

Lecture-5

Computing Camera Parameters

Computing Camera Parameters

- Using known 3-D points and corresponding image points, estimate camera matrix employing pseudo inverse method of section 1.6 (Fundamental of Computer Vision).
- Compute camera parameters by relating camera matrix with estimated camera matrix.
 - Extrinsic
 - Translation
 - Rotation
 - Intrinsic
 - Horizontal and vertical focal lengths
 - Translation o_x and o_y

Comparison

$$\hat{M} = \begin{bmatrix} \hat{m}_{11} & \hat{m}_{12} & \hat{m}_{13} & \hat{m}_{14} \\ \hat{m}_{21} & \hat{m}_{22} & \hat{m}_{23} & \hat{m}_{24} \\ \hat{m}_{31} & \hat{m}_{32} & \hat{m}_{33} & \hat{m}_{34} \end{bmatrix}$$

$$M = \begin{bmatrix} -f_x r_{11} + r_{31} o_x & -f_x r_{12} + r_{32} o_x & -f_x r_{13} + r_{33} o_x & -f_x T_x + T_z o_x \\ -f_y r_{21} + r_{31} o_y & -f_y r_{22} + r_{32} o_y & -f_y r_{23} + r_{33} o_y & -f_y T_y + T_z o_y \\ r_{31} & r_{32} & r_{33} & T_z \end{bmatrix}$$

Computing Camera Parameters: Estimating scale

estimated

$$\hat{M} = \mathbf{g} M$$

Since M is defined up to a scale factor

$$\begin{bmatrix} \hat{m}_{11} & \hat{m}_{12} & \hat{m}_{13} & \hat{m}_{14} \\ \hat{m}_{21} & \hat{m}_{22} & \hat{m}_{23} & \hat{m}_{24} \\ \hat{m}_{31} & \hat{m}_{32} & \hat{m}_{33} & \hat{m}_{34} \end{bmatrix} = \mathbf{g} \begin{bmatrix} -f_x r_{11} + r_{31} o_x & -f_x r_{12} + r_{32} o_x & -f_x r_{13} + r_{33} o_x & -f_x T_x + T_z o_x \\ -f_y r_{21} + r_{31} o_y & -f_y r_{22} + r_{32} o_y & -f_y r_{23} + r_{33} o_y & -f_y T_y + T_z o_y \\ r_{31} & r_{32} & r_{33} & T_z \end{bmatrix}$$

$$\sqrt{\hat{m}_{31}^2 + \hat{m}_{32}^2 + \hat{m}_{33}^2} = |\mathbf{g}| \sqrt{r_{31}^2 + r_{32}^2 + r_{33}^2} = |\mathbf{g}|$$

Divide each entry of \hat{M} by $|\mathbf{g}|$.

Computing Camera Parameters: estimating third row of rotation matrix and translation in depth

$$\begin{bmatrix} \hat{m}_{11} & \hat{m}_{12} & \hat{m}_{13} & \hat{m}_{14} \\ \hat{m}_{21} & \hat{m}_{22} & \hat{m}_{23} & \hat{m}_{24} \\ \hat{m}_{31} & \hat{m}_{32} & \hat{m}_{33} & \hat{m}_{34} \end{bmatrix} = \mathbf{g} \begin{bmatrix} -f_x r_{11} + r_{31} o_x & -f_x r_{12} + r_{32} o_x & -f_x r_{13} + r_{33} o_x & -f_x T_x + T_z o_x \\ -f_y r_{21} + r_{31} o_y & -f_y r_{22} + r_{32} o_y & -f_y r_{23} + r_{33} o_y & -f_y T_y + T_z o_y \\ r_{31} & r_{32} & r_{33} & T_z \end{bmatrix}$$

$$T_z = s \hat{m}_{34}, \quad s = \pm 1$$

$$r_{3i} = s \hat{m}_{3i}, \quad i = 1, 2, 3$$

Computing Camera Parameters

$$\begin{bmatrix} \hat{m}_{11} & \hat{m}_{12} & \hat{m}_{13} & \hat{m}_{14} \\ \hat{m}_{21} & \hat{m}_{22} & \hat{m}_{23} & \hat{m}_{24} \\ \hat{m}_{31} & \hat{m}_{32} & \hat{m}_{33} & \hat{m}_{34} \end{bmatrix} = \mathbf{g} \begin{bmatrix} -f_x r_{11} + r_{31} o_x & -f_x r_{12} + r_{32} o_x & -f_x r_{13} + r_{33} o_x & -f_x T_x + T_z o_x \\ -f_y r_{21} + r_{31} o_y & -f_y r_{22} + r_{32} o_y & -f_y r_{23} + r_{33} o_y & -f_y T_y + T_z o_y \\ r_{31} & r_{32} & r_{33} & T_z \end{bmatrix}$$

Let

$$q_1 = [\hat{m}_{11} \quad \hat{m}_{12} \quad \hat{m}_{13}]$$

$$q_2 = [\hat{m}_{21} \quad \hat{m}_{22} \quad \hat{m}_{23}]$$

$$q_3 = [\hat{m}_{31} \quad \hat{m}_{32} \quad \hat{m}_{33}]$$

Computing Camera Parameters: origin of image

$$\begin{aligned}
q_1^T q_3 &= \hat{m}_{11} \hat{m}_{31} + \hat{m}_{12} \hat{m}_{32} + \hat{m}_{13} \hat{m}_{33} \\
\hat{m}_{11} \hat{m}_{31} + \hat{m}_{12} \hat{m}_{32} + \hat{m}_{13} \hat{m}_{33} &= \\
&\quad (-f_x r_{11} + r_{31} o_x \quad -f_x r_{12} + r_{32} o_x \quad -f_x r_{13} + r_{33} o_x)(r_{31} \quad r_{32} \quad r_{33}) \\
&= (-f_x r_{11} \quad -f_x r_{12} \quad -f_x r_{13})(r_{31} \quad r_{32} \quad r_{33}) + \\
&\quad (r_{31} o_x \quad r_{32} o_x \quad r_{33} o_x)(r_{31} \quad r_{32} \quad r_{33}) \\
&= (r_{31} o_x \quad r_{32} o_x \quad r_{33} o_x)(r_{31} \quad r_{32} \quad r_{33}) \\
&= (r_{31}^2 o_x^2 + r_{32}^2 o_x^2 + r_{33}^2 o_x^2) \\
&= o_x (r_{31}^2 + r_{32}^2 + r_{33}^2) \\
&= o_x
\end{aligned}$$

Therefore:

$$\begin{aligned}
o_x &= q_1^T q_3 \\
o_y &= q_2^T q_3
\end{aligned}$$

Computing Camera Parameters: vertical and horizontal focal lengths

$$\begin{aligned}
q_1^T q_1 &= \hat{m}_{11} \hat{m}_{11} + \hat{m}_{12} \hat{m}_{12} + \hat{m}_{13} \hat{m}_{13} \\
\hat{m}_{11} \hat{m}_{11} + \hat{m}_{12} \hat{m}_{12} + \hat{m}_{13} \hat{m}_{13} &= \\
&\quad (-f_x r_{11} + r_{31} o_x \quad -f_x r_{12} + r_{32} o_x \quad -f_x r_{13} + r_{33} o_x)(-f_x r_{11} + r_{31} o_x \quad -f_x r_{12} + r_{32} o_x \quad -f_x r_{13} + r_{33} o_x) \\
&= (-f_x r_{11} + r_{31} o_x)^2 + (-f_x r_{12} + r_{32} o_x)^2 + (-f_x r_{13} + r_{33} o_x)^2 \\
&= (f_x^2 r_{11}^2 + r_{31}^2 o_x^2) + (f_x^2 r_{12}^2 + r_{32}^2 o_x^2) + (f_x^2 r_{13}^2 + r_{33}^2 o_x^2) \\
&= f_x^2 (r_{11}^2 + r_{12}^2 + r_{13}^2) + o_x^2 (r_{31}^2 + r_{32}^2 + r_{33}^2) \\
&= f_x^2 + o_x^2 \\
q_1^T q_1 &= f_x^2 + o_x^2 \\
\sqrt{q_1^T q_1 - o_x^2} &= f_x
\end{aligned}$$

Therefore:

$$\begin{aligned}
f_x &= \sqrt{q_1^T q_1 - o_x^2} \\
f_y &= \sqrt{q_2^T q_2 - o_y^2}
\end{aligned}$$

Computing Camera Parameters: remaining rotation and translation parameters

$$M = \begin{bmatrix} -f_x r_{11} + r_{31} o_x & -f_x r_{12} + r_{32} o_x & -f_x r_{13} + r_{33} o_x & -f_x T_x + T_z o_x \\ -f_y r_{21} + r_{31} o_y & -f_y r_{22} + r_{32} o_y & -f_y r_{23} + r_{33} o_y & -f_y T_y + T_z o_y \\ r_{31} & r_{32} & r_{33} & T_z \end{bmatrix}$$

$$r_{1i} = \mathbf{S}(0_x \hat{m}_{3i} - \hat{m}_{1i}) / f_x, \quad i=1,2,3$$

$$r_{2i} = \mathbf{S}(0_y \hat{m}_{3i} - \hat{m}_{2i}) / f_y, \quad i=1,2,3$$

$$T_x = \mathbf{S}(0_x T_z - \hat{m}_{14}) / f_x$$

$$T_y = \mathbf{S}(0_y T_z - \hat{m}_{24}) / f_y$$

Application

$$M = \begin{bmatrix} .17237 & -.15879 & .01879 & 274.943 \\ .131132 & .112747 & .2914 & 258.686 \\ .000346 & .0003 & .00006 & 1 \end{bmatrix}$$



FIGURE 8: PHOTOGRAPH OF SAN FRANCISCO



FIGURE 9: MAP OF SAN FRANCISCO

Camera location: intersection of California And Mason streets, at an elevation of 435 feet Above sea level. The camera was oriented At an angle of 8^0 above the horizon. $f_{s_x}=495$, $f_{s_y}=560$.

Application

$$M = \begin{bmatrix} -.175451 & -.10520 & .00435 & 297.83 \\ .02698 & -.09635 & .2303 & 249.574 \\ .00015 & -.00016 & .00001 & 1.0 \end{bmatrix}$$

Camera location: at an elevation of 1200 feet
Above sea level. The camera was oriented
At an angle of 4^0 above the horizon. $f_{s_x}=876$,
 $f_{s_y}=999$.



FIGURE 10 ANOTHER PHOTOGRAPH OF SAN FRANCISCO



FIGURE 11 MAP OF SAN FRANCISCO

Pose estimation: Object Recognition

- To determine the orientation and position of an object which would result in the projection of given 3-D points into a given set of image points.
 - 3-D points are given from the model
 - 2-D points are given from the image
 - Determine 3-D rotation(orientation), and 3-D translation (position)

Pose Estimation

$$(X', Y', Z') \xrightarrow{\text{Rotation}} (X, Y, Z) \xrightarrow{\text{trans}} (X + T_x, Y + T_y, Z + T_z) \xrightarrow{\text{perspect}} (x', y')$$

$$(x', y') = \left(\frac{f(X + T_x)}{Z + T_z}, \frac{f(Y + T_y)}{Z + T_z} \right)$$

Image displacements instead of
3-D translations

$$(x', y') = \left(\frac{fX}{Z + D_z} + D_x, \frac{fY}{Z + D_z} + D_y \right) = (fXc + D_x, fYc + D_y) \quad c = \frac{1}{Z + D_z}$$

Error in x coordinates:

$$E_{x'} = \frac{\partial x'}{\partial D_x} \Delta D_x + \frac{\partial x'}{\partial D_y} \Delta D_y + \frac{\partial x'}{\partial D_z} \Delta D_z + \frac{\partial x'}{\partial \mathbf{f}_x} \Delta \mathbf{f}_x + \frac{\partial x'}{\partial \mathbf{f}_y} \Delta \mathbf{f}_y + \frac{\partial x'}{\partial \mathbf{f}_z} \Delta \mathbf{f}_z$$

Pose Estimation

Derivatives

$$(x', y') = \left(\frac{fX}{Z + D_z} + D_x, \frac{fY}{Z + D_z} + D_y \right) = (fXc + D_x, fYc + D_y)$$

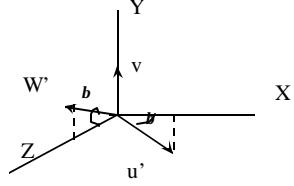
$$\frac{\partial x'}{\partial D_x} = 1$$

$$\frac{\partial x'}{\partial \mathbf{f}_y} = \frac{\partial x'}{\partial X} \frac{\partial X}{\partial \mathbf{f}_y} + \frac{\partial x'}{\partial Z} \frac{\partial Z}{\partial \mathbf{f}_y} \quad \text{Chain rule}$$

$$\frac{\partial x'}{\partial \mathbf{f}_y} = \frac{\partial X}{\partial \mathbf{f}_y} \frac{f}{Z + D_z} - \frac{fX}{(Z + D_z)^2} \frac{\partial Z}{\partial \mathbf{f}_y}$$

Pose Estimation

$$R_{-b}^Y = \begin{bmatrix} \cos b & 0 & -\sin b \\ 0 & 1 & 0 \\ \sin b & 0 & \cos b \end{bmatrix}$$



$$R_{f_y}^Y = \begin{bmatrix} \cos f_y & 0 & \sin f_y \\ 0 & 1 & 0 \\ -\sin f_y & 0 & \cos f_y \end{bmatrix}$$

$$\frac{\partial X}{\partial f_y} = -X' \sin f_y + Z' \cos f_y = Z$$

$$X = X' \cos f_y + Z' \sin f_y$$

$$\frac{\partial Y}{\partial f_y} = 0$$

$$Y = Y'$$

$$Z = -X' \sin f_y + Z' \cos f_y$$

$$\frac{\partial Z}{\partial f_y} = -X' \cos f_y - Z' \sin f_y = -X$$

Pose Estimation

$$E_{x'} = \frac{\partial x'}{\partial D_x} \Delta D_x + \frac{\partial x'}{\partial D_y} \Delta D_y + \frac{\partial x'}{\partial D_z} \Delta D_z + \frac{\partial x'}{\partial \mathbf{f}_x} \Delta \mathbf{f}_x + \frac{\partial x'}{\partial \mathbf{f}_y} \Delta \mathbf{f}_y + \frac{\partial x'}{\partial \mathbf{f}_z} \Delta \mathbf{f}_z$$

$$E_{y'} = \frac{\partial y'}{\partial D_x} \Delta D_x + \frac{\partial y'}{\partial D_y} \Delta D_y + \frac{\partial y'}{\partial D_z} \Delta D_z + \frac{\partial y'}{\partial \mathbf{f}_x} \Delta \mathbf{f}_x + \frac{\partial y'}{\partial \mathbf{f}_y} \Delta \mathbf{f}_y + \frac{\partial y'}{\partial \mathbf{f}_z} \Delta \mathbf{f}_z$$

$$\begin{bmatrix} \frac{\partial x'}{\partial D_x} & \frac{\partial x'}{\partial D_y} & \frac{\partial x'}{\partial D_z} & \frac{\partial x'}{\partial \mathbf{f}_x} & \frac{\partial x'}{\partial \mathbf{f}_y} & \frac{\partial x'}{\partial \mathbf{f}_z} \\ \vdots & & & & & \\ \frac{\partial y'}{\partial D_x} & \frac{\partial y'}{\partial D_y} & \frac{\partial y'}{\partial D_z} & \frac{\partial y'}{\partial \mathbf{f}_x} & \frac{\partial y'}{\partial \mathbf{f}_y} & \frac{\partial y'}{\partial \mathbf{f}_z} \\ \vdots & & & & & \end{bmatrix} \begin{bmatrix} \Delta D_x \\ \Delta D_y \\ \Delta D_z \\ \Delta \mathbf{f}_x \\ \Delta \mathbf{f}_y \\ \Delta \mathbf{f}_z \end{bmatrix} = \begin{bmatrix} E_{x'} \\ E_{y'} \end{bmatrix}$$

$$A\Delta = E$$

$$\Delta = (AA^T)^{-1} A^T E$$

Least squares fit

Derivatives and Averages

Derivatives and Averages

- Derivative: Rate of change of some quantity
 - Speed is a rate of change of a distance
 - Acceleration is a rate of change of speed
- Average (Mean)
 - The numerical result obtained by dividing the sum of two or more quantities by the number of quantities

Derivative

$$\frac{df}{dx} = \lim_{\Delta x \rightarrow 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x) = f_x$$

$$v = \frac{ds}{dt} \quad \text{speed}$$

$$a = \frac{dv}{dt} \quad \text{acceleration}$$

Examples

$$y = x^2 + x^4 \quad y = \sin x + e^{-x}$$

$$\frac{dy}{dx} = 2x + 4x^3 \quad \frac{dy}{dx} = \cos x + (-1)e^{-x}$$

Second Derivative

$$\frac{df_x}{dx} = f''(x) = f_{xx}$$

$$y = x^2 + x^4$$

$$\frac{dy}{dx} = 2x + 4x^3$$

$$\frac{d^2y}{dx^2} = 2 + 12x^2$$

Discrete Derivative

$$\frac{df}{dx} = \lim_{\Delta x \rightarrow 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x)$$

$$\frac{df}{dx} = \frac{f(x) - f(x - 1)}{1} = f'(x)$$

$$\frac{df}{dx} = f(x) - f(x - 1) = f'(x)$$

(Finite Difference)

Discrete Derivative

$$\frac{df}{dx} = f(x) - f(x-1) = f'(x) \quad \text{Left difference}$$

$$\frac{df}{dx} = f(x) - f(x+1) = f'(x) \quad \text{Right difference}$$

$$\frac{df}{dx} = f(x+1) - f(x-1) = f'(x) \quad \text{Center difference}$$

Example

	F(x)=10	10	10	10	20	20	20
Left difference	F'(x)=0	0	0	0	10	0	0
	F''(x)=0	0	0	0	10	-10	0

-1 1 left difference
1 -1 right difference
-1 0 1 center difference

Derivatives in Two Dimensions

$f(x, y)$

(partial Derivatives) $\frac{\partial f}{\partial x} = f_x = \lim_{\Delta x \rightarrow 0} \frac{f(x, y) - f(x - \Delta x, y)}{\Delta x}$

$\frac{\partial f}{\partial y} = f_y = \lim_{\Delta y \rightarrow 0} \frac{f(x, y) - f(x, y - \Delta y)}{\Delta y}$

(f_x, f_y) Gradient Vector

magnitude $= \sqrt{(f_x^2 + f_y^2)}$

direction $= q = \tan^{-1} \frac{f_y}{f_x}$

$\Delta^2 f = f_{xx} + f_{yy}$ = Laplacian

Derivatives of an Image

	-1 0 1	-1 -1 -1	
Derivative & average	-1 0 1	0 0 0	Prewit
	-1 0 1	1 1 1	
	f_x	f_y	

$$I(x, y) = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix} \quad I_x = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 30 & 30 & 0 & 0 \\ 0 & 30 & 30 & 0 & 0 \\ 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Derivatives of an Image

$$I(x, y) = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix} \quad I_y = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Average

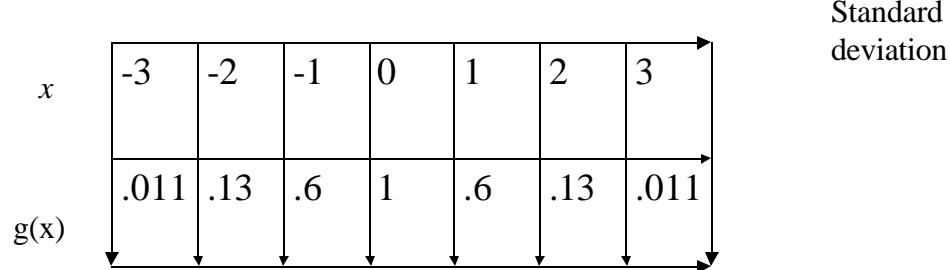
$$I = \frac{I_1 + I_2 + \dots + I_n}{n} = \frac{\sum_{i=1}^n I_i}{n}$$

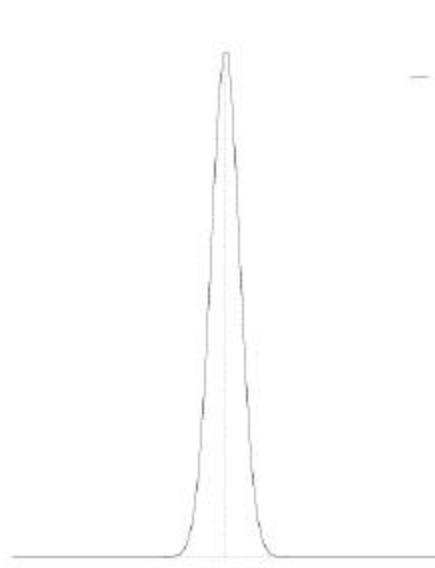
Weighted Average

$$I = \frac{w_1 I_1 + w_2 I_2 + \dots + w_n I_n}{n} = \frac{\sum_{i=1}^n w_i I_i}{n}$$

Gaussian

$$g(x) = e^{\frac{-x^2}{2\sigma^2}}$$





Gaussian

- Most natural phenomenon can be modeled by Gaussian.
- Take a bunch of random variables of any distribution, find the mean, the mean will approach to Gaussian distribution.
- Gaussian is very smooth function, it has infinite no of derivatives.

Gaussian

- Fourier Transform of Gaussian is Gaussian.
- If you convolve Gaussian with itself, it is again Gaussian.
- There are cells in human brain which perform Gaussian filtering.
 - Laplacian of Gaussian edge detector

Carl F. Gauss

- Born to a peasant family in a small town in Germany.
- Learned counting before he could talk.
- Contributed to Physics, Mathematics, Astronomy,...
- Discovered most methods in modern mathematics, when he was a teenager.

Carl F. Gauss

- Some contributions
 - Gaussian elimination for solving linear systems
 - Gauss-Seidel method for solving sparse systems
 - Gaussian curvature
 - Gaussian quadrature

Noise

- Image contains noise due to
 - Lighting variations
 - Lens de-focus
 - Camera electronics
 - Surface reflectance
- Remove noise
 - Averaging
 - Weighted averaging

Example

$F(x)=10$	10	10	10	20	20	20
$n(x)=0$	5	0	0	3	0	0
$F\sim(x)=10$	15	10	10	23	20	20
$H(x)=10$	12	12	14	17	21	20

Edge Detection

- Find edges in the image
- Edges are locations where intensity changes the most
- Edges can be used to represent a shape of an object

Edge Detection

- Images contain noise, need to remove noise by averaging, or weighted averaging
- To detect edges compute derivative of an image (gradient)
- If gradient magnitude is high at pixel, intensity change is maximum, that is an edge pixel
- If Laplacian (second derivative) is zero then at that point the first derivative is maximum, that point is an edge pixel.

Edge Detectors

- Prewit
- Sobel
- Roberts
- Marr-Hildreth (Laplacian of Gaussian)
- Canny (Gradient of Gaussian)

Derivatives of an Image

$$\begin{array}{ccc} & -1 & 0 & 1 \\ \text{P} & -2 & 0 & 2 \\ \text{Sobel} & -1 & 0 & 1 \\ & f_x & & f_y \end{array}$$

$$\begin{array}{cc} 0 & 1 \\ -1 & 0 \end{array} \quad \begin{array}{cc} 1 & 0 \\ 0 & -1 \end{array}$$

Roberts

$$f_x \qquad \qquad \qquad f_y$$

Laplacian of Gaussian

- Filter the image by weighted averaging (Gaussian)
- Find Laplacian of image
- Detect zero-crossings

$$\Delta^2 f = f_{xx} + f_{yy} = \text{Laplacian}$$

Canny Edge Detector

- Filter the image with Gaussian
- Find the gradient magnitude
- Edges are maxima of gradient magnitude