Review of Computer Vision Techniques

Jason Rebello 16/05/2017



Part I : What is Computer Vision and how is an image formed

Part || : Feature Detection and Feature Matching

Part ||| : Feature Tracking and Prediction

Part IV : Applications (Bag Of Words)



What is Computer Vision and How is an Image Formed



Introduction |

Image Processing: Image Manipulation (Motion compensation, Filtering)



Filtered





Noise Removal

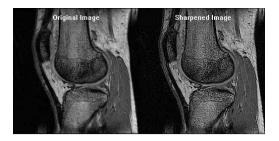


Image Sharpening

Computer Vision: Scene Interpretation



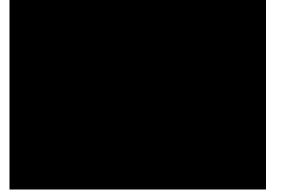
Semantic Segmentation



3D Reconstruction



Introduction | Computer Vision systems



Autonomous driving Source: Tesla



Structure from Motion Source: DrCalleOlsson

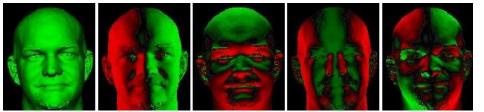
Optical Character Recognition



Surveillance Source: Ben Benfold & Ian Reid



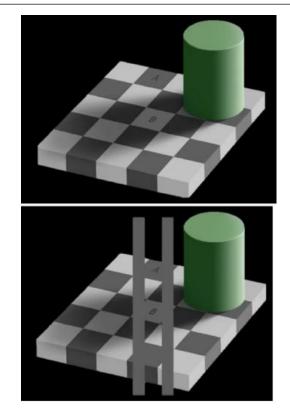
Introduction | Computer Vision is hard



Shadow Effects

| Dani | el Ke | rsten | |
|----------------|-------|----------------|--|
| Davi Pascal | | Knill 1assi | |
| Isabel | | | |

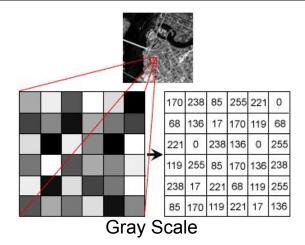
Motion from shadows Source: Dan Kersten



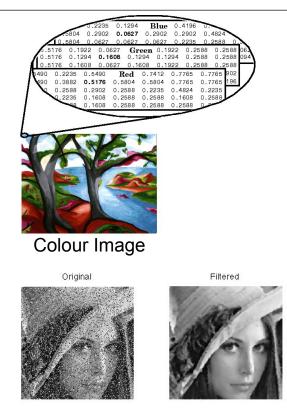
Local vs Global Perception



Introduction | Image Representations



- Images are thought of Functions
- Images: Sample 2D space Quantize Intensity
- Noise is another function combined with original function



Salt and Pepper Noise

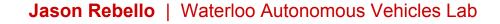
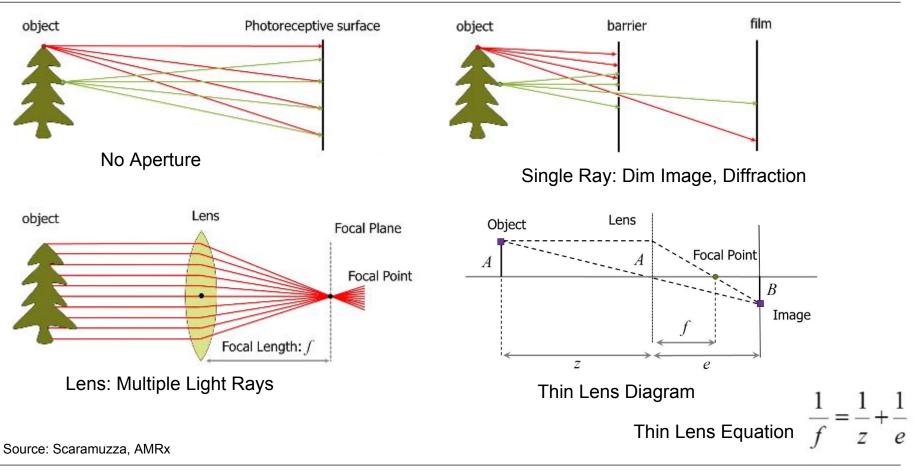




Image Formation | Cameras and Lenses



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WATERLOO

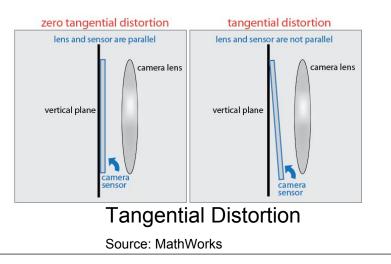
Image Formation | Distortions



No distortion



Barrel distortion





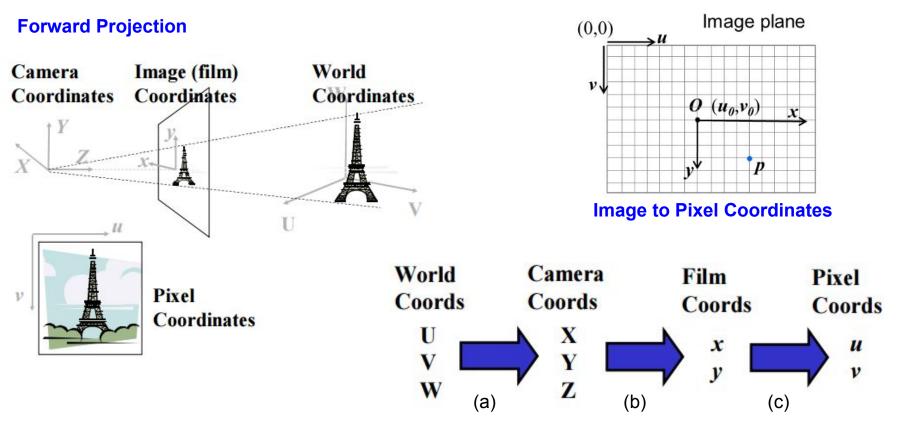
Pincushion



Radial Distortion

Source: Scaramuzza





Source: Robert Collins,

-CSE486



- (a) Extrinsic Transformation (Rotation + Translation)
 - Transforms points from World to Camera coordinate Frame
 - Homogeneous coordinates allow for easy matrix multiplication

(b),(c) Perspective Projection

X Y V Z W

Perspective Projection Eqns

$$x = f \frac{X}{Z}$$

$$y = f \frac{Y}{Z}$$
derived via similar
triangles rule
$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} f/s_x & 0 & o_x & 0 \\ 0 & f/s_y & o_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$u = \frac{x'}{z'}$$

$$v = \frac{y'}{z'}$$
Camera Coordinates
$$V = \frac{y'}{z'}$$
Projective Projection Eqns
$$u = \frac{x}{z'}$$
Projective Projection Eqns
$$u = \frac{x}{z'}$$

$$v = \frac{y'}{z'}$$
Projective Projection Eqns
$$V = \frac{y'}{z'}$$
Projective Projective Projection Eqns
$$V = \frac{y'}{z'}$$
Projective Projective Projection Eqns
$$V = \frac{y'}{z'}$$
Projective Proje



End of Part I |





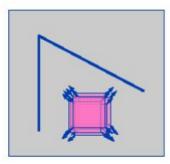
Feature Detection and Feature Matching



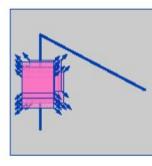
Feature Detectors |

Need to find reliably detectable and discriminable locations in images

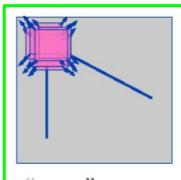
- Repeatability (Across images)
- Precise (Location)
- Saliency (Distinctive description)
- Compactness (Few features)
- Locality (Size of descriptor region)



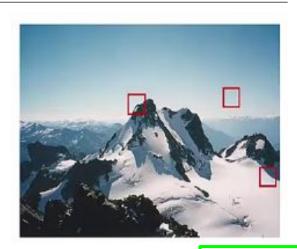
"flat" region: no change in all directions



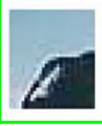
"edge": no change along the edge direction



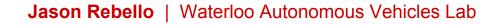
"corner": significant change in all directions





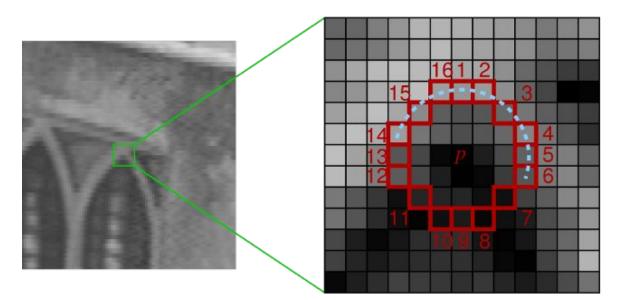


Source: Mubarak Shah





- Let 'P' be point of interest
- Select threshold 't'
- Consider 16 pixels around Point 'P'
- 'P' is a corner if 'n' consecutive pixels with corresponding intensity greater or less than intensity of 'P' exist
- Shi-Tomasi, GFTT, BRIEF, SURF, SIFT



Features from Accelerated Segment Test

Source: OpenCV



- Image Convolution using Sobel Operator

- Consider a grayscale image I. Calculate the variation in the gradient by sweeping a window in x and y direction
- Approximation in matrix form
- Determine Score for each window
- Score using Eigen values $det(M) = \lambda_1 \lambda_2$ $trace(M) = \lambda_1 + \lambda_2$

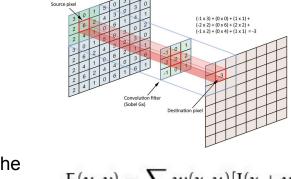
$$E(u,v) = \sum_{x,y} w(x,y) [I(x+u,y+v) - I(x,y)]^2$$

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} \left(\sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}$$

$$R = det(M) - k(trace(M))^2$$

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



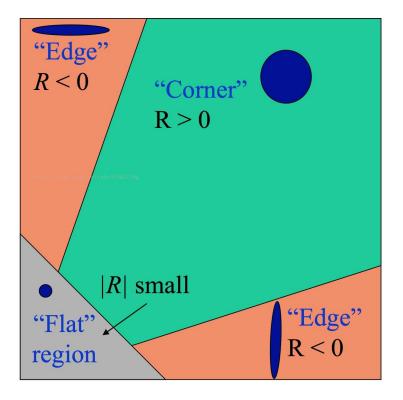




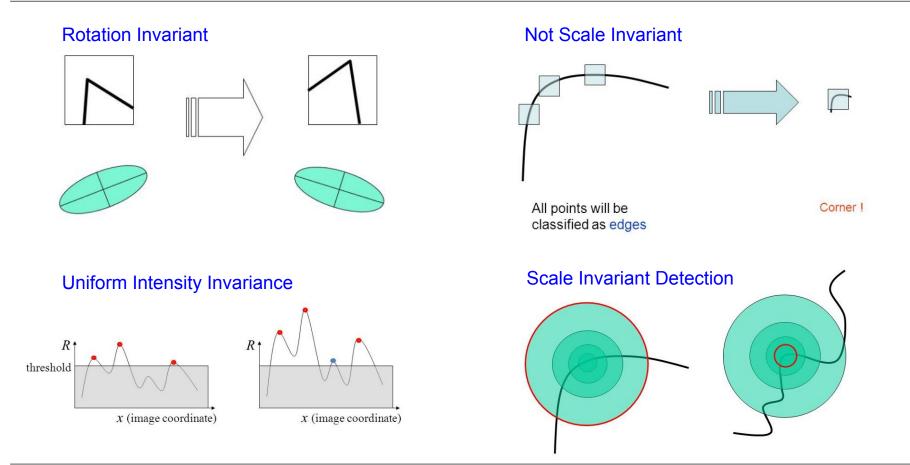
Feature Detectors | Harris Score Value

$$R = \det(M) - \alpha \operatorname{trace}(M)^2 = \lambda_1 \lambda_2 - \alpha (\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)

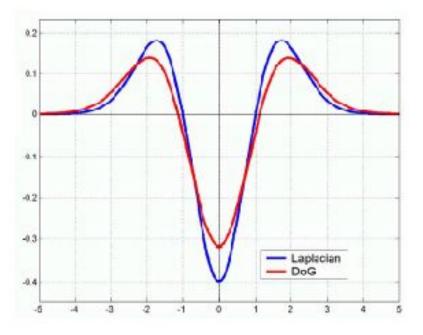




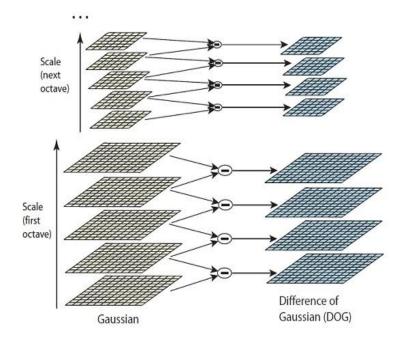




Laplacian of Gaussian vs Difference of Gaussian

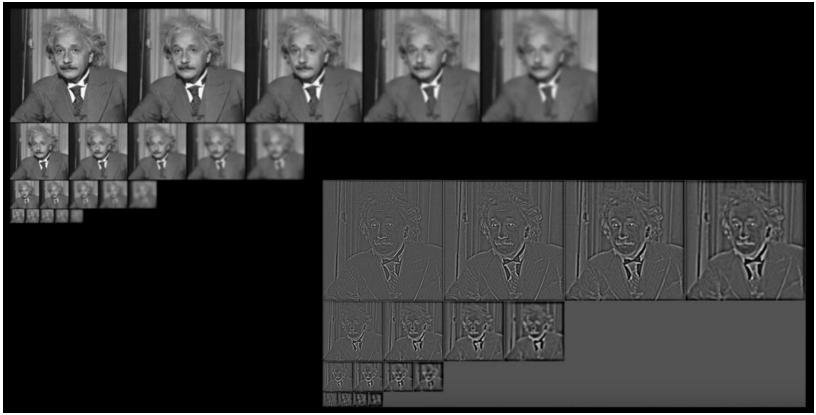


Scale Space Generation





Extrema at different scales

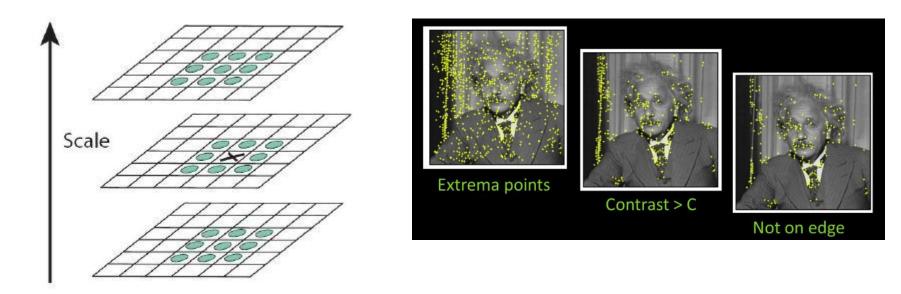


Source: Aaron Bobik



Find Maxima in Scale Space

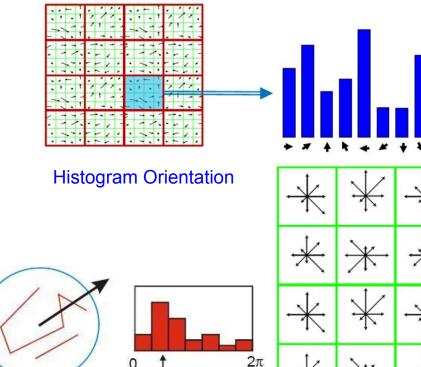
SIFT Feature Points



Source: Aaron Bobik



- Find Gradients of image patch
- Get Dominant Orientation using 36 bins and applying gaussian weighting.
- Highest Peak is dominant orientation
- Take 16x16 region around Keypoint and rotate to dominant orientation
- Divide into 16 sub-blocks of 4x4 and create orientation histogram with 8 bins
- Stack histogram to get 128 Dimensional Descriptor



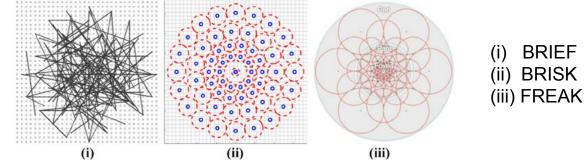
Dominant Orientation

128 Dimensional Descriptor



Feature Descriptors | Descriptor Comparison

| | Sampling pattern | Orientation calculation | Sampling pairs |
|-------|---|--|-------------------------|
| BRIEF | None. | None. | Random. |
| ORB | None. | Moments. | Learned pairs. |
| BRISK | Concentric circles with more points on outer rings. | Comparing gradients of long pairs. | Using only short pairs. |
| FREAK | Overlapping Concentric circles with more points on inner rings. | Comparing gradients of preselected 45 pairs. | Learned pairs. |



Source: Gil



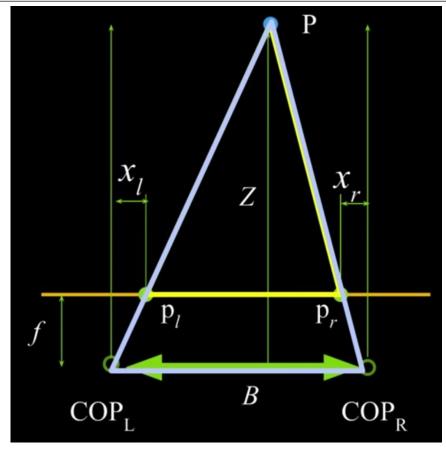




Feature Tracking and Prediction



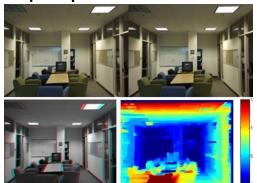
Stereo Vision |





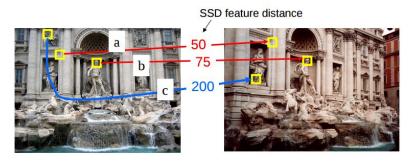
$$\frac{B - x_l + x_r}{Z - f} = \frac{B}{Z}$$
$$Z = f \frac{B}{x_l - x_r}$$

$$X_1 - X_r = disparity$$

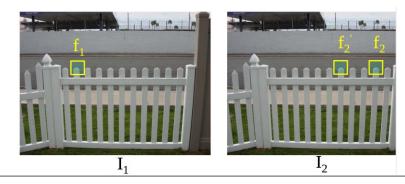




- Sum of Square differences between two descriptors f_1 and f_2
- What value of threshold to use ?



- How to resolve ambiguous matches ? Ratio distance = $SSD(f_1, f_2) / SSD(f_1, f_2)$
- Ambiguous matches will have ratio close to 1





Feature Tracking | Optical Flow

- Determine apparent motion of object in consecutive frames
- Given pixel in I(x,y,t), find nearby pixels of same intensity in I(x,y,t+1)



Brightness Constancy Constraint:

$$0 = I(x + u, y + v, t + 1) - I(x, y, t)$$

Small Motion Constraint:

$$I(x+u, y+v) \approx I(x, y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v$$

$$(u,v)$$

$$I(x,y,t)$$

$$I(x,y,t+1)$$

Source: Aaron Bobik



Feature Tracking | KLT

- $I_x I_y$ are space image derivatives
- I, is time image derivative
- u v are unknowns

$$I_x u + I_y v + I_t = 0$$

Optical Flow Equation

- 5x5 window gives 25 equations per pixel.

$$\begin{bmatrix} I_x(\mathbf{p}_1) & I_y(\mathbf{p}_1) \\ I_x(\mathbf{p}_2) & I_y(\mathbf{p}_2) \\ \vdots & \vdots \\ I_x(\mathbf{p}_{25}) & I_y(\mathbf{p}_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} I_t(\mathbf{p}_1) \\ I_t(\mathbf{p}_2) \\ \vdots \\ I_t(\mathbf{p}_{25}) \end{bmatrix}$$

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

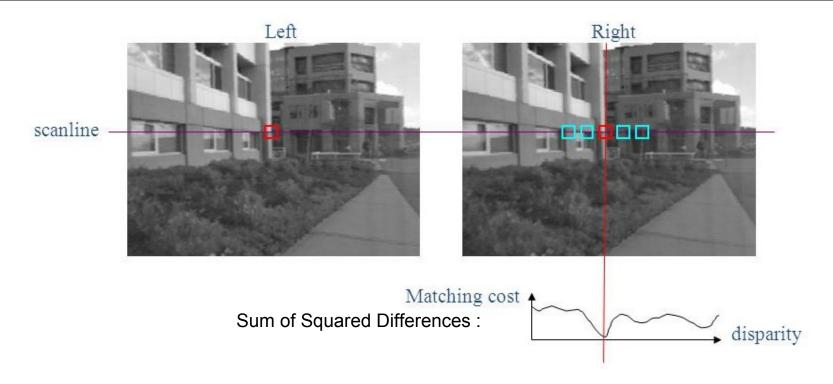
$$A^T A \qquad A^T b$$

Solution: $\mathbf{d} = (\mathbf{A}^{\mathsf{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathsf{T}}\mathbf{b}$

Source: Aaron Bobik



Feature Prediction | Parallel image planes

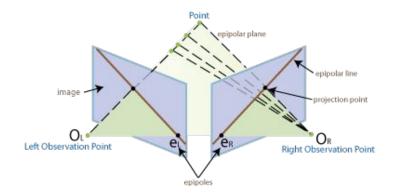


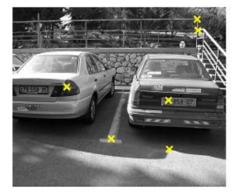
What if the image planes weren't parallel?

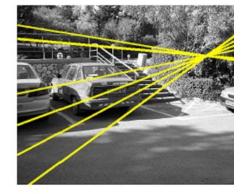


Feature Prediction | Epipolar Geometry

- Lines project to lines in the image
- All epipolar lines intersect at epipole
- One dimensional search for correspondence
- Parallel image planes have epipole at infinity

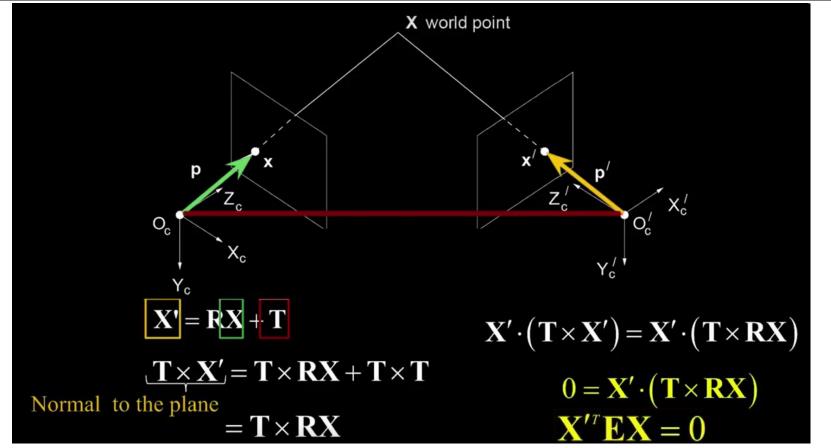








Epipolar Geometry | Essential Matrix



Source: Aaron Bobik



Epipolar Geometry | Fundamental matrix

$$\begin{pmatrix} \mathbf{K}_{int,right}^{-1} \mathbf{p}_{im,right} \end{pmatrix}^{\mathrm{T}} \mathbf{E} \begin{pmatrix} \mathbf{K}_{int,left}^{-1} \mathbf{p}_{im,left} \end{pmatrix} = 0$$

$$\mathbf{p}_{im,right}^{\mathrm{T}} \begin{pmatrix} \mathbf{K}_{int,right}^{-1} \end{pmatrix}^{T} \mathbf{E} \mathbf{K}_{int,left}^{-1} \end{pmatrix} \mathbf{p}_{im,left} = 0$$
"Fundamental matrix": **F**

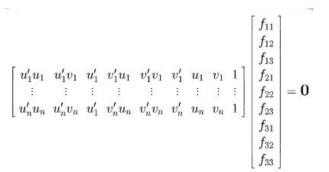
$$\mathbf{p}_{im,right}^{\mathrm{T}} \mathbf{F} \mathbf{p}_{im,left} = \mathbf{0} \text{ or } \mathbf{p}^{T} \mathbf{F} \mathbf{p}' = 0$$

$$\mathbf{l} = \mathbf{F} \mathbf{p}' \text{ is the epipolar line in the p image associated with p'$$

Source: Aaron Bobik

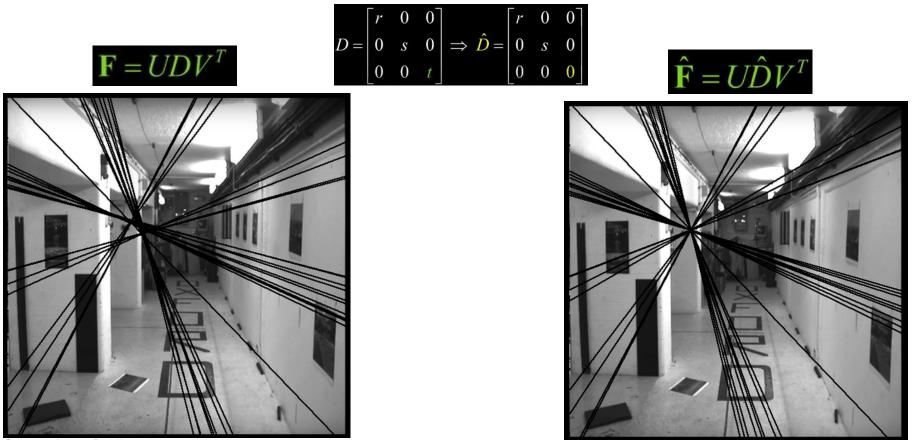
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Calculate F from minimum 8 correspondences





Epipolar Geometry | Fundamental Matrix

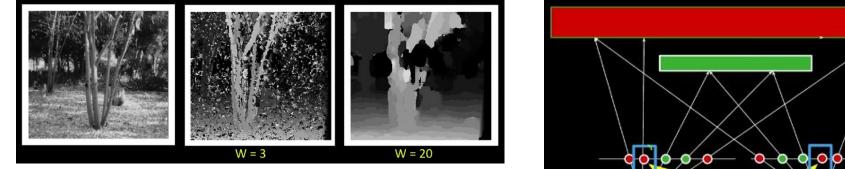


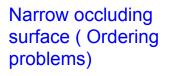
Source: Aaron Bobik

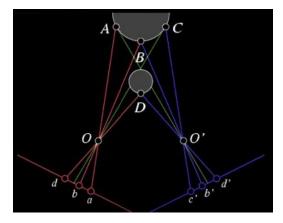


Window Size









Occluded pixels

Source: Aaron Bobik





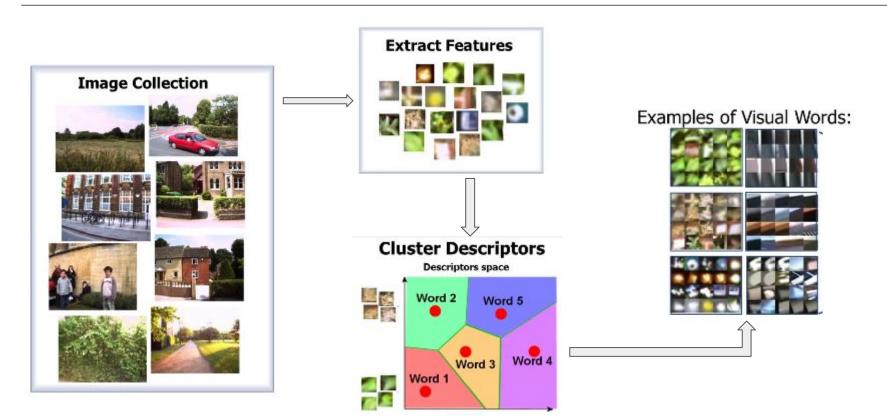




Bag of Words



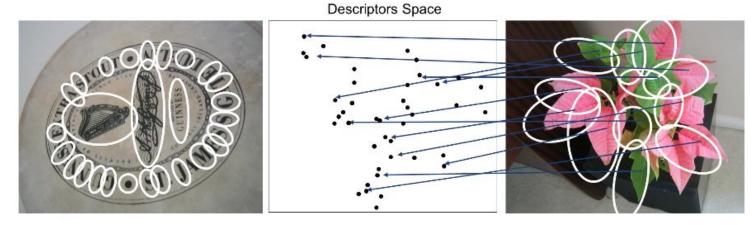
Place Recognition | Overview



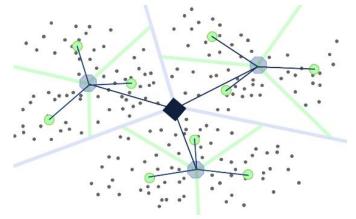
Source: Margarita Chli



Extract Features using SIFT descriptor



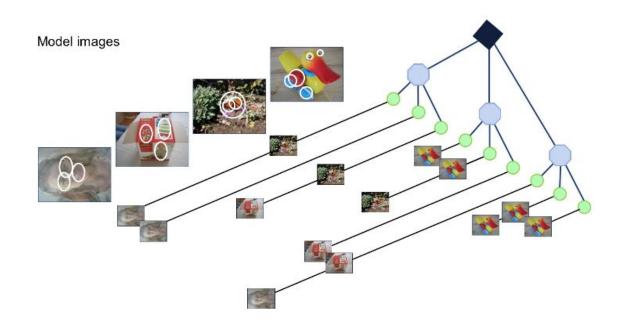
Hierarchical Clustering to get Visual Words



Source: Margarita Chli



- Pass each image through Vocabulary Tree
- Get Visual words based on features of image
- Use inverted file index (Visual word to image mapping) for quick test time

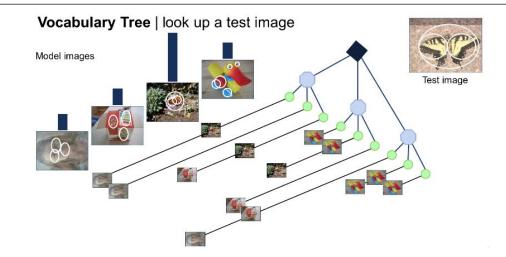


Source: Margarita Chli



Place Recognition | Test Image

- Extract Features from Test Image
- Find corresponding Visual Words
- Determine closest match



- term frequency: frequency of word w_i in image $j: tf_{ij} = \frac{n_{i,j}}{\sum_{k} n_{k,j}}$
- inverse document frequency: $idf_i = \log \frac{|D|}{|\{d : w_i \in d\}|}$ No. all images (documents) No. all images containing w_i

• tf-idf of word
$$w_i$$
 in image j is: $= tf_{ij} \cdot idf_i$

Source: Margarita Chli



Questions |



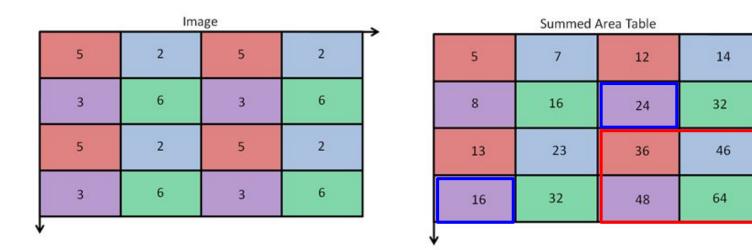


Read and Summarize:

- 1) SURF Detector and Descriptor
- 2) ORB Detector and Descriptor



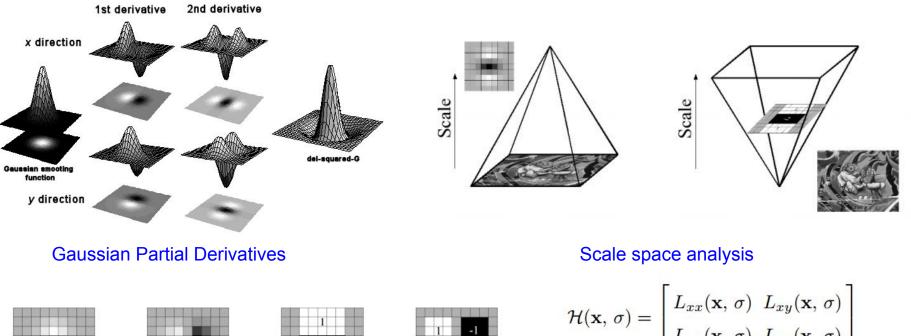
SURF Detector | Integral Image



Create: 16 + 12 - 7 + 3 = 24Create: 16 + 23 - 13 + 6 = 32Query: 64 + 16 - 32 - 32 = 16same as 6+5+3+2 = 16



SURF Detector | Speeded Up Robust Features

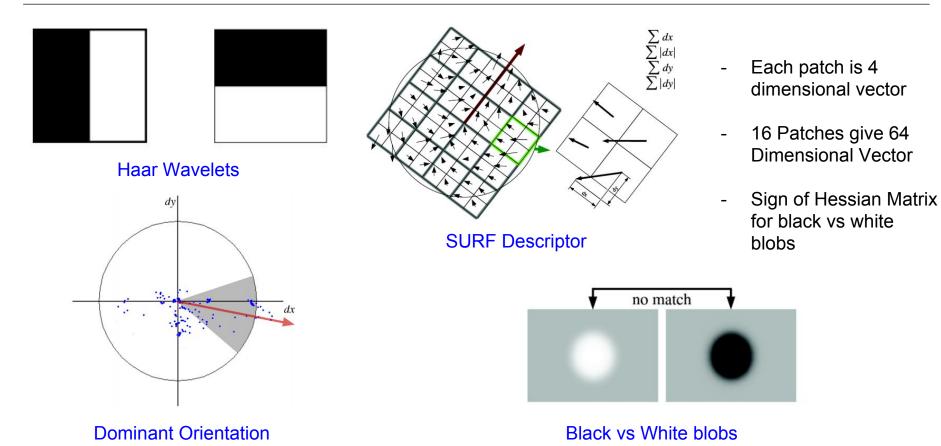


$$\mathcal{H}(\mathbf{x}, \sigma) = \begin{bmatrix} L_{xx}(\mathbf{x}, \sigma) & L_{xy}(\mathbf{x}, \sigma) \\ L_{xy}(\mathbf{x}, \sigma) & L_{yy}(\mathbf{x}, \sigma) \end{bmatrix}$$
$$\det(\mathcal{H}_{approx}) = D_{xx}D_{yy} - (wD_{xy})^2.$$

Hessian Matrix and Determinant



SURF Descriptor |

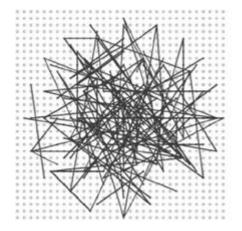




- FAST corner Detector
- Harris Corner Measure
- FAST detected at multiple levels in the Pyramid for Scale Invariance

BRIEF: Binary Robust Independent Elementary Features

- Random Selection of pairs of Intensity Values
- Fixed sampling Pattern of 128, 256 or 512 pairs
- Hamming Distance to compare descriptors (XOR)





ORB Descriptor |

$$m_{pq} = \sum_{x,y} x^p y^q I(x,y)$$

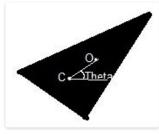
Patch moments

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right)$$

Center of Mass

$$\theta = \operatorname{atan2}(m_{01}, m_{10})$$

Orientation



Learning the

paris

Angle Calculation

- 1. Run each test against all training patches.
- 2. Order the tests by their distance from a mean of 0.5, forming the vector T.
- 3. Greedy search:
 - (a) Put the first test into the result vector R and remove it from T.
 - (b) Take the next test from T, and compare it against all tests in R. If its absolute correlation is greater than a threshold, discard it; else add it to R.
 - (c) Repeat the previous step until there are 256 tests in R. If there are fewer than 256, raise the threshold and try again.
 - 300K Keypoints
 - 205590 Possible Tests
 - 256 dimensional descriptor

