Deep Learning for Computer Vision

# Scale Space, Image Pyramids and Filter Banks


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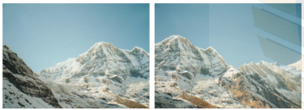
# Review



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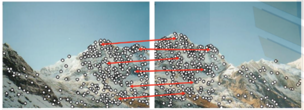

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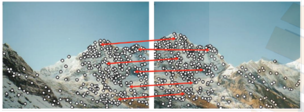

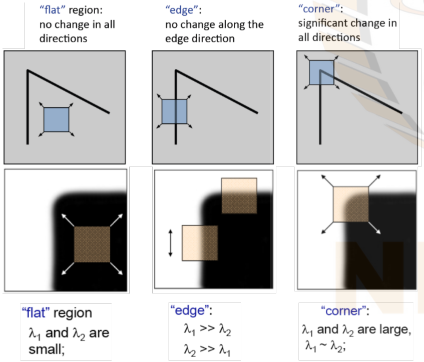
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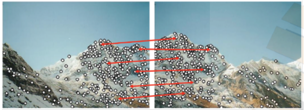

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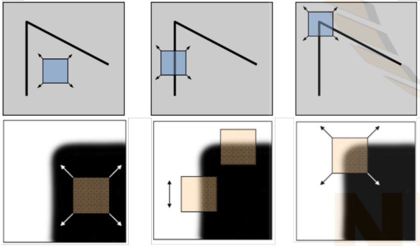

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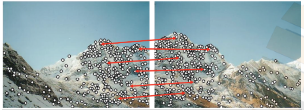

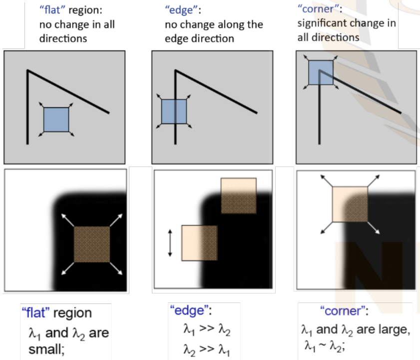

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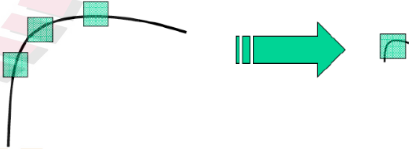

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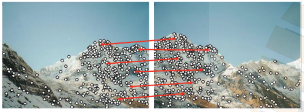

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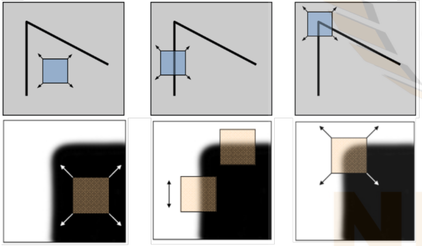

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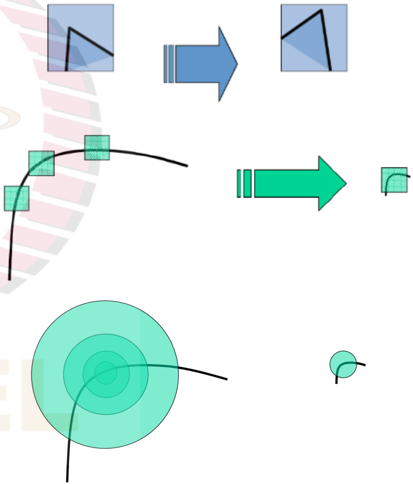

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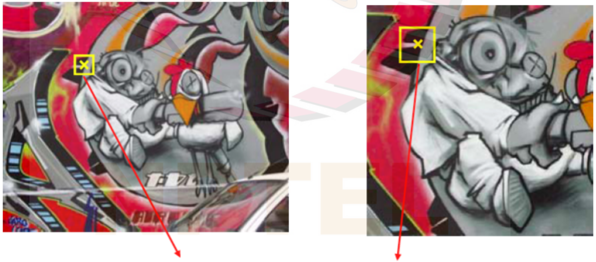
  - More efficient to extract features stable in both location and scale.
  - Find scale that gives local maxima of a function $f$ in both position and scale.



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

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Function responses for increasing scale (scale signature).


*Credit: R Urtasun*

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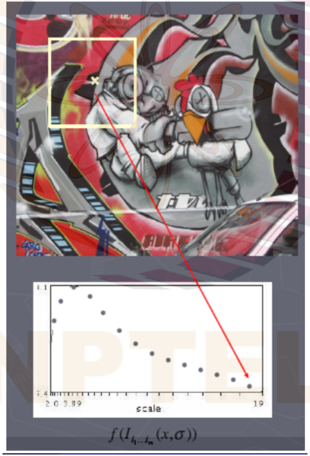


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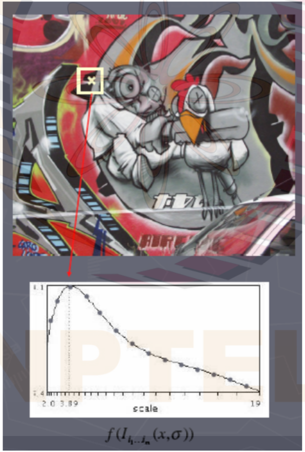


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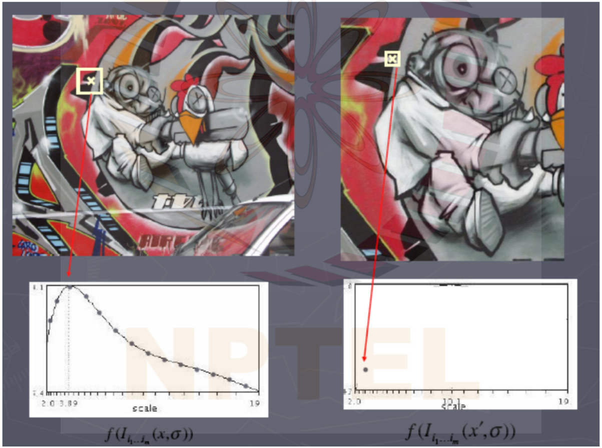


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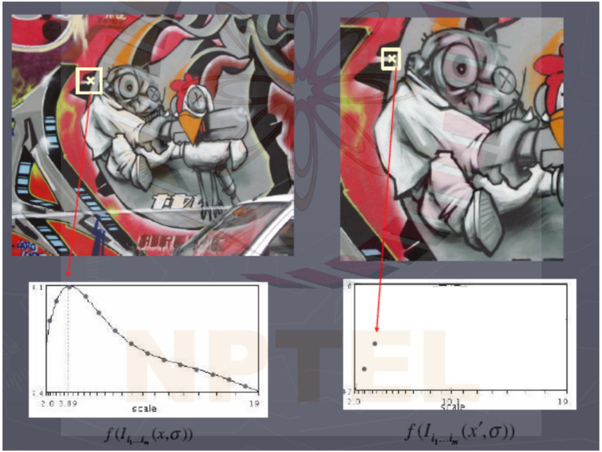


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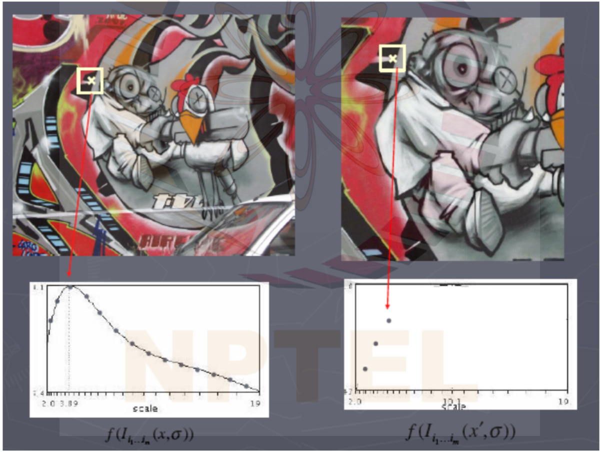


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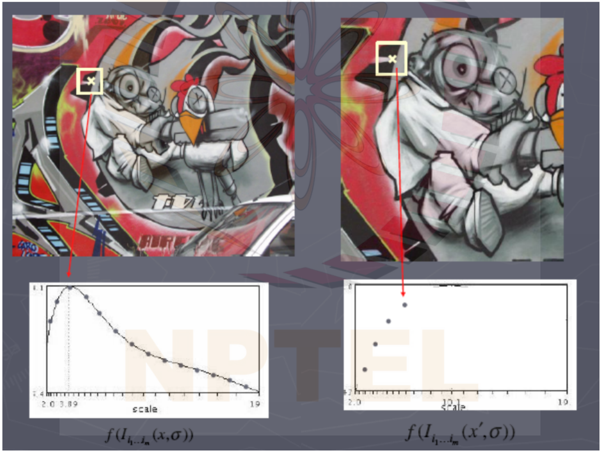


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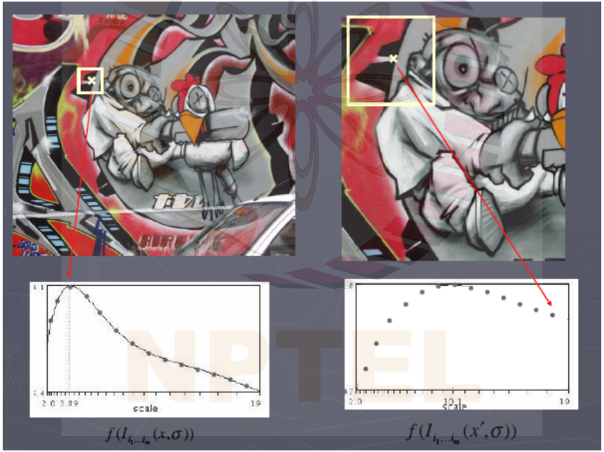


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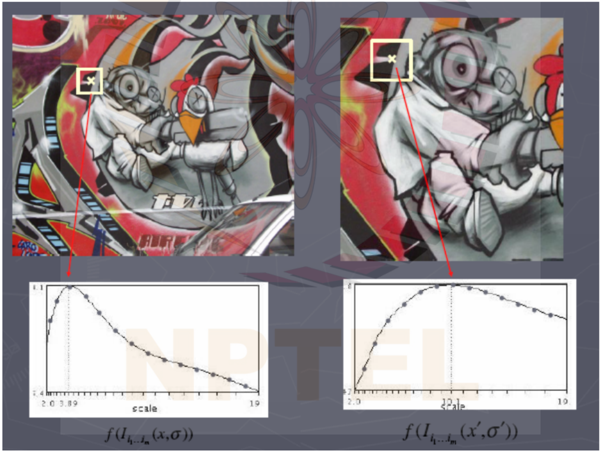


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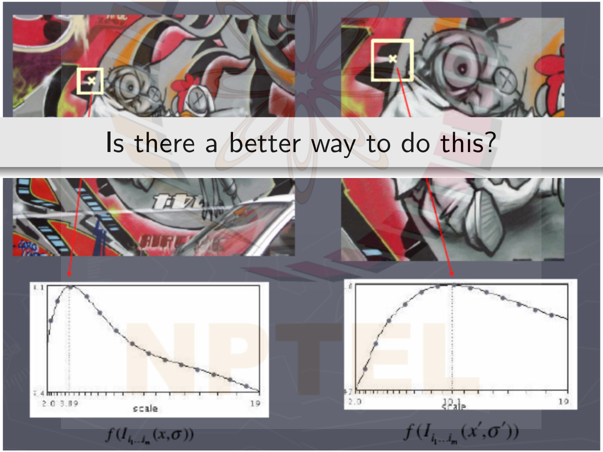



Is there a better way to do this?

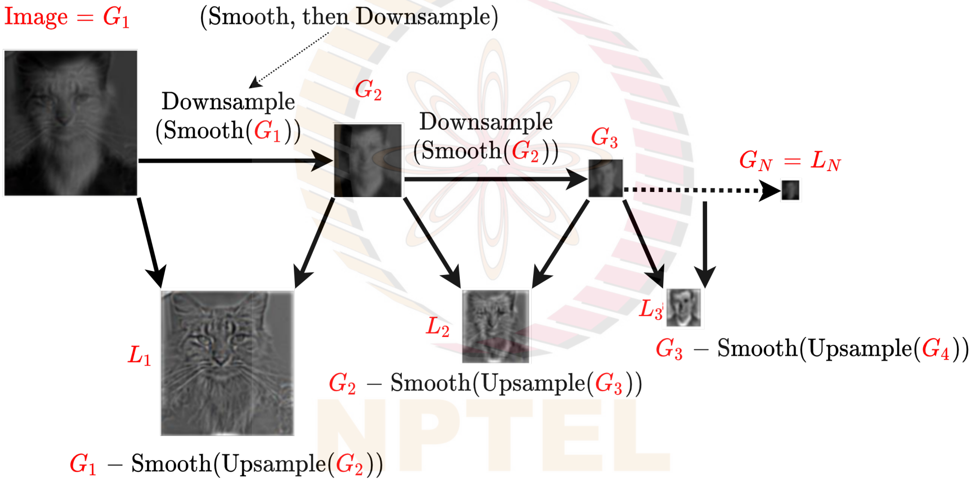
# Automatic Scale Selection: Implementation

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

Sometimes need to create in-between levels, e.g., a $\frac{3}{4}$ size image.

*Credit: R Urtasun*

# Gaussian and Laplacian Pyramid




*Credit: Derek Hoiem*

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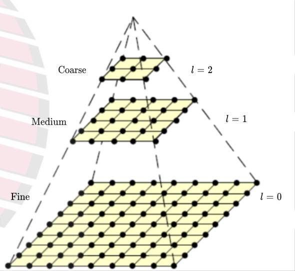

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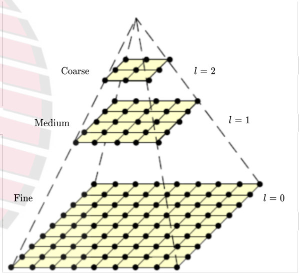


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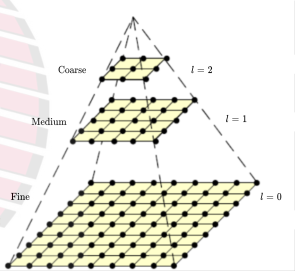


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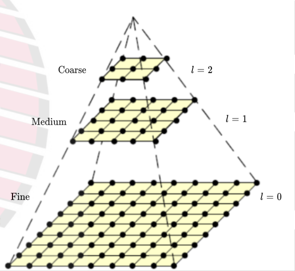


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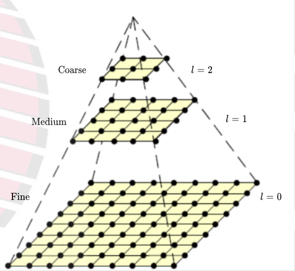


- Compute Gaussian pyramid.
- Align with coarse pyramid.
- Successively align with finer pyramids.
  - Search smaller range.

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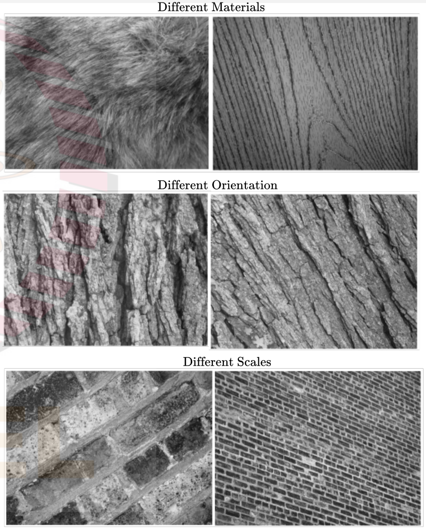


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Conveys more information that can be exploited to match regions of interest in images.

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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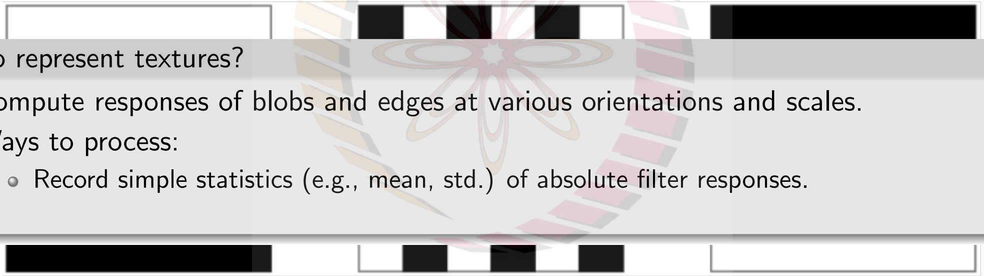

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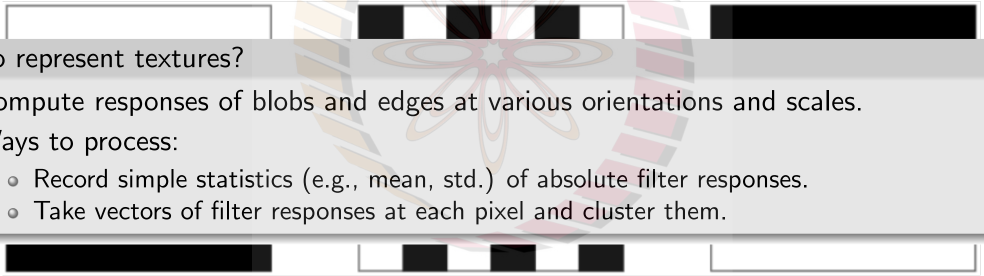

### How to represent textures?

- Compute responses of blobs and edges at various orientations and scales.
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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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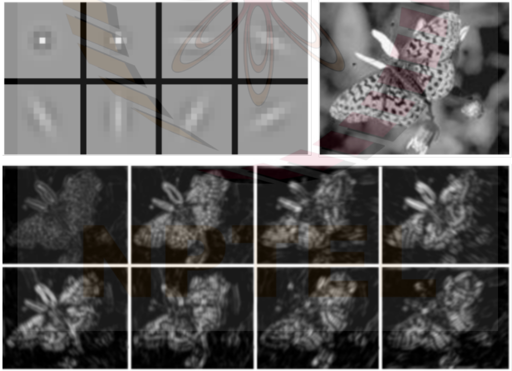
- Process image with each filter and keep responses (or squared/abs responses).



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## Gabor Filters

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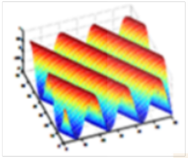
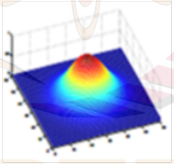
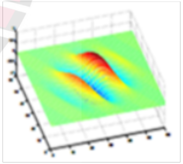
- Special classes of bandpass filters (i.e., they allow a certain 'band' of frequencies and reject the others).
- A Gabor filter can be viewed as a sinusoidal signal of particular frequency and orientation, modulated by a Gaussian wave.



A sinusoid oriented $30^\circ$ with x-axis

A 2-D Gaussian





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:

$x' = x \cos\theta + y \sin\theta$

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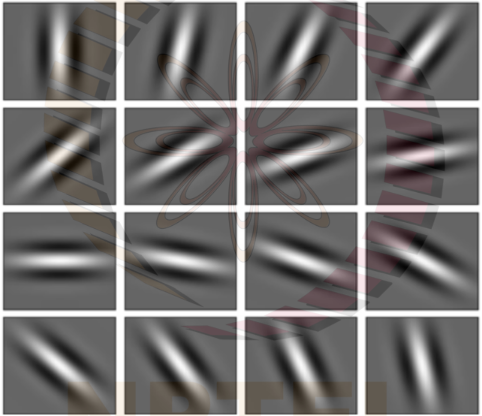
$\gamma$ – Spatial aspect ratio and specifies the ellipticity of the support of Gabor function.

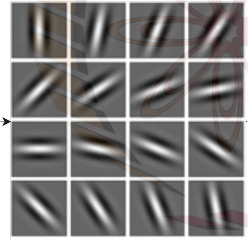
# Gabor Filter Banks



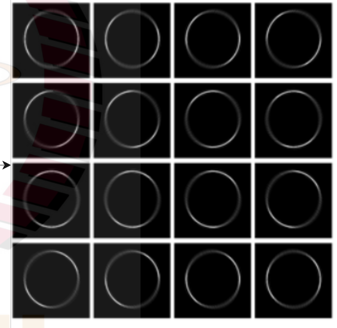
Bank of 16 Gabor filters at an orientation of 11.250 (i.e. if the first filter is at 00.00, then the second will be at 11.25, the third will be at 22.50, and so on.)

# 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

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- For an isotropic Gaussian filter, $G(x, y) = e^{-(x^2+y^2)}$,

$$G_1^{\theta^\circ} = G_1^{0^\circ} \cos(\theta) + G_1^{90^\circ} \sin(\theta)$$

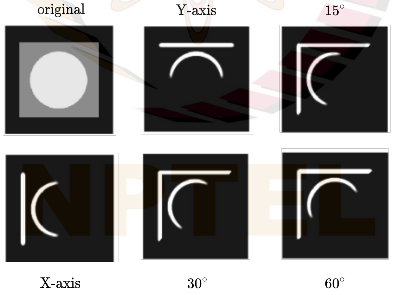
# Steerable Filter Banks

Steerable Filters are a class of oriented filters that can be expressed as a linear combination of a set of basis filters.

- For an isotropic Gaussian filter, $G(x, y) = e^{-(x^2+y^2)}$,

$$G_1^{\theta^\circ} = G_1^{0^\circ} \cos(\theta) + G_1^{90^\circ} \sin(\theta)$$

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



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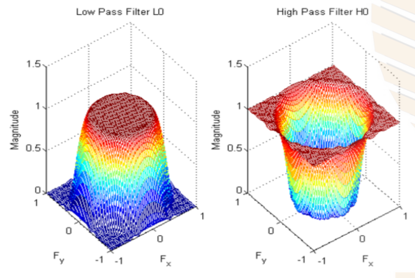


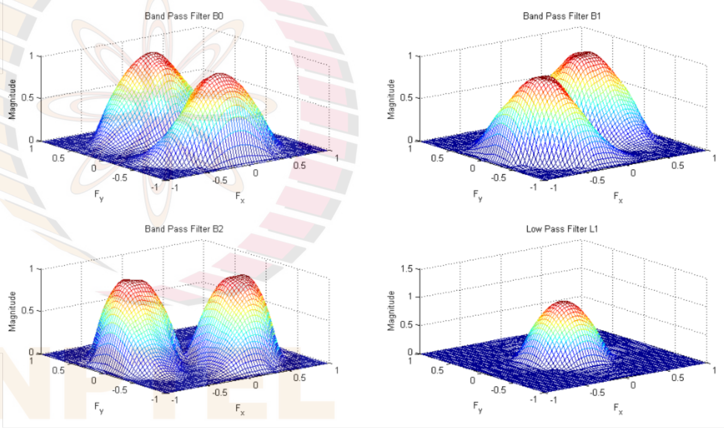

# Homework

## 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?