

Lecture 2 - Historical Vision Problems

- Images as points
 - Images as functions
 - Convolution
 - Filtering
 - Blurring
 - Edge Detection
 - Template matching
- } Tools

Categories:

Reduction	Matching	Fitting
$- X^* = \underset{x}{\operatorname{argmin}} f(I, x)$ $\uparrow \quad \quad \quad \uparrow$	$- X^* = \underset{x}{\operatorname{argmin}} d(X, X_T)$ $\uparrow \quad \quad \quad \uparrow \uparrow$	$- \Theta^* = \underset{\Theta}{\operatorname{argmin}} g(I; \Theta)$ $\uparrow \quad \quad \quad \uparrow \uparrow$
<ul style="list-style-type: none"> - Indexing - Id-free expression recognition - Featurization 	<ul style="list-style-type: none"> - Img search - Optical flow - Img registration 	<ul style="list-style-type: none"> - Model fitting - Neural nets - Structure from motion

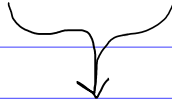
→ Why categorize?

- Similar problems = similar solutions

Plan for lecture:

- Work through example problem: image registration
- Learn about structure tensor
- Learn about homographies

Image Registration



Uses:

- Image stitching →
- Camera stabilization
- Motion reconstruction



Goal:

- Find a transform $T(\cdot)$ that maps points in one image to the same real-world points in another.

How?

Idea 1: Direct fitting

- Parametrize T by Θ : $T = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 \\ \theta_4 & \theta_5 & \theta_6 \\ \theta_7 & \theta_8 & 1 \end{bmatrix}$

- Define a loss: $f(\mathcal{I}_1, \mathcal{I}_2; \Theta) = \sum_{\substack{(x,y) \in \\ \mathcal{I}_1 \cap \mathcal{I}_2}} \left\| \mathcal{I}_1(x,y) - \frac{1}{T(\mathcal{I}_2(x,y))} \right\|_2^2$

- Find the Θ^* that minimizes f !

→ Intractable \leadsto

Idea #2: Point Fitting

- Identify "unique" or distinctive points in both images
- Match up which ones correspond to the same points
- Fit the transform that maps these points to each other

★ Useful example of:

- Reduction - of points to descriptive features
- Matching - those points to each other
- Fitting - the transform

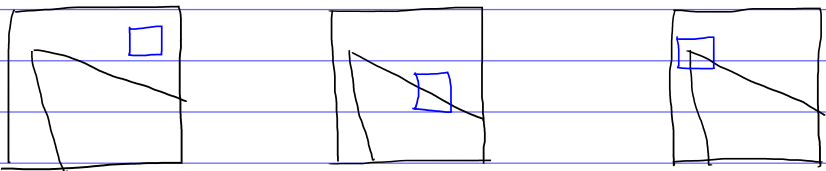
Step 1: Finding Points of Interest

- What makes a point distinct?



* We want corners. Flat areas and long edges aren't unique enough.

Property of corners: Small shifts in any direction change the neighborhood.



Define a measure of the corner-ness of the neighborhood around a point by how much the neighborhood changes with a small shift $[\Delta x, \Delta y]^T$:



$$f(\Delta x, \Delta y) = \sum_{x,y \in W} [I(x,y) - I(x+\Delta x, y+\Delta y)]^2$$

Taylor Expansion: $I_x = \frac{\partial I}{\partial x}$ $I_y = \frac{\partial I}{\partial y}(x,y)$

$$I(x+\Delta x, y+\Delta y) \approx I(x,y) + \Delta x \cdot I_x + \Delta y \cdot I_y + \text{H.O.T.}$$

$$f(\Delta x, \Delta y) = \sum_{x,y \in W} [I(x,y) - I(x,y) + \Delta x I_x + \Delta y I_y]^2$$

$$= \sum_{x,y \in W} [\Delta x^2 I_x^2 + 2\Delta x \Delta y I_x I_y + \Delta y^2 I_y^2]$$

$$= \sum_{x,y \in W} \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$f(\Delta x, \Delta y) = \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \underbrace{\begin{bmatrix} \sum_{x,y \in W} I_x^2 & \sum_{x,y \in W} I_x I_y \\ \sum_{x,y \in W} I_x I_y & \sum_{x,y \in W} I_y^2 \end{bmatrix}}_{M_w} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$I_x(x,y) =$$

$$I_y(x,y) =$$

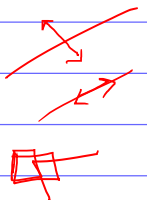
M_w = the structure tensor

Flat : Any $(\Delta x, \Delta y) \rightarrow \text{low } f$

Edges : One $(\Delta x, \Delta y) \rightarrow \text{high } f$

One $(\Delta x, \Delta y) \rightarrow \text{low } f$

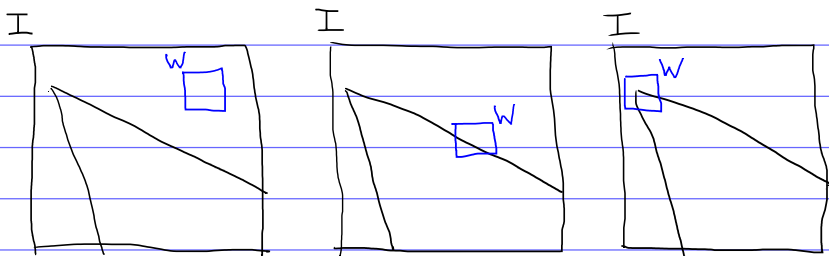
Corners : Any $(\Delta x, \Delta y) \rightarrow \text{high } f$





$$f(\Delta x, \Delta y) = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}^T \underbrace{\begin{bmatrix} \sum_{x,y \in W} I_x^2 & \sum_{x,y \in W} I_x I_y \\ \sum_{x,y \in W} I_x I_y & \sum_{x,y \in W} I_y^2 \end{bmatrix}}_{\text{flat edges corner } M_W} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

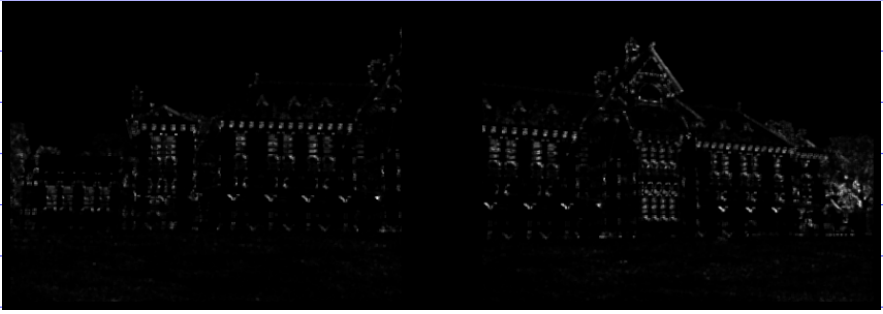
	flat	edges	corner	M_W
λ_+	low	high	high	
λ_-	low	low	high	



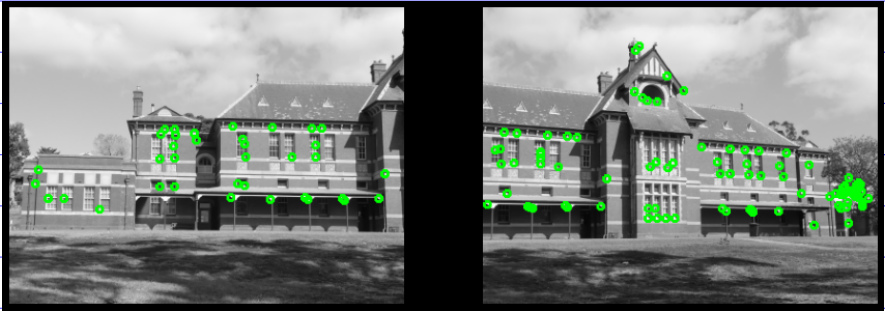
λ_+	\downarrow	λ_+	\uparrow	λ_+	\uparrow
λ_-	\downarrow	λ_-	\downarrow	λ_-	\uparrow

$$\underline{g(W)} = \min_{\Delta x, \Delta y} f_W(\Delta x, \Delta y) = \underline{\lambda_-} \text{ of } M_W$$

Map of $g(W)$ over both images:



Local maxima:



Next: How do we compare points in the two images to see which ones match each other?

Have: $g(W): (m \times m) \mapsto \text{LD}$
 \hookrightarrow good for detection
 \hookrightarrow bad for description

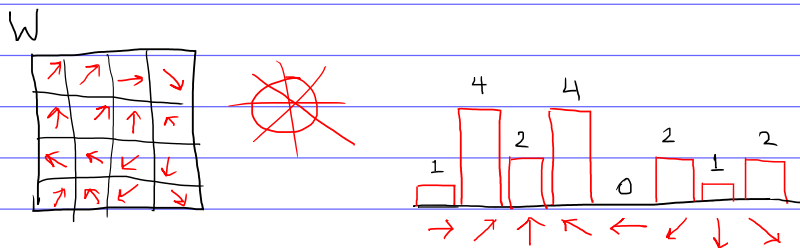
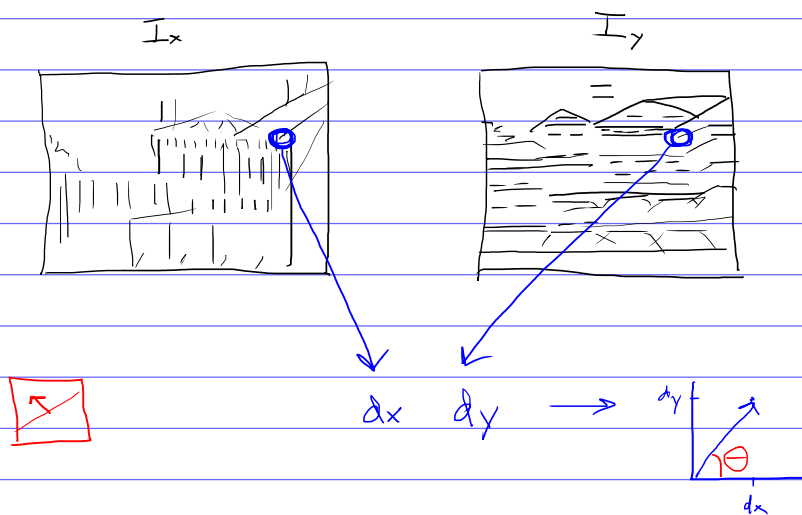
Want: $h(W): (m \times n) \mapsto \text{ND}$

Featurization

- A reduction process where we convert/compress visual information into a uniform representation for comparison or processing

→ Representation is usually a vector, but sometimes a graph, string, or other object

- Simple example algorithm: HOG (Histogram of Oriented Gradients)

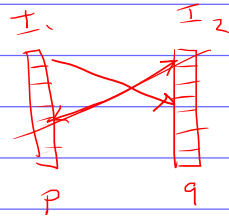


$$\text{feature} = [1, 4, 2, 4, 0, 2, 1, 2]_{16}$$

Next: Which features from image 1 match with which features from image 2?

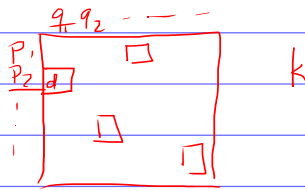
Options:

- Brute force search



- Hungarian Algorithm

$$\underline{d(p_i, q_i)} \geq 0$$

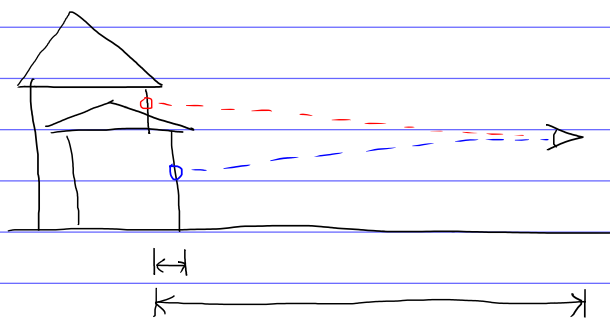


Last step! Find the transform that maps matched points onto each other.

We have, for $i = \{1, 2, \dots, \underline{n}\}$,

$$[\underline{x}_1^i, \underline{y}_1^i] \longleftrightarrow [\underline{x}_2^i, \underline{y}_2^i]$$

Perspective changes relate coplanar points with a homography.



Homography:

$$w \cdot \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix}$$

↳ homogeneous coordinates

$$w = gx_2 + hy_2 + 1$$

$$\begin{bmatrix} x_1(gx_2 + hy_2 + 1) \\ y_1(gx_2 + hy_2 + 1) \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x_2 a + y_2 b + c + 0d + 0e + 0f - x_2 x_2 g - x_1 y_2 h \\ 0a + 0b + 0c + x_2 d + y_2 e + f - y_1 x_2 g - y_1 y_2 h \\ 0a + 0b + 0c + x_2 g + y_2 h + 1 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2 x_2 & -x_1 y_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -y_1 x_2 & -y_1 y_2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \\ h \end{bmatrix}$$

$$E_i = \left\| \underbrace{\begin{bmatrix} x_1^i & y_1^i & 1 & 0 & 0 & 0 & -x_1^i x_2^i & -x_1^i y_2^i \\ 0 & 0 & 0 & x_2^i & y_2^i & 1 & -y_1^i x_2^i & -y_1^i y_2^i \end{bmatrix}}_{A_i} H - \underbrace{\begin{bmatrix} x_1^i \\ y_1^i \end{bmatrix}}_{b_i} \right\|_2^2$$

$$\arg\min_H \sum_{i=1}^n E_i$$

$$= \left\| \underbrace{\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_n \end{bmatrix}}_A H - \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{bmatrix}}_b \right\|_2$$

$$H^* = A^+ b$$

Recap:

- Three broad categories of CV problem:

Ex:			
	Reduction	Matching	Fitting
Image Registration	Corner finding	Feature matching	Homography estimation
	Featurization		

- Structure tensor & corner operator
- Featurization with HOG
- Feature matching with Hungarian Alg.
- Homography estimation via OLS