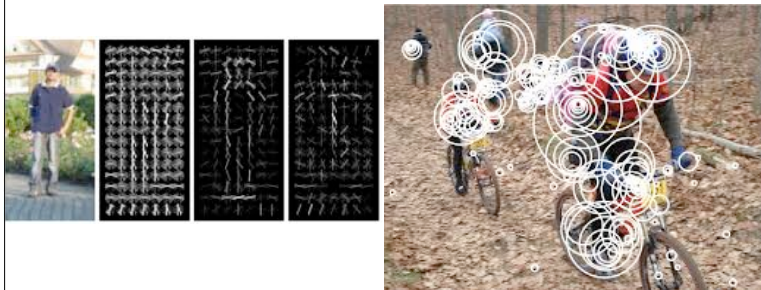


Descriptors for CV



2017



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1

Content

1. Introduction
2. Histograms
3. HOG
4. LBP
5. Haar Wavelets
6. Deep based descriptors
7. Video based descriptor
8. How to compare descriptors
9. BoW paradigm

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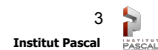
2

Introduction: Image descriptors

- Descriptor: a high level representation of an image or video.
- Descriptor: a vector
- Useful for:
 - geometric based matching
 - image retrieval,
 - object recognition and categorization,
 -

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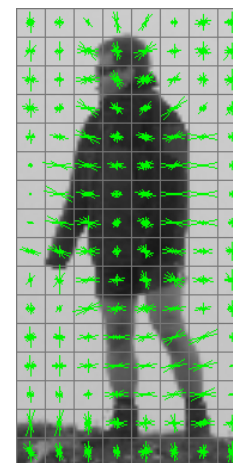
3



3

Introduction:

Dense and Sparse descriptors



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4

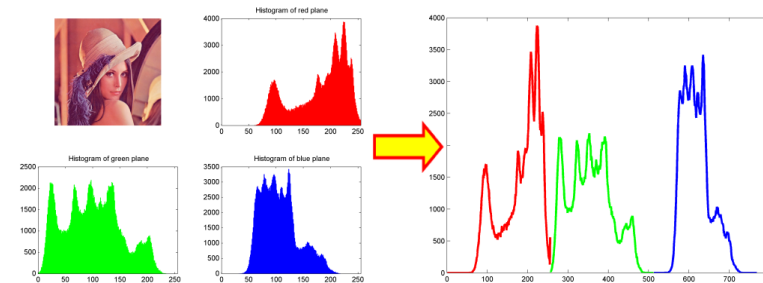
Some dense Descriptors

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Color RGB histogram

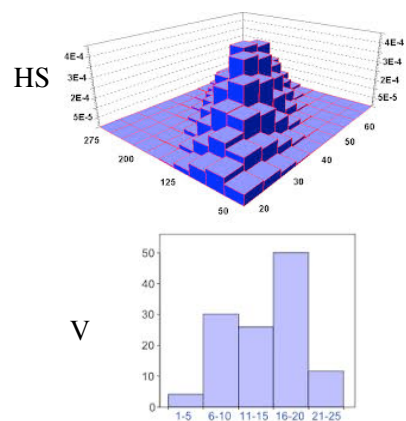
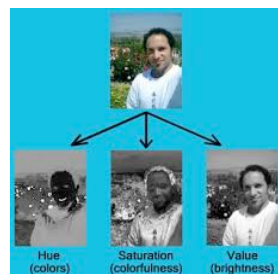


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Color HS+V histogram

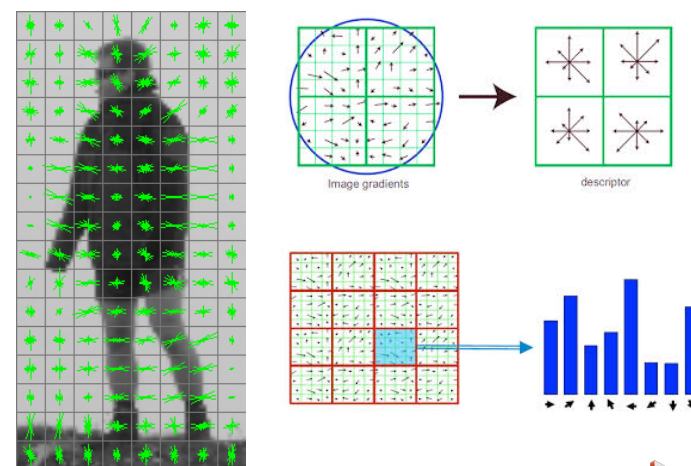


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Histogram of oriented gradients (HOG)

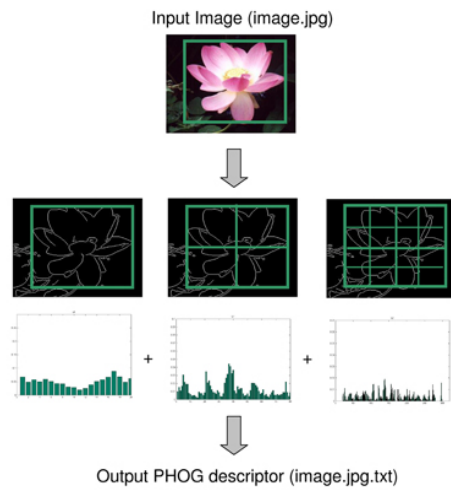


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Histogram of oriented gradients (HOG)

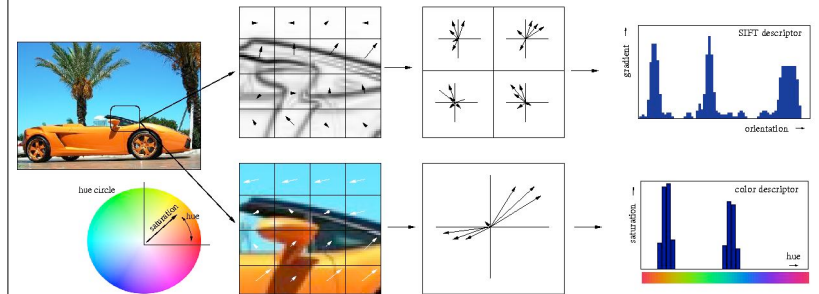


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Combining histograms

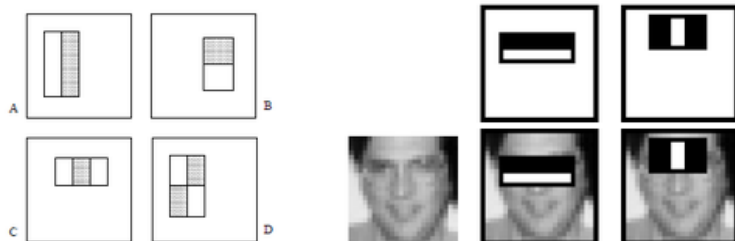


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Haar Wavelets

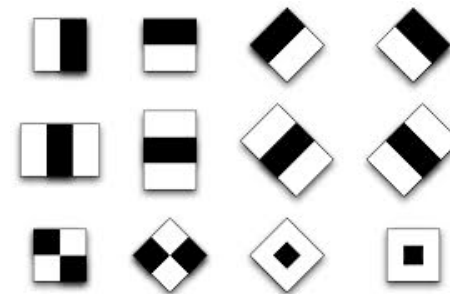


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Haar Wavelets



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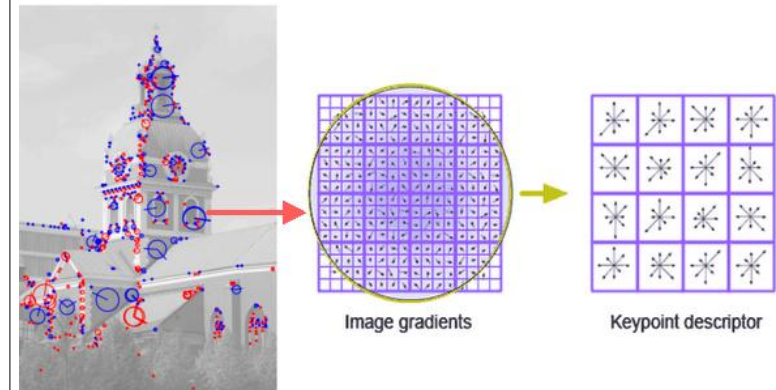
Some Sparse Descriptors

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SIFT



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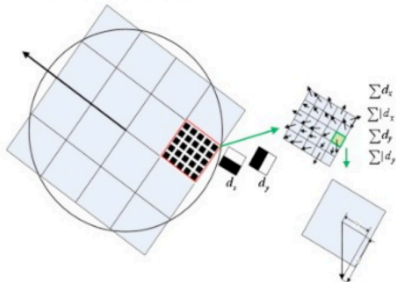
14

SURF

Speeded Up Robust Features **SURF**

- Approximate derivatives with Haar wavelets
- Exploit integral images

Citations:
4500 (2012)



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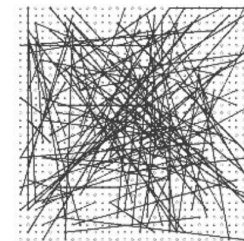
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BRIEF

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).



Citations:
149 (2012)

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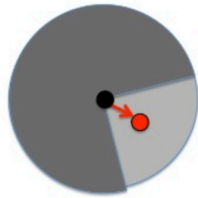
16

ORB

Oriented FAST and Rotated BRIEF

- Add rotation invariance to BRIEF
- Orientation assignment based on the intensity centroid

Citations:
43 (2012)

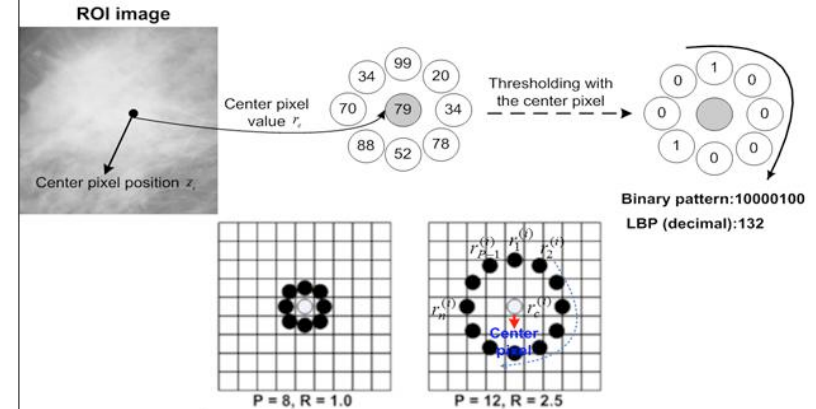


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LBP: local binary pattern

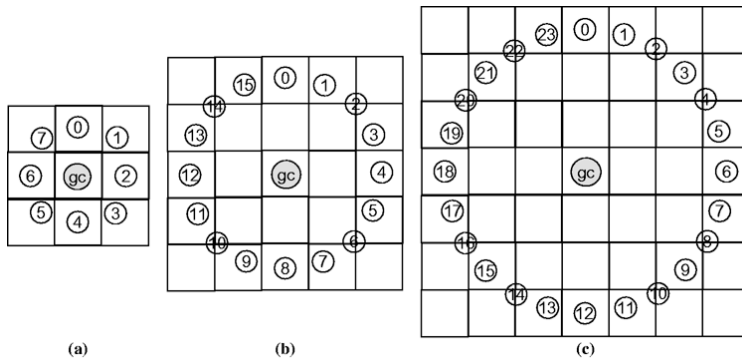


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LBP: local binary pattern



Notes: (a) P = 8, R = 1; (b) P = 16, R = 2; (c) P = 24, R = 3

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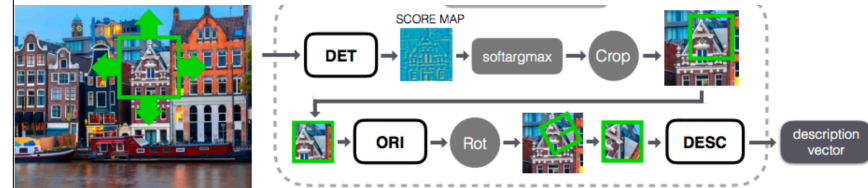
19

LIFT: Learned Invariant Feature Transform

Kwang Moo Yi^{*1}, Eduard Trulls^{*1}, Vincent Lepetit², Pascal Fua¹

¹Computer Vision Laboratory, Ecole Polytechnique Fédérale de Lausanne (EPFL)

²Institute for Computer Graphics and Vision, Graz University of Technology
{kwang.yi, eduard.trulls, pascal.fua}@epfl.ch, lepetit@icg.tugraz.at

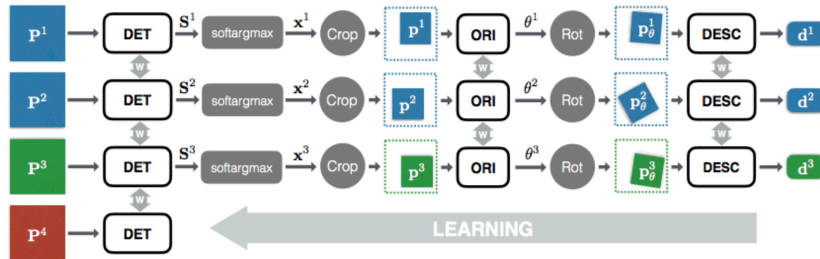


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LIFT: Learned Invariant Feature Transform

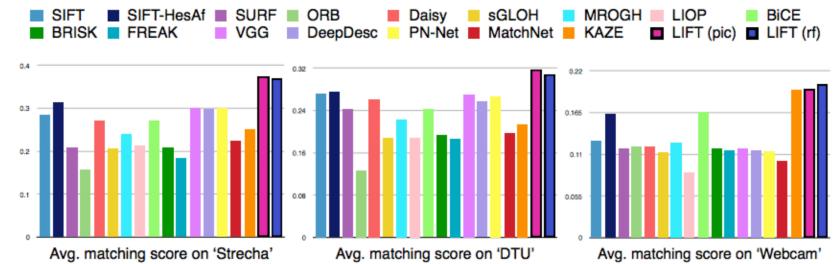


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LIFT: Learned Invariant Feature Transform

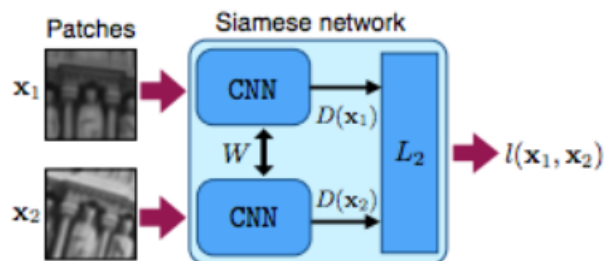


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Deep Neural network descriptor for matching



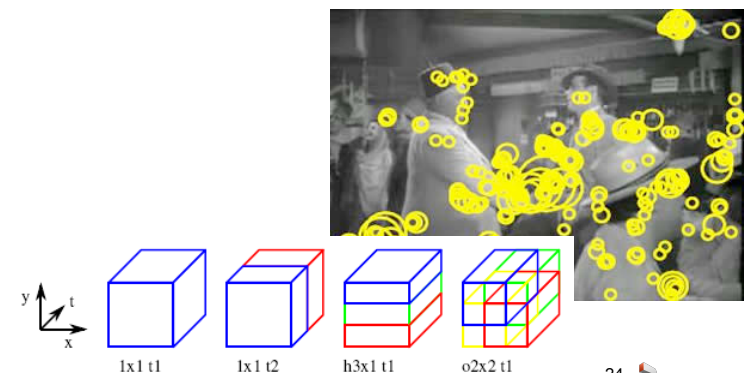
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Video based descriptors (HOG/HOF)

$$\mu = g(., \sigma_i^2, \tau_i^2) * \begin{pmatrix} L_x^2 & L_x L_y & L_x L_t \\ L_x L_y & L_y^2 & L_y L_t \\ L_x L_t & L_y L_t & L_t^2 \end{pmatrix}$$



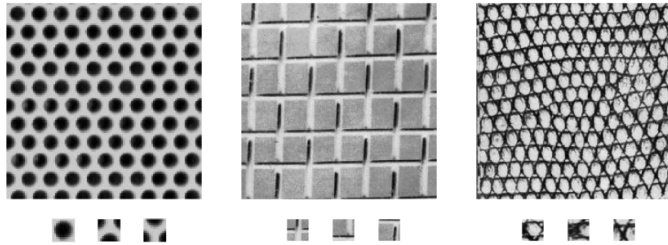
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Bag of Words (bag of features models)

Origin 1: texture recognition



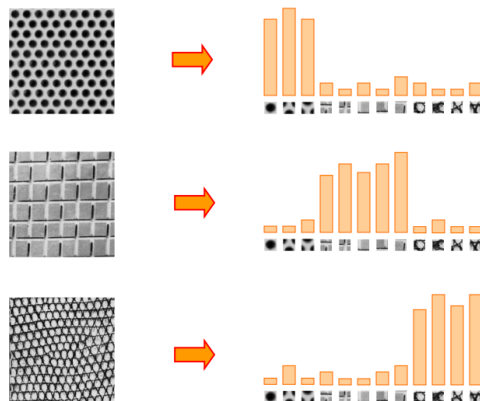
Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Content

1. Introduction
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8. BoW paradigm

Bag of Words (bag of features models)

Origin 1: texture recognition



Bag of Words (bag of features models)

Origin 2: text analysis (Frequency of words of a dictionary, Salton & McGill (1983))



Bag of Words

1. extract features



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Bag of Words

2. learn visual vocabulary



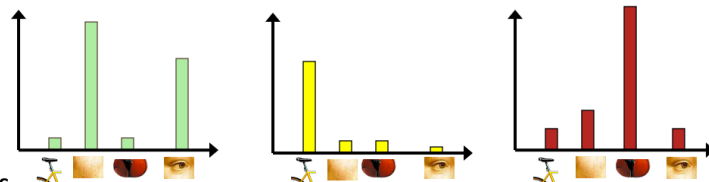
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Bag of Words

3. represent images by frequencies of « visual words »



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Bag of features for image classification

Given an image to classify:

1. Extract features
2. Quantize features using visual vocabulary
3. Represent images by frequencies of «visual words»
4. Estimate the class using a previously learn classifier (eg. SVM, KNN, AdaBoost,...)

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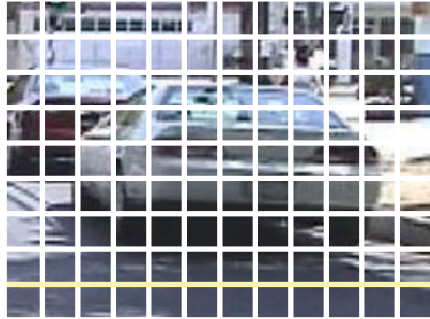
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Bag of features for image classification

1. Feature extraction

Regular grid

- Vogel & Schiele, 2003
- Fei-Fei & Perona, 2005



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Bag of features for image classification

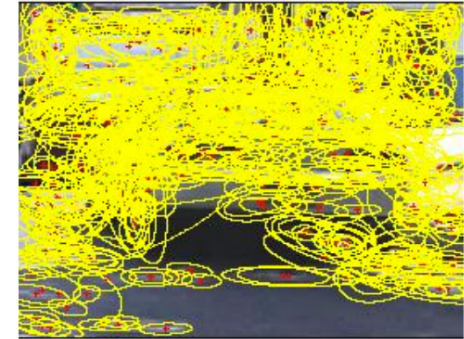
1. Feature extraction

Regular grid

- Vogel & Schiele, 2003
- Fei-Fei & Perona, 2005

Interest point detector

- Csurka et al. 2004
- Fei-Fei & Perona, 2005
- Sivic et al. 2005



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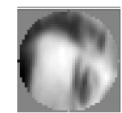
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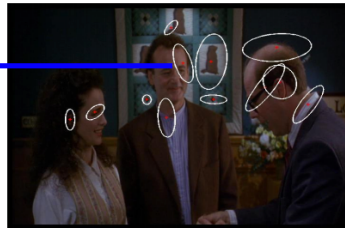
Bag of features for image classification

1. Feature extraction

Compute SIFT
descriptor
[Lowe'99]



Normalize patch



Detect patches

- [Mikojaczyk and Schmid '02]
- [Mata, Chum, Urban & Pajdla, '02]
- [Sivic & Zisserman, '03]

Slide credit: Josef Sivic

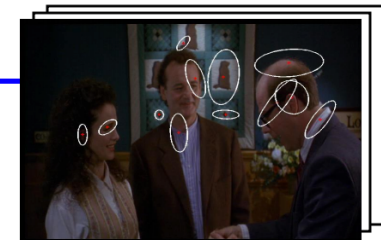
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Bag of features for image classification

1. Feature extraction



Slide credit: Josef Sivic

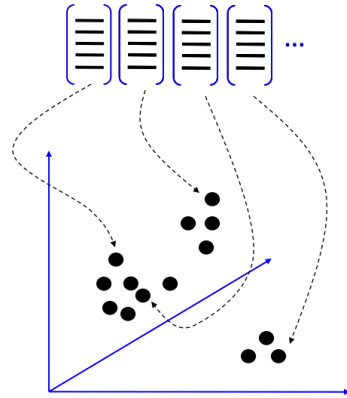
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Bag of features for image classification

2. Learning the visual vocabulary



Slide credit: Josef Sivic

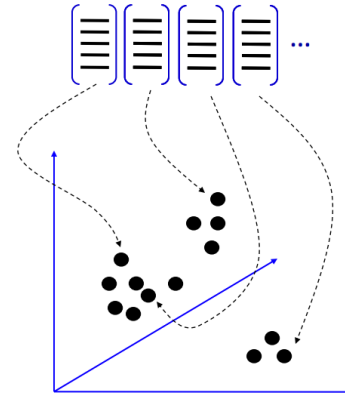
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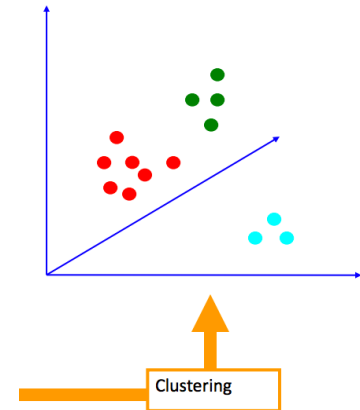
Bag of features for image classification

2. Learning the visual vocabulary



Slide credit: Josef Sivic

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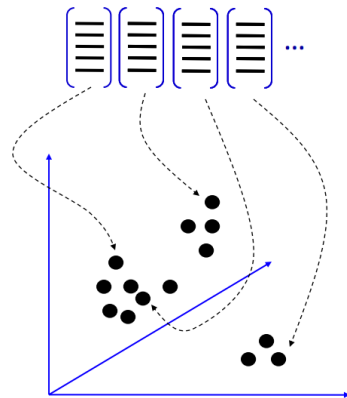


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Bag of features for image classification

2. Learning the visual vocabulary



Slide credit: Josef Sivic

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Bag of features for image classification

2. Learning the visual vocabulary

The codebook is used for quantizing features

- A vector quantizer takes a feature vector and maps it to the index of the nearest codevector in a codebook
- Codebook = visual vocabulary
- Codevector = visual word

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Bag of features for image classification

2. Learning the visual vocabulary

The codebook is used for quantizing features

- A vector quantizer takes a feature vector and maps it to the index of the nearest codevector in a codebook
- Codebook = visual vocabulary
- Codevector = visual word

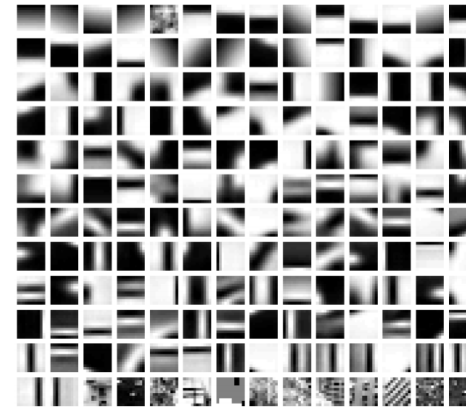
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Bag of features for image classification

2. Learning the visual vocabulary *exemple of visual vocabulary*



Fei-Fei et al. 2005

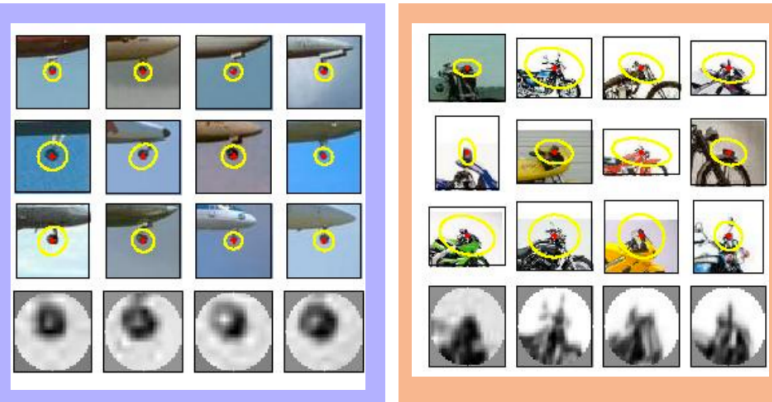
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Bag of features for image classification

2. Learning the visual vocabulary *exemple of visual words*



Sivic et al. 2005

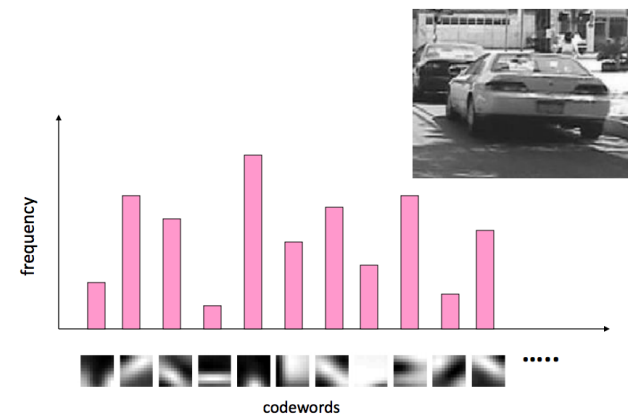
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3. Image representation *exemple of codewords*



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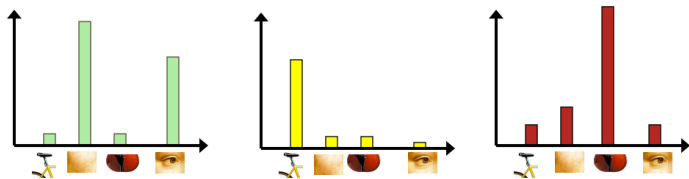
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Bag of features for image classification

4. Image classification

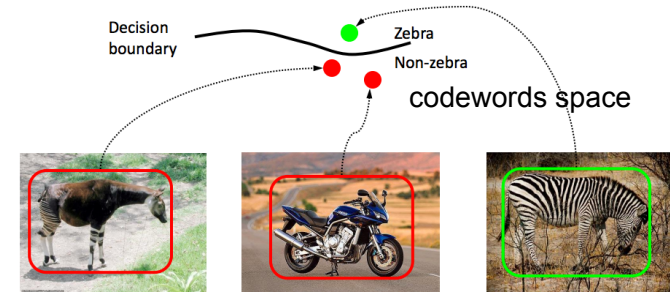
- Given the bag-of-features representations of images from different classes, how do we learn a model for distinguishing them?



Bag of features for image classification

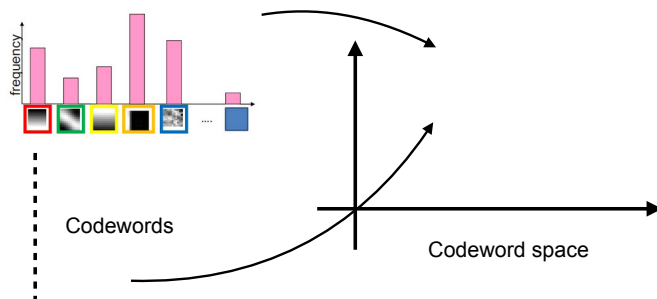
4. Image classification: discriminative method

- Learn a decision rule (classifier) assigning bag-of-features representations of images to different classes



Bag of features for image classification

4. Image classification: discriminative method



We need a to define a distance between codewords

Bag of features for image classification

4. Image classification: discriminative method

Minkowski-form distance:

$$D(X, Y) = \left(\sum_i |f(i; X) - f(i; Y)|^p \right)^{1/p}$$

CHI2 distance:

$$D(X, Y) = \sum_i \frac{(f(i; X) - \hat{f}(i))^2}{\hat{f}(i)},$$

$$\hat{f}(i) = [f(i; X) + f(i; Y)]/2$$

We need a to define a distance between codewords

Bag of features for image classification

4. Image classification: discriminative method

Kullback-Leiber divergence

$$D(X, Y) = \sum_i f(i; X) \log \frac{f(i; X)}{f(i; Y)},$$

Battacharyya distance

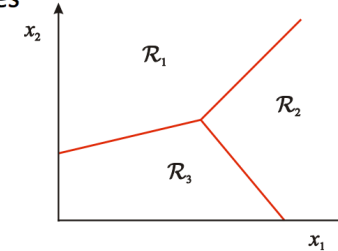
$$BC(p, q) = \sum_{x \in X} \sqrt{p(x)q(x)}$$

We need a to define a distance between codewords

Bag of features for image classification

4. Image classification: discriminative method

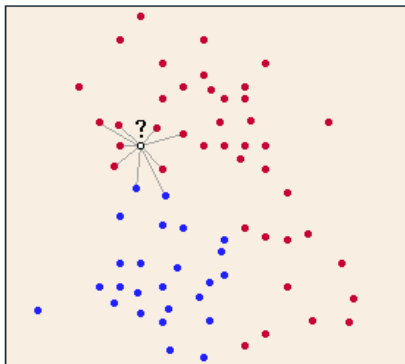
- Assign input vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Bag of features for image classification

4. Image classification: discriminative method

KNN: K- Nearest Neighbors

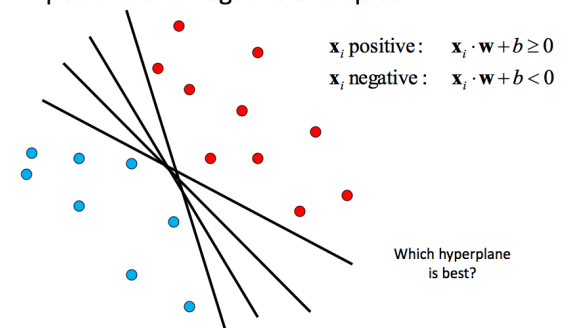


Bag of features for image classification

4. Image classification: discriminative method

linear classifiers

- Find linear function (*hyperplane*) to separate positive and negative examples



$$\mathbf{x}_i \text{ positive: } \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$$

$$\mathbf{x}_i \text{ negative: } \mathbf{x}_i \cdot \mathbf{w} + b < 0$$

Bag of features for image classification

4. Image classification: discriminative method

and much more ...

SVM, ...

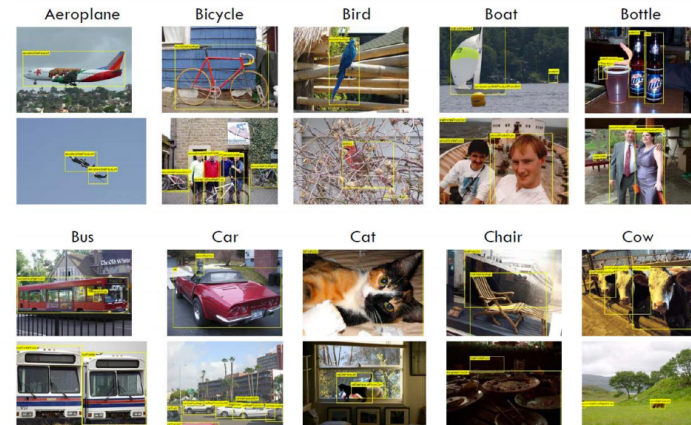
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Bag of features for image classification

Results from Pascal VOC Challenge 2010



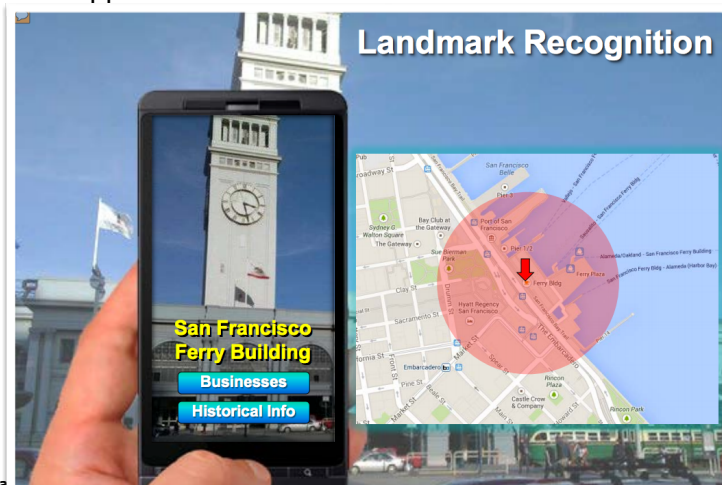
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Bag of features for image classification

AR Applications



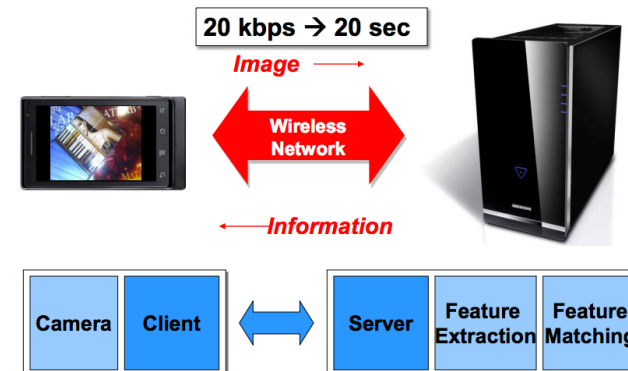
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Bag of features for image classification

AR Applications

Architecture A: Send Image



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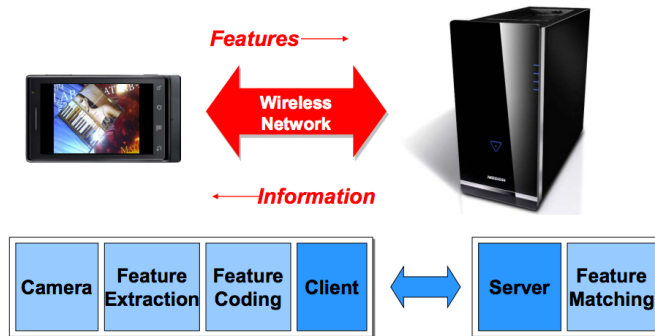
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AR Applications

Architecture B: Send Features

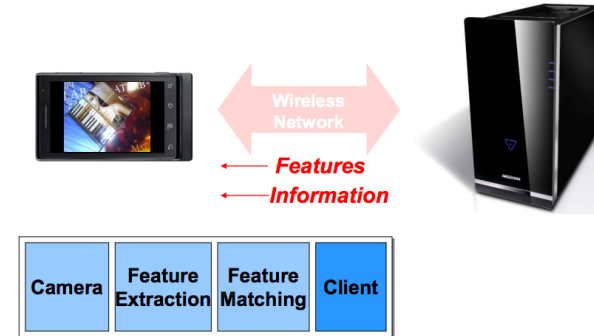


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Bag of features for image classification

AR Applications

Architecture C: Features on Mobile Device



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