Fast Edge Detection Using Structured Forests

Piotr Dollár, C. Lawrence Zitnick [1]

Zhihao Li (zhihaol@andrew.cmu.edu)

Computer Science Department
Carnegie Mellon University

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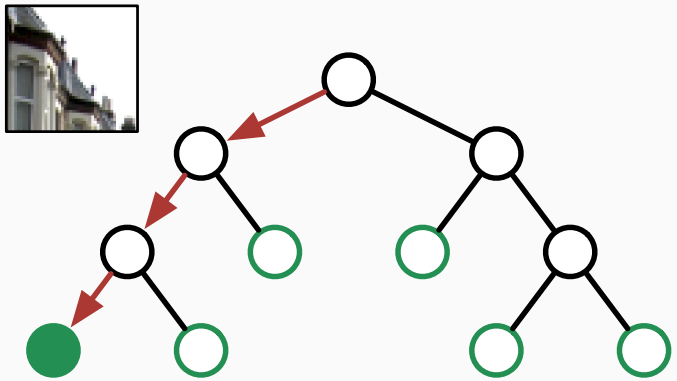
Introduction



Decision Tree

A **decision tree** $f_t(x)$ classifies a sample $x \in \mathcal{X}$ by recursively branching left or right down the tree until a leaf node is reached. Specifically, each node j in the tree is associated with a binary *split function*:

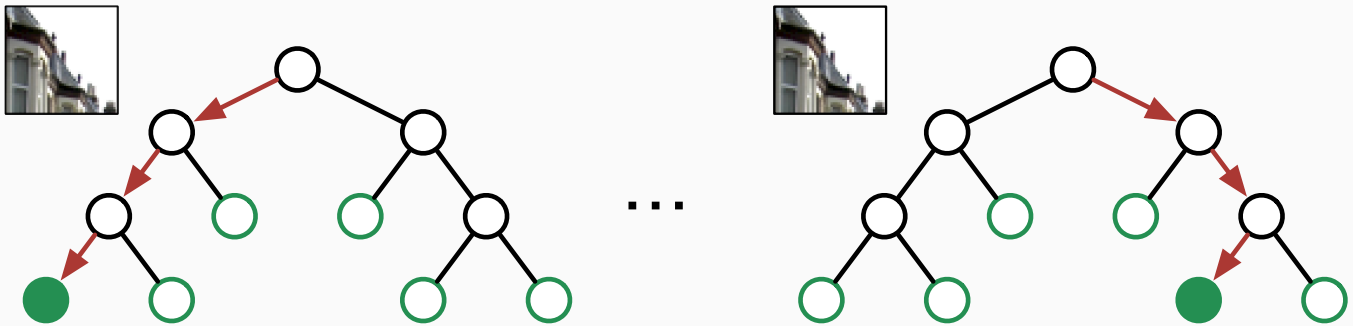
$$h(x, \theta_j) \in \{0, 1\}$$

with parameters θ_j. If $h(x, \theta_j) = 0$ node j sends x left, otherwise right.

Training Decision (Classification) Trees

Each tree is trained independently in a recursive manner. For a given node j and training set $\mathcal{S}_j \subset \mathcal{X} \times \mathcal{Y}$, the goal is to find parameters θ_j of the split function $h(x, \theta_j)$ that maximizes *Information Gain*, or equivalently, minimizing *Entropy*.

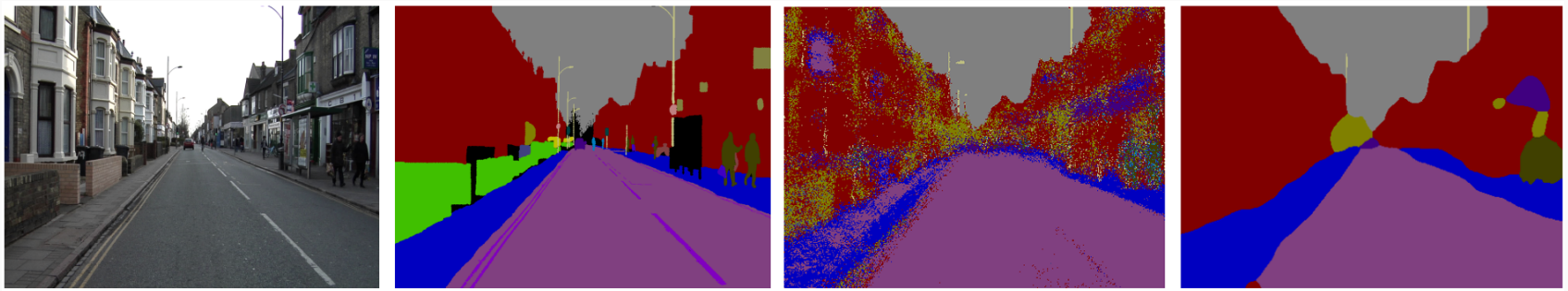
Random Forests



Randomness and Optimality

Individual decision trees exhibit high variance and tend to overfit. Decision forests ameliorate this by training multiple de-correlated trees and combining their output. **In effect, accuracy of individual trees is sacrificed in favor of high diversity ensemble.**

Structured Learning



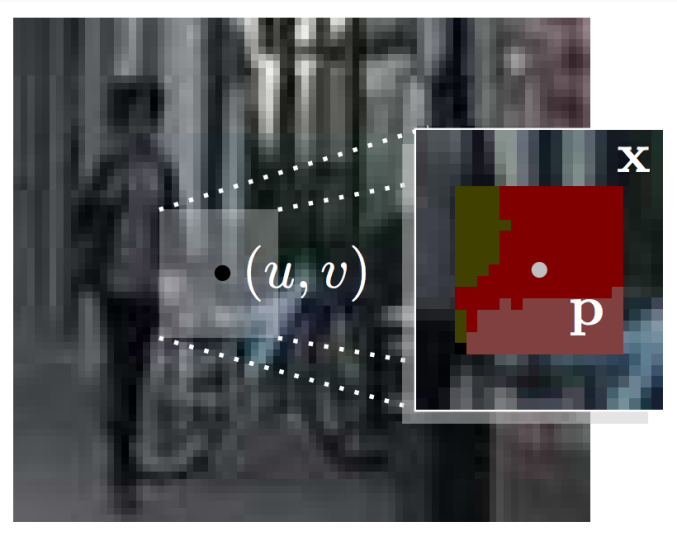
In traditional classification approaches, input data samples are assigned to single, *atomic* class labels, acting as arbitrary identifiers without any dependencies among them. For many computer vision problems however, this model is limited because the label space of a classification task exhibits an inherently topological structure. Therefore, **we try to address the problems by making the classifier aware of the local topological structure of the output label space.**

Kontschieder, Peter, et al. ICCV 11' [2]

Structured Random Forests

Overview

We extend random forests to general structured output spaces $\mathcal{Y}$. Of particular interest for computer vision is the case where $x \in \mathcal{X}$ represents an image patch and $y \in \mathcal{Y}$ encodes the corresponding local image annotation (e.g., a segmentation mask or set of semantic image labels).



Overview

Training random forests with structured labels is very challenging. Therefore, we want to reduce this problem to a simpler one.

- We use the observation that **approximate measures of information gain suffice to train effective random forest classifiers**. 'Optimal' splits are not necessary or even desired.
- Our core idea is to map all the structured labels $y \in \mathcal{Y}$ at a given node into a discrete set of labels $c \in \mathcal{C}$, where $\mathcal{C} = \{1, ..., k\}$, such that *similar* structured labels y are assigned to the same discrete label c.
- Given $\mathcal{C}$, information gain calculated directly from $\mathcal{C}$ can serve as a proxy for the information gain over the structured labels $\mathcal{Y}$. As a result, at each node we can leverage existing random forest training procedures to learn structured random forests effectively.

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Intermediate Mapping Π

For edge detection, the labels $y \in \mathcal{Y}$ are 16×16 segmentation masks. We first transform the output label patch to another space:

$$\Pi : \mathcal{Y} \to \mathcal{Z}$$

We define $z = \Pi(y)$ to be a long binary vector that encodes whether every pair of pixels in y belong to the same or different segments.

We therefore utilize a broadly applicable two-stage approach of first mapping $\mathcal{Y} \to \mathcal{Z}$ followed by a straightforward mapping of $\mathcal{Z} \to \mathcal{C}$.

Information Gain Criterion

We map a set of structured labels $y \in \mathcal{Y}$ into a discrete set of labels $c \in \mathcal{C}$, where $\mathcal{C} = \{1, ..., k\}$, such that labels with similar z are assigned tothe same discrete label c.

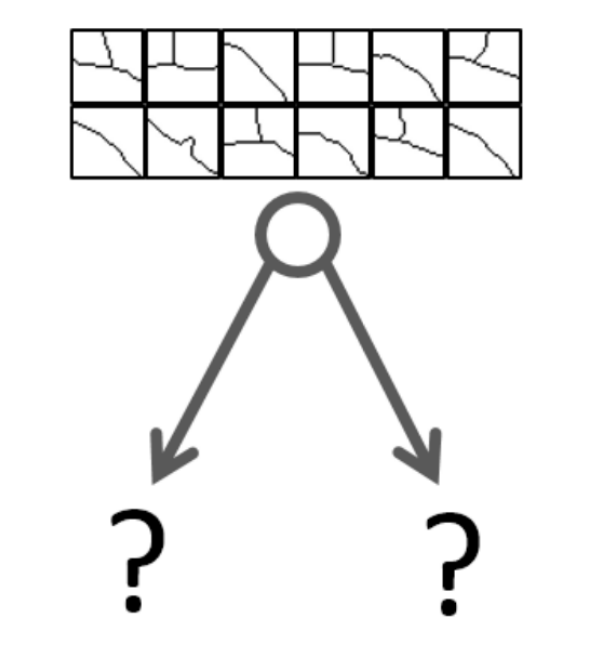
Get $\mathcal{C}$ from $\mathcal{Z}$

1. Cluster z into k clusters using K-means
2. Quantize z based on the top $\log_2(k)$ PCA dimensions

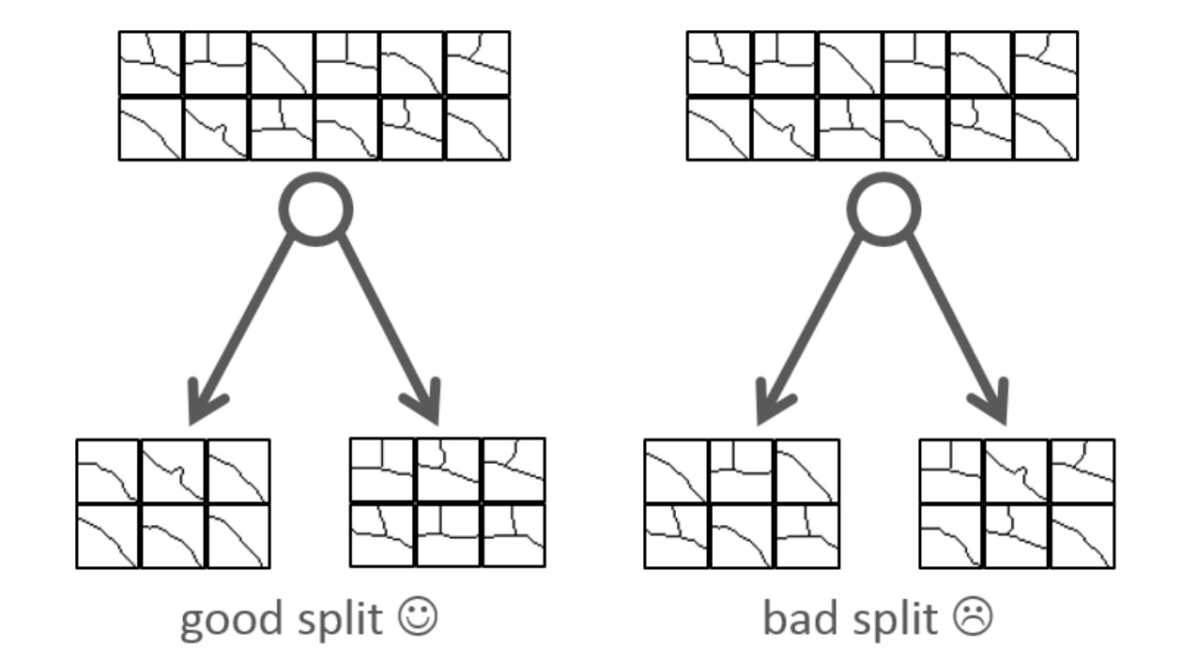
Both approaches perform similarly but the latter is slightly faster.

Now, the Structured Random Forest training problem is reduced to a ordinary random forest training problem.

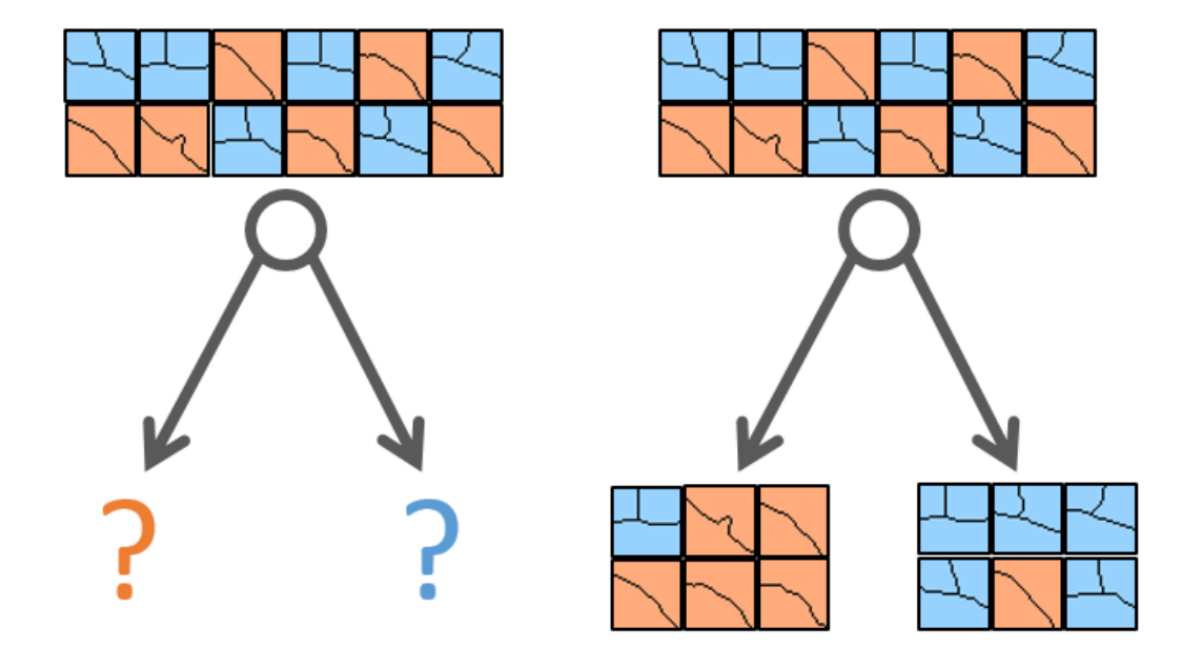
Training a Node in Action



Training a Node in Action



Training a Node in Action



Ensemble Model

To combine a set of n labels $y_1, y_2, \ldots, y_n$, we select the label y_k whose z_k is the medoid, i.e. the z_k that minimizes the distances to all other z_j.

Edge Detection

DEMO

Experiment Results

Overview

The experiments are performed on Berkeley Segmentation Dataset and Benchmark (BSDS500) and NYU Depth (NYUD) dataset.

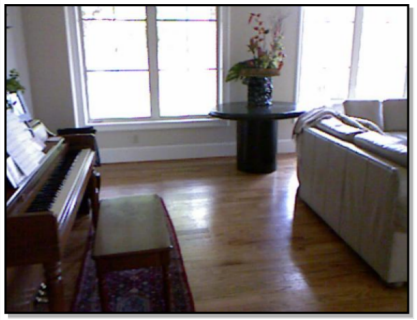
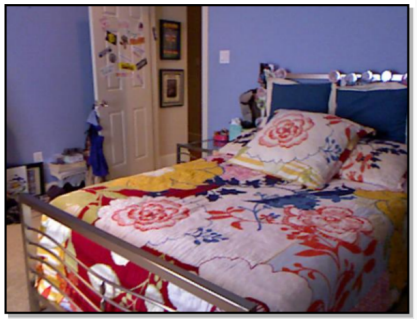
ODS Fixed contour threshold

OIS Per-image best threshold

AP Average Precision

R50 Recall at 50% precision


Examples from BSDS

Examples from NYUD

BSDS

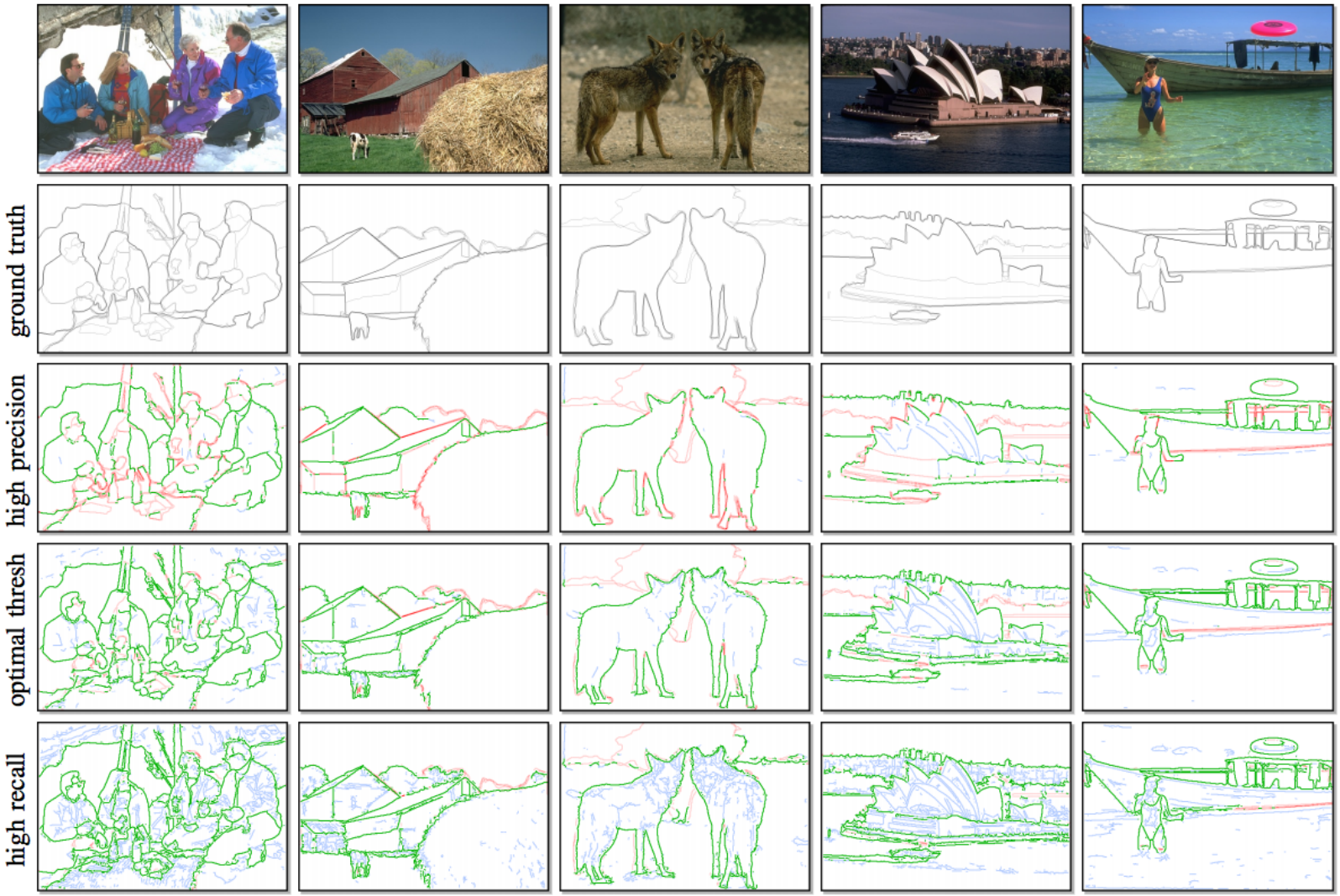
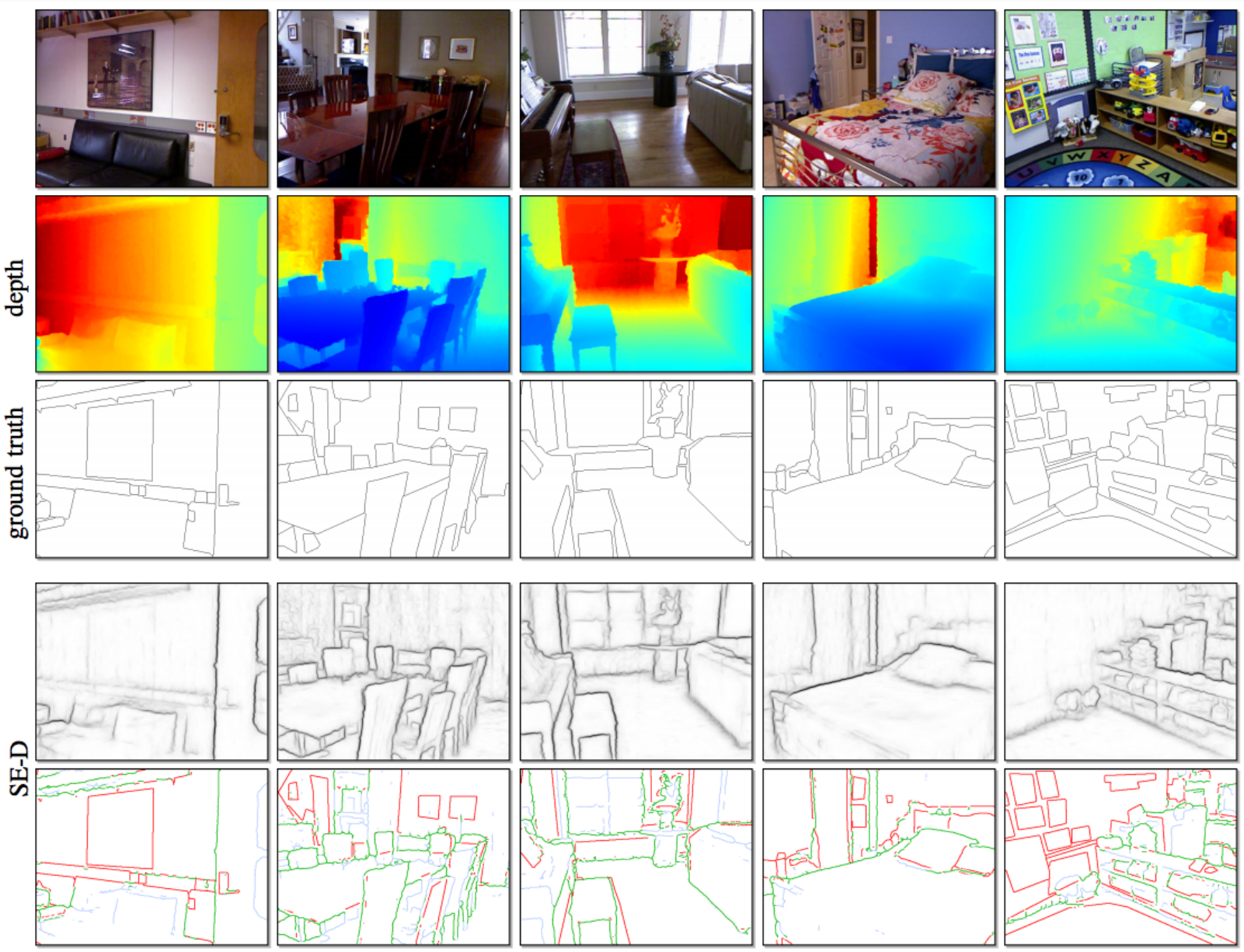


Fig. 4. Visualizations of matches and errors of SE+MS+SH compared to BSDS ground truth edges. Edges are thickened to two pixels for better visibility; the color coding is green=true positive, blue=false positive, red=false negative. Results are shown at three thresholds: high precision (T≈.26, P≈0.88, R=.50), ODS threshold (T≈.14, P=R≈.75), and high recall (T≈.05, P=.50, R≈0.93).

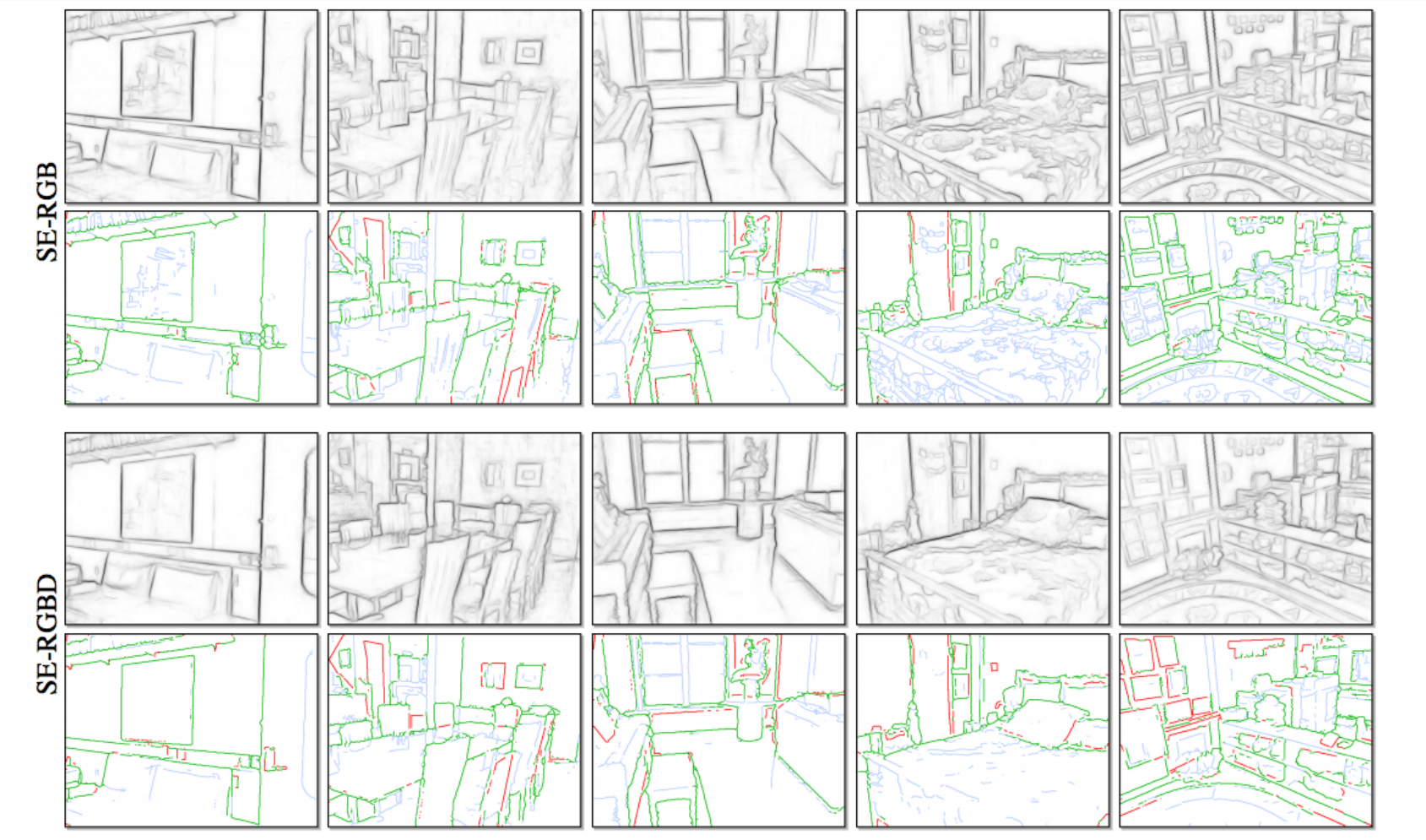
BSDS

	ODS	OIS	AP	R50	FPS
Human	.80	.80	-	-	-
Canny	.60	.63	.58	.75	15
Felz-Hutt [16]	.61	.64	.56	.78	10
Normalized Cuts [10]	.64	.68	.45	.81	-
Mean Shift [9]	.64	.68	.56	.79	-
Hidayat-Green [23]	.62†	-	-	-	20
BEL [13]	.66†	-	-	-	1/10
Gb [30]	.69	.72	.72	.85	1/6
gPb + GPU [8]	.70†	-	-	-	1/2‡
ISCRA [42]	.72	.75	.46	.89	1/30‡
gPb-owt-ucm [1]	.73	.76	.73	.89	1/240
Sketch Tokens [31]	.73	.75	.78	.91	1
DeepNet [27]	.74	.76	.76	-	1/5‡
SCG [41]	.74	.76	.77	.91	1/280
SE+multi-ucm [2]	**.75**	**.78**	.76	.91	1/15
SE	.73	.75	.77	.90	**30**
SE+SH	.74	.76	.79	**.93**	12.5
SE+MS	.74	.76	.78	.90	6
SE+MS+SH	**.75**	.77	**.80**	**.93**	2.5

NYUD



NYUD



NYUD

	ODS	OIS	AP	R50	FPS
gPb-owt-ucm [1]	.63	.66	.56	.79	1/360
Silberman [44]	.65	.66	.29	.84	1/360+
gPb+NG [21]	.68	.71	.63	.86	1/375
SE+NG+ [22]	**.71**	**.72**	**.74**	**.90**	1/15
SE-D	.64	.65	.66	.80	**7.5**
SE-RGB	.65	.67	.65	.84	**7.5**
SE-RGBD	.69	.71	.72	.89	5

Cross Dataset Generalization

	ODS	OIS	AP	R50	FPS
NYUD / NYUD	.65	.67	.65	.84	7.5
BSDS / NYUD	.64	.66	.63	.83	7.5
BSDS / BSDS	.75	.77	.80	.93	2.5
NYUD / BSDS	.73	.74	.77	.91	2.5

Train/Test

Across all performance measure, scores degrade by about 1 point when using the BSDS dataset. These experiments provide strong evidence that our approach could serve as a general purpose edge detector without the necessity of retraining.

Conclusion

Conclusion

1. Use structured learning to predict the labels for a patch a time, taking into consideration the spatial layout of the output label space
2. Generalized random forest training method using approximation

Questions?

References I


P. Dollár and C. L. Zitnick.
Fast edge detection using structured forests.
Pattern Analysis and Machine Intelligence, IEEE Transactions on, 37(8):1558–1570, 2015.


P. Kontschieder, S. Rota Bulò, H. Bischof, and M. Pelillo.
Structured class-labels in random forests for semantic image labelling.
In *Computer Vision (ICCV), 2011 IEEE International Conference on*, pages 2190–2197. IEEE, 2011.

Supplementary

Intermediate Mapping Π

$\mathcal{Z}$ may be high dimensional. For example, for edge detection there are $\binom{16\times16}{2} = 32640$ unique pixel pairs in a 16×16 segmentation mask, so computing z for every y would be expensive.

- We sample m dimensions of $\mathcal{Z}$, resulting in a reduced mapping $\Pi_\phi : \mathcal{Y} \to \mathcal{Z}$ parametrized by ϕ. During training, a distinct mapping Π_ϕ is randomly generated and applied to training labels $\mathcal{Y}_j$ at each node j.
- PCA to further reduce the dimensionality of $\mathcal{Z}$.

In practice, we use Π_ϕ with $m = 256$ dimensions followed by PCA projection to at most 5 dimensions.

Edge Detection Overview

Our learning approach predicts a structured 16×16 segmentation mask from a larger 32×32 image patch. Given an image, we predict a *segmentation mask* indicating segment membership for each pixel and a binary *edge map*.

Input Feature We construct a 7228 dimensional feature vector by considering color, scale, gradient and etc.

Mapping Function Let $y \in \mathcal{Y}$ be a 256 dimensional vector and z be a $\binom{256}{2}$ vector of the pairwise difference between every dimension of y. We reduce dimension of z to 256 and cluster to 2 clusters.

Ensemble Model The predictions are merged by simply averaging.

Efficiency Structured output is computed densely with a stride of 2 pixels, and we use a forest consists of 4 trees. Thus $16^2 \times 4/4 = 256$ votes per pixel.

Multiscale Detection (SE+MS) & Edge Sharpening (SE+SH)

Multiscale Detection (SE+MS)

Given an input image, we run our edge detection algorithm on original, half and double resolution version of the image and average the results.

Edge Sharpening (SE+SH)

We observed that predicted edge maps from our structured edge detector are somewhat diffuse. Therefore, we introduce a new *sharpening* procedure.

1. For each segment s, we compute its mean color μ_s
2. Iteratively update the assigned segment for each pixel by assigning it to the segment which minimizes $\|\mu_s - x(j)\|_2$