Images as Functions.

$\boxed{\text{Lambertian model}}$

$$I(u) = P(R(x))$$

where $R(x) = \rho\, l(x)^T n(x)$

$\boxed{\text{Potts model}}$

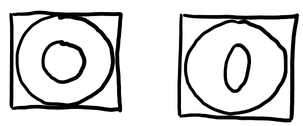
$$E(I) = \beta \sum_{s=1}^{n-1} \sum_{t=1}^{n} \mathbb{1}_{\{I(s,t) \neq I(s+1,t)\}} + \beta \sum_{s=1}^{n} \sum_{t=1}^{n-1} \mathbb{1}_{\{I(s,t) \neq I(s,t+1)\}}$$

$\boxed{\text{Phong shading model}}$ differs from Lambertian model in two ways:
ambient lightening & specular lighting

In the context of scale-space, define the characteristic scale as the scale that produces the peak of the Laplacian response

2D transformation

		DoF	Preserve
translation 平移	$\begin{bmatrix} 1 & 0 & t_1 \\ 0 & 1 & t_2 \\ 0 & 0 & 1 \end{bmatrix}$	2	orientation
rigid	$\begin{bmatrix} \cos\theta & -\sin\theta & t_1 \\ \sin\theta & \cos\theta & t_2 \\ 0 & 0 & 1 \end{bmatrix}$	3	lengths
similarity	$\begin{bmatrix} sR & t \\ 0^T & 1 \end{bmatrix}$	4	angles
affine	$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix}$	6	parallelism
projective	$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix}$	8	straight lines



Would the selected scale that maximizes the DoG with respect to the signal for two images the same? No

The DoG/SIFT description mechanism is based on finding the dominant direction of the gradient of the direction. ⇒ rotation invariance

Can these two images have the same dominant gradient direction? Yes.

Invariance

	Illu	Rotation	Scale	Affine
Harris corner	✓	✓	✗	✗
DoG	✓	✓	✓	✗

eigenval window size

$$G(x,y,k\sigma) - G(x,y,\sigma) \approx (k-1)\sigma^2 L$$

Is it always the same dominant direction for these two images? No.

What is an extension of these ideas to have these two images always yield the same descriptor?

Instead of just the dominant rotation, compute the Affine Frame.

$\boxed{\text{Piecewise constant Mumford-Shah}}$

$$E(\hat{f}, \partial; f) = \sum (\hat{f} - f)^2 + \sum (\nabla \hat{f})^2 + \partial \hat{f}$$

$\boxed{\text{Basic assumption in eigenface}}$

face is not centered, tilted, different lighting, different back-ground.

strength:
fast, simple, straight forward training
performs well in constrained setting

$\boxed{\text{Real lights are complicated}}$

- source: sun, incandescent bulb, fluorescent
- different spectra, directions
- time varying

Sample exam

homography plane : Deg Free = 8

CV hardness: viewpoint illumination scale structure context variation ; background clutter.

$\boxed{\text{Normalized cut criterion}}$ avoids degenerate single-node cuts by dividing inter-region cut by intra-region similarity across both regions that would generate cut

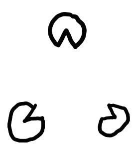
numerator is weight of the edges along cut

$\boxed{\text{Gestalt}}$

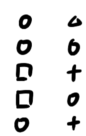
Equivocation : figure-ground (reversible)

Continuance :

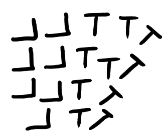
Closure :



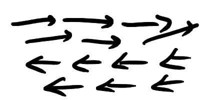
Grouping through proximity



... orientation



Common Fate



$\boxed{\text{Bayer pattern}}$ facilitates the acquisition of color images from only one CCD/chip by tiling red green and blue filer over the photoreceptive sensors in the chip that can later be composed into a dense color im.

$\boxed{\text{SIFT}}$ descriptor is more robust to pose and intra-class variation than simple patch or bank of filters thanks to histogram

Scale of traditional SIFT is decided by DoG response.

$\boxed{\text{Wavelet Transform}}$

$\boxed{\text{狮子}}$ $\boxed{\text{长颈鹿}}$

Highest-detail coeff of 狮子 + lowest detail coeff from 长颈鹿 :

长颈鹿轮廓 + 狮子毛发.

Mid-level detail set to zero :

边界出现锯尺状

20% coeff from 狮子 randomly swapped for 鹿.

狮子轮廓，长颈鹿基本看不见

Highest-detail of 鹿 × 5

对比度增加

Stitch 3 images.

step 1: find 2D affine transformation

$[u_1\ v_1]^T \cdots [u_N\ v_N]^T$

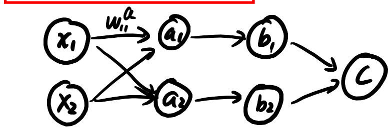
match $[x_1\ y_1]^T \cdots [x_N\ y_N]^T$

$$A^* = \arg\min_A \left\| A\begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} - \begin{bmatrix} x_i \\ y_i \end{bmatrix} \right\|_2^2$$

$$= \arg\min_A \left\| \begin{bmatrix} u_1 & v_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & u_1 & v_1 & 1 \\ & & \vdots & & & \\ u_N & v_N & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & u_N & v_N & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} - \begin{bmatrix} x_1 \\ y_1 \\ \vdots \\ x_N \\ y_N \end{bmatrix} \right\|_2^2$$

$$= \arg\min_A \| U\,\mathrm{vec}(A) - X \|_2^2$$

$\boxed{\text{Neural Network}}$



$$\begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} W_{11}^a & W_{12}^a \\ W_{21}^a & W_{22}^a \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} w_{11}^b & 0 \\ 0 & w_{22}^b \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$c = \begin{bmatrix} w_1^c & w_2^c \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = w^c w^b w^a \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Linear ⇒ cannot separate XOR problem.

Gradient feature

SIFT / HOG

Scale invariance may not be needed

RANSAC $s=3$ points

$p=0.5$ $P=0.99$ success

$$S = \frac{\log(1-P)}{\log(1-p^s)} = 34.488$$

⇒ at least 35 RANSAC trails.