

SemanticPaint

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Outline

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- **5** Discussion and Outlook



Introduction



Introduction



State of the Art



Acquisition and Reconstruction

| Who | What | How |
|-----------------------|-----------------------|-----------------------------|
| Levoy et. al. 2000 | world-scale 3D models | offline, from online images |
| Newcombe et. al. 2011 | online 3D scanning | KinectFusion |
| Pradeep et.al. 2013 | 3D reconstructiona | sparse tracking and |
| | with 1 RGB camera | stereo reconstruction |
| | | on par with KinectFusion |



Scene Understanding

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



Pipeline



Voxel Oriented Patch features



Figure: Colours shown in RGB for illustration purposes.

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

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



Random Forest

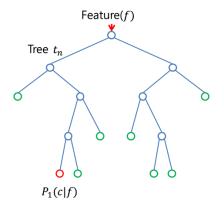


Figure: Single tree

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



Streaming Random Forest

Information Gain:

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

Shannon Entropy:

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



SRF - Reservoir Splitting

$$\mathcal{R}_{n} = \left(\mathcal{T}_{n} = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\}, m_{n} = 20 \right) \begin{array}{c} P(l \mid \mathcal{T}_{n}) \\ \hline \downarrow \\ \hline \mathcal{T}_{n}^{L}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{L}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right\} P(l \mid \bar{\mathcal{T}}_{n}^{R}) \\ \hline \mathcal{T}_{n}^{R}(\theta_{n}) = \left\{\begin{array}{c} \bullet & \bullet \\ \bullet & \bullet \\ \end{array}\right$$



Dynamic Conditional Random Field

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

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



CRF - User Interactions

Touching:

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

Encircling:

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



CRF - Predictions and Smoothnes

Predictions:

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

Smoothnes:

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



Mean-Field Inference

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

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

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

Frame at time t initialized with:

$$\widetilde{Q}_{i}^{t}(x_{i}) = \gamma Q_{i}^{t-1}(x_{i}) + (1 - \gamma)P_{F}^{t-1}(x_{i} = l|\mathbf{D}), \ \gamma \in [0, 1]$$
 (11)



Results



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

Table: Feature Comparison

| Feature | LivingRoom | Bedroom | Kitchen | Desk | Average |
|----------------------|------------|---------|---------|--------|---------|
| VOP | 94.57% | 88.31% | 82.58% | 90.29% | 88.94% |
| \triangle 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

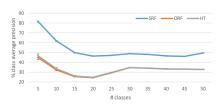


Figure: Average Precision

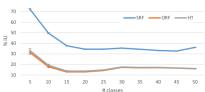


Figure: Intersection/Union

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

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





Discussion and Outlook



Summary

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



Failures

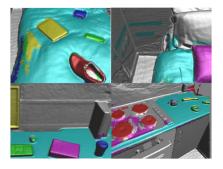


Figure: Failure cases.

- bleeding
- illumination change
- viewpoint change



Future Work

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



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