

Challenges in Image Segmentation

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4 Tightly Coupled Problems



Image Segmentation, Object Detection, Visual Saliency and 3D Scene Layout

Why Image Segmentation Is Difficult?

- What is a good number of segments?
 - What is the purpose of the segmentation?
 - Visual-saliency-based segmentation may be more meaningful
 - Object-recognition-based segmentation may be more relevant
- Human uses 3D information to segment (e.g., occlusion) while computers have only 2D image information
- Human uses semantics to group pixels while computers are very weak in semantic understanding

Simplest Cases

- Blue Screen Technology





Image Segmentation Types

- Interactive segmentation (with human assistance)

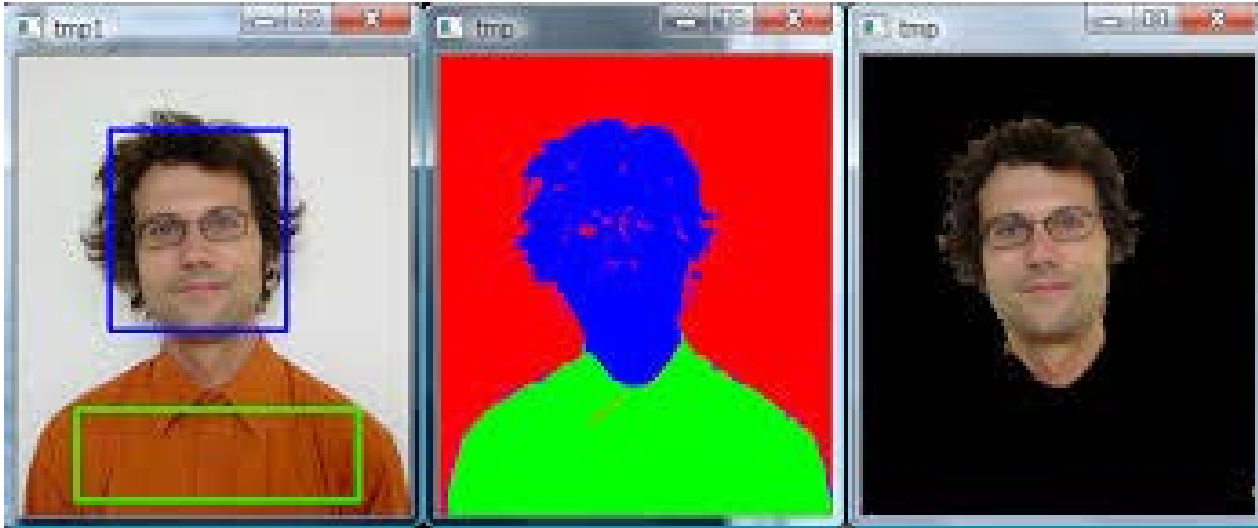
<https://www.youtube.com/watch?v=aOqOwM-Qbtg>

- Automatic segmentation

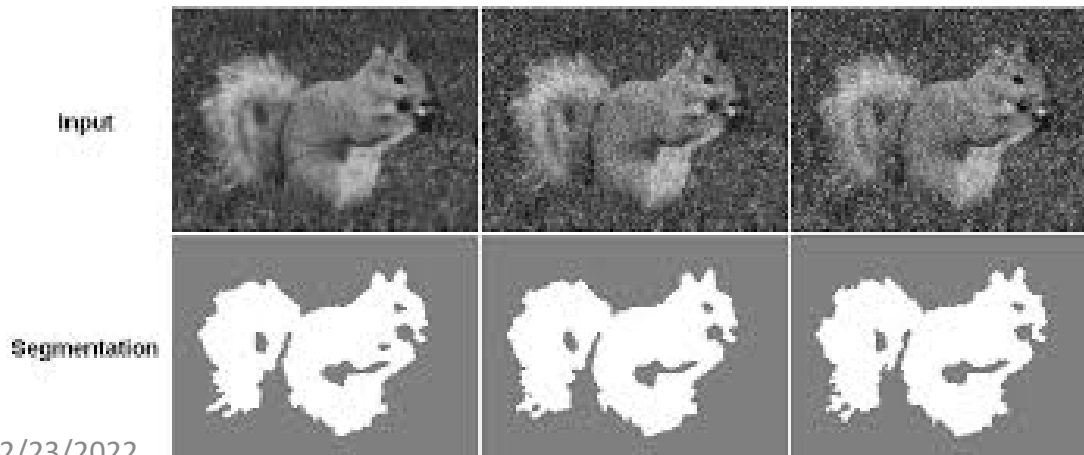
Without human assistance

Image Segmentation Tasks

- From Two Groups (Foreground and Background) to Multiple Groups



- From Gray-Scale Images to Color Images



Several Ideas

- Contour detection (contour serves as a separator)
 - Active contour
- Region growing
 - Watershed
- Graph-based
 - Pixels are nodes, their similarity is defined by an edge value
 - Very similar -> small edge value
 - Very different -> large edge value
 - How to define similarities? mostly related to color (could be others)
- Supapixel methods

Supapixel Methods

- Supapixel algorithms group pixels into perceptually meaningful regions while respecting potential object contours, and thereby can replace the rigid pixel grid structure
- Due to the reduced complexity, superpixels were popular for various unsupervised computer vision applications
 - Examples: multiclass object segmentation, depth estimation, human pose estimation, and object localization.

Simple Linear Iterative Clustering (SLIC)

- Cluster pixels in the five-dimensional color and pixel coordinate space (e.g., r, g, b, x, y)
- Initialization
 - Begin with a collection of K cluster centers initialized at an equally sampled regular grid on the image of N pixels
 - For each cluster, you define for a localized window $2S \times 2S$ centered at the cluster center, where $S = \sqrt{N/K}$ is the roughly the space between the seed cluster centers
- Iteration
 - Check whether the pixel within the $2S \times 2S$ local window should be assigned to the cluster center or not (by comparing the distance in 5D space to the cluster center)
 - Once you loop through all the clusters, you can update the cluster center by averaging over the cluster members. Iterate the pixel-to-cluster assignment process till convergence or maximum iterations reached

SLIC Superpixel Method

- Simple Linear Iterative Clustering (SLIC)



SLIC Superpixel Method

- Simple Linear Iterative Clustering (SLIC)



SLIC Superpixel Method

- Simple Linear Iterative Clustering (SLIC)

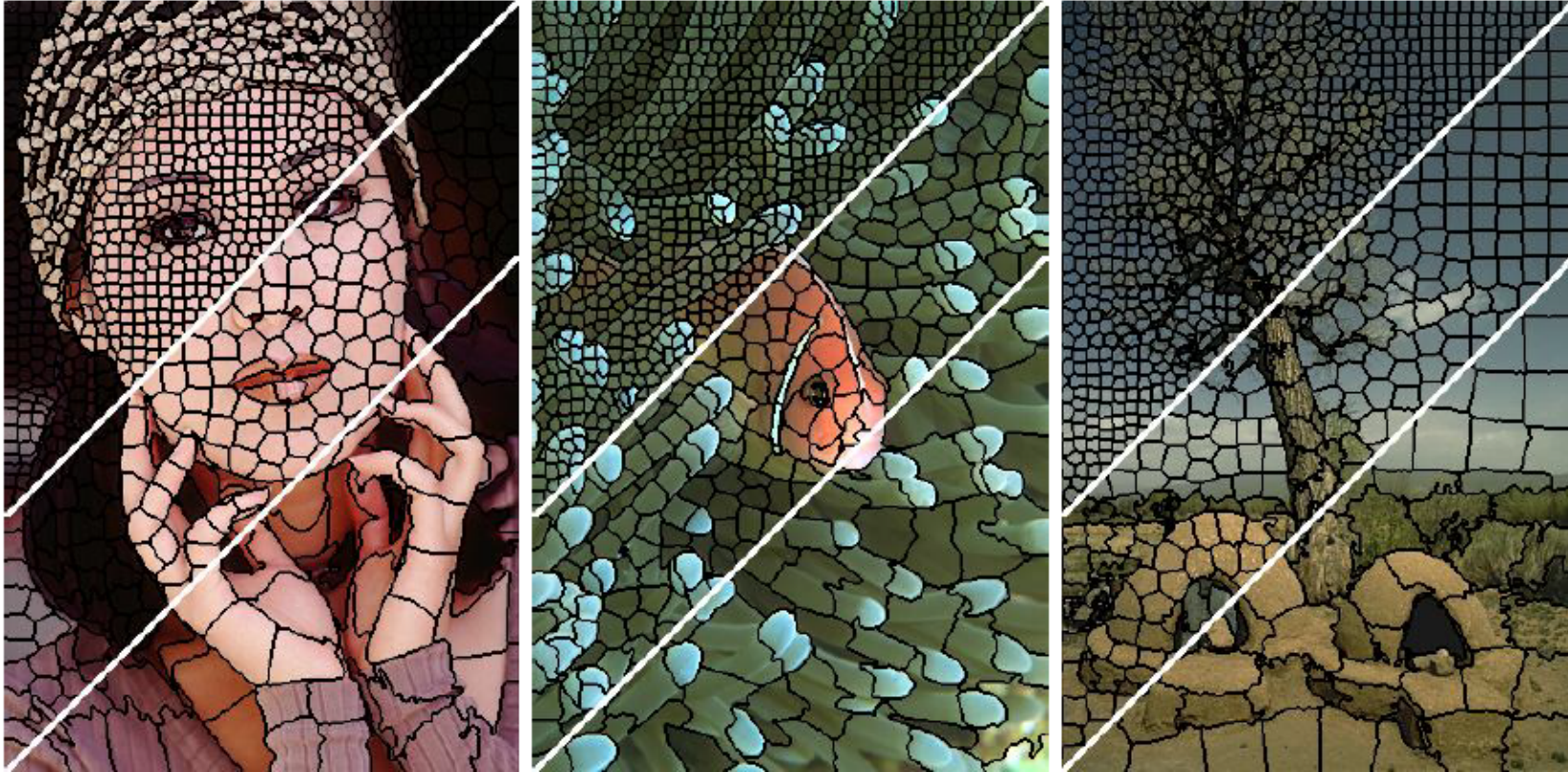


Fig. 1. Image segmented using our algorithm into superpixels of (approximate) size 64, 256, and 1024 pixels. The superpixels are compact, uniform in size, and adhere well to region boundaries.

Recent Trend: Supervised Image Segmentation

- PASCAL VOC Image Segmentation Dataset (2005-2012)
- Homepage: <http://host.robots.ox.ac.uk/pascal/VOC/>
- 20 Object Classes + 1 Background Class

20 Semantic Classes in PASCAL VOC

aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, diningtable, dog, horse, motorbike, person, potted plant, sheep, sofa, train, and tv/monitor.



Pascal VOC Image Segmentation Datasets (1)



Pascal VOC Image Segmentation Datasets (2)



Semantic Segmentation versus Instance Segmentation

Instance
Segmentation

Semantic
Segmentation



Image

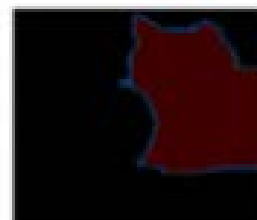
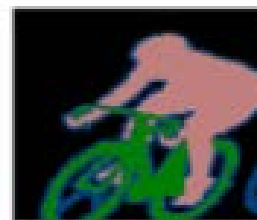
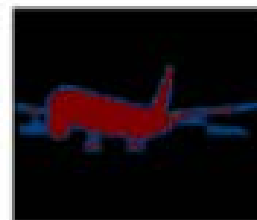
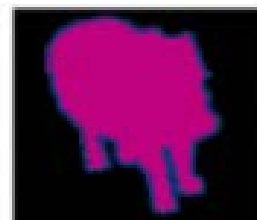
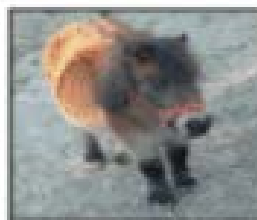
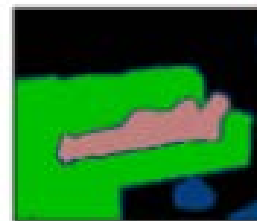


Object



Class

More Examples



(a) Image

(b) GT

(a) Image

(b) GT