

SemanticPaint

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Outline

- ① Introduction
- ② State of the Art
- ③ Pipeline
- ④ Results
- ⑤ Discussion and Outlook

Introduction

State of the Art

Scene Understanding

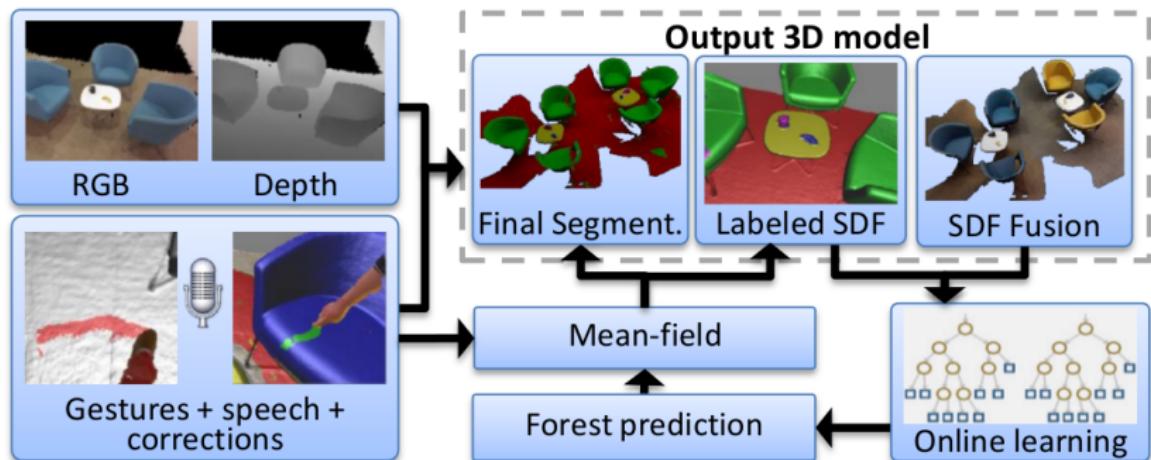
Who	What	How
Valentin et. al. 2013	inference on mesh from TSDF	RGB and geom. features CRF segmentation
Kim et. al. 2013	reconstruction segmentation	Voxel-based CRF with visibility constraints
Herbst et. al. 2014	reconstruction segmentation	online model updates change detection

Model-based SLAM

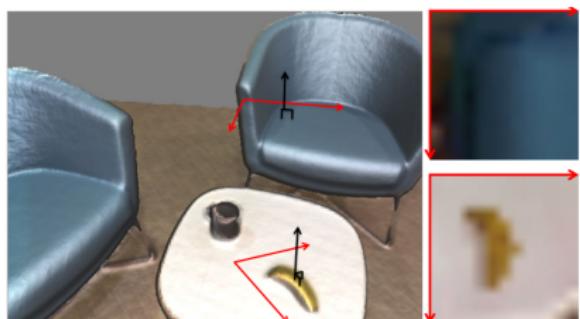
Who	What	How
Newcombe et. al. 2011	online 3D SLAM	model-based tracking global TSDF volume
Salas-Moreno et al. 2013	object-level SLAM	offline object database pose-object graph
Pradeep et.al. 2013	3D reconstruction with 1 RGB camera	sparse tracking and stereo reconstruction on par with KinectFusion

Pipeline

Pipeline Overview



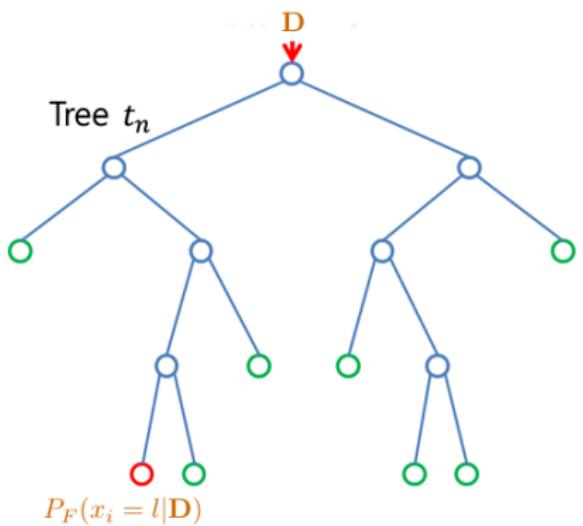
Voxel Oriented Patch features


$$(\mathbf{p} - \mathbf{p}_i) \cdot (\mathbf{n})_i = 0$$

$r \times r, r = 13px$ with $10 \frac{mm}{pixel}$
CIELab
Rotated to dominant gradient direction

Figure: Colours shown in RGB for illustration purposes.

Random Forest



bagged trees
greedy training
bootstrapped data
off-line, all data at once
voting for final result
 $(i, l) \in \mathcal{S}$ - (voxel, label) pairs
 $f(i, \theta)$ - split functions
 Θ - distribution of split functions
 $P_F(x_i = l|\mathbf{D})$ - class conditional probability

Figure: Single tree

Streaming Random Forest

- Node n: Reservoir R_n with a list of samples T_n , $|T_n| \leq K$
- First K samples added
- Current samples swapped with new ones with decreasing probability
- Split node if: $|R_n| > N$

Information Gain:

$$G(R_n, R_n^L, R_n^R) = H(R_n) - \sum_{d \in \{L, R\}} \frac{|R_n^d|}{|R_n|} H(R_n^d) \quad (1)$$

Shannon Entropy:

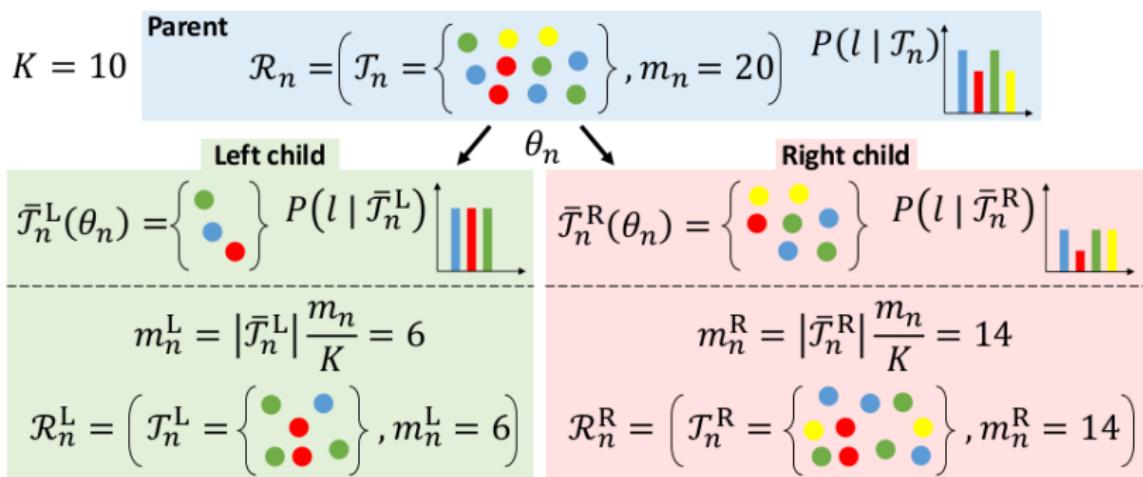
$$H(R_n) = - \sum_{(l,i) \in T_n} p(c_i = l) \log p(c_i = l) \quad (2)$$

$H(R_n)$ computed from a node's class distribution

SRF - Reservoir Splitting

m_n - number of samples seen at node n

$P(l|T_n)$ - normalized class distribution of R_n



Dynamic Conditional Random Field

Joint class probability distribution for the volume \mathcal{V} :

$$P(\mathbf{x}|\mathbf{D}) = \prod_{i \in \mathcal{V}} \left(\psi_i(x_i) \prod_{j \in \mathcal{E}_i} \psi_{ij}(x_i, x_j) \right) \quad (3)$$

Labeling Energy at time t :

$$E_t(\mathbf{x}) = \sum_{i \in \mathcal{V}} \left(\phi_i(x_i) + \sum_{j \in \mathcal{E}_i} \phi_{ij}(x_i, x_j) \right) + K \quad (4)$$

where:

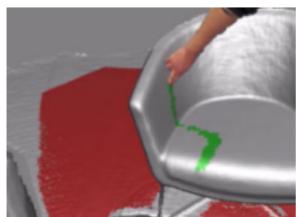
$\phi_i(x_i)$ - cost of assigning a label

$\phi_{ij}(x_i, x_j)$ - cost of assuming different labels

\mathcal{E}_i - neighbourhood of voxel i

CRF - User Interactions

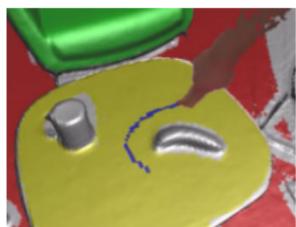
Touching:



$$\phi_i(l) = \begin{cases} 0 & \text{if } l = l_T \\ \infty & \text{otherwise} \end{cases} \quad (5)$$

T — touched pixels

Encircling:



$$\phi_i(l) = \begin{cases} \log P_E(fg|\mathbf{a}_i) & \text{if } l = fg \\ \log(1 - P_E(fg|\mathbf{a}_i)) & \text{if } l = bg \end{cases} \quad (6)$$

P_E from GMM
fg — inside
bg — outside

CRF - Predictions and Smoothnes

Predictions:

$$\phi_i(l) = -\log P_F(x_i = l | \mathbf{D}) \quad (7)$$

P_F — Streaming Random Forest prediction

Smoothnes:

$$\phi_{ij}(x_i, x_j) = \theta_p e^{-||\mathbf{p}_i - \mathbf{p}_j||} + \theta_a e^{-||\mathbf{a}_i - \mathbf{a}_j||} + \theta_n e^{-||\mathbf{n}_i - \mathbf{n}_j||} \quad (8)$$

$\theta_p, \theta_a, \theta_n$ — paramters

\mathbf{p}_i — position

\mathbf{a}_i — appearance

\mathbf{n}_i — normal vector

Mean-Field Inference

$P(\mathbf{x})$ approximated by $Q(\mathbf{x})$ under $KL(Q||P)$:

$$Q_i^t(l) = \frac{1}{Z_i} e^{M_i(l)}, \quad t = 1, \dots, T \quad (9)$$

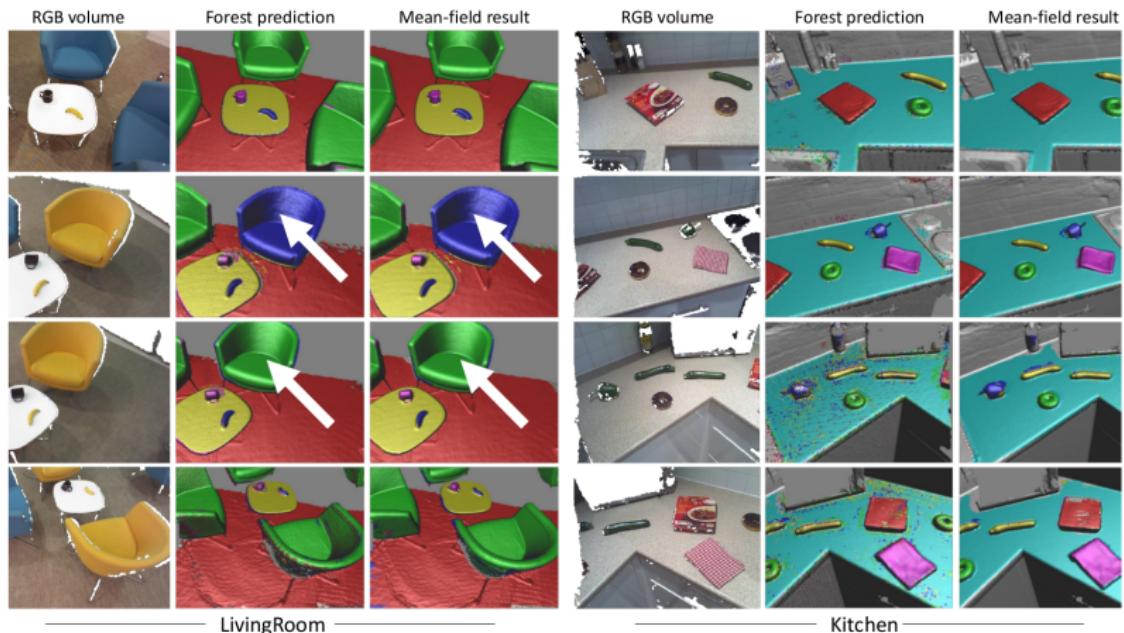
$$M_i(l) = \phi_i(l) + \sum_{l' \in \mathcal{L}} \sum_{j \in \mathcal{E}_i} Q_j^{t-1}(l') \phi_{ij}(l, l') \quad (10)$$

Frame at time t initialized with:

$$\tilde{Q}_i^t(x_i) = \gamma Q_i^{t-1}(x_i) + (1 - \gamma) P_F^{t-1}(x_i = l | \mathbf{D}), \quad \gamma \in [0, 1] \quad (11)$$

Results

Segmentation



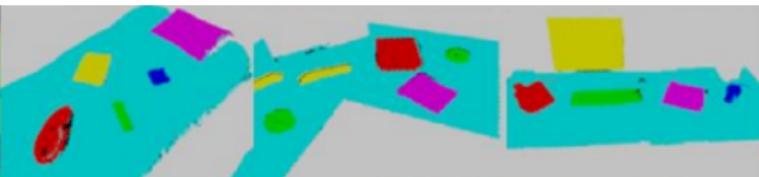
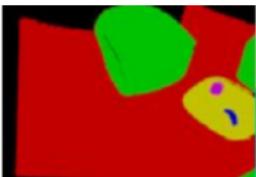
Segmentation

Table: Segmentation Results

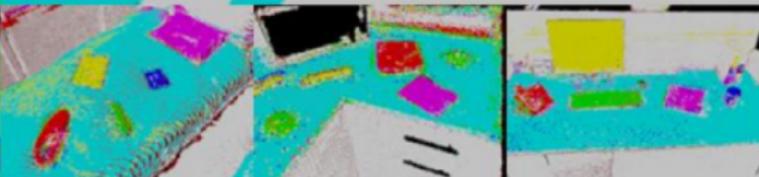
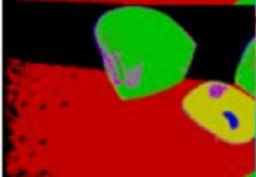
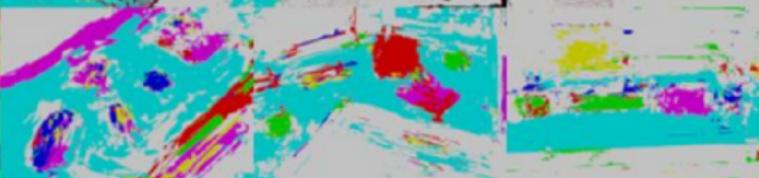
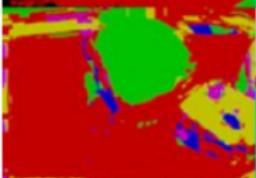
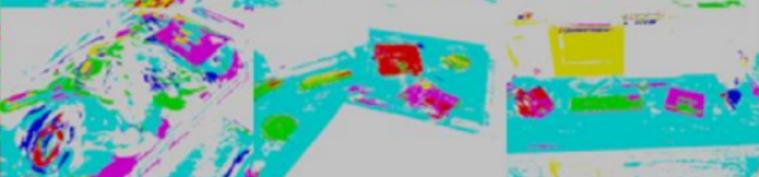
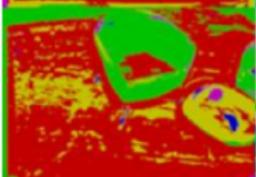
Component	LivingRoom	Bedroom	Kitchen	Desk	Average
User Interaction	99.35%	97.61%	96.09%	97.73%	97.7%
Forest Prediction	94.57%	88.31%	82.58%	90.29%	88.94%
Final Inference	96.26%	95.19%	90.69%	95.55%	94.42%

Features

Ground truth



VOP

Diff. of
RGB
meansDepth
probe

Features

Table: Feature Comparison

Feature	Living Room	Bedroom	Kitchen	Desk	Average
VOP	94.57%	88.31%	82.58%	90.29%	88.94%
△ RGB mean	80%	71.84%	76.29%	73.42%	75.39%
Depth Probe	77.54%	61.79%	84.9%	68.9%	73.06%
Color Probe	56.39%	65.68%	60.77%	60.74%	60.9%
SURF	43.74%	67.12%	57%	58.13%	56.5%
SPIN	58.77%	43.22%	48.41%	36.1%	46.63%

Streaming Random Forest

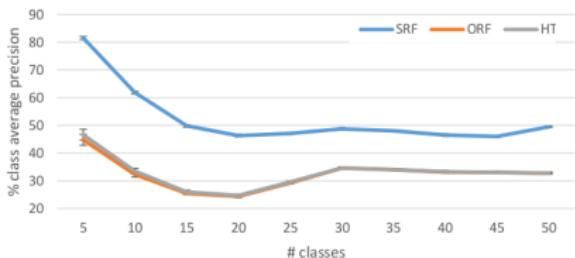


Figure: Average Precision

Data:
300 objects
51 classes
full revolution
3 points of view

SRF - Streaming Random Forest
ORF - Online Random Forest
HT - Hoeffding Tree

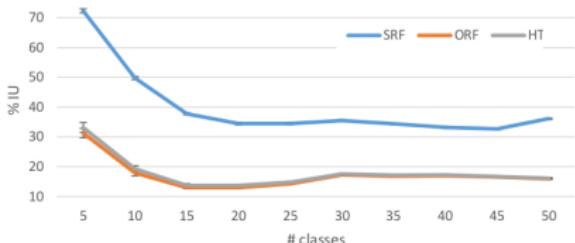


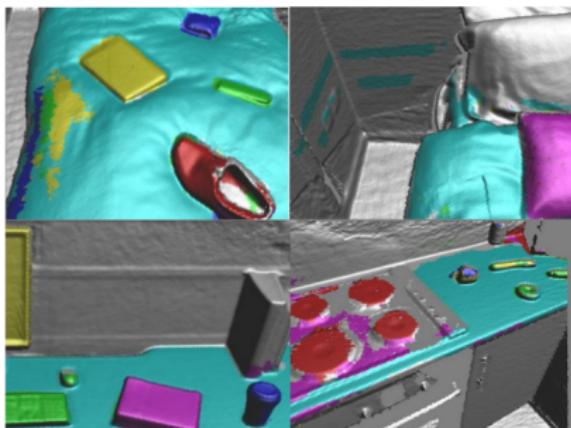
Figure: Intersection/Union

Discussion and Outlook

Summary

- customized models of 3D environments
- fully interactive
- online and real time
- no pretraining

Failures



- bleeding
- illumination change
- viewpoint change

Figure: Failure cases.

Future Work

- discriminative geometrical features
- priors for class properties (vertical walls)
- class priors for different environments
- outdoor environments
- better scalability

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Q&A?

