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Object Detection and Recognition II

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Plan for today

- Dense feature template approaches:
  - Histogram of Oriented Gradients (HoG)
  - Deformable parts models (DPM)

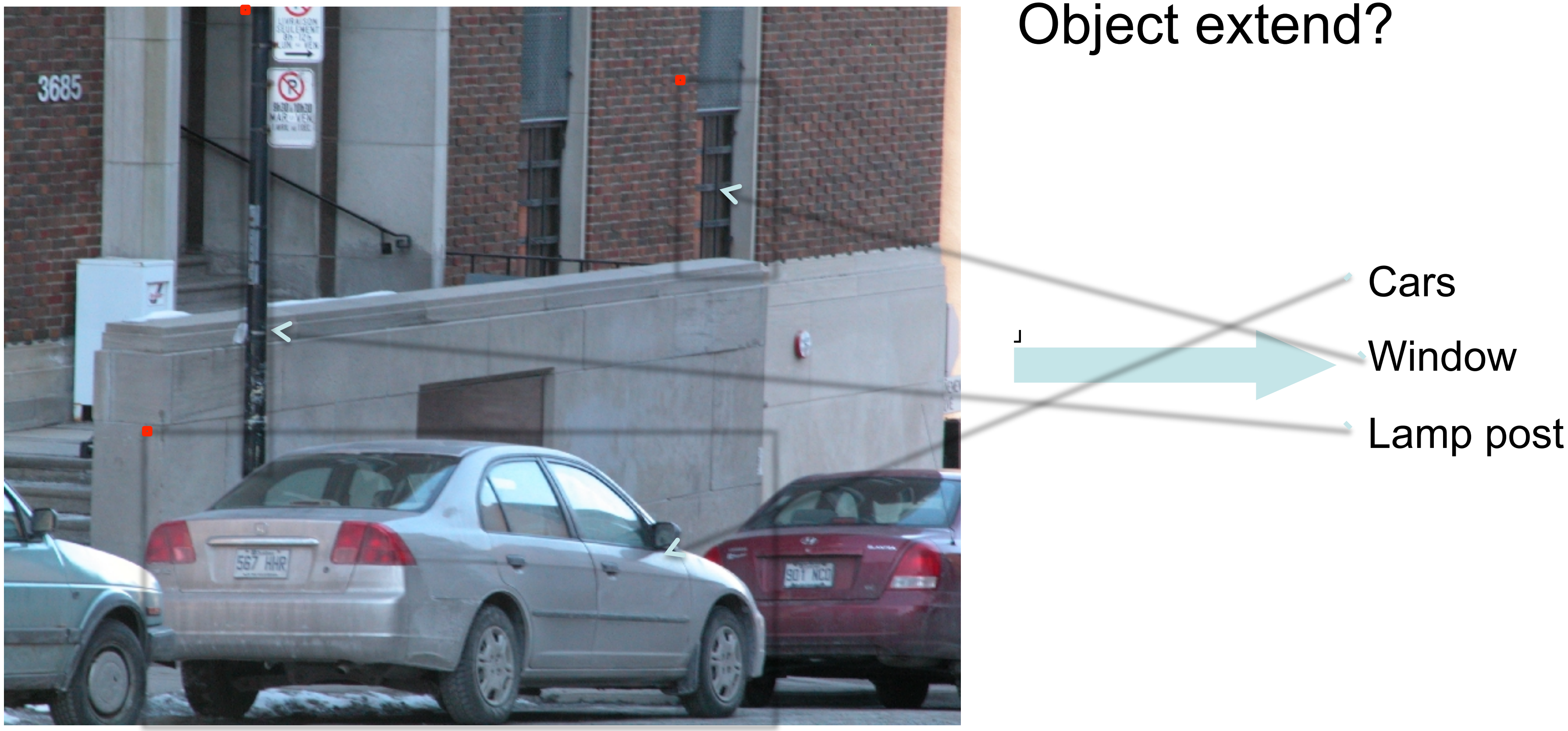
- Exercise class: Work on Assignment 2

Object detection and recognition

What is in this image?

Where?

Object extend?



Dense feature template approaches

Dense feature template approaches

Training:

- Extract features on object examples
- Train one or more classifiers to discriminate between object categories and background category

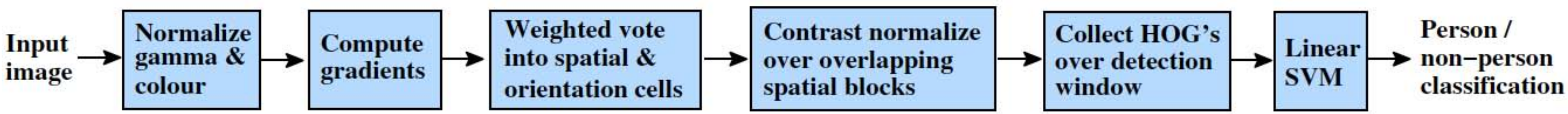
Query image:

- Apply the classifier to a detection window
- Slide the detection window across the image at all positions and scales
- Reduce nearby matches to avoid double detection (non-maxima suppression)

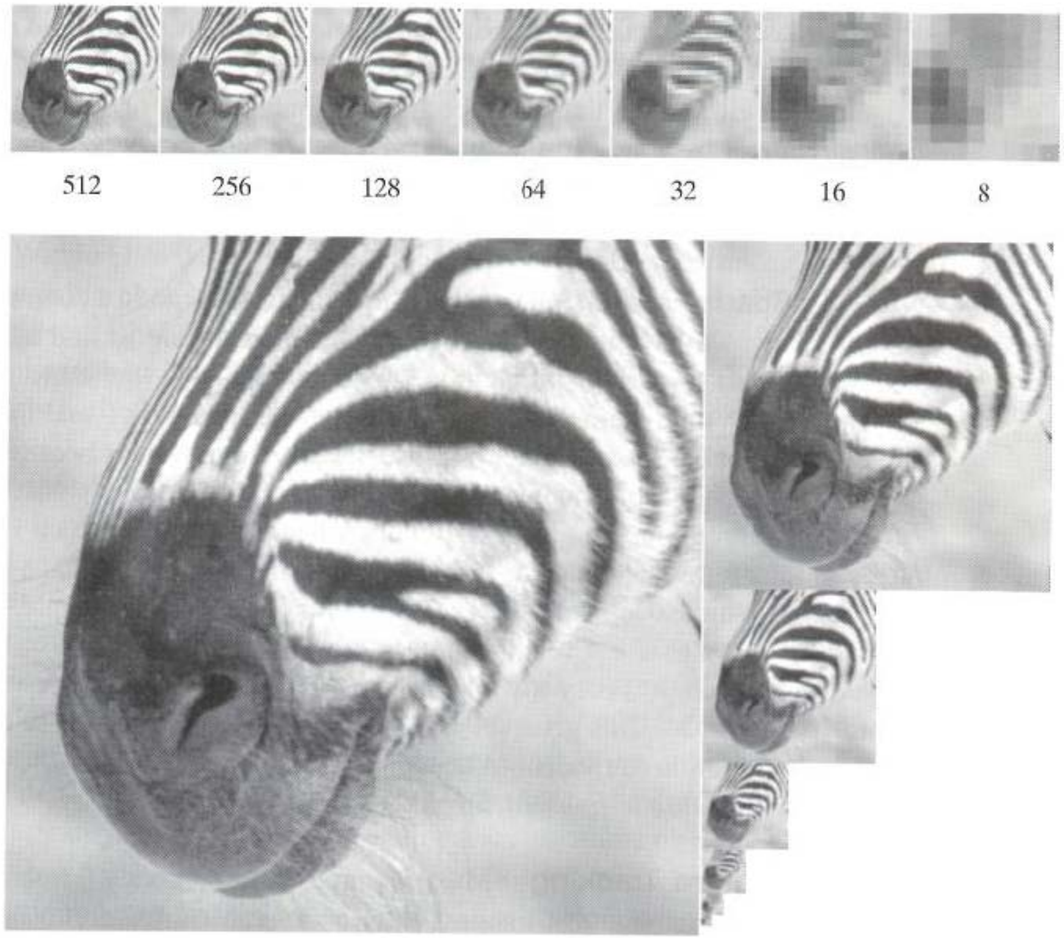
Example: Detecting people / pedestrians

Object detection using Histograms of Oriented Gradients (HoG) features (Dalal & Triggs'05)

- Using the sliding detection window approach $(64 \times 128 \text{ pixels})$.
- Normalization of image prior to detection:
  - Use all RGB channels
  - Optional: Apply power law gamma correction to each channel $I_{\text{out}} = cI_{\text{in}}^{\gamma}$
- Compute gradient image pyramid:

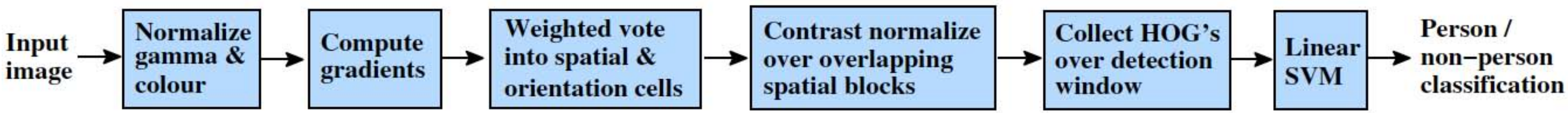


Recall: The Gaussian pyramid



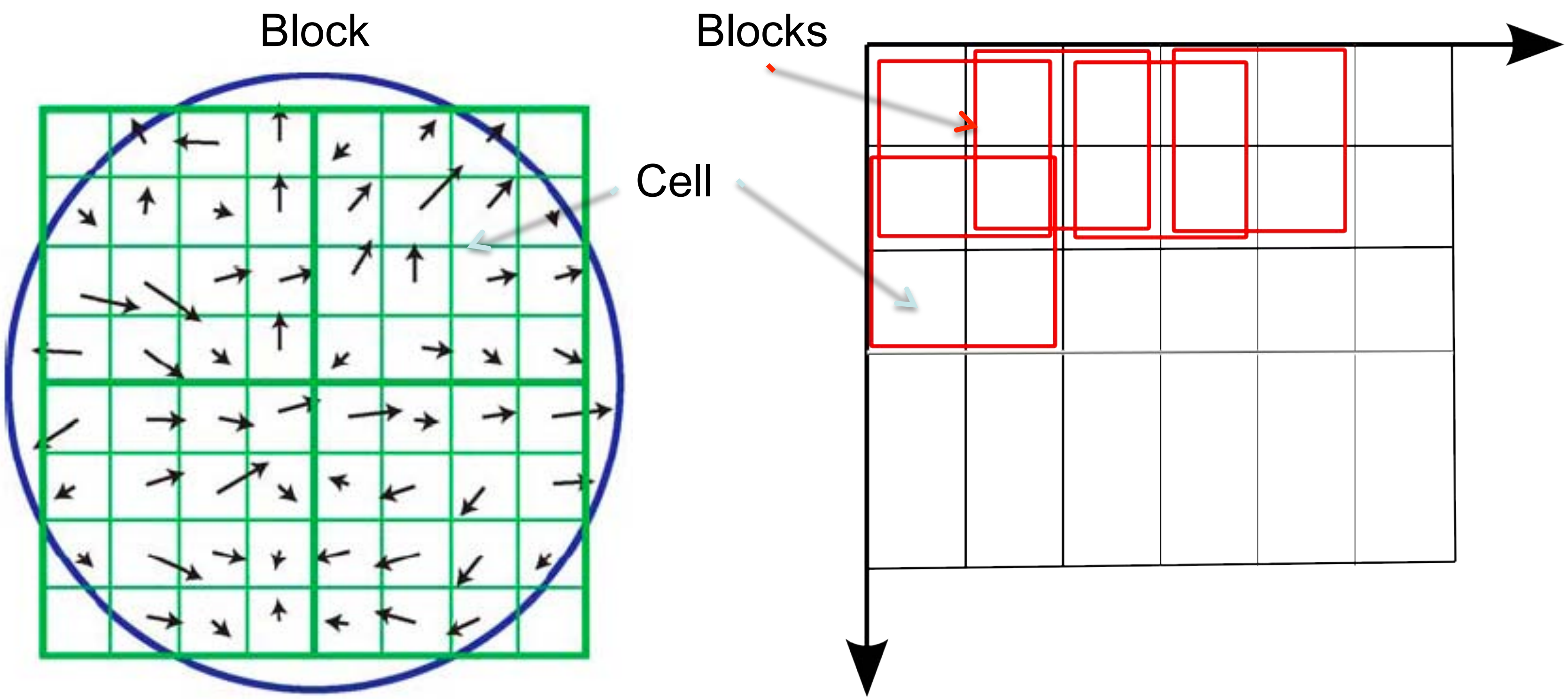
Object detection using Histograms of Oriented Gradients (HoG) features (Dalal & Triggs'05)

- Using the sliding detection window approach $(64 \times 128 \text{ pixels})$.
- Normalization of image prior to detection:
  - Use all RGB channels
  - Optional: Apply power law gamma correction to each channel $I_{\text{out}} = cI_{\text{in}}^{\gamma}$
- Compute gradient image pyramid:
  - For each color channel, compute intensity gradients
  - For each pixel, pick the gradient from the color channel with largest gradient magnitude (simple color gradient)
  - Detail: Dalal & Triggs do not pre-smooth the image and use the derivative approximation filter $[-1,0,1]$



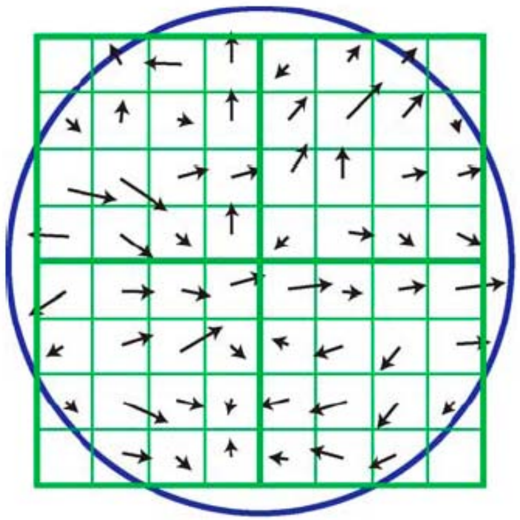
Histograms of Oriented Gradients (HoG) feature
(Applied to detection window)

- Divide the detection window into 8 x 8 pixels non-overlapping cells.
- Divide the detection window into 16 x 16 pixels overlapping (8 pixel stride) blocks covering 2 x 2 cells.



Histograms of Oriented Gradients (HoG) feature
(Applied to detection window)

- In each cell:
  - Compute a 9-bin gradient orientation histogram for the range $0°$ to $180°$ (different from SIFTs range of $0°$ to $360°$)
  - Use gradient magnitude weighting and linear interpolation in neighbor bins (just as in SIFT).
  - Use a Gaussian window function centered on the block to weigh gradients magnitude contributions to histograms as a function of distance to block center (just as in SIFT).

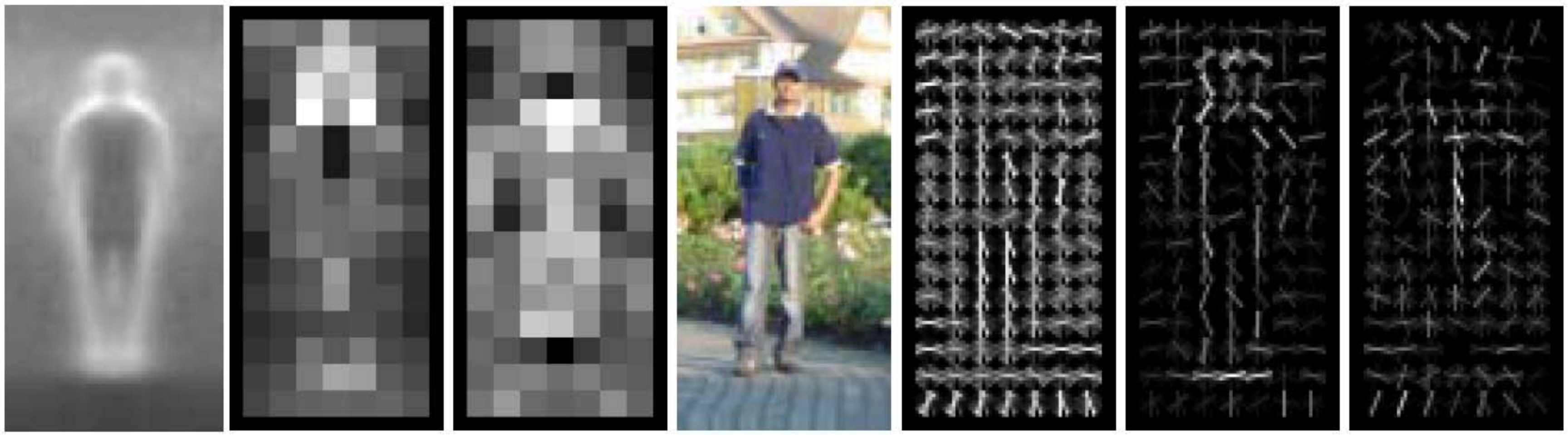


Histograms of Oriented Gradients (HoG) feature
(Applied to a detection window)

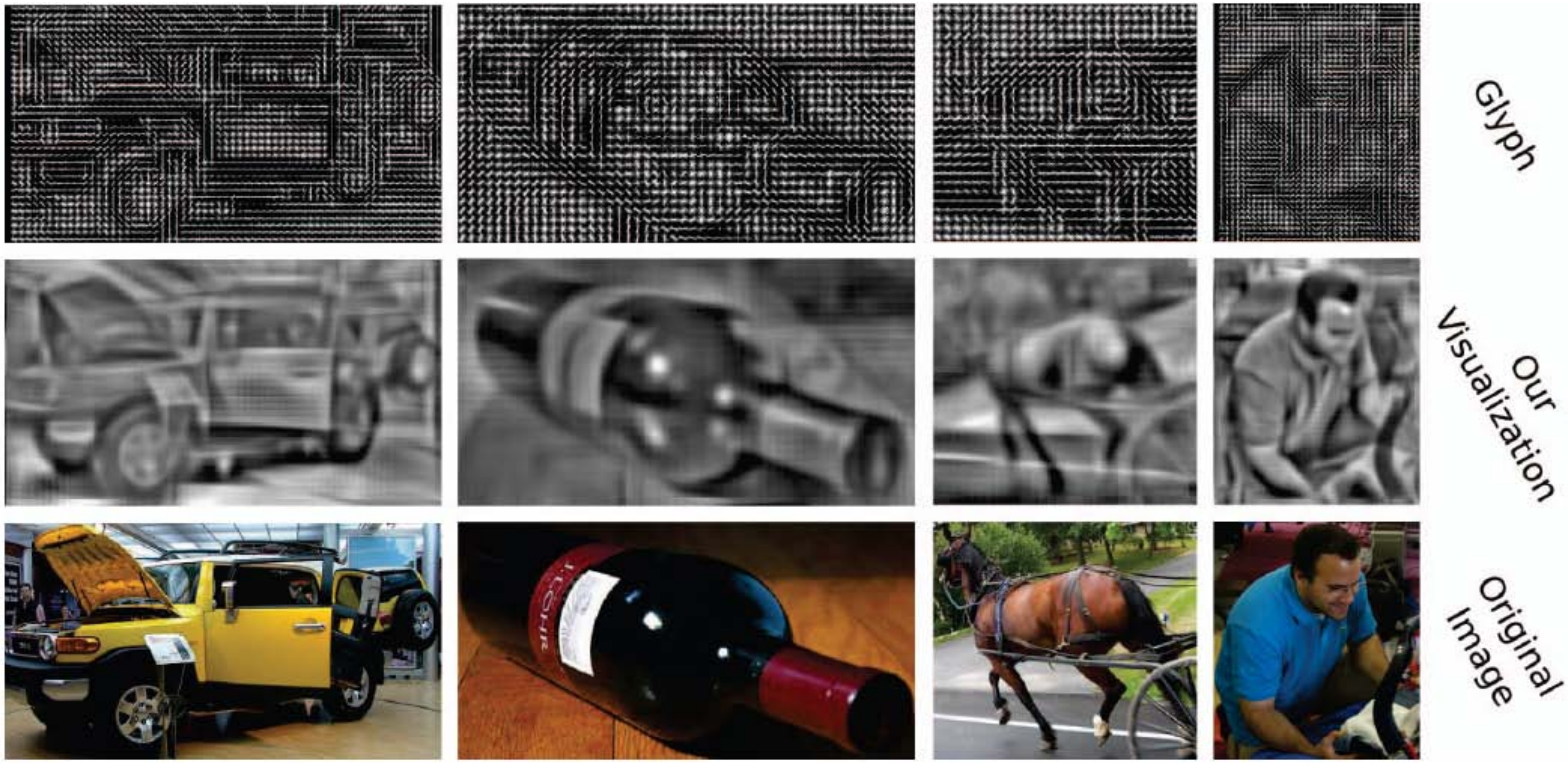
- For each block:
  - Concatenate cell histogram vectors to a feature vector $\mathbf{F}$
  - Normalize feature vector:
    - Euclidean: $\mathbf{F} = \mathbf{F} \Big/ \sqrt{\|\mathbf{F}\|^2 + \varepsilon^2}$
    - Peak clipping followed by renormalization (just as in SIFT)

- For detection window:
  - Concatenate block feature vectors to form a joint feature vector for whole of detection window
  - Dimensionality for 64 x 128 = 8192 pixels detection window: 9 bins x (7 x 15) blocks = 945 dimensions
  - Apply a classifier to the joint feature vector – the detection window (Dalal & Triggs uses a linear Support Vector Machine (SVM))

HoG features visualized



More human-friendly visualization of HoG



Vondrick et al 2013

Dense feature template approaches

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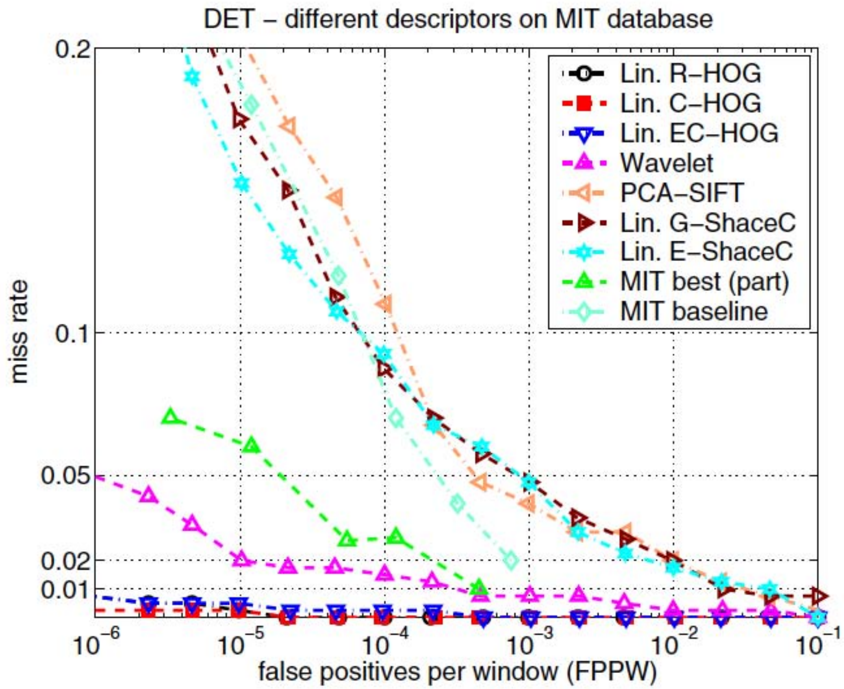
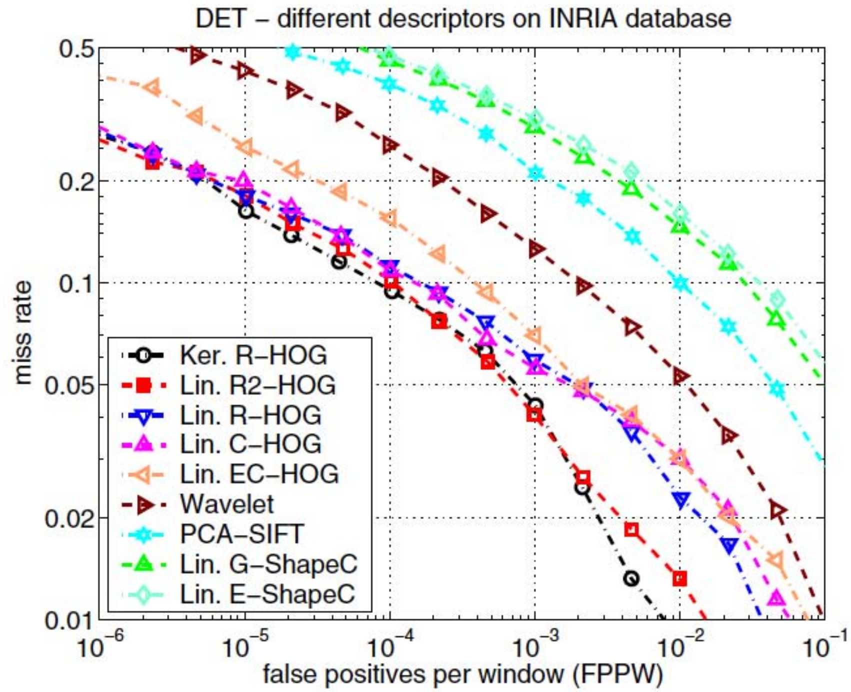
HoG results on detecting humans





Confusion matrix revisited

- Receiver operating characteristic (ROC):
  - TPR = TP / P (Recall)
  - FPR = FP / N
- Miss rate:
  - 1-recall = FN / P
- False positives per window tested:
  - FPPW = FP / (P+N)

		actual value		
		p	***n***	**total**
prediction outcome	***p'***	True Positive	False Positive	P'
	n'	False Negative	True Negative	N'
	total	P	N	

From Wikipedia 2012

Problems

This approach:

- Not really robust to occlusions – e.g. body parts being partially hidden, or intra-class variation.

- Not robust to rotations, e.g. a rotation of the object in the image plane.

Part based models

- Objects consist of parts which can help resolve partial occlusion.

- Being able to detect parts can provide cues about the presence of an object (feedback loop).

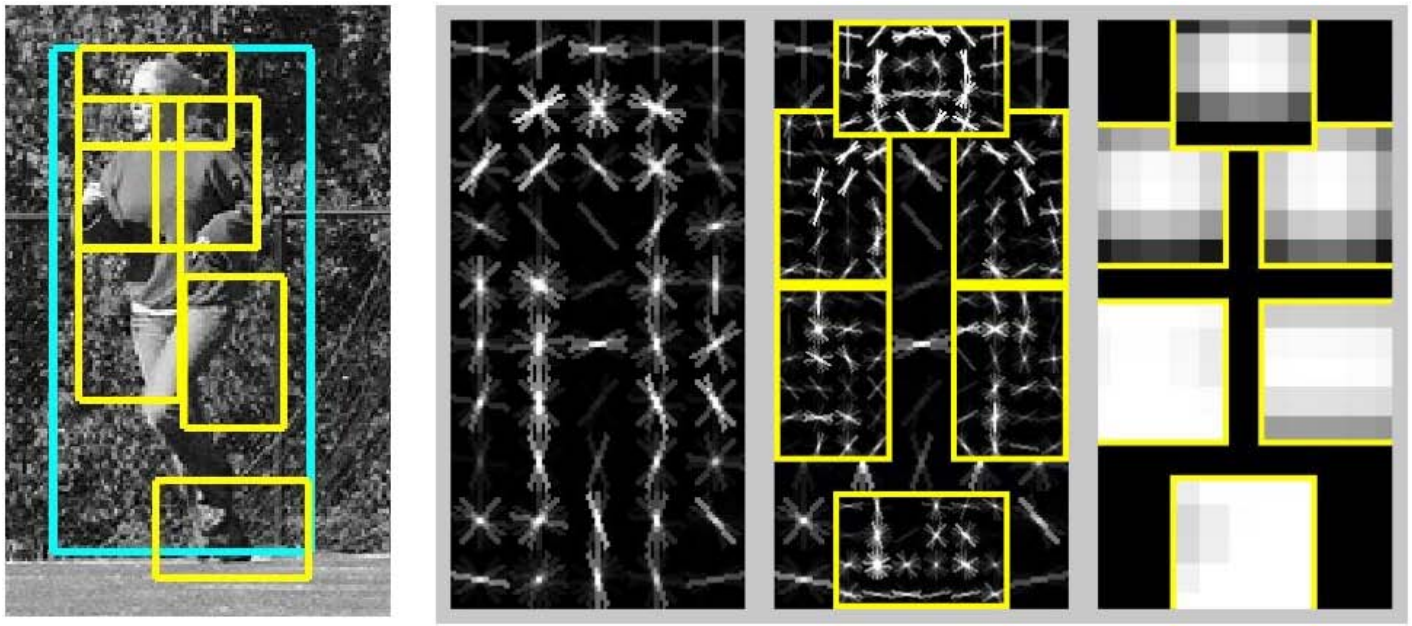
- Parts allow us to generalize models to handle large intra-class variation.

Deformable Parts Model (DPM)

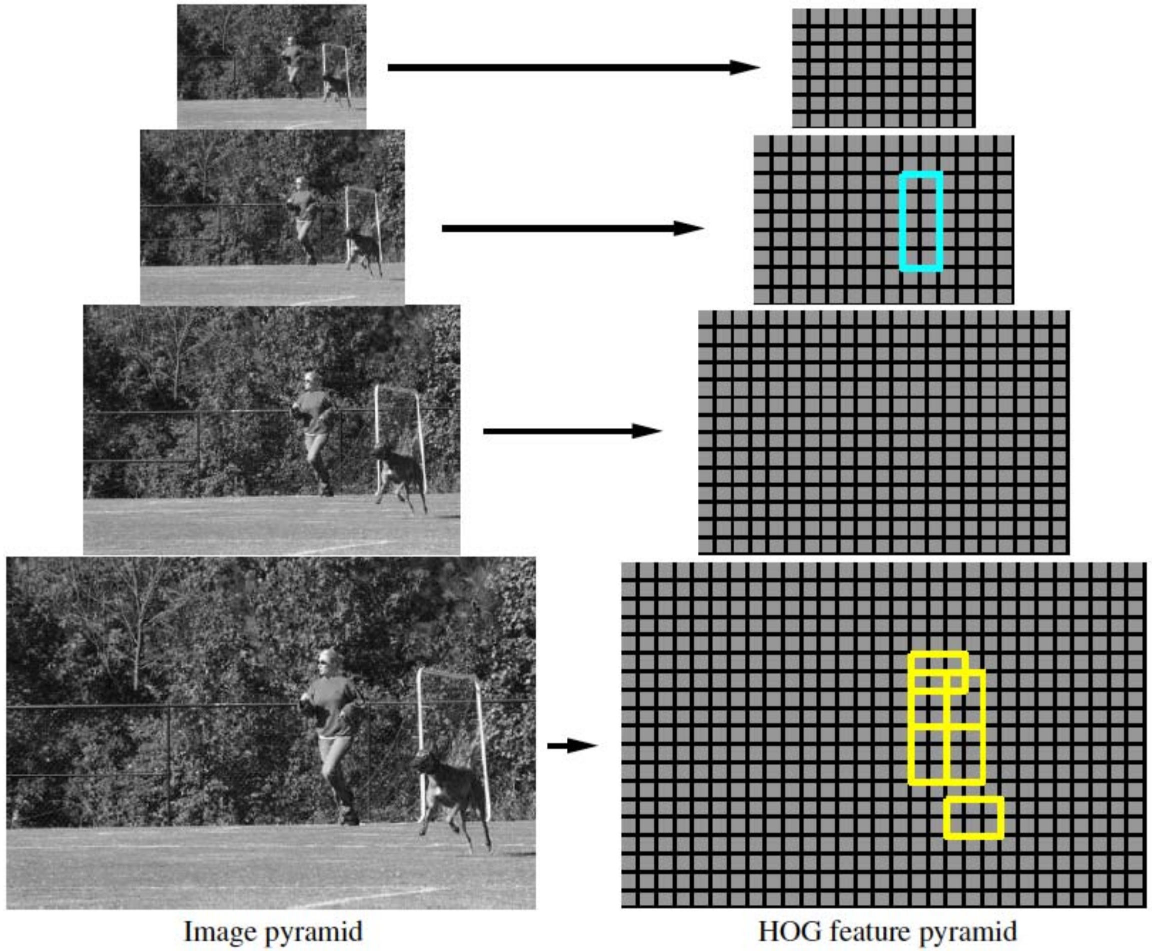
by Felzenszwalb et al CVPR 2008 & IJCV 2010

Deformable parts model consists of:

- A root filter (HoG)
- Parts models (HoG at higher resolution)
- Spatial parts placement model within root filter (a quadratic cost function per part)



Multi-scale detection in DPM

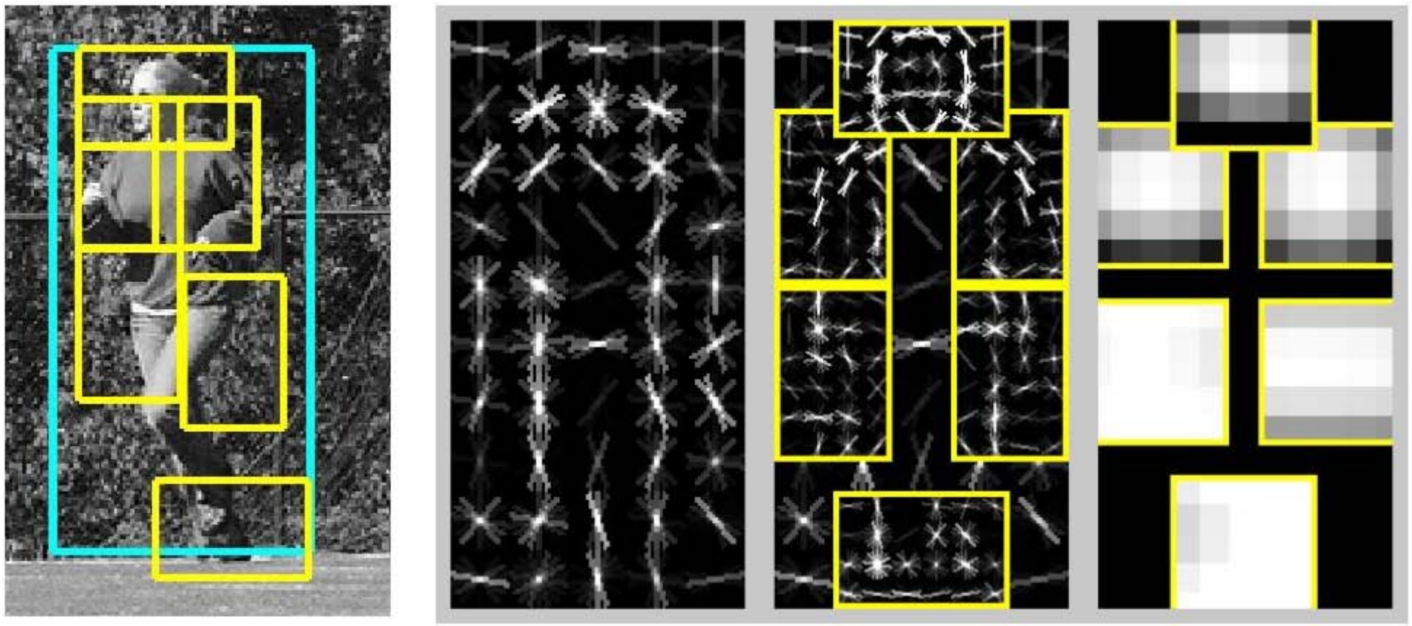


Deformable Parts Model (DPM)
by Felzenszwalb et al CVPR 2008 & IJCV 2010

- Detection by filtering HoG pyramids

$$\text{Response}(x,y,l) = \sum_{x',y'} F(x',y') \cdot \text{HoG}(x+x', y+y', l)$$

- Apply filter across the HoG pyramid and compute Score(x,y,l) = Root + Parts – Deformation cost



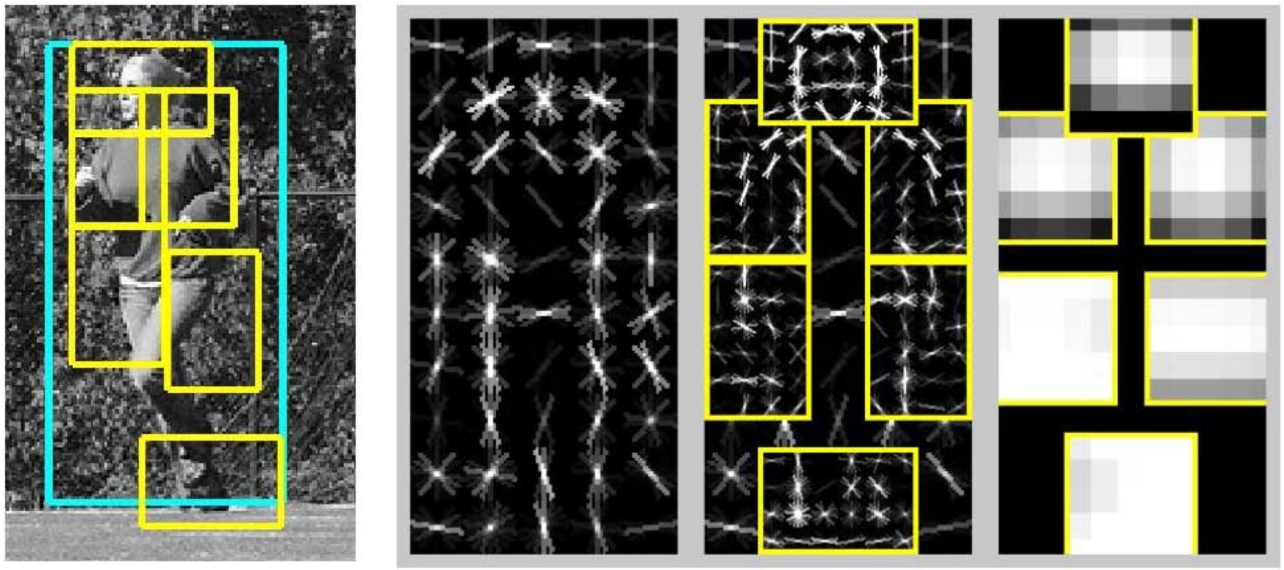
Deformable Parts Model (DPM)
by Felzenszwalb et al CVPR 2008 & IJCV 2010

- Filters and parts displacement parameters are learnt with a SVM classifier using latent variable SVM classifier

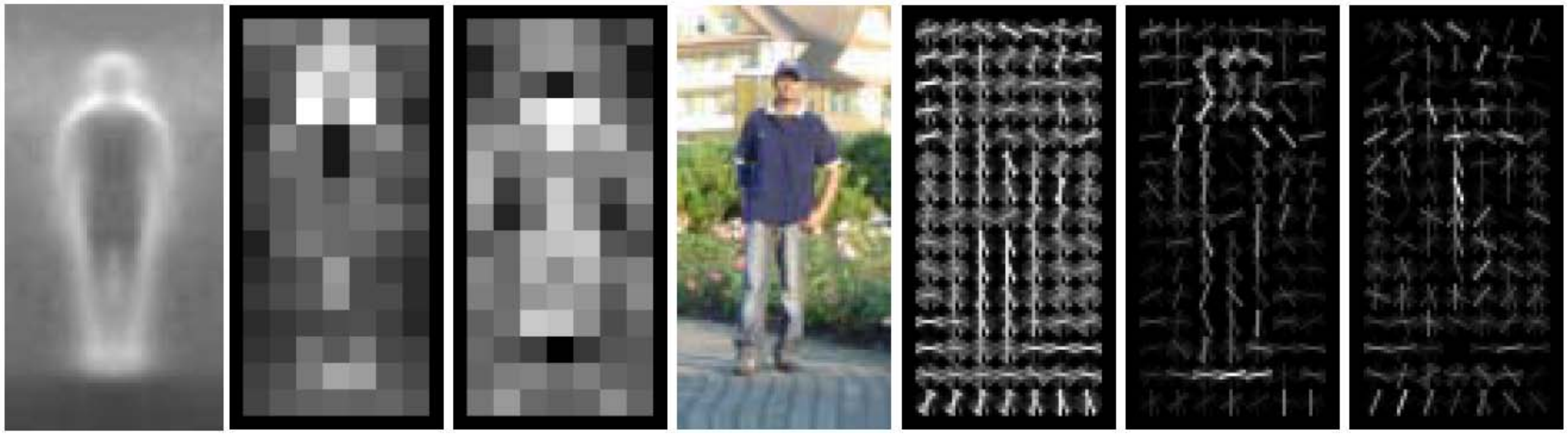
$$f_\beta(x) = \max_z \beta \cdot \Phi(x,z) \quad \text{, labels } f_\beta(x) > 0 \ \text{ or } \ f_\beta(x) \le 0$$

$$\beta = \left(F_0, F_1, \ldots, F_n, d_1, \ldots, d_n\right)$$

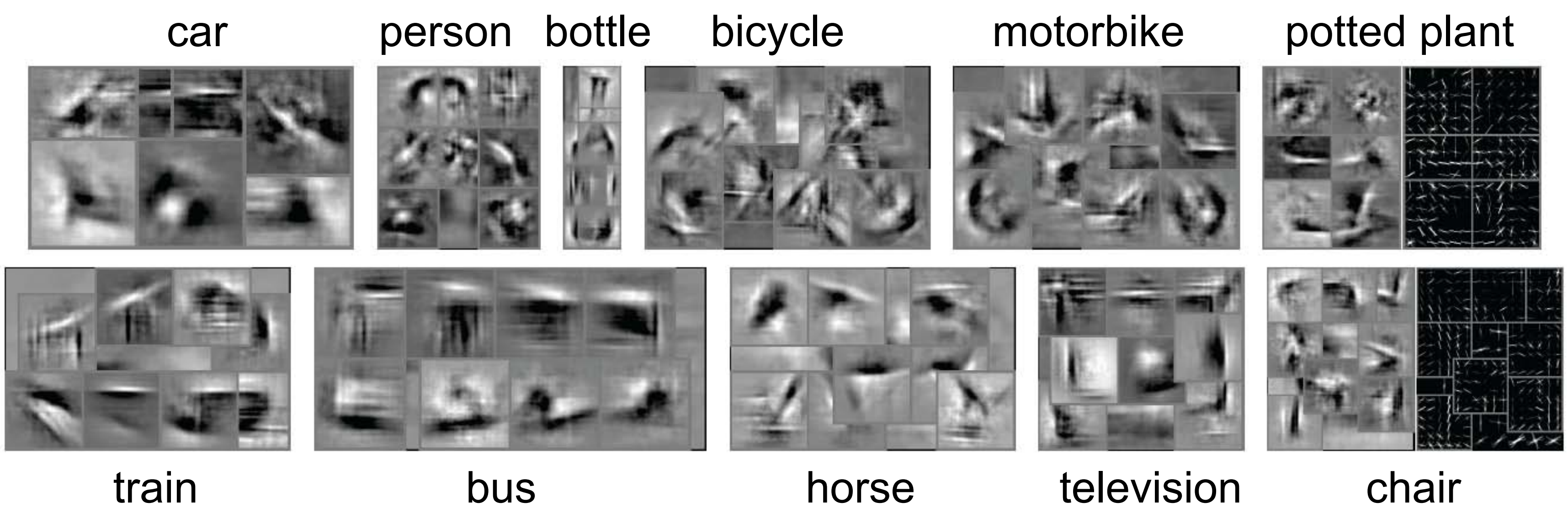
$$\Phi(x,z) = \left(\mathrm{HoG}_0(x), \mathrm{HoG}_1(x), \ldots, \mathrm{HoG}_n(x), -\phi_d(x_1), \ldots, -\phi_d(x_n)\right)$$



Root classifier similar to original HoG



Visualization of some DPM parts features



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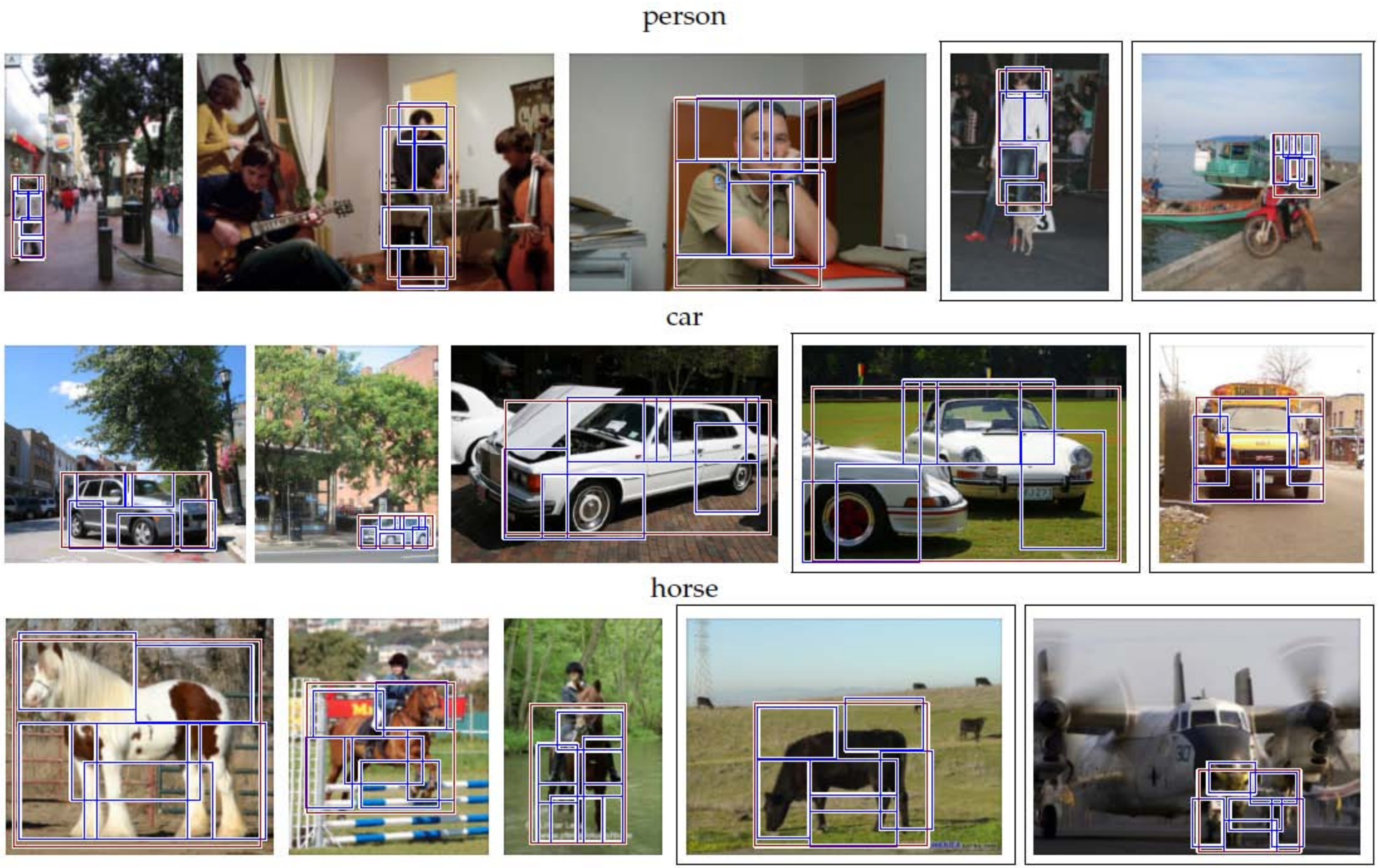
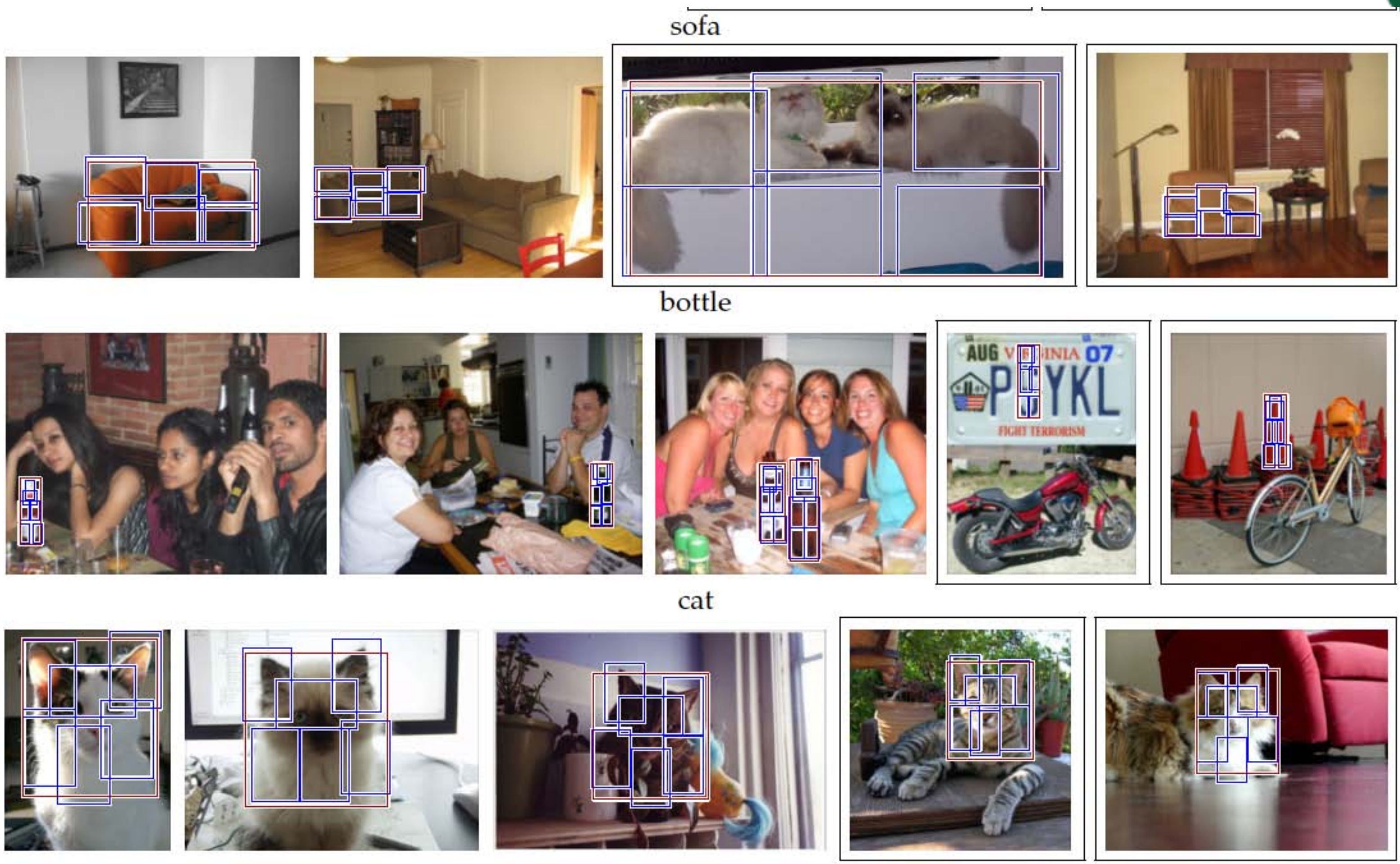
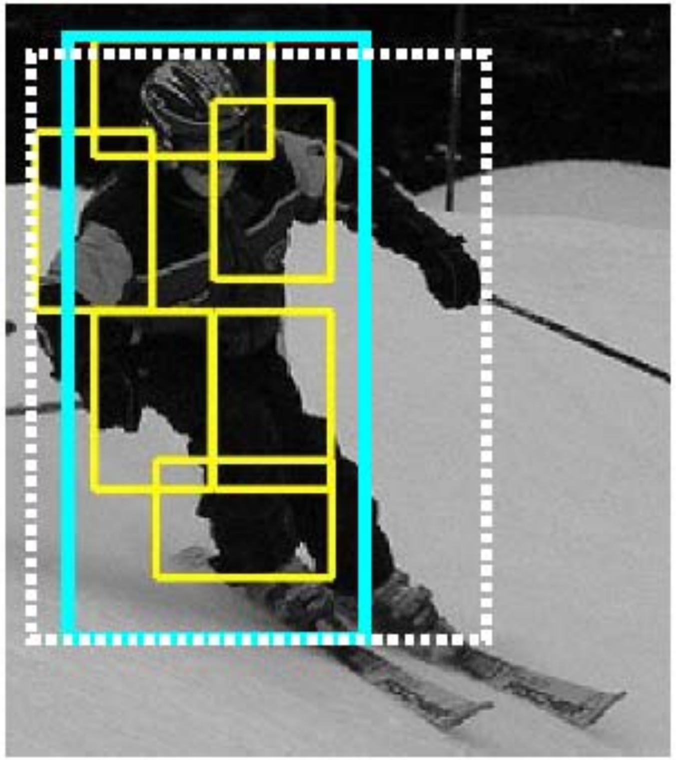
DPM results



DPM results

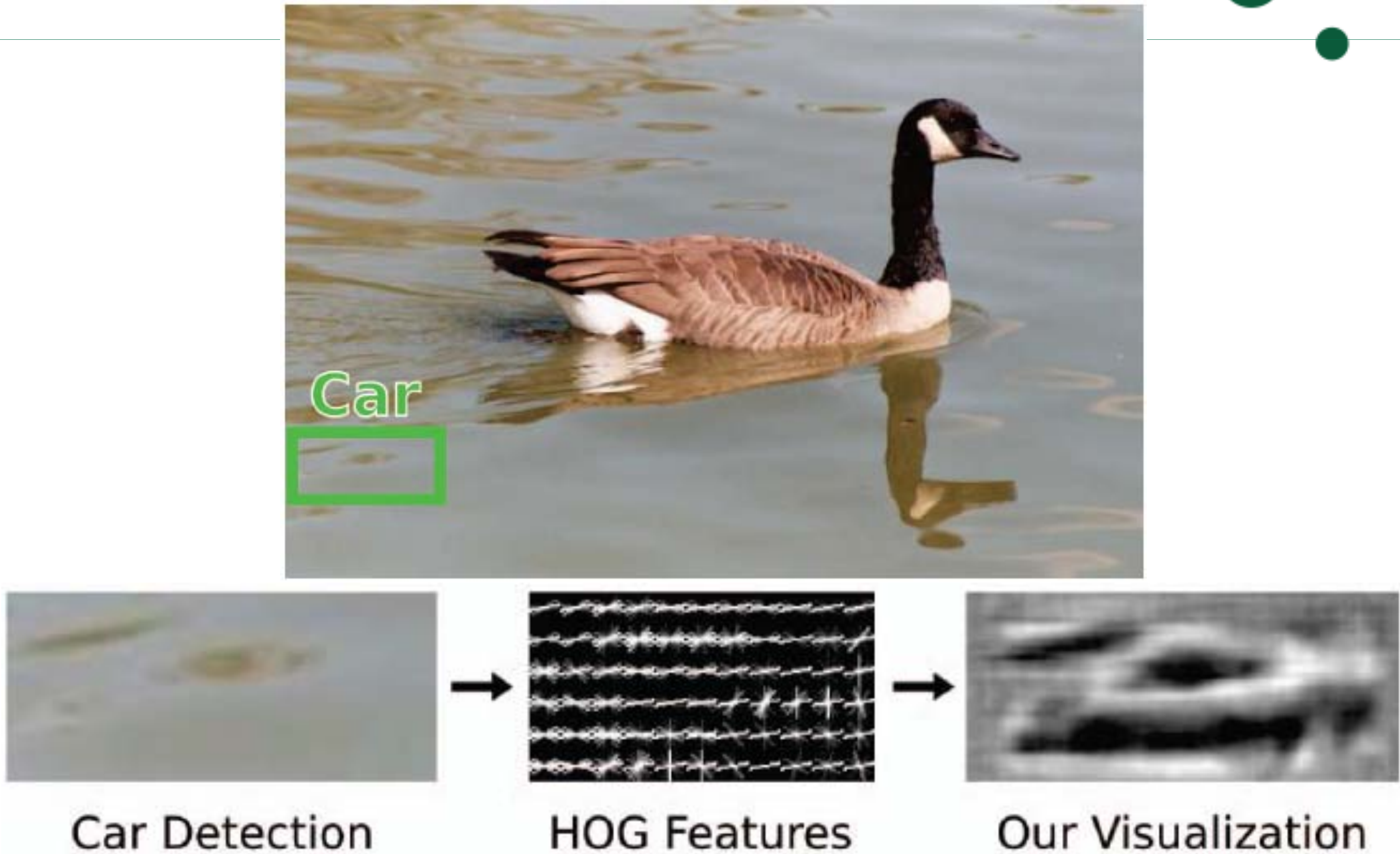


Hard negative examples for person detector



- Felzenszwalb et al propose a learning strategy to improve performance of this type of examples.

Visualization of the cause of failure



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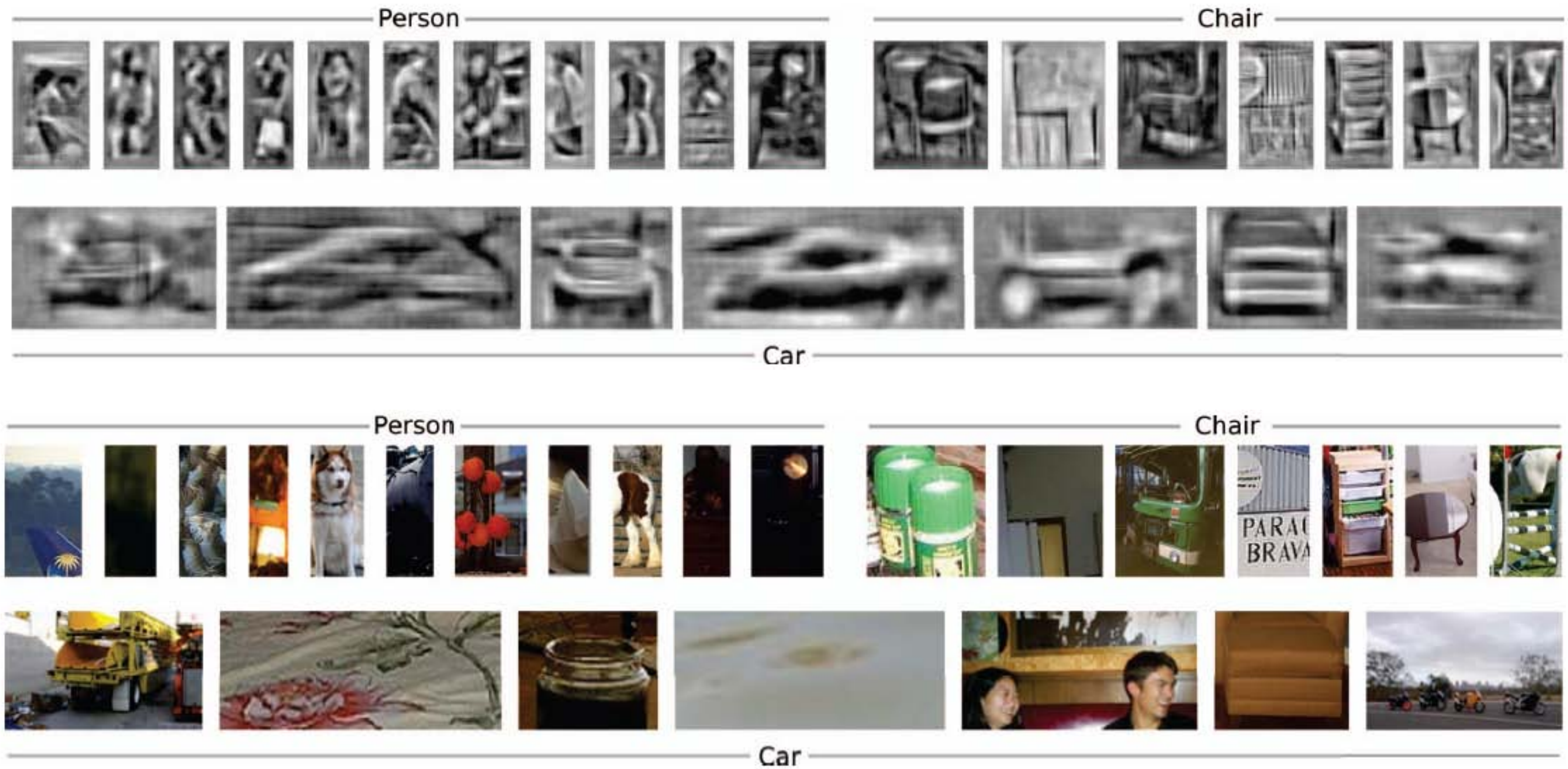
Do you see the same objects as DPM?



Vondrick et al 2013

Other approaches in object recognition / detection

- Bag of visual words together with interest points
- Shape features (instead of only texture / local structure)
- Object taxonomies (e.g. using language resources such as WordNet – a database of cognitve synonyms)
- Domain specific knowledge (e.g. taxonomy of flower or bird species)

Summary

- For object detection and recognition we can use:
  - Interest point based approaches (can be extended to bag of visual words)
  - Dense feature template approaches
  - Parts models
- Dense feature template approaches:
  - Histogram of Oriented Gradients (HoG)
  - Deformable parts models (DPM)
- HoG captures first order structure locally and encodes higher order structure through cell grid. Maybe we can do better?

Literature

Reading material:

- Everingham et al IJCV 2010 (State of the art)
- Dalal & Triggs (CVPR'05) (HoG details)
- Felzenszwalb et al CVPR 2008 (DPM details)

Or

- Felzenszwalb et al IEEE T-PAMI 2010 (DPM details)

Additional material:

- Vondrick et al (ICCV 2013) (Visualizing HoG and DPM)