CAD-DEFORM: DEFORMABLE FITTING OF CAD MODELS TO 3D SCANS

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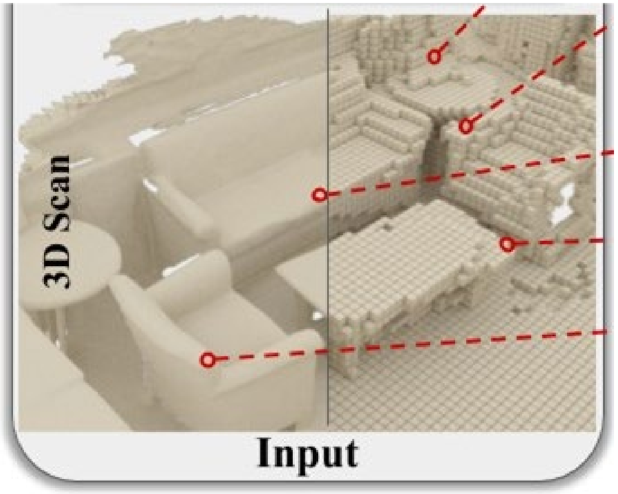
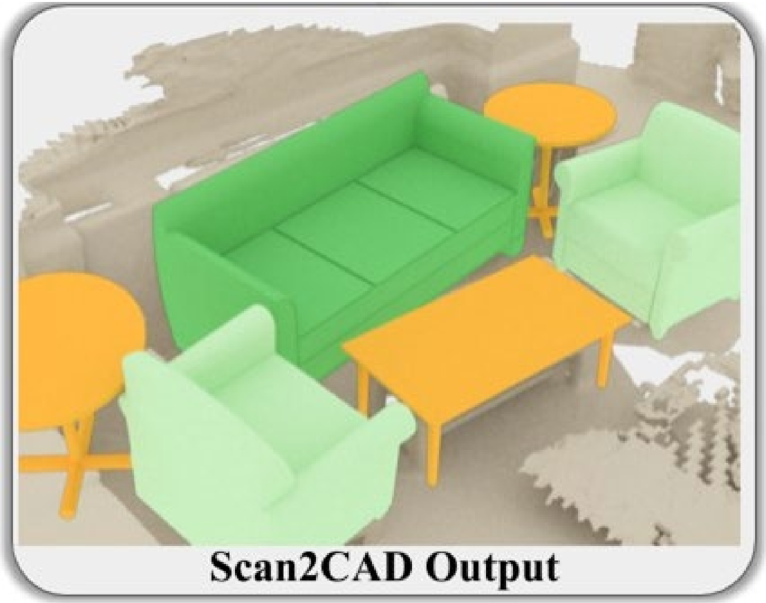
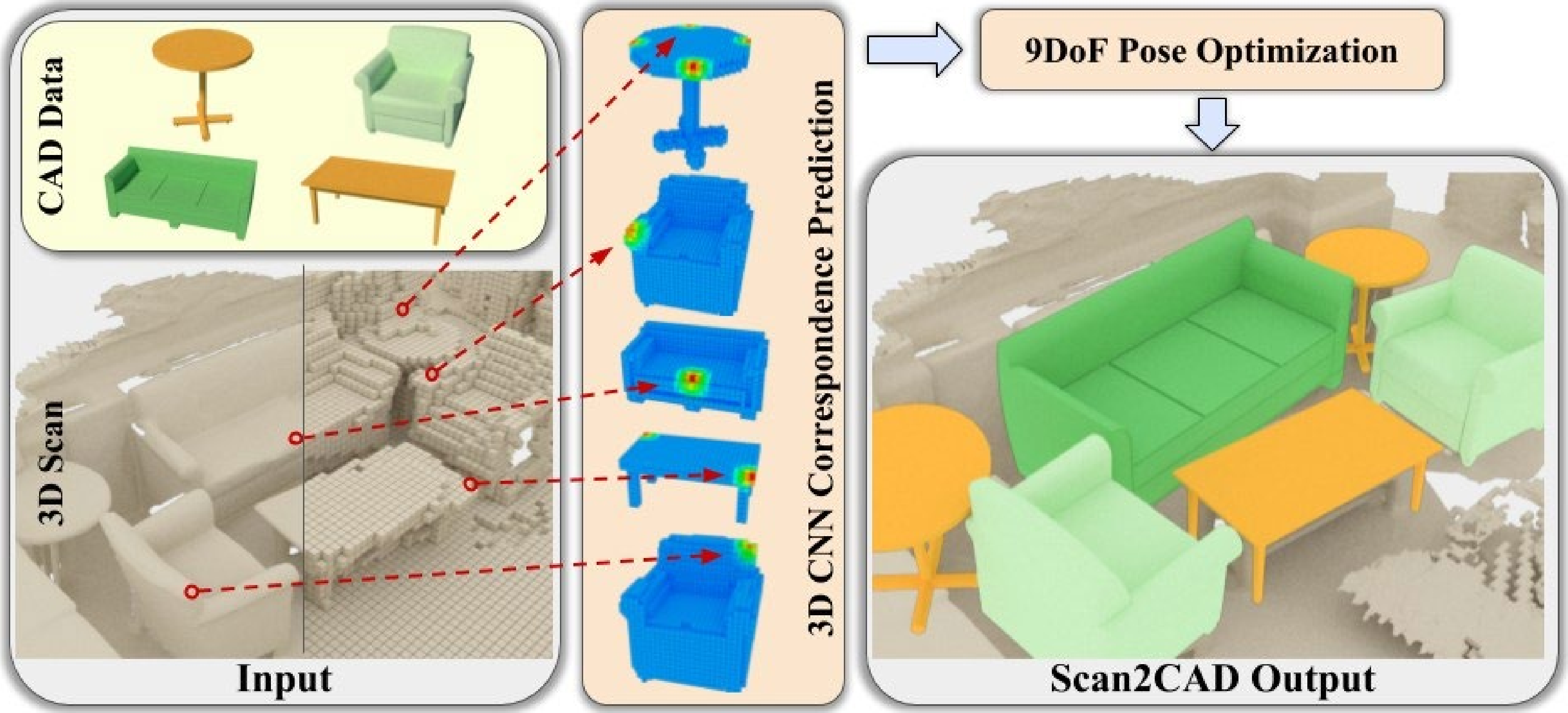
The task: point cloud → set of meshes

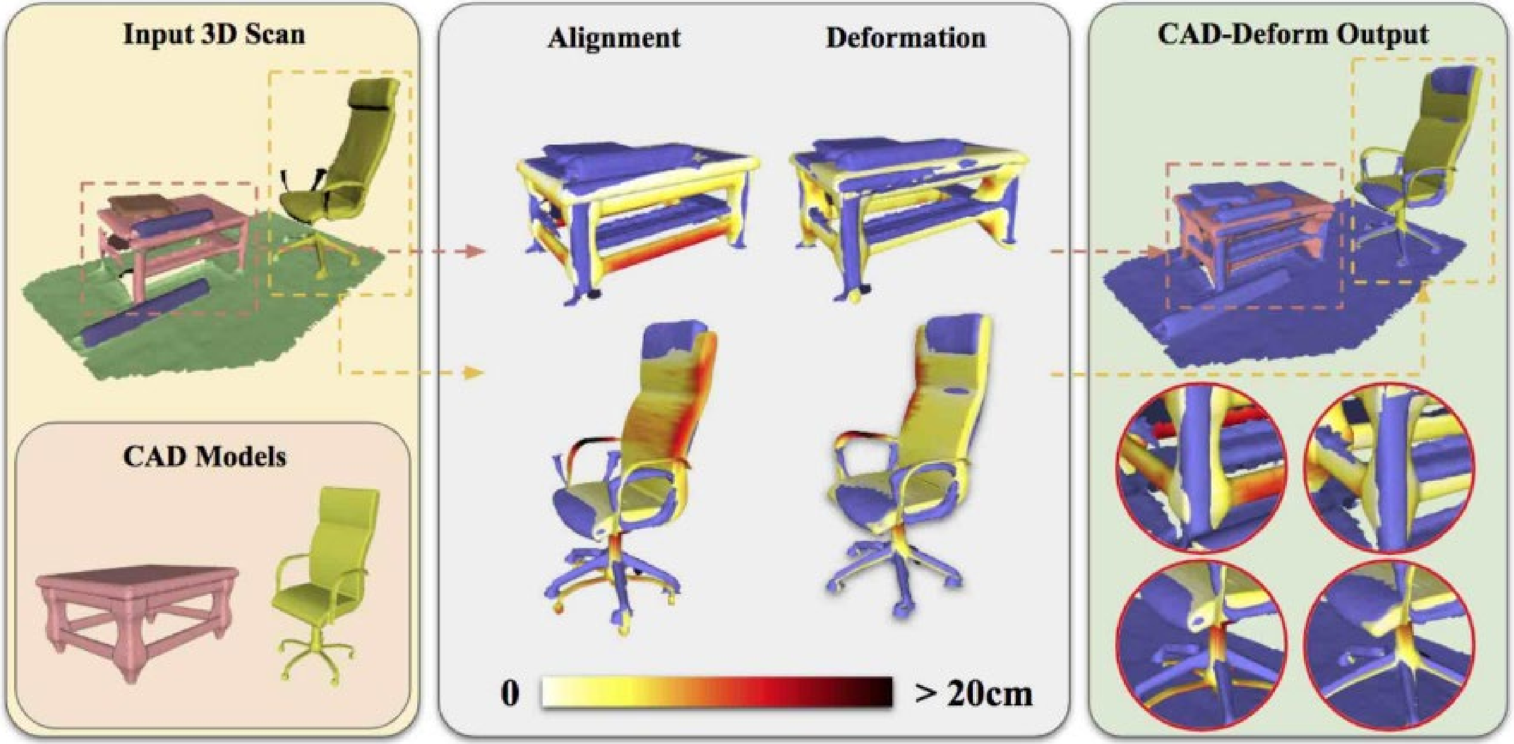




Past work: Scan2CAD (ScanNet+ShapeNet)

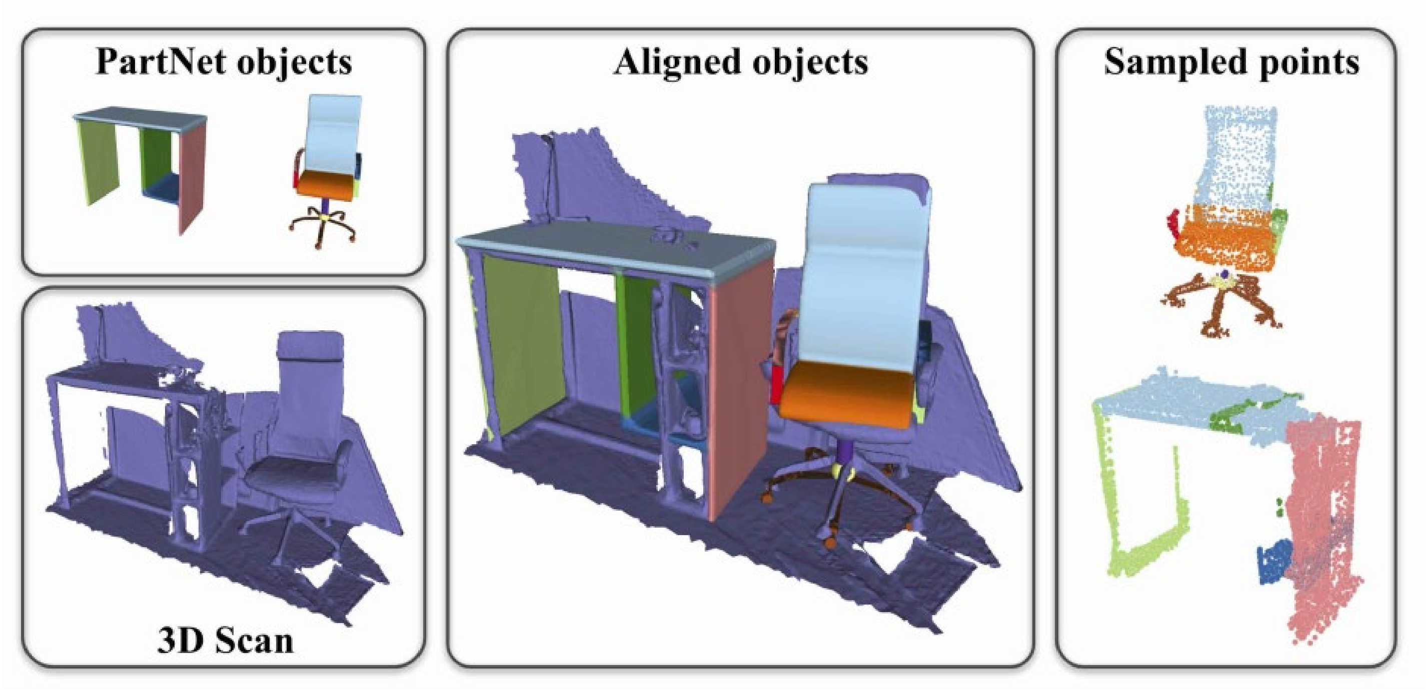


CAD-Deform



Input 3D Scan
CAD Models
Alignment
Deformation
0
> 20cm
CAD-Deform Output

Dataset - Scan2CAD (ScanNet+ShapeNet) +PartNet



Deformation: Optimize energy

Input:

$$\mathcal{E}(\mathbf{V},\mathbf{P}) = \underbrace{\boxed{E_{\text{shape}} + \alpha_{\text{smooth}} E_{\text{smooth}} + \alpha_{\text{sharp}} E_{\text{sharp}}}}_{\text{quadratic problem}} + \alpha_{\text{data}} E_{\text{data}},$$

$$E_{\text{shape}} = \underbrace{\sum_{e \in \mathbf{E}} \| T_e(\mathbf{V}) - T_e^0 \|_2^2;}_{\text{deviation}} \qquad E_{\text{smooth}} = \sum_{f \in \mathbf{F}} \sum_{e_i, e_j \in f} \| T_{e_i}(\mathbf{V}) - T_{e_j}(\mathbf{V}) \|_2^2;$$

$$E_{\text{sharp}} = \sum_{k=1}^{n_p} \sum_{e_s \in \mathbf{E}^k_{\text{sharp}}} \| T_{e_s}(\mathbf{V}) - T_{e_{s+1}}(\mathbf{V}) \|_2^2; \qquad E_{\text{data}} = f_{\text{data}}(\mathbf{V},\mathbf{P}).$$

How to compare vertices and points?

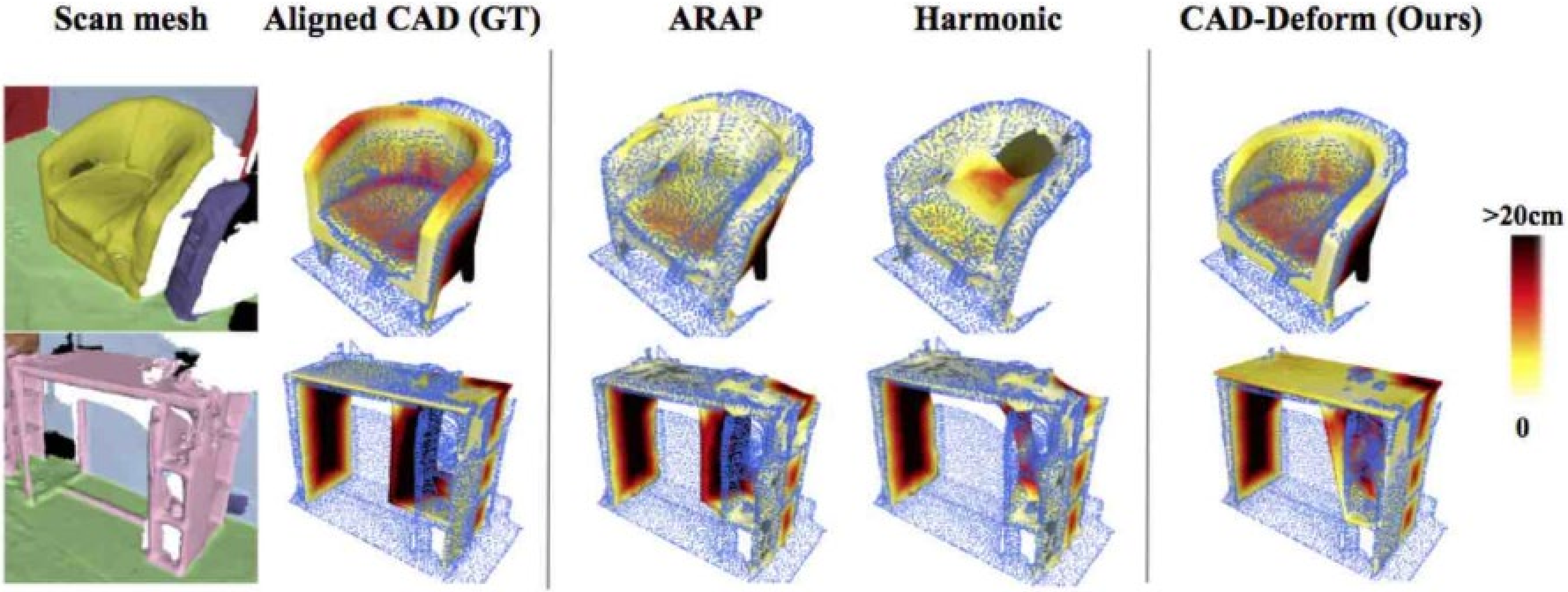
If start close to target, can use a priori correspondences:

$$f^{\text{nn}}_{\text{data}}(\mathbf{V},\mathbf{P}) = \sum_{c \in \mathbf{C}} \sum_{p \in \mathbf{P}_c} \| p - v_{\iota^c(p)} \|_2^2.$$

When far from target use screened attraction:

$$f^{\text{p2p}}_{\text{data}}(\mathbf{V},\mathbf{P}) = \sum_{c \in \mathbf{C}} \sum_{v \in \mathbf{V}_c} \sum_{p \in \mathbf{P}_c} \xi^{\sigma}(p, \mathbf{V}_c) \left(d^{\varepsilon}(v - p) \right)^2,$$

Results: deformations improve fit while maintaining shape



Results: deformations fit well independent of alignment input

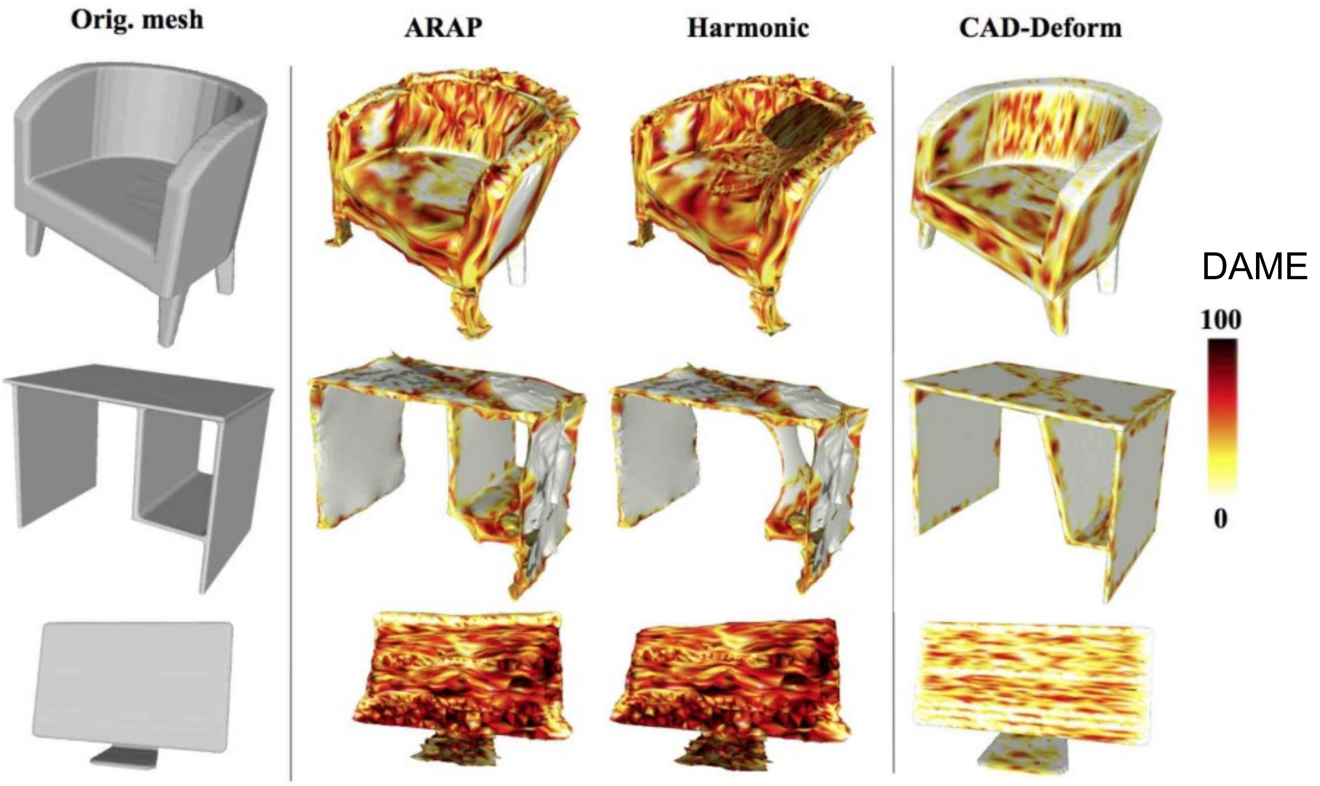
Method	Class avg. GT	Class avg. S2C [9]	Class avg. E2E [10]	Instance avg. GT	Instance avg. S2C [9]	Instance avg. E2E [10]
# TPs	1410	499	882	1410	499	882
TP undeformed	89.2	83.7	88.5	90.6	79.4	93.9
Ours: NN only	89.7	84.3	89.0	91.4	84.7	94.4
Ours: p2p only	90.3	88.3	89.4	91.6	90.3	94.9
Ours: w/o smooth	90.6	**90.0**	89.6	92.3	90.3	95.0
Ours: w/o sharp	90.3	86.9	**90.6**	92.3	89.4	**95.2**
CAD-Deform	**91.7**	89.8	90.3	**93.1**	**92.8**	94.6

Table 1: Comparative evaluation of our deformations to true positive (TP) alignments by non-deformable approaches in terms of Accuracy (%). Note that deformations improve performance for all considered alignment approaches.

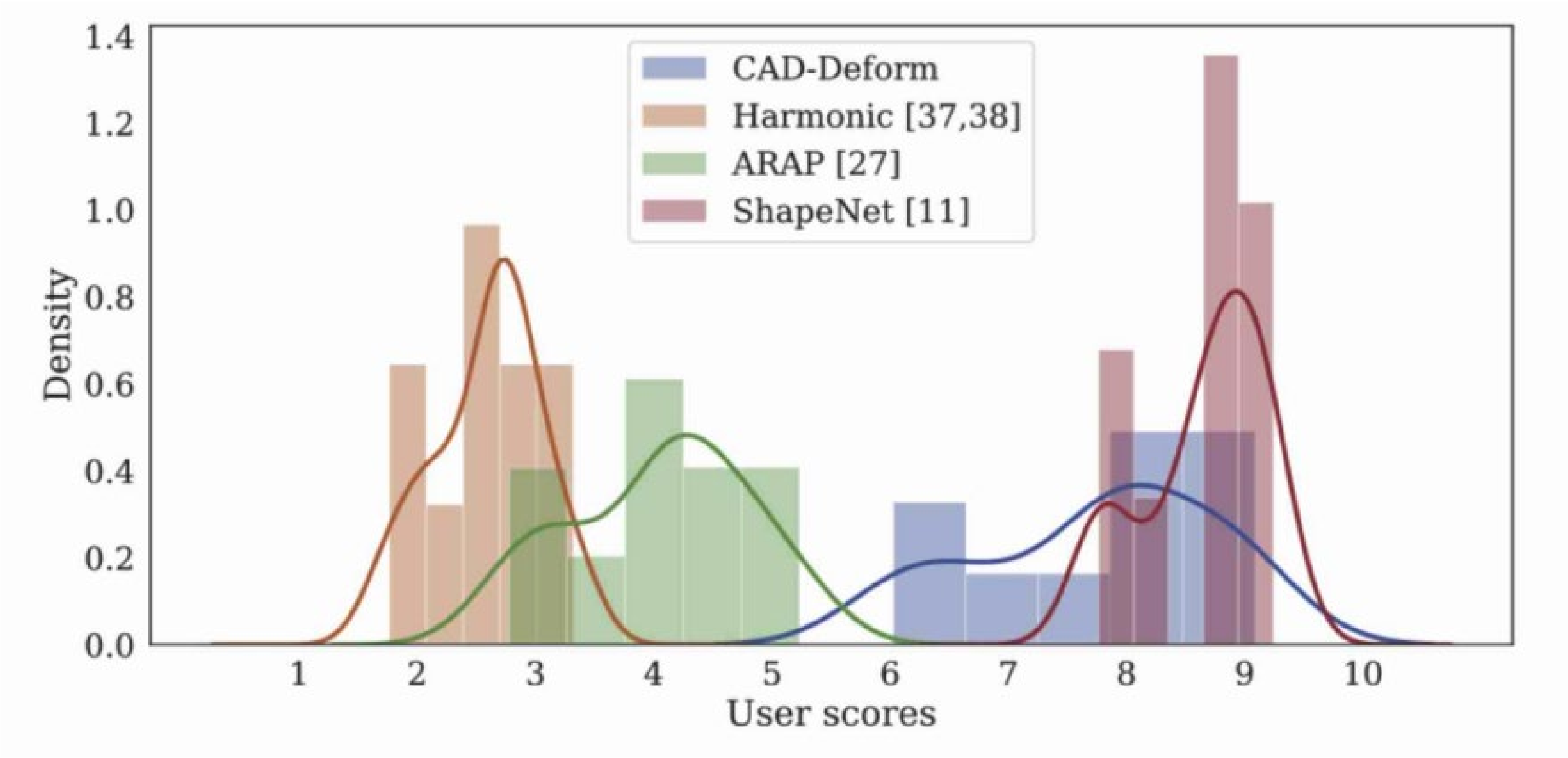
Method	bookshelf	cabinet	chair	display	table	trashbin	other	class avg.	avg.
# instances	142	162	322	86	332	169	197	201.4	1410
Ground-truth	88.0	75.2	94.8	98.9	89.6	96.6	81.4	89.2	90.6
Ours	**90.5**	**82.2**	**95.4**	**99.1**	**91.0**	**98.6**	**84.8**	**91.7**	**93.1**

Table 2: Comparative evaluation of our approach to non-deformable ground-truth and baselines in terms of scan approximation Accuracy (%). We conclude that our deformations improve fitting accuracy across all object classes by 2.5 % on average.

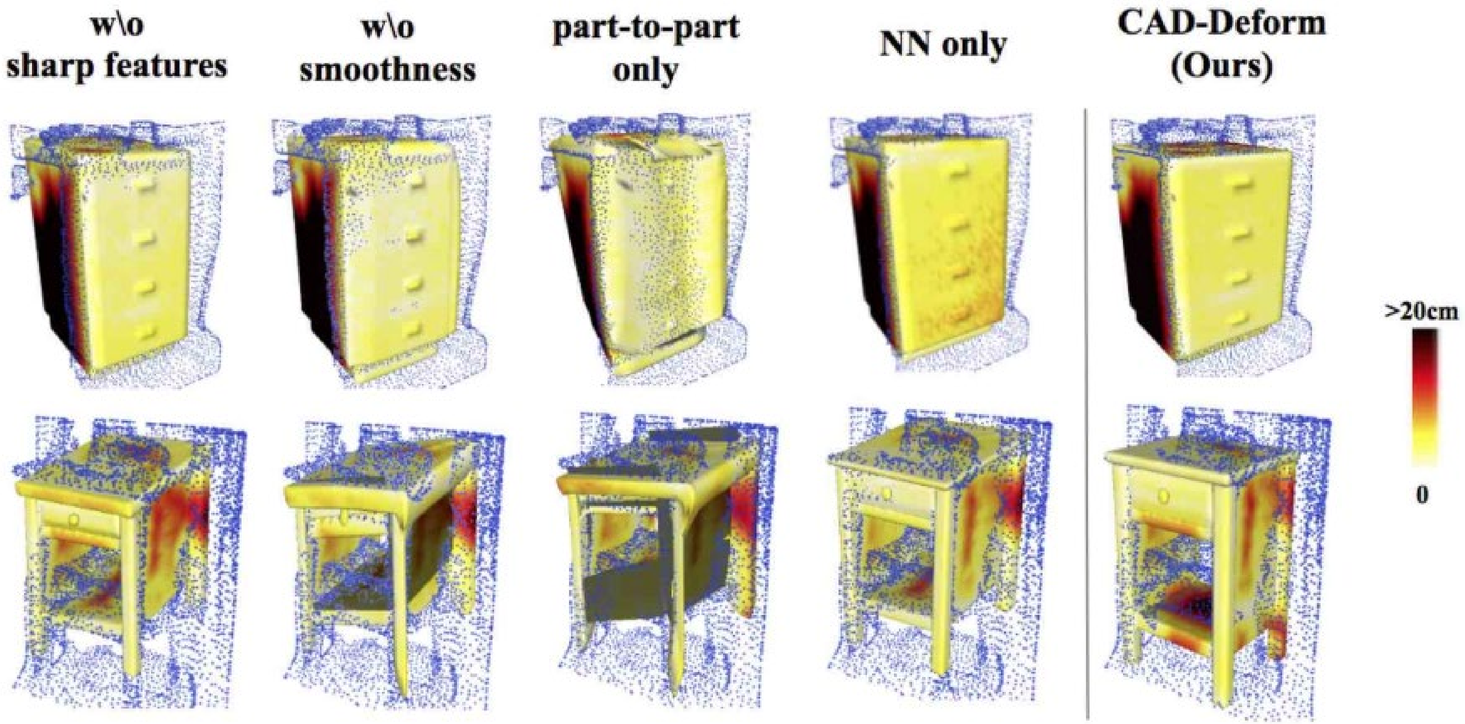
Results: produces higher quality surfaces



Results: produces higher quality surfaces



Results: balances fit-to-scan and perceptual quality

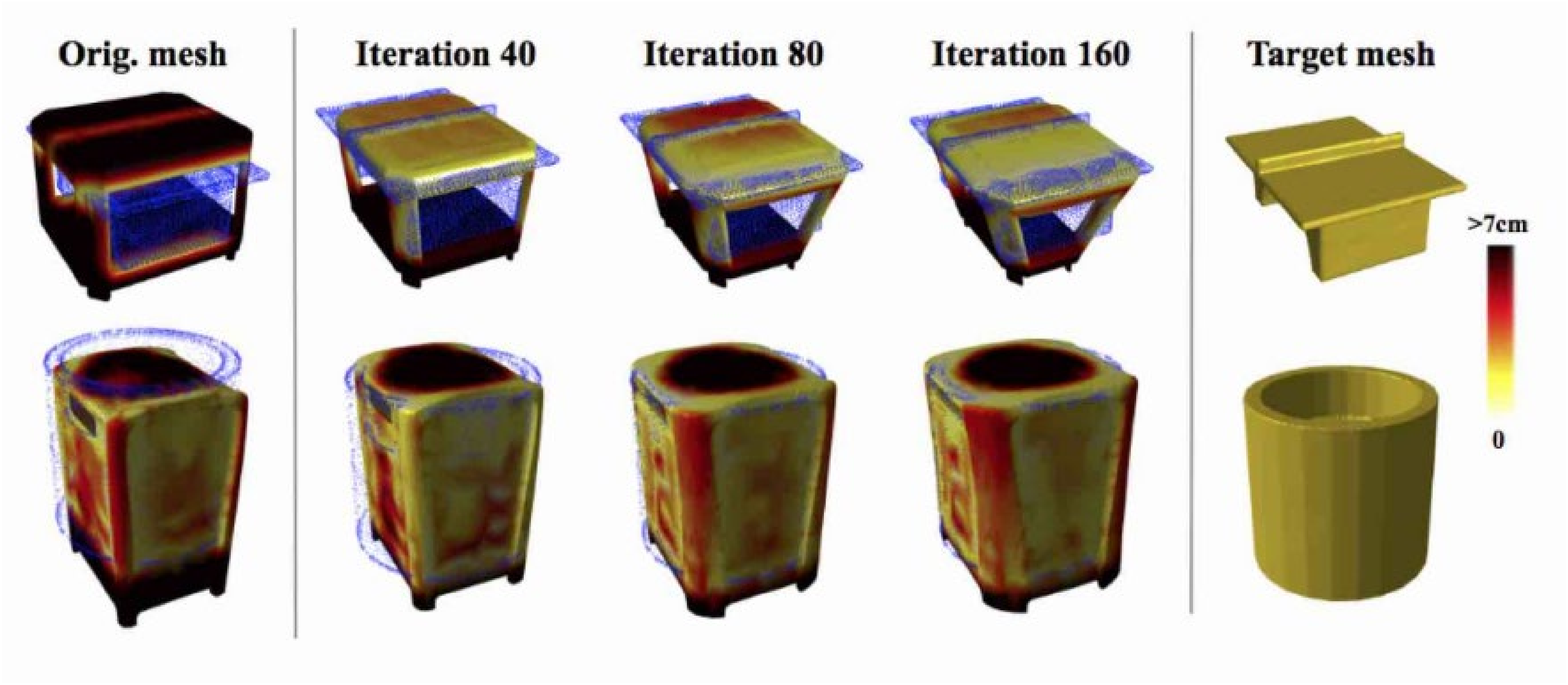


Conclusions

- Goal: mesh representations of real world scene from 3D scans
- Balance accuracy and high-perceptual quality
- Propose adding a deformation to Scan2CAD
- Deformation minimizes a composite energy function:
  - Uses semantic part structures
  - Enforces smooth transformations
  - Preserves sharp geometric features
  - Minimizes difference to point cloud
- First step in improving accuracy while preserving perceptual quality through deformation

Extra slides

Results: attempts shape interpolation



Results: attempts at various level of segmented objects

Accuracy, %	class avg.	avg.
Ground-truth	89.22	90.56
Level 1 (object)	89.25	90.79
Level 2	89.16	91.21
Level 3	89.40	91.05
Level 4 (parts)	**91.65**	**93.12**

Optimization of non-linear part

The data term is highly nonlinear, but solving the complete optimization problem can be done efficiently using A_{quad}^{-1} as the preconditioner. For our problem, we use the preconditioned L-BFGS optimizer summarized in Algorithm 1.

Algorithm 1: Preconditioned L-BFGS mesh optimization (PL-BFGS)

$M_{\text{precond}} = A_{\text{quad}}^{-1}$ `// stored as LU decomposition`

$\overline{\mathbf{V}} = T_m^0(\overline{\mathbf{V}}^0)$

for $i \leftarrow 0$ **to** N_{iter} **do**

$\quad g_{\text{tot}} = \alpha_{\text{data}} {}^{\mathrm{d}E_{\text{data}}}/_{\mathrm{d}p} + A_{\text{quad}}\overline{\mathbf{V}} + b$

$\quad \overline{\mathbf{V}} = \text{L-BFGS-step}(\overline{\mathbf{V}}, g_{\text{tot}}, M_{\text{precond}})$

end