

# Generating Object Candidates from RGB-D Images and Point Clouds

Helge Wrede

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# Outline

Introduction

Methods Overview

The Data

- RGB-D Images

- Point Clouds

- Microsoft Kinect

Generating Object Candidates

- Superpixel

- SLIC

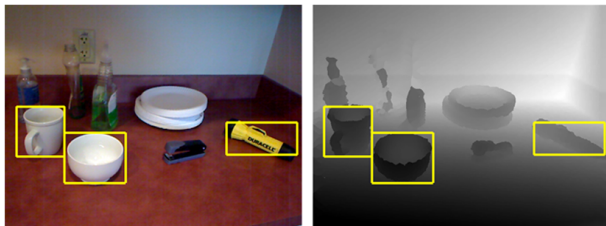
- Supervoxel

- Selective Search

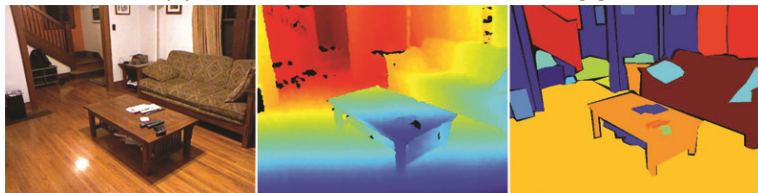
Uses

Summary

# Introduction



(a) Bounding box object candidates. [1]



(b) Segmented object candidates. [2]

**Figure:** Two types of object candidates generated from RGB-D images.

## 2D

- ▶ BING [3]
- ▶ SLIC [4]
- ▶ Selective Search [5]

## 3D

- ▶ Objectness [6]
- ▶ Shape Analyses [7]
- ▶ Spectral Clustering [8]
- ▶ Selective Search [9]

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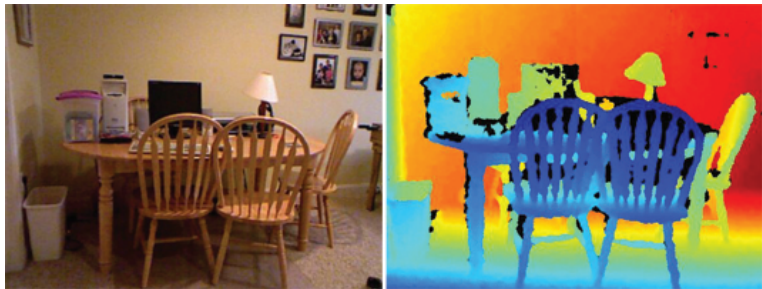
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## RGB-D Images



**Figure:** Image from the NYU Depth V2 dataset; RGB on the left and Depth on the right. [2]

# RGB-D Images

## Structure

- ▶ Color in one image
- ▶ Depth in another image

# RGB-D Images

## Structure

- ▶ Color in one image
- ▶ Depth in another image

## RGB image

- ▶ RGB camera



# RGB-D Images

## Structure

- ▶ Color in one image
- ▶ Depth in another image

## RGB image

- ▶ RGB camera

## Depth image

- ▶ Active stereo
- ▶ Time-of-flight
- ▶ Passive stereo

# Point Clouds



**Figure:** Example image of a point cloud. [10]

## Structure

- ▶ 3D coordinates (X, Y, Z) relative to the camera
- ▶ Color (RGB/HSV/LAB/etc.)

# Point Clouds

## Structure

- ▶ 3D coordinates (X, Y, Z) relative to the camera
- ▶ Color (RGB/HSV/LAB/etc.)

## Generation

- ▶ Color information
- ▶ Depth information
- ▶ Camera position

# Microsoft Kinect



(a) Kinect V1 (Xbox 360)



(b) Kinect V2 (Xbox One)

Figure: Both versions of the Microsoft Kinect. [11]

## V1

- ▶ RGB camera
- ▶ Structured-light camera (active stereo)

## V1

- ▶ RGB camera
- ▶ Structured-light camera (active stereo)

## V2

- ▶ RGB camera
- ▶ Time-of-flight camera

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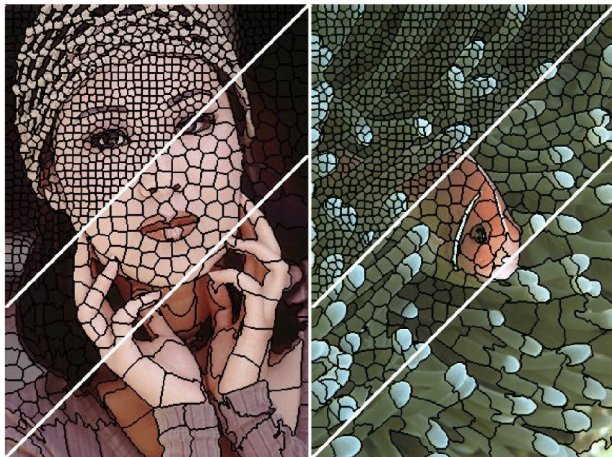
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## Superpixel



**Figure:** Images segmented into superpixels of size 64, 256 and 1024 pixels (approx.) using SLIC. [4]

# Supapixel

## Properties

- ▶ Region with similar information
- ▶ Obtained from images

## Generated with SLIC

## SLIC (Simple Linear Iterative Clustering) [4]

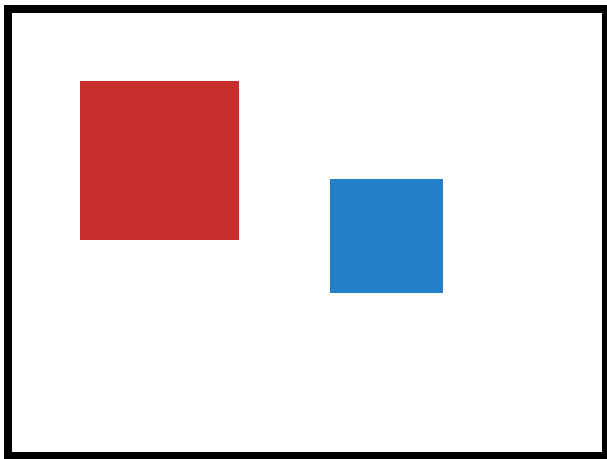


Figure: Initial image.

## SLIC (Simple Linear Iterative Clustering) [4]

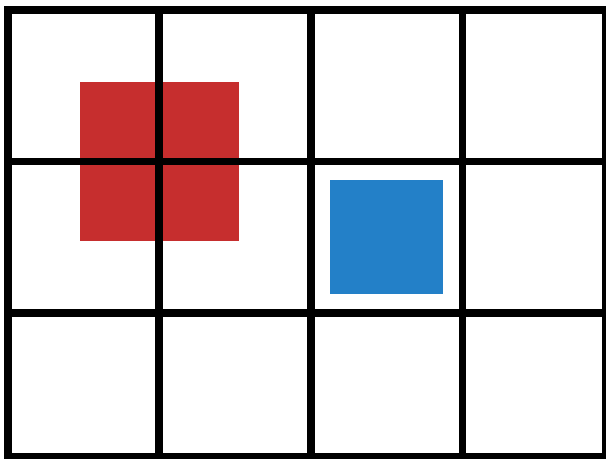


Figure: Seeding grid placed.

## SLIC (Simple Linear Iterative Clustering) [4]

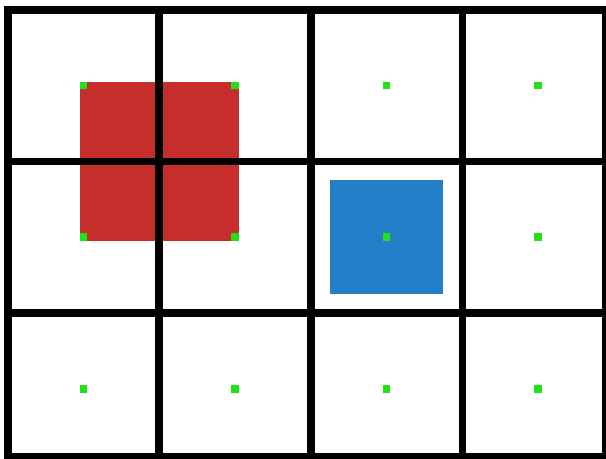


Figure: Seeding centers placed.

## SLIC (Simple Linear Iterative Clustering) [4]

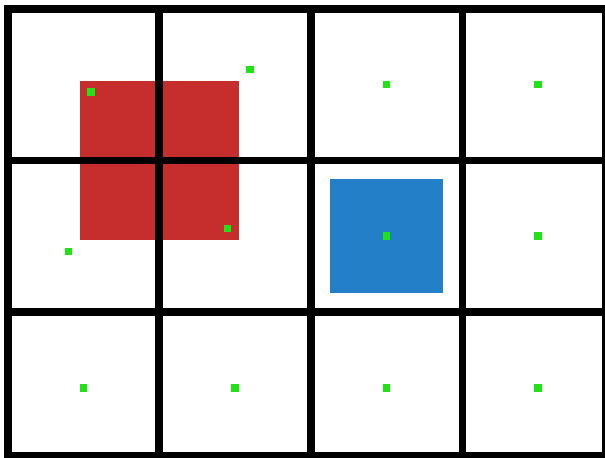


Figure: Centers moved away from edges and corners.

## SLIC (Simple Linear Iterative Clustering) [4]

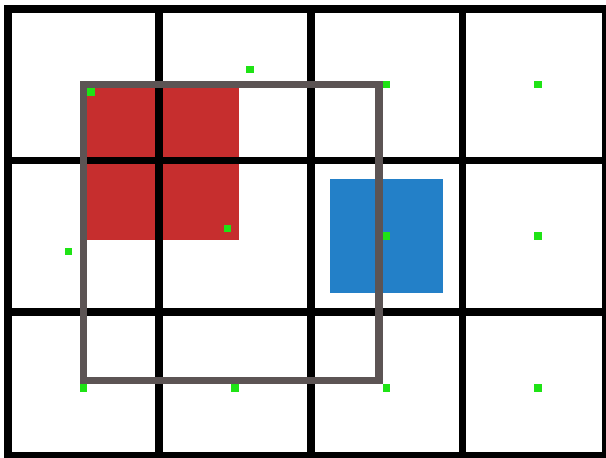


Figure: The area to search for fitting pixels.

## SLIC (Simple Linear Iterative Clustering) [4]

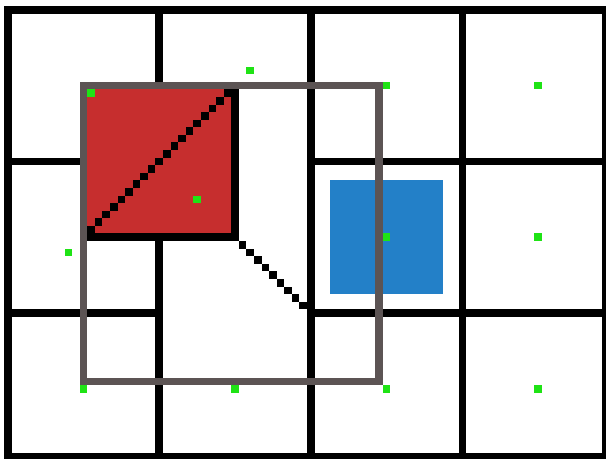
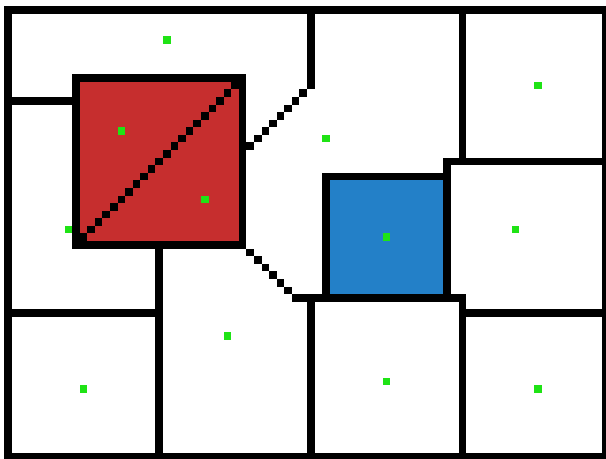


Figure: A few iterations of adding pixels and recentering.



## SLIC (Simple Linear Iterative Clustering) [4]



**Figure:** The superpixels after recentering and adding similar pixels.

## Method Summary

- ▶ Subdivide the image
- ▶ Seed the centers
- ▶ Move the centers based on gradients
- ▶ Search neighbourhood for similar pixels
- ▶ Adjust the centers based on added pixels
- ▶ Add more similar pixels and adjust centers until finished

# Supervoxel

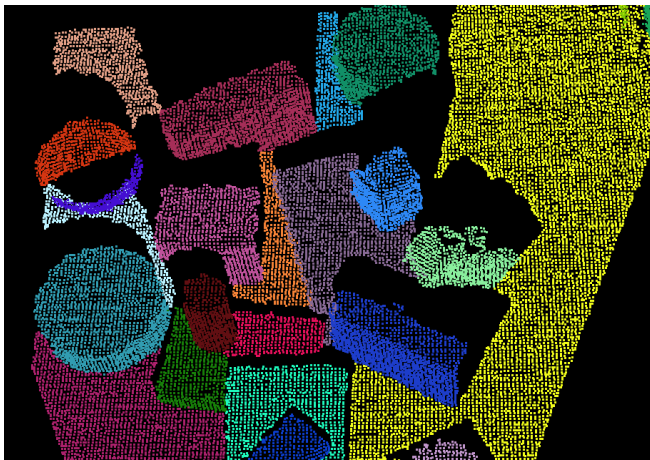


Figure: Spectral supervoxel clustering of cluttered table-top scene. [13]

# Supervoxel

## Properties

- ▶ Superpixel in 3D
- ▶ Obtained from point clouds

# Supervoxel

## Properties

- ▶ Superpixel in 3D
- ▶ Obtained from point clouds

## Generation [9]

- ▶ K-means clustering
- ▶ Seed voxel in every cluster
- ▶ Combine all subsets of seed voxels
- ▶ Assign voxel to nearest supervoxel
- ▶ Update supervoxel centers

# Supapixel and Supervoxel

## Advantages

- ▶ Reduces complexity
- ▶ Potentially increases processing speed

# Supapixel and Supervoxel

## Advantages

- ▶ Reduces complexity
- ▶ Potentially increases processing speed

## Disadvantages

- ▶ One extra step
- ▶ Needs to be accurate
- ▶ Might be too slow for realtime applications

## 2D Selective Search

- ▶ Uses superpixels
- ▶ Iteratively merge adjacent superpixels based on similarity
  - Color (Histogram)
  - Texture (Gradient derivation)
  - Size (Fraction of the image)
  - Fill (Compactness)



## 2D Selective Search

- ▶ Uses superpixels
- ▶ Iteratively merge adjacent superpixels based on similarity
  - Color (Histogram)
  - Texture (Gradient derivation)
  - Size (Fraction of the image)
  - Fill (Compactness)

## 3D Selective Search

- ▶ Uses supervoxels
- ▶ Iteratively merge adjacent supervoxels based on similarity
  - Color (Histogram)
  - Volume (Fraction of the point cloud)

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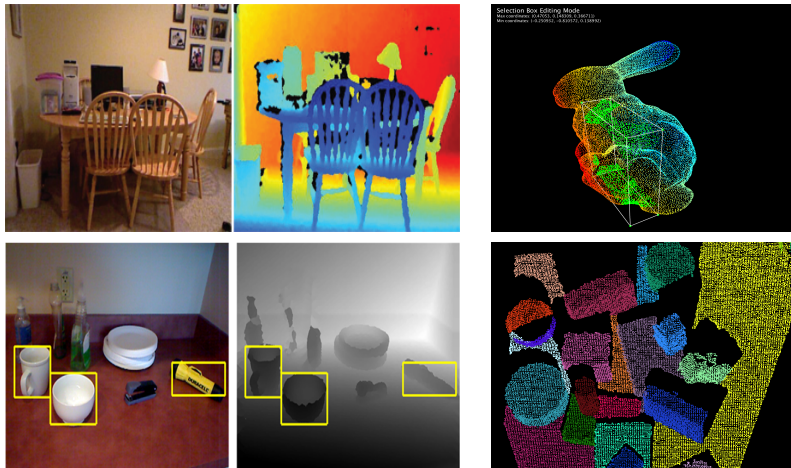
Summary

## Collision Detection

### Building Block for

- ▶ Tracking
- ▶ Classification
- ▶ Recognition
- ▶ Orientation

# Summary



(a) RGB-D images and the generated object candidates.

(b) Point clouds and the generated supervoxels.

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