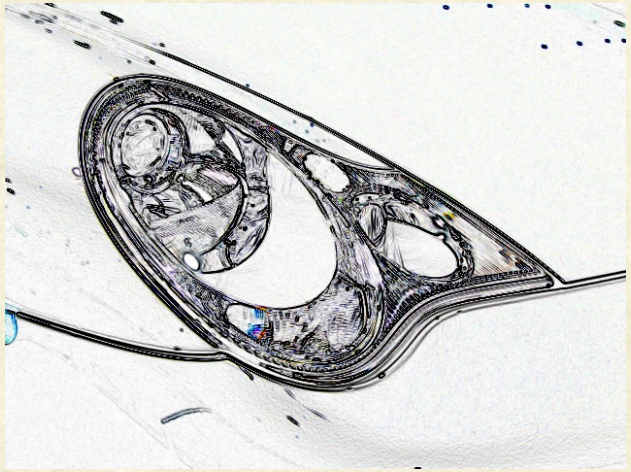
CS7.505: Computer Vision

Spring 2022: Pedestrian Detection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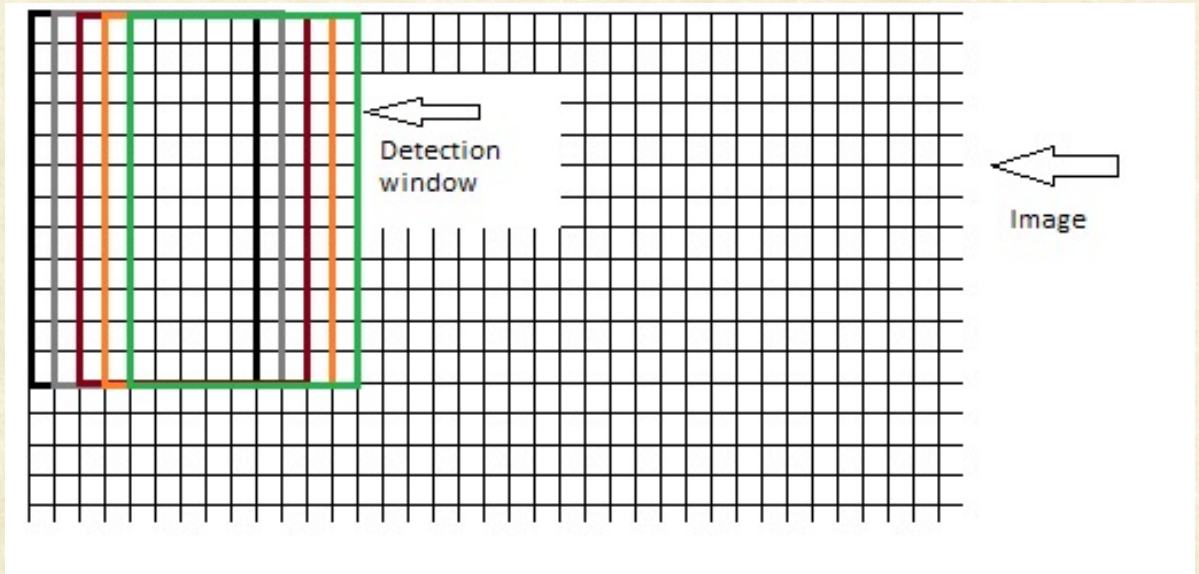
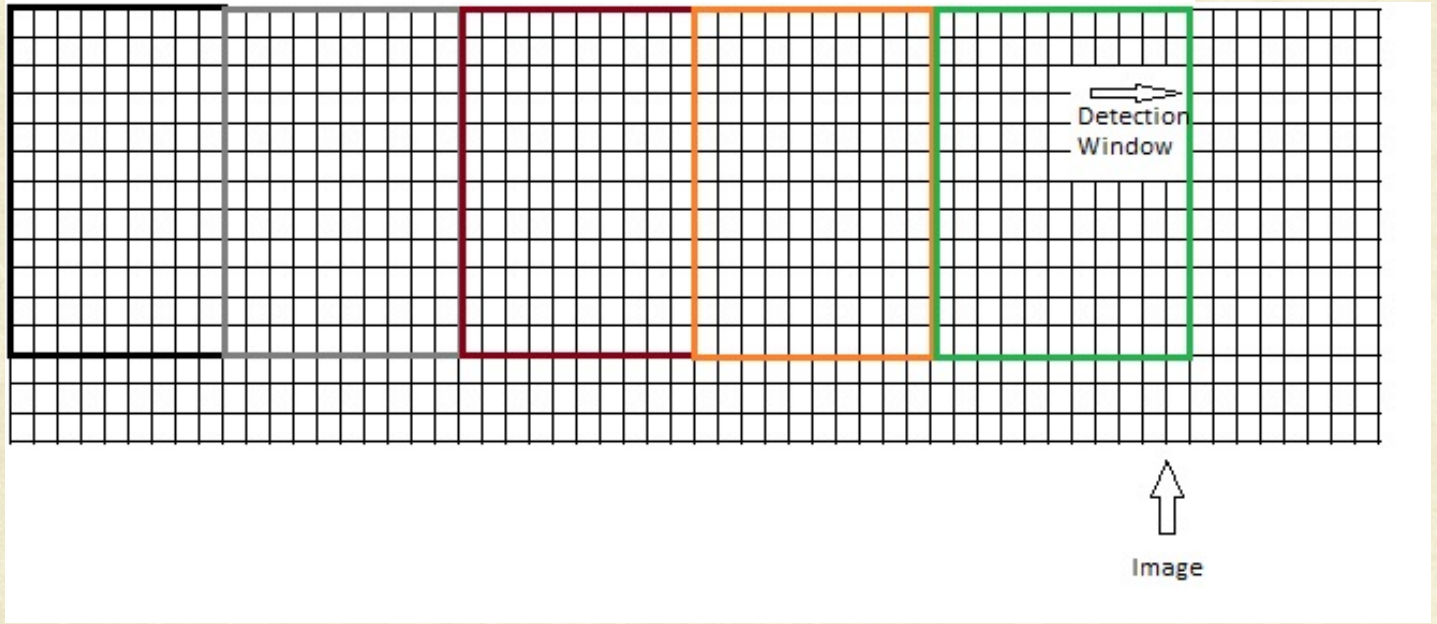
Detection: Classifying Windows



Classify each window



Challenges

- Pose
- Appearance
- Background

Clothing

Illumination

Occlusion, Scale

Articulation

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 for classification
  - - 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

Feature Sets

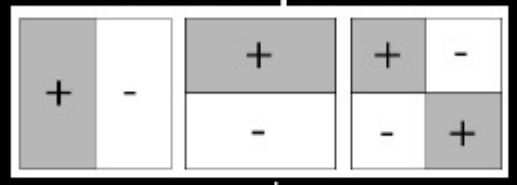
- Haar wavelets + SVM:
  - Papageorgiou & Poggio (1998,2000)
  - Mohan et al (2001)
  - DePoortere et al (2002)
- Rectangular differential features + adaBoost:
  - Viola & Jones(2001)
- Parts based binary orientation position histogram + adaBoost:
  - Mikolajczk et al (2004)
- Edge templates + nearest 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)

Support Vector Machine Detector

(Papageorgiu & Poggio, 1998)

Training set

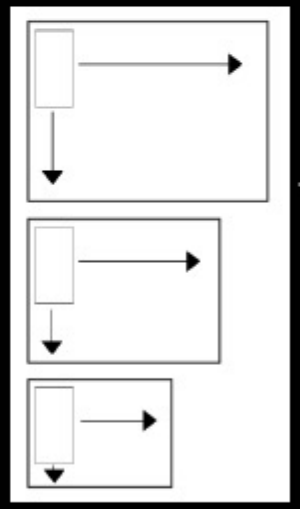
descriptors



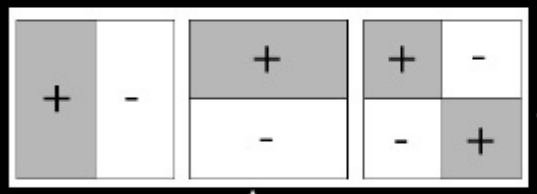
training

Support vector machine

test



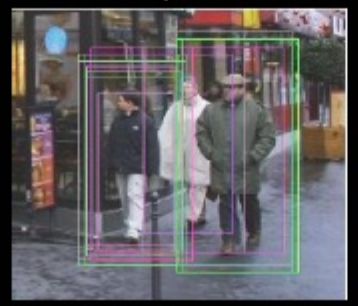
Multi-scale search



descriptors

Test image

results



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

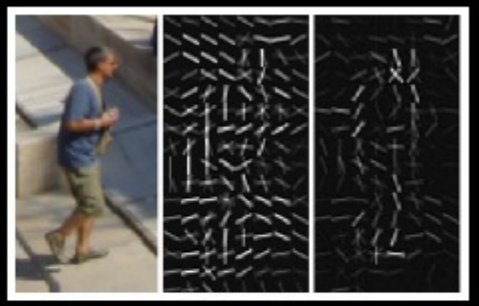
Slides from Sminchisescu

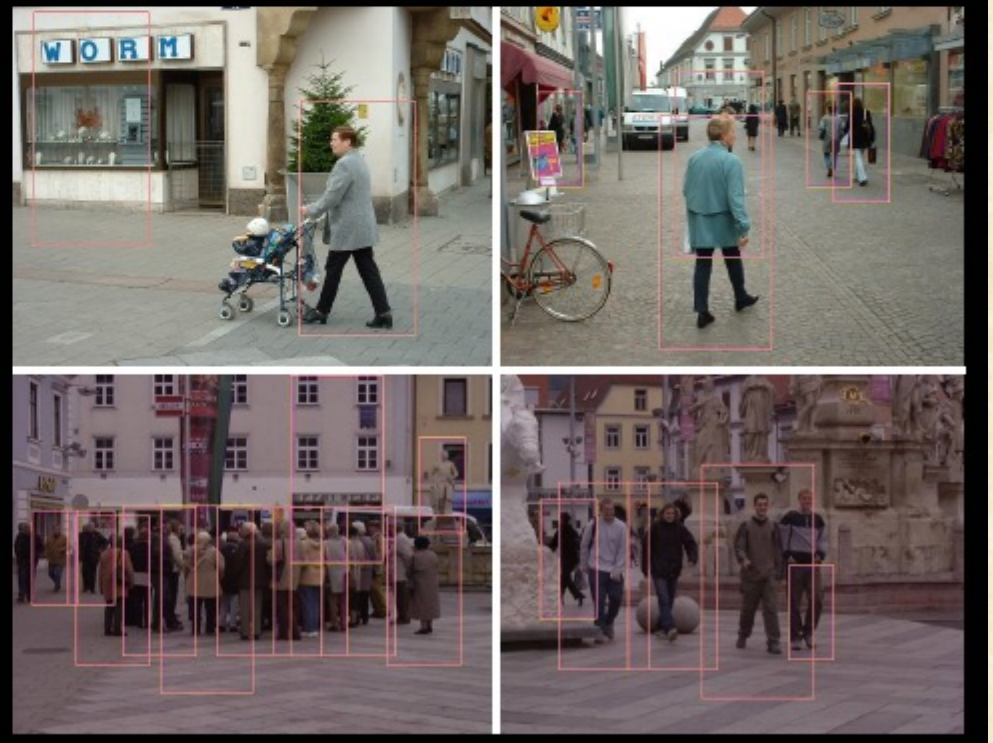
2d Global Detector

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

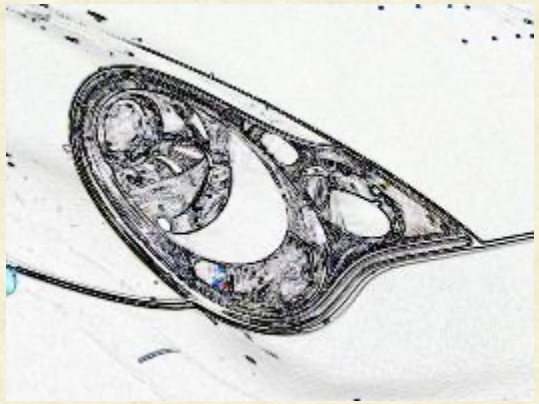
Importance weight responses





Slides from Sminchisescu

Histogram of Oriented Gradients for Human Detection: Dalal and Triggs [CVPR 2005]



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

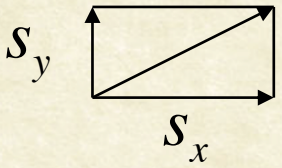
- Derivatives
  - One sided: $$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$
  - Two sided: $$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x-h)}{2h}$$
- Filter masks in x-direction
  - One sided:

-1	1

  - Two sided:

-1	0	1

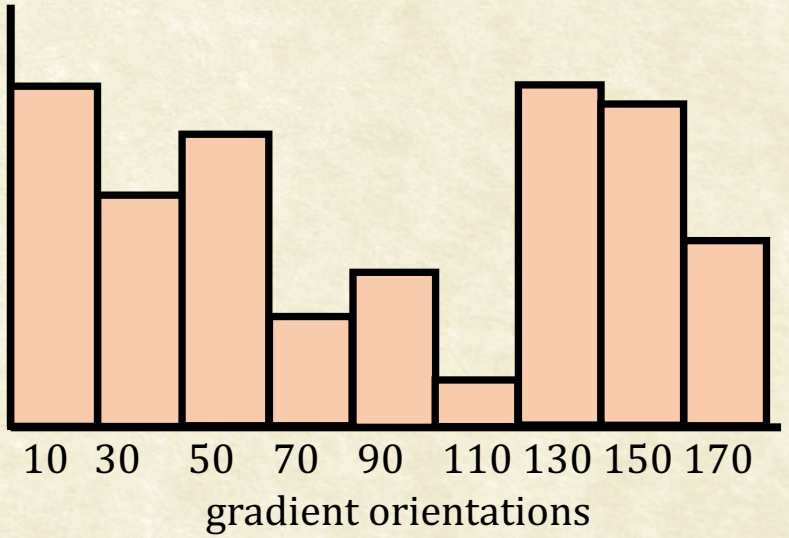
- Gradient:



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

Creating Histograms

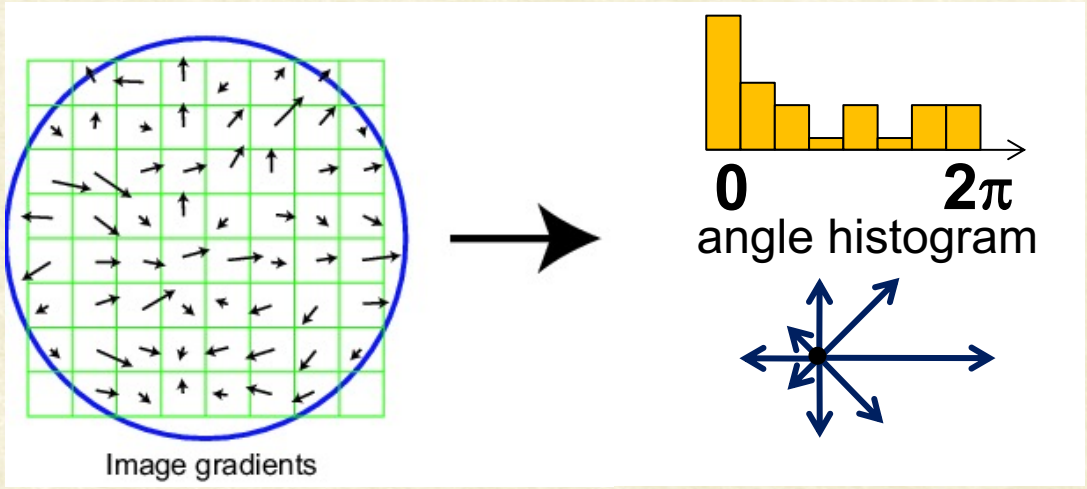
- Gradient histograms measure the orientations and strengths of image gradients within an image region

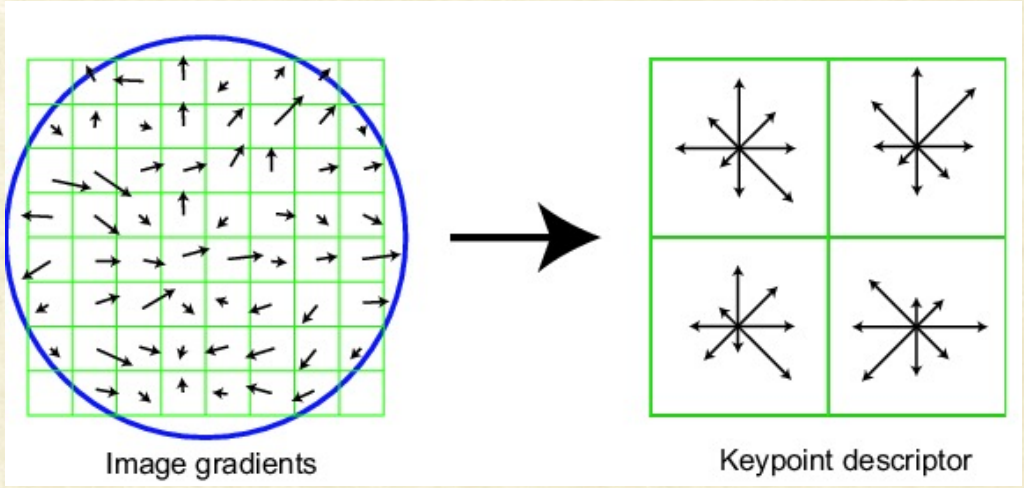


Recap: SIFT descriptor

SIFT was a gradient-based descriptor, typically used in combination with an interest point detector

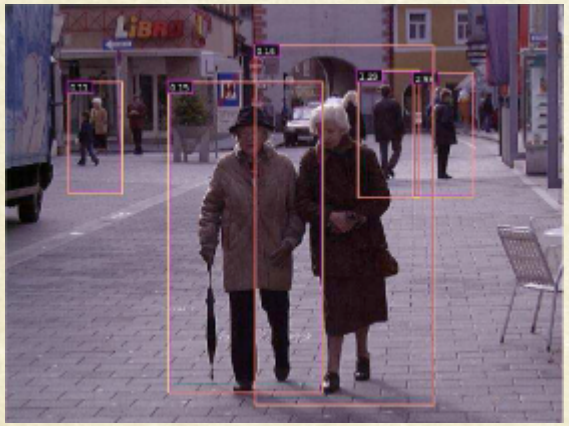
- Region is a grid of 16x16 pixels
- 4x4 regions = 16 histograms (concatenated)
- Histograms: 8 orientation bins, gradients weighted by gradient magnitude
- Final descriptor has 128 dimensions and is normalized to compensate for illumination differences

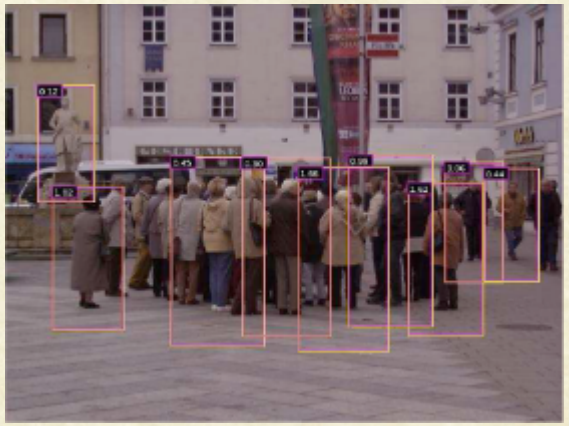




Histograms of Oriented Gradients (HOG)

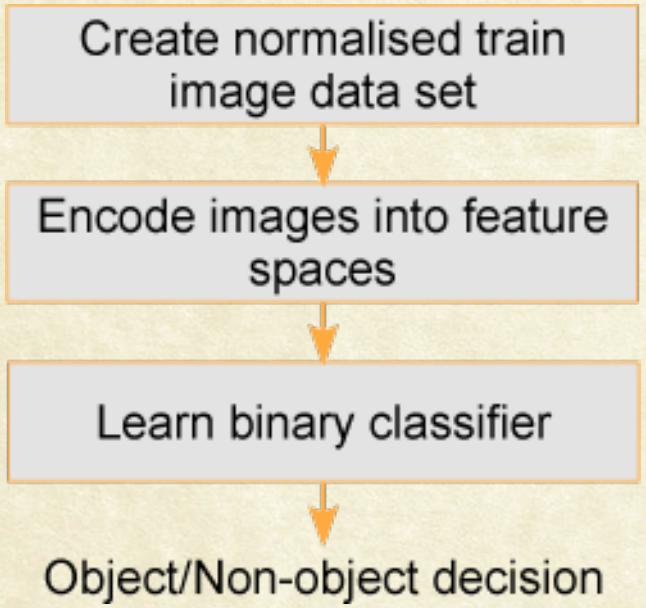
- Histogram of Oriented Gradients for Human Detection
  - Navneet Dalal & Bill Triggs (INRIA Rhône-Alps), CVPR 2005
- Global descriptor for the complete body
- Very high-dimensional: ~4000 dimensions
- Significant improvement over SoTA





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

Scan image at all scales and locations

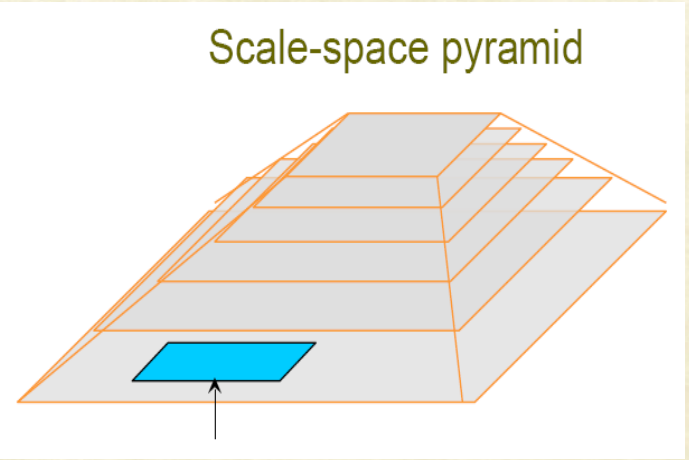
Sliding window over each scale

Run classifier to obtain object/non-object decisions

Simple SVM prediction

Fuse multiple detections in 3-D position & scale space

Object detections with bounding boxes



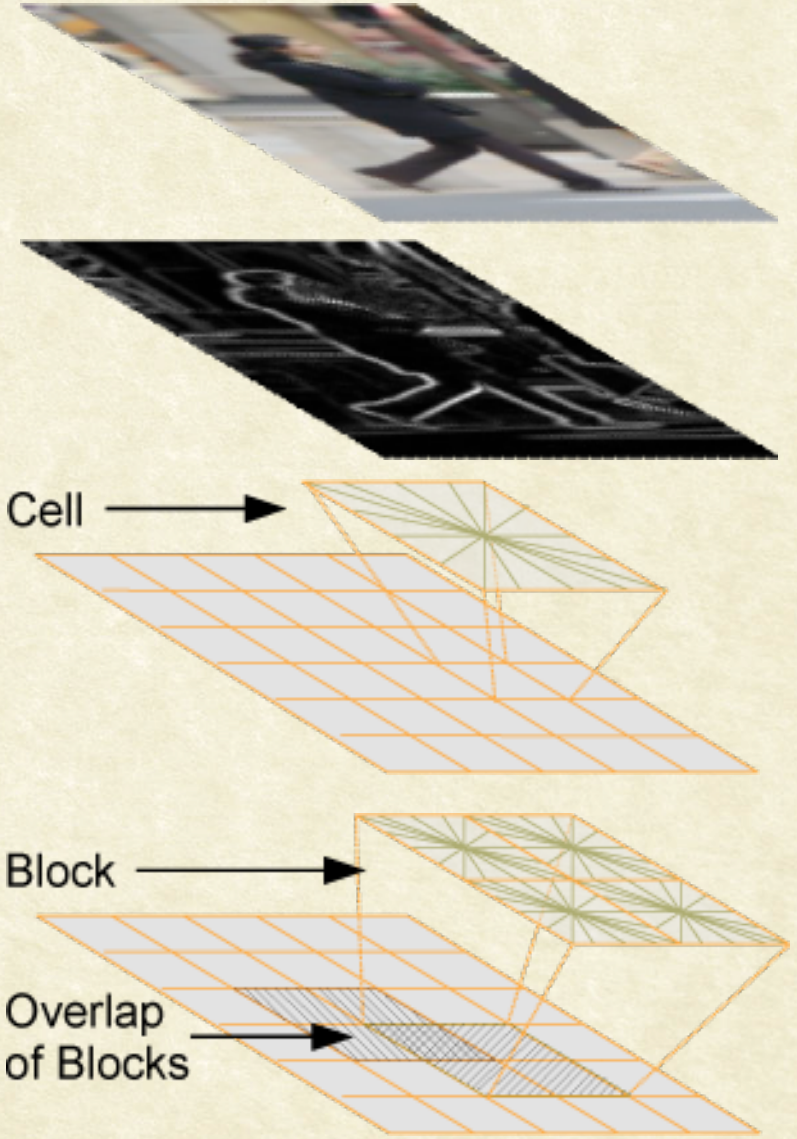
Descriptor

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

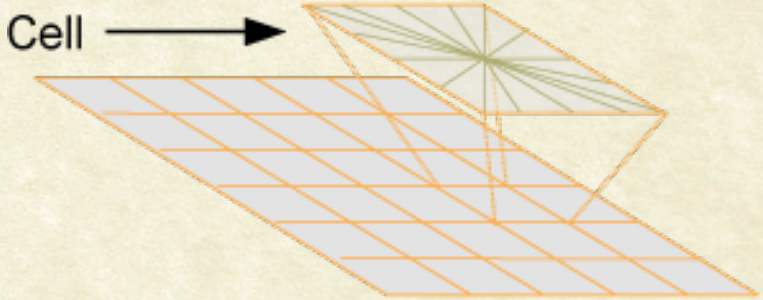


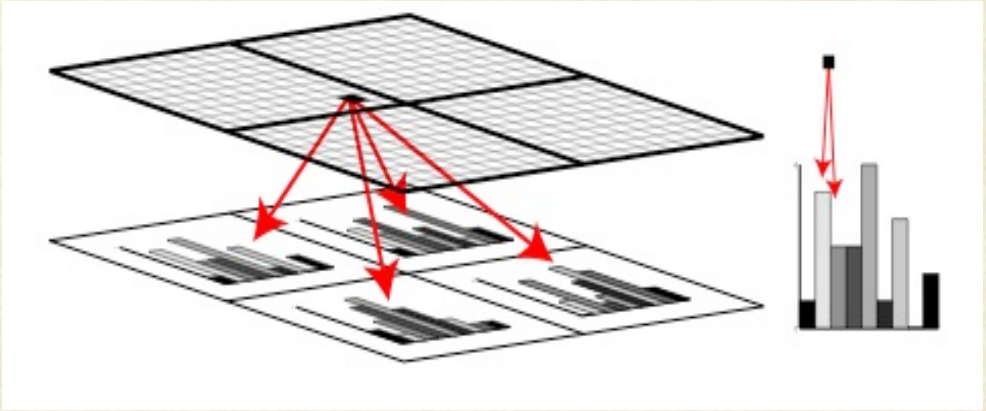
Gradients

- 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

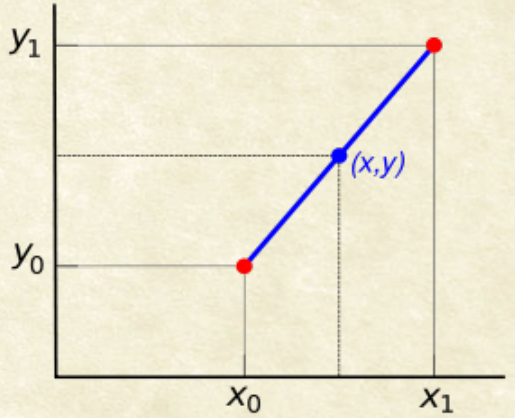




Linear and Bilinear Interpolation for Subsampling

Linear:

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

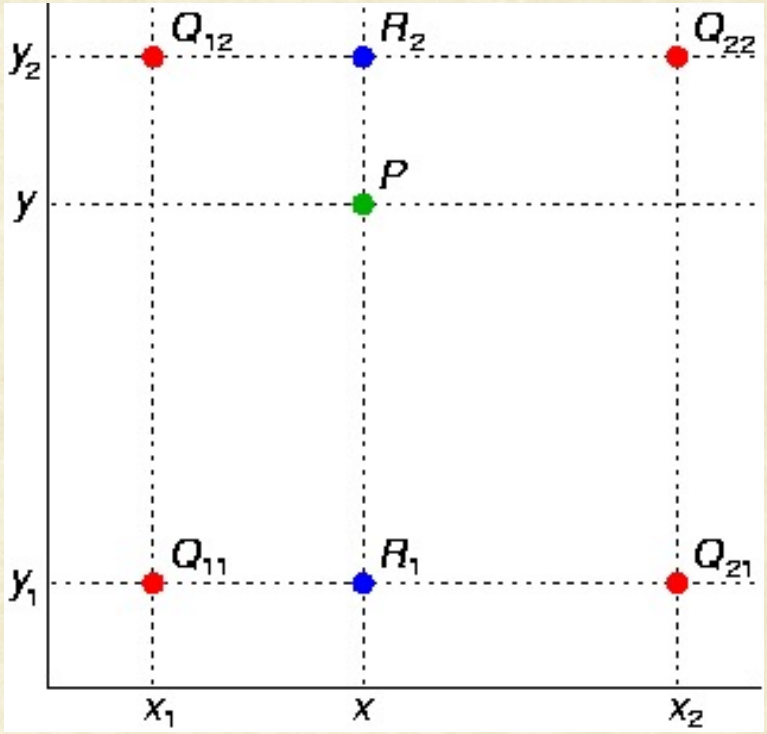


Bilinear:

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

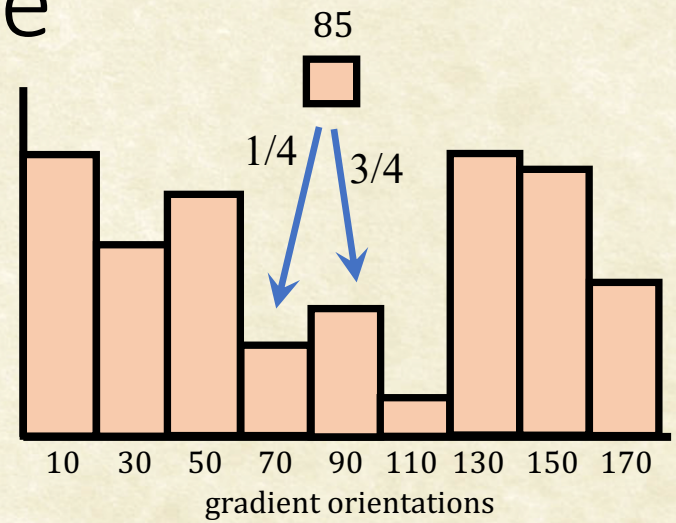
$$f(R_2) = \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}), \text{ where } R_2 = (x, y_2)$$

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

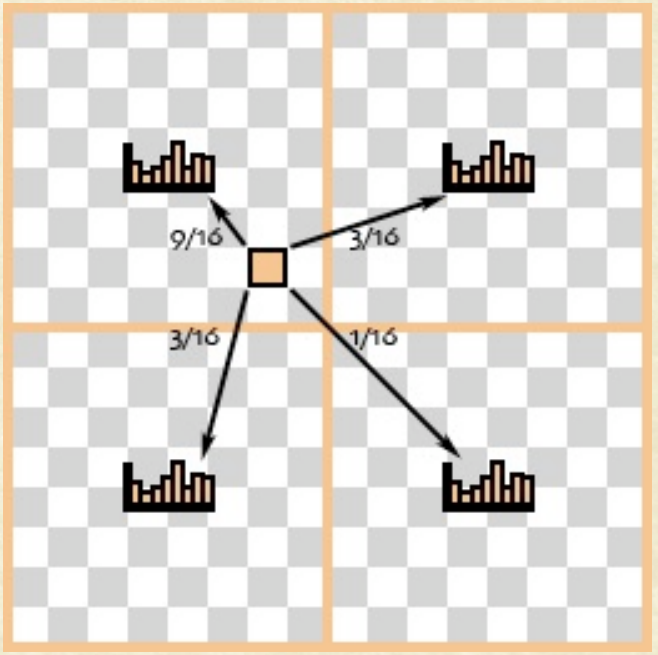


Histogram Interpolation Example

- 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

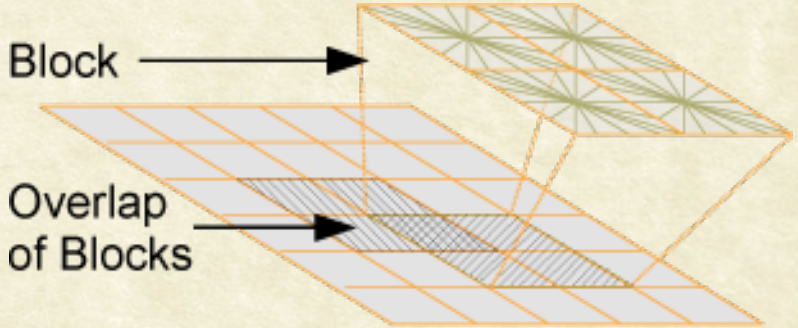


Blocks

- Overlapping blocks of 2x2 cells

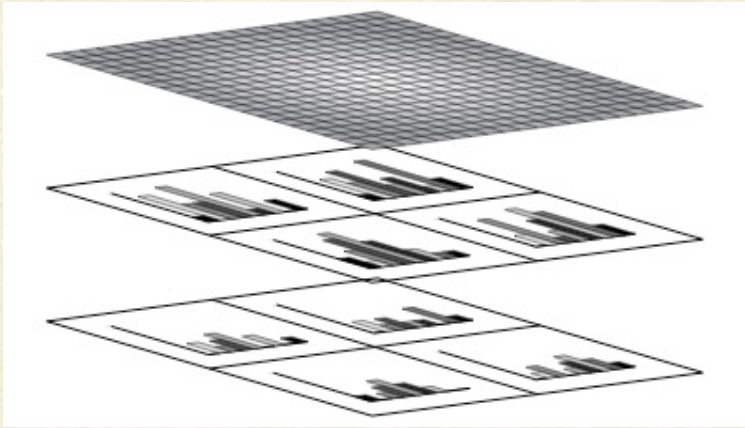
- Cell histograms are concatenated and then normalized
  - Several occurrences of each cell with different normalizations in the final descriptor

- Normalization
  - Different norms possible (L2, L2hys etc.)
  - Select the most effective (L2)



Blocks

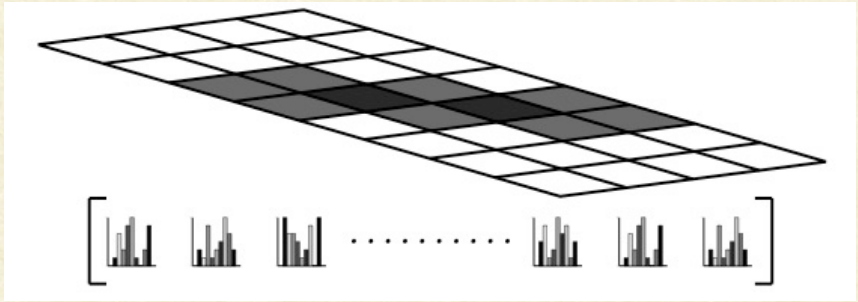
- Gradient magnitudes are weighted according to a Gaussian spatial window



- Distant gradients contribute less to the histogram

Final Descriptor

- Concatenation of Blocks



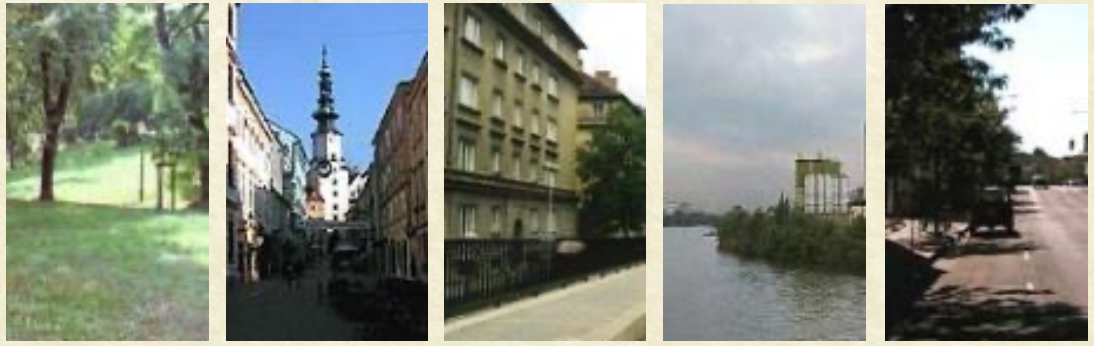
- Visualization:

Engineering

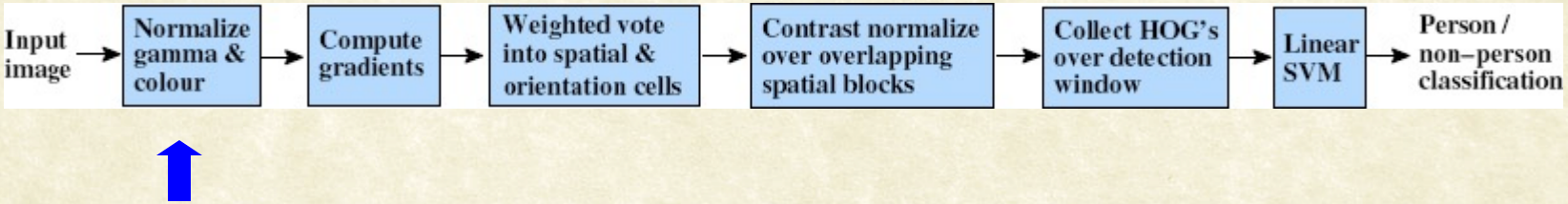
- Developing a feature descriptor requires a lot of engineering
  - Testing of parameters (e.g., size of cells, blocks, number of cells in a block, size of overlap)
  - Normalization schemes (e.g., L1, L2-Norms etc., gamma correction, pixel intensity normalization)
- An extensive evaluation of different 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 (96 x 160 px)
- Carefully aligned and resized
- Wide variety of backgrounds
- Hard negative selection for refinement



Method Summary



- Color Space: Tested with
  - RGB
  - LAB
  - Grayscale
- Gamma Normalization and Compression
  - Square root
  - Log
  - None

-1	0	1

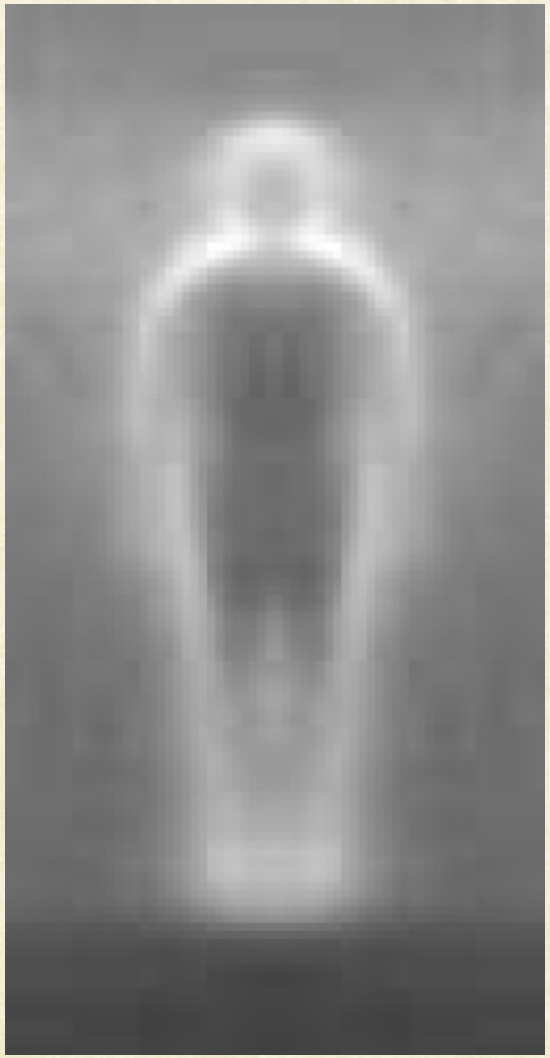
centered

-1	1

uncentered

1	-8	0	8	-1

cubic-corrected



0	1
-1	0

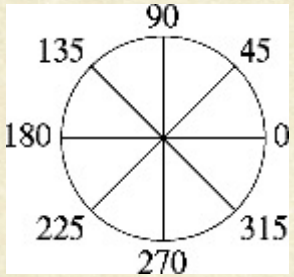
diagonal

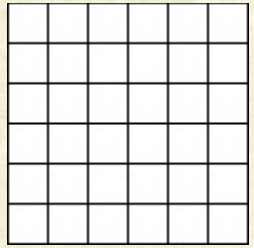
-1	0	1
-2	0	2
-1	0	1

Sobel

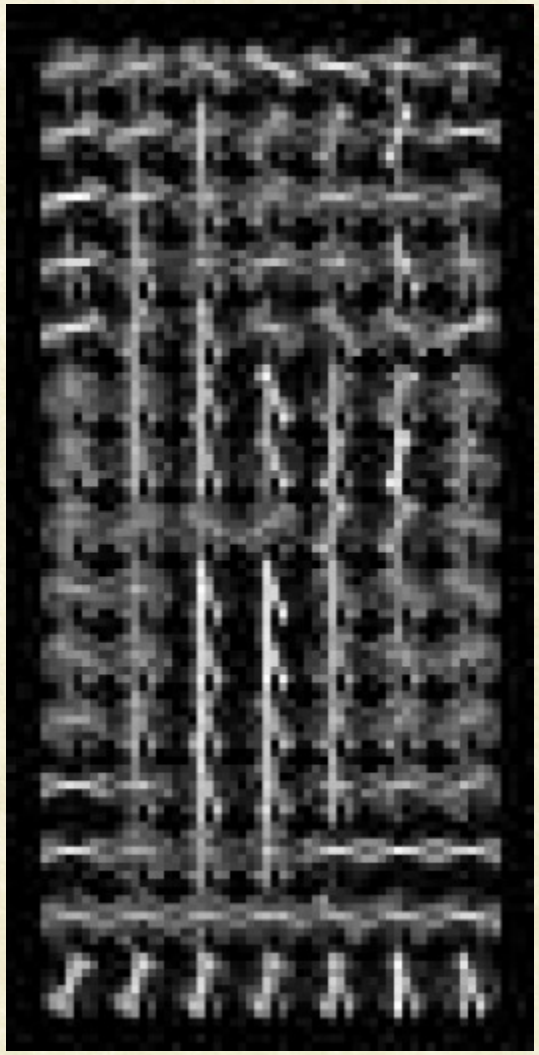
- Histogram of gradient orientations

  -Orientation -Position

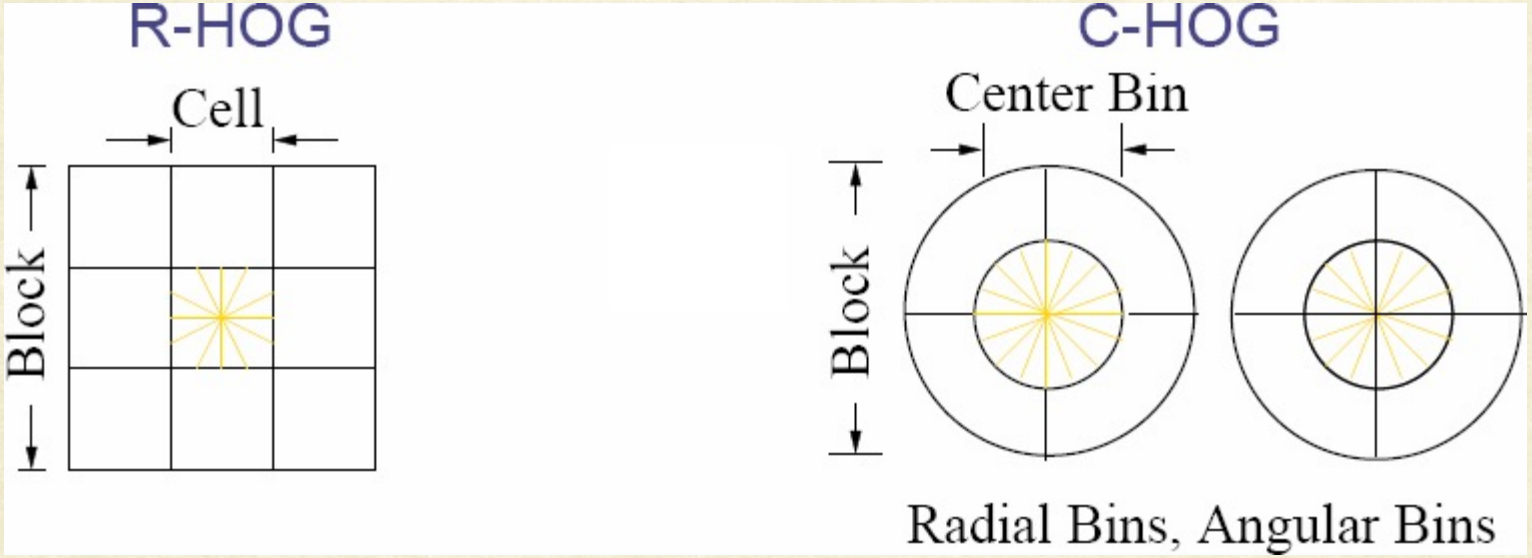


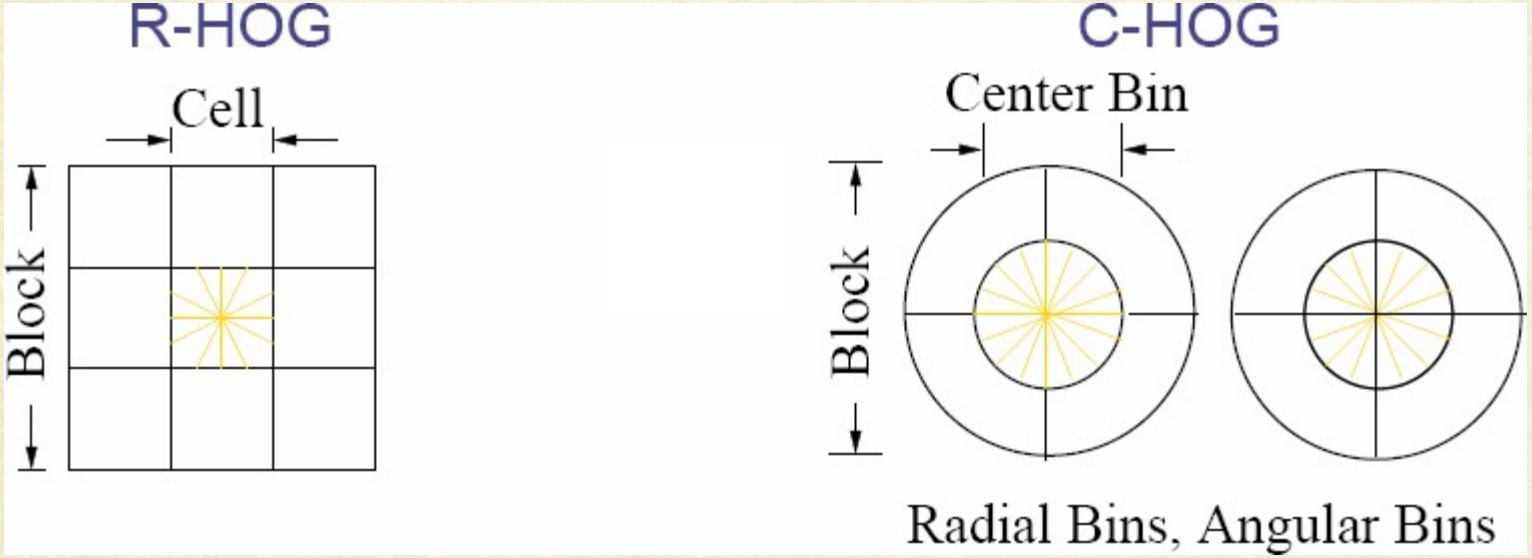


- Weighted by magnitude




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



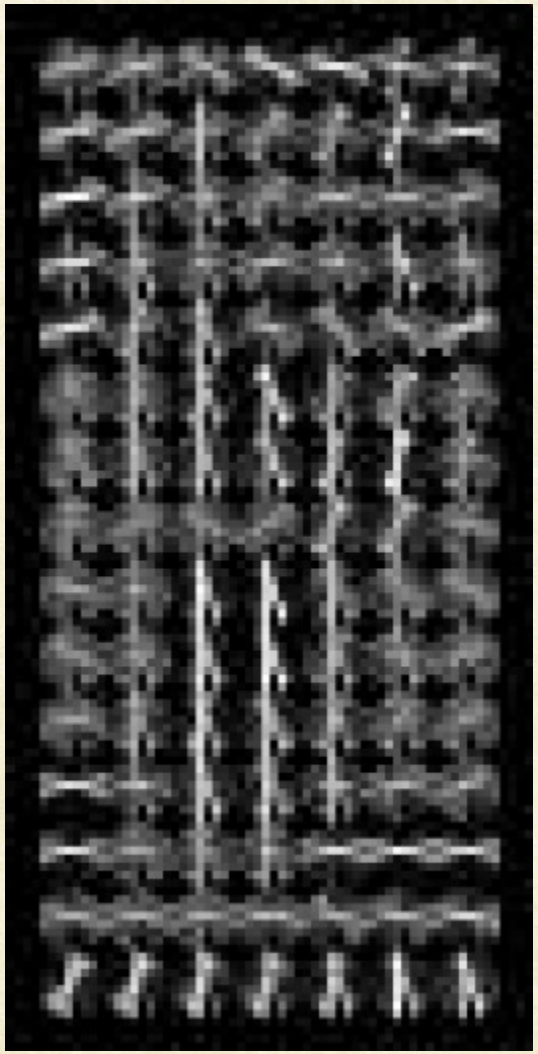
$L1 - norm : v \longrightarrow v/(||v||_1 + \epsilon)$

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

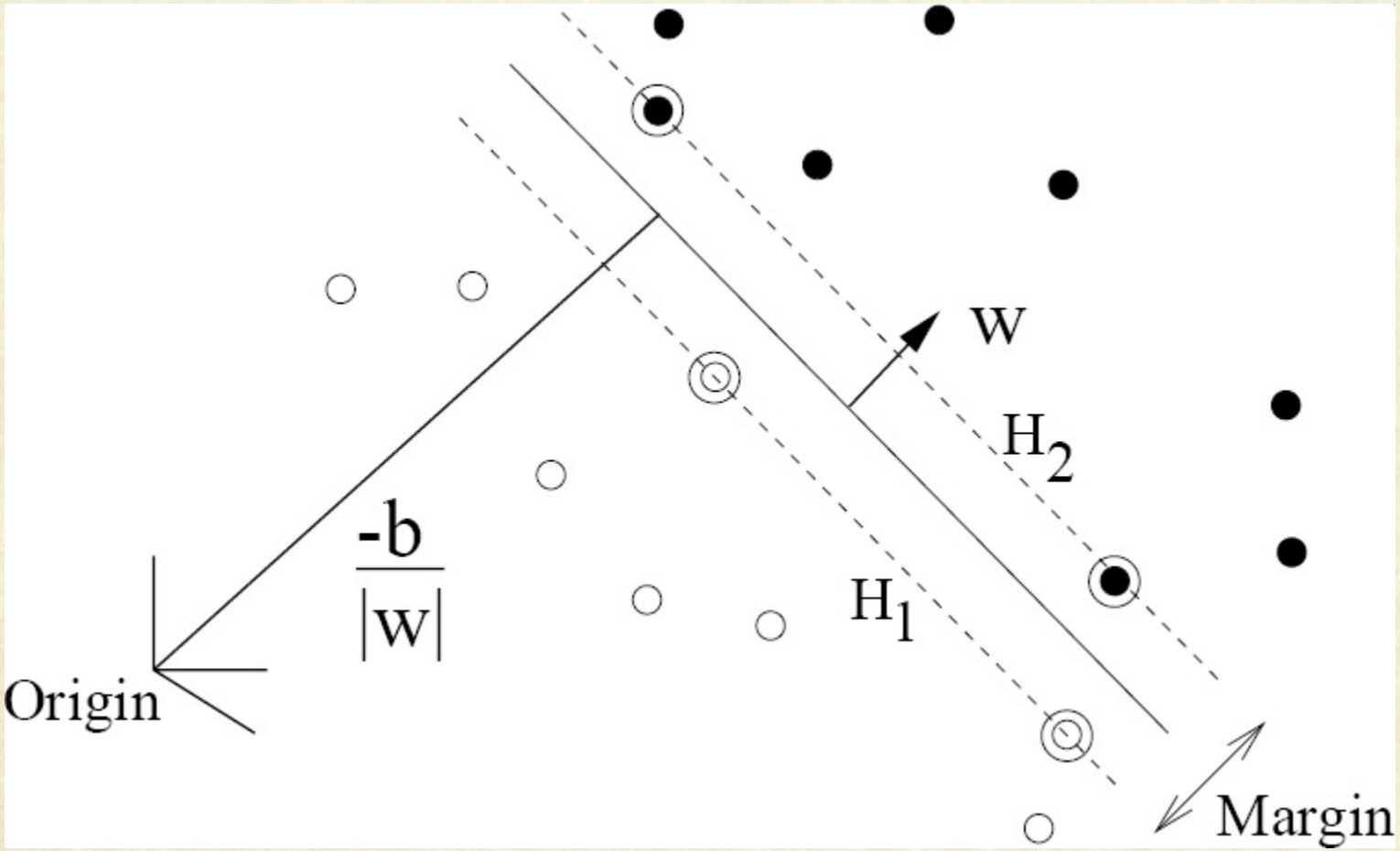
$L2 - norm : v \longrightarrow v/\sqrt{||v||_2^2 + \epsilon^2}$

$L2 - hys$: 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
Collect HOG's over detection window
Linear SVM
Person / non−person classification


w
H_2
H_1
$\frac{-b}{|w|}$
Origin
Margin


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

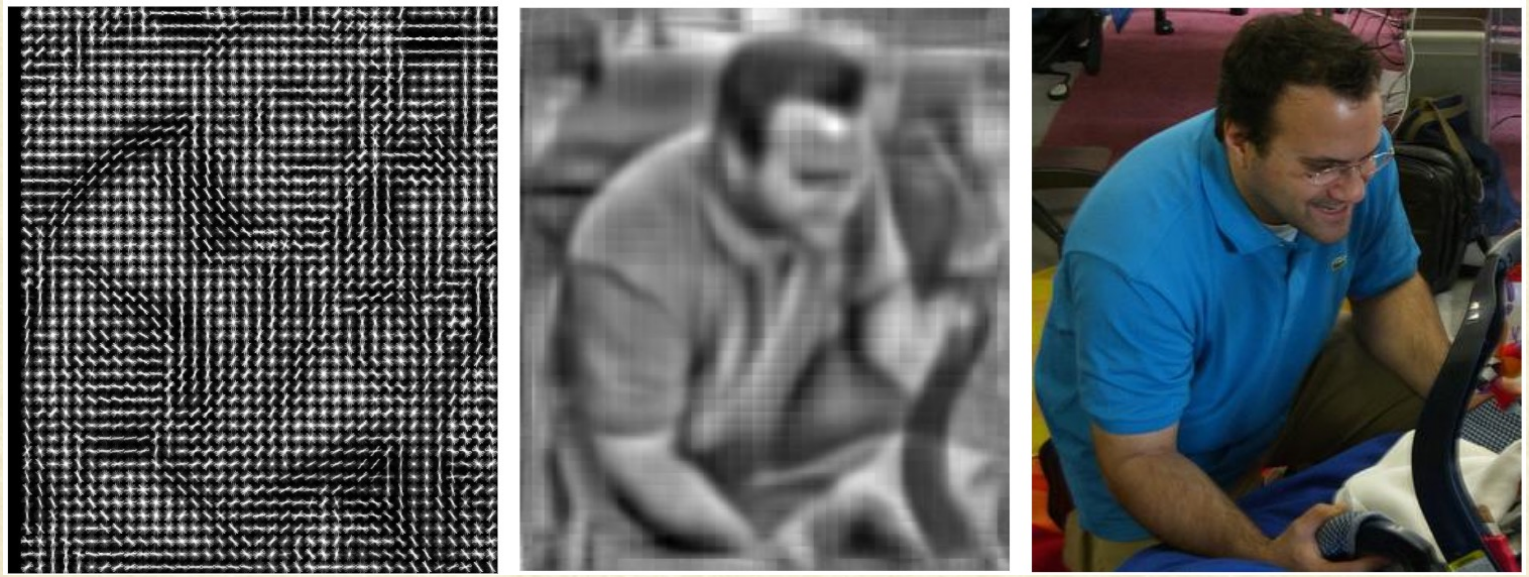

0.16

Results:

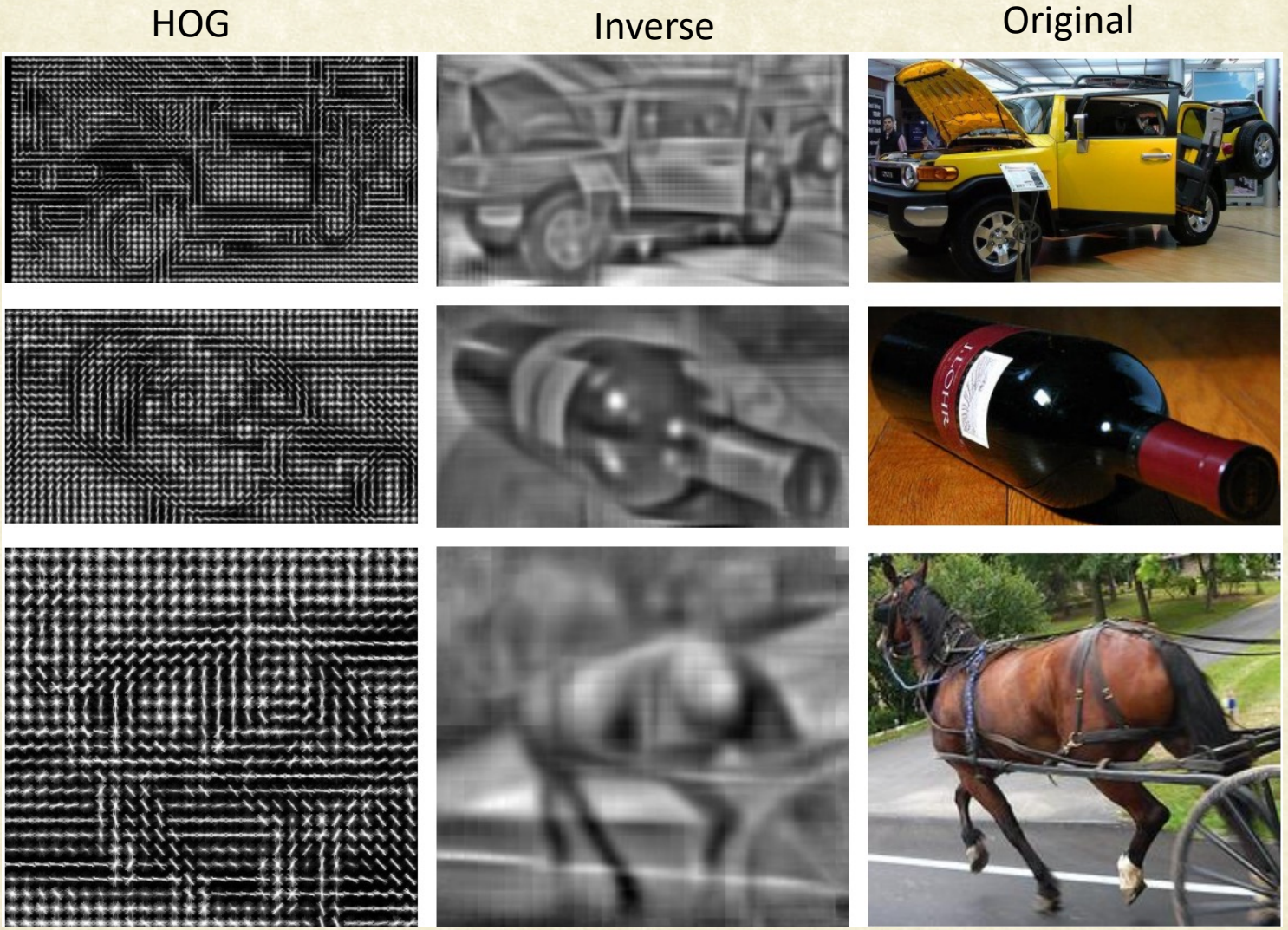
HOGgles: Visualizing Object Detection Features

Carl Vondrick, Aditya Khosla, Hamed Pirsiavash, Tomasz Malisiewicz, and Antonio Torralba (MIT), ICCV 2013

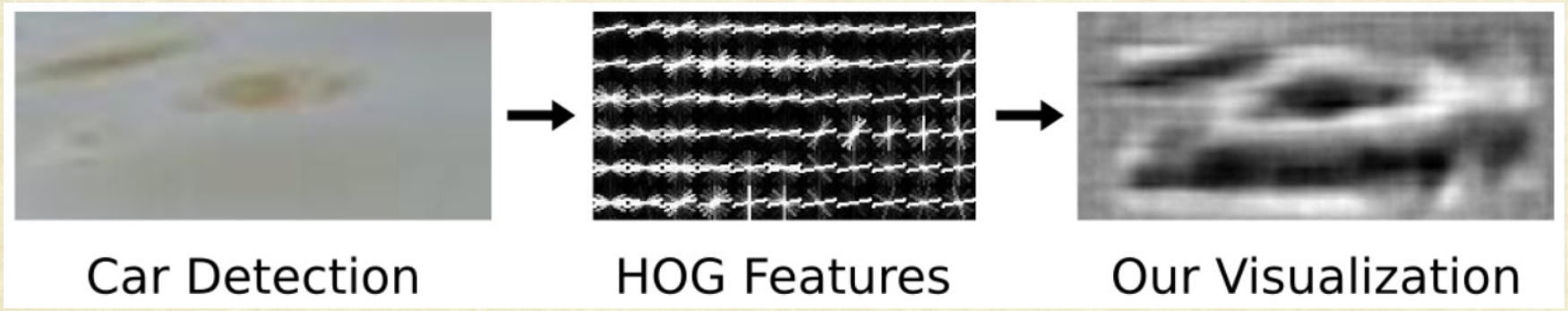
- Sparse dictionary based encoding of images.
- Use weights from sparse HOG Basis to form image



IHOG: Inverting HOG



What went wrong? IHOG



Newer Approaches, Datasets

1. P. Felzenszwalb, D. McAllester, D. Ramanan, “A Discriminatively Trained, Multiscale, Deformable Part Model”, CVPR, 2008. *(PAMI Longuet-Higgins Prize, 2018)*
2. S. Walk, N. Majer, K. Schindler and B. Schiele, “New Features and Insights for Pedestrian Detection”, CVPR 2010.
3. Piotr Dollár, S. Belongie and P. Perona, ”The Fastest Pedestrian Detector in the West”, BMVC 2010
4. P. Dollár, R. Appel and W. Kienzle, “Crosstalk Cascades for Frame-Rate Pedestrian Detection”, ECCV 2012. *(faster than [3])*

- Caltech Pedestrian Detection Benchmark
  http://www.vision.caltech.edu/Image_Datasets/CaltechPedestrians/
- WIDER Face & Pedestrain Challenge – Tr2: Pedestrian Detection
  http://wider-challenge.org

Questions?