



Lecture #16

Image Pyramids, Super Pixels, and Fourier Transforms

Garrett Wells
revised September 24, 2024

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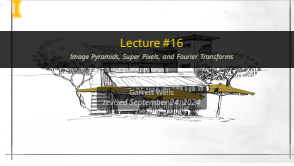


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Motion Detection

- ▶ Motion Size Estimation
- ▶ Motion Localization
- ▶ Motion Reporting/Visualization

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└ Review

└ Review

- ▶ Goal: *Segment an image into areas of similar color.*
- ▶ Segmented areas with similar color are “super pixels”
- ▶ Typically uses a clustering algorithm

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└ Review

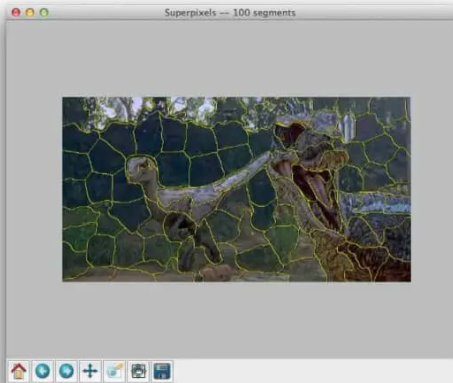
└ Super Pixels

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Super Pixels

Example

Example from [1], using scikit



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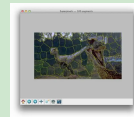
└ Review

└ Super Pixels

Super Pixels

Example

Example from [1], using scikit



Benefits:

1. Computational Efficiency
2. Perceptual Significance
3. Oversegmentation
4. Graphing

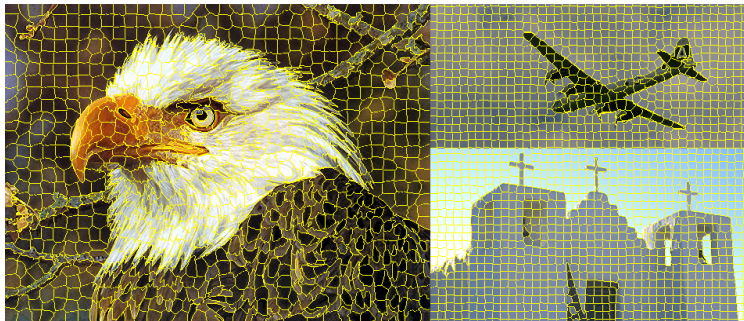


Figure: OpenCV Docs Example [2]

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└ Review

└ Super Pixels

Super Pixels

Benefits:

1. Computational Efficiency
2. Perceptual Significance
3. Oversegmentation
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Figure: OpenCV Docs Example [2]

1. reduces the complexity of the image...
2. pixels grouped together by due to commonalities such as color or texture patterns
3. *Oversegmentation* means that important boundaries in the image are found, but some may be excessive. This is beneficial, as it means no pixels are lost.
4. Instead of constructing graphs which are thousands of pixels, we can graph between super pixels which already contain connected/related pixels. Much more efficient.

Super Pixels in OpenCV

Documentation [2]

```
# install opencv-contrib-python first
# pip install opencv-contrib-python
# Linear Spectral Sampling
cv.ximgproc.createSuperpixelLSC(image,          # input image, 3
                               region_size=10, # choose average
                               ratio=0.075f    # enforces compac
)

```

```
# Superpixels Extracted via Energy Driven Sampling
cv.ximgproc.createSuperpixelSEEDS(...)
# Simple Linear Iterative Clustering
cv.ximgproc.createSuperpixelSLIC(...)
```

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└ Super Pixels

└ Super Pixels in OpenCV

Documentation [2]

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Image Pyramids

- Uses:
 - object detection
 - upscaling/downscaling an image

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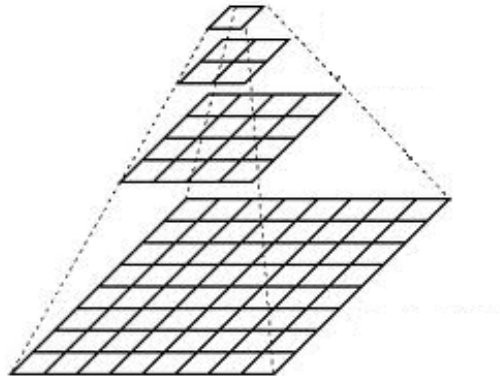
- └─Image Pyramids
 - └─Image Pyramids

Image Pyramids

- Uses:
 - object detection
 - upscaling/downscaling an image

Image Pyramids

- ▶ Creates a “pyramid” of images at different resolutions [3]
- ▶ Highest resolution at bottom, lowest on top
- ▶ Different Construction Methods:
 - ▶ Gaussian
 - ▶ Laplacian



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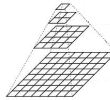
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└ Image Pyramids

└ Image Pyramids

Image Pyramids

- ▶ Creates a “pyramid” of images at different resolutions [3]
- ▶ Highest resolution at bottom, lowest on top
- ▶ Different Construction Methods:
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 - ▶ Laplacian



Pyramid Down Algorithm:

1. Start with current resolution, $M \times N$
2. Construct next "Octave" (image with 1/4 current resolution)
 - 2.1 Allocate image with dimensions, $M/2 \times N/2$.
 - 2.2 Fill each pixel in Octave by sampling 5 pixels from level below with Gaussian weights.
 - 2.3 Repeat from 2 until target resolution reached.

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└ Image Pyramids

└ Gaussian Pyramid

└ Gaussian Pyramid

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- ☞ Allows us to check image at each size for present features.

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└ Image Pyramids

└ Gaussian Pyramid

└ Gaussian Pyramid

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Gaussian Pyramid in OpenCV

```
output_img = cv.pyrDown(src,          # input image
                        dstsize=Size(), # output img size
                        borderType=cv.BORDER_DEFAULT # how to fill in edges
)
# same parameters here
cv.pyrUp(...)
```

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└ Image Pyramids

└ Gaussian Pyramid

└ Gaussian Pyramid in OpenCV

Gaussian Pyramid in OpenCV

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Laplacian Pyramid

- ▶ Formed from Gaussian pyramids
- ▶ Produces edge image
- ▶ Formed by taking difference between current level in Gaussian, and the expanded upper level of Gaussian
- ▶ No OpenCV function

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└ Image Pyramids

└ Laplacian Pyramid

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Laplacian Pyramid

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Fourier Transforms

- ▶ Image is composed of signals
- ▶ Pixel values map to frequencies [4]
- ▶ Applications
 1. Filtering by frequency
 2. Edge Detection
 3. Blurring/Sharpening
 4. Rotation
 5. *etc.*

Fourier Transforms: 3B1B [↗](#)

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└─ Fourier Transforms

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Fourier Transforms

- ▶ Image is composed of signals
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Fourier Transforms: 3B1B [↗](#)

Fourier Transforms in OpenCV

```
# discrete fourier transform
cv.dft(src,          # input image/array 1D or 2D
      flags=0,       # transformation flags
      nonzeroRows=0  # assumes # rows of nonzero data
)
```

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└─ Fourier Transforms

└─ Fourier Transforms in OpenCV

Fourier Transforms in OpenCV

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[1] A. Rosebrock, "Segmentation: A SLIC Superpixel Tutorial using Python," PyImageSearch. (Jul. 28, 2014), [Online]. Available: <https://pyimagesearch.com/2014/07/28/a-slic-superpixel-tutorial-using-python/> (visited on 09/24/2024).

[2] "OpenCV: Superpixels," (), [Online]. Available: https://docs.opencv.org/3.4/df/d6c/group__ximgproc__superpixel.html (visited on 09/24/2024).

[3] "OpenCV: Image Pyramids," (), [Online]. Available: https://docs.opencv.org/4.x/d5/d0f/tutorial_js_pyramids.html (visited on 09/24/2024).

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[2]	"OpenCV: Superpixels," (), [Online]. Available: https://docs.opencv.org/3.4/df/d6c/group__ximgproc__superpixel.html (visited on 09/24/2024).
[3]	"OpenCV: Image Pyramids," (), [Online]. Available: https://docs.opencv.org/4.x/d5/d0f/tutorial_js_pyramids.html (visited on 09/24/2024).

- [4] "OpenCV 3 Image Fourier Transform : OpenCV FFT & DFT - 2020," (),
[Online]. Available:
https://www.bogotobogo.com/python/OpenCV_Python/python_opencv3_Image_Fourier_Transform_FFT_DFT.php (visited on
09/24/2024).