SemanticPaint

Adam Kosiorek

Advisor: M.Eng. Keisuke Tateno

10.12.2015

Outline

Introduction

State of the Art

Scene Understanding

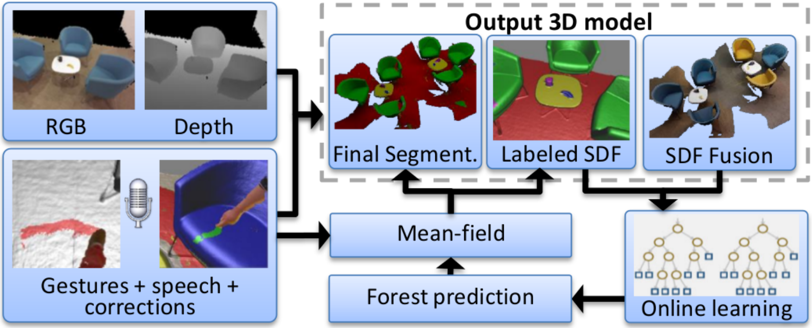
Who	What	How
Valentin et. al. 2013	inference on mesh from TSDF	RGB and geom. features CRF segmentation
Kim et. al. 2013	reconstruction segmentation	Voxel-based CRF with visibility contraints
Herbst et. al. 2014	reconstruction segmentation	online model updates change detection

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

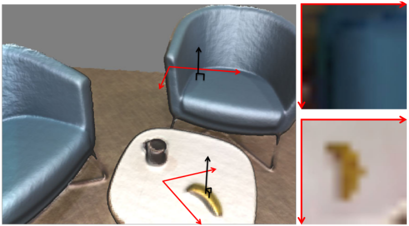


Figure: Colours shown in RGB for illustration purposes.

$(\mathbf{p} - \mathbf{p}_i) \cdot (n)_i = 0$
$r \times r$, $r = 13px$ with $10\frac{mm}{pixel}$
CIELab
Rotated to dominant gradient direction

Random Forest

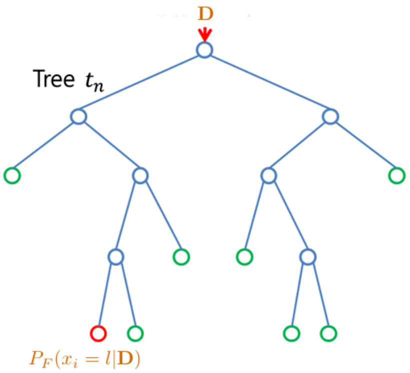


Figure: Single tree

bagged trees
greedy training
bootstraped 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

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:

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

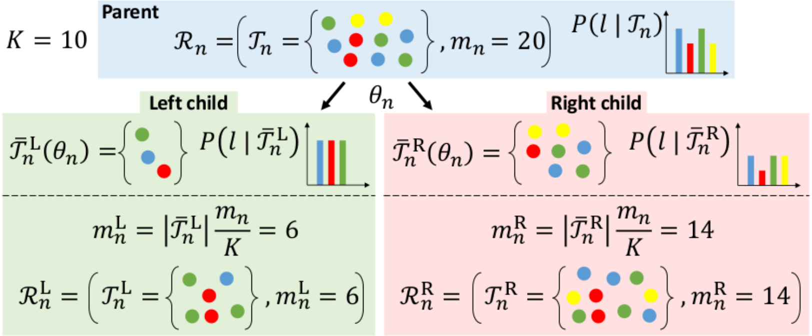
Shannon Entropy:

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

$H(R_n)$ 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 $\mathcal{V}$:

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

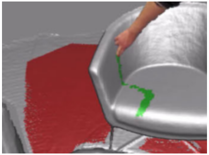
Labeling Energy at time t:

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

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

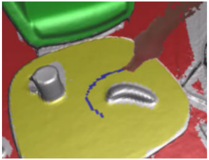
Touching:



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

T — touched pixels

Encircling:



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

P_E from GMM
fg — inside
bg — outside

CRF - Predictions and Smoothnes

Predictions:

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

P_F — Streaming Random Forest prediction

Smoothnes:

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

θ_p, θ_a, θ_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 $KL(Q||P)$:

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

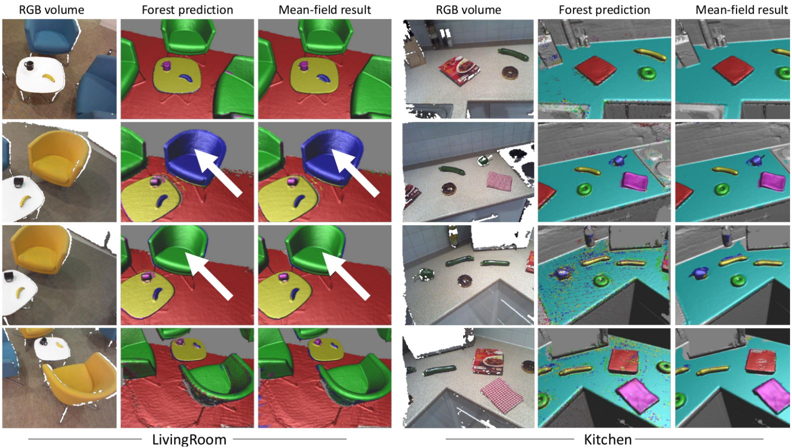
$$M_i(l) = \phi_i(l) + \sum_{l' \in \mathcal{L}} \sum_{j \in \mathcal{E}_i} Q_j^{t-1}(l') \phi_{ij}(l, l') \tag{10}$$

Frame at time t initialized with:

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

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%

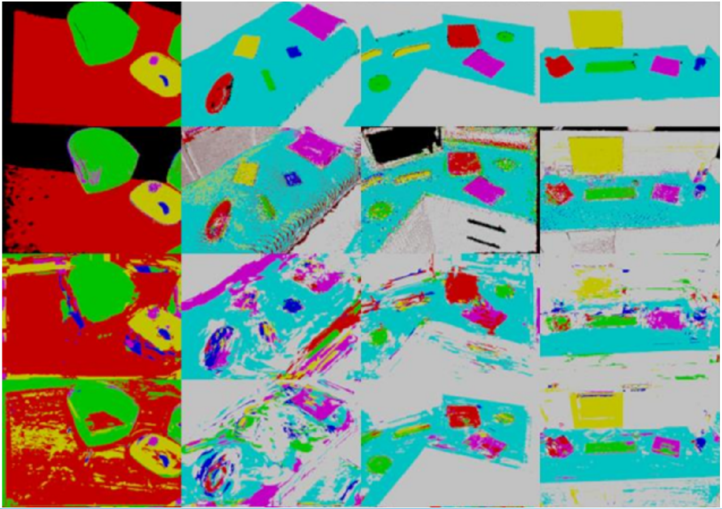
Features

Ground truth

VOP

Diff. of RGB means

Depth probe



Features

Table: Feature Comparison

Feature	LivingRoom	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

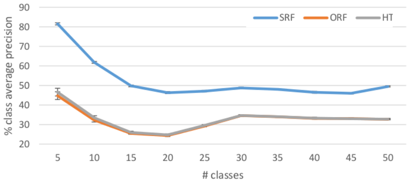


Figure: Average Precision

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

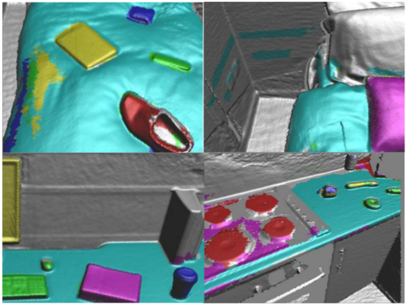


Figure: Failure cases.

- bleeding
- illumination change
- viewpoint change

Future Work

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

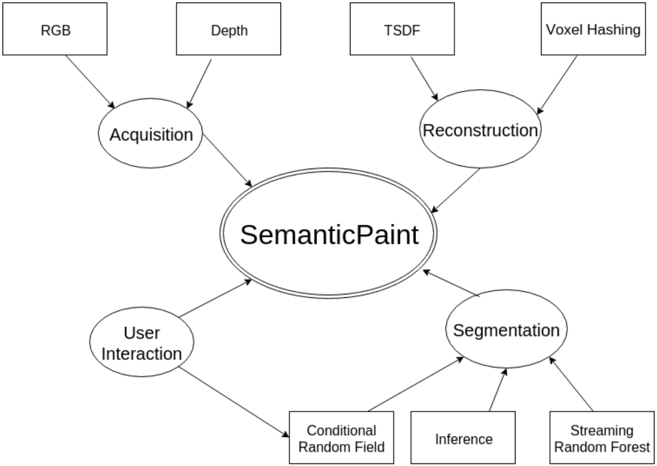
References

- Roberts, L. G. 1963. Machine perception of three-dimensional solids. Ph.D. thesis, Massachusetts Institute of Technology.
- Kim, B.-S. et. al. 2013. 3D scene understanding by voxel-CRF. In Proc. ICCV.
- Pradeep, V. et. al. 2013. Monofusion: Real-time 3D reconstruction of small scenes with a single web camera. In Proc. ISMAR.
- Herbst, E. et.al. 2014. Toward online 3-d object segmentation and mapping. In IEEE International Conference on Robotics and Automation (ICRA).
- Valentin, J. P. et. al. 2013. Mesh based semantic modelling for indoor and outdoor scenes. In Proc. CVPR.
- Salas-Moreno, R. F. et. al. 2013. SLAM++: Simultaneous localisation and mapping at the level of objects. In Proc. CVPR.
- Newcombe , R. A. et. al. 2011. KinectFusion: Real-time dense surface mapping and tracking. In Proc. ISMAR.
- Curless , B. et. al. 1996. A volumetric method for building complex models from range images. In Proceedings of the 23rd annual conference on Computer graphics and interactive techniques. ACM, 303312.
- Niessner , M. et. al. 2013. Real-time 3D reconstruction at scale using voxel hashing. ACM TOG 32, 6

References cont'd

- Saffari , A. et. al. 2009. On-line random forests. In IEEE ICCV Workshop.
- Vitter , J. S. 1985. Random sampling with a reservoir. ACM TOMS 11, 1.
- Lower , D. G. 1999. Object recognition from local scale-invariant features. In Proc. ICCV.
- Lafferty , J. et. al. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data.
- Ktahenbl, P. et. al. 2011. Efficient inference in fully connected CRFs with Gaussian edge potentials. In NIPS.
- Koller , D. et.al , N. 2009. Probabilistic Graphical Models: Principles and Techniques. MIT Press
- Domingos, P. et. al. 2000. Mining high-speed data streams. In Proc. SIGKDD.
- Lai, K. et. al. 2011. A large-scale hierarchical multi-view rgb-d object dataset. In Proc. ICRA.
- Valentin, J. et. al. 2015. SemanticPaint: Interactive 3D Labeling and Learning at your Fingertips. SIGGRAPH.

Q&A?


RGB
Depth
TSDF
Voxel Hashing
Acquisition
Reconstruction
SemanticPaint
User Interaction
Segmentation
Conditional Random Field
Inference
Streaming Random Forest