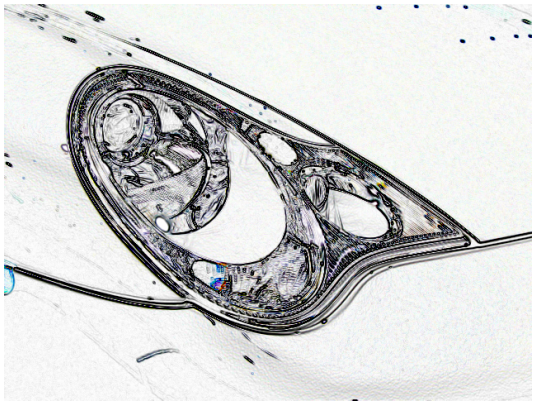
CSE578: Computer Vision

Spring 2017:

Object Detection and Recognition: HoG + SVM: Pedestrian Detection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[Slides Generously Borrowed from Various Sources]


CHANGE

Challenges

- Wide variety of articulated poses
- Variable appearance/clothing
- Complex backgrounds
- Unconstrined illumination
- Occlusions
- Different Scales

Discriminative vs. Generative Models

- Generative:
  - + Possibly interpretable
  - + Models the object class/can draw samples
  - - Model variability unimportant to classification task
  - - Hard to build good models with a few parameters

- Discriminative:
  - + Appealing when infeasible to model data itself
  - + Often excels in practice
  - - May not provide uncertainty in predictions
  - - Non-interpretable

Global vs. Part-Based

- Global people detectors vs. part-based detectors

- Global approaches:
  - A single feature description for the complete person
- Part-Based Approaches:
  - Individual feature descriptors for body parts / local parts

Advantages and Disadvantages

- Part-Based
  - Better able to deal with moving body parts
  - Better handle occlusion, overlaps
  - Requires more complex reasoning

- Global approaches
  - Typically simple, i.e. we train a discriminative classifier on top of the feature descriptions
  - Work well for small resolutions
  - Typically does detection via classification, i.e. uses a binary classifier

Gradient Histograms

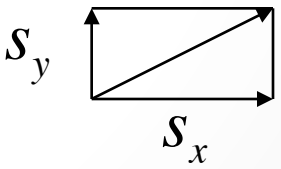
- Extremely and successful in the vision
- Avoids hard decisions vs. edge based features
- Examples:
  - SIFT (Scale-Invariant Image Transform)
  - GLOH (Gradient Location and Orientation Histogram)
  - HOG (Histogram of Oriented Gradients)

Computing Gradients

- Derivatives
- One sided: $f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$
- Two sided: $f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x-h)}{2h}$

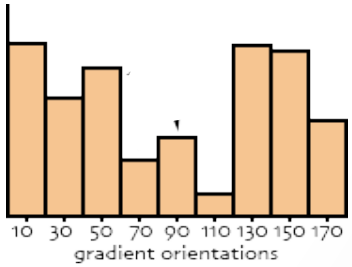
- Filter masks in x-direction
  - One sided: | -1 | 1 |
  - Two sided: | -1 | 0 | 1 |

- Gradient:
  - Magnitude: $s = \sqrt{s_x^2 + s_y^2}$
  - Orientation: $\theta = \arctan(\frac{s_y}{s_x})$



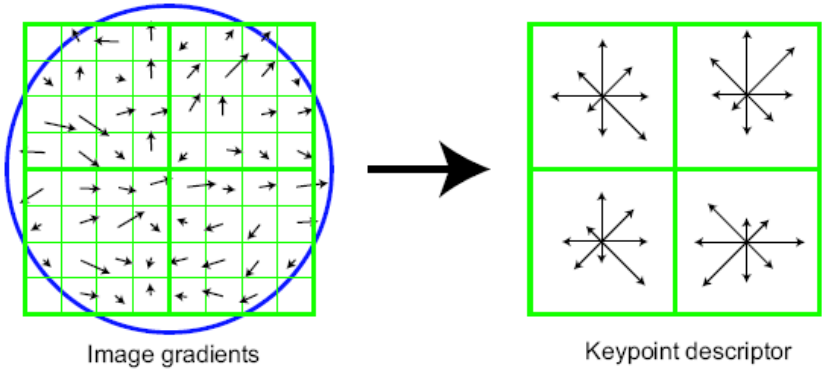
Histograms

- Gradient histograms measure the orientations and strengths of image gradients within an image region



Example: SIFT descriptor

- The most popular gradient-based descriptor
- Typically used in combination with an interest point detector



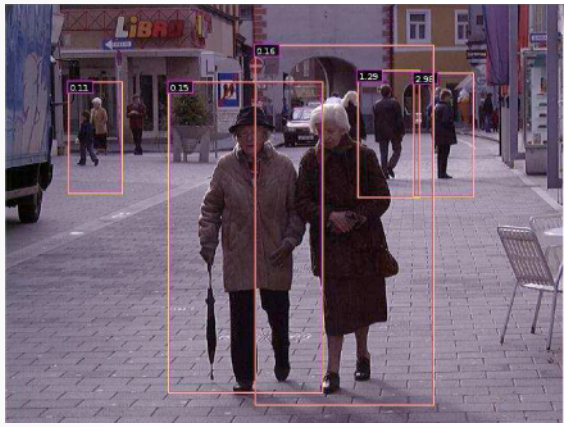
  - Region rescaled to a grid of 16x16 pixels
  - 4x4 regions = 16 histograms (concatenated)
  - Histograms: 8 orientation bins, gradients weighted by gradient magnitude
  - Final descriptor has 128 dimensions and is normalized to compensate for illumination differences

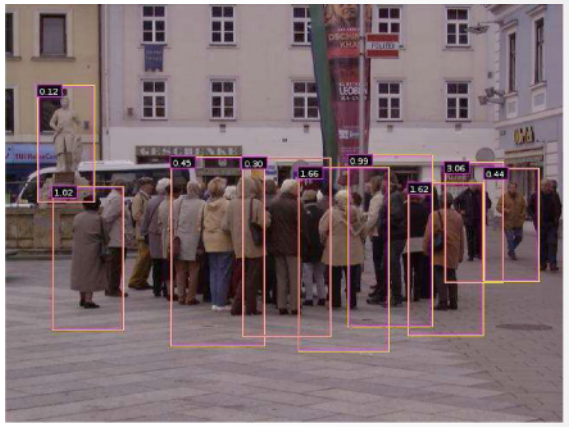
Histograms of Oriented Gradients

- Gradient-based feature descriptor developed for people detection
  - Authors: Dalal & Triggs (INRIA Grenoble, F)
- Global descriptor for the complete body
- Very high-dimensional
  - Typically ~4000 dimensions

HOG

Very promising results on challenging data sets



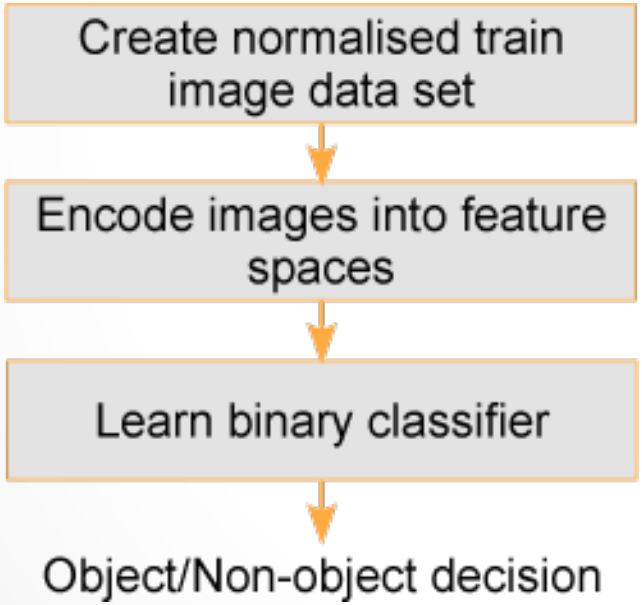


Phases

1. Learning Phase
2. Detection Phase

Detector: Learning Phase

1. Learning



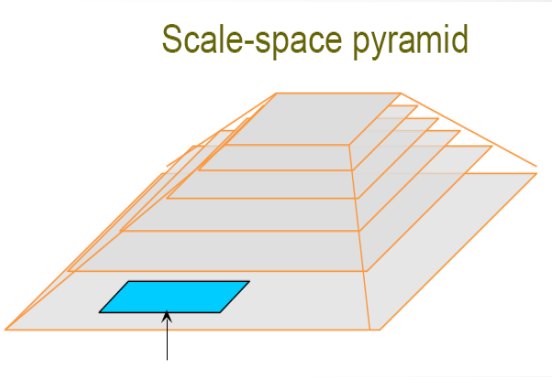
Set of cropped images containing pedestrians in normal environment

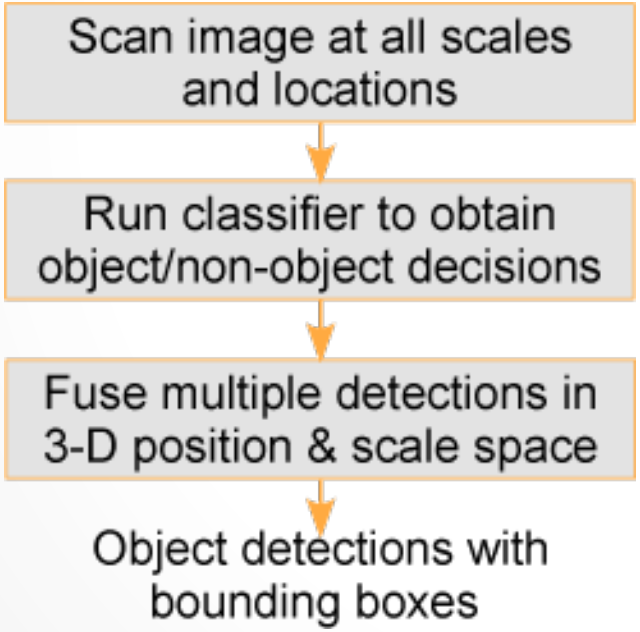
Global descriptor rather than local features

Using linear SVM

Detector: Detection Phase

2. Detection





Sliding window over each scale

Simple SVM prediction

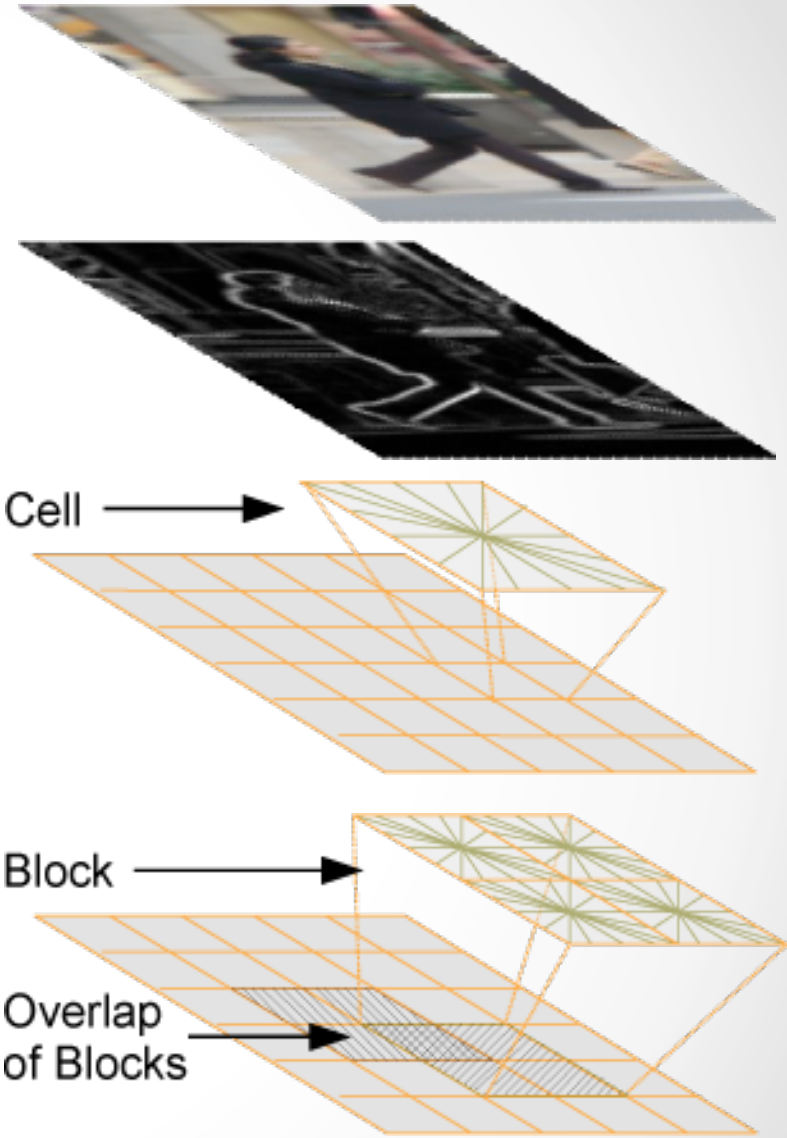
Descriptor

1. Compute gradients on an image region of 64x128 pixels

2. Compute histograms on ‘cells’ of typically 8x8 pixels (i.e. 8x16 cells)

3. Normalize histograms within overlapping blocks of cells (typically 2x2 cells, i.e. 7x15 blocks)

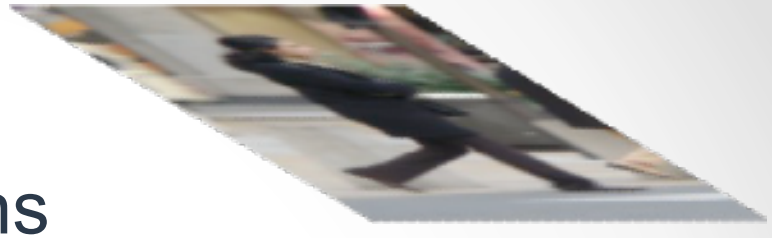
4. Concatenate histograms



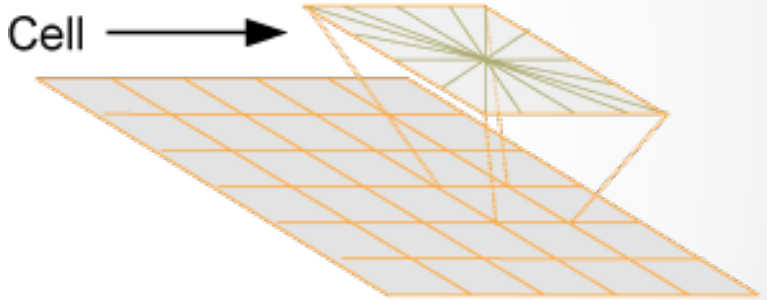
Gradients

- Convolution with [-1 0 1] filters
- No smoothing
- Compute gradient magnitude+direction
- Per pixel: color channel with greatest magnitude -> final gradient

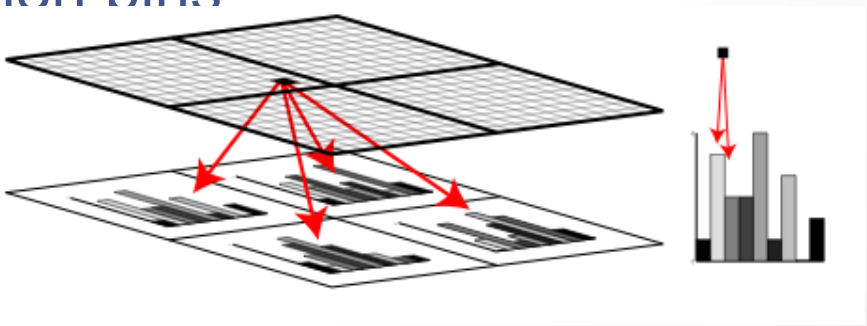
Cell histograms



- 9 bins for gradient orientations (0-180 degrees)
- Filled with magnitudes



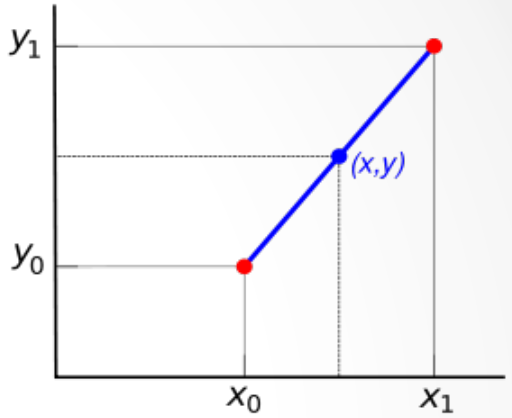
- Interpolated trilinearly:
  - Bilinearly into spatial cells
  - Linearly into orientation bins



Linear and Bilinear Interpol. for Subsampling

Linear:

$$y = y_0 + (x - x_0)\frac{y_1 - y_0}{x_1 - x_0}$$

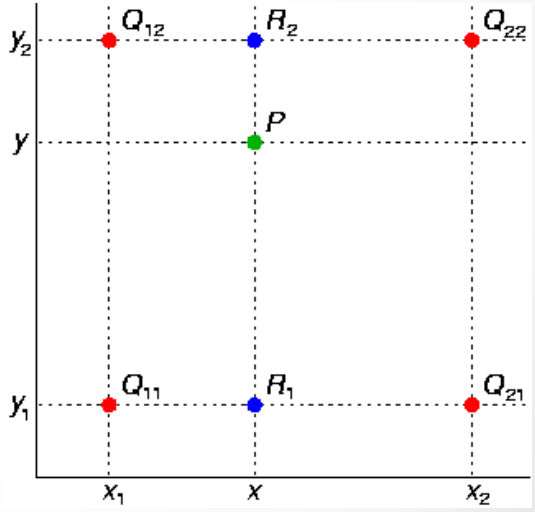


Bilinear:

$$f(R_1) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21}) \quad \text{where} \quad R_1 = (x, y_1),$$

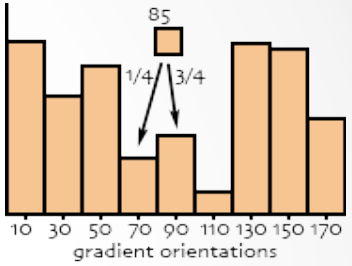
$$f(R_2) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}) \quad \text{where} \quad R_2 = (x, y_2).$$

$$f(P) \approx \frac{y_2 - y}{y_2 - y_1} f(R_1) + \frac{y - y_1}{y_2 - y_1} f(R_2).$$

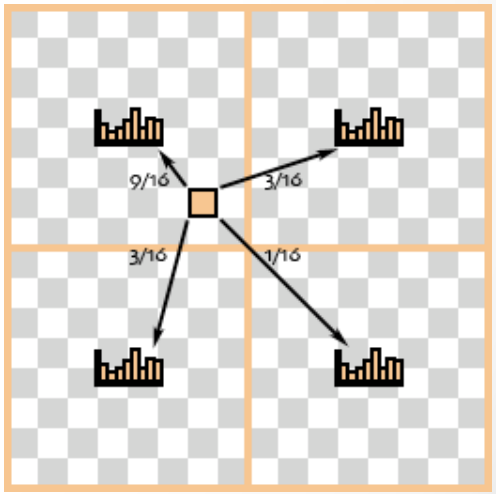


Histogram Interpolation Example

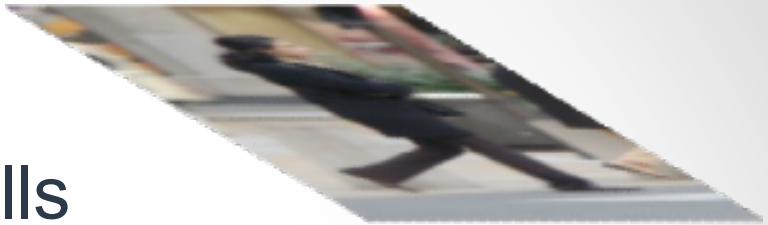
- θ=85 degrees
- Distance to bin centers
  - Bin 70 -> 15 degrees
  - Bin 90 -> 5 degress
- Ratios: 5/20=1/4, 15/20=3/4



- Distance to bin centers
  - Left: 2, Right: 6
  - Top: 2, Bottom: 6
- Ratio Left-Right: 6/8, 2/8
- Ratio Top-Bottom: 6/8, 2/8
- Ratios:
  - 6/8*6/8 = 36/64 = 9/16
  - 6/8*2/8 = 12/64 = 3/16
  - 2/8*6/8 = 12/64 = 3/16
  - 2/8*2/8 = 4/64 = 1/16



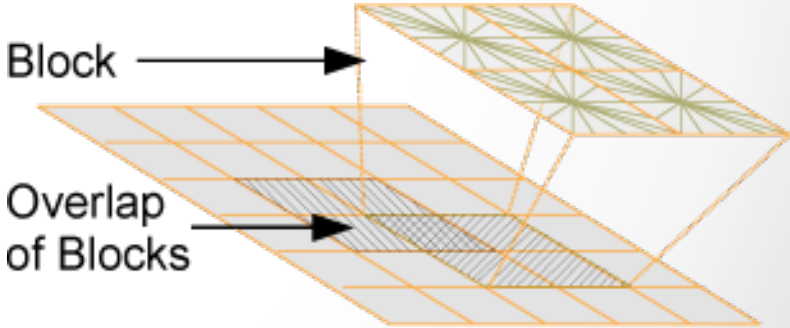
Blocks



- Overlapping blocks of 2x2 cells

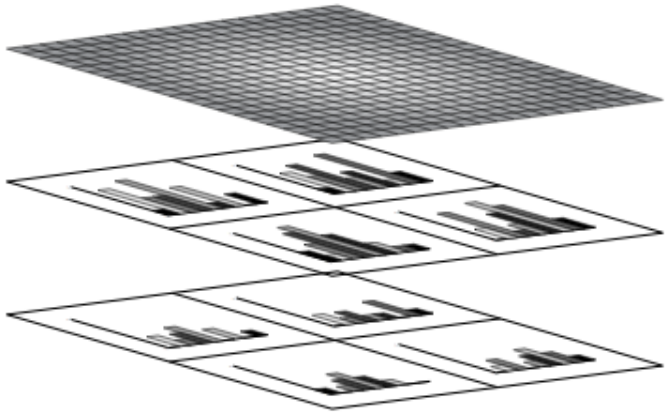
- Cell histograms are concatenated and then normalized
  - Several occurrences of each cell with different normalizations in the final descriptor

- Normalization
  - Different norms possible (L2, L2hys etc.)
  - We add a normalization epsilon to avoid division by zero



Blocks

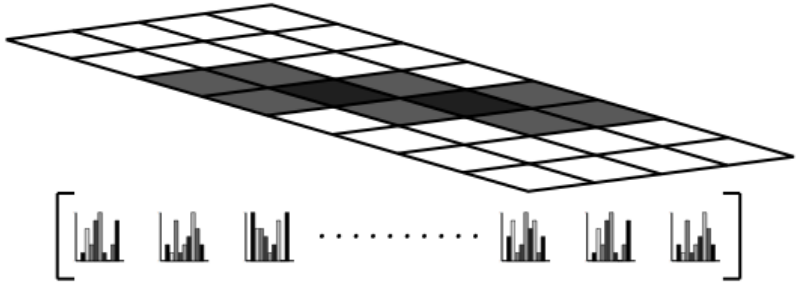
- Gradient magnitudes are weighted according to a Gaussian spatial window



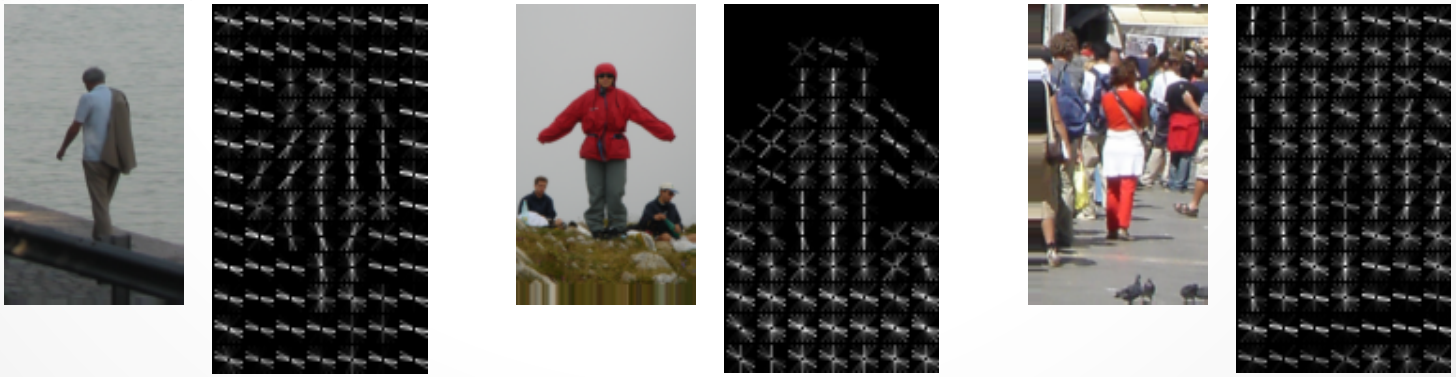
- Distant gradients contribute less to the histogram

Final Descriptor

- Concatenation of Blocks



- Visualization:



Engineering

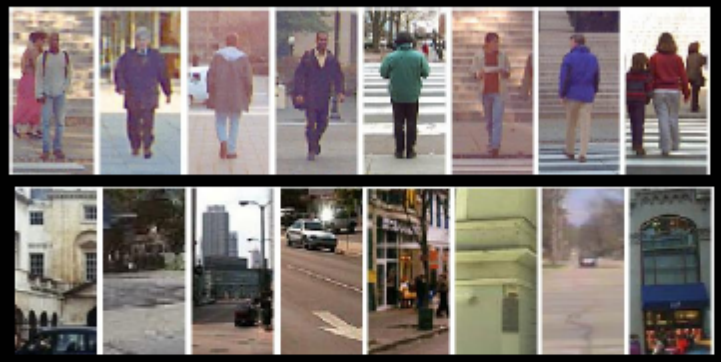
- Developing a feature descriptor requires a lot of engineering
  - Testing of parameters (e.g. size of cells, blocks, number of cells in a block, size of overlap)
  - Normalization schemes (e.g. L1, L2-Norms etc., gamma correction, pixel intensity normalization)
- An extensive evaluation of different choices was performed, when the descriptor was proposed
- It is not only the idea, but also the engineering effort

Training Set

- More than 2000 positive & 2000 negative training images (96x160px)
- Carefully aligned and resized
- Wide variety of backgrounds

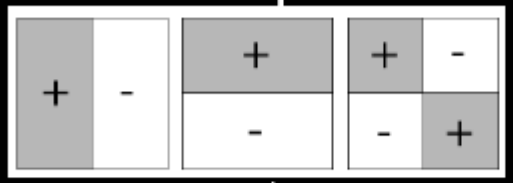
Support Vector Machine Detector

(Papageorgiu & Poggio, 1998)



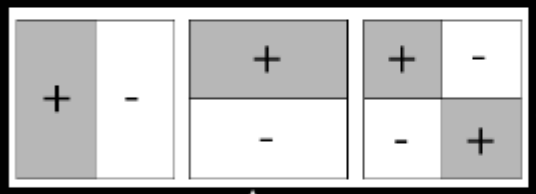
Training set

descriptors

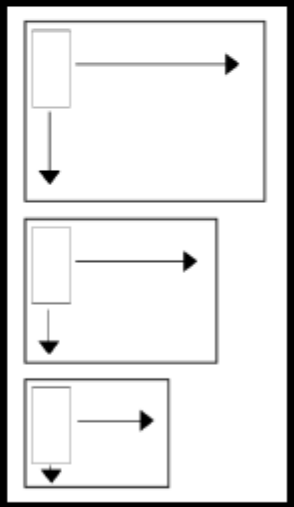


training

Support vector machine



descriptors



Multi-scale search

test

results

Test image

Slides from Sminchisescu

Dynamic Pedestrian Detection

Viola, Jones and Snow, ICCV 2003

- Train using AdaBoost, about 45,000 possible features
- Efficient and reliable for distant detections (20x15), 4fps

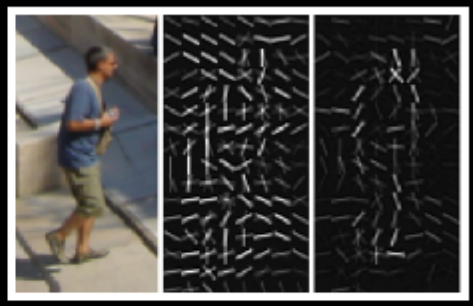
Slides from Sminchisescu

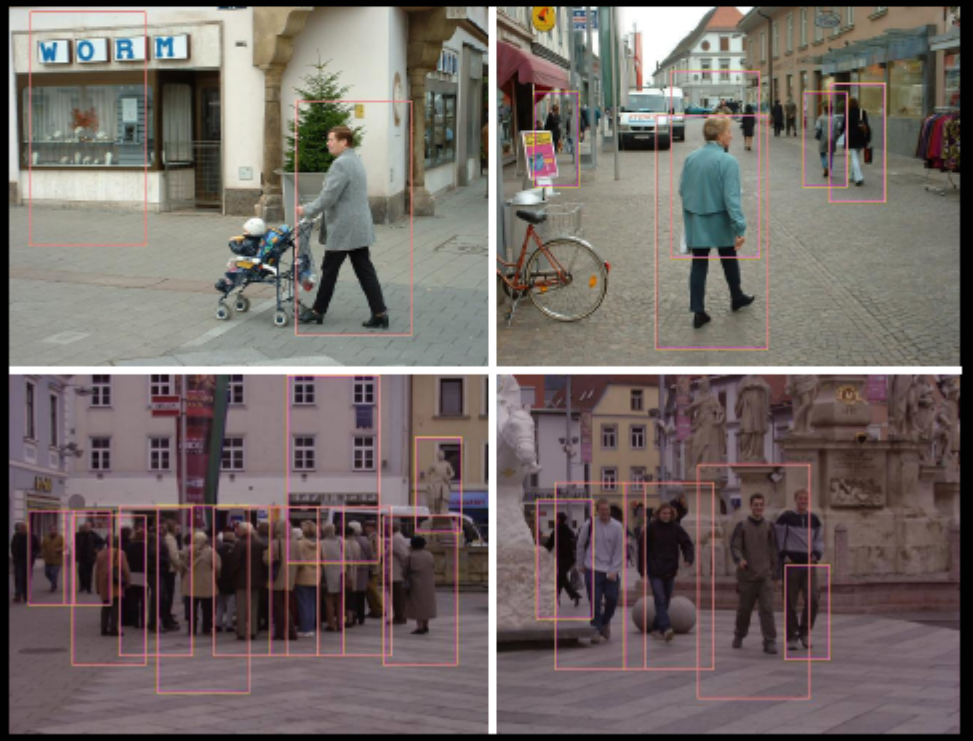
2d Global Detector

Dalal and Triggs, CVPR 2005

- 3-D Histogram of Oriented Gradients (HOG) as descriptors
- Linear SVM for runtime efficiency
- Tolerates different poses, clothing, lighting and background
- Currently works for fully visible upright persons

Importance weight responses





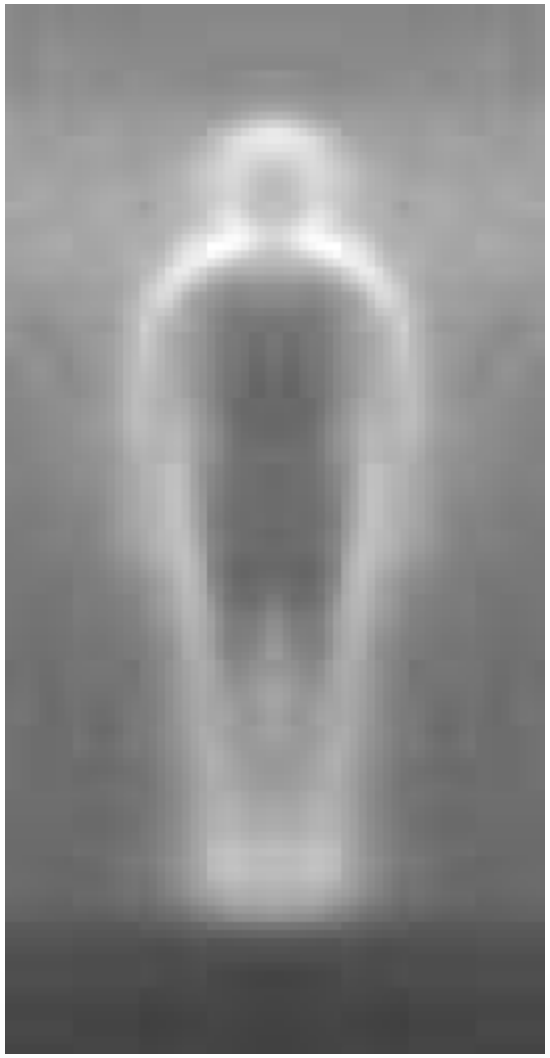
Slides from Sminchisescu

Feature Sets

- Haar wavelets + SVM:
  - Papageorgiou & Poggio (2000)
  - Mohan et al (2001)
  - DePoortere et al (2002)
- Rectangular differential features + adaBoost:
  - Viola & Jones(2001)
- Parts based binary orientation position histogram + adaBoost:
  - Mikolajczk et al (2004)
- Edge templates + nearest neighbor:
  - Gavrila & Philomen (1999)
- Dynamic programming:
  - Felzenszwalb & Huttenlocher (2000),
  - Loffe & Forsyth (1999)
- Orientation histograms:
  - C.F. Freeman et al (1996)
  - Lowe(1999)
- Shape contexts:
  - Belongie et al (2002)
- PCA-SIFT:
  - Ke and Sukthankar (2004)

Method Summary

- Tested with
  - RGB
  - LAB
  - Grayscale
- Gamma Normalization and Compression
  - Square root
  - Log



-1	0	1

centered

-1	1

uncentered

1	-8	0	8	-1

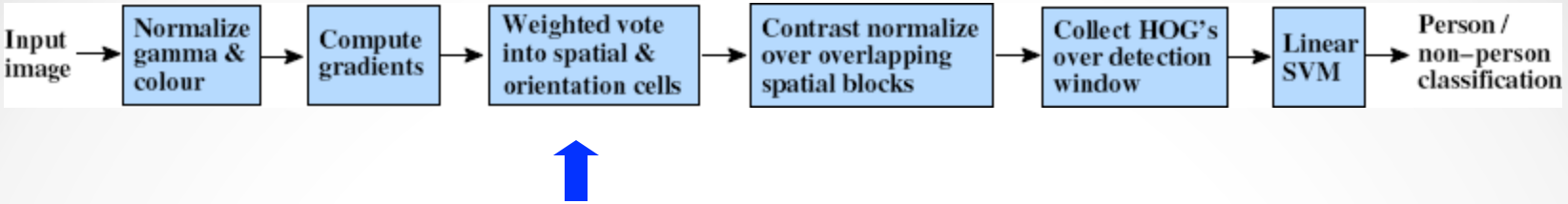
cubic-corrected

0	1
-1	0

diagonal

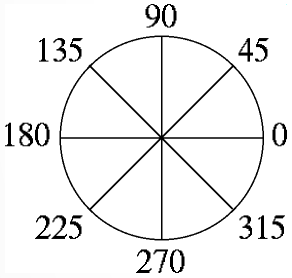
-1	0	1
-2	0	2
-1	0	1

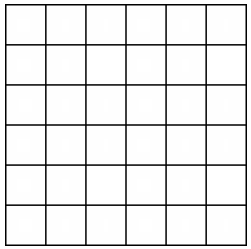
Sobel



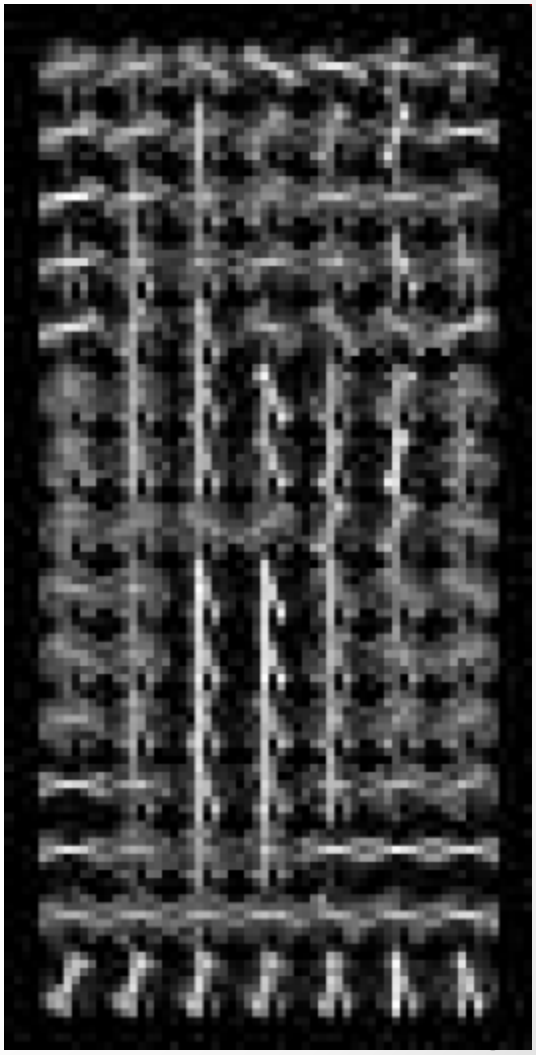
- Histogram of gradient orientations

  -Orientation -Position

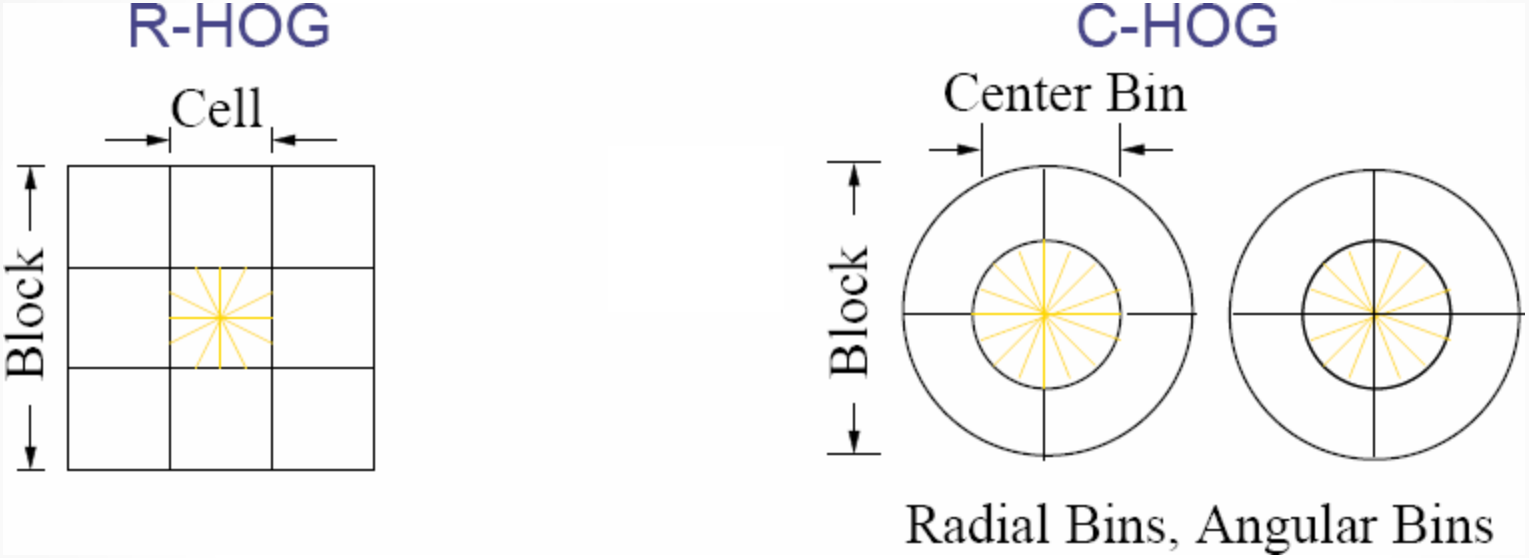


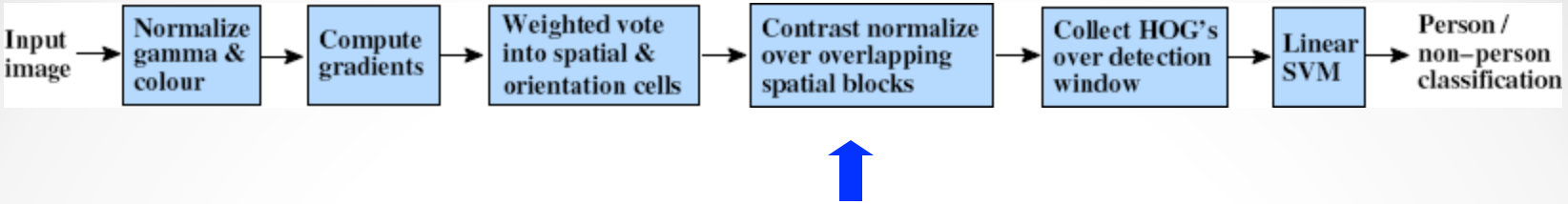


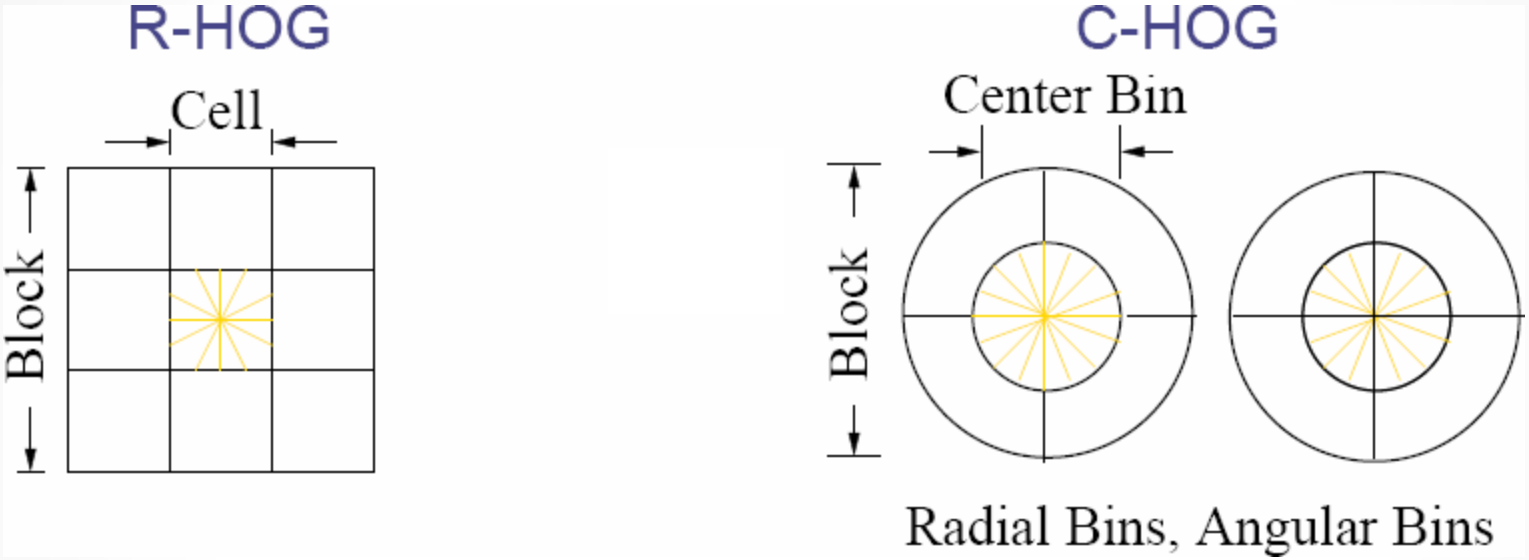
  - Weighted by magnitude




Input image
Normalize gamma & colour
Compute gradients
Weighted vote into spatial & orientation cells
Contrast normalize over overlapping spatial blocks
Collect HOG's over detection window
Linear SVM
Person / non−person classification


R-HOG
Cell
Block
C-HOG
Center Bin
Block
Radial Bins, Angular Bins



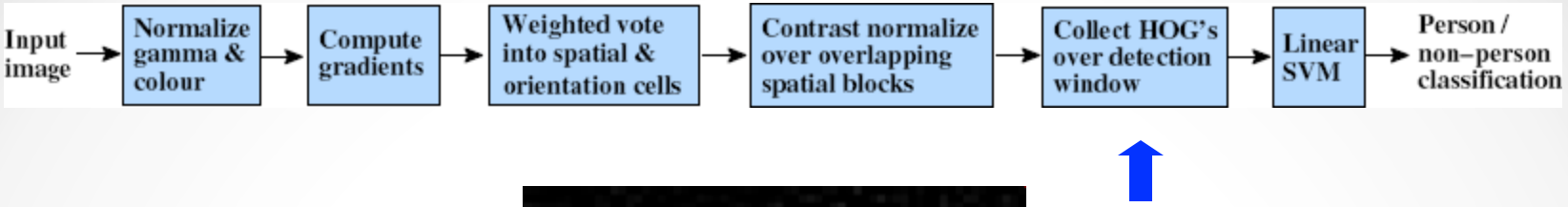


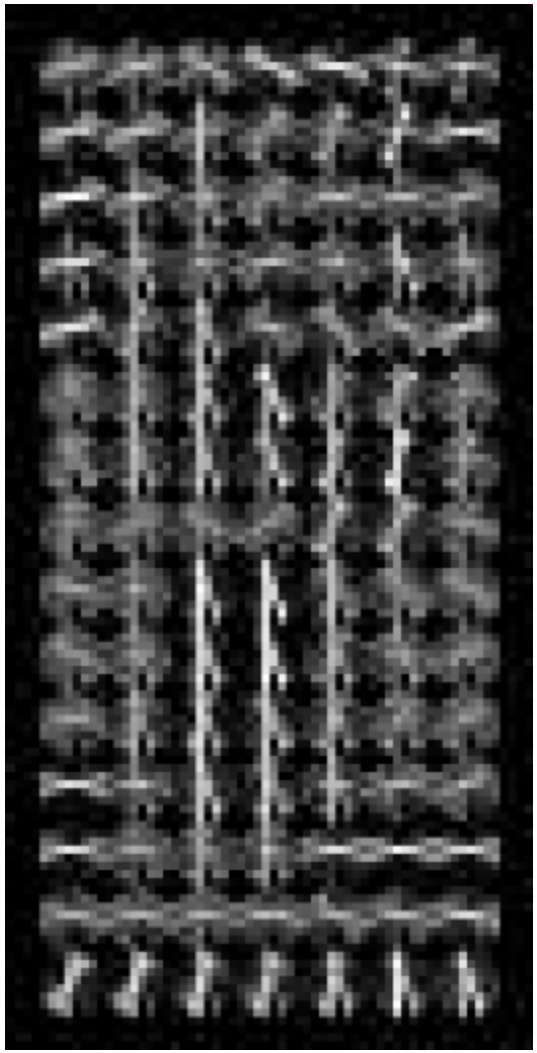
$L1-norm: v \longrightarrow v/(||v||_1+\epsilon)$

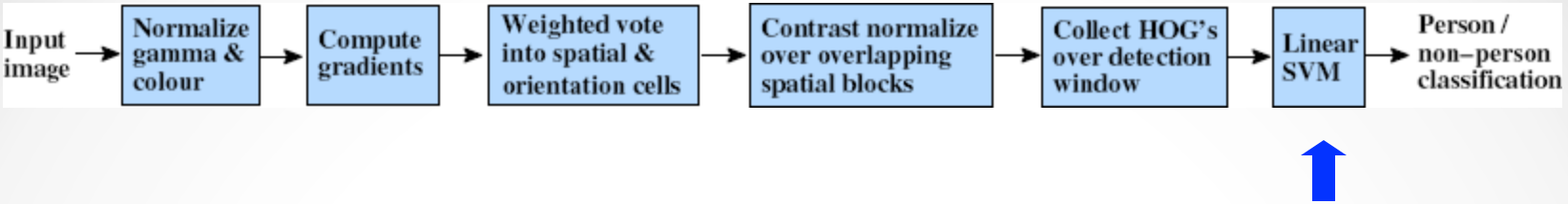
$L1-sqrt: v \longrightarrow \sqrt{v/(||v||_1+\epsilon)}$

$L2-norm: v \longrightarrow v/\sqrt{||v||_2^2+\epsilon^2}$

$L2-hys$: L2-norm, plus clipping at .2 and renomalizing


Input image
Normalize gamma & colour
Compute gradients
Weighted vote into spatial & orientation cells
Contrast normalize over overlapping spatial blocks
Collect HOG's over detection window
Linear SVM
Person / non−person classification




Input image
Normalize gamma & colour
Compute gradients
Weighted vote into spatial & orientation cells
Contrast normalize over overlapping spatial blocks
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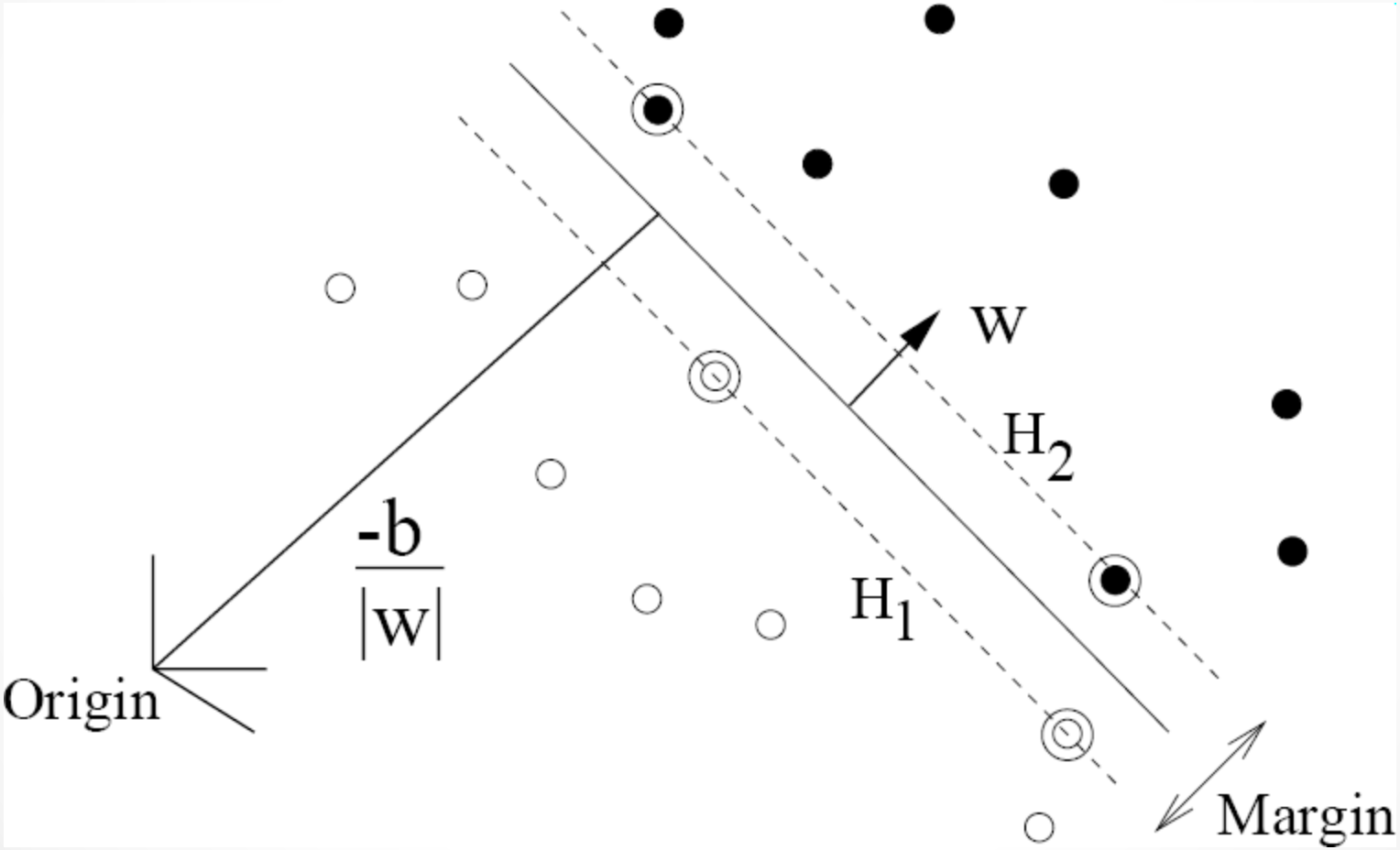
w
H2
H1
-b
|w|
Origin
Margin


Input image
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0.16


0.62
1.21