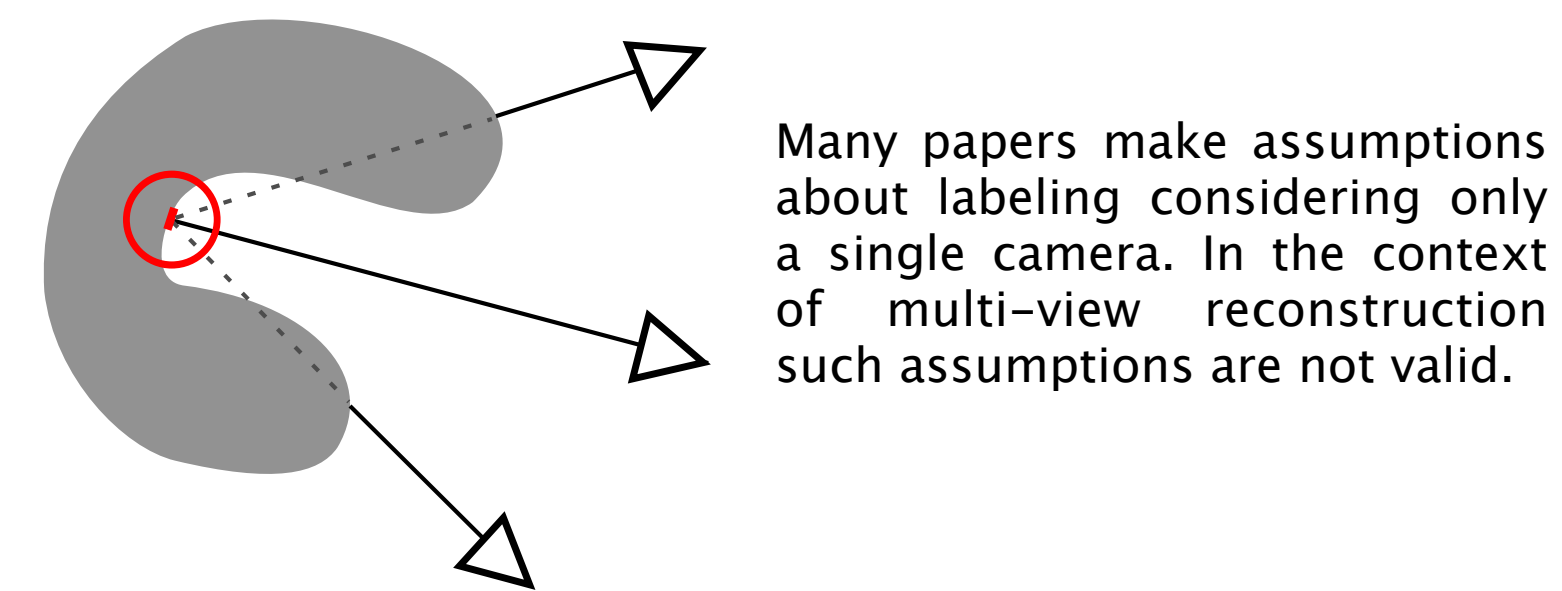


Abstract

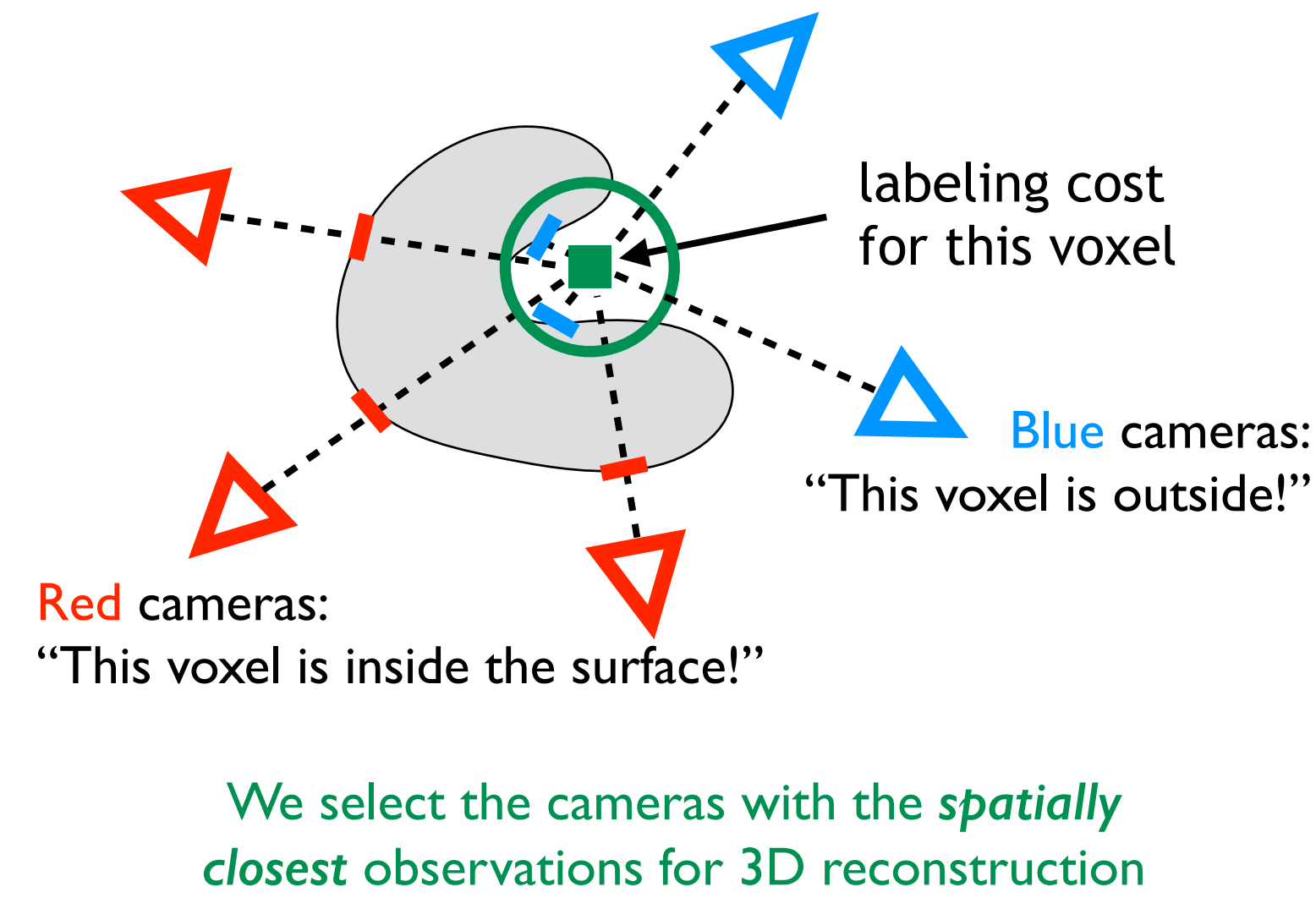
We propose a novel labeling cost for multi-view reconstruction. Existing approaches use data terms that are vulnerable to common challenges, such as low-textured regions or specularities. Our new probabilistic method implicitly discards outliers and can be shown to become more exact the closer to the true object surface. Our approach is simple to implement, can be readily integrated into many existing multi-view stereo approaches, and achieves top results among all published methods on the Middlebury Dino Sparse dataset.

Motivation

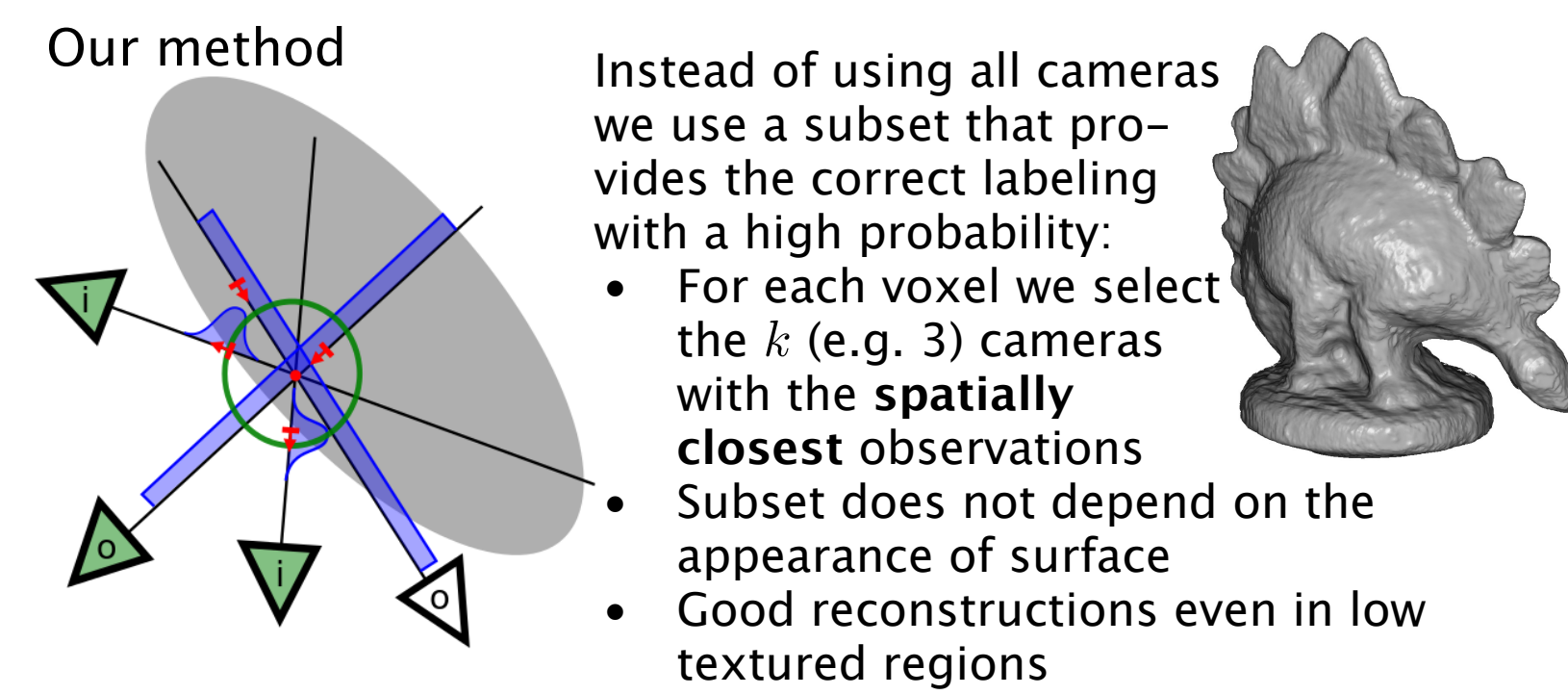
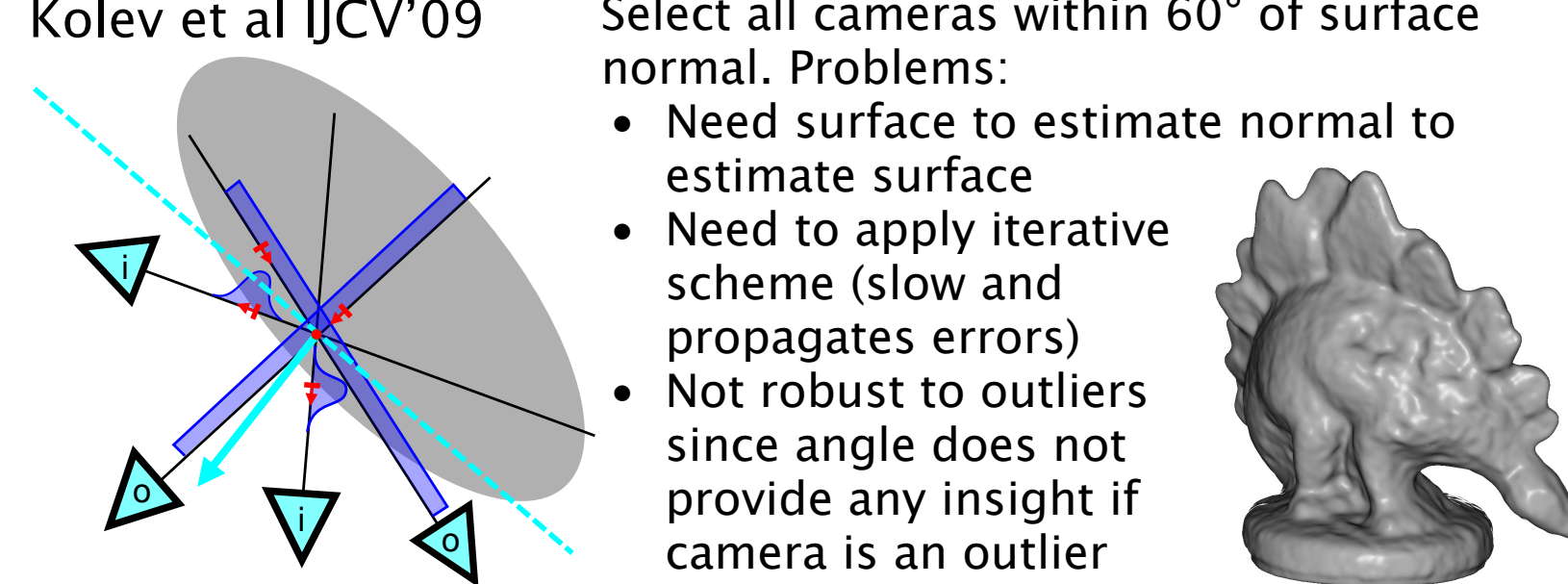


Main Idea

- Not all cameras can provide information about all voxels
- Many voxels are not visible for a camera
 - Especially in low textured areas some cameras provide unreliable information – outliers
 - Observations closer to the voxel in question are more reliable



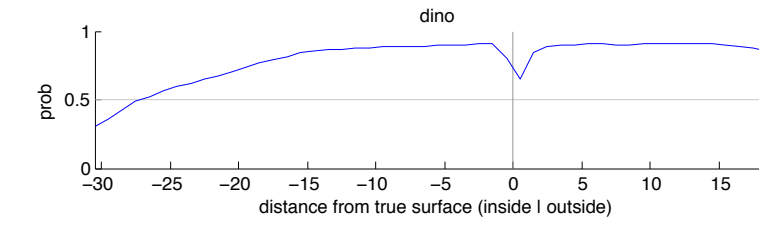
Comparison with Related Work



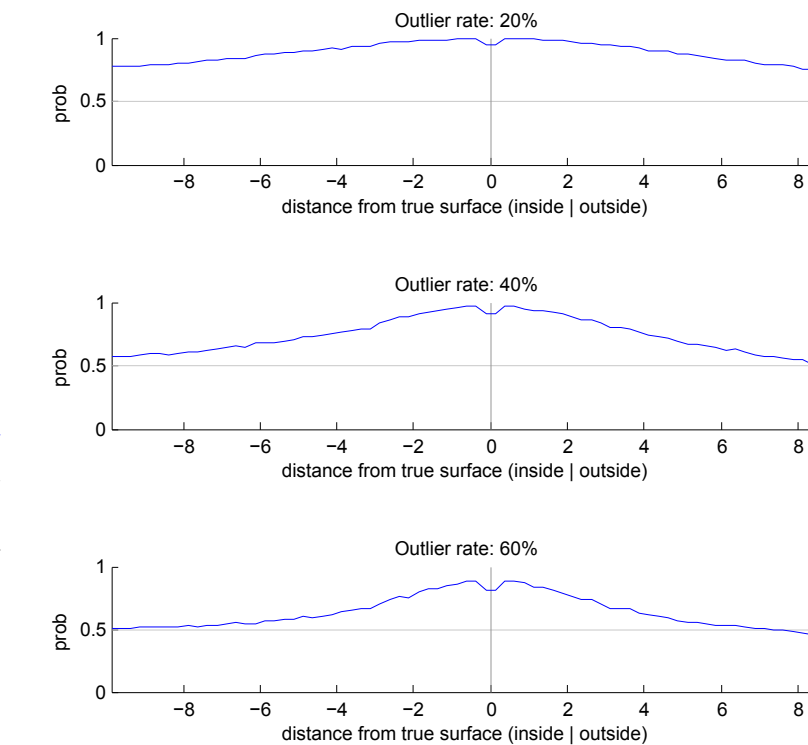
Accuracy of Camera Selection

Influence of outliers on the labeling:
Measure percentage of correct decision as a function of the distance from the surface.

dino dataset



Synthetic experiment



Useful property:

Close to the object surface:

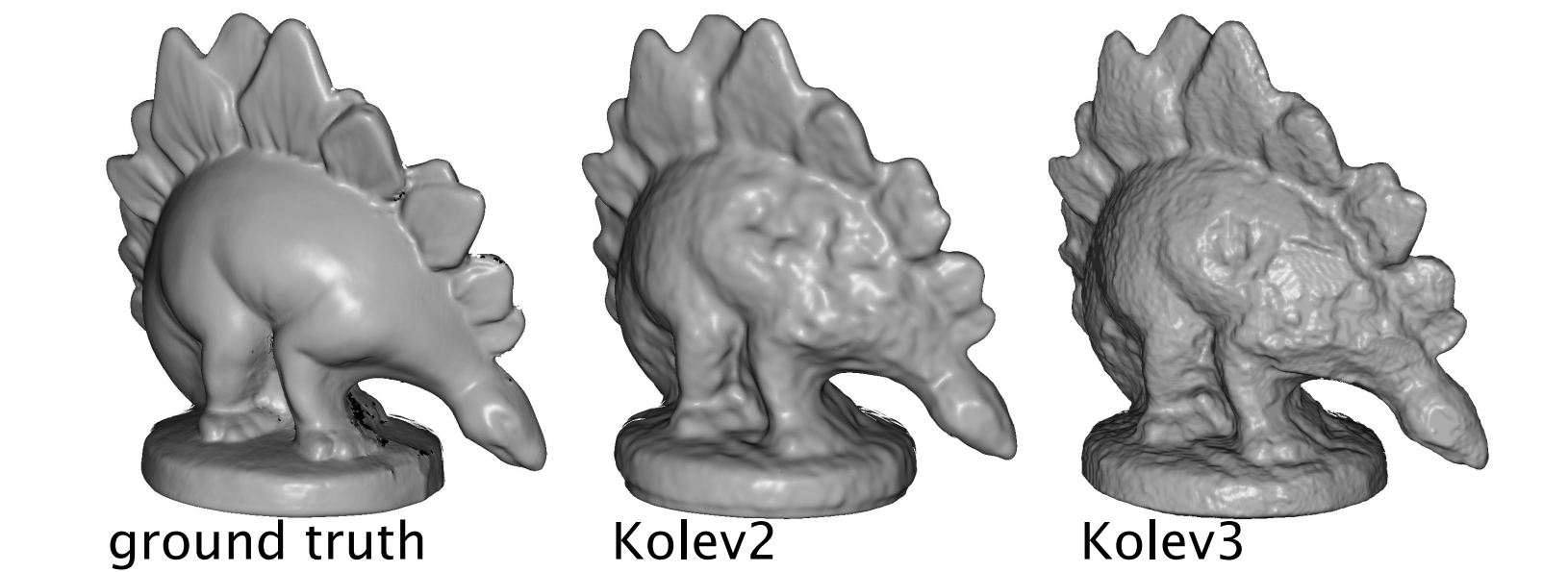
- Method selects cameras that have correct observations with a high probability
- No knowledge about the location of the surface necessary!

Further away from the surface:

- No need for precise labeling here
- Outliers will not harm the overall result
- Noisy labels that are far from the surface will be smoothed by the framework

Middlebury Benchmark Results

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
Kostrikov			0.57	99.1	0.79	95.8	0.35	99.6	0.37	99.3		
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
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
Tsinghua_BBNC											0.3	99.1
Liu2					0.65	96.9					0.51	98.7
Kolev3			0.7	98.3	0.97	92.7			0.42	99.5	0.48	98.6
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
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
Liu					0.96	89.6					0.59	98.3
Kolev2			0.72	97.8	1.04	91.8			0.43	99.4	0.53	98.3



Volumetric 3D Reconstruction

3D segmentation into foreground and background

$$u : V \rightarrow \{0, 1\}$$

Labeling costs $\rho_{obj}(\mathbf{x})$ and $\rho_{bck}(\mathbf{x})$

$$E(u) = \underbrace{\int_V \rho(\mathbf{x}) |\nabla u(\mathbf{x})| dx}_{\text{smoothing term}} + \lambda \underbrace{\int_V (\rho_{obj}(\mathbf{x}) - \rho_{bck}(\mathbf{x})) u(\mathbf{x}) dx}_{\text{labeling cost}}$$

Perform relaxation

$$u : V \rightarrow [0, 1]$$

Extract object by thresholding

$$u_{min}(\mathbf{x}) = \arg \min_{u(\mathbf{x})} E(u)$$

$$u_\nu(\mathbf{x}) = \mathbf{1}\{u_{min}(\mathbf{x}) \geq \nu\}$$

Standard discontinuity cost $\rho(\mathbf{x})$

We will concentrate on the labeling costs $\rho_{obj}(\mathbf{x})$ and $\rho_{bck}(\mathbf{x})$

Find minimum with Primal-Dual method:

$$\xi_{i,j,k}^{(t+1)} = \Pi_K(\xi_{i,j,k}^{(t)} + \eta \nabla u_{i,j,k}^{(t)})$$

$$u_{i,j,k}^{(t+1)} = \Pi_{[0,1]}(u_{i,j,k}^{(t)} + \theta(\text{div}(\xi_{i,j,k}^{(t+1)}) - b_{i,j,k}))$$

$$\bar{u}_{i,j,k}^{(t+1)} = 2u_{i,j,k}^{(t+1)} - u_{i,j,k}^{(t)}$$

Labeling Costs

For each voxel \mathbf{x} and for each camera j with location \mathbf{c}_j :
Estimate the intersection of camera the view ray r with the surface

$$r_{j,\mathbf{x}}(t) = \mathbf{c}_j + \frac{\mathbf{x} - \mathbf{c}_j}{\|\mathbf{x} - \mathbf{c}_j\|} t$$

Best consistency score between camera j and all others:

$$S_{j,\mathbf{x},max} = \max_t S_j(r_{j,\mathbf{x}}(t))$$

Corresponding position along the ray $r \rightarrow$ depth:

$$t_{j,\mathbf{x},max} = \arg \max_t S_j(r_{j,\mathbf{x}}(t))$$

We can use these values to compute the costs:

$$\rho_{bck}^{ij}(\mathbf{x}) = -\log(\mu^{\mathbf{1}\{t_{j,\mathbf{x},max} > t_{j,\mathbf{x}}\}} (1 - \mu)^{(1 - \mathbf{1}\{t_{j,\mathbf{x},max} > t_{j,\mathbf{x}}\}}))$$

$$\rho_{obj}^{ij}(\mathbf{x}) = -\log(\mu^{\mathbf{1}\{t_{j,\mathbf{x},max} < t_{j,\mathbf{x}}\}} (1 - \mu)^{(1 - \mathbf{1}\{t_{j,\mathbf{x},max} < t_{j,\mathbf{x}}\}}))$$

$$\rho_{bck}(\mathbf{x}) - \rho_{obj}(\mathbf{x}) = -\log \prod_{j=1}^k \frac{P(B_{i_1} \cdots B_{i_k} | C_{i_j})}{P(O_{i_1} \cdots O_{i_k} | C_{i_j})}$$

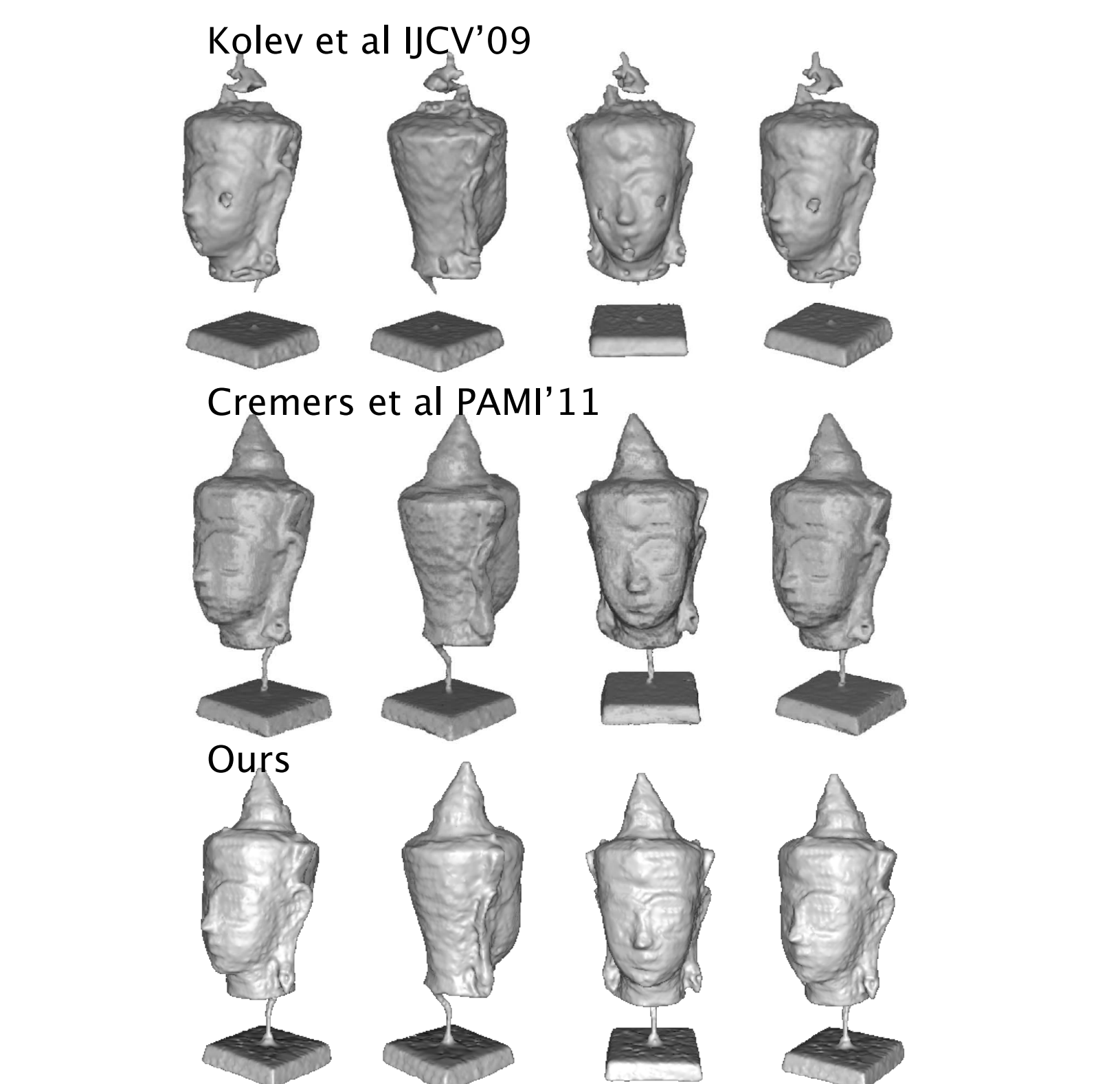
$$= \sum_{j=1}^k \rho_{bck}^{ij}(\mathbf{x}) - \sum_{j=1}^k \rho_{obj}^{ij}(\mathbf{x})$$

Note that we select this particular subset of cameras:

$$N_d(\mathbf{x}) = \{j \in \{1, \dots, N\} \mid |t_{j,\mathbf{x},max} - t_{j,\mathbf{x}}| \leq d\}$$

$$d_{min}(\mathbf{x}) = \min_d \text{ s. t. } |N_d(\mathbf{x})| \geq k$$

Results Comparison



Results

