Deep Learning for Computer Vision

Scale Space, Image Pyramids and Filter Banks

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Department of Computer Science and Engineering
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Review

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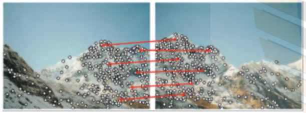

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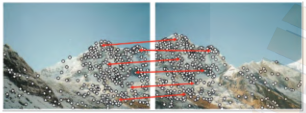

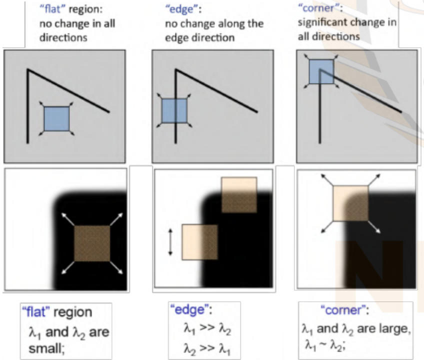
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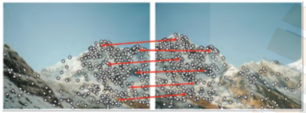

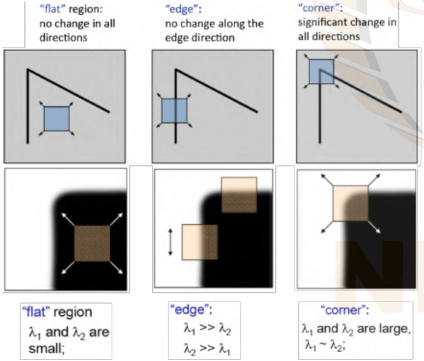

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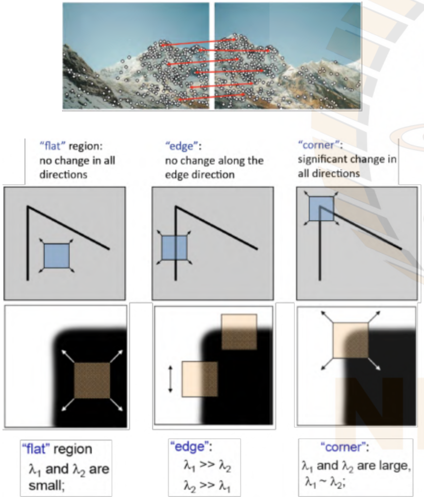

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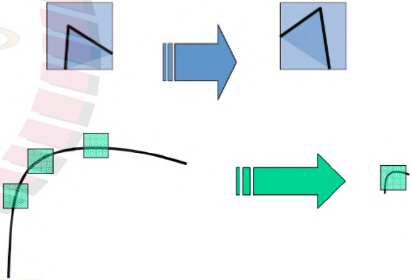

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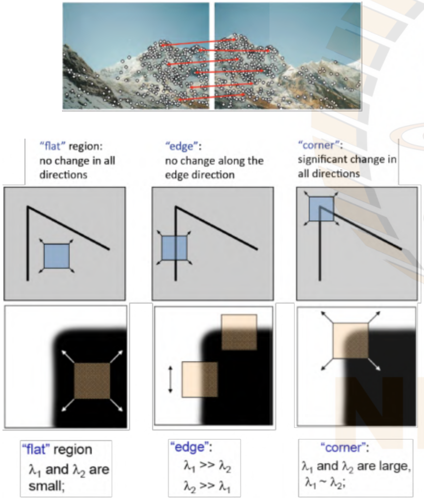
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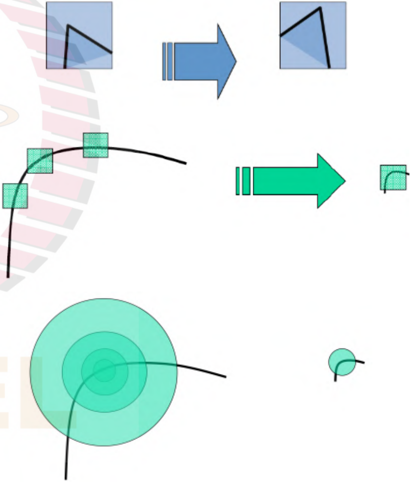

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  - When does this work?
  - More efficient to extract features stable in both location and scale.
  - Find scale that gives local maxima of a function f in both position and scale.

$$f(I_{i_1 \dots i_m}(x, \sigma)) = f(I_{i_1 \dots i_m}(x', \sigma'))$$

Automatic Scale Selection

Function responses for increasing scale (scale signature).

Credit: R Urtasun

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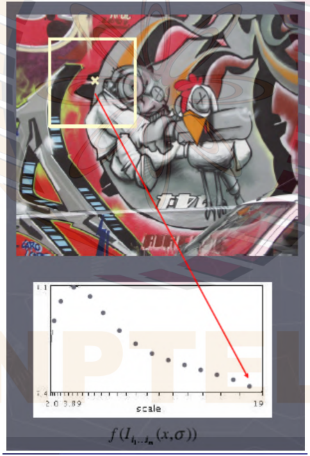

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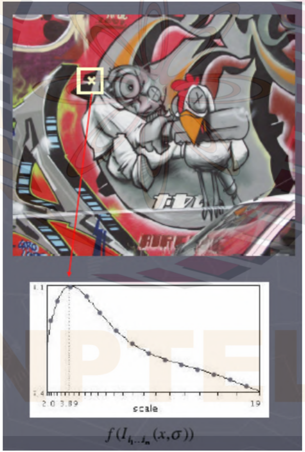

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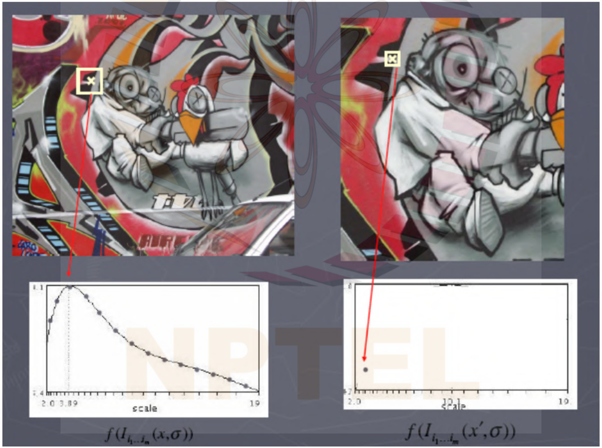

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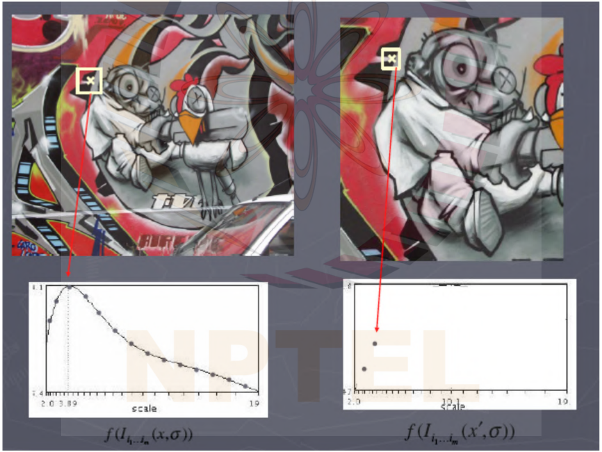

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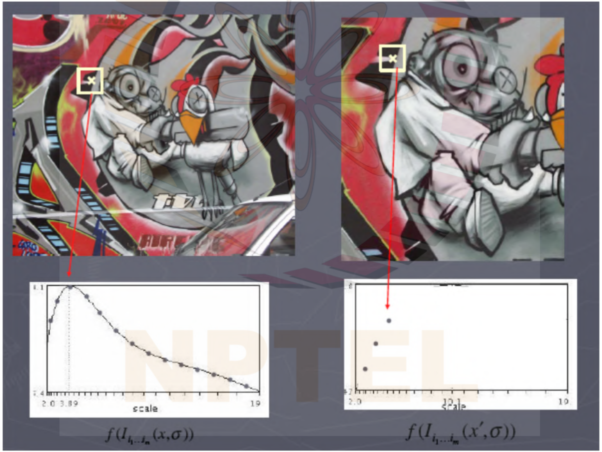

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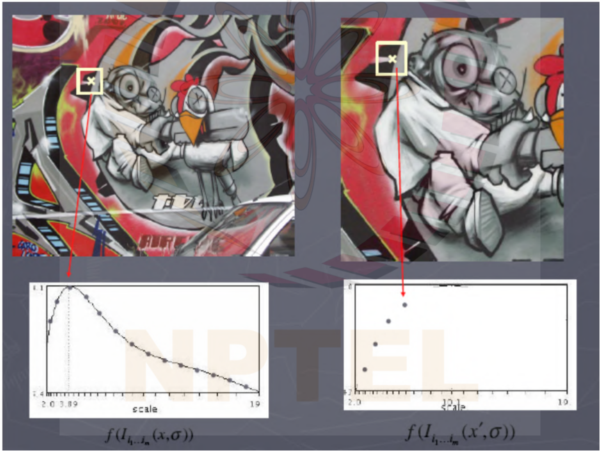

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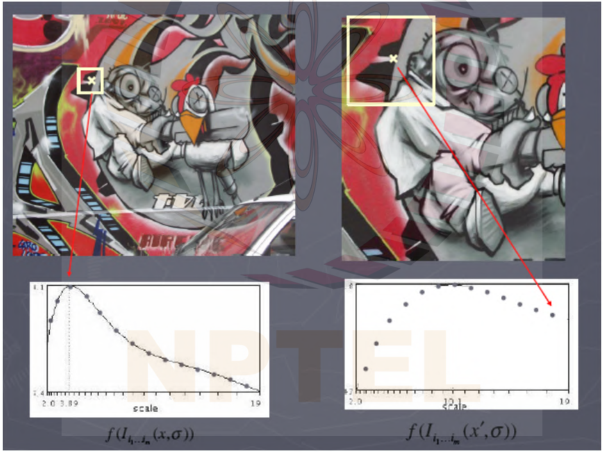

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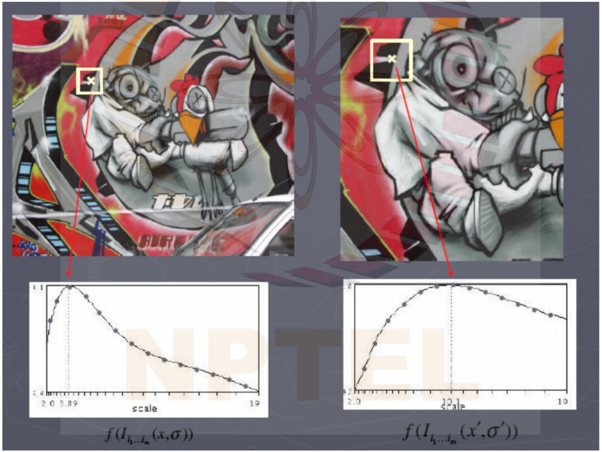

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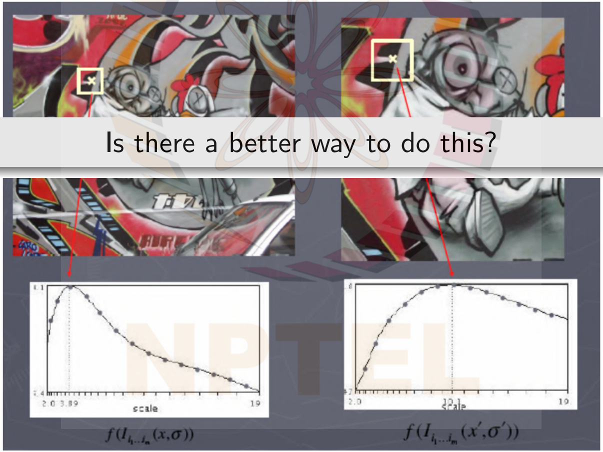

Is there a better way to do this?

Automatic Scale Selection: Implementation

Instead of computing f for larger and larger windows, we can implement using a fixed window size with a Gaussian pyramid.

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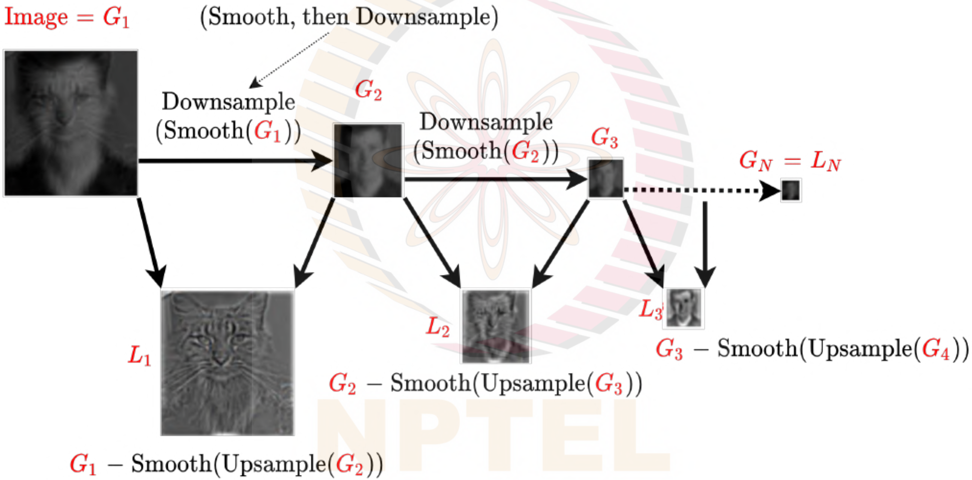
Gaussian and Laplacian Pyramid



Credit: Derek Hoiem

Image Pyramids: Uses

- Compression

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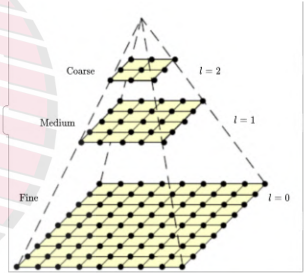

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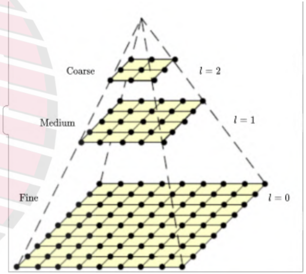

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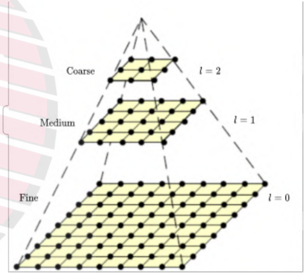

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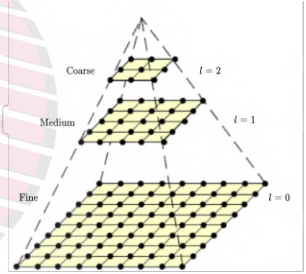

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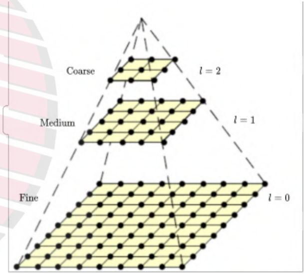

- Compute Gaussian pyramid.
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  - Search smaller range.

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Texture in Images

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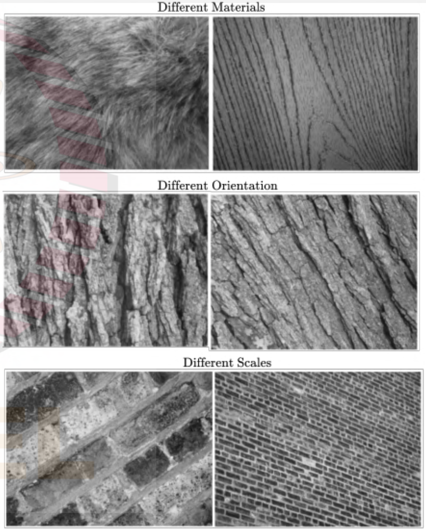

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Texture in Images

Conveys more information that can be exploited to match regions of interest in images.

Histogram conveys 50% white pixels and 50% black pixels

(Block Pattern) (Checkerboard Pattern) (Striped Pattern)

Drastically different textures

Credit: Linda G Shapiro

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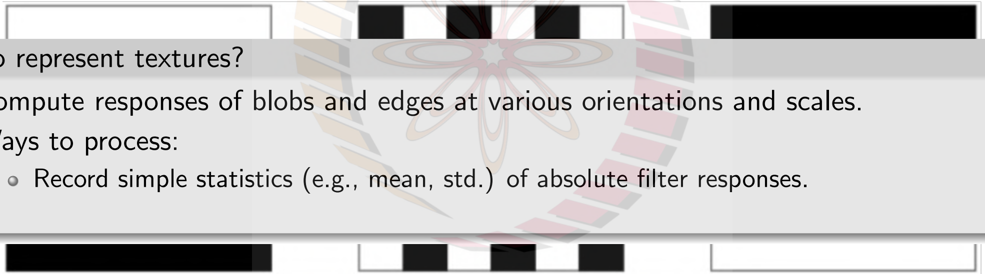

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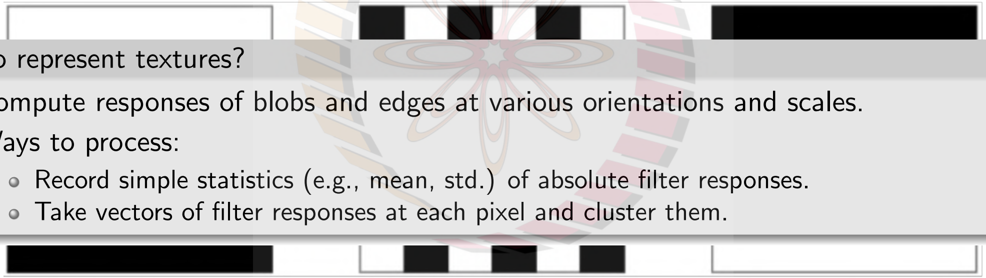

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  - Take vectors of filter responses at each pixel and cluster them.

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Filter Banks

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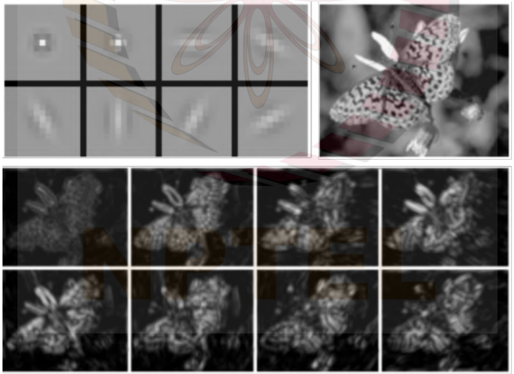
- Process image with each filter and keep responses (or squared/abs responses).



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Gabor Filters

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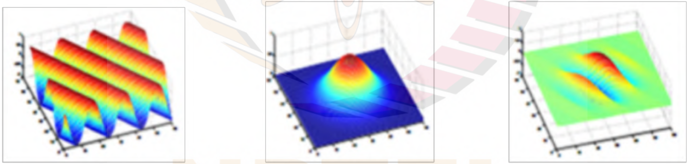
- A Gabor filter can be viewed as a sinusoidal signal of particular frequency and orientation, modulated by a Gaussian wave.

A 2-D Gaussian



A sinusoid oriented 30° with x-axis A corresponding 2-D Gabor Filter

A 2-D Gabor filter obtained by modulating the sine wave with a Gaussian

2-D Gabor Filter

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = e^{-\left(\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)} e^{i\left(2\pi \frac{x'}{\lambda} + \psi\right)}$$

where:
$x' = x \cos\theta + y \sin\theta$
$y' = -x \sin\theta + y \cos\theta$
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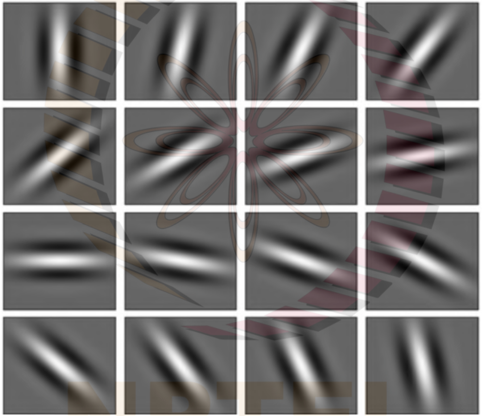
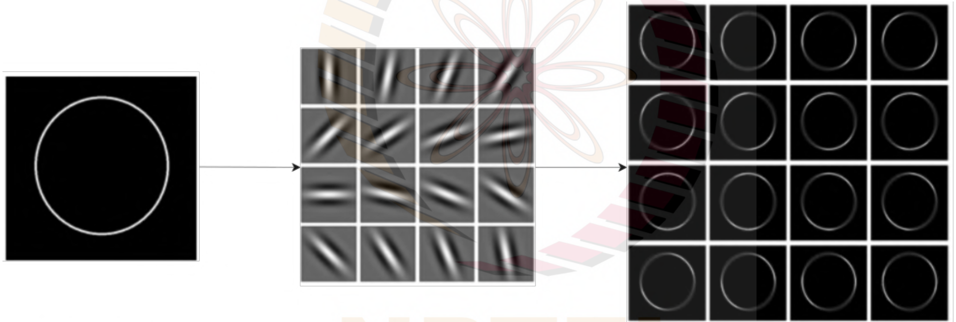
γ – Spatial aspect ratio and specifies the ellipticity of the support of Gabor function.

Gabor Filter Banks



Bank of 16 Gabor filters at an orientation of 11.250 (i.e. if the first filter is at 00.00, then the second will be at 11.25, the third will be at 22.50, and so on.)

Gabor Filter Banks



Input Image of a Circle

A bank of 16 Gabor filters

Output Image of the circle after passed through indiviual Gabor filters

Steerable Filter Banks

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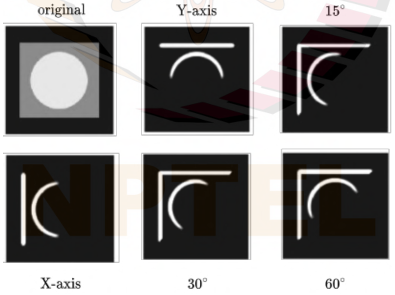
where $G_1^{\theta^\circ}$ is the first derivative of G at angle θ.



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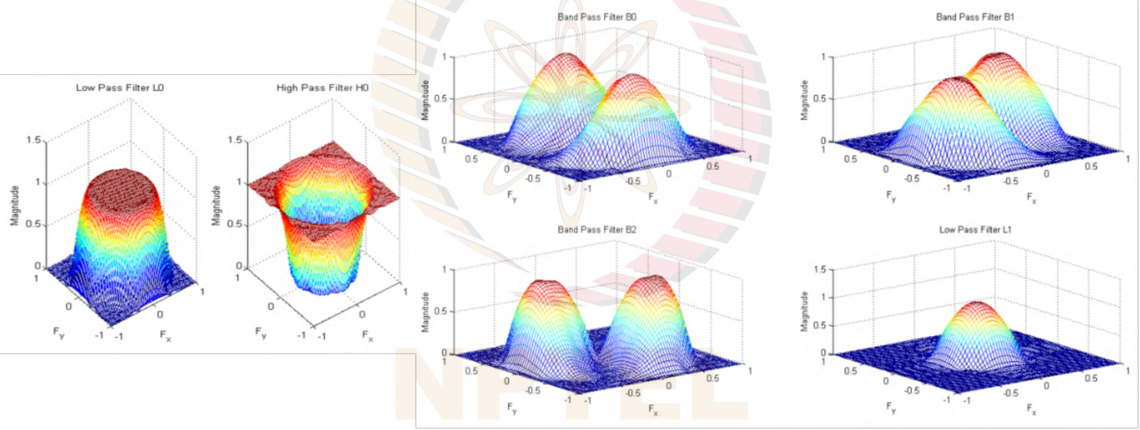

Homework

Readings

- Chapter 2, Szeliski, *Computer Vision: Algorithms and Applications*

Questions

- Why is camouflage attire effective? How?
- How is texture different from noise?
- Will scale-invariant filters be effective in matching pictures containing Matryoshka (or Russian nesting) dolls?