Robust 6D Object Pose Estimation with Stochastic Congruent Sets

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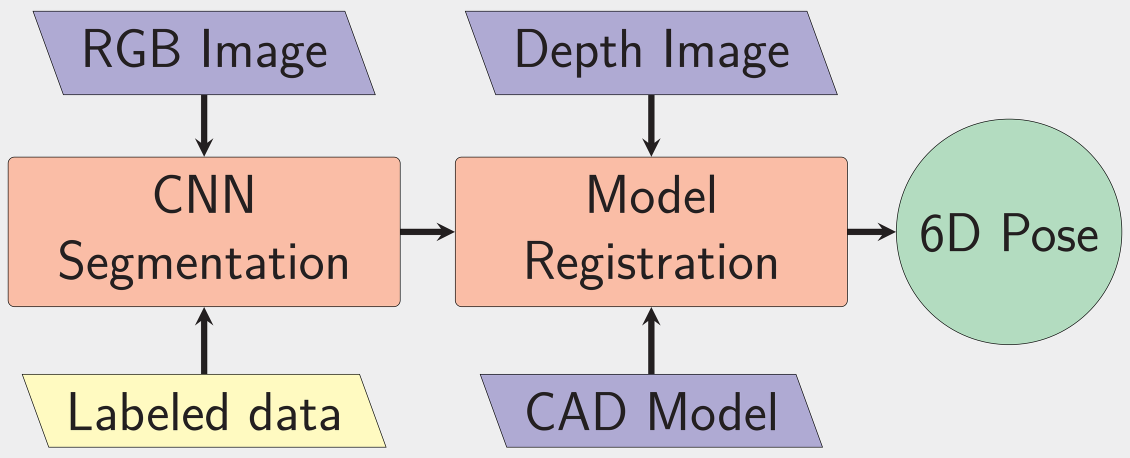
6D Pose Estimation Problem

Objective:

- Input: RGB-D scene, CAD models for known objects in scene.
- Output: Translation ($t \in R^3$) and Rotation ($R \in SO(3)$) for each object.

Popular Pose Estimation Pipeline:



Motivation

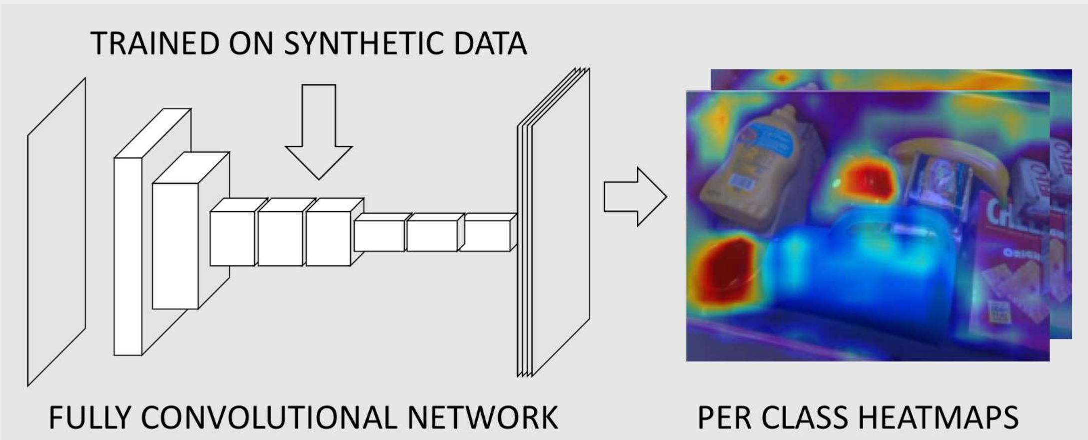
- Collecting labeled training data requires substantial manual effort. Our goal is to train the CNN using synthetic data.
- Often hard segmentation decision results in over/under segmentation due to the domain gap between synthetic and real data.

Prior algorithms like Super4PCS,

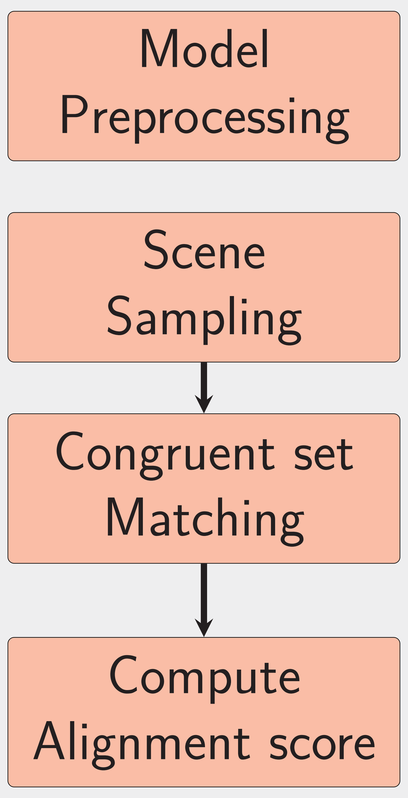
- Use **deterministic segments**, resulting in sub-optimal solutions in the above mentioned error cases.
- **Randomly sample** set of points on the segment and find congruent sets on the object model. This requires several iterations to get a high probability of success.

Proposed Solution

- We propose to use a stochastic representation of the output from FCN for model registration.



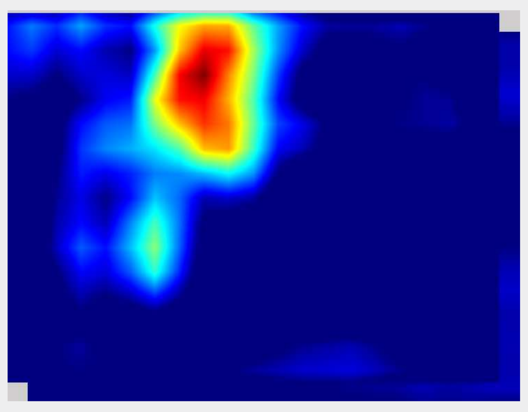
- We combine a global geometric descriptor with the soft segmentation output of the CNN to propose a fast and robust optimization process.



Scene Sampling

- The objective of this step is to sample a set of 4 points B = $\{b_1, b_2, b_3, b_4\}$ on the scene with a high joint probability of these points belonging to the object O_k

Input image (I)



Prior: $\pi(p_i \in O_k)$

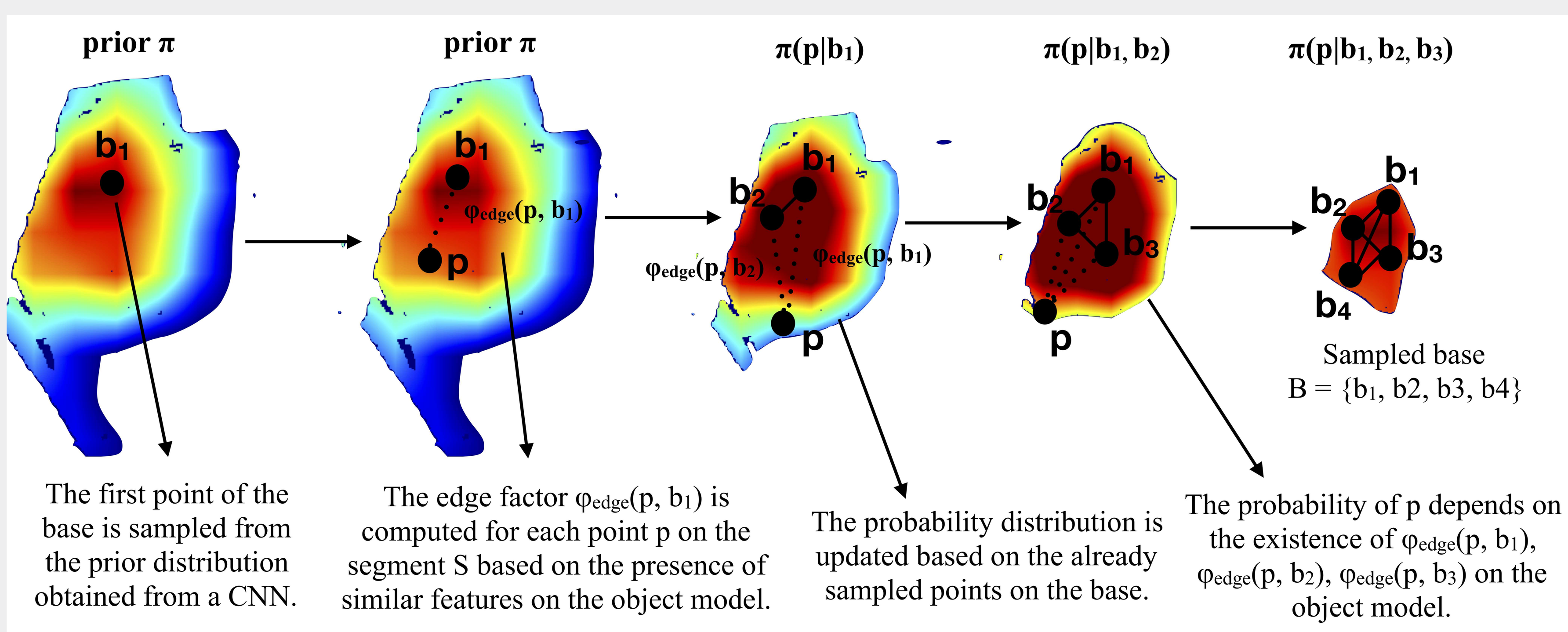
Object models $M_1, \dots M_n$

$$\Pr(B \rightarrow O_k) = \frac{1}{Z}\Pi_{i=1:4}\{\phi_{node}(b_i)\Pi_{j<i}\phi_{edge}(b_i, b_j)\} \quad (1)$$

$$\phi_{node}(b_i) = \pi(b_i \in O_k) \quad (2)$$

$$\phi_{edge}(b_i, b_j) = \begin{cases} 1, & \text{if } \mid MAP(M_k, \mathrm{PPF}(b_i, b_j)) \mid > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

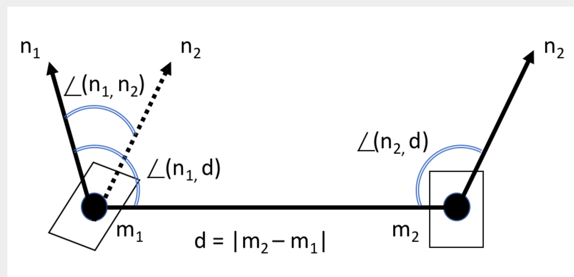
where, ϕ_{node} is the independent pixel probability from FCN, ϕ_{edge} is the pairwise probability computed from lookup table (MAP) generated in pre-processing step.



Model pre-processing

- Point pair features are computed for each pair of points on the object model.

$$PPF(m_1, m_2) = (\|\, d \,\|_2, \angle(n_1, d), \angle(n_2, d), \angle(n_1, n_2))$$

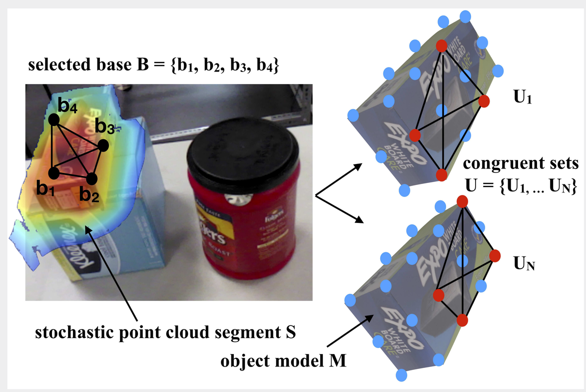


- A lookup table is generated for each object, that maps feature vectors to a set of pair of points that share the same point pair features.

$$MAP(M_k, f) : f \rightarrow \{(m_i, m_j) \in M_k \mid PPF(m_i, m_j) = f)\}$$

Congruent Set Matching

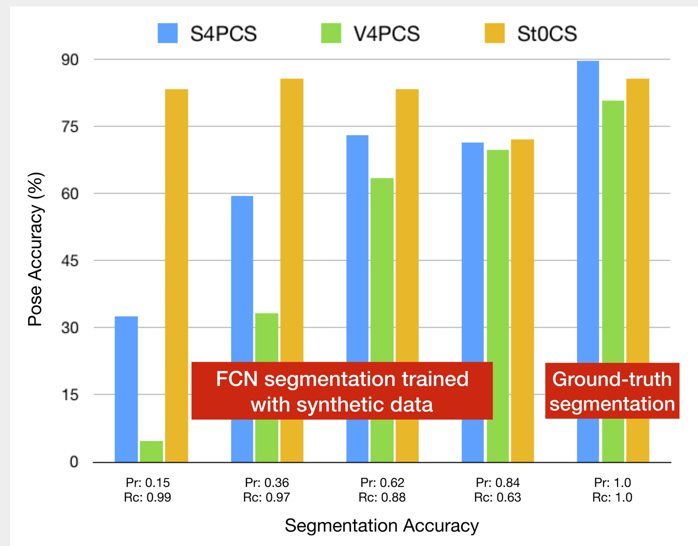
- For the sampled base, a set of congruent 4-points is found on the model.
- Congruency is determined by pair of points sharing the same features and intersecting line segments maintaining affine invariant ratios.
- `Pointset alignment score` is computed for each pose hypothesis generated from congruent sets.



Experiments

- We evaluate the accuracy of the pose with highest pointset alignment score.
- Area under the accuracy-threshold curve (AUC) is used to evaluate pose success on the YCB dataset.

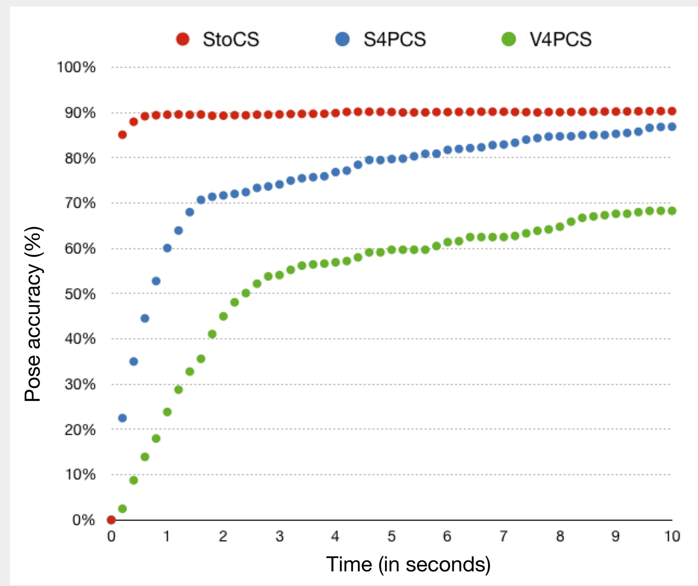
Method	Pose success	Time
PoseCNN	57.37%	0.2s
PoseCNN+ICP	76.53%	10.6s
PPF-Hough	83.97%	7.18s
Super4PCS	87.21%	43s
V4PCS	77.34%	4.32s
StoCS (OURS)	**90.1%**	**0.59s**



Robustness test with varying segmentation accuracy

- Mean rotation and translation error is reported on the Amazon picking challenge (APC) dataset for different registration techniques.

Method	Rot. error	Tr. error	Time
Super4PCS	8.83°	1.36cm	28.01s
V4PCS	10.75°	5.48cm	4.66s
StoCS (OURS)	**6.29°**	**1.11cm**	**0.72s**



Anytime results for different registration techniques

- Computation time for the different components of the registration process.

Method	Base Sampling	Set Extraction	Set Verification	#Set per base
Super4PCS	0.0045s	2.43s	19.98s	1957.18
V4PCS	0.0048s	1.98s	0.36s	46.61
StoCS (OURS)	**0.0368s**	**0.27s**	**0.37s**	**53.52**

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