INFO - H - 501

Pattern recognition and image analysis

2 - recognition

Object recognition

• How do we recognize objects?

Object recognition

- How do we recognize objects?
 - object defined by sample
 - by usage
 - by definition
 - by context

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Object recognition

- direct approach
 - e.g. pattern matching
 - face recognition using PCA
- feature based approach
 - supervised classification: recall
 - corner-based: bag-of-visual word
 - edge histogram
 - Viola & Jones

- find a pattern h(i,j) in the f(i,j) image
- matching criteria

$$C_1(u, v) = \frac{1}{\max_{(i,j)\in V} |f(i+u, j+v) - h(i, j)|}$$

$$C_2(u,v) = \frac{1}{\sum_{(i,j)\in V} |f(i+u,j+v) - h(i,j)|}$$

$$C_3(u,v) = \frac{1}{\sum_{(i,j)\in V} [f(i+u,j+v) - h(i,j)]^2}$$

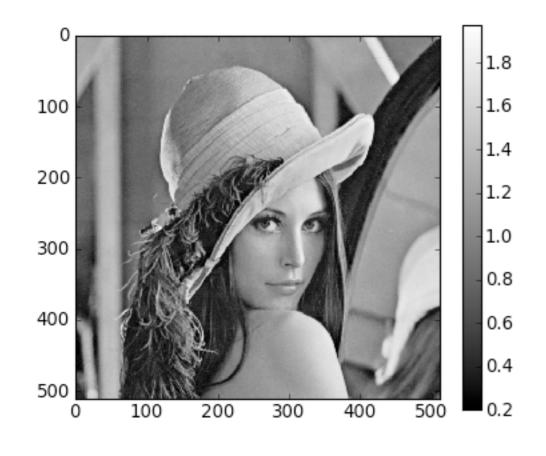
correlation

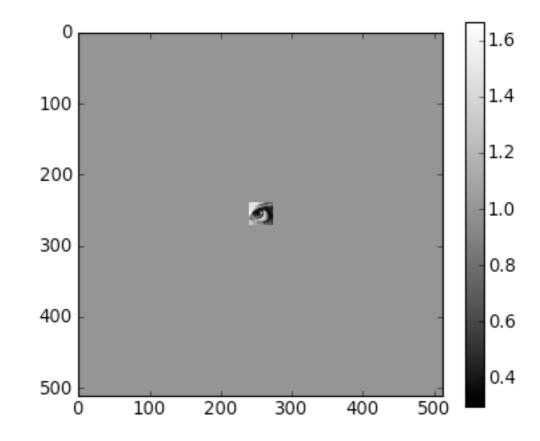
$$f(x) \circ g(x) = \int_{-\infty}^{+\infty} f^*(\alpha)g(x + \alpha) d\alpha$$

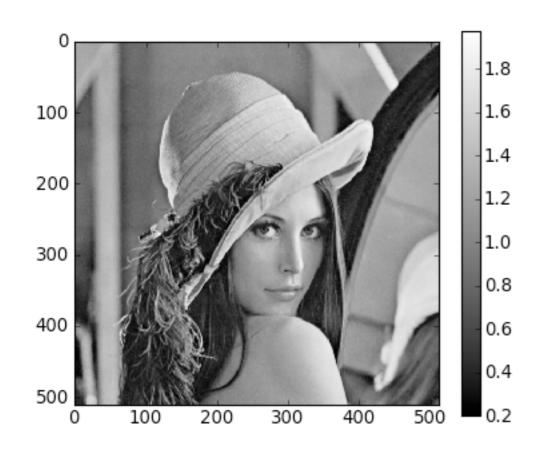
$$f(x) \circ g(x) = \mathcal{F}^{-1}(F^*(u, v)G(u, v))$$

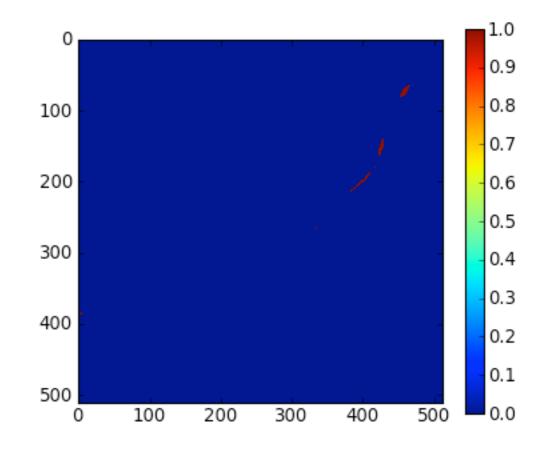












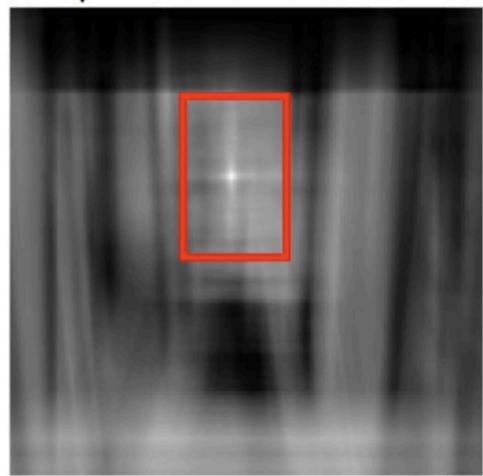
This is a chair



Find the chair in this image

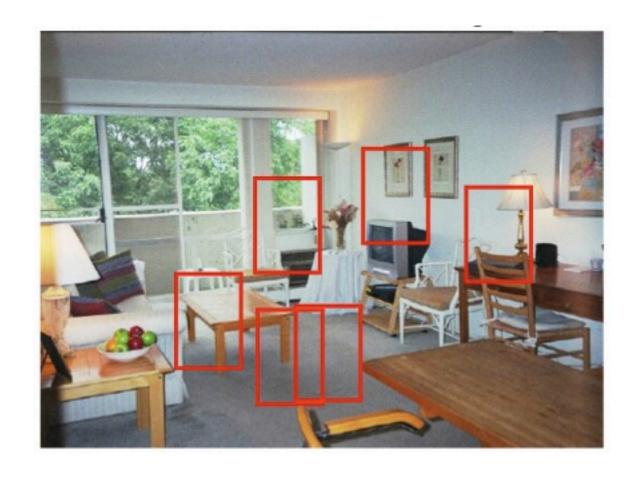


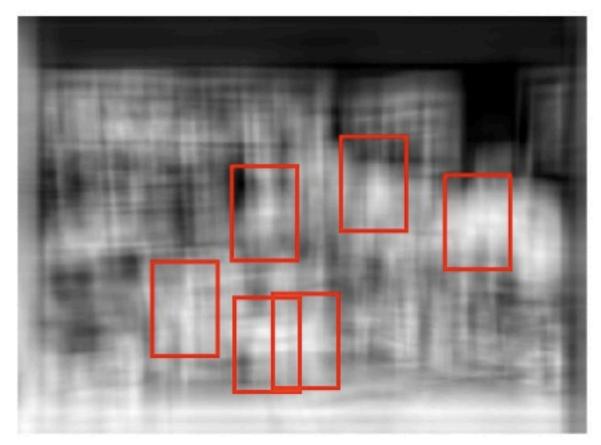
Output of normalized correlation



http://people.csail.mit.edu/torralba/shortCourseRLOC/index.html

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Face recognition using PCA

- Eigen Faces
- How to recognise a face from an image database?

- 1 pixel = 1 feature
- e.g. 64x64 = 4096
- gray level
- centered face
- same resolution
- averaged



- 1 pixel = 1 feature
- e.g. 64x64 = 4096
- gray level
- centered face
- same resolution
- averaged
- variable change
- PCA (principal Component Analysis)



$$\mathbf{X} = [g_{00} \ g_{01} \ g_{02} \dots g_{63 \ 63}]^T$$

• after variable change, one axe is a principal face

• one face = linear combination of variables









PCA (Principal Component Analysis)

- eigen values of the covariance matrix
- eigen vectors sorted by increasing eigen valus
- N first eigen values
 - signature
 - compression
- recognition:
 - the new face is projected into new axes
 - euclidian distance

- Advantages
 - fast
 - easy (naive)
- Limitations
 - sensitive to exposition
 - variable to view pose
 - other approaches more robust
 - limitation due to the number of dimensions

- How to compute eigen values for large dimensions?
- example 64x64 = 4096 dim.
- covariance matrix = 4096x4096!

$$\mathbf{X} = [g_{00} \ g_{01} \ g_{02} \dots g_{63 \ 63}]^T$$

$$\Sigma_{ij} = \operatorname{cov}(X_i, X_j) = \operatorname{E}\left[(X_i - \mu_i)(X_j - \mu_j)\right]$$
$$\mu_i = \operatorname{E}(X_i)$$

- matrix rank = number of images
- if N examples, N-1 eigen values <> 0

$$\mathbf{S}\mathbf{v}_{i} = \mathbf{T}^{T}\mathbf{T}\mathbf{v}_{i} = \lambda_{i}\mathbf{v}_{i}$$

$$\mathbf{T}\mathbf{T}^{T}\mathbf{u}_{i} = \lambda_{i}\mathbf{u}_{i}$$

$$\mathbf{T}^{T}\mathbf{T}\mathbf{T}^{T}\mathbf{u}_{i} = \lambda_{i}\mathbf{T}^{T}\mathbf{u}_{i}$$

$$oldsymbol{ ext{v}}_i = \mathbf{T}^T \mathbf{u}_i$$
 is eigen vector of S

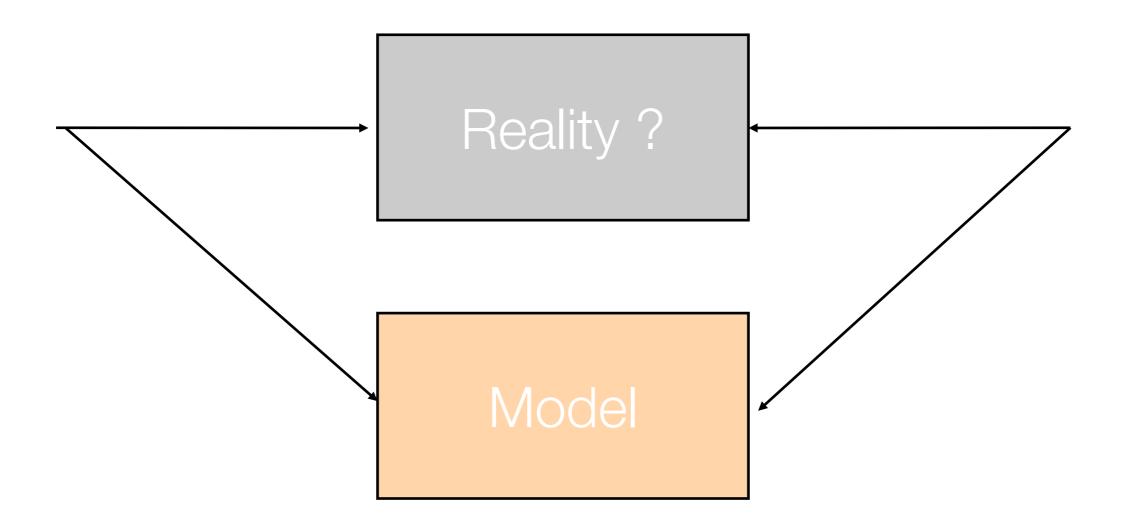
Supervised classification

recall

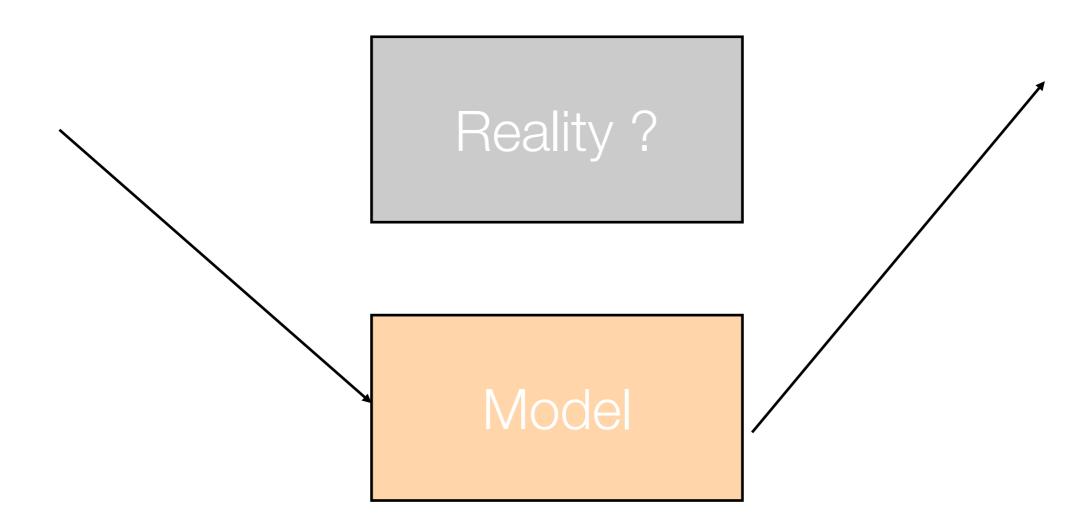
Machine learning

- Unknown underlying real world
- Model
- Data
 - input
 - output
- aims:
 - Inference (value)
 - Prediction (class)

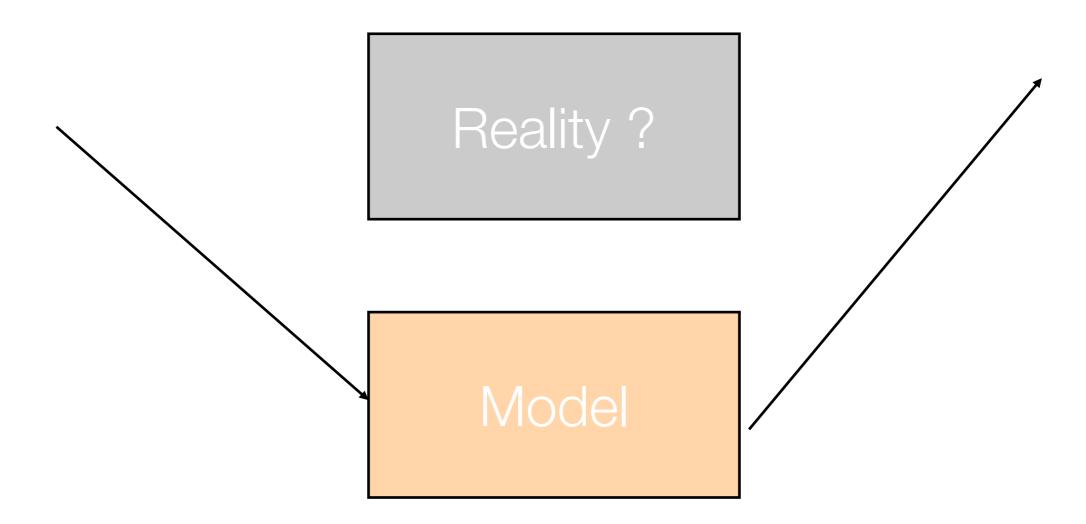
Modelisation



Inférence



Classification



Model

- Variable complexity
- Linear / non linear
- output = value
- output = class
- •! stationarity
- Various methods, Bayes, neural network, decision tree, SVM,...

Modèle

Methods

- number of available data
- number of features
- type of features
- feature space
- distance definition
- discriminent function

Supervised classification

- Matching
- nearest neighbor
- Bayes
- discriminant analysis
- neural network
- decision tree

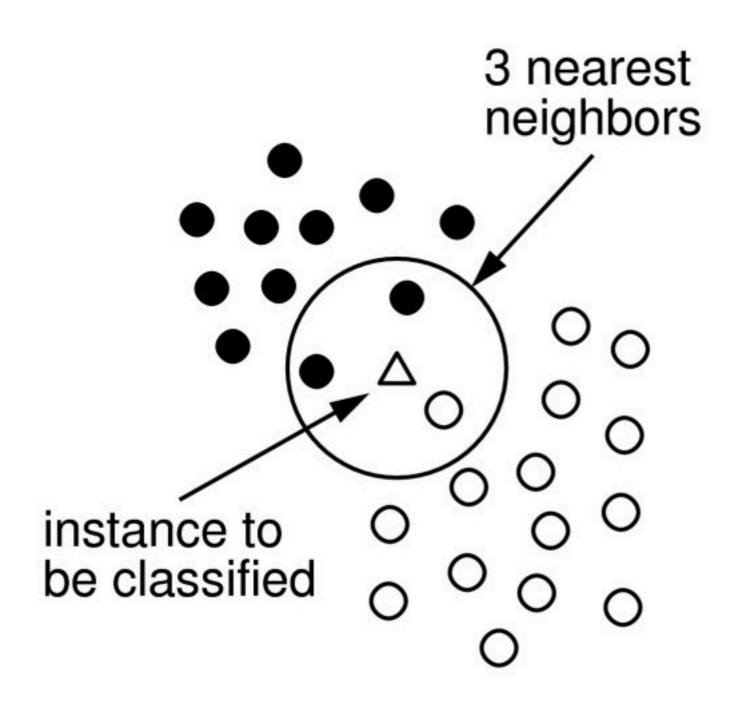
• ...

Nearest neighbor

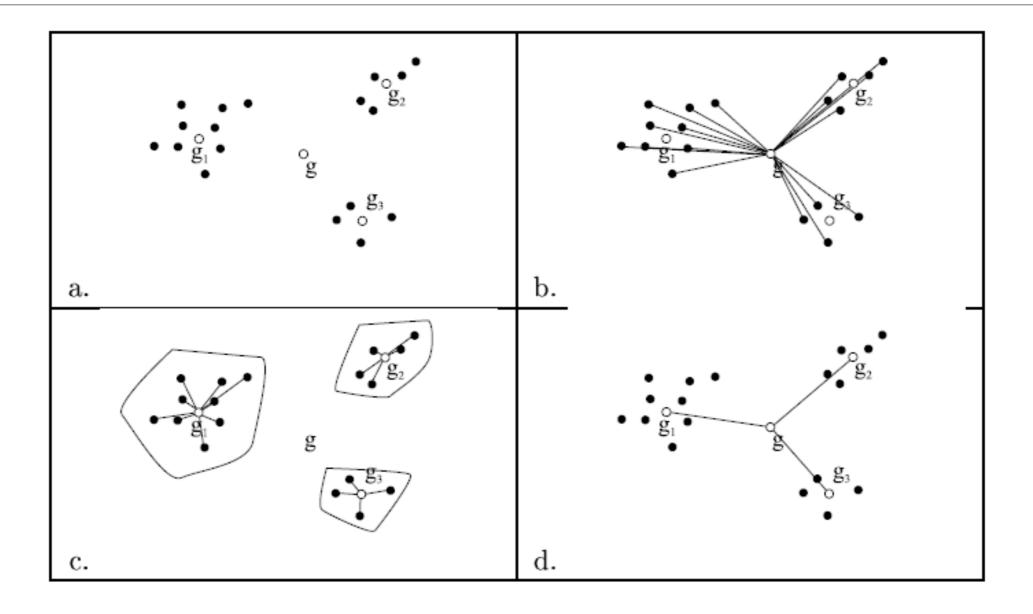
distance

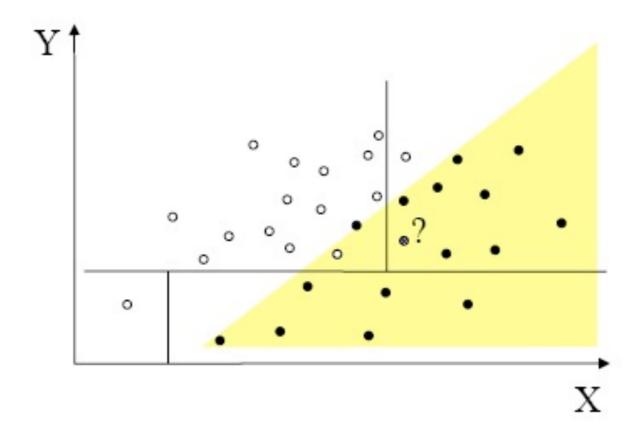
normalisation

Nearest neighbor



Discriminent analysis





entropy measure

$$entropy(T) = -\sum_{k=1}^{q} p_k \log(p_k) \qquad \qquad \sum_{k=1}^{q} p_k = 1$$

entropy

$$info(T) = -\sum_{k=1}^{q} \frac{\#(C_k, T)}{\#(T)} \log_2 \left(\frac{\#(C_k, T)}{\#(T)} \right)$$

entropy gain

$$info_X(T) = \sum_{i=1}^{n} \frac{\#(T_i)}{\#(T)} \quad info(T_i)$$

$$gain(X) = info(T) - info_X(T)$$

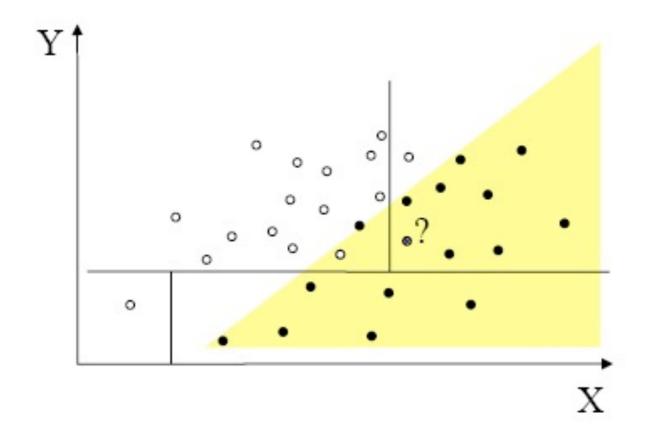
• in order to limit small leaves: split info

$$split \ info(X) = -\sum_{i=1}^{n} \frac{\#(T_i)}{\#(T)} \log_2 \left(\frac{\#(T_i)}{\#(T)}\right)$$

$$gain \ ratio(X) = \frac{gain(X)}{split \ info(X)}$$

 process applied recursively until number of case in leave are all of the same class or # = 2

Pruning

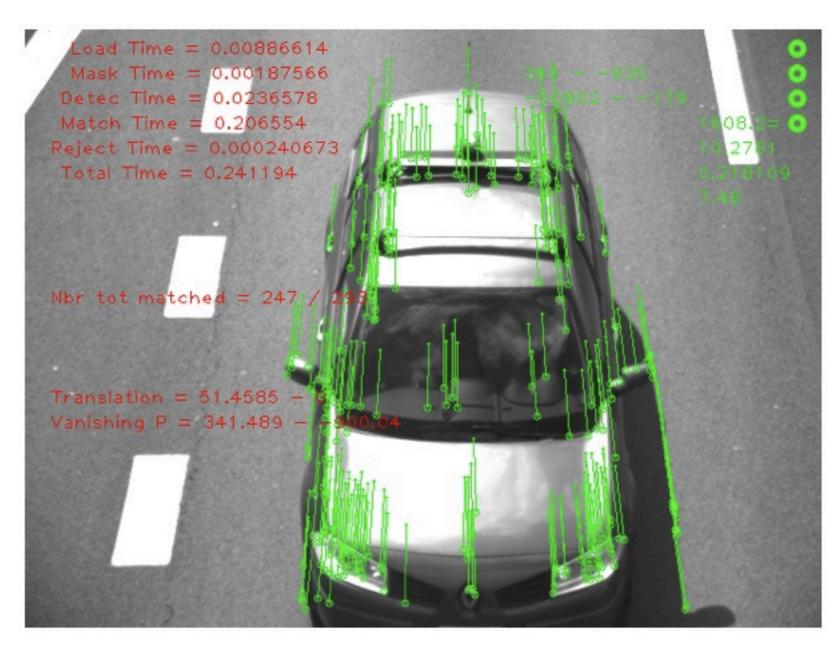


Object detection/recognition: Bag of visual word

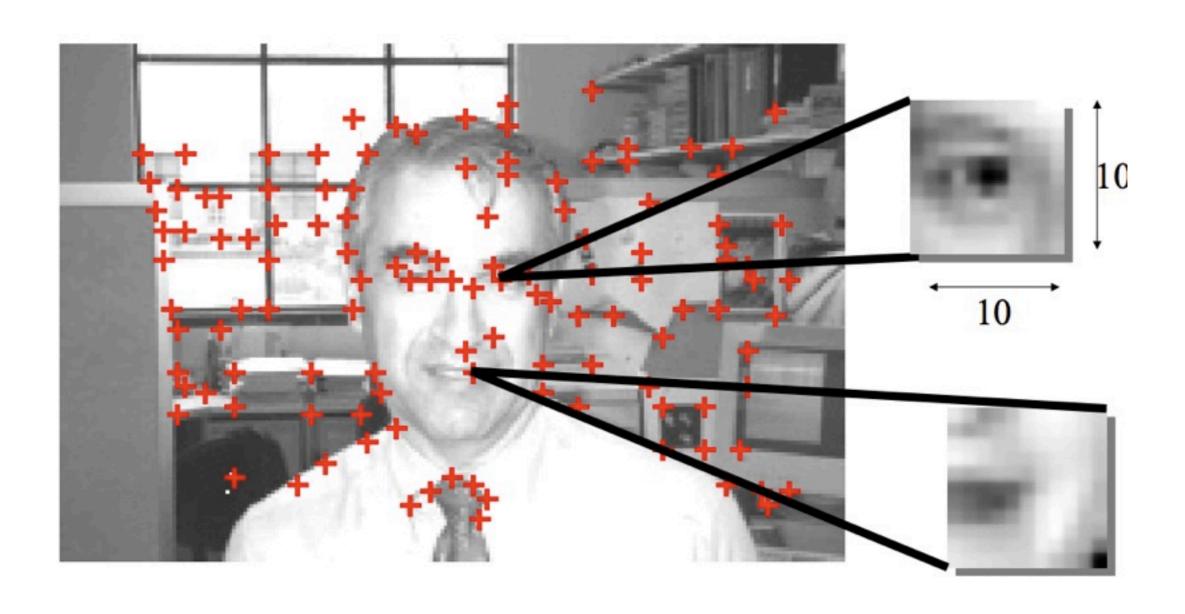
- initial usage: bag of word
 - text recognition
- General idea:
 - image contains remarkable points
 - distribution of these points is a signature
 - machine learning algorithm allows recognition
 - no segmentation

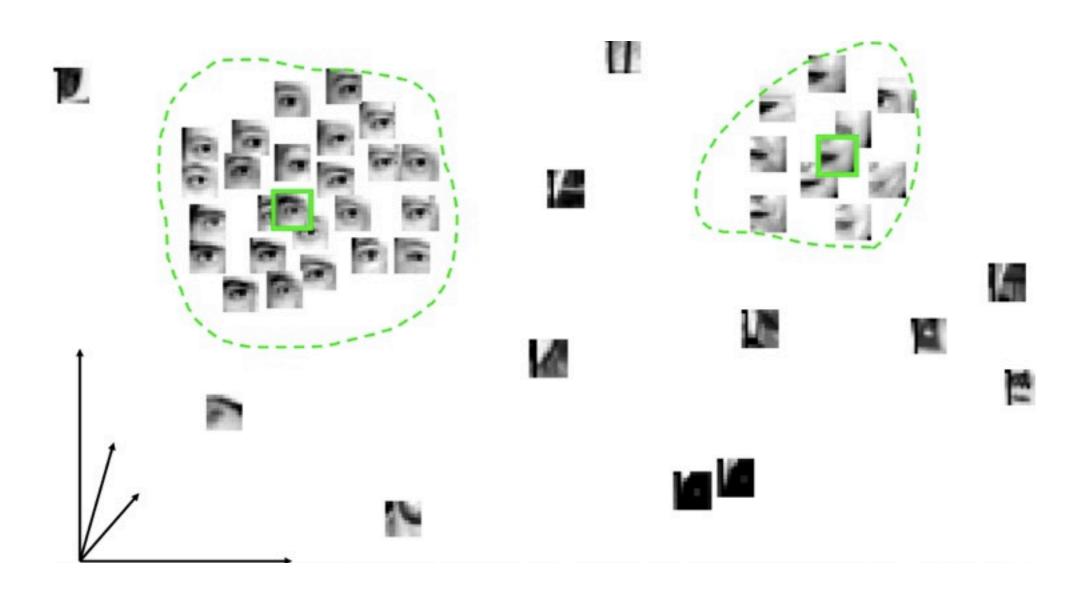
Bag of visual word

- find robust remarkable points
 - Harris corners
 - Sift, surf, fast
- normalized patches
- build vocabulary
 e.g. k-means



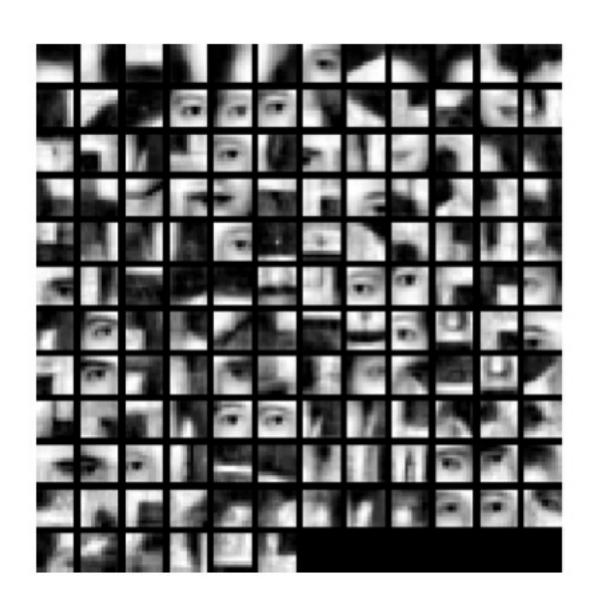
Ch. Kaes





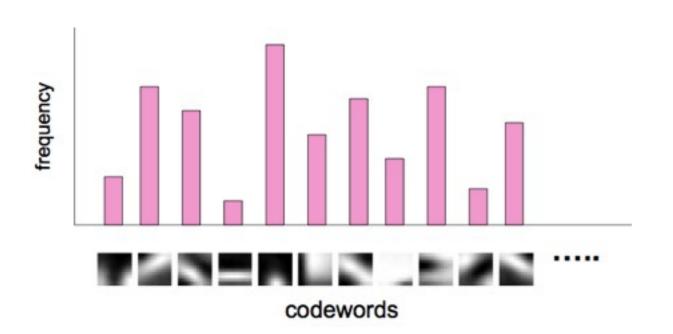


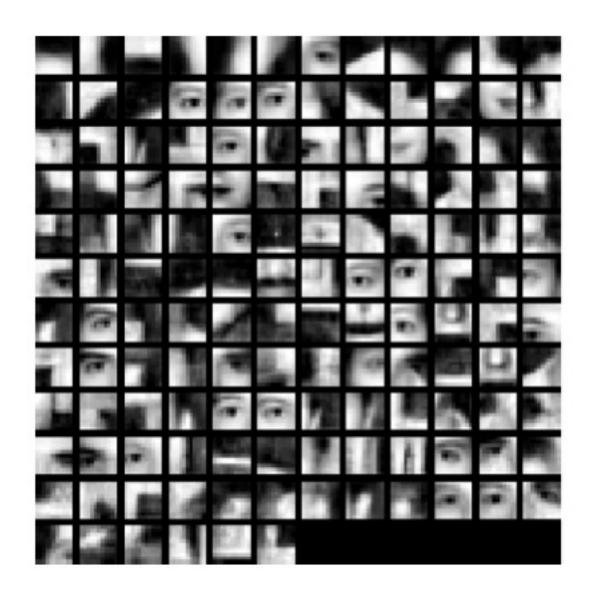
100-1000 images



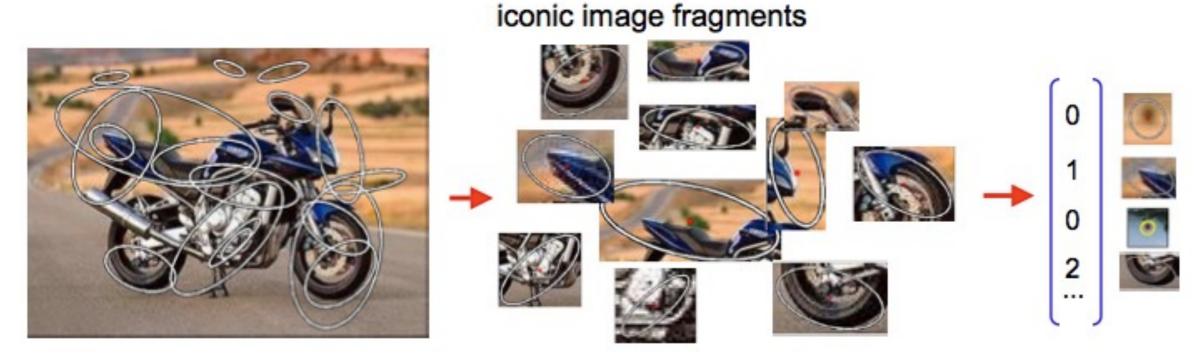
~100 visual words

- Visual word book
- histogram of word is the signature for an image

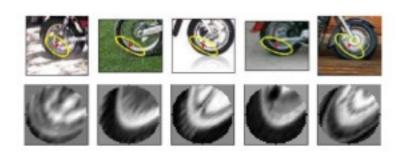




~100 visual words

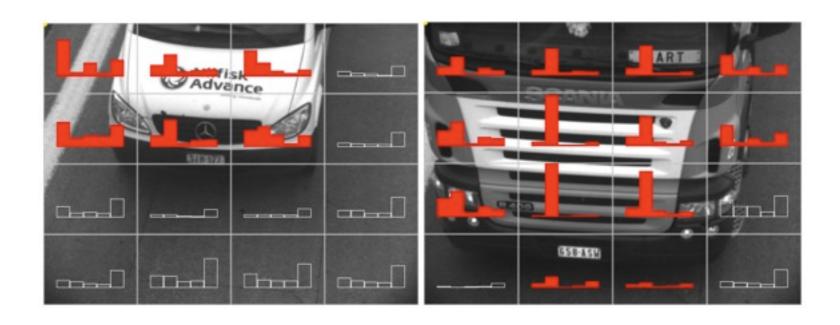


- detection of robust points
- extraction of point descriptors
- find the closest match in the word book
- compare signature with database
- no segmentation
- no localization



Edge histogram

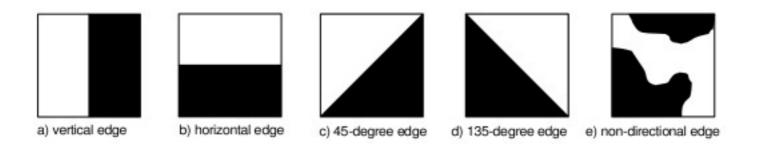
- basically a texture descriptor
- edge histogram computed on image parts
 - edge detection
 - grouped by image part
- histogram are then combined in one unique signature



Ch. Kaes

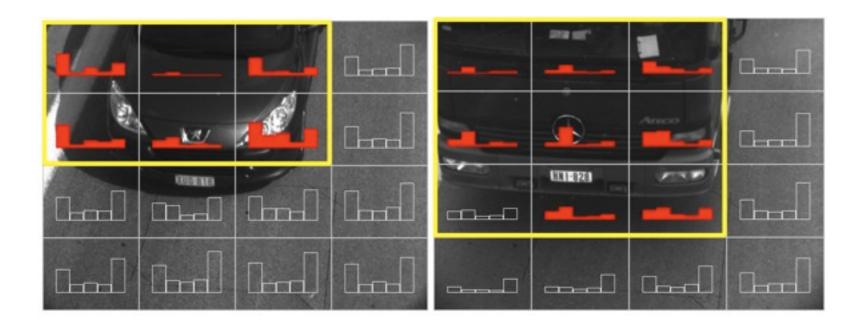
Edge histogram

• different edge type measures (directional / un-directional)



Edge histogram

- spatial localization:
 - adaptive approach
 - only histogram different to background are grouped into signature
 - signature are compared using supervised classification e.g. SVM



Ch. Kaes



