A Randomized Ensemble Approach to Industrial CT Segmentation

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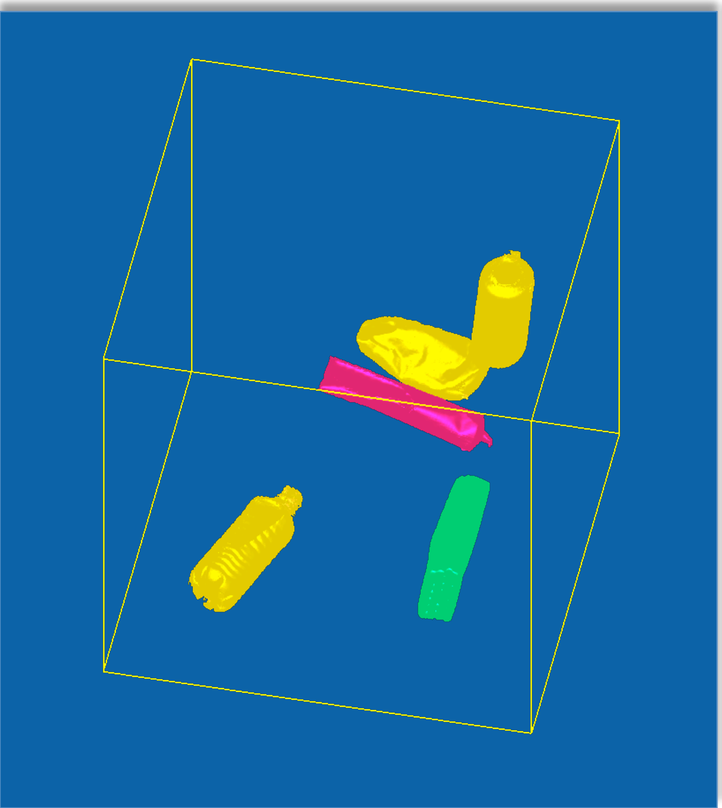

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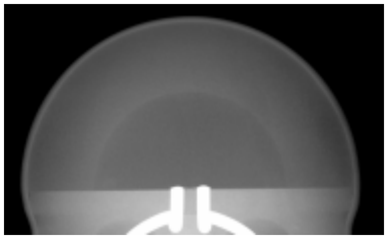
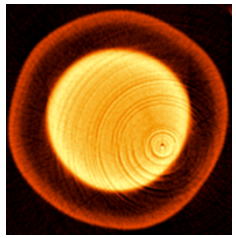
Project Goal: Advance Industrial CT Segmentation and Feature Detection Through Coupled Algorithms

- Non-Destructive Evaluation is central to many mission critical areas

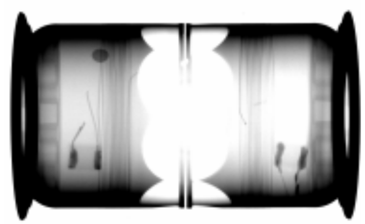
WCI **NIF** **PLS** **GS**



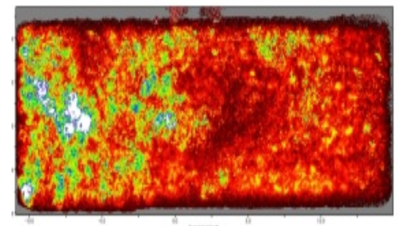
Stockpile Stewardship



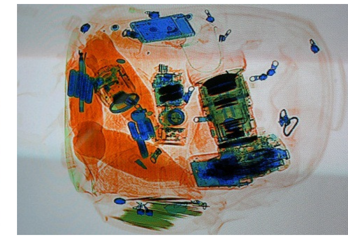
Nuclear Fuel



Hohlraum Target



Material Characterization



Transportation Security

- The goal is to identify objects, materials, and/or features in a noisy, cluttered, and compromised environment

- The traditional pipeline of reconstruction, segmentation, detection is well established but inflexible and often inadequate

Reconstruction → **Segmentation** → **Detection**

Image Segmentation Algorithms Can be Sub-Optimal Even with Exact Inference

Optimization Error

Algorithm

Estimation Error

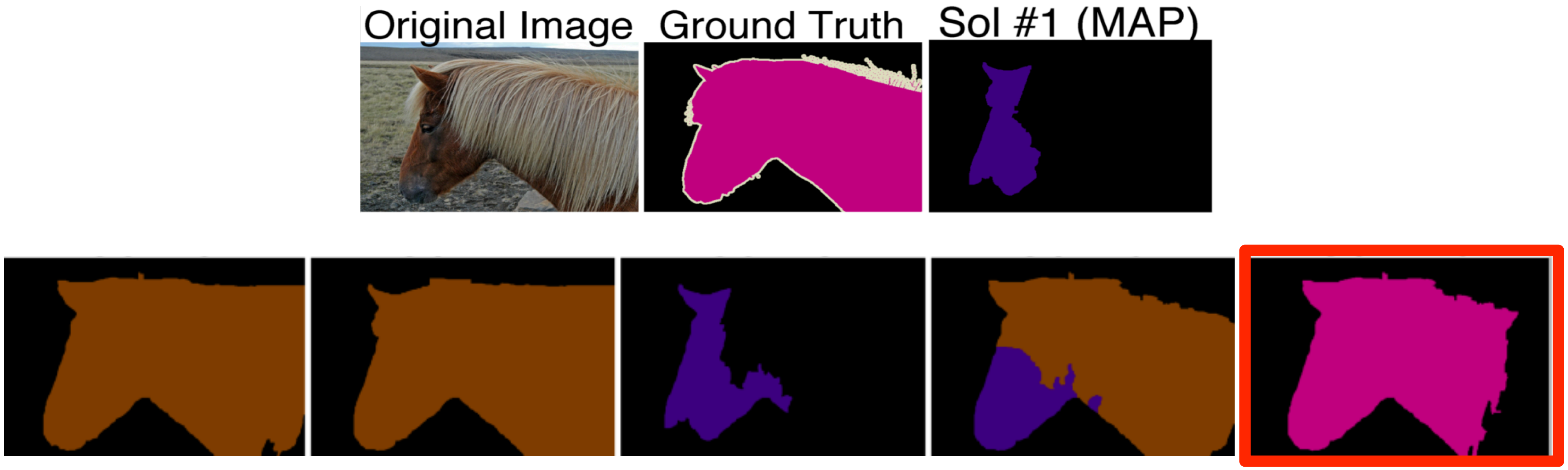
Finite Training

Approximation Error

Model Inadequacy

All Segmentation Algorithms Produce the Maximum A Posteriori (MAP) Solution for a given set of parameters

Ensemble-based Approaches Can Alleviate Some Shortcomings of Segmentation Algorithms



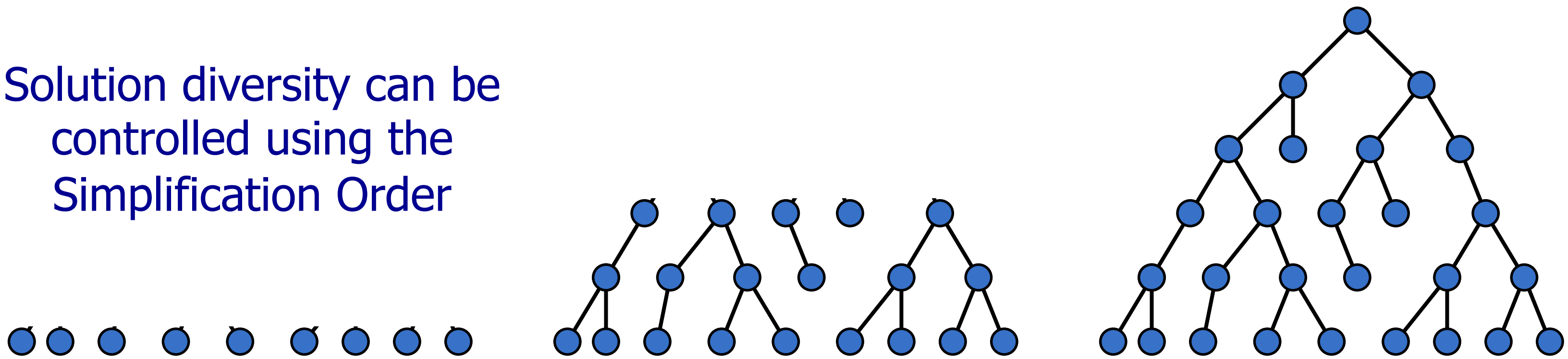
Multiple Hypotheses using a Sequential Forward Selection Strategy

- Better exploration of the solution space - Most Probable Vs. Diverse Hypotheses
- Hypotheses *re-ranking* using "Discriminative Features"
- Can be more robust to noise and artifacts than the MAP solution

Picking a Base Model and the Required Amount of Diversity is Very Challenging

- Industrial CT Images contain severe metal artifacts in form of streaks, blooming, or cupping
- Virtually all segmentation strategies rely on *features* (values, shape, etc.) to define *segments* (e.g. Region growing)
- We propose to use a simple greedy bottom-up simplification to generate the MAP solution

Solution diversity can be controlled using the Simplification Order



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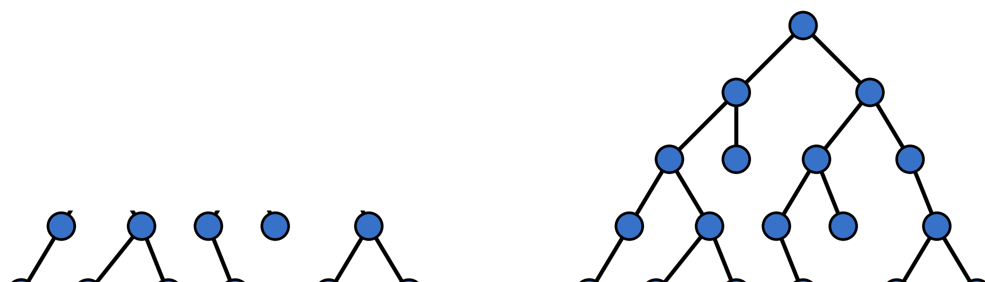
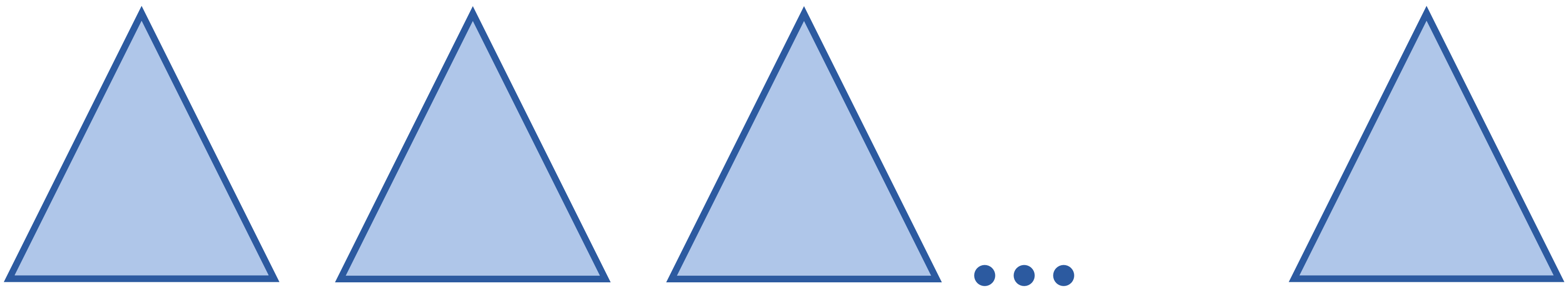


Avoid binding choices by exploring all potential hierarchies

Create Ensemble of Randomized Hierarchies to Explore the Space of Potentially Useful Segmentations

- Randomized simplification order to account for inevitable mistakes



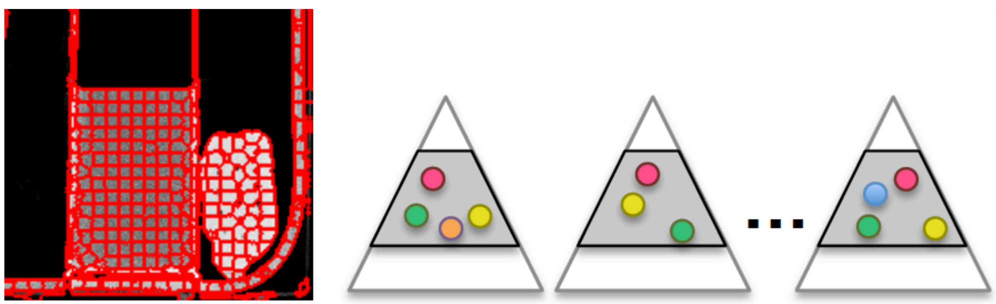
- Instead of picking the "best" hypothesis choose "best" segments
  - Labeled training data (as done by existing security systems)
- Fuse information from selected segments using consensus segmentations
- Highly flexible approach to address segmentation and related challenges by easily integrating semantic information

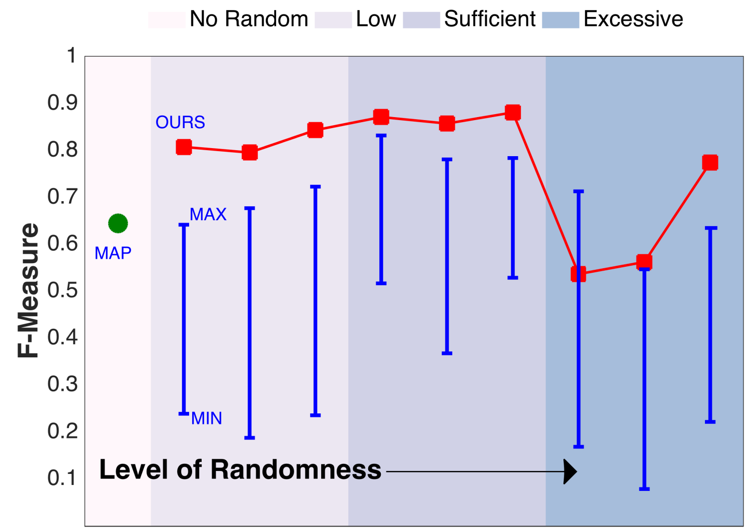
Problem: Improved Segmentation of Airport Luggage Into Multiple Threat Classes

- Task: Find and classify multiple threats and pseudo-threats in a collection of bags provided by the ALERT Center of Excellence
- Data: ~200 scans containing:
  - Background: clothes, water, books, etc.
  - Threats: Saline solution, modeling clay, rubber sheets
  - Pseudo-threats: threat materials in small quantities
- Challenge:
  - Poor reconstruction leading to difficult segmentation and poor detection
- Solution:
  - Improve segmentation of threat objects using labeled training data

Step 1: Build Multiple Segmentation Hypotheses

- Construct multiple hierarchical segmentations by randomizing the merge order

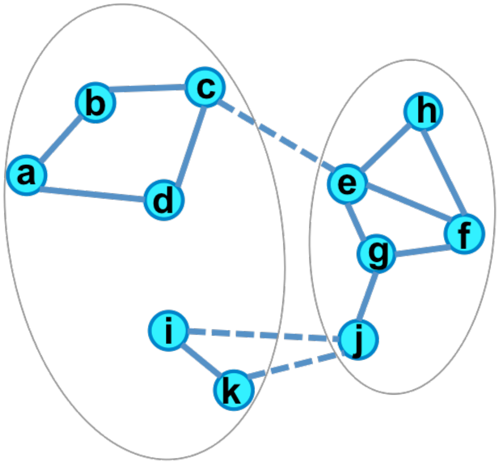




- Amount of randomness balances the required number of hierarchies and the amount of diversity

Step 2: Select Candidate Segments using Discriminative Features

- Build discriminative features for all segments in a hierarchy based on intensity and shape characteristics
  - Intensity histogram, shape histogram, surface-to-volume ratio, area
  - Local Discriminant Embedding with supervised data can effectively infer the underlying manifold



$$\max_{\mathbf{V}} \frac{\overbrace{\mathrm{Tr}[\mathbf{V}^T\mathbf{X}^T\mathbf{L}'\mathbf{X}\mathbf{V}]}^{\text{inter-class}}}{\underbrace{\mathrm{Tr}[\mathbf{V}^T\mathbf{X}^T\mathbf{L}\mathbf{X}\mathbf{V}]}_{\text{intra-class}}}$$

- We adopt a reference-based classification scheme to determine the segment labels

$$S(r, g_i^k) = 1 - \frac{\overbrace{\gamma}^{\text{lower incomplete gamma}}\left(\frac{k}{2}, \overbrace{\frac{d(r,g_i^k)}{2}}^{\chi^2 \text{ distance}}\right)}{\underbrace{\Gamma}_{\text{gamma}}\left(\frac{t}{2}\right)}$$

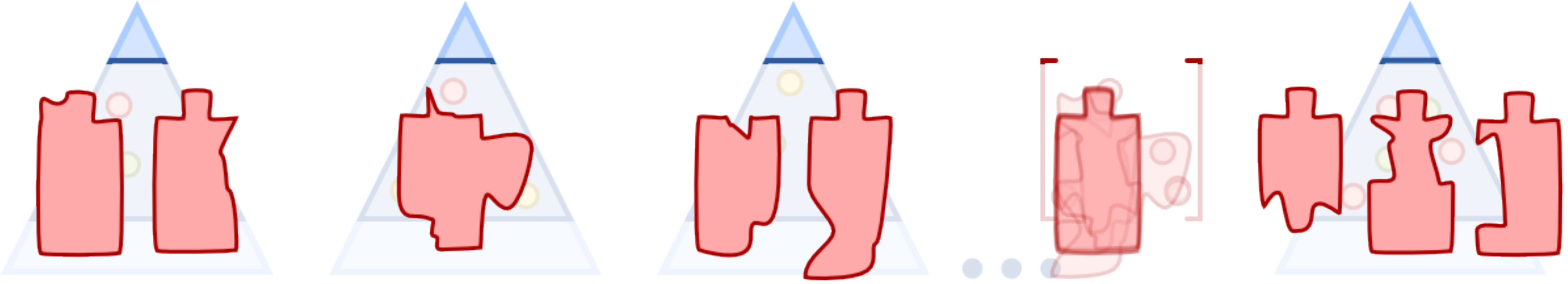
Step 3: Consensus Inference using GraphCuts

- Identify top-ranked segments for each object, and obtain per-object "best" segmentation using consensus inference
- We formulate a graphcut optimization to obtain the final segmentation

Unary Potential

Pairwise Potential

$$\sum_{r_i^0 \in V_0} F_d(\alpha_i) + \lambda \sum_{e_{i,j}^0 \in E_0} F_s(\alpha_i, \alpha_j)$$



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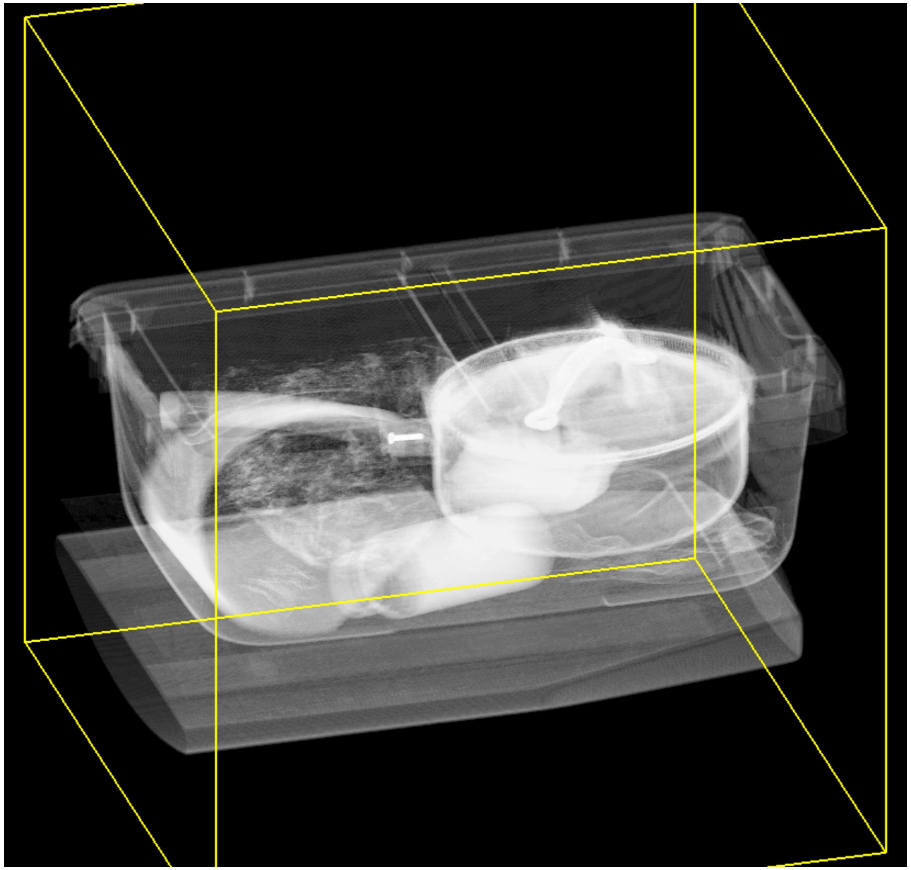
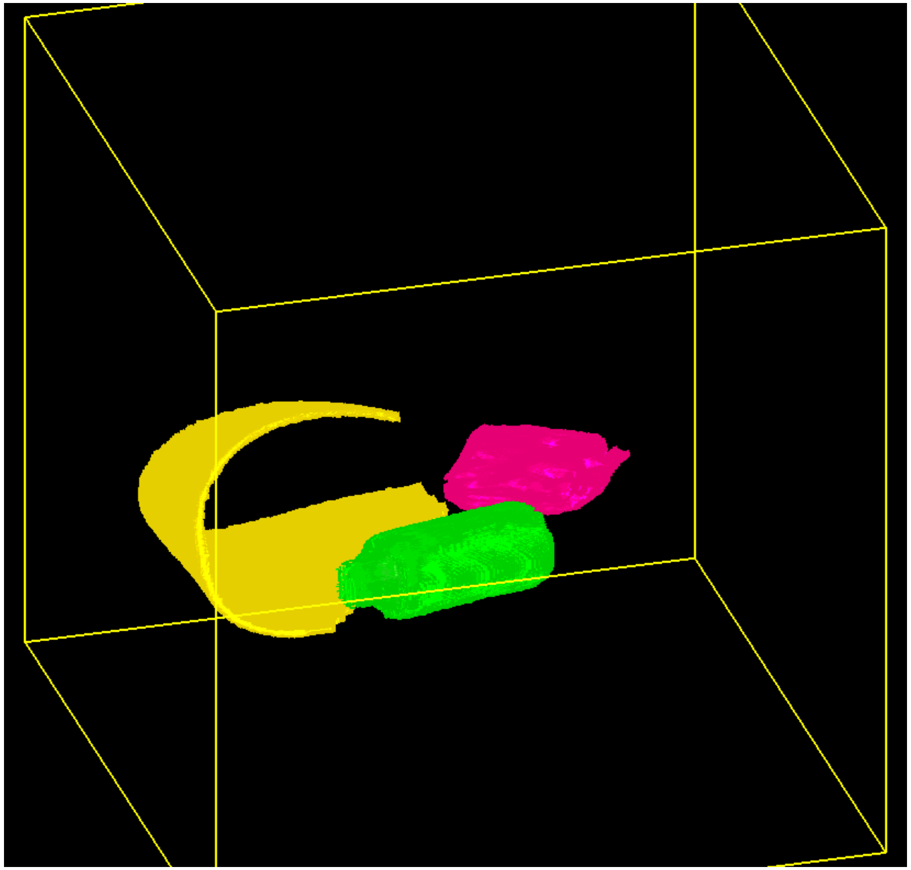
Significantly improves the segmentation performance by:

- Compensating for reconstruction artifacts through randomization
- Allowing detection on a wide range of levels in the hierarchies

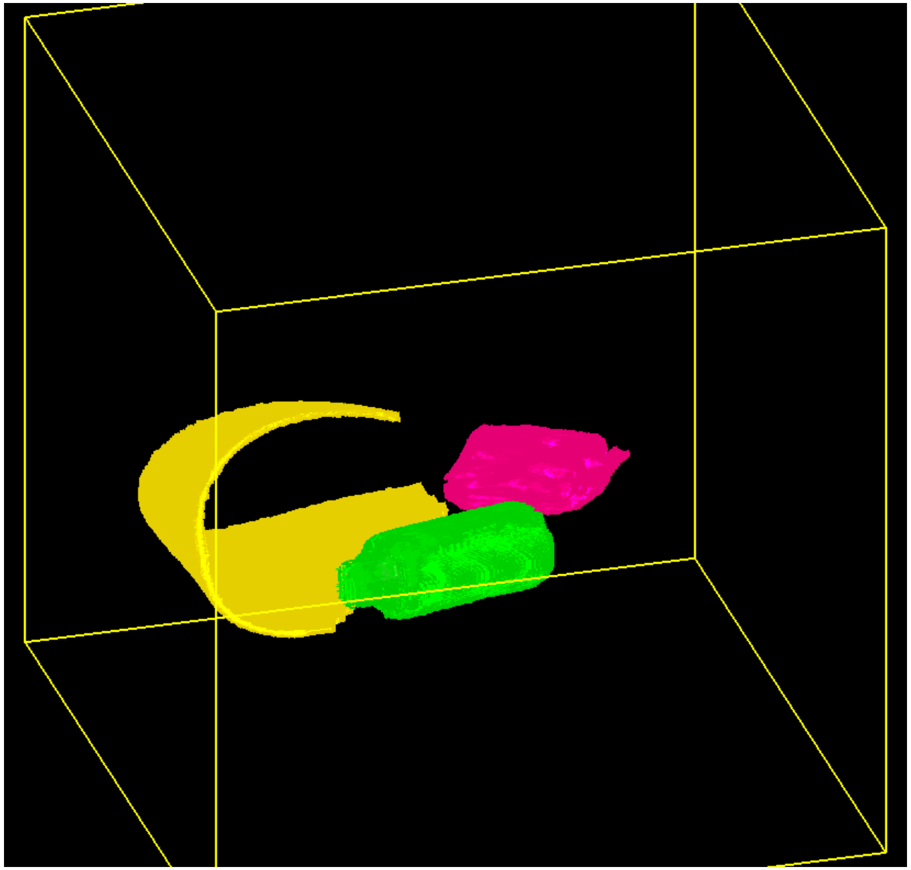
Ensemble Segmentations Out-Perform Existing Techniques





Ground Truth

Ensemble Segmentations Out-Perform Existing Techniques



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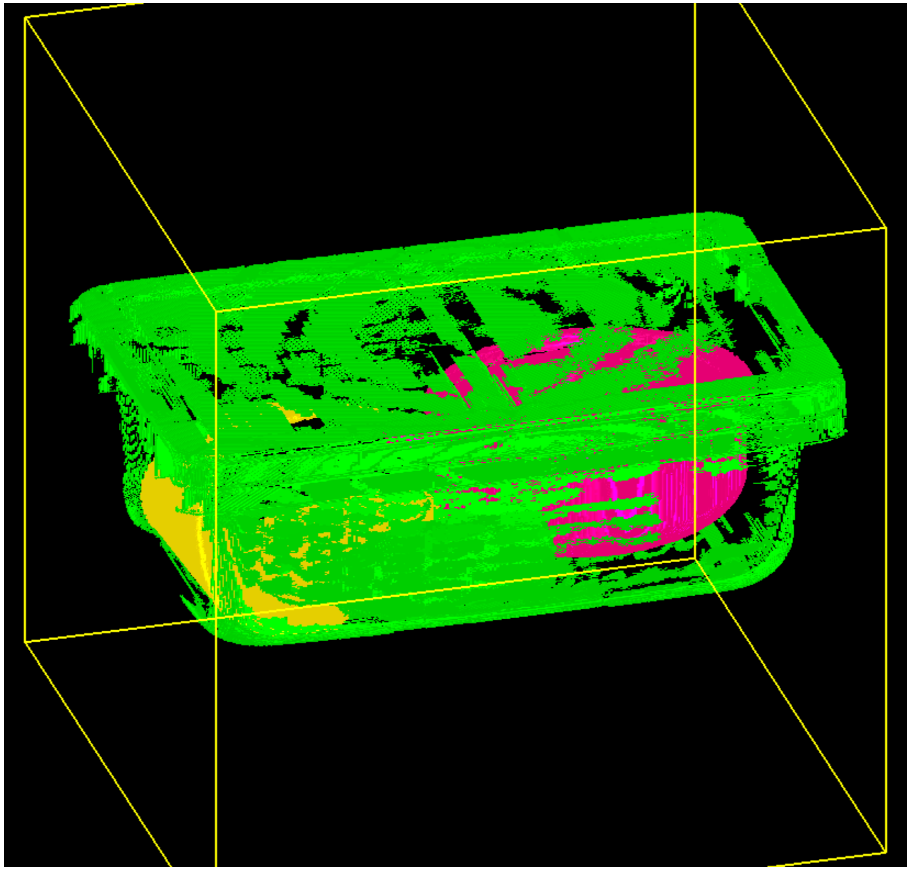
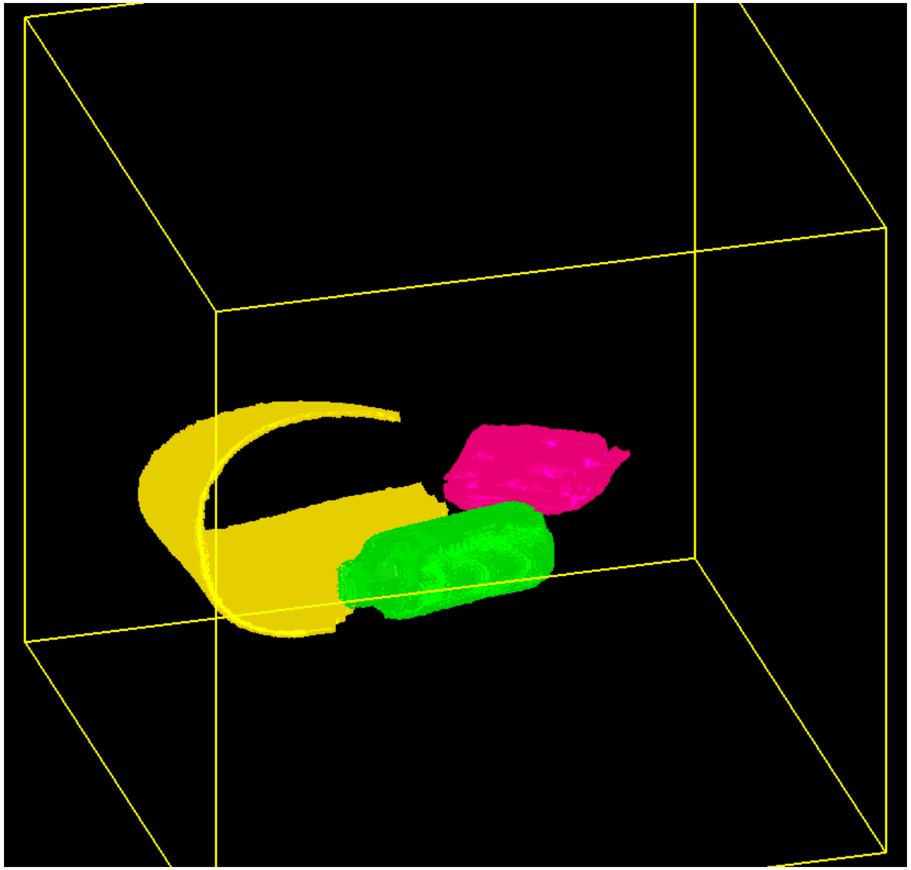


Hand-Tuned Region Growing

Ensemble Segmentations Out-Perform Existing Techniques



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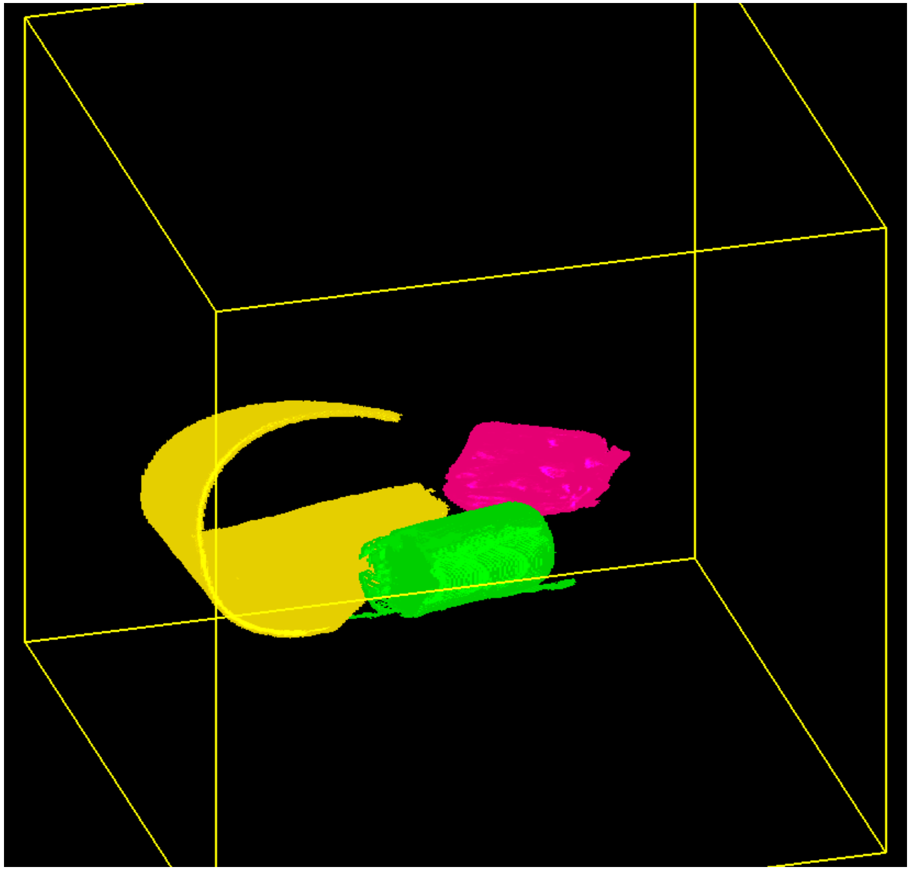
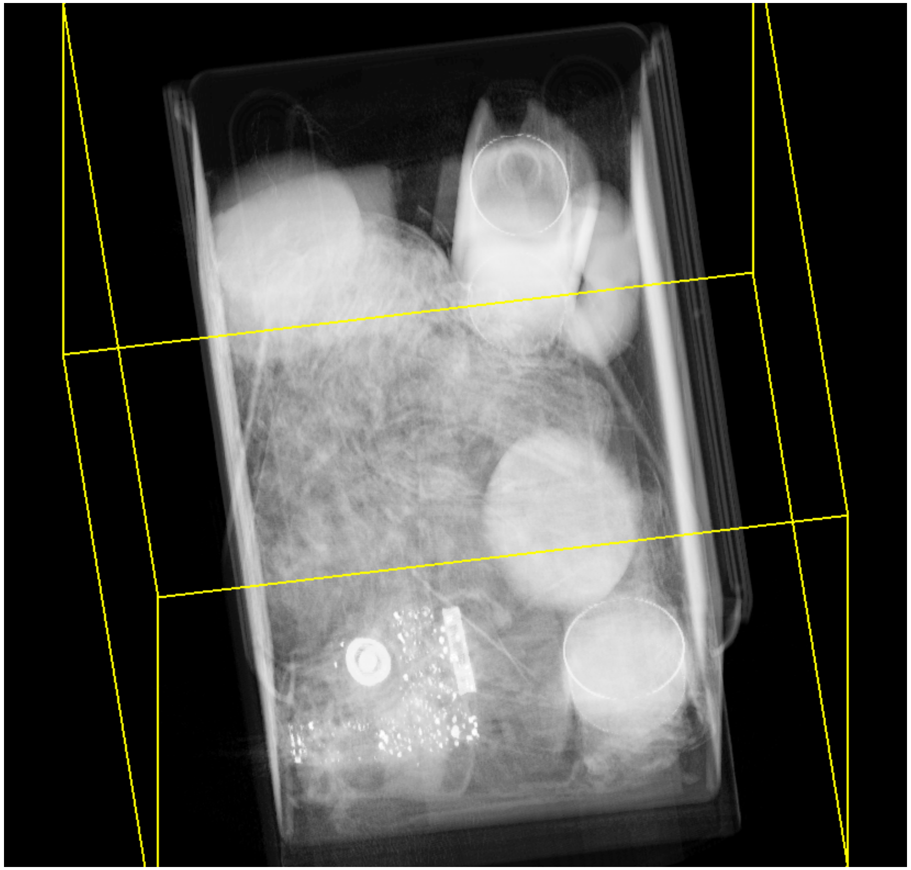
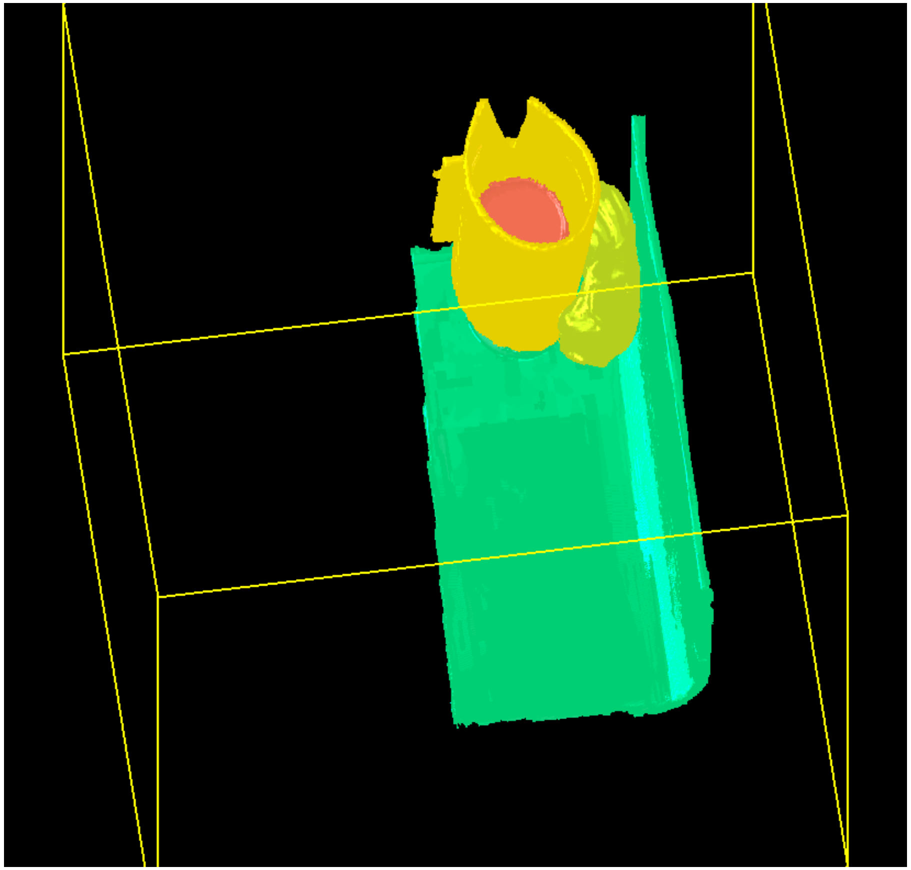


Our Approach

Ensemble Segmentations Out-Perform Existing Techniques





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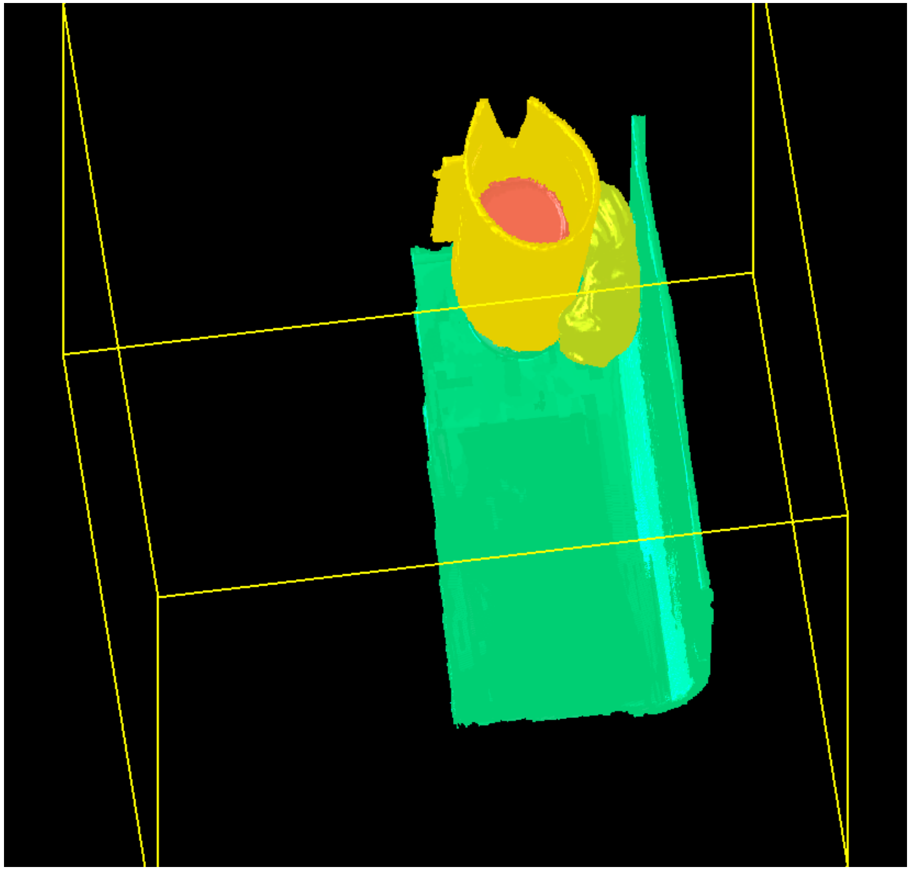

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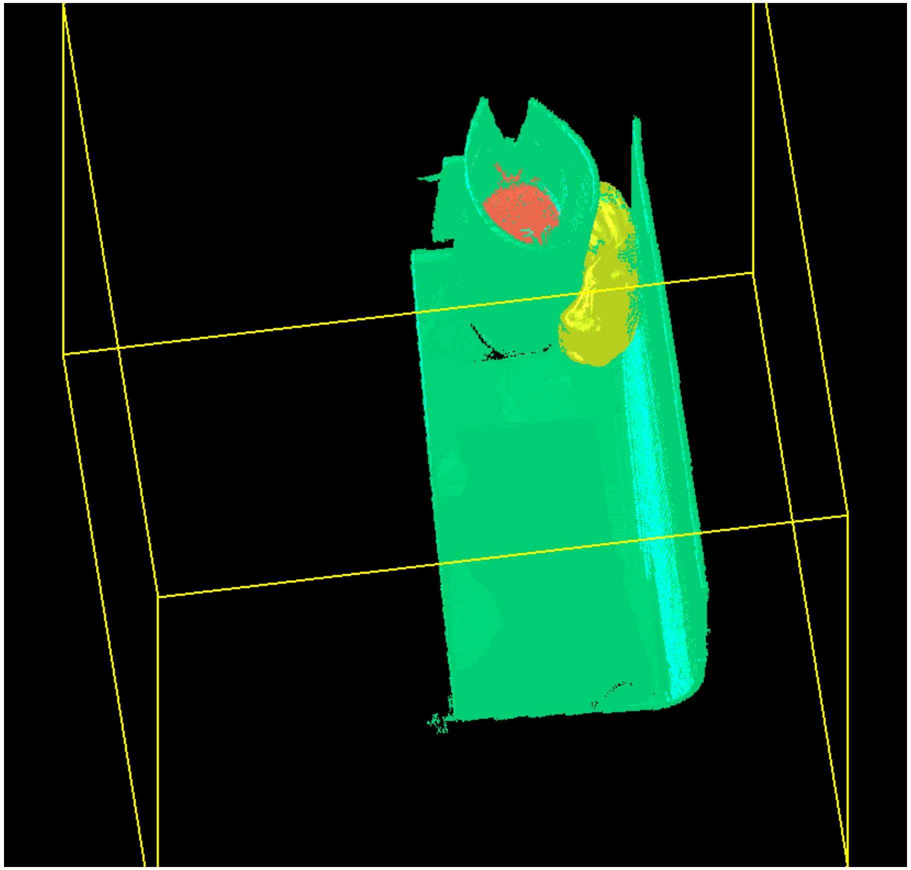

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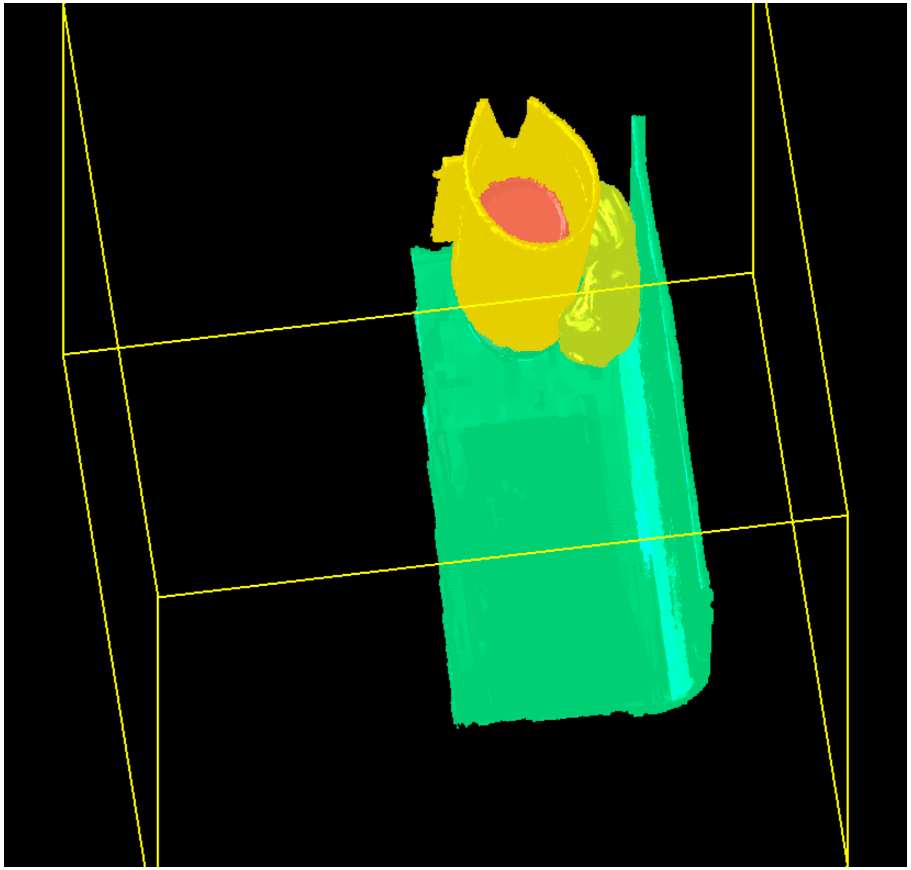

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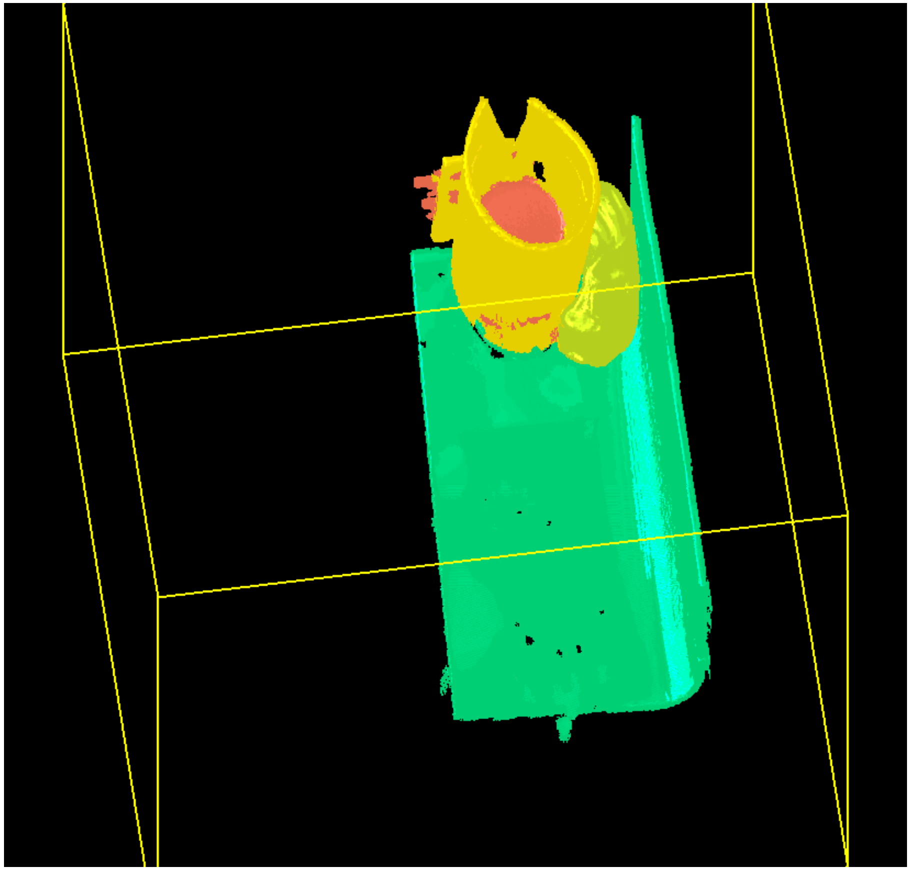

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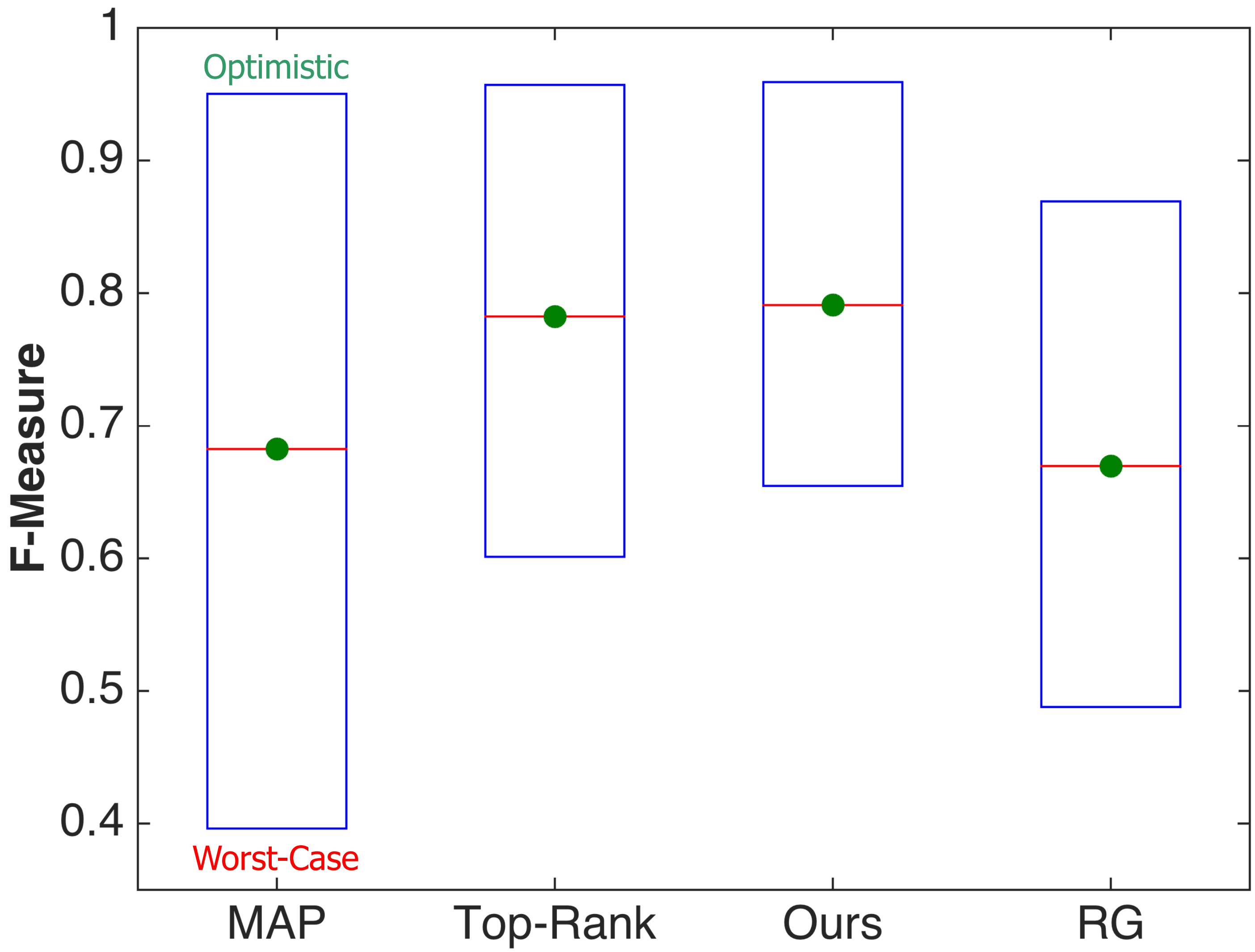

Summary

- Independent of the specific low or high level features – Promising results on natural images and CT volumes
- Using appropriate strategies for creating diverse hypotheses, even a simple base model is sufficient to build an effective ensemble
- Highly robust against noise and artifacts – Worst-case behavior is significantly superior to hand-tuned approaches
- Presents opportunities to integrate semantic knowledge, i.e., to bridge the gap between *segmentation* and *detection*