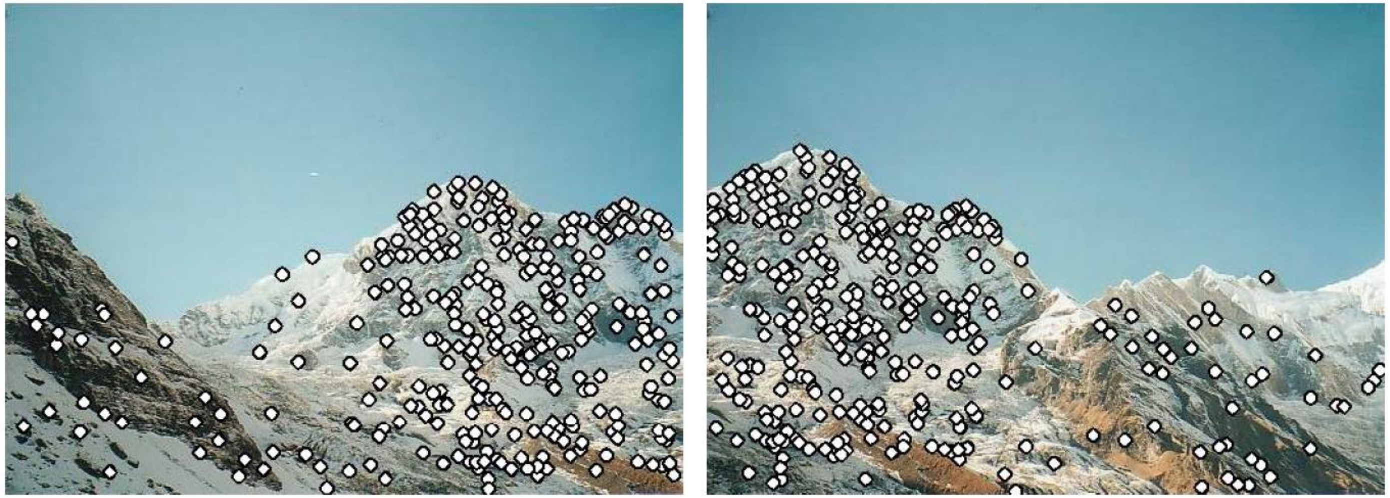


COMP9517: Computer Vision

Feature Representation

Part 1

What are Features?

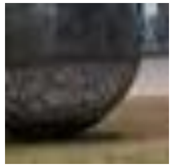


Image Features

- Image features are essentially vectors that are a compact representation of images
- They represent important information shown in an image
- Intuitive examples of image features:
  - Blobs
  - Edges
  - Corners
  - Ridges
  - Circles
  - Ellipses
  - Lines
  - Etc…

Image Features

- We need to represent images as feature vectors for further processing in a more efficient and robust way

- Examples of further processing include:
  - Object detection
  - Image segmentation
  - Image classification
  - Content-based image retrieval
  - Image stitching
  - Object tracking

Object Detection

Segmentation

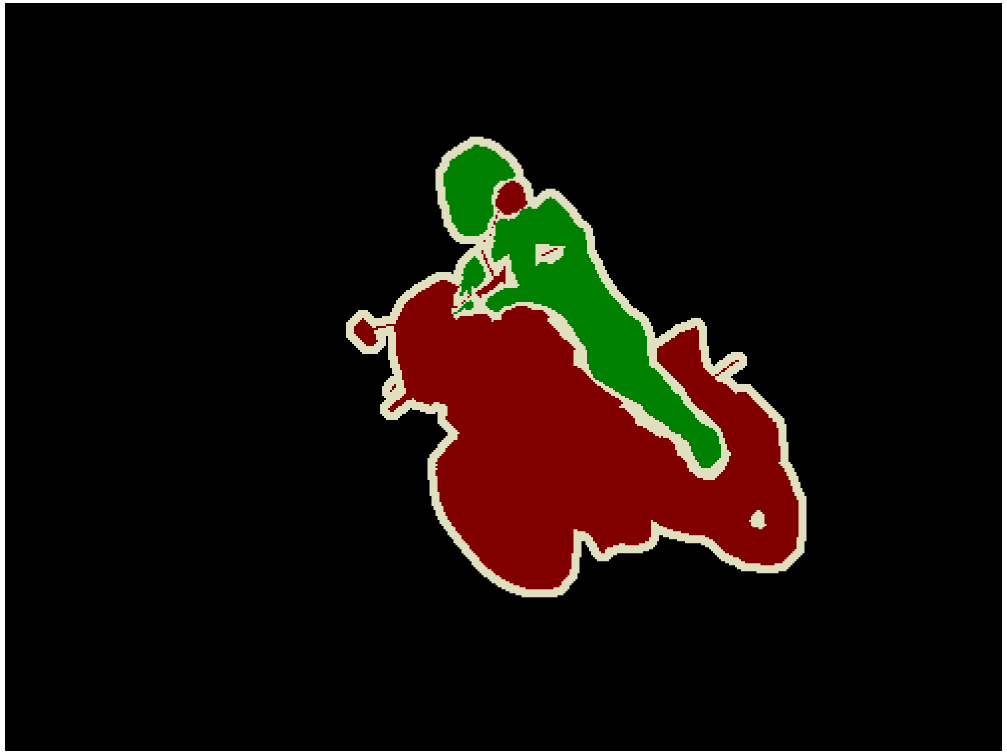
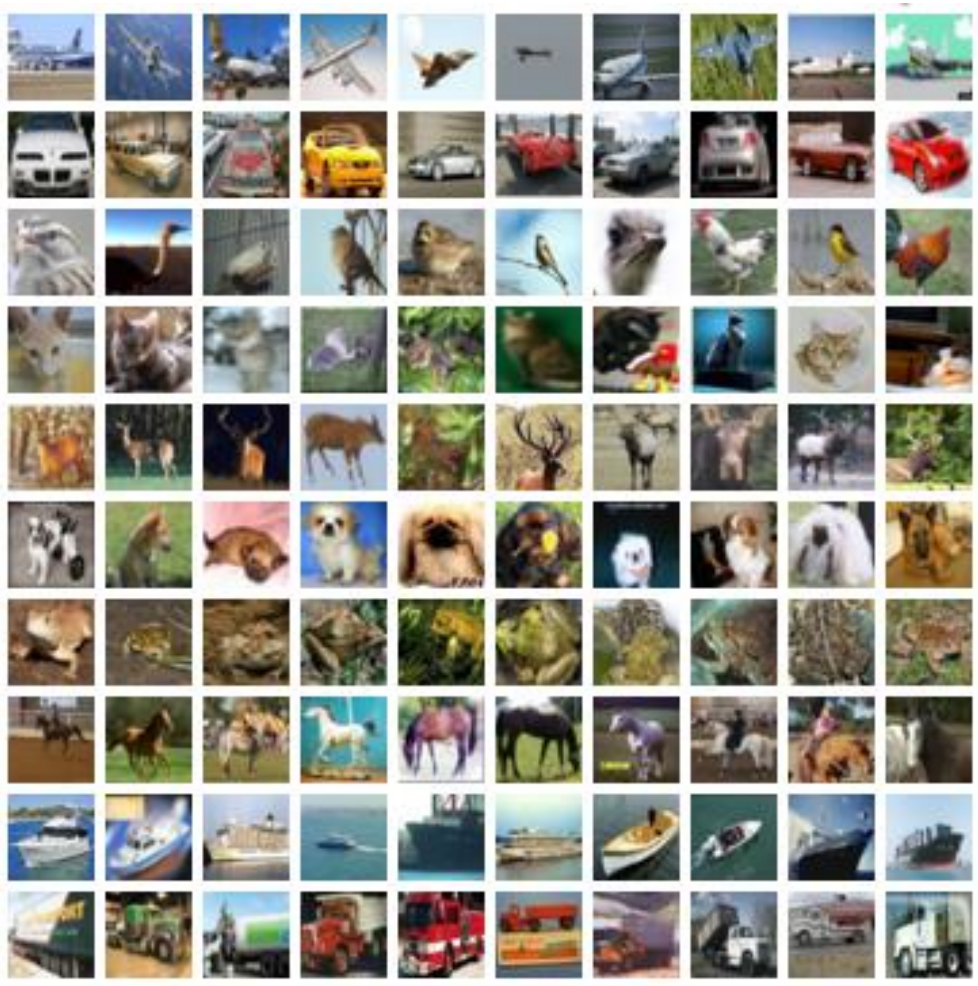


Image Classification



Content-Based Image Retrieval

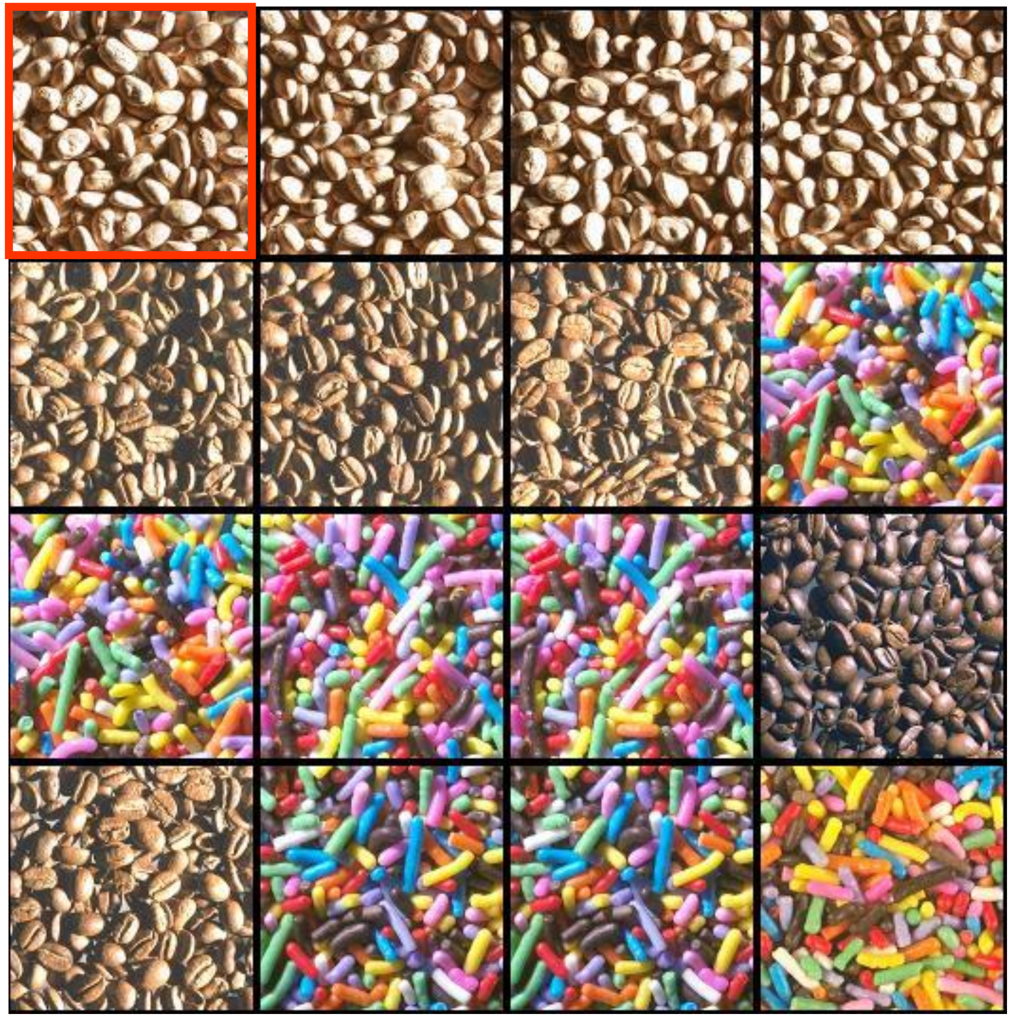
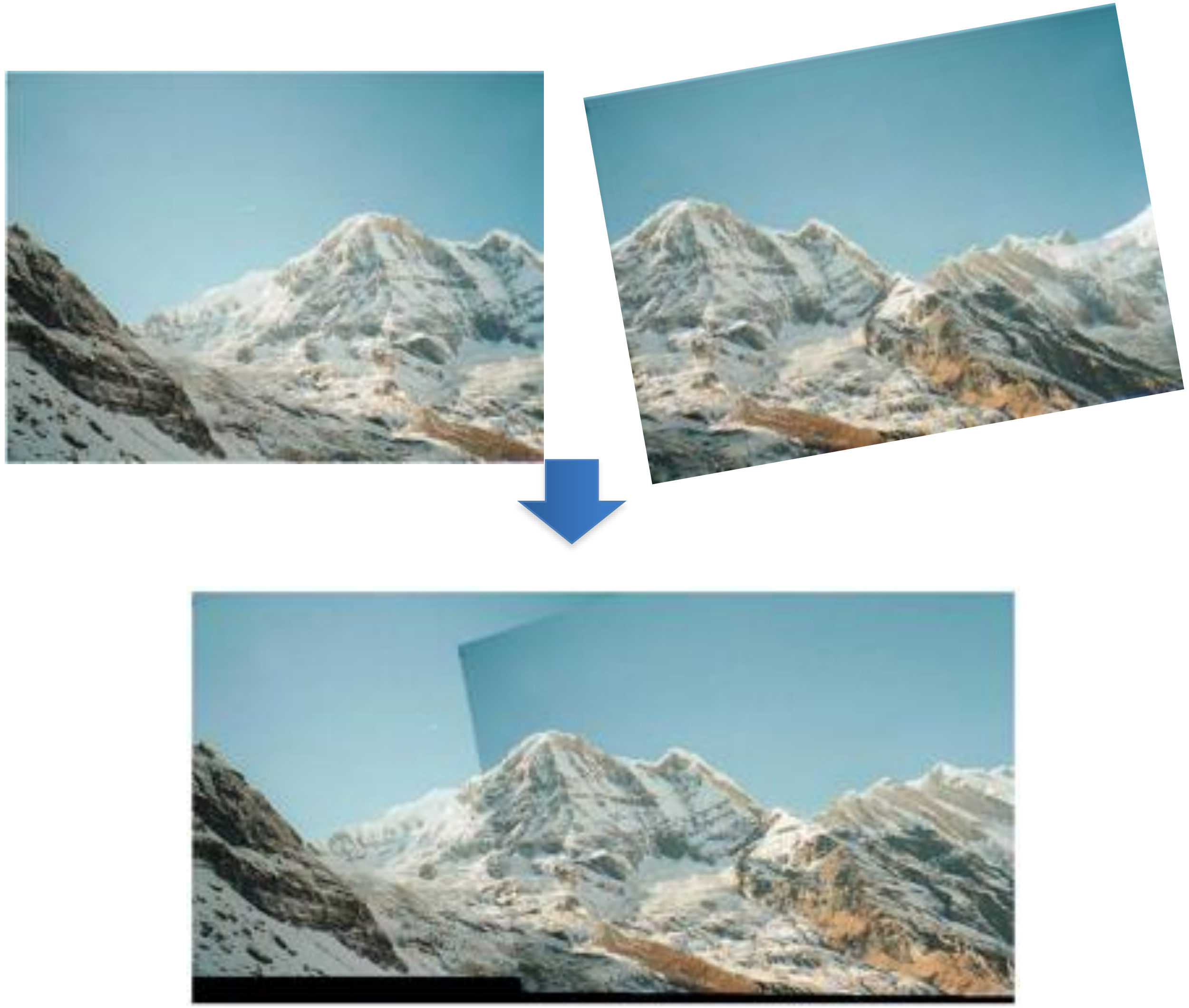


Image Stitching



Object Tracking

Properties of Features

- Why not just use pixels values directly?
  - Pixel values change with light intensity, colour and direction
  - They also change with camera orientation
  - And they are highly redundant
- Repeatability (robustness)
  - Should be detectable at the same locations in different images despite changes in illumination and viewpoint
- Saliency (descriptiveness)
  - Similar salient points in different images should have similar features
- Compactness (efficiency)
  - Fewer features
  - Smaller features

General Framework

Object detection

Image segmentation

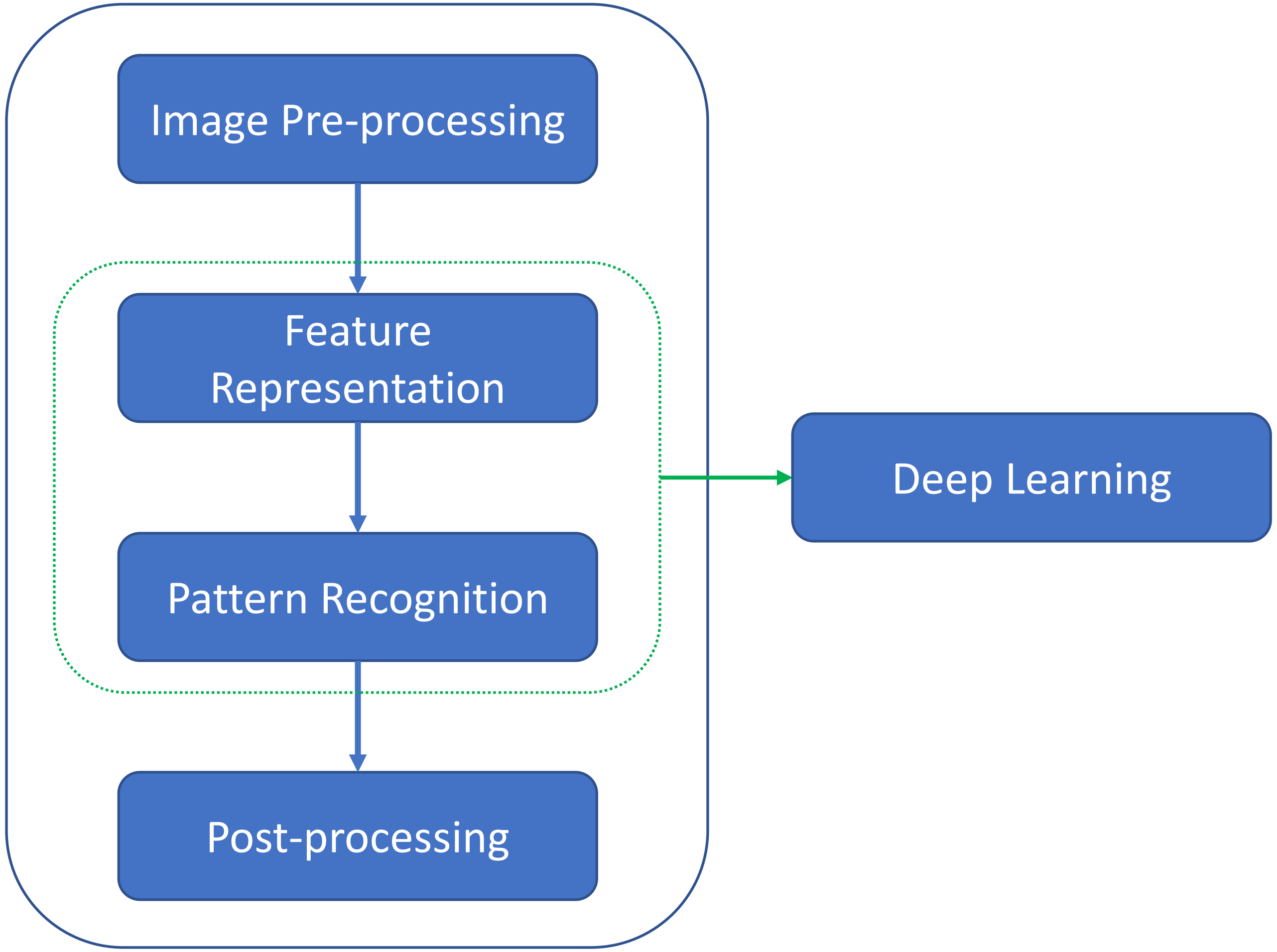
Image classification

Image retrieval

Image stitching

Object tracking

…



Feature Types

- Colour features
  - Colour histogram
  - Colour moments
- Texture features
  - Haralick texture features
  - Local binary patterns (LBP)
  - Scale-invariant feature transform (SIFT)
  - Texture feature encoding
- Shape features
  - Basic shape features
  - Shape context
  - Histogram of oriented gradients (HOG)

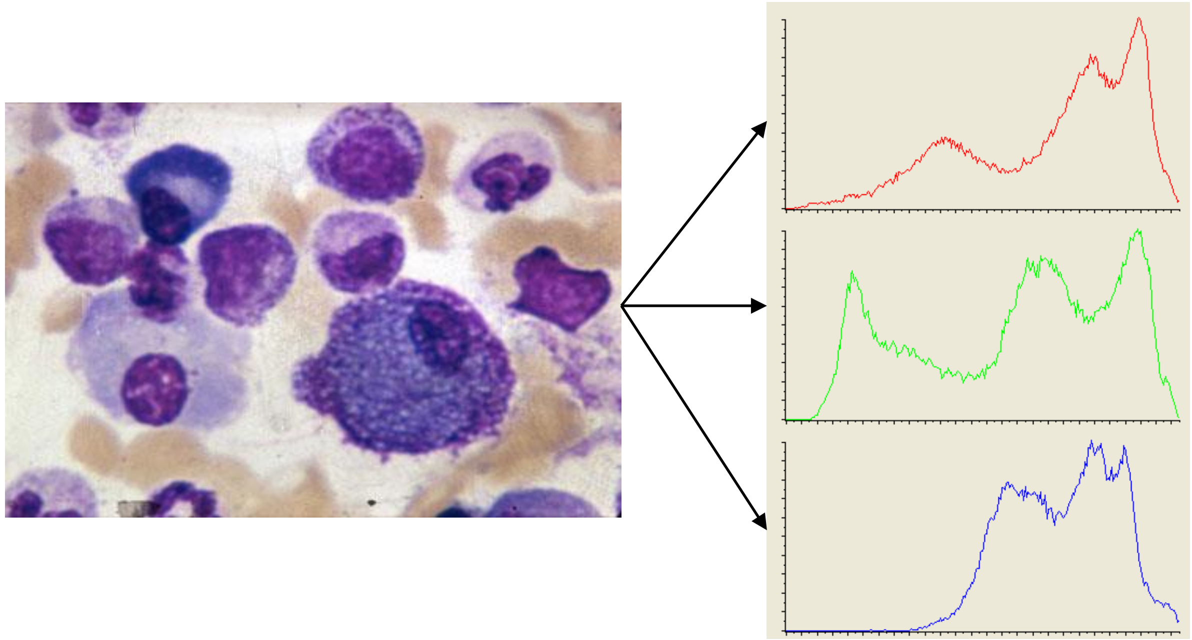
Colour Features

- **Colour** is the simplest feature to compute, and is invariant to image scaling, translation and rotation.
- Example: colour-based image retrieval

http://labs.tineye.com/multicolr/

Colour Histogram

- Represent the global distribution of pixel colours in an image
  - Step 1: Construct a histogram for each colour channel (R, G, B)
  - Step 2: Concatenate the histograms (vectors) of all channels as the final feature vector



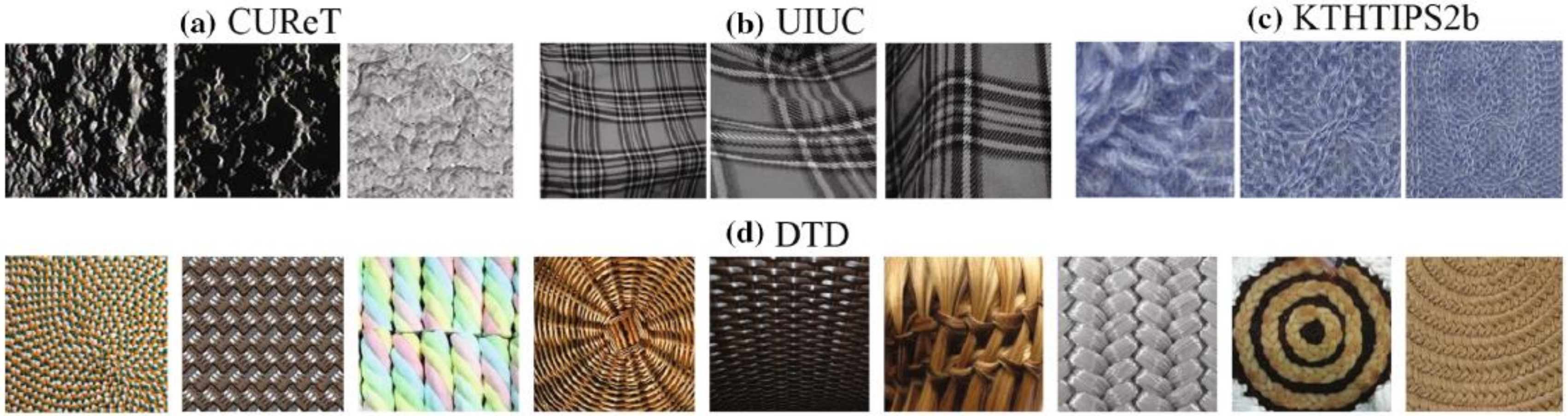
Colour Moments

f_{ij} is the value of the *i*-th colour component of pixel *j* and *N* is the number of pixels in the image

- Another way of representing colour distributions
  - First-order moment $$\boxed{\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij}}$$ (*mean*)
  - Second-order moment $$\boxed{\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^2\right)^{\frac{1}{2}}}$$ (*variance*)
  - Third-order moment $$\boxed{s_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^3\right)^{\frac{1}{3}}}$$ (*skewness*)
- Moments based representation of colour distributions
  - Gives a feature vector of only 9 elements (for RGB images)
  - Lower representation capability than the colour histogram

Texture Features

- **Texture** is a powerful discriminating feature for identifying visual patterns with properties of homogeneity that cannot result from the presence of only a single color or intensity
- Example: texture classification



https://arxiv.org/abs/1801.10324

Haralick Features

- Haralick features give an array of statistical descriptors of image patterns to capture the spatial relationship between neighbouring pixels, that is, textures
  - Step 1: Construct the gray-level co-occurrence matrix (GLCM)
  - Step 2: Compute the Haralick feature descriptors from the GLCM

610 IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, VOL. SMC-3, NO. 6, NOVEMBER 1973

Textural Features for Image Classification

ROBERT M. HARALICK, K. SHANMUGAM, AND ITS'HAK DINSTEIN

***Abstract*—Texture is one of the important characteristics used in identifying objects or regions of interest in an image, whether the image be a photomicrograph, an aerial photograph, or a satellite image. This paper describes some easily computable textural features based on gray-tone spatial dependancies, and illustrates their application in category-**

array. If $L_x = \{1,2,\cdots,N_x\}$ and $L_y = \{1,2,\cdots,N_y\}$ are the X and Y spatial domains, then $L_x \times L_y$ is the set of resolution cells and the digital image I is a function which assigns some gray-tone value $G \in \{1,2,\cdots,N_g\}$ to each and every

Haralick Features

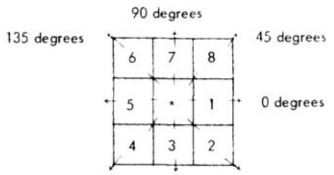


Fig. 1 Resolution cells 1 and 5 are 0° (horizontal) nearest neighbors to resolution cell *; resolution cells 2 and 6 are 135° nearest neighbors; resolution cells 3 and 7 are 90° nearest neighbors; and resolution cells 4 and 8 are 45° nearest neighbors to *. (Note this information is purely spatial, and has nothing to do with gray-tone values.)

- Step 1: Construct the GLCMs
  - Given a distance d at an orientation angle ϑ, then $p_{(d,\vartheta)}(l_1, l_2)$, being the (l_1, l_2) coefficient of the corresponding matrix $\mathbf{P}_{(d,\vartheta)}$, is the co-occurrence count or probability of going from a grey level l_1 to another grey level l_2 with an inter-sample spacing of d along the axis making an angle ϑ with the x axis.
  - If the number of distinct gray levels in the quantized image is L, then the co-occurrence matrix **P** will be of size $L \times L$.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

original 4 × 4 image

$$\mathbf{P}_{(1,0°)} = \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix} \qquad \mathbf{P}_{(1,135°)} = \begin{bmatrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$$

co-occurrence matrix construction

Haralick Features

- Step 1: Construct the GLCMs
  - For computational efficiency, the number of gray levels (*L*) can be reduced by binning (similar to histogram binning), e.g. $L = 256/n$, with *n* a constant factor.
  - Different co-occurrence matrices can be constructed by using various combinations of distance (*d*) and angular directions (ϑ).
  - On their own, these co-occurrence matrices do not provide any measure of texture that can easily be used as texture descriptors.
  - The information in the co-occurrence matrices needs to be further extracted as a set of feature values => Haralick descriptors.

Haralick Features

- Step 2: Compute the Haralick descriptors from the GLCMs
  - One set of Haralick descriptors for each GLCM corresponding to a particular distance (*d*) and angular direction (*ϑ*)

Angular Second Moment	$\sum_i \sum_j p(i,j)^2$
Contrast	$\sum_{n=0}^{N_g-1} n^2 \{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j)\}, \lvert i-j \rvert = n$
Correlation	$\frac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$ where μ_x , μ_y , σ_x , and σ_y are the means and std. deviations of p_x and p_y , the partial probability density functions
Sum of Squares: Variance	$\sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse Difference Moment	$\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$
Sum Average	$\sum_{i=2}^{2N_g} i p_{x+y}(i)$ where x and y are the coordinates (row and column) of an entry in the co-occurrence matrix, and $p_{x+y}(i)$ is the probability of co-occurrence matrix coordinates summing to $x+y$

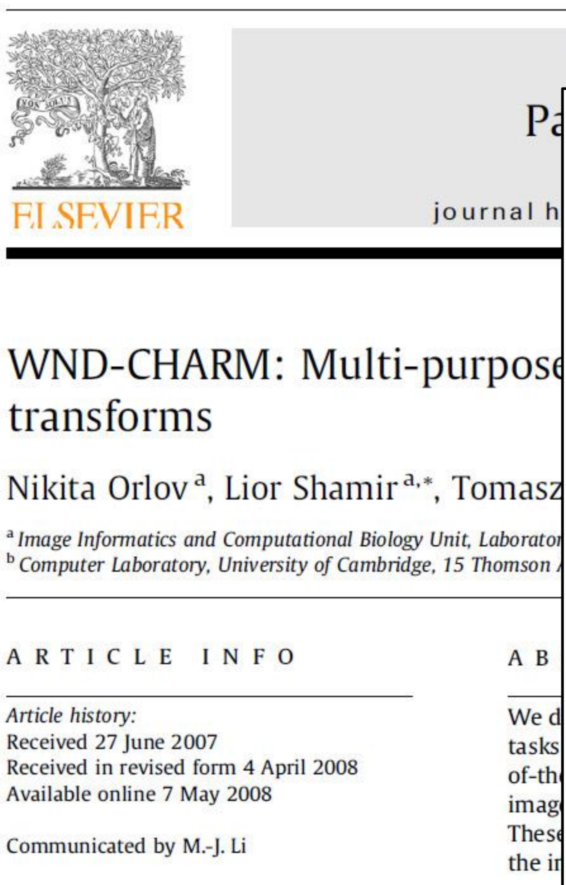
Haralick Features

- Step 2: Compute the Haralick descriptors from the GLCMs
  - One set of Haralick descriptors for each GLCM corresponding to a particular distance (*d*) and angular direction (*ϑ*)

Sum Variance	$\sum_{i=2}^{2N_g}(i-f_8)^2 p_{x+y}(i)$
Sum Entropy	$-\sum_{i=2}^{2N_g} p_{x+y}(i)\log\{p_{x+y}(i)\} = f_8$
Entropy	$-\sum_i \sum_j p(i,j)log(p(i,j))$
Difference Variance	$\sum_{i=0}^{N_g-1} i^2 p_{x-y}(i)$
Difference Entropy	$-\sum_{i=0}^{N_g-1} p_{x-y}(i)\log\{p_{x-y}(i)\}$
Info. Measure of Correlation 1	$\frac{HXY-HXY1}{\max\{HX,HY\}}$
Info. Measure of Correlation 2	$(1-\exp[-2(HXY2-HXY)])^{\frac{1}{2}}$ where $HXY=-\sum_i\sum_j p(i,j)\log(p(i,j))$, HX , HY are the entropies of p_x and p_y , $HXY1 = -\sum_i\sum_j p(i,j)\log\{p_x(i)p_y(j)\}$ $HXY2 = -\sum_i\sum_j p_x(i)p_y(j)\log\{p_x(i)p_y(j)\}$
Max. Correlation Coeff.	Square root of the second largest eigenvalue of $\mathbf{Q}$ where $\mathbf{Q}(i,j)=\sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$

Application Example

https://doi.org/10.1016/j.patrec.2008.04.013


Pattern Recognition Letters 29 (2008) 1684–1693

Contents lists available at ScienceDirect

Pattern Recognition Letters

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WND-CHARM: Multi-purpose
transforms

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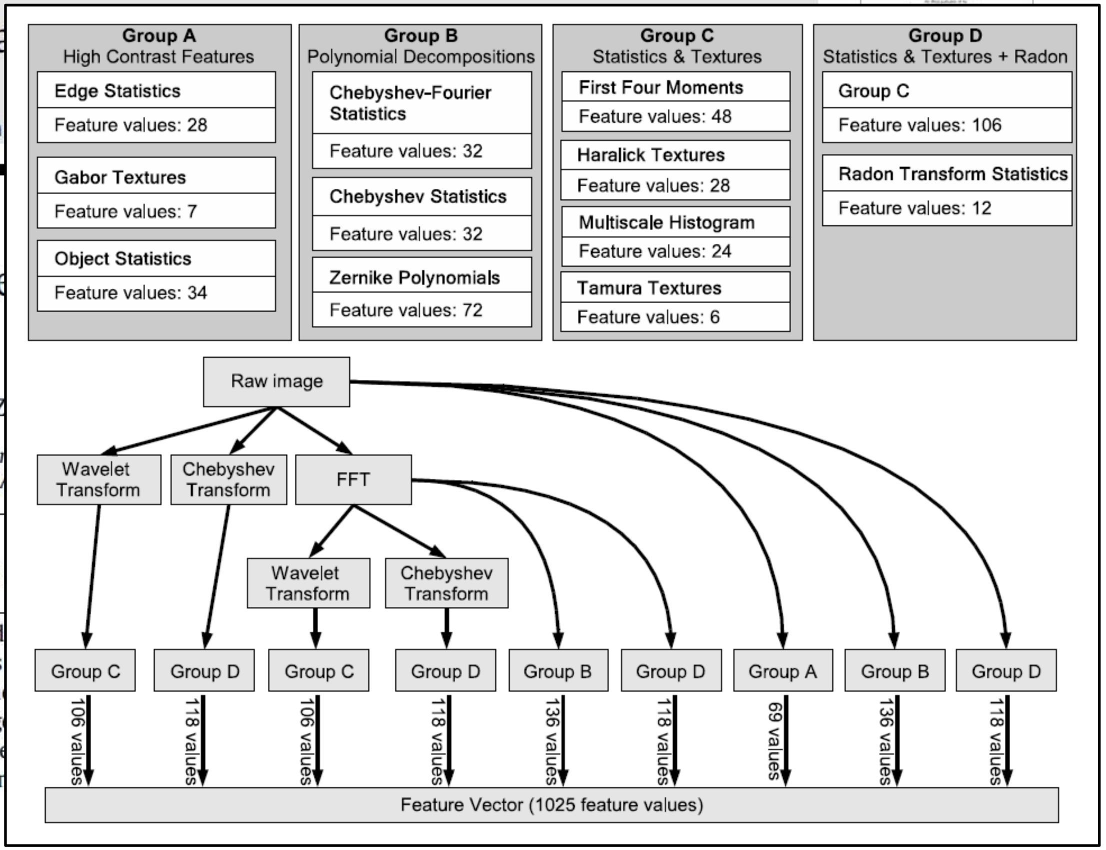
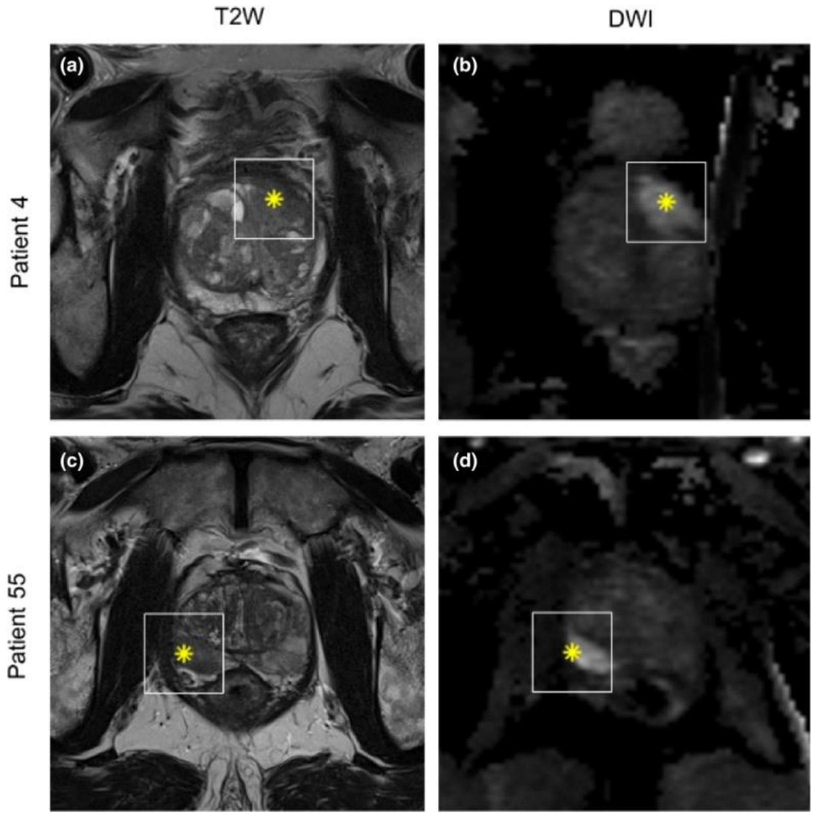


Application Example

- Commonly used nowadays in medical imaging studies due to its simplicity and interpretability



C. Jensen et al.
Assessment of prostate cancer prognostic Gleason grade group using zonal-specific features extracted from biparametric MRI using a KNN classifier
Journal of Applied Clinical Medical Physics, 2019
https://doi.org/10.1002/acm2.12542

1. Pre-processing
2. Extract Haralick, run-length, and histogram features from the region of interest
3. Feature selection
4. Classification using kNN

Local Binary Patterns

- Describe the spatial structure of local image texture
  - Divide the image into cells of *N* x *N* pixels (e.g. *N* = 16 or 32)
  - Compare each pixel in a cell to each of its 8 neighbouring pixels:
    If the centre pixel's value is greater than the neighbour's value,
    write "0", otherwise write "1"
  - This gives an 8-digit binary pattern per pixel after comparing with all 8 neighbouring pixels, representing a value in the range 0…255

100	155	110	210
157	187	222	100
219	218	255	210
215	218	255	233

0	0	1	
1	218	1	
0	1	1	

0 0 1 1 1 1 0 1

61

Local Binary Patterns

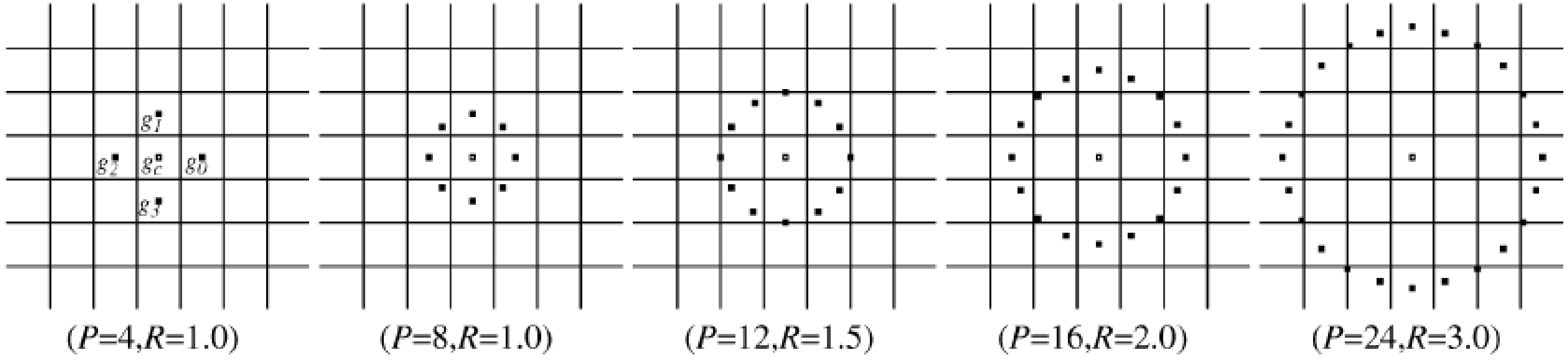
- Describe the spatial structure of local image texture (cont.)
  - Generate the histogram for all pixels in the cell, computing the frequency of each 8-digit binary number occurring in the cell
  - This gives a 256-bin histogram (the LBP feature vector)
  - Combine the histograms of all cells to obtain the image-level LBP feature descriptor

100	155	110	210
157	187	222	100
219	218	255	210
215	218	255	233

→ A histogram of 256 elements

Local Binary Patterns

- LBP can be multi-resolution and rotation-invariant
  - Multi-resolution: varying the distance between the centre pixel and neighbouring pixels, and the number of neighbouring pixels



T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7):971-987, 2002. https://doi.org/10.1109/TPAMI.2002.1017623

Local Binary Patterns

- LBP can be multi-resolution and rotation-invariant
  - Rotation-invariant: varying the way of constructing the 8-digit binary number, e.g. performing bitwise shift to derive the smallest number

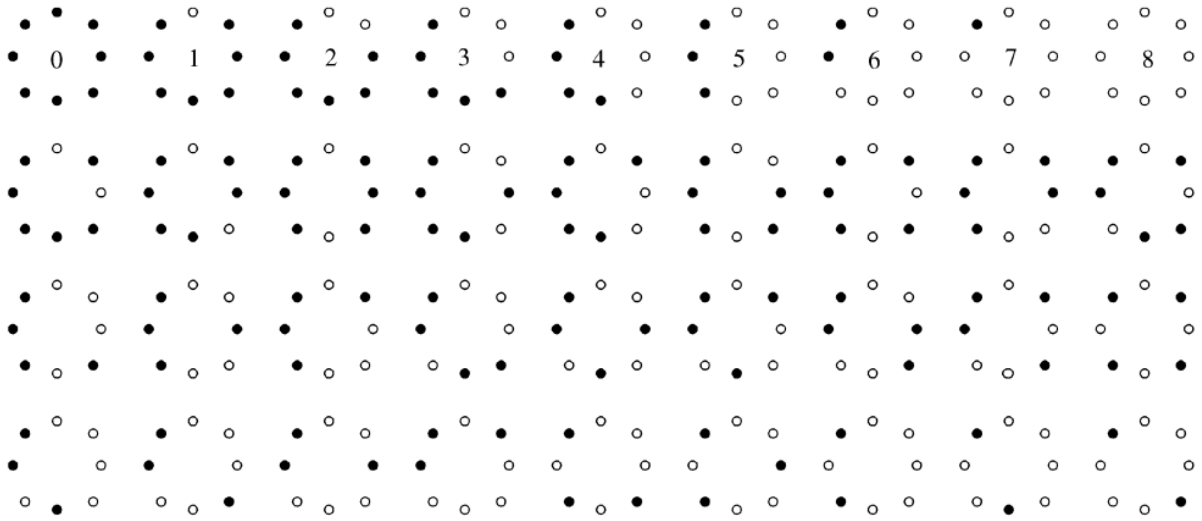
Example:

$$\left.\begin{array}{l} 1\,1\,1\,1\,0\,0\,0\,0 = 240 \\ 1\,1\,1\,0\,0\,0\,0\,1 = 225 \\ 1\,1\,0\,0\,0\,0\,1\,1 = 195 \\ 1\,0\,0\,0\,0\,1\,1\,1 = 135 \\ 0\,0\,0\,0\,1\,1\,1\,1 = 15 \\ 0\,0\,0\,1\,1\,1\,1\,0 = 30 \\ 0\,0\,1\,1\,1\,1\,0\,0 = 60 \\ 0\,1\,1\,1\,1\,0\,0\,0 = 120 \end{array}\right\}\ 15$$

Note: not all patterns have 8 shifted variants (e.g. 11001100 has only 4)

Local Binary Patterns

- LBP can be multi-resolution and rotation-invariant
  - Rotation-invariant: varying the way of constructing the 8-digit binary number, e.g. performing bitwise shift to derive the smallest number
    => this reduces the LBP feature dimension from 256 to 36

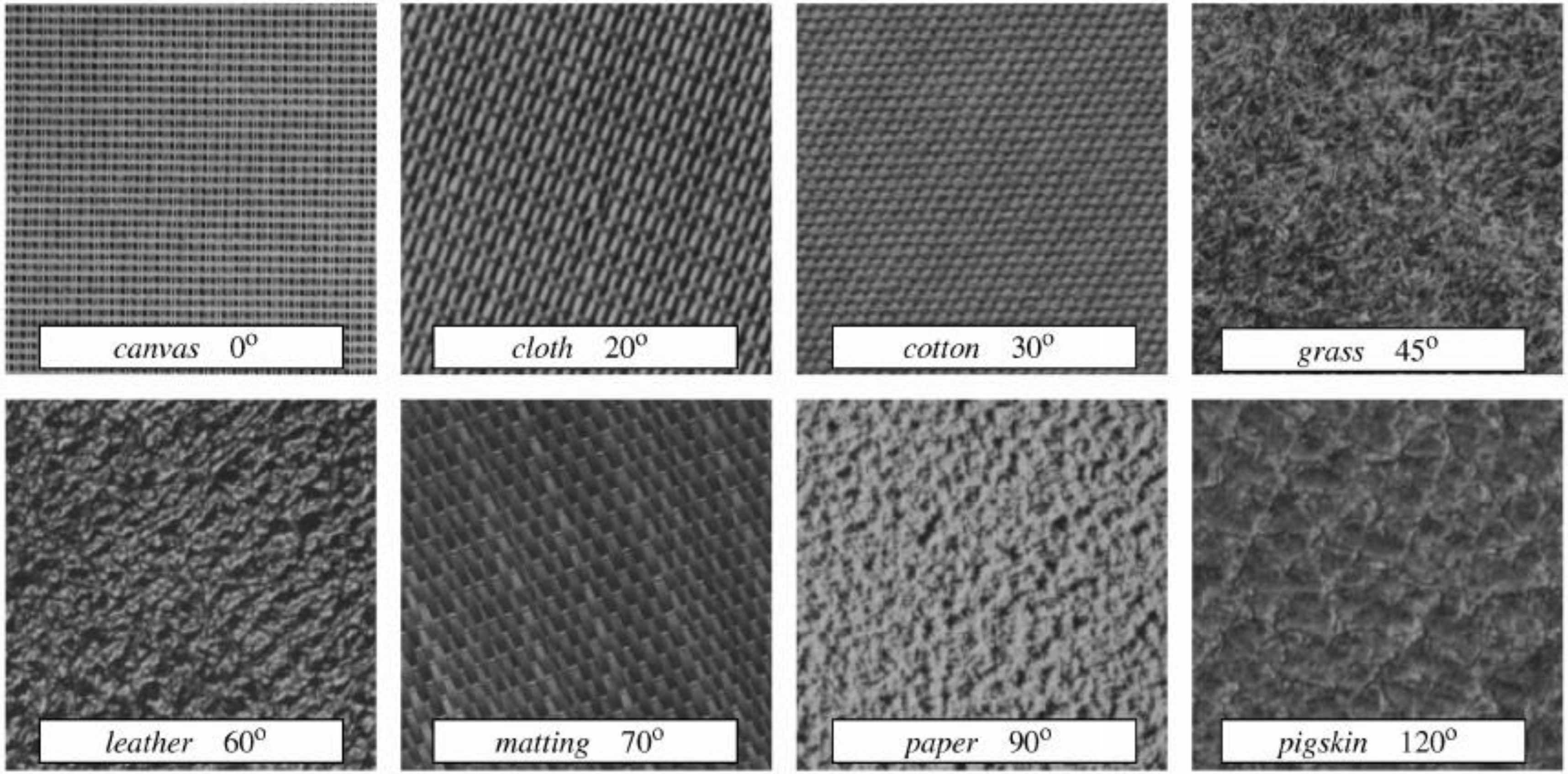


T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7):971-987, 2002. https://doi.org/10.1109/TPAMI.2002.1017623

Application Example

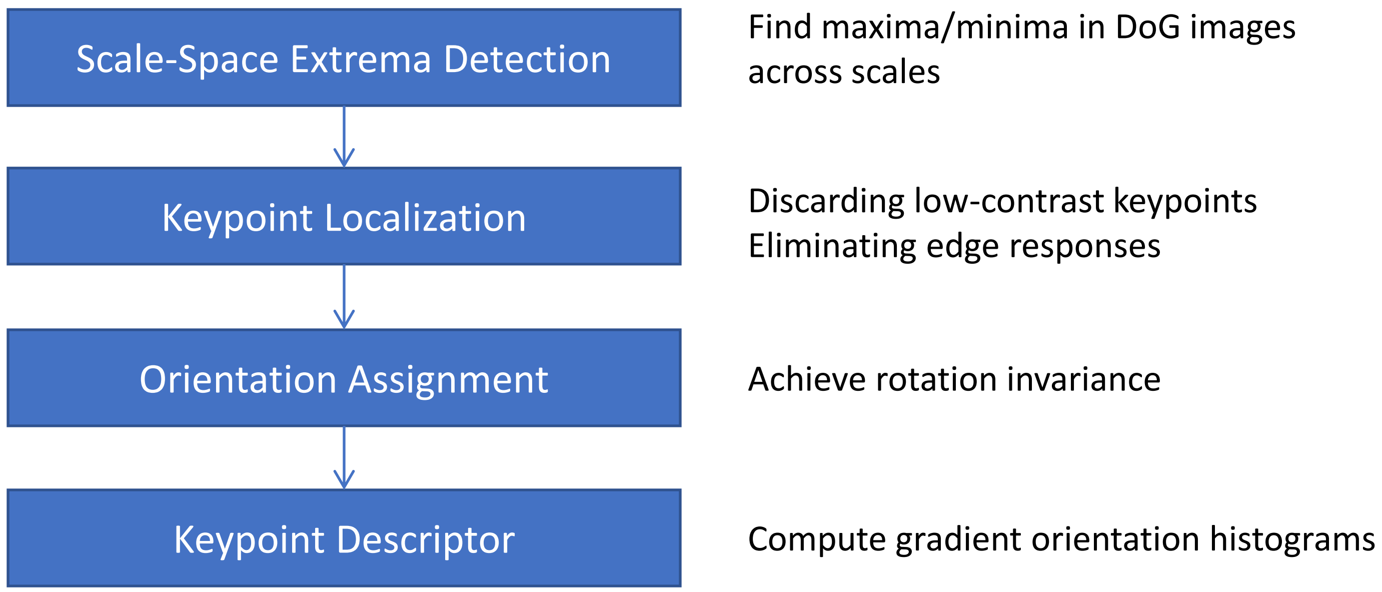
P,R	$LBP_{P,R}$	
	BINS	RESULT
8,1	10	88.2
16,2	18	98.5
24,3	26	99.1
8,1+16,2	10+18	99.0
8,1+24,3	10+26	99.6
16,2+24,3	18+26	99.0
8,1+16,2+24,3	10+18+26	99.1

- Texture classification



Scale-Invariant Feature Transform

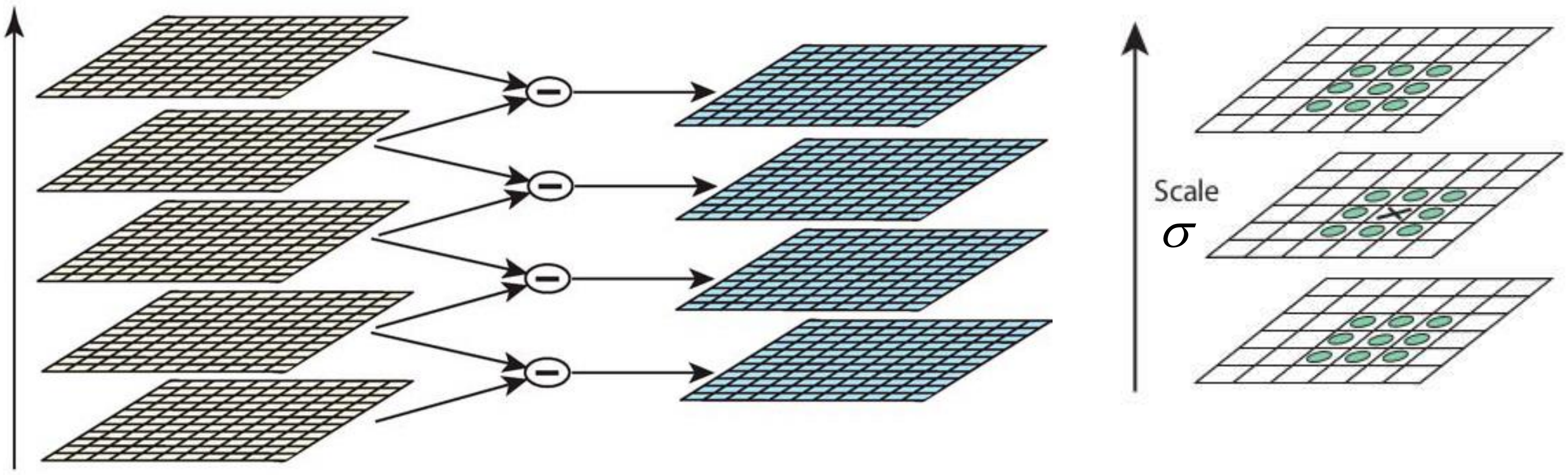
- SIFT feature describes the texture features in a localised region around a keypoint
- SIFT descriptor is invariant to uniform scaling, orientation, and partially invariant to affine distortion and illumination changes



SIFT Extrema Detection

- Detect maxima and minima in the scale space of the image

Gaussian
scale
σ



$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \qquad D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” Int. J. Comput. Vis. 60(2):91-110, November 2004. https://doi.org/10.1023/B:VISI.0000029664.99615.94

SIFT Keypoint Localization

- Improve and reduce the set of found keypoints
  - Use 3D quadratic fitting in scale-space to get subpixel optima
  - Reject low-contrast and edge points using Hessian analysis

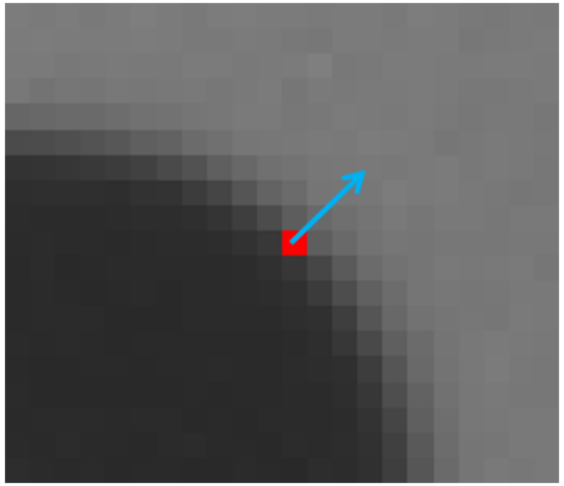
Initial keypoints from scale-space optima

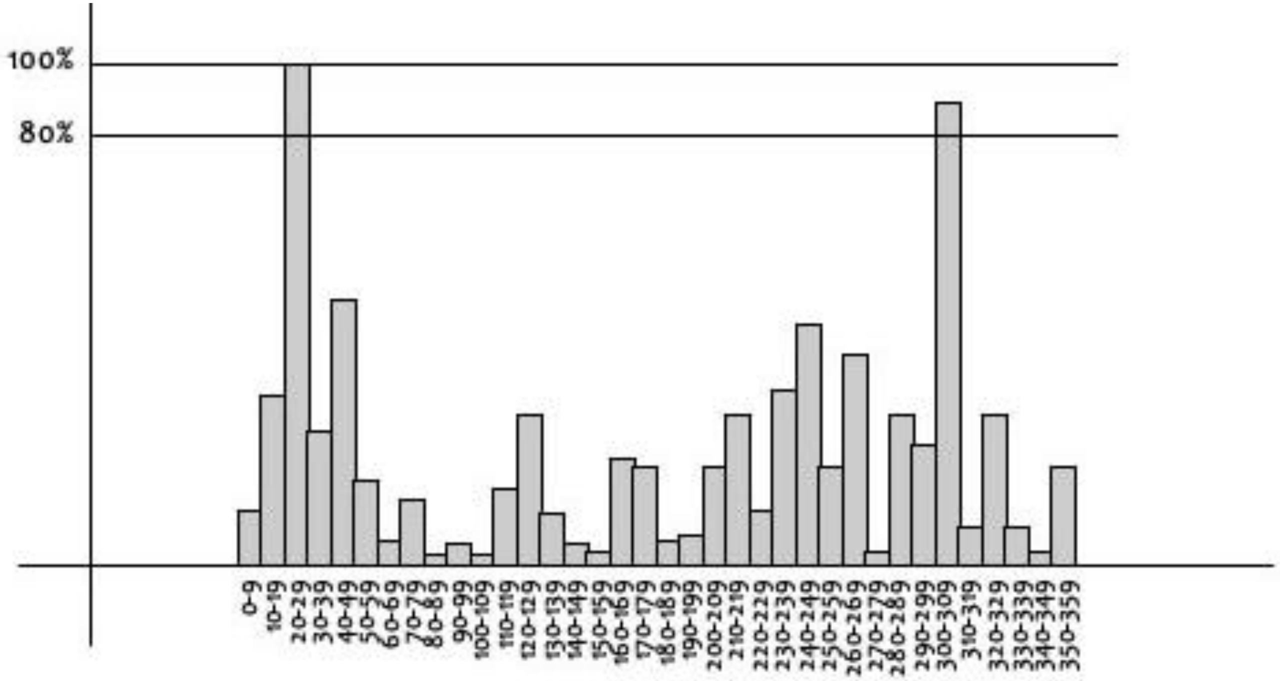
Keypoints after rejecting low-contrast points

Final keypoints after rejecting edge points

SIFT Orientation Assignment

- Estimate keypoint orientation using local gradient vectors
  - Make an orientation histogram of local gradient vectors
  - Find the dominant orientations from the peaks of the histogram





SIFT Keypoint Descriptor

- 4 x 4 array of gradient histogram weighted by magnitude
- 8 bins in gradient orientation histogram
- Total 8 x 4 x 4 array = 128 dimensions

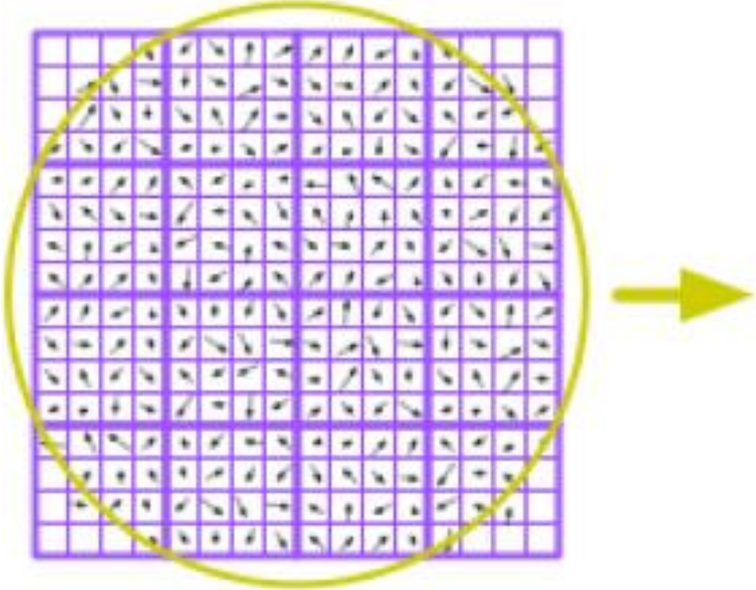
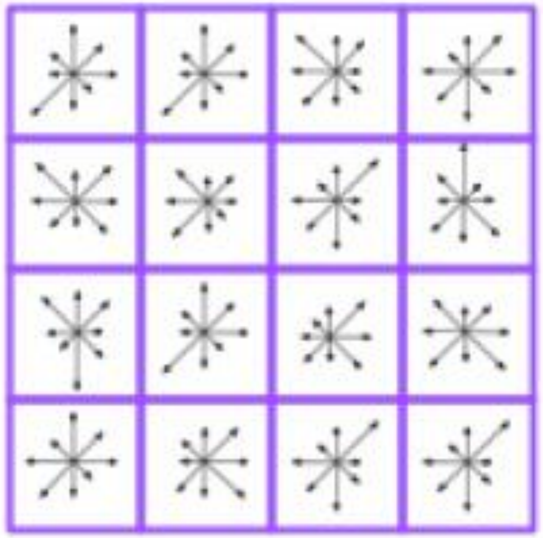


Image gradients



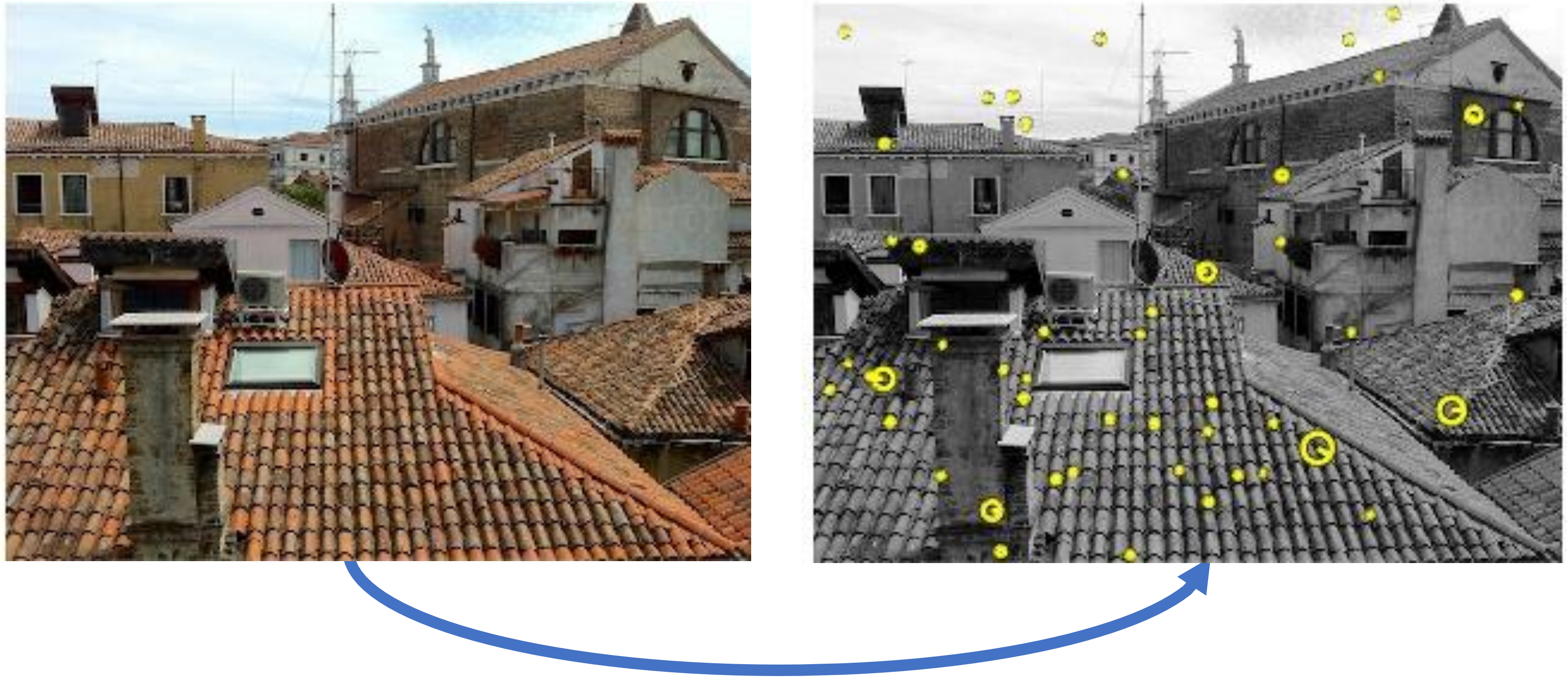
Keypoint Descriptor

Application Example

- Image matching

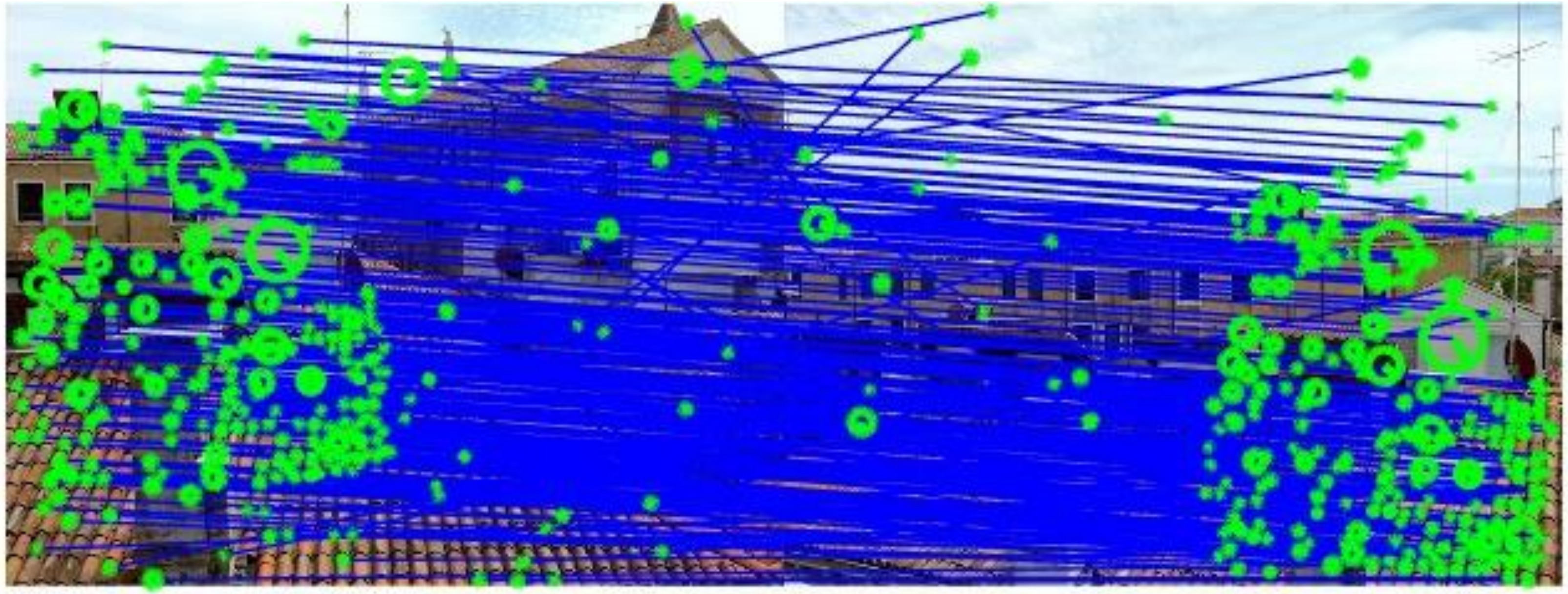
Application Example

- Image matching
  - Find SIFT keypoints



Application Example

- Image matching
  - Find best matching between SIFT keypoints

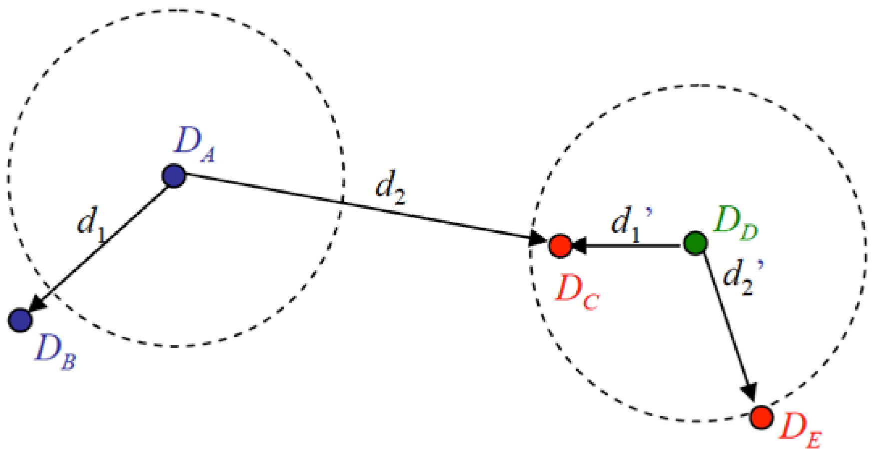


Descriptor Matching

- Nearest Neighbour Distance Ratio

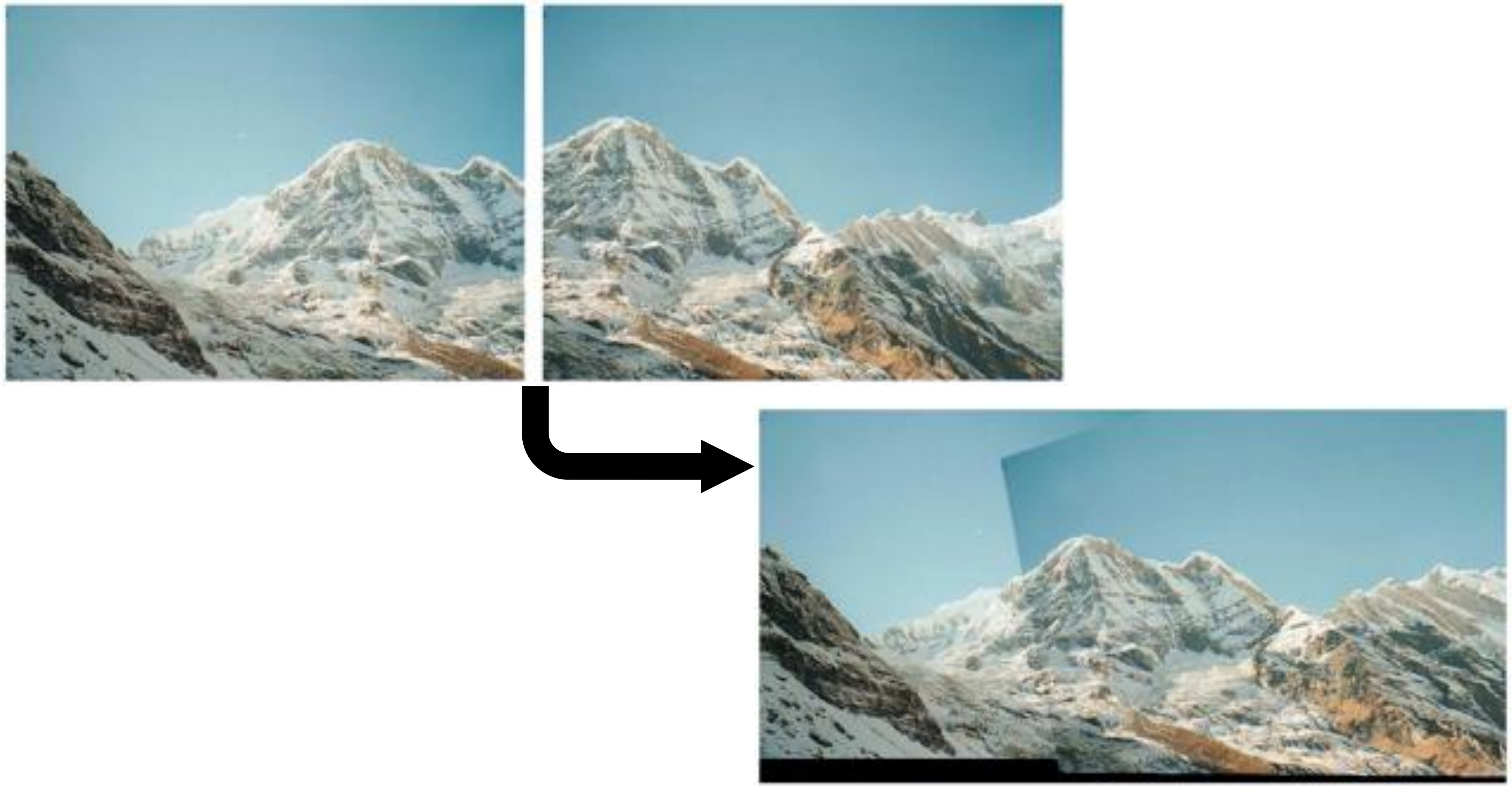
$$NNDR = \frac{d_1}{d_2} = \frac{\left\| D_A - D_B \right\|}{\left\| D_A - D_C \right\|}$$

  - d1 is the distance to the first nearest neighbour
  - d2 is the distance to the second nearest neighbour
  - Neighbours in feature space



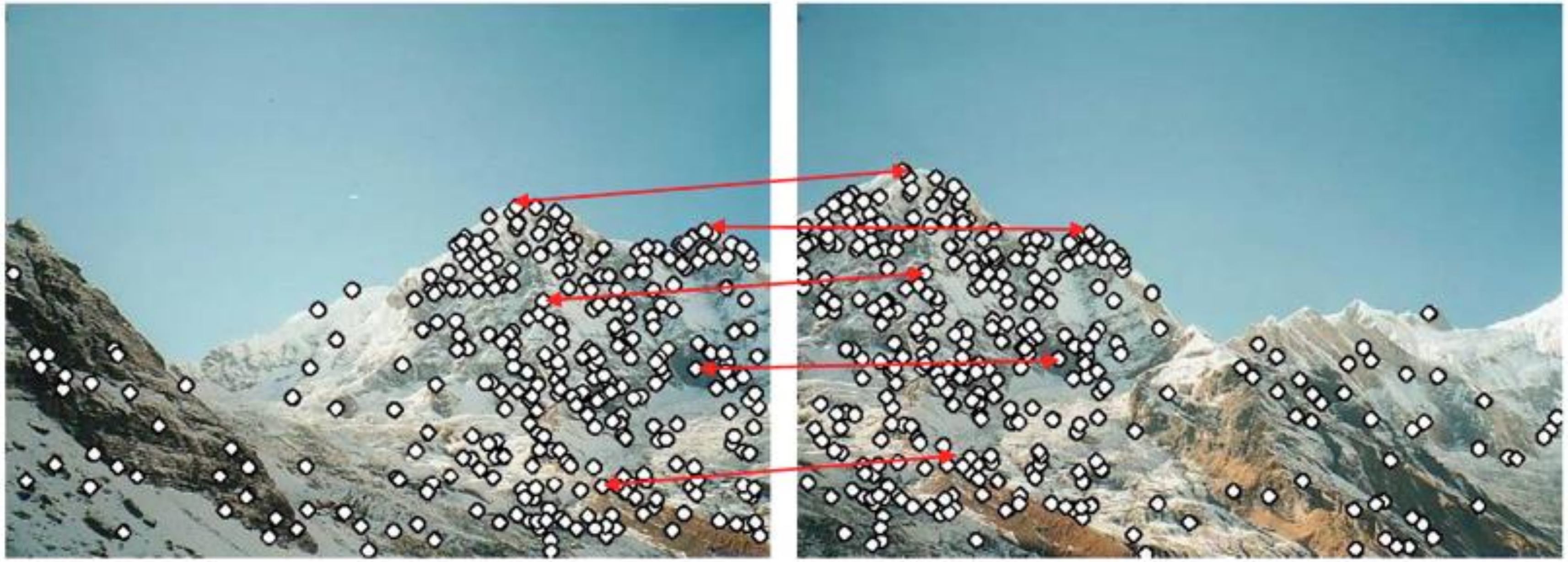
Application Example

- Image stitching



Application Example

- Image stitching
  - Find SIFT keypoints and feature correspondences



Application Example

- Image stitching
  - Find the right spatial transformation

Transformations

original

translation

rotation

scale

shear

perspective

Transformations

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Scale

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & \alpha_x \\ \alpha_y & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Shear

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\Theta & -\sin\Theta \\ \sin\Theta & \cos\Theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Rotate

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Translate

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Affine

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

Projective

Fitting and Alignment

- Least-squares (LS) fitting of corresponding keypoints $(\mathbf{x}_i, \mathbf{x}_i^{'})$

$$E_{LS} = \sum_i \|\mathbf{r}_i\|^2 = \sum_i \left\| f(\mathbf{x}_i; \mathbf{p}) - \mathbf{x}_i^{'} \right\|^2$$

where $\mathbf{p}$ are the parameters of the transformation f

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad \Rightarrow \quad \begin{bmatrix} x & y & 0 & 0 & 1 & 0 \\ 0 & 0 & x & y & 0 & 1 \\ & & \cdots & & & \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} a \\ b \\ d \\ e \\ c \\ f \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ \vdots \end{bmatrix}$$

$$\Downarrow$$

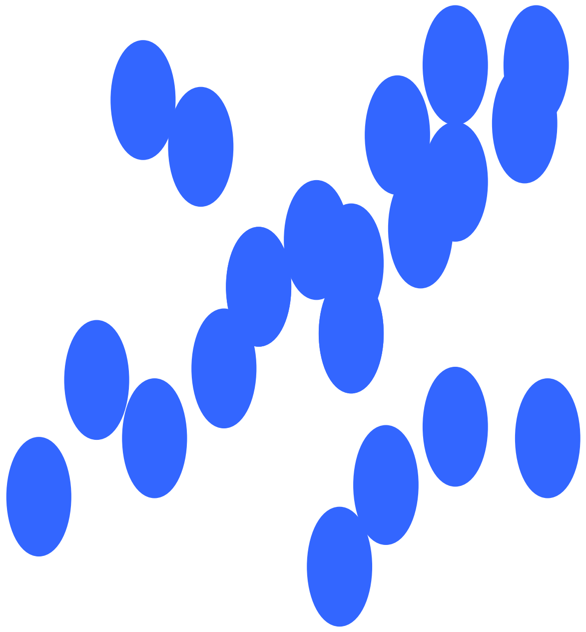
$$\mathbf{p} = [\mathbf{A}^{\mathrm{T}} \mathbf{A}]^{-1} \mathbf{A}^{\mathrm{T}} \mathbf{b} \quad \Leftarrow \quad \mathbf{Ap} = \mathbf{b}$$

Fitting and Alignment

- RANdom SAmple Consensus (RANSAC) fitting
  - Least-squares fitting is hampered by outliers
  - Some kind of outlier detection and rejection is needed
  - Better use a subset of the data and check inlier agreement
  - RANSAC does this in a iterative way to find the optimum

Fitting and Alignment

- RANSAC



(line fitting example)

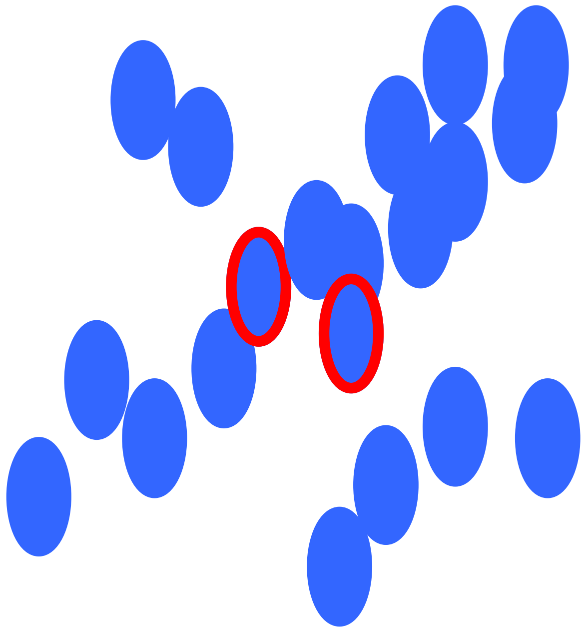
Algorithm:

1. **Sample** (randomly) the number of points required to fit the model
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Fitting and Alignment

- RANSAC



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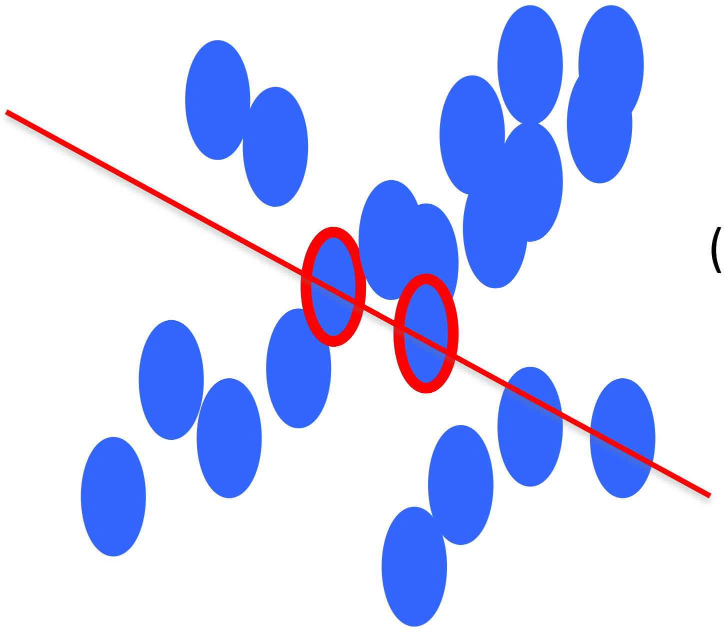

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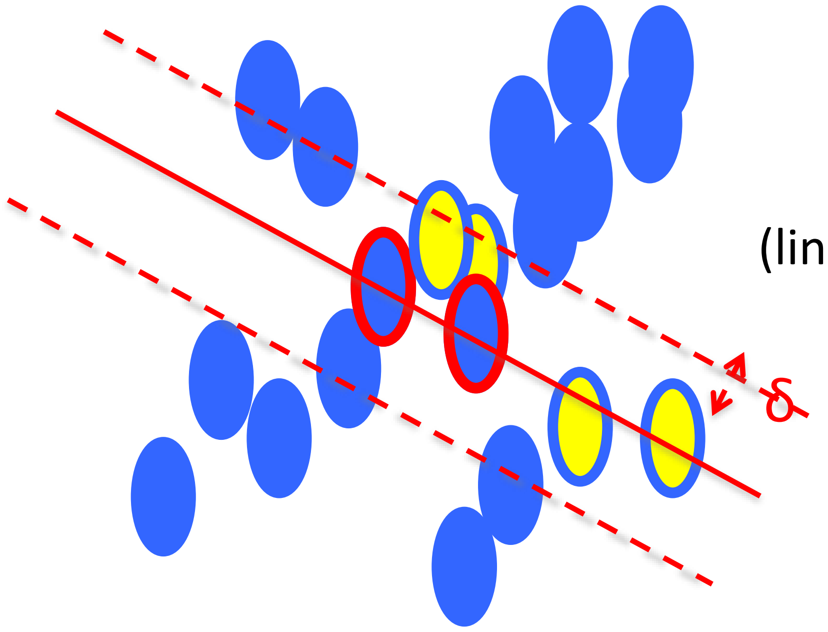

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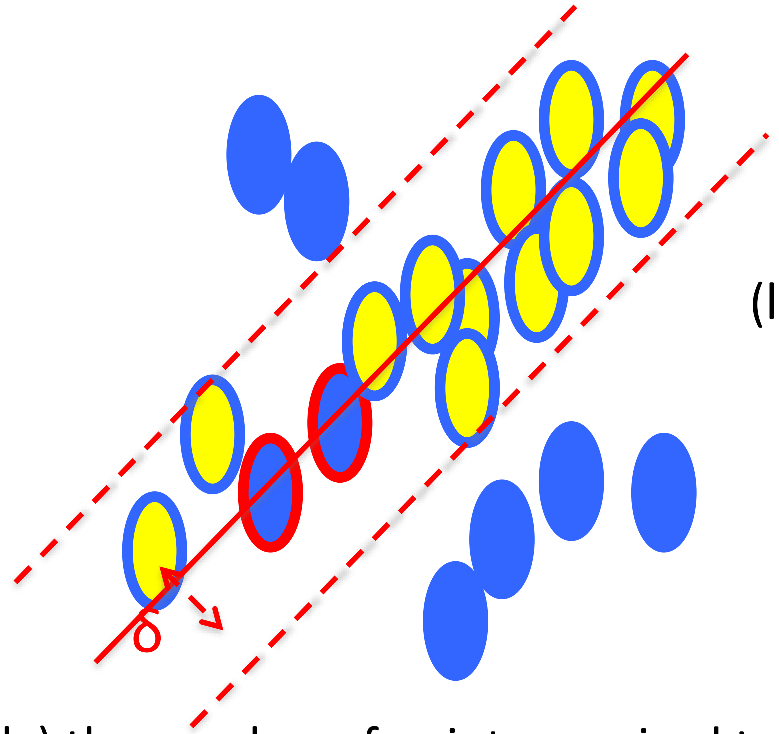
Fitting and Alignment

- RANSAC



(line fitting example)

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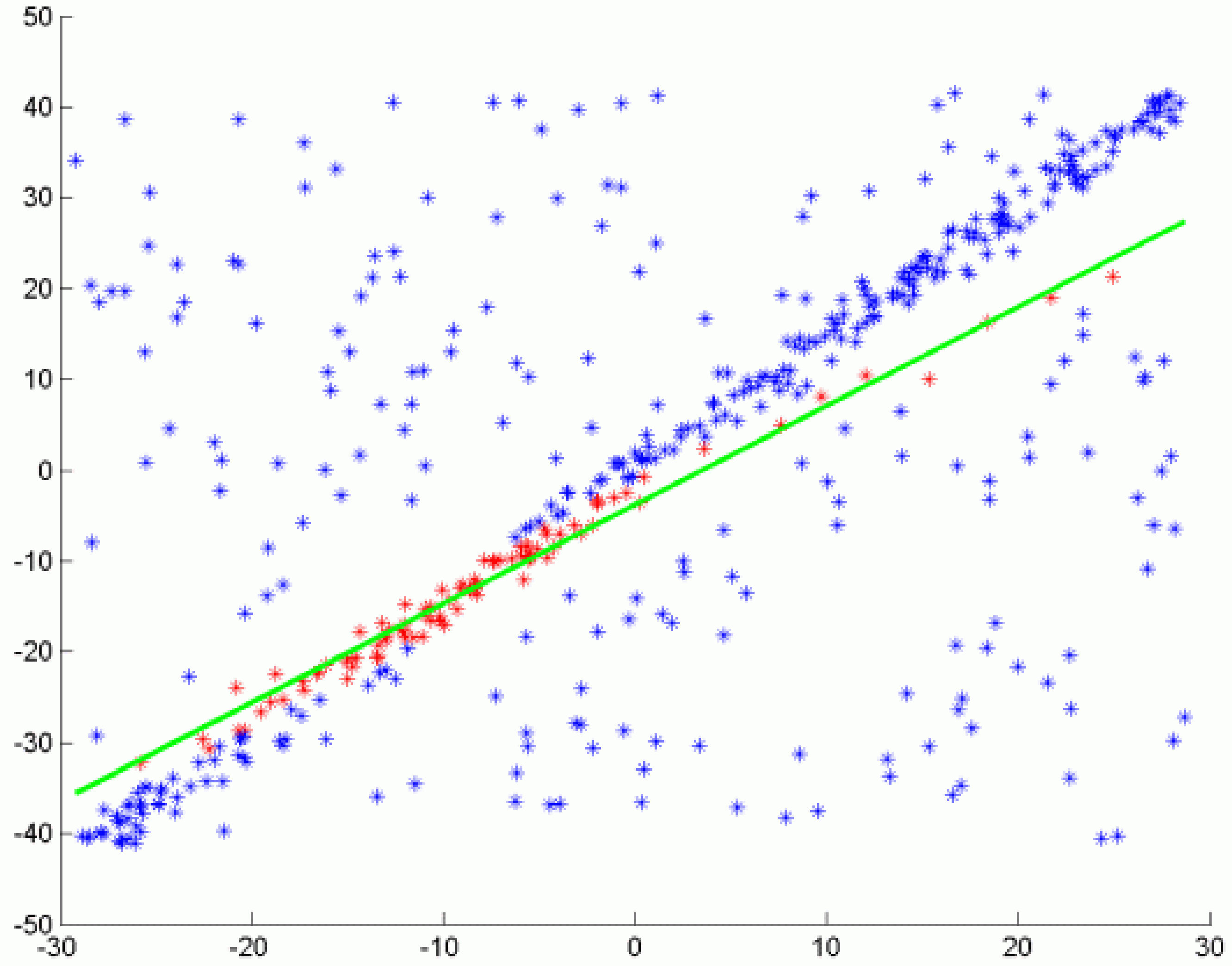
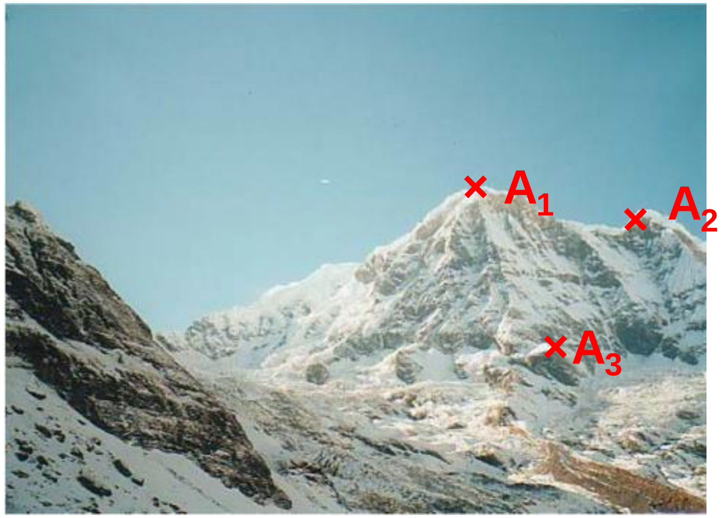


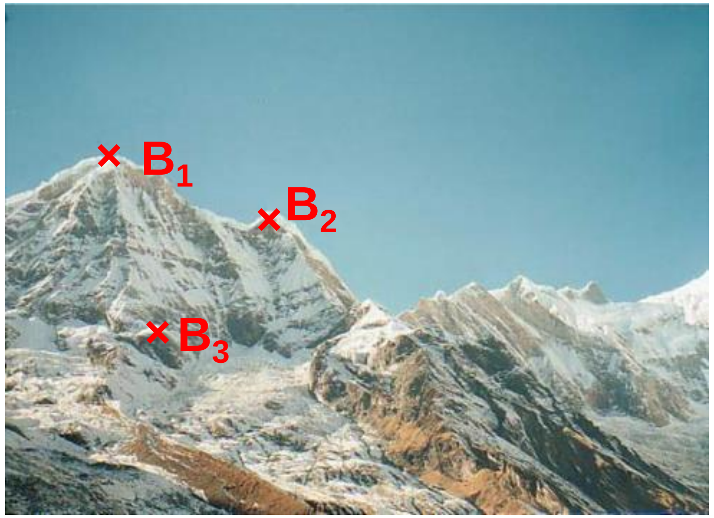
50
40
30
20
10
0
-10
-20
-30
-40
-50
-30
-20
-10
0
10
20
30

Fitting and Alignment

- Given matched points A and B, estimate the translation

$$\begin{bmatrix} x_i^B \\ y_i^B \end{bmatrix} = \begin{bmatrix} x_i^A \\ y_i^A \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

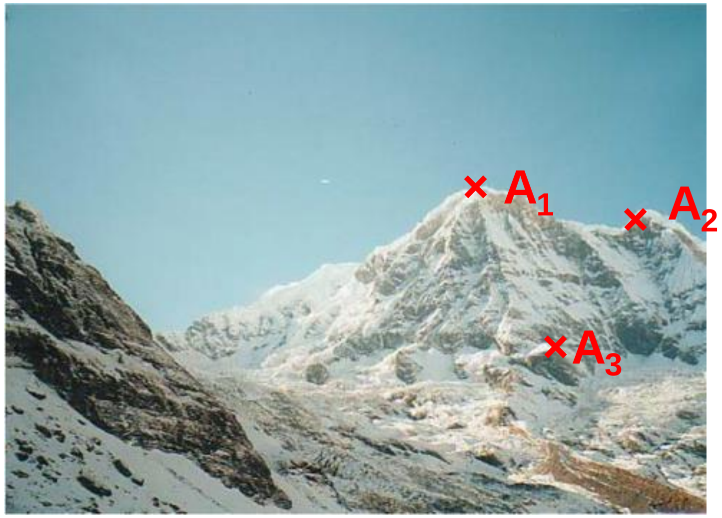


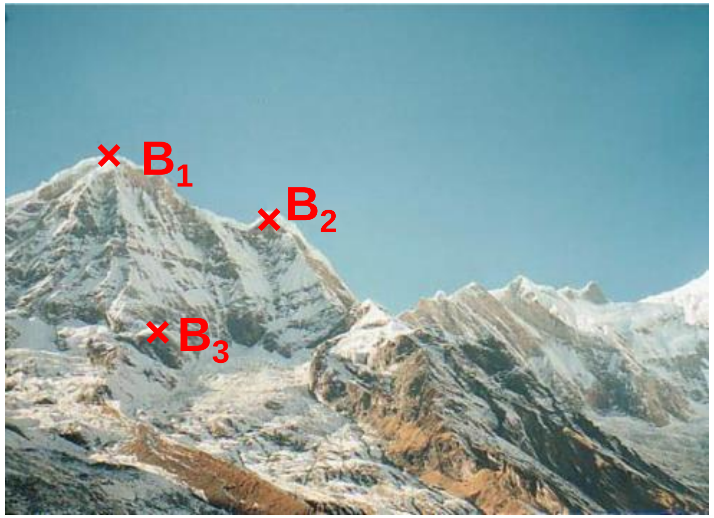


Alignment by RANSAC

1. Sample a set of matching points (1 pair)
2. Solve for transformation parameters
3. Score parameters with number of inliers
4. Repeat steps 1-3 N times

$$\begin{bmatrix} x_i^B \\ y_i^B \end{bmatrix} = \begin{bmatrix} x_i^A \\ y_i^A \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$



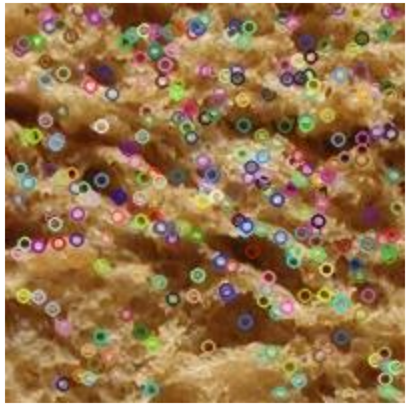


Application Example

- SIFT-based texture classification – how to do this?

bread

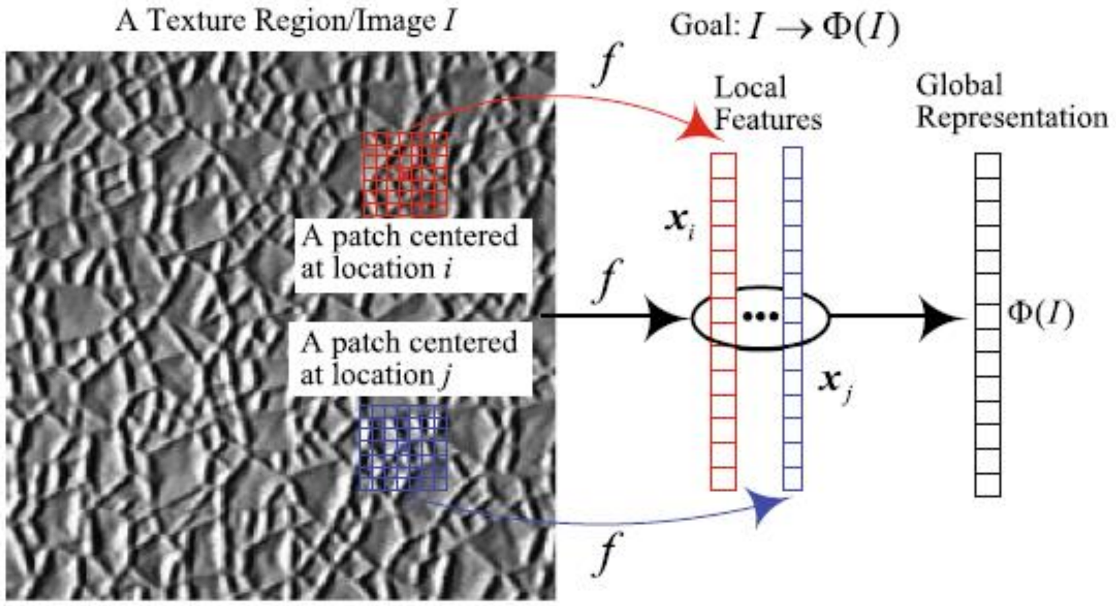
cracker



Problem: the number of SIFT keypoints (and thus the number of SIFT feature descriptors) may vary highly between images

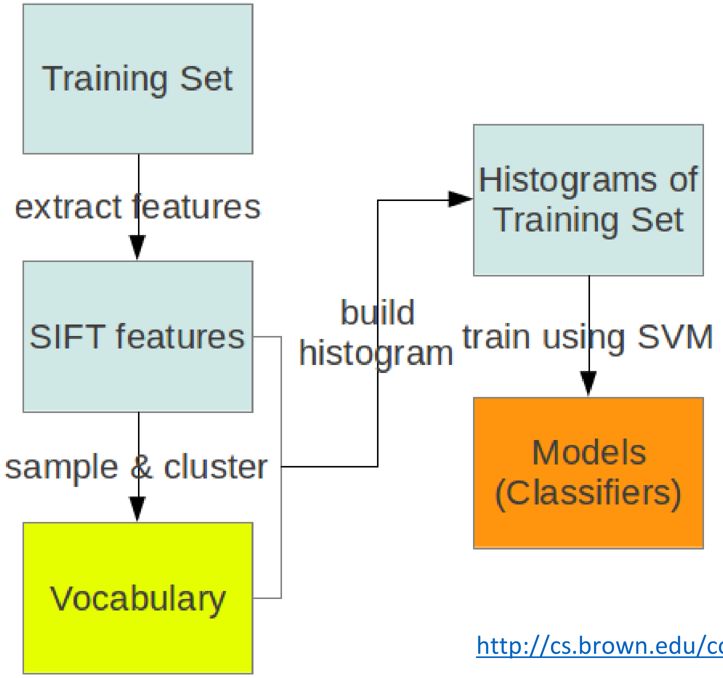
Feature Encoding

- Global encoding of local SIFT features
  - Integrate the local features (SIFT keypoint descriptors) of an image into a global vector to represent the whole image



Feature Encoding

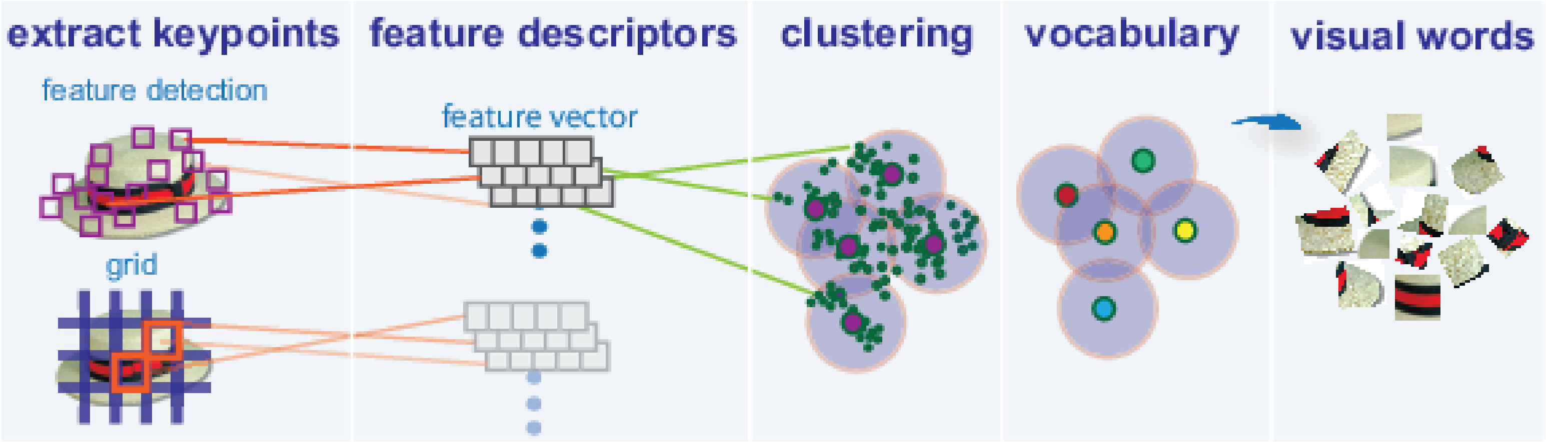
- Most popular method: Bag-of-Words (BoW)
  - The variable number of local image features are encoded into a fixed-dimensional histogram to represent each image



http://cs.brown.edu/courses/cs143/2011/results/proj3/hangsu/

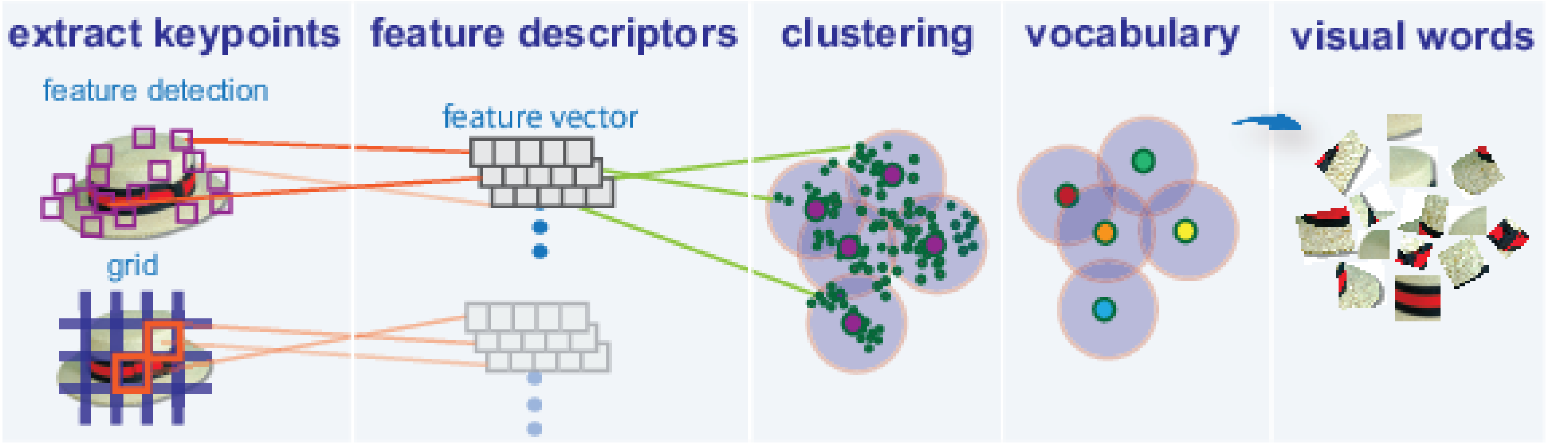
Feature Encoding

- Bag-of-Words (BoW) – step 1
  - Create the vocabulary from the set of local descriptors (SIFT keypoint descriptors) extracted from the training data
  - This vocabulary represents the categories of local descriptors



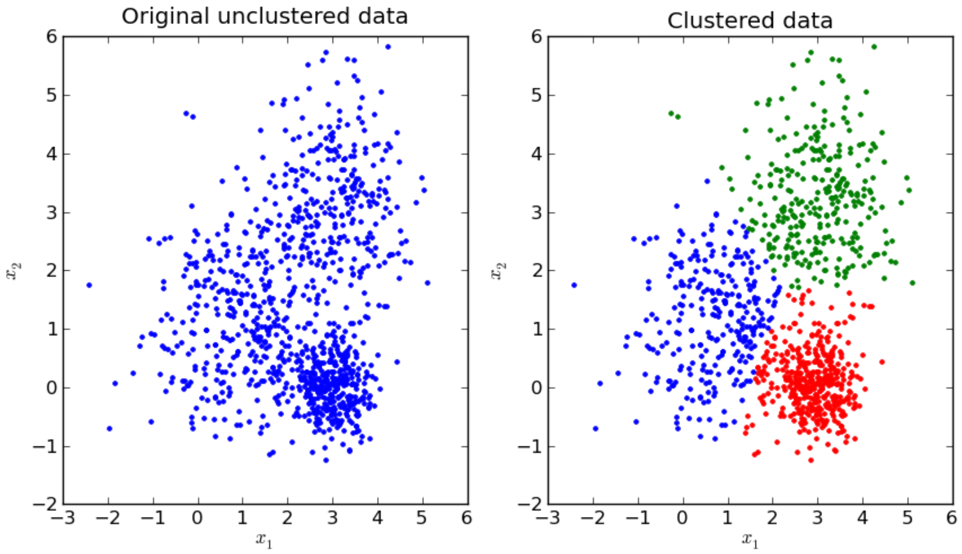
Feature Encoding

- Bag-of-Words (BoW) – step 1
  - Main technique used to create the vocabulary: *k-means clustering*
  - k-means clustering is one of the simplest and most popular unsupervised learning approaches that perform automatic clustering (partitioning) of the training data into multiple categories

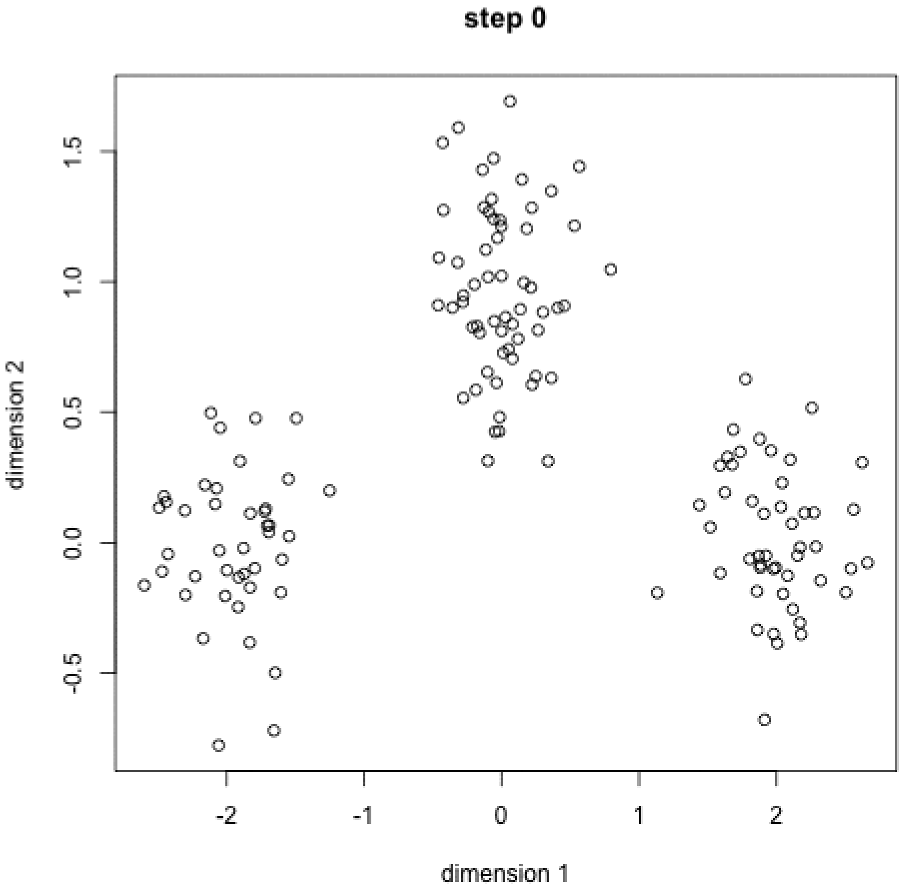


Feature Encoding

- Bag-of-Words (BoW) – step 1
  - K-means clustering:
    - Initialize: *k* cluster centres, typically randomly
    - Iterate: 1) Assign data (feature vectors) to the closest cluster (Euclidean distance)
      2) Update cluster centres as the mean of the data samples in each cluster
    - Terminate: When converged or the number of iterations reaches the maximum

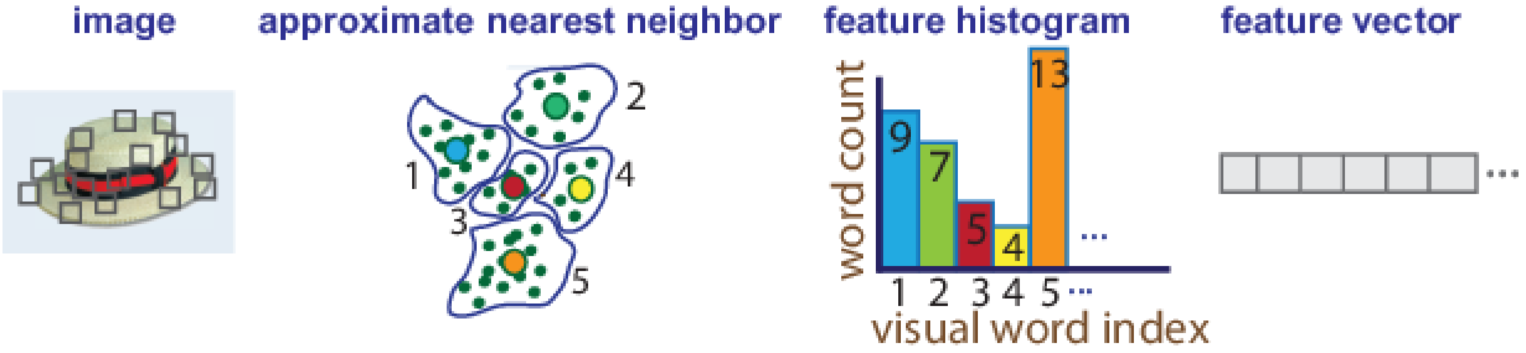


K-Means Clustering



Feature Encoding

- Bag-of-Words (BoW) – step 2
  - The cluster centres are the "visual words" which form the "vocabulary" that is used to represent an image
  - An individual local feature descriptor (e.g. SIFT keypoint descriptor) is assigned to one visual word with the smallest distance



Feature Encoding

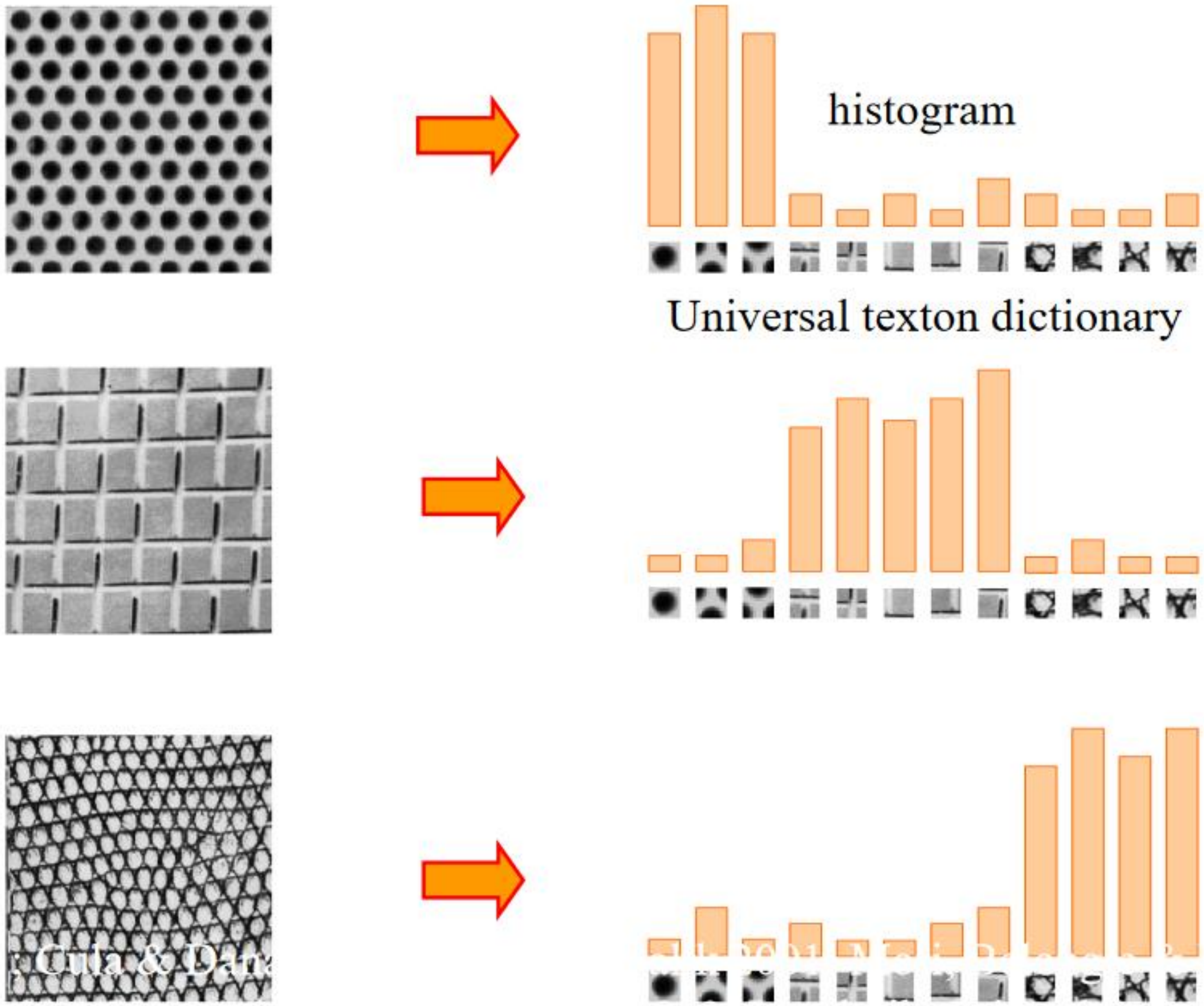
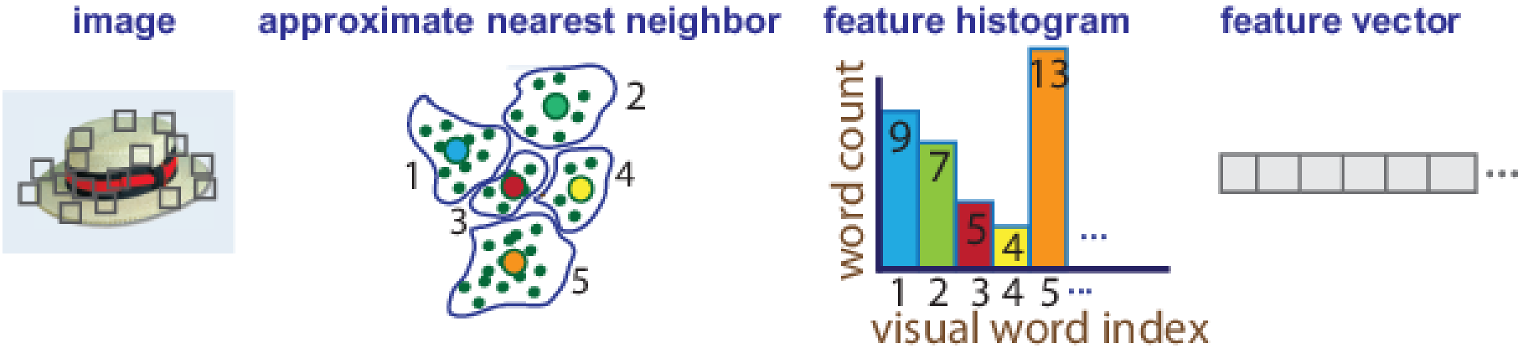


Image from Cordelia Schmit

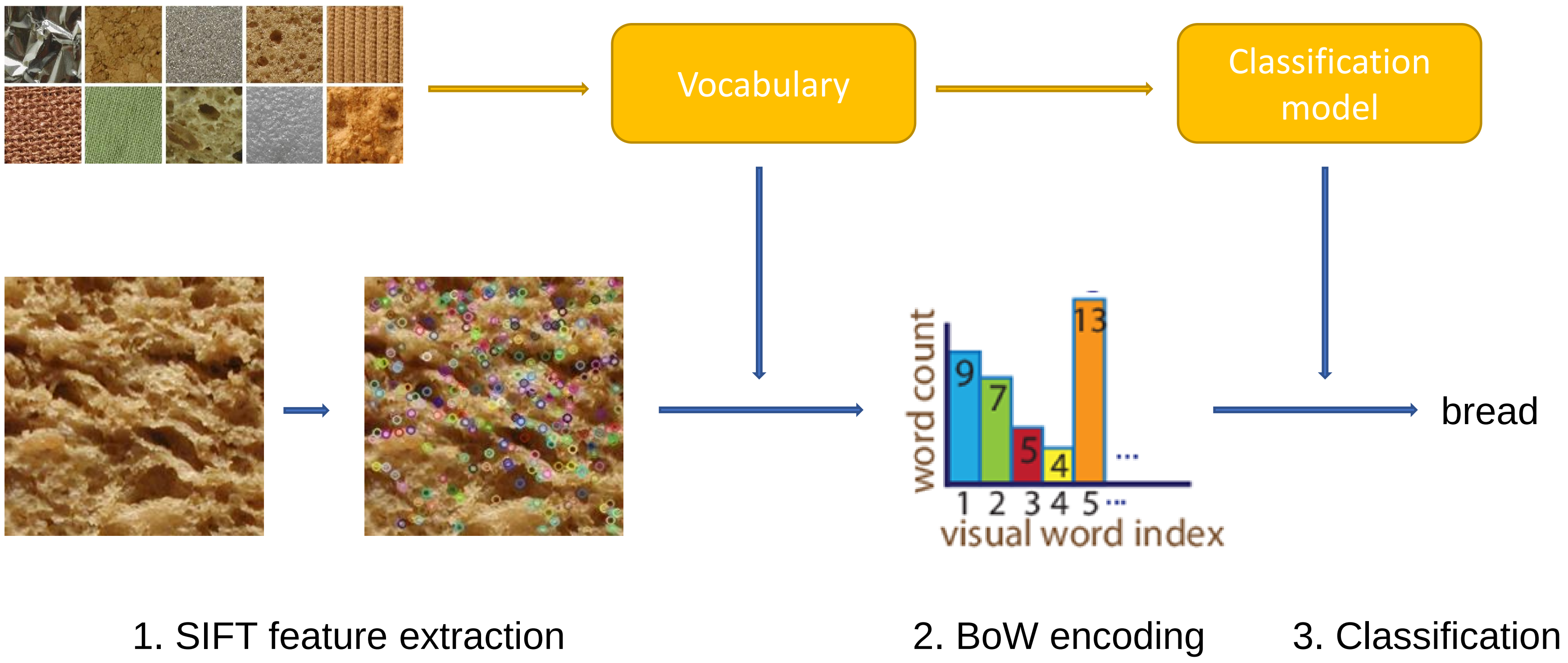
Feature Encoding

- Bag-of-Words (BoW) – step 2
  - For an image the number of local feature descriptors assigned to each visual word is computed
  - The numbers are concatenated into a vector which forms the BoW representation of the image



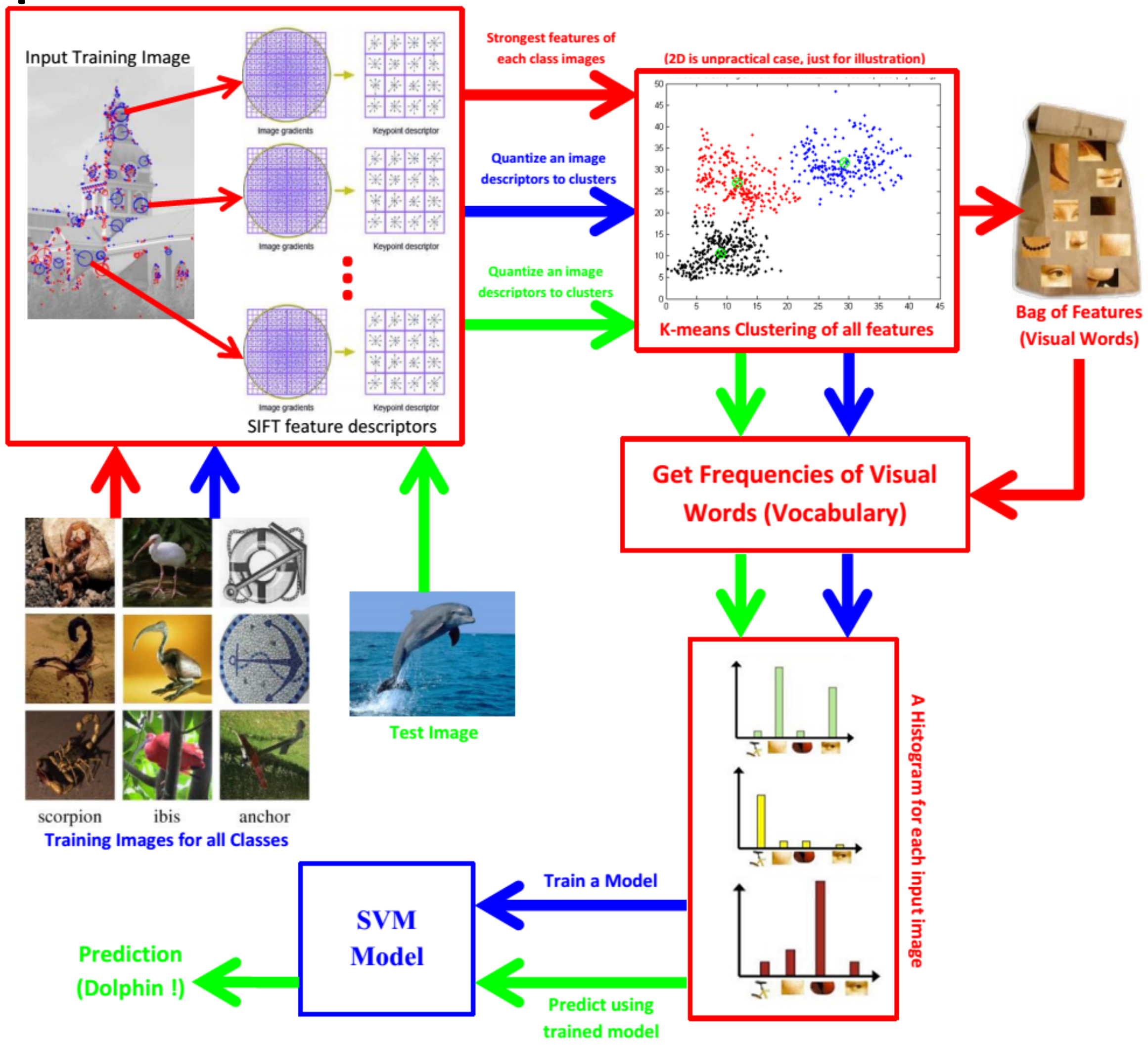
Application Example

- SIFT-based texture classification



Application Example

- SIFT-based texture classification



Build vocabulary

Train classifier

Classify image

http://heraqi.blogspot.com/2017/03/BoW.html

Feature Encoding

- Local features can be other types of features, not just SIFT
  - LBP, SURF, BRIEF, ORB
- There are also more advanced techniques than BoW
  - VLAD, Fisher Vector
- A very good source of additional information is VLFeat.org
  - http://www.vlfeat.org/

Summary

- Feature representation is essential in solving almost all types of computer vision problems
- Most commonly used image features:
  - Colour features (Part 1)
    - Colour moments and histogram
  - Texture features (Part 1)
    - Haralick, LBP, SIFT
  - Shape features (Part 2)
    - Basic, shape context, HOG

Summary

- Other techniques described (Part 1)
  - Descriptor matching
  - Feature encoding (Bag-of-Words)
  - k-means clustering
  - Alignment and RANSAC
  - Spatial transformations

- To be discussed (Part 2)
  - Shape features
  - Shape matching
  - Sliding window detection

References and Acknowledgements

- Szeliski, Chapter 4 (in particular Sections 4.1.1 to 4.1.3 and 4.3.2), Chapter 6 (in particular Sections 6.1.1 to 6.1.4)
- Some content are extracted from the above resource, James Hays slides, slides from Michael A. Wirth and Cordelia Schmit
- L. Liu et al., From BoW to CNN: two decades of texture representation for texture classification, International Journal of Computer Vision, 2019
- And other resources as indicated by the hyperlinks