Perceptual Organization and Recognition of Indoor Scene from RGB-D Images

Saurabh Gupta, Pablo Arbeláez, Jitendra Malik UC Berkeley

Input

Output



RGB



Depth



Near

Input



RGB



Depth

Input Reorganization



RGB



Depth

Reorganization



Input

RGB



Depth

Reorganization



Input

RGB





```
Bottom-Up
Segmentation
```

Input

Reorganization



RGB



Bottom-Up

Segmentation



Amodal Completion

Input

Reorganization

Semantic Segmentation



RGB



Depth



Bottom-Up Segmentation



Amodal Completion

Reorganization Input Segmentation Bottom-Up RGB Segmentation Depth

> Amodal Completion

Semantic



Anand et al., IJRR12, Contextually Guided Semantic Labeling and Search for 3D Point Clouds [Cornell] Modeled context using structural SVMs for semantic segmentation in full 3D Scenes

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Ren et al., CVPR12, RGB-(D) scene labeling: Features and algorithms [UW, Intel] Using Kernel descriptor features and Tree path context for semantic segmentation

Anand et al., IJRR12, Contextually Guided Semantic Labeling and Search for 3D Point Clouds [Cornell] Modeled context using structural SVMs for semantic segmentation in full 3D Scenes

Ren et al., CVPR12, RGB-(D) scene labeling: Features and algorithms [UW, Intel] Using Kernel descriptor features and Tree path context for semantic segmentation Silberman et al., ECCV12, Indoor segmentation and support inference from RGBD images **[NYU]**

Bottom-up and semantic segmentation, and inference of support relations in RGBD Scenes

- Also introduced a RGBD dataset (NYUD2) with semantic segmentation labels (~1500 images, ~900 classes)

- Looked at a 4 class semantic segmentation (floor, structure, furniture, props)



Adapt the gPb-ucm machinery from Arbeláez et al. from RGB to RGB-D images

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Input RGB Image

Adapt the gPb-ucm machinery from Arbeláez et al. from RGB to RGB-D images



Input RGB Image



Oriented Local Gradients

Adapt the gPb-ucm machinery from Arbeláez et al. from RGB to RGB-D images



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Oriented Local Gradients

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Arbeláez et al., PAMI 2011, Contour Detection and Hierarchical Image Segmentation.

Martin et al., PAMI 2004, Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues

Adapt the gPb-ucm machinery from Arbeláez et al. from RGB to RGB-D images



Input RGB Image



Adapt the gPb-ucm machinery from Arbeláez et al. from RGB to RGB-D images



Input RGB Image



Input Depth Image



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Multi-scale Local Gradients

Normal Gradient

Normal Gradient
































RGB

gPb-UCM(RGB)



This Work (RGB-D)

D



Less distracted by albedo





Less distracted by albedo

Higher Recall

Higher Precision

D

This Work (RGB-D)



This Work (RGB-D)

Less distracted by albedo

Higher Recall

Higher Precision

More Complete Objects

D



RGB



gPb-UCM(RGB)

Less distracted by albedo

Higher Recall

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D

......



This Work (RGB-D)







Bottom Up Segmentation Performance

Performance

Contours

	20110013		ODS	OIS	AP
	Arbeláez et al.	RGB	0.62	0.65	0.55
	Silberman et al.	RGB-D	0.65	0.65	-
_	This Work	RGB-D	0.69	0.71	0.70



Precision Recall Curve on Contours

Performance

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Regions

		ODS	OIS	bestC
Arbeláez et al.	RGB	0.55	0.60	0.69
Silberman et al.	RGB-D	0.61	0.61	0.63
This Work	RGB-D	0.62	0.67	0.75



Precision Recall Curve on Contours

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Regions

This Work	RGB-D	0.62	0.67	0.75
Silberman et al.	RGB-D	0.61	0.61	0.63
Arbeláez et al.	RGB	0.55	0.60	0.69
		ODS	OIS	bestC



Precision Recall Curve on Contours

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Precision Recall Curve on Contours

















Completing contiguous surfaces behind occluders



Completing contiguous surfaces behind occluders



Wall

Kanizsa et al., Praeger Publishers, 1979, Organization in Vision: Essays on Gestalt Perception.

Completing contiguous surfaces behind occluders



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Completing contiguous surfaces behind occluders





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Image









Image

























Image































Image









Image

























Image









Image



Completions





















Image









Image

























Image













Image





Completions















Image









Image

























Semantic Segmentation with RGB-D



Semantic Segmentation with RGB-D



40 Class Task

Scene Surfaces - Floors, walls, ceiling, windows, doors, ...

Furniture - Beds, chairs, sofa, table,

desks, ...

Objects - Pillow, books, towel, box, ...



Ground Truth 40 Class

40 Class Task

Scene Surfaces - Floors, walls, ceiling, windows, doors, ...

Furniture - Beds, chairs, sofa, table,

desks, ...

Objects - Pillow, books, towel, box, ...

Original 4 Class Task

(as introduced by Silberman et al. ECCV 12)

Floor, Structure, Furniture and Objects



Ground Truth 40 Class



Ground Truth 4 Class



Superpixels





Superpixels













- Appearance - SIFT on CIE-LAB, oriented edge energy

- Geometry - Absolute size, height above ground and angle with gravity ...

- Appearance SIFT on CIE-LAB, oriented edge energy
- Geometry Absolute size, height above ground and angle with gravity ...



- Appearance SIFT on CIE-LAB, oriented edge energy
- Geometry Absolute size, height above ground and angle with gravity ...



- Appearance SIFT on CIE-LAB, oriented edge energy
- Geometry Absolute size, height above ground and angle with gravity ...



- Appearance SIFT on CIE-LAB, oriented edge energy
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Height above Ground



Joint Histogram to give **Geocentric Textons**

Generic Features
Generic Features

Generic Features

- Geocentric Pose
 - Orientation Features
 - Height above ground
- Size Features
 - Spatial extent
 - Surface Area
 - Is clipped/occluded

- Shape Features
 - Planarity
 - Strength of local geometric gradients

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Original point cloud may not be in a geocentric frame

Original point cloud may not be in a geocentric frame

Current Gravity Direction Estimate

Original point cloud may not be in a geocentric frame

Current Gravity Direction Estimate

Original point cloud may not be in a geocentric frame

Current Gravity Direction Estimate

Current Estimate of horizontal and vertical surfaces

Original point cloud may not be in a geocentric frame

Current Gravity
Direction
EstimateCurrent
Estimate of
horizontal and
vertical
surfaces

Original point cloud may not be in a geocentric frame



Original point cloud may not be in a geocentric frame



Horizontal

Vertical

Original point cloud may not be in a geocentric frame



Original point cloud may not be in a geocentric frame



Horizontal

Vertical

Results

Image







Output









Image



Output















Semantic Segmentation

Performance (I/U = Pascal Segmentation Metric)

	Silberman ECCV 12	Ren et al. CVPR 12	Our			Silberman ECCV 12	Ren et al. CVPR 12	Our
wall	61	60	68		picture	36	32	40
floor	78	75	81		counter	33	39	47
cabinet	33	37	48		blinds	40	27	44
bed	40	42	55	· ·	desk	4.6	10	10
chair	32	33	40		shelves	3.3	6.1	5.1
sofa	25	28	44		curtain	27	28	34
table	21	17	30		dresser	13	7	22
door	5.9	13	8.3		pillow	19	20	28
window	30	28	33	- · ·	mirror	4.4	18	19
bookshelf	23	17	20		floor mat	7.2	20	22

Silberman et al., ECCV12, Indoor segmentation and support inference from RGBD images. Ren et al., CVPR12, RGB-(D) scene labeling: Features and algorithms

Semantic Segmentation

Aggregate Performance (Frequency weighted I/U)

	Silberman et al. ECCV 12	Ren et al. CVPR 12	Our
4 class task (Floor, Structure, Furniture, Props)	56.31	59.19	64.9
40 class task (Walls, Floor, Cabinet, Bed, Chair, Sofa, Table,)	38.23	37.64	45.29

Silberman et al., ECCV12, Indoor segmentation and support inference from RGBD images. Ren et al., CVPR12, RGB-(D) scene labeling: Features and algorithms

Task

Classify the given scene into bedroom, living room, kitchen, ...

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Approach

Use the inferred semantic class labels to predict the scene class

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Mean Diagonal = .47

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Scene Context

Using this inferred scene as additional features improves semantic segmentation accuracy by ~1%

Semantic Segmentation with RGB-D



Thank You

Code, benchmarks and results will be available on our group's website soon http://www.eecs.berkeley.edu/Research/Projects/CS/vision/