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 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

Gradient Histograms

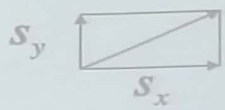
- Extremely and successful in the vision
- Avoids hard decisions vs. edge based features
- Examples:
  - SIFT (Scale-Invariant Image Transform)
  - GLOH (Gradient Location and Orientation Histogram)
  - HOG (Histogram of Oriented Gradients)

Computing Gradients

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

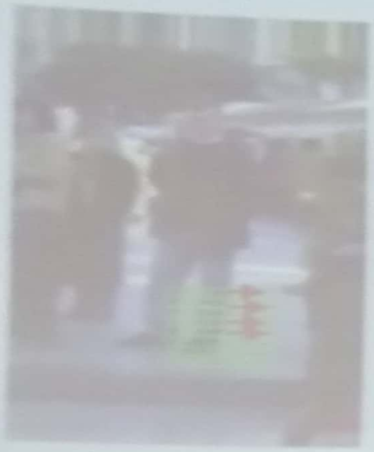
- Filter masks in x-direction
  - One sided: $\begin{bmatrix} -1 & 1 \end{bmatrix}$
  - Two sided: $\begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$

- 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



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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

Create normalised train image data set	Set of cropped images containing pedestrians in normal environment
↓ Encode images into feature spaces	Global descriptor rather than local features
↓ Learn binary classifier	Using linear SVM
↓ Object/Non-object decision	

Detector: Detection Phase

2. Detection

Scan image at all scales and locations

↓

Run classifier to obtain object/non-object decisions

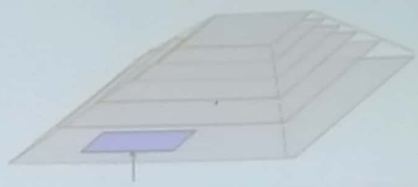
↓

Fuse multiple detections in 3-D position & scale space

↓

Object detections with bounding boxes

Scale-space pyramid



Sliding window over each scale

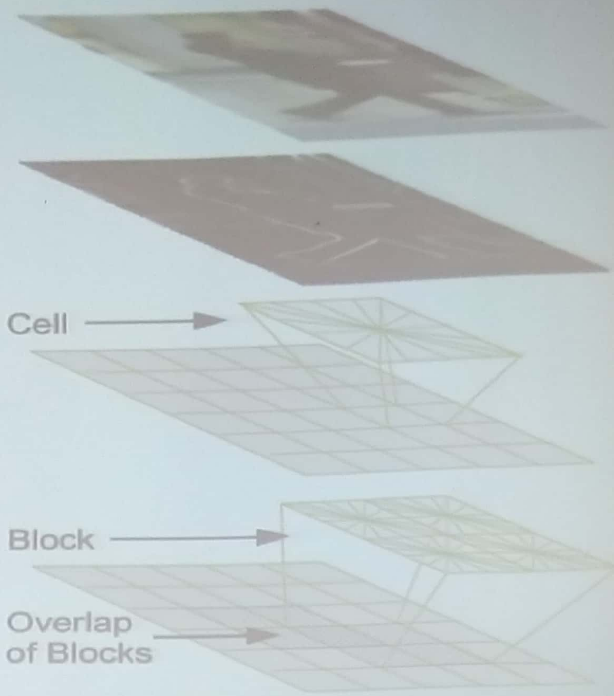
Simple SVM prediction

Descriptor

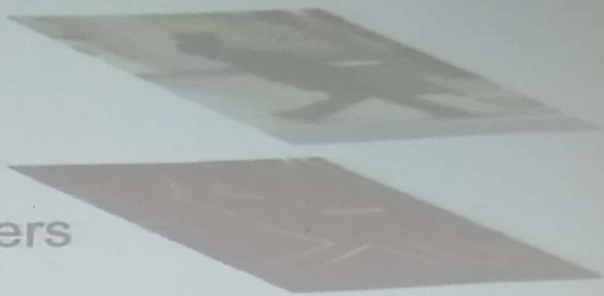
1. Compute gradients on an image region of 64x128 pixels

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

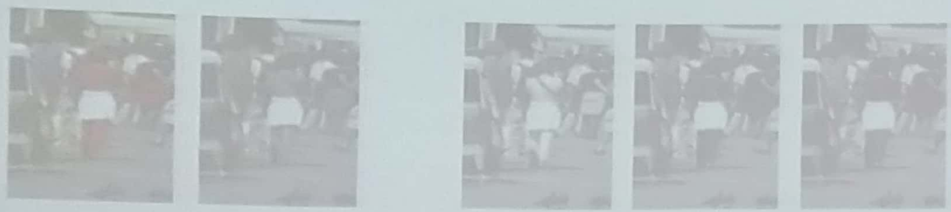
3. Normalize histograms within overlapping blocks of cells (typically 2x2 cells, i.e. 7x15 blocks)



Gradients

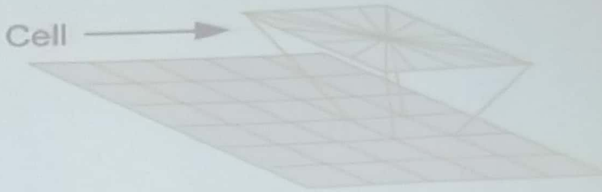


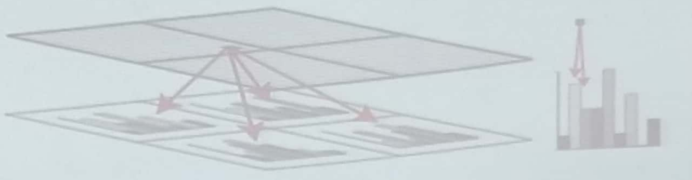
- Convolution with [-1 0 1] filters
- No smoothing
- Compute gradient magnitude+direction
- Per pixel: color channel with greatest magnitude -> final gradient



Cell histograms

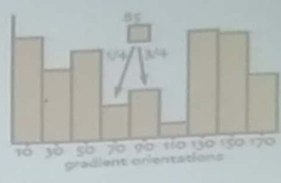
- 9 bins for gradient orientations (0-180 degrees)
- Filled with magnitudes
- Interpolated trilinearly:
  - Bilinearly into spatial cells
  - Linearly into orientation bins



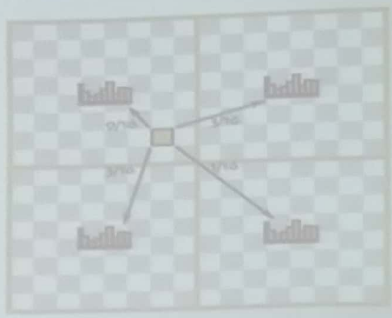


Histogram Interpolation Example

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

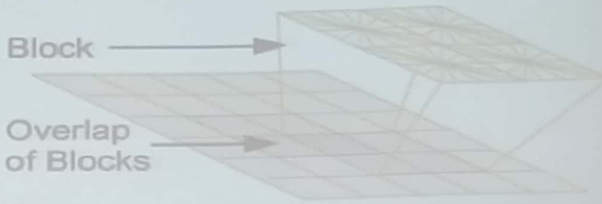


- Distance to bin centers
  - Left: 2, Right: 6
  - Top: 2, Bottom: 6
- Ratio Left-Right: 6/8, 2/8
- Ratio Top-Bottom: 6/8, 2/8
- Ratios:
  - 6/8*6/8 = 36/64 = 9/16
  - 6/8*2/8 = 12/64 = 3/16
  - 2/8*6/8 = 12/64 = 3/16
  - 2/8*2/8 = 4/64 = 1/16



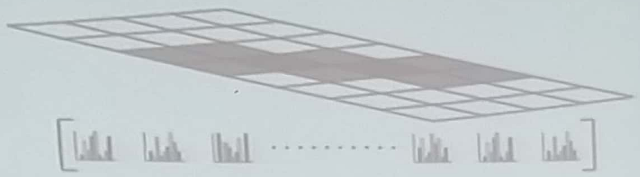
Blocks

- 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.)
  - Add a normalization epsilon to avoid division by zero



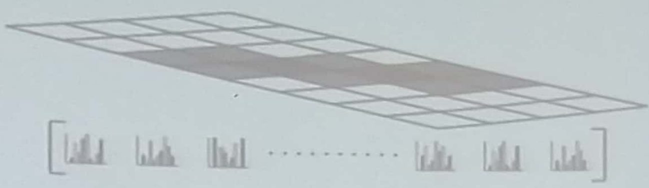
Final Descriptor

- Concatenation of Blocks

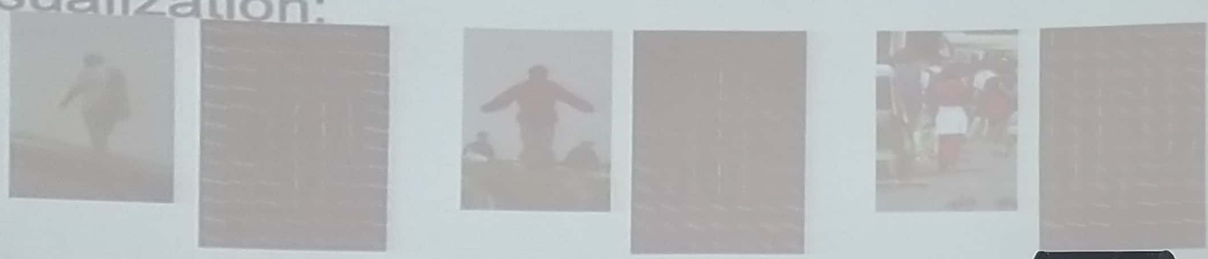


Final Descriptor

- Concatenation of Blocks



- Visualization:

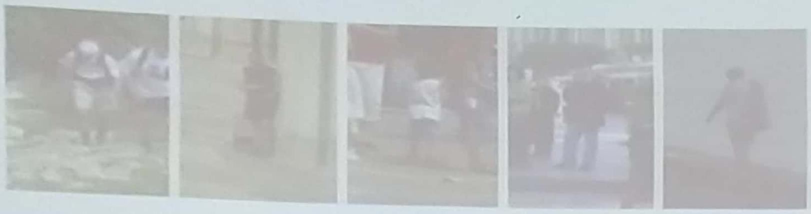


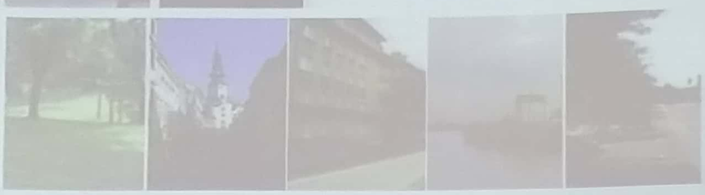
Engineering

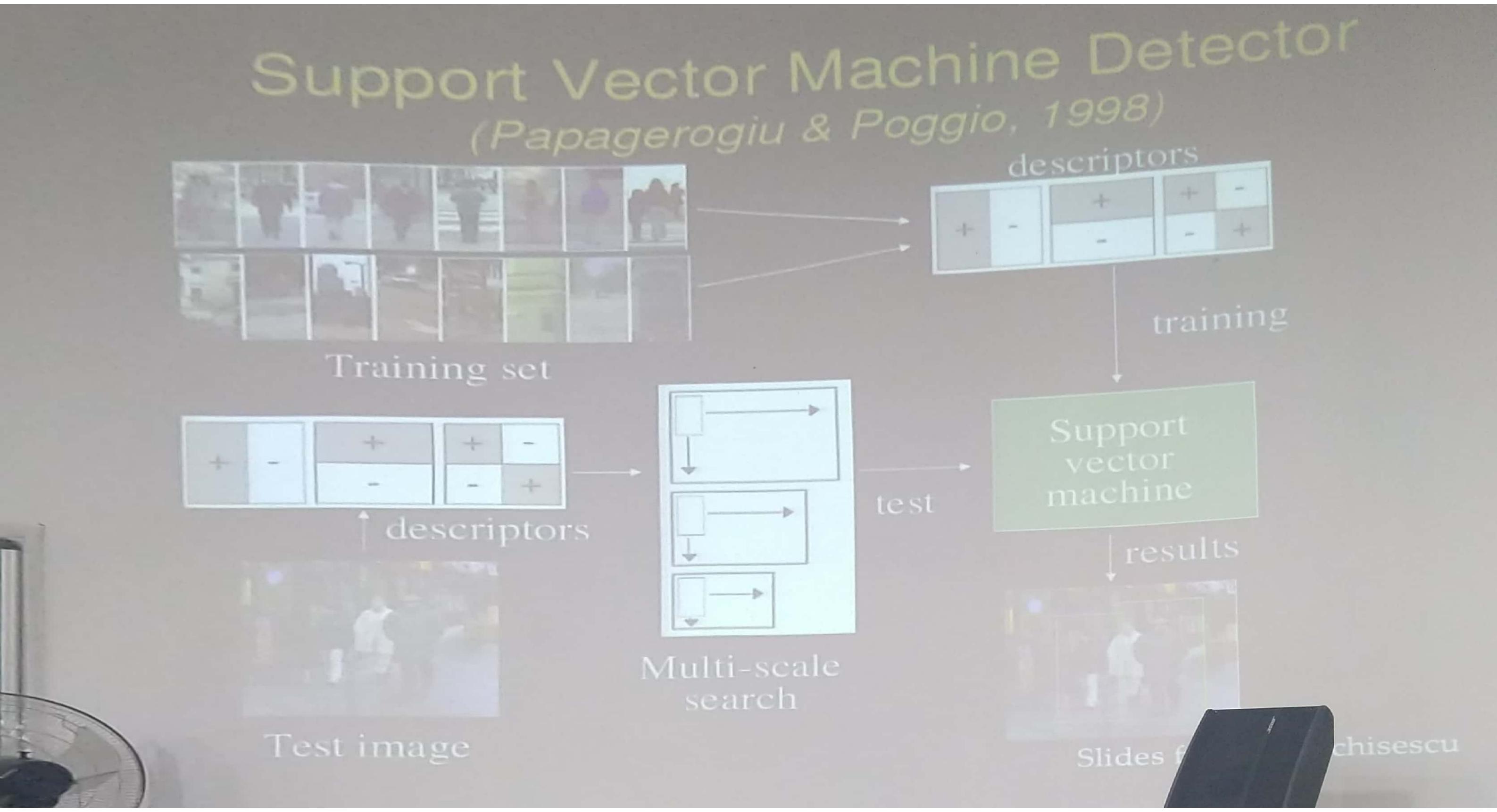
- Developing a feature descriptor requires a lot of engineering
  - Testing of parameters (e.g. size of cells, blocks, number of cells in a block, size of overlap)
  - Normalization schemes (e.g. L1, L2-Norms etc., gamma correction, pixel intensity normalization)
- An extensive evaluation of different 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







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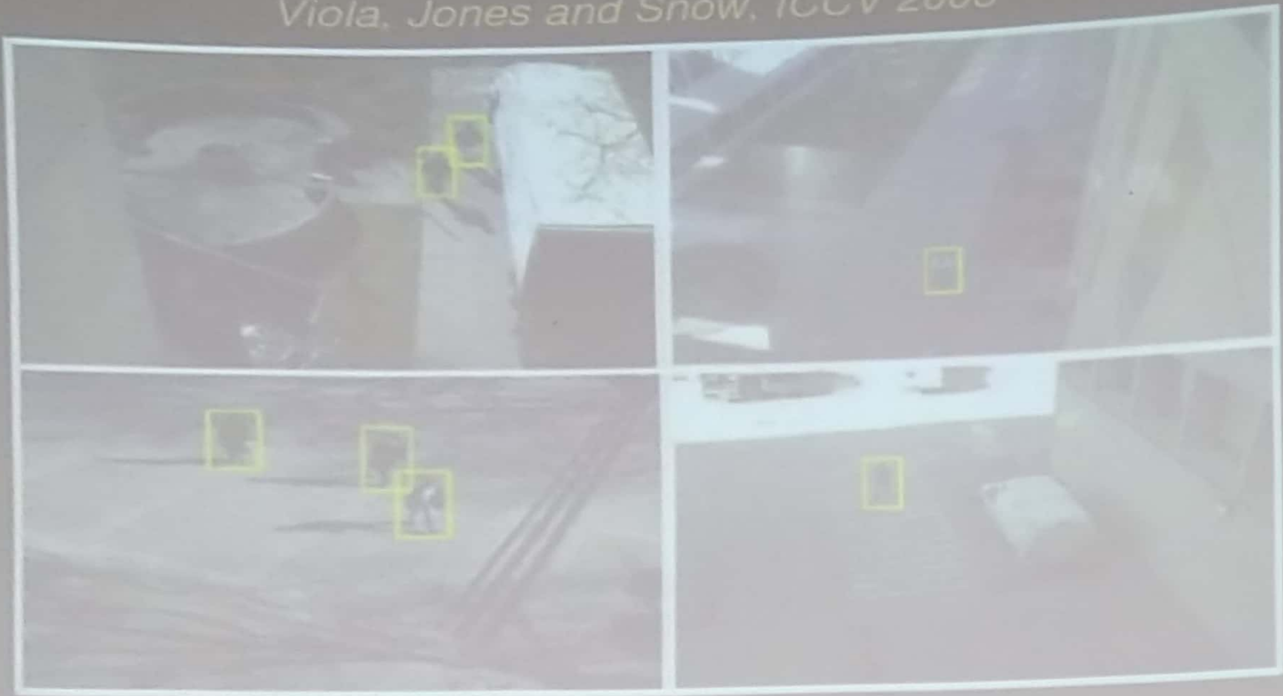
Dynamic Pedestrian Detection

Viola, Jones and Snow, ICCV 2003



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

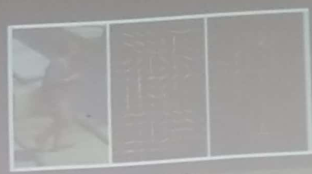
Slides f chisescu

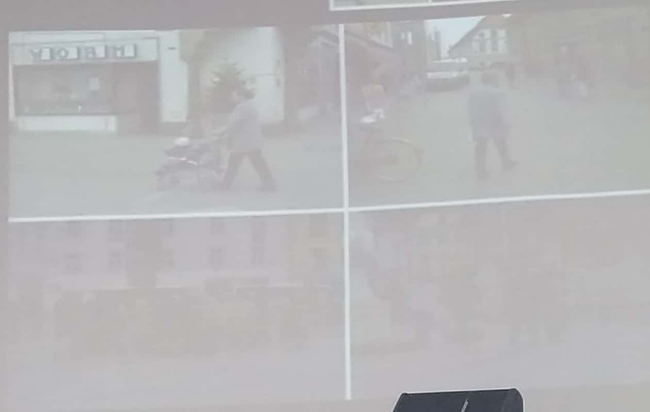
2d Global Detector

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





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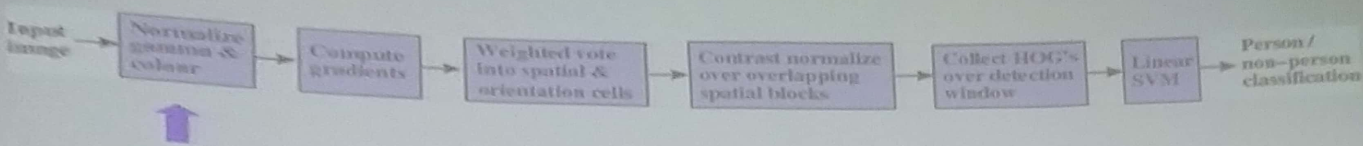
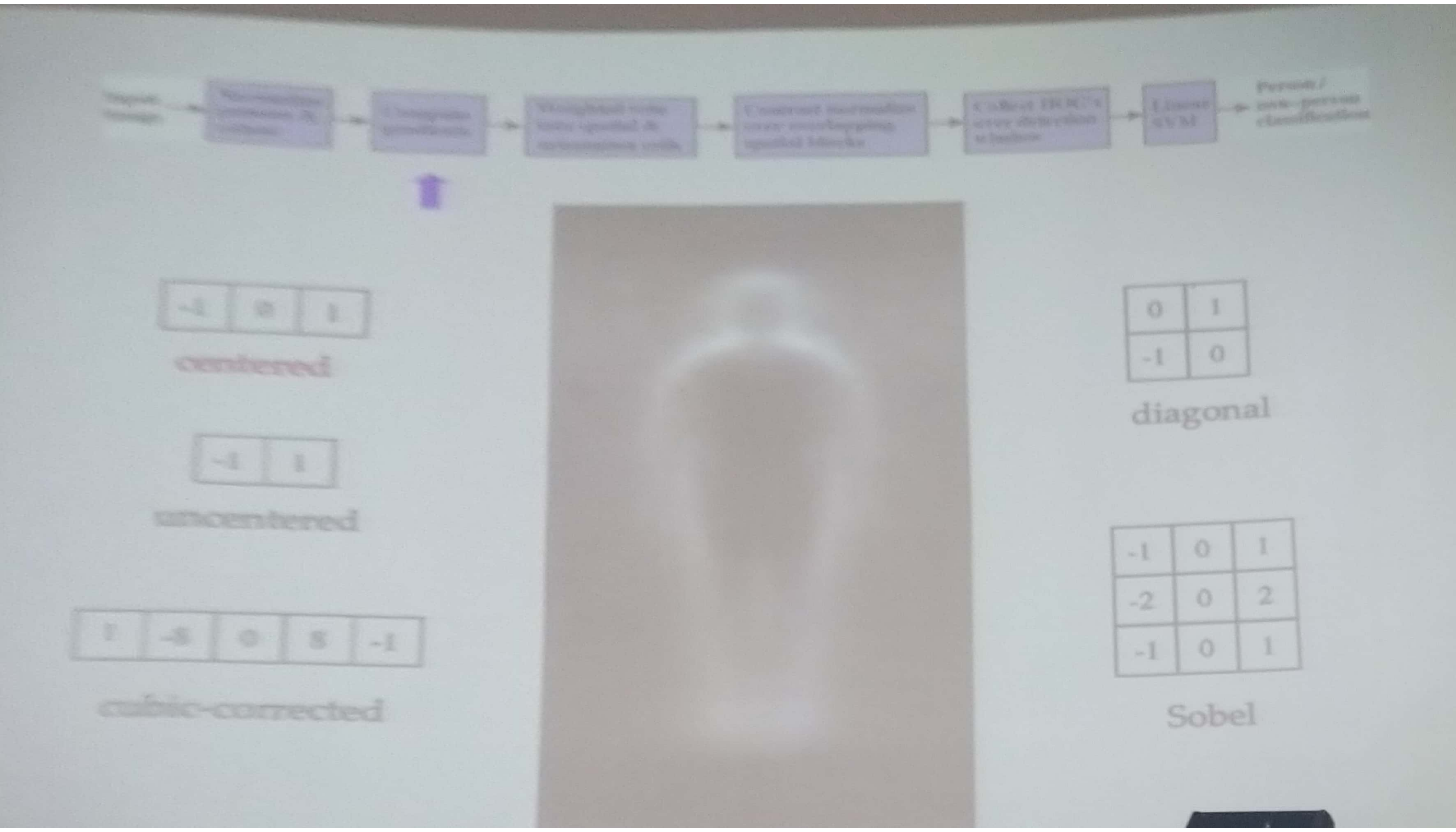
Feature Sets

- 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)

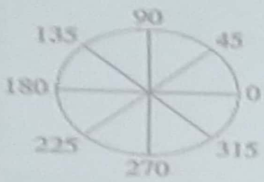


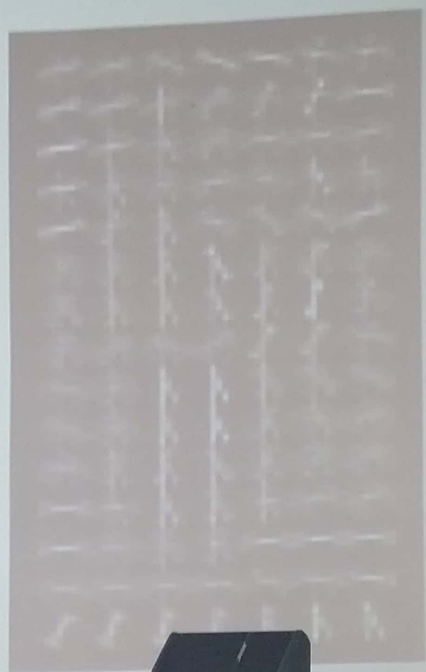
- Color Space: Tested with
  - RGB
  - LAB
  - Grayscale
- Gamma Normalization and Compression
  - Square root
  - Log
  - None


-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

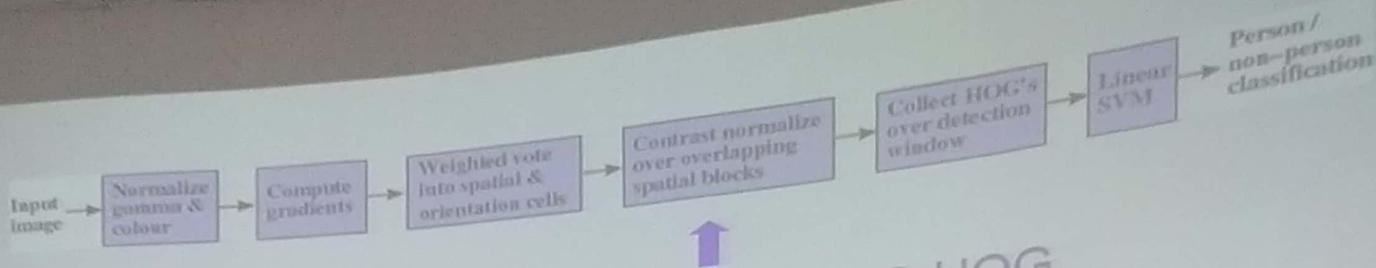
Input image → Normalize gamma & colour → Compute gradients → Weighted vote into spatial & orientation cells → Contrast normalize over overlapping spatial blocks → Collect HOG's over detection window → Linear SVM → Person / non-person classification

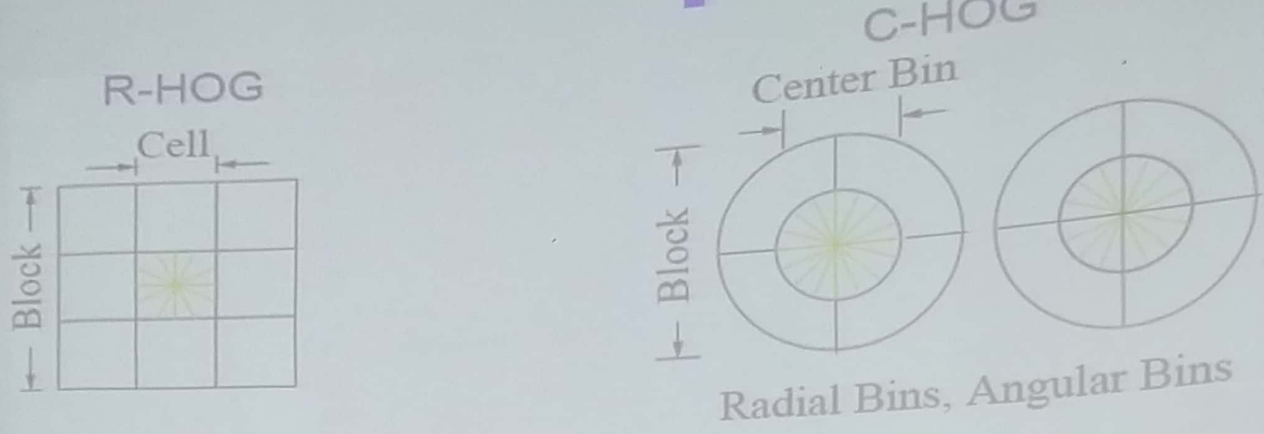
- Histogram of gradient orientations
  - -Orientation -Position





  - Weighted by magnitude



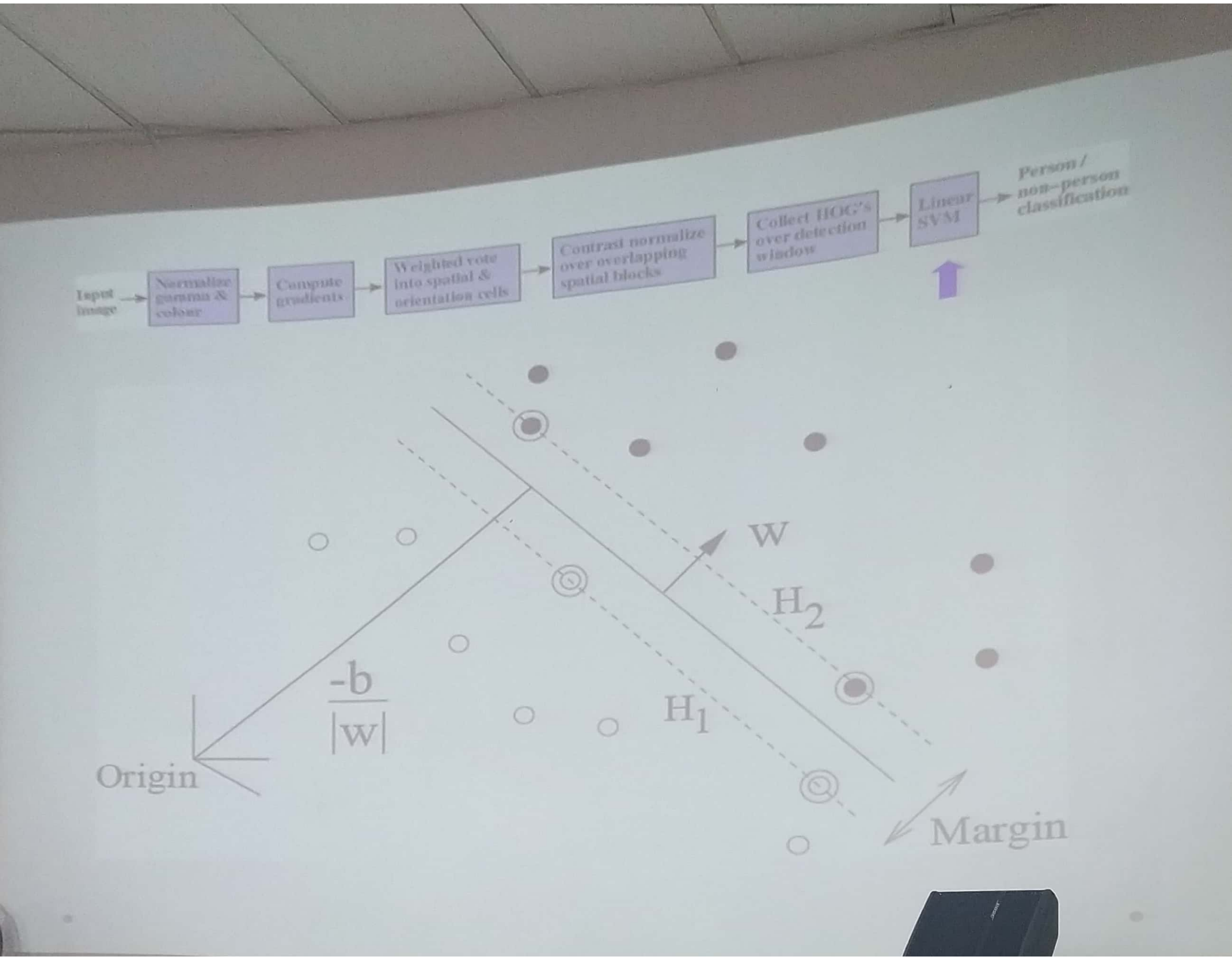


$L1-norm : v \longrightarrow v/(||v||_1 + \epsilon)$

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

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

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



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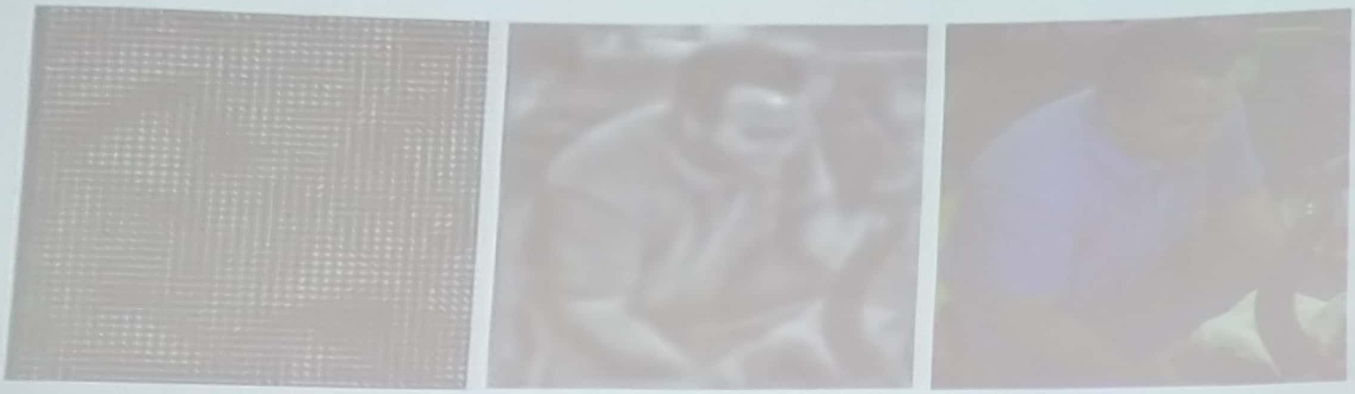
HOGgles: Visualizing Object Detection Features

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



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