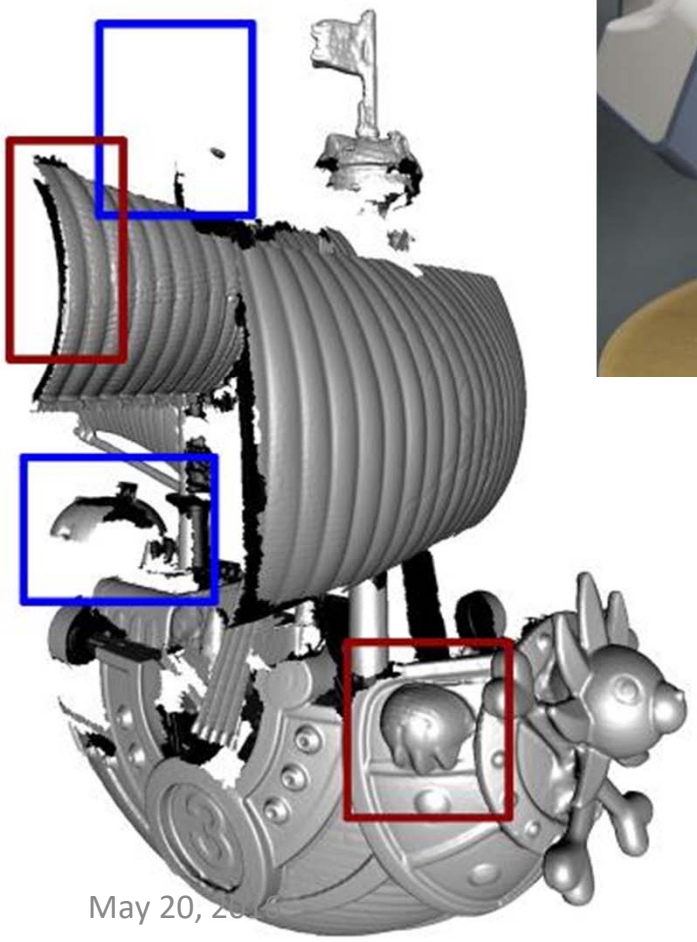


Local point density



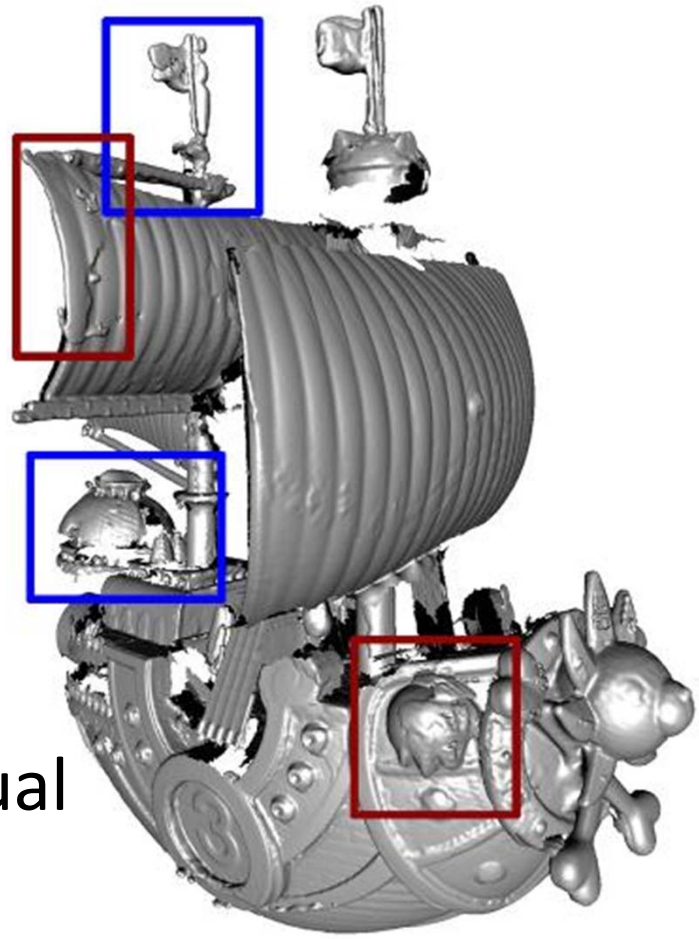
Ours

Compare with Manual Scan



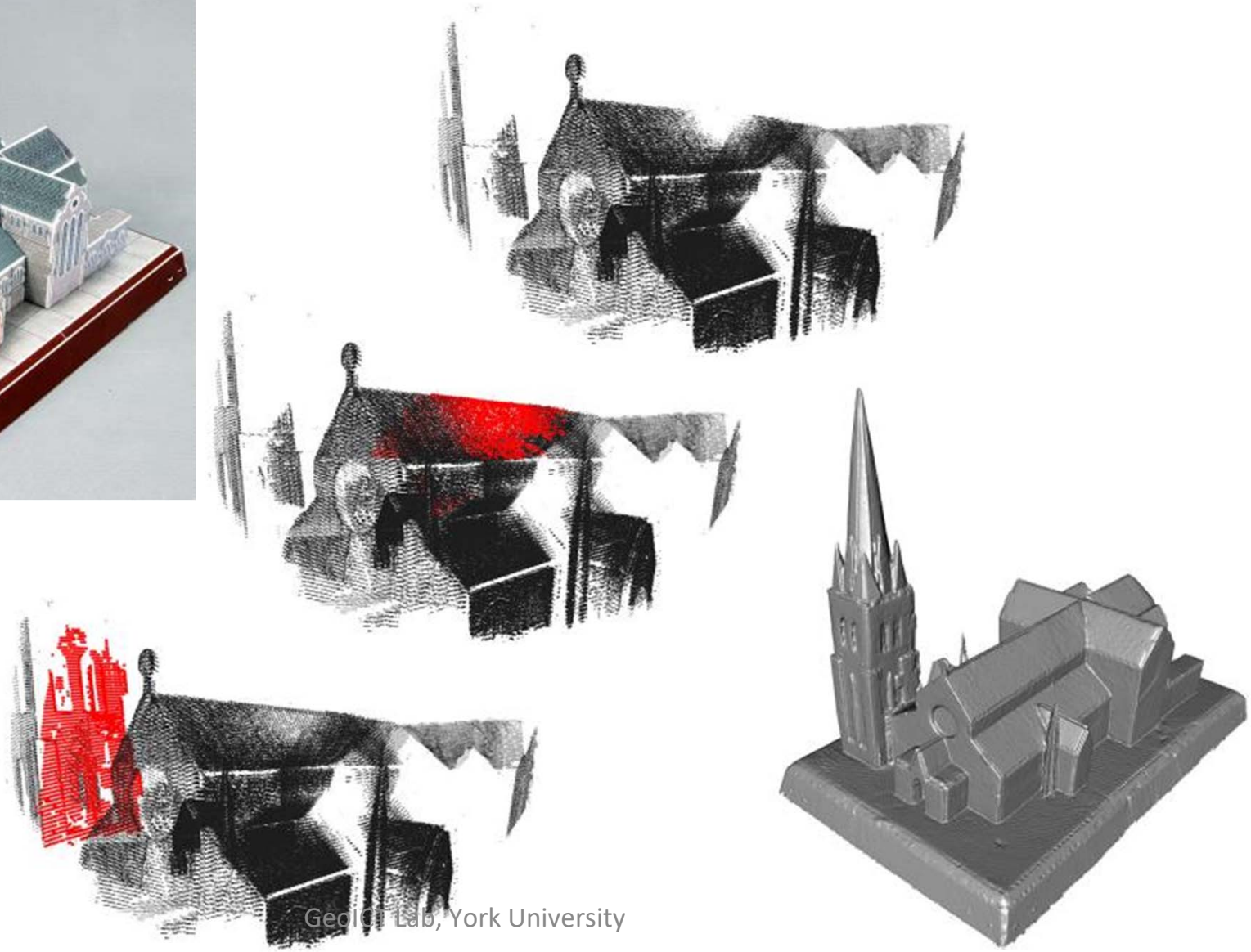
Ours

Manual scan



With Texture Mapping

Outdoor Scan Simulation



Future Work

- **Incorporating more advanced sensor models and searching in 6D pose space.**
- **Semi-automatic interactive scanning: provide visual feedback for user-operated capturing systems.**
- **Proactive scanning: avoid self-occlusion by introducing interaction with the scanned object.**
- **Optimize the scanning path, rather than frame by frame.**
- **Automatic scan for large-scale outdoor scenes.**

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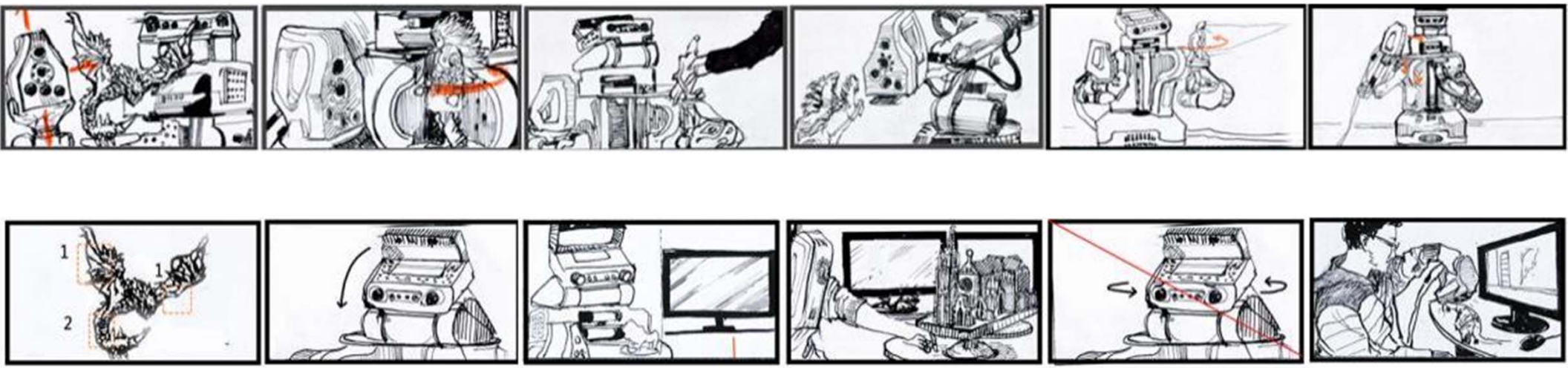
Thank you!

Source codes and data are available at the project page

Welcome to visit our PRZ robot.



Abstract

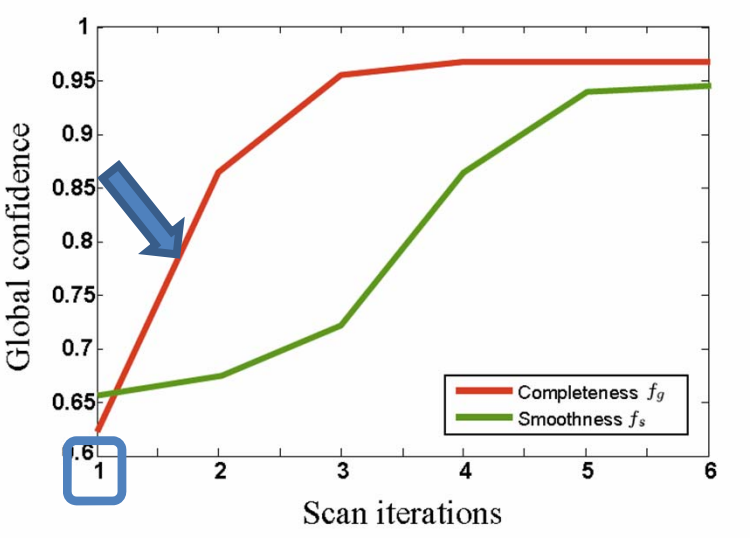
A quality-driven, Poisson-guided autonomous scanning method is discussed in this talk. Unlike previous scan planning techniques, the presented method does not aim to minimize the number of scans needed to cover the object's surface, but rather to ensure the high quality scanning of the model. This goal is achieved by placing the scanner at strategically selected Next-Best-Views (NBVs) to ensure progressively capturing the geometric details of the object, until both completeness and high fidelity are reached. The technique is based on the analysis of a Poisson field and its geometric relation with an input scan. A confidence map that reflects the quality/fidelity of the estimated Poisson iso-surface is computed, which guides the generation of a viewing vector field, as well as the selection of a set of NBVs. The algorithm is tested on two different robotic platforms, a PR2 mobile robot and a one-arm industry robot. We demonstrated the advantages of our method through a number of autonomous high quality scannings of complex physical objects, as well as performance comparisons against state-of-the-art methods.

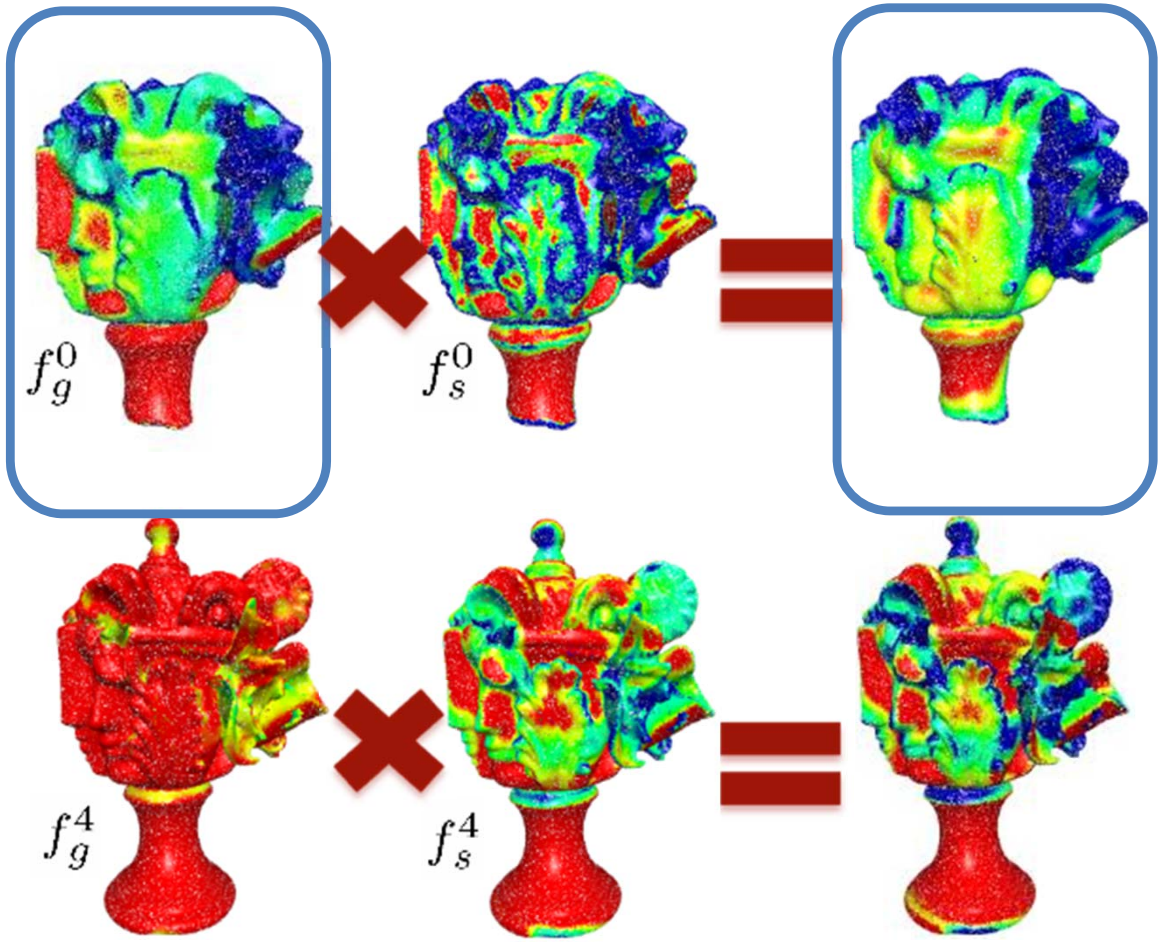
Time Table

Operation	Time (sec)	Percentage
Robot motion/capture	463	65%
Scan consolidation/registration	178	25%
NBV computation	71	10%

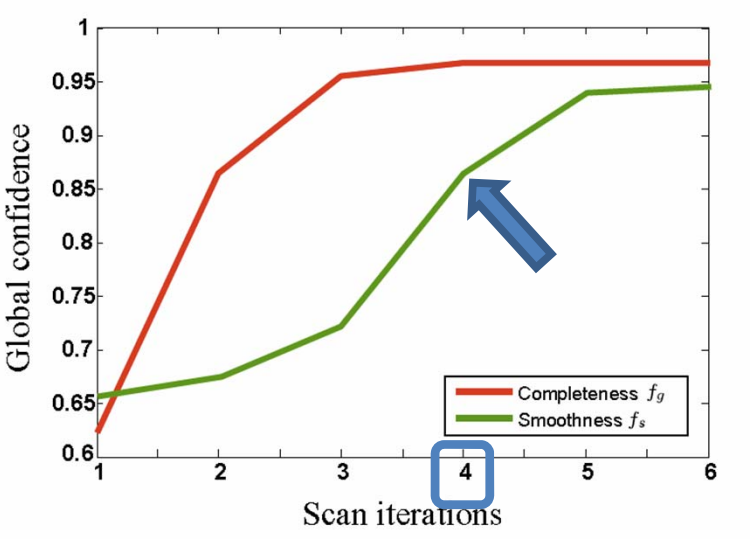
#Fig	#Pt	#Iter	#NBV	Time (min)
Figure 1	1828K	8	105	124
Figure 2	513K	3	35	41
Figure 10	406K	2	23	26
Figure 12	543K	2	25	29
Figure 13	2117K	10	127	154
Figure 14	376K	3	36	37
Figure 15	1777K	8	96	115
Figure 17	714K	4	41	49
Figure 18	4140K	15	213	235

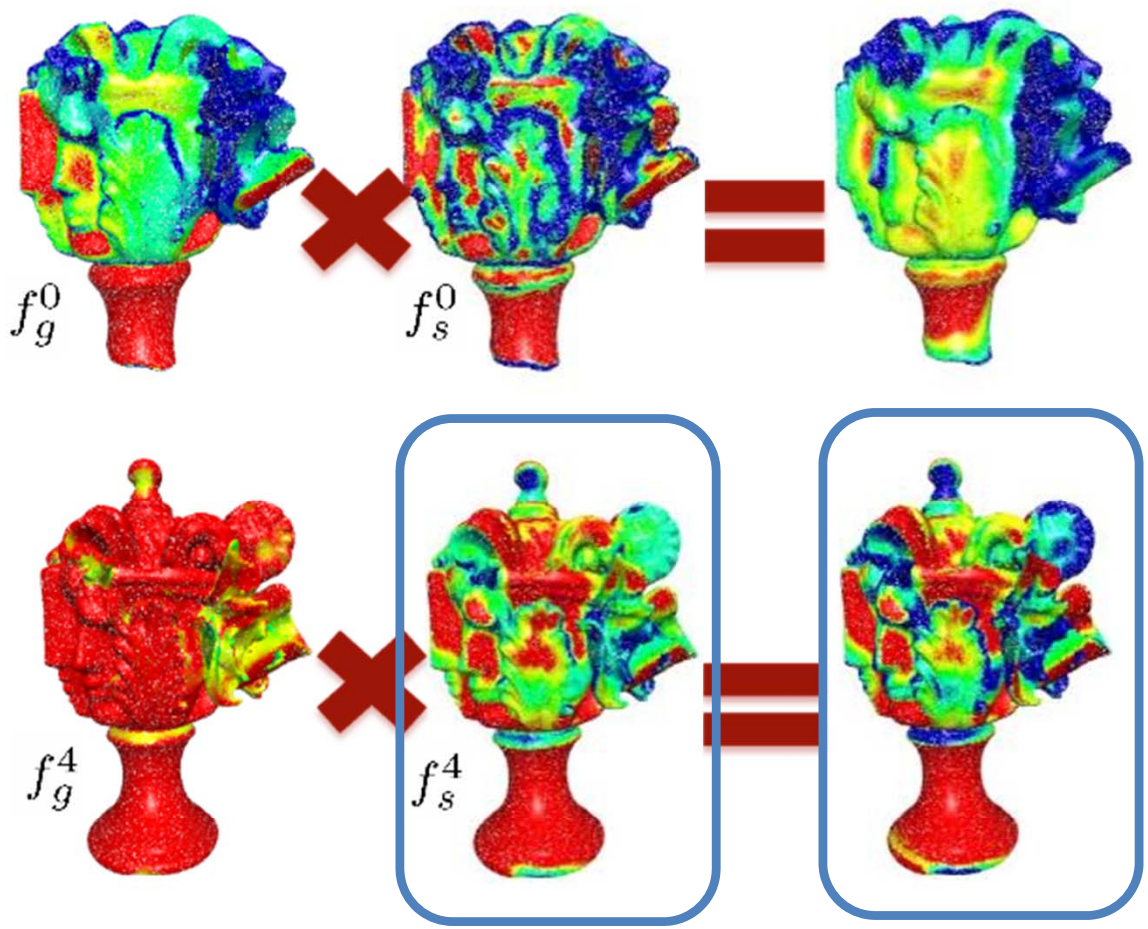
Combination: $f(s_k) = f_g(s_k, n_k) f_s(s_k, n_k)$





Combination: $f(s_k) = f_g(s_k, n_k) f_s(s_k, n_k)$



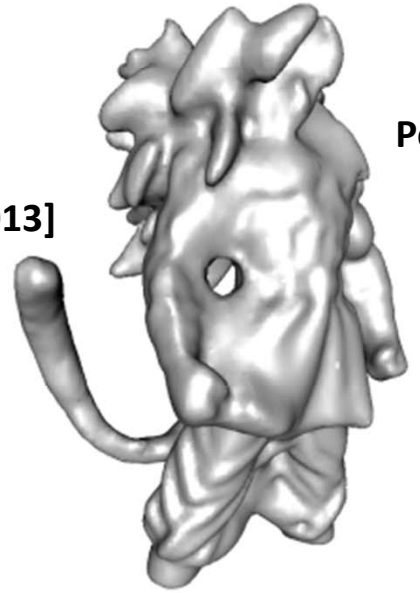


Iso-points extraction

Scanned input

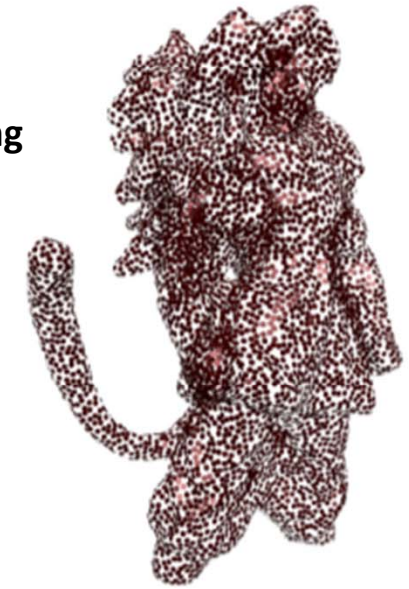
$Q = \{q_j\}_{j \in J} \subset \mathbb{R}^3$

Screened Poisson Reconstruction [Kazhdan and Hoppe 2013]



Tentative iso-surface

Poisson-disk Sampling [Corsini et al. 2012]

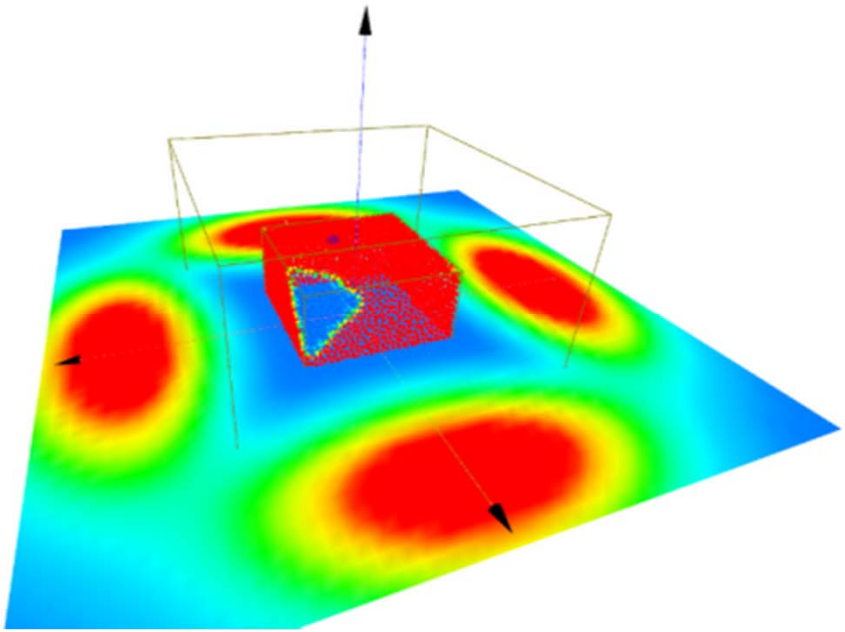


Iso-points

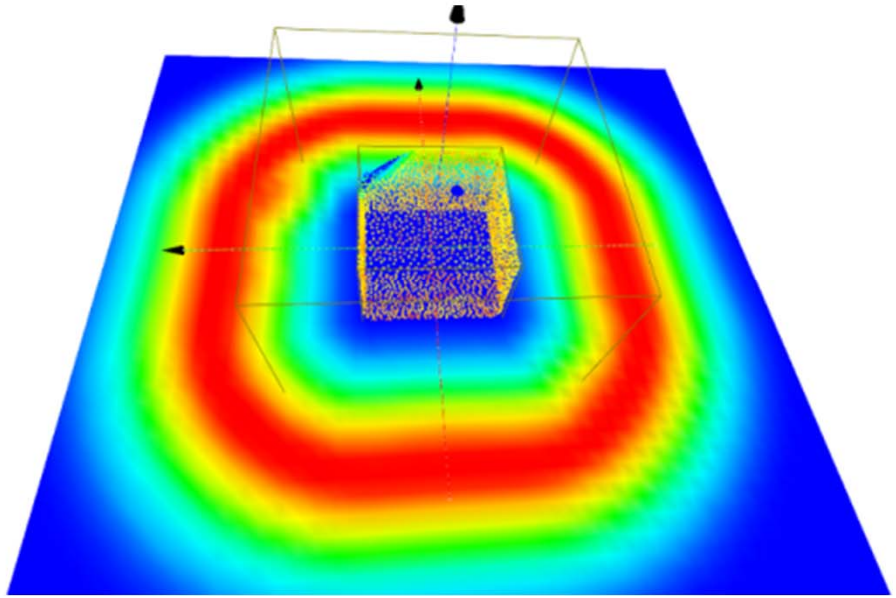
$S = \{(s_k, \mathbf{n}_k)\}_{k \in K} \subset \mathbb{R}^6$

Why maximum instead of sum?

$$g(v_i) = \max_{s_k}\{w(v_i, s_k)(1 - f(s_k))\}$$

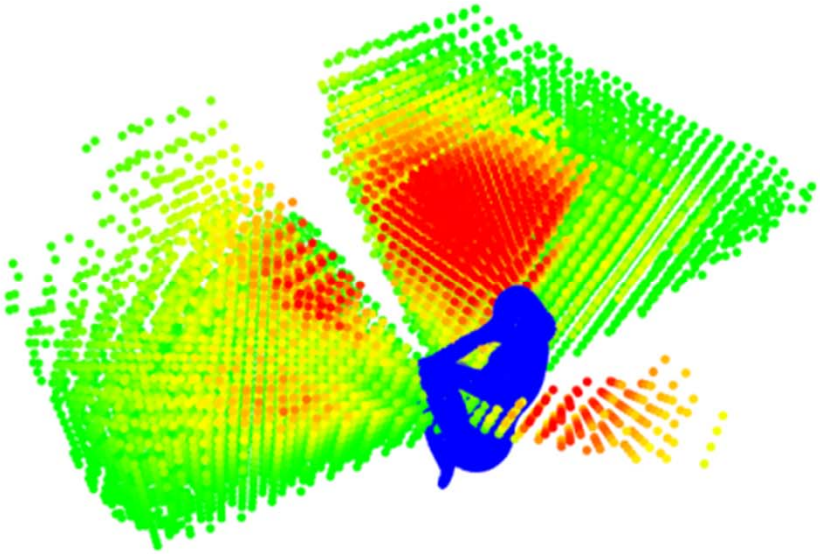


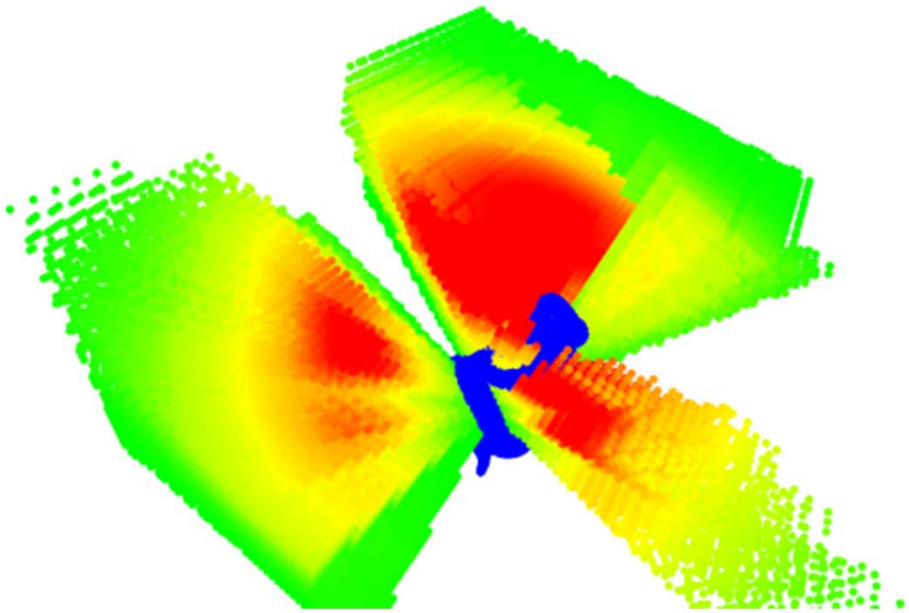
Using sum



Using maximum

Different grid resolution





Resolution: 62X62X62
Time: 0.001 sec

Resolution: 125X125X125
Time: 0.01 sec