

# Lecture-07

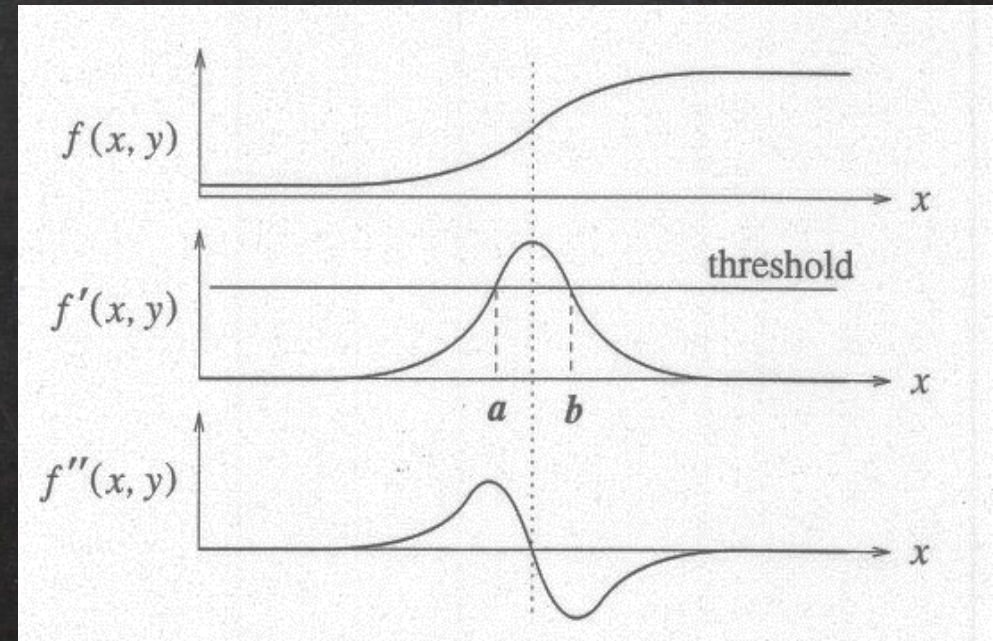
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## Feature Extraction



# Laplacian/Laplacian of Gaussian

- Second Derivative Operators





# Laplacian/Laplacian of Gaussian

- The Laplacian  $L(x, y)$  of an image with pixel intensity values  $f(x, y)$  is given by:

$$\nabla^2 f = L(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

- The gradient of  $f$  in both  $x$  and  $y$  direction are:

$$G_x \cong f[i, j + 1] - f[i, j]$$

$$G_y \cong f[i, j] - f[i + 1, j]$$



# Laplacian/Laplacian of Gaussian

- The second derivatives along the x and y directions are

$$\frac{\partial^2 f}{\partial x^2} = \frac{\partial G_x}{\partial x} = \frac{\partial (f[i, j + 1] - f[i, j])}{\partial x}$$

$$\frac{\partial^2 f}{\partial x^2} = \frac{\partial (f[i, j + 1])}{\partial x} - \frac{\partial (f[i, j])}{\partial x}$$



# Laplacian/Laplacian of Gaussian

$$\frac{\partial^2 f}{\partial x^2} = f[i, j + 2] - f[i, j + 1] - (f[i, j + 1] - f[i, j])$$

$$\frac{\partial^2 f}{\partial x^2} = f[i, j + 2] - 2f[i, j + 1] + f[i, j]$$

- However, this approximation is centered about the pixel  $[i, j + 1]$ .

Therefore, by replacing  $j$  with  $j - 1$ , we obtain

$$\frac{\partial^2 f}{\partial x^2} = f[i, j + 1] - 2f[i, j] + f[i, j - 1]$$



# Laplacian/Laplacian of Gaussian

- which is the desired approximation to the second partial derivative centered about  $[i, j]$ . Similarly,

$$\frac{\partial^2 f}{\partial y^2} = f[i + 1, j] - 2f[i, j] + f[i - 1, j]$$

- By combining these two equations into a single operator, the following mask can be used to approximate the Laplacian:

$$\nabla^2 f = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$



# Laplacian/Laplacian of Gaussian

- Using one of these kernels, the Laplacian can be calculated using standard convolution methods.

|    |    |    |  |    |    |    |
|----|----|----|--|----|----|----|
| 0  | -1 | 0  |  | -1 | -1 | -1 |
| -1 | 4  | -1 |  | -1 | 8  | -1 |
| 0  | -1 | 0  |  | -1 | -1 | -1 |



# LoG ('Laplacian of Gaussian')

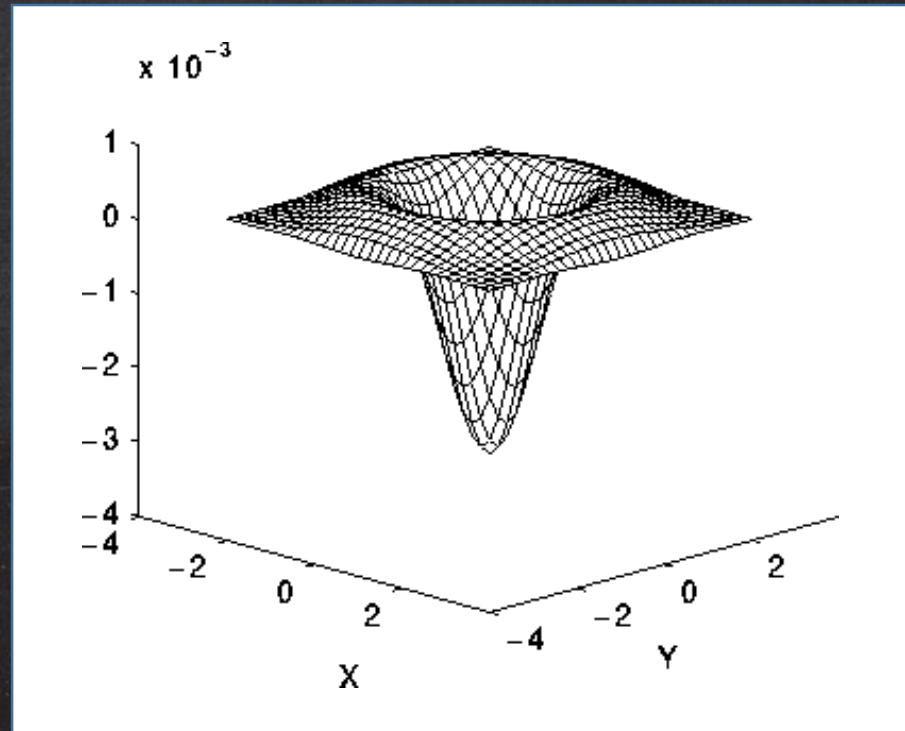
- The 2-D LoG function centered on zero and with Gaussian standard deviation  $\sigma$  has the form:

$$LoG(x, y) = -\frac{1}{\pi\sigma^4} \left[ 1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$



# LoG ('Laplacian of Gaussian')

$$LoG(x, y) = -\frac{1}{\pi\sigma^4} \left[ 1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$





# LoG ('Laplacian of Gaussian')

- A discrete kernel that approximates this function (for a Gaussian  $\sigma = 1.4$ )

|   |   |   |     |     |     |   |   |   |
|---|---|---|-----|-----|-----|---|---|---|
| 0 | 1 | 1 | 2   | 2   | 2   | 1 | 1 | 0 |
| 1 | 2 | 4 | 5   | 5   | 5   | 4 | 2 | 1 |
| 1 | 4 | 5 | 3   | 0   | 3   | 5 | 4 | 1 |
| 2 | 5 | 3 | -12 | -24 | -12 | 3 | 5 | 2 |
| 2 | 5 | 0 | -24 | -40 | -24 | 0 | 5 | 2 |
| 2 | 5 | 3 | -12 | -24 | -12 | 3 | 5 | 2 |
| 1 | 4 | 5 | 3   | 0   | 3   | 5 | 4 | 1 |
| 1 | 2 | 4 | 5   | 5   | 5   | 4 | 2 | 1 |
| 0 | 1 | 1 | 2   | 2   | 2   | 1 | 1 | 0 |



