Part VI:
Local Feature Extraction

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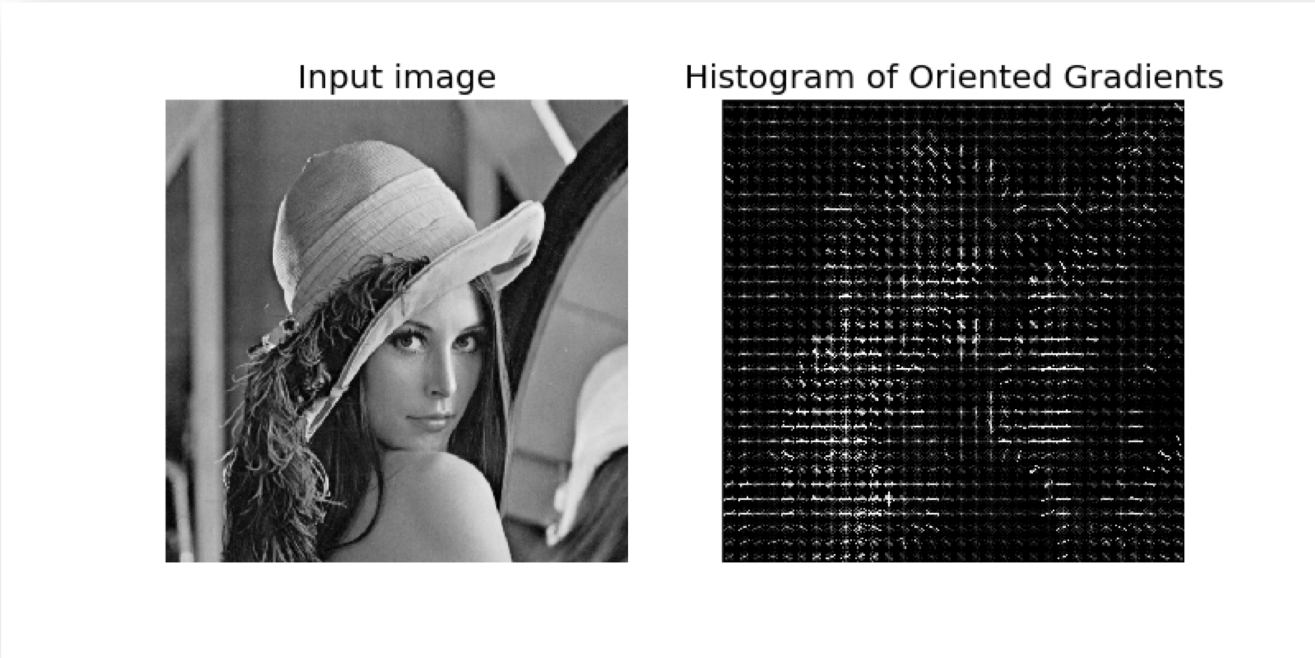
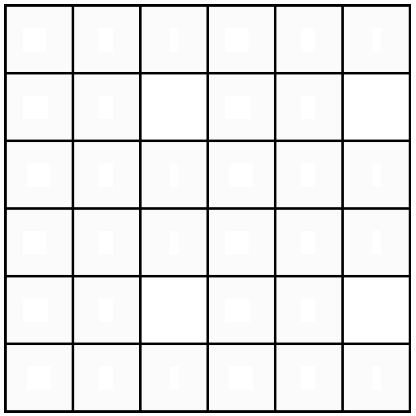
Use of gradients – HOG

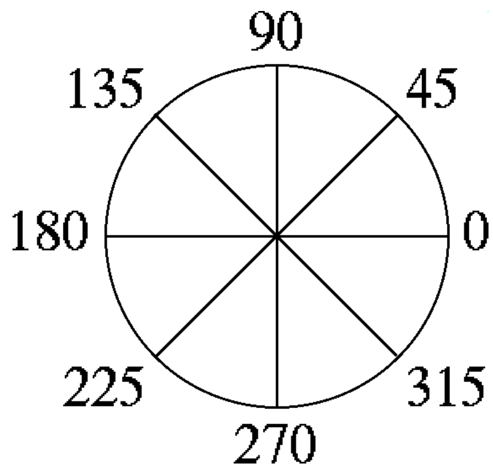
- Intensity and direction of edges is one of the most salient features that help us characterizing objects



Histogram of oriented gradients – HOG

- Divide the image into **small cells**
- Cells can be **rectangular** or **radial**
- For each pixel in the cell **compute the orientation** of edges





HOG

- Each pixel within the cell casts a weighted vote for an **orientation-based histogram** based on the values found in the gradient computation
- In other words, each cell is represented through a **1D array of gradient directions**
- The vote is based on the **gradient magnitude**
- **Intensity is locally normalized**, to account for illumination changes and shadowing especially when using larger areas (blocks), consisting of more cells
- Normalization of the cell energy is performed in the RGB or LAB color space

Normalization

- Blocks can be of rectangular (R-HOG) or circular (C-HOG) shape
- Normalization can be computed using different metrics, such as L1 and L2 norm

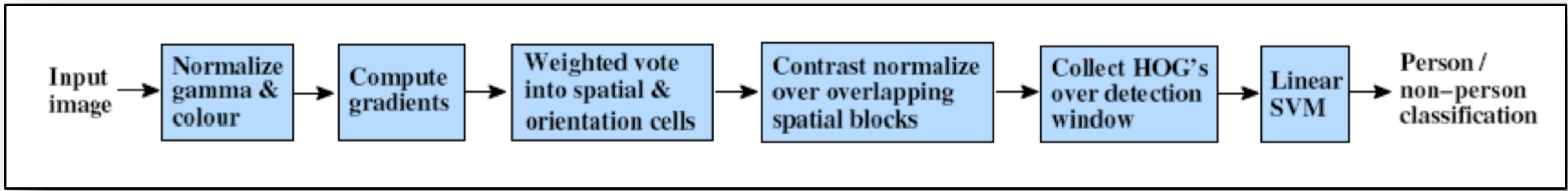
L1-Norm
$$f = \frac{v}{(\|v\|_1 + e)}$$

L2-Norm
$$f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$$

- v is the non-normalized vector of the histograms for a given block
- e is a small constant

Classification

- The HOG representation is the feature-set used for learning
- General application in object detection
- Good results in human detection
  - Binary classification (human vs non-human)

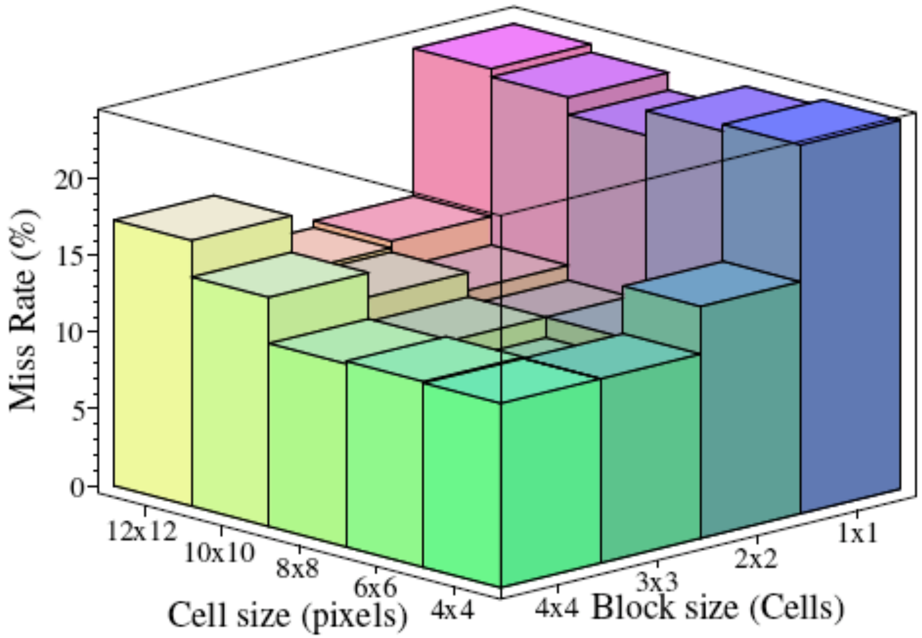


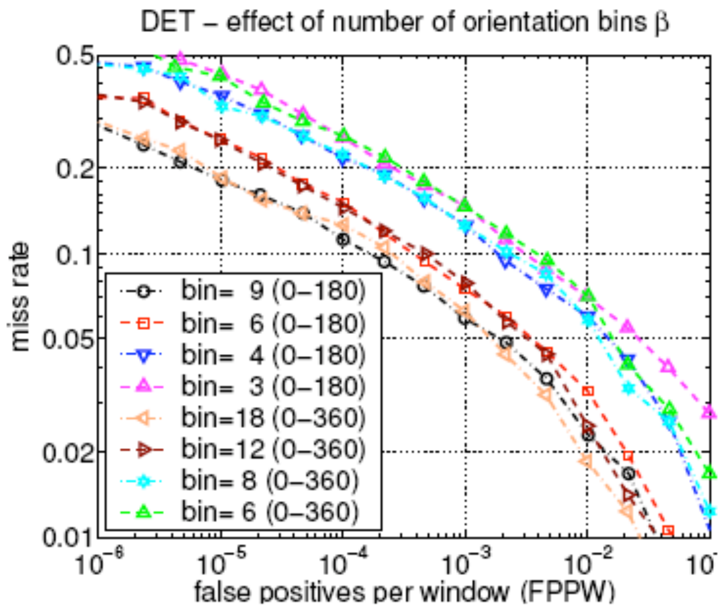
Configuration

- Dalal and Triggs (2005):
  - Input data are arranged in a 64x128 window
  - Cells of 8x8 pixels
  - Blocks of 2x2 cells
  - Each cell is a 9-bin histogram
  - Each block is represented by the concatenated feature vector (36D)
  - Blocks overlap
  - 7x15 blocks in a 64x128 window

Dalal, Navneet, and Bill Triggs. "Histograms of Oriented Gradients for Human Detection." *International Conference on Computer Vision & Pattern Recognition (CVPR'05)*

Performance





Miss rate as function of the cell and block size

Miss rate as function of the number of HOG bins

Comments

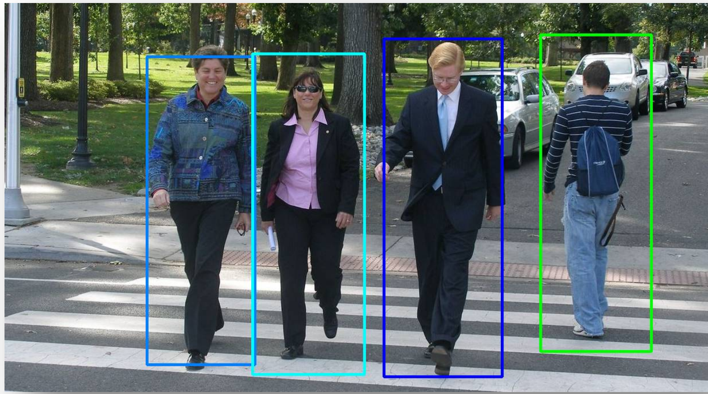
- For good performance use:
  - fine scale derivatives (no smoothing)
  - many orientation bins
  - moderately sized, strongly normalized, overlapping descriptor blocks.

The problem of scale

- The algorithm by Dalal and Triggs is very efficient at single scale
- In videos, human can be detected at different size
- Analysis at multi-scale → complexity increases considerably
- Use Integral Histogram
  - Within the 64x128 multiple windows are considered
  - Different size, location, and aspect ratio

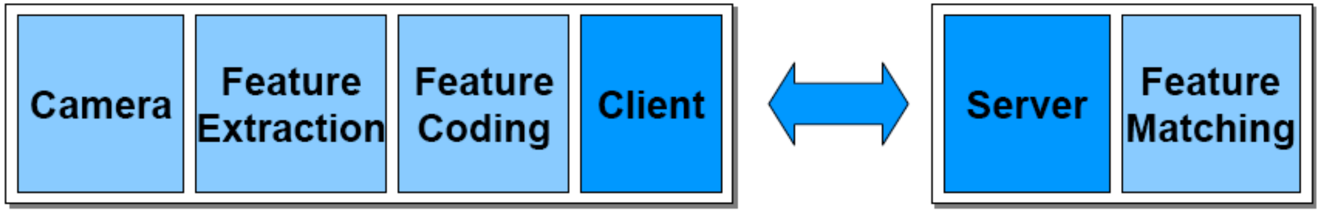
Feature compression

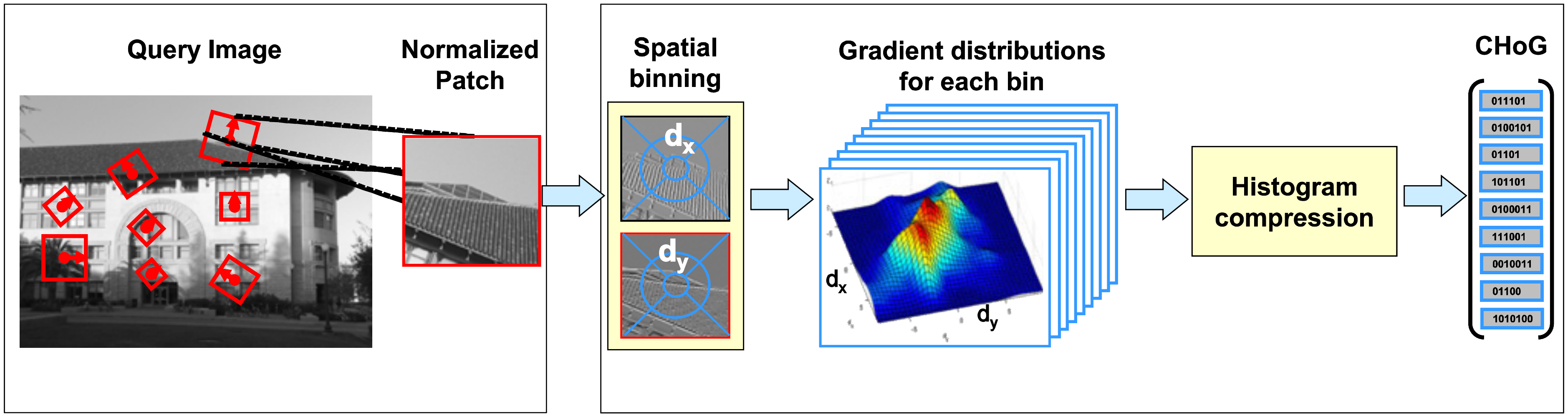
- The extracted features can be
  - processed online
  - sent over the Internet and matched real time



- Applications:
  - Surveillance and monitoring
  - Augmented reality
  - Media retrieval

Feature compression

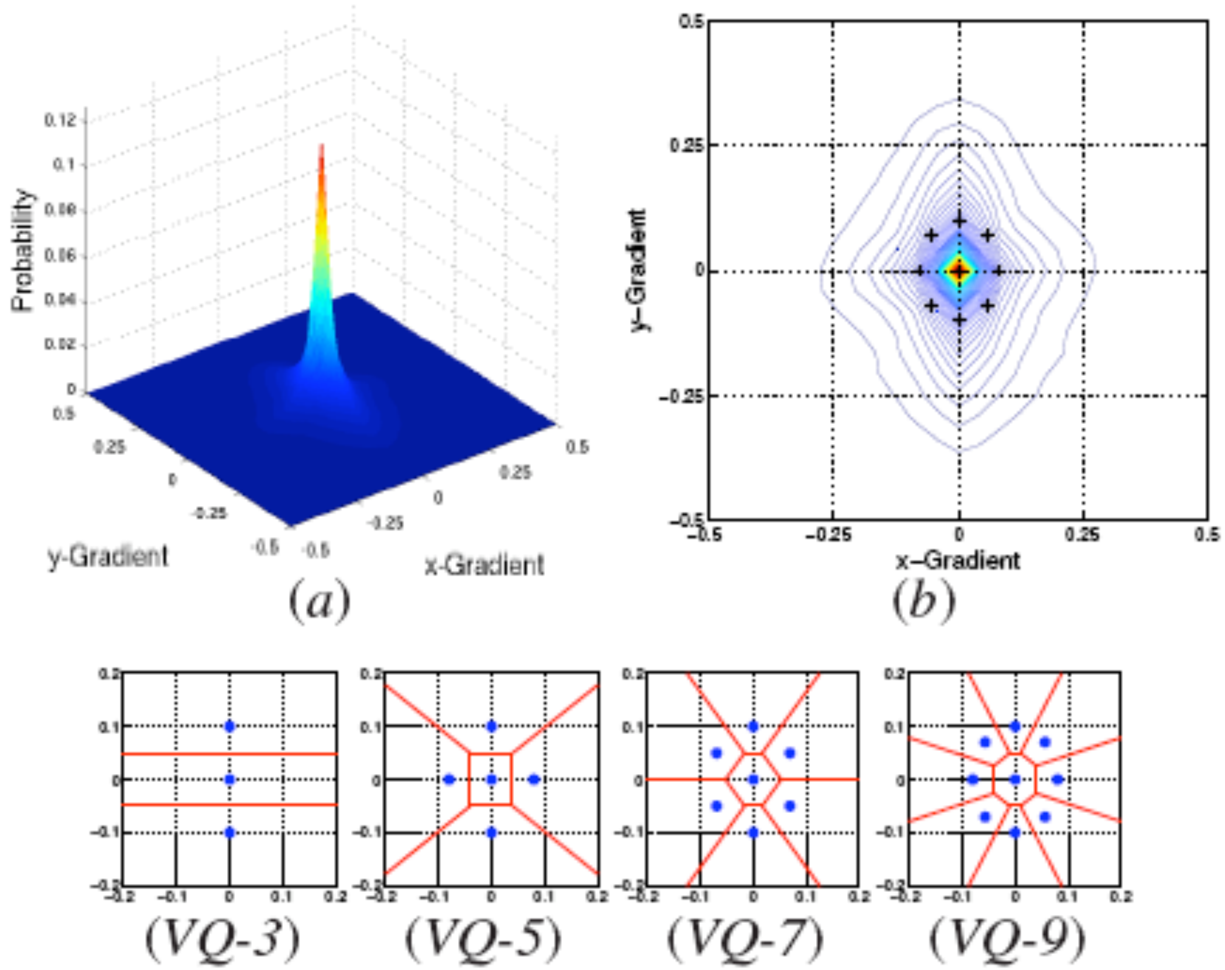




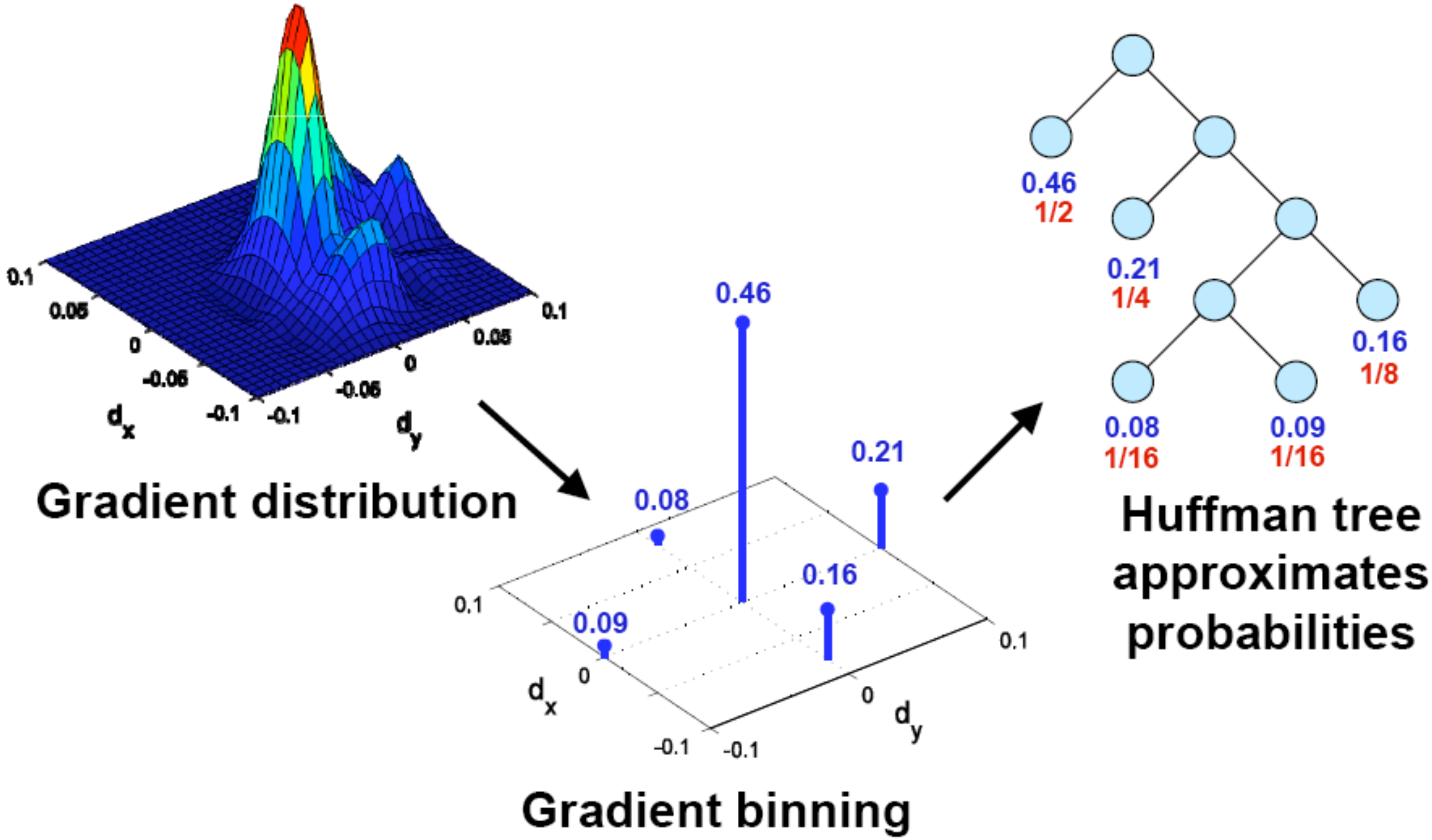
Interest Point Detection **Computation of feature descriptors**

Chandrasekhar et al. CHoG: Compressed Histogram of Gradients - A low bit rate feature descriptor, CVPR 2009
Chandrasekhar et al. Compressed Histogram of Gradients: A Low-Bitrate Descriptor , IJCV 2011

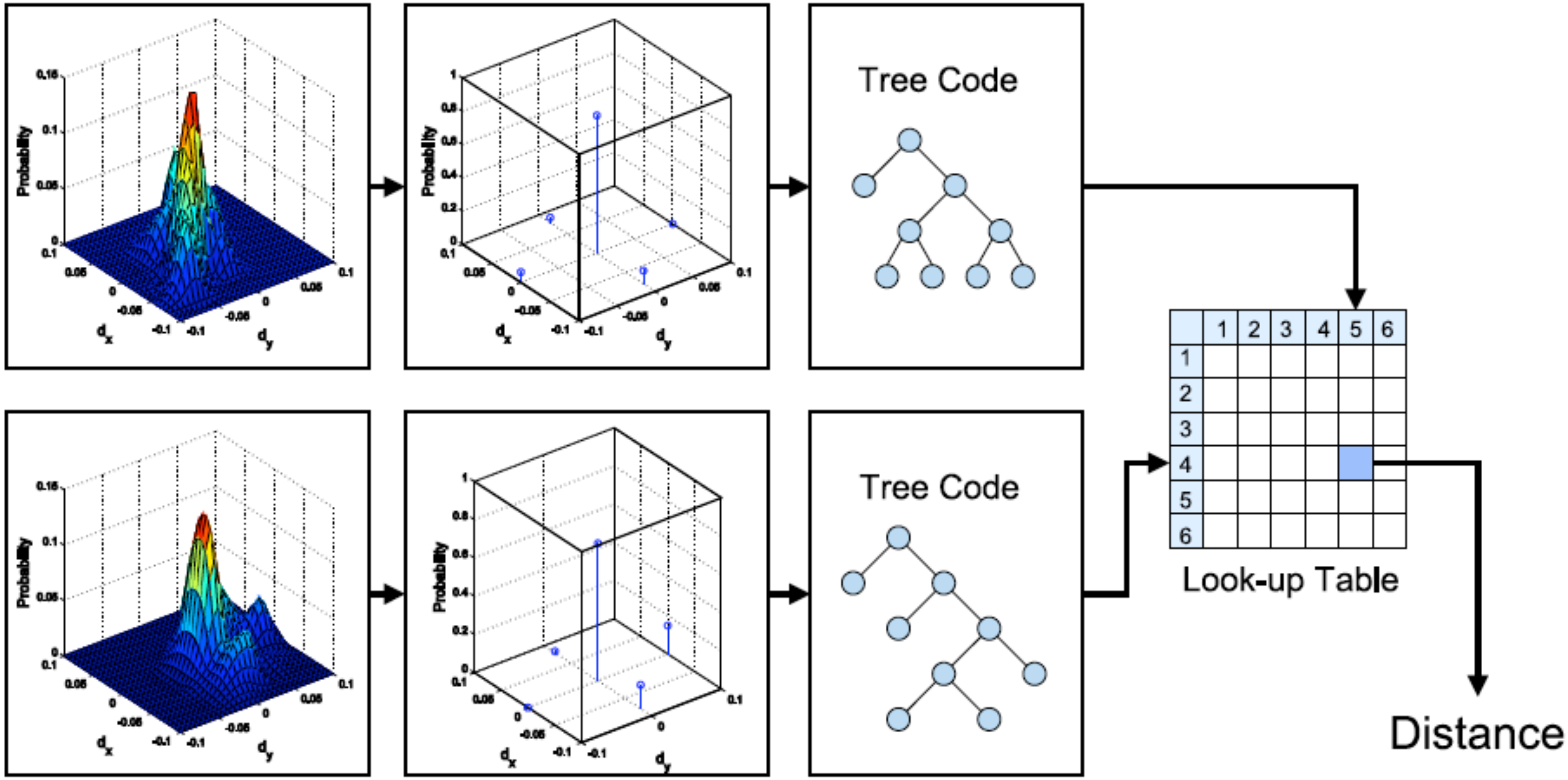
Histogram binning



Huffman coding



Search and match



SIFT: Scale Invariant Feature Transform

- Extraction of salient points (keypoints) in the image for:
  - Object detection
  - Tracking
  - Image matching
- The idea is to make the image of concern <u>scale-invariant</u>

Lowe, David G. "Distinctive image features from scale-invariant keypoints." *International journal of computer vision* 60.2 (2004): 91-110.

SIFT: how to

1. Construct a subspace representation of the image and progressively apply a Gaussian smoothing filter
2. At every iteration, each image becomes a blurred version of the previous one
3. Find keypoints
4. Compute the descriptor

SIFT - filtering

$$L(x,y,\sigma) = I(x,y) * \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2})$$

- $I(x,y)$ is the image
- $L(x,y,\sigma)$ is the scale space of the image after convolution.
- $L(x,y,\sigma)$ is the result of the filter subject to σ
- σ defines the strength of the filter

SIFT - octaves

- We build-up a so-called **octave** collecting the images of the **same size** and each one represents a **blurred** version of the previous one

- Mathematically, the blurring is controlled via the value of σ, hence if the current image is blurred with σ, the next one goes with $k\sigma$ and so on

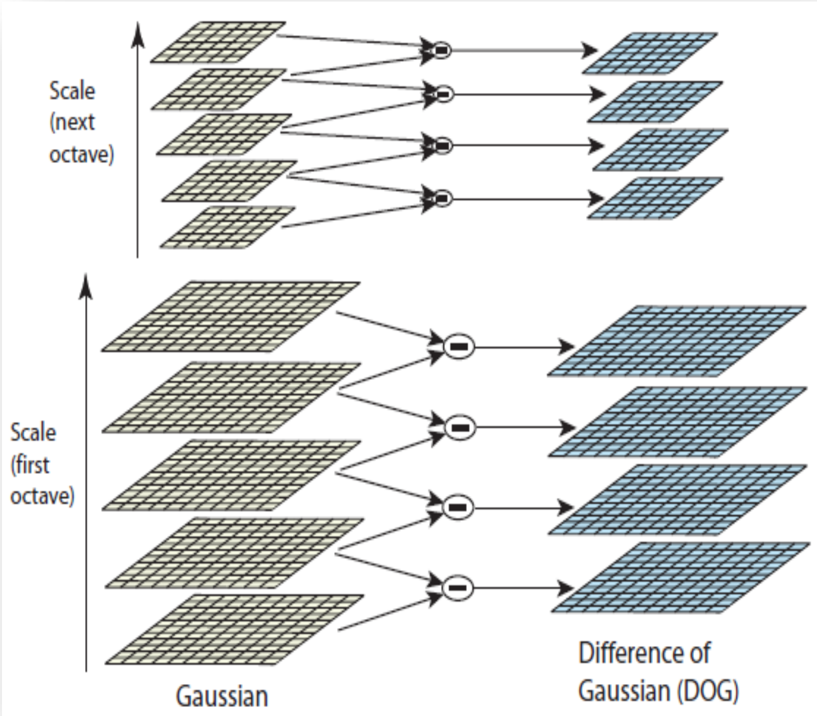
- To build-up the **next octave**, the original image is down-sampled to **half** its size and the blurring operation is repeated in the same manner

- Theoretically octaves can be created as long as the image can be downsampled.

SIFT - DoG

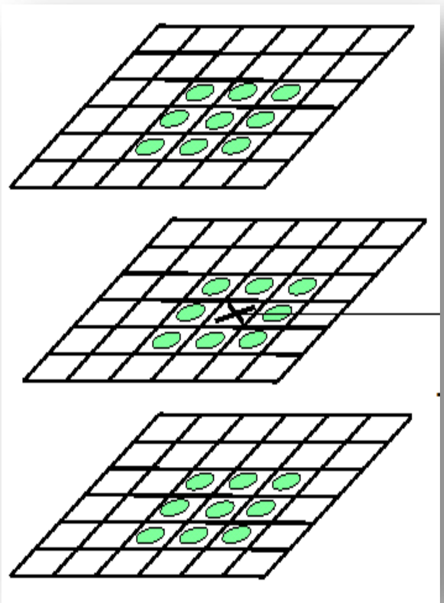
- A difference of Gaussians (DOG) is then obtained by subtracting each Gaussian image **within** an octave from the previous one. Hence, for N image samples, (N-1) DOGs can be obtained subject to:

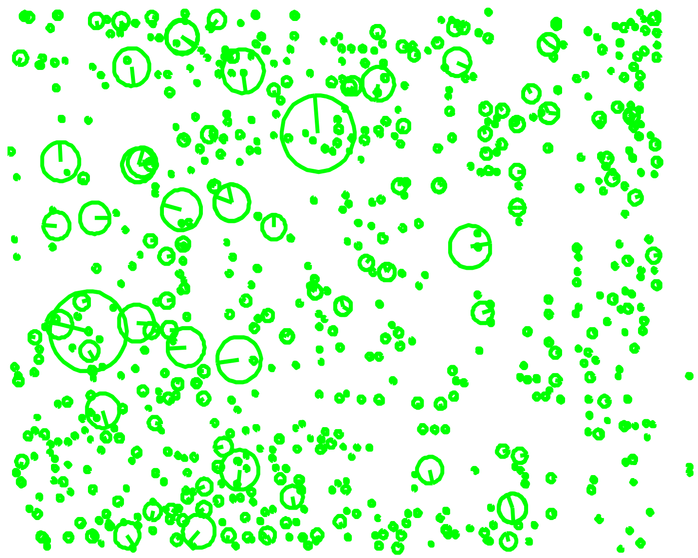
$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$



SIFT - Keypoint selection

- To grab the most salient points from the DOGs, each pixel from a given DOG is compared to its 26 neighbors (8 in the same scale, 9 above and 9 below).
- A pixel is kept as a key-point only if it is greater (i.e. maxima) or smaller (i.e. minima) than its neighbors.





(a)

SIFT – Stability of the keypoint and refinement

- The selection of the point might be noisy
- Apply a second order Taylor expansion, where $X=(x,y,s)$

$$D(\mathrm{X}) = D + \frac{\partial D^T}{\partial \mathrm{X}}\mathrm{X} + \frac{1}{2}\mathrm{X}^T \frac{\partial^2 D}{\partial \mathrm{X}^2}\mathrm{X}$$

- Setting the derivative of D(X) to zero, the maxima and minima can be obtained

SIFT - Edges

- DoG function exhibits strong response over the edges
- Edges are not necessarily good keypoints
- At the candidate keypoint location, the Hessian matrix is computed

$$H = \begin{pmatrix} D_{xx} & D_{yx} \\ D_{xy} & D_{yy} \end{pmatrix}$$

- Let us consider $r=\alpha/\beta$, where α and β are the largest and smallest eigenvalue in magnitude. If the equation is satisfied for a certain r_{th}, then the keypoint is strong

$$\frac{Tr(H)^2}{Det(H)} < \frac{(r+1)^2}{r}$$

SIFT - Orientation

- The eigenvalues of H are proportional to the principal curvatures of D
- For the points that exhibit a good curvature in both dimensions, the gradient and orientations are computed.
- This step achieves the invariance to rotation

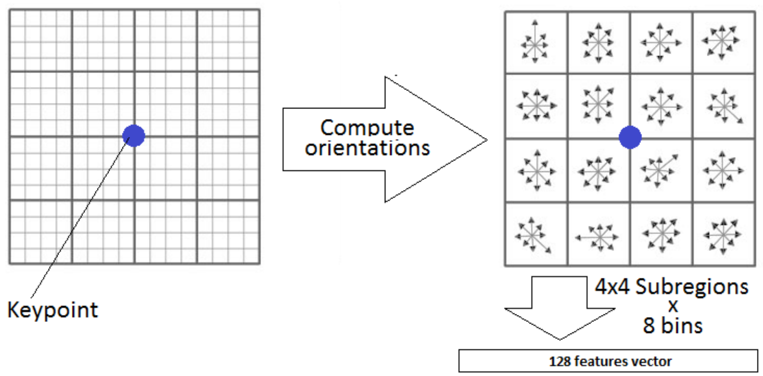
$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\theta(x,y) = \tan^{-1}(L(x,y+1) - L(x,y-1)) / (L(x+1,y) - L(x-1,y))$$

- The region within which *m* and θ are computed is relative to the scale of the keypoint, the higher the scale (smoothing), the larger the computation region

SIFT – The feature vector

- From the orientations a 36-bin histogram is computed
- If a keypoint exhibits multiple peaks in the histogram that are higher than 80% of the highest peak, a new keypoint is instantiated with same location and scale.
- The 16x16 area (oriented according to the key-point orientation computed before) around the selected keypoint is divided in 4x4 regions, and for each of them a histogram of the gradients (8bins) is computed
- This turns out in a descriptor of 128 elements: 4x4x8



Feature Matching

- Once the descriptor is constructed, search and match can be performed
- Matching usually done by
  - Nearest neighbor search
  - Optimization (e.g. RANSAC)

https://docs.opencv.org/2.4/doc/tutorials/features2d/feature_flann_matcher/feature_flann_matcher.html