Computer Vision 2 – Lecture 4

Tracking by Detection (28.04.2016)

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Computer Vision
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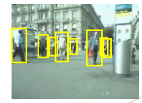
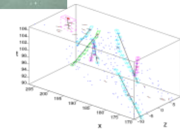
Content of the Lecture

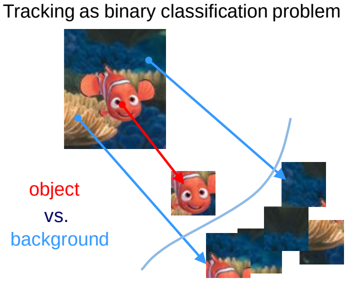
- Single-Object Tracking
  - *Background modeling*
  - Template based tracking
  - *Color based tracking*
  - *Contour based tracking*
  - Tracking by online classification
  - **Tracking-by-detection**
- Bayesian Filtering
- Multi-Object Tracking
- Visual Odometry
- Visual SLAM & 3D Reconstruction





Recap: Tracking as Online Classification

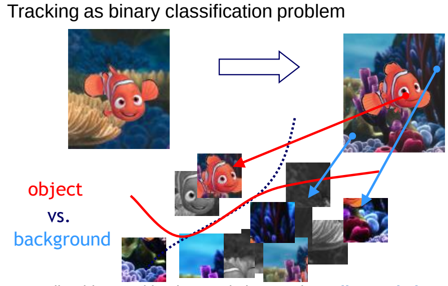
- Tracking as binary classification problem



Slide credit: Helmut Grabner Image source: Disney/Pixar

Recap: Tracking as Online Classification

- Tracking as binary classification problem



  - Handle object and background changes by **online updating**

Slide credit: Helmut Grabner Image source: Disney/Pixar

Recap: AdaBoost – "Adaptive Boosting"

- Main idea [Freund & Schapire, 1996]
  - Iteratively select an ensemble of classifiers
  - Reweight misclassified training examples after each iteration to focus training on difficult cases.
- Components
  - $h_m(\mathbf{x})$: "weak" or base classifier
    - Condition: <50% training error over any distribution
  - $H(\mathbf{x})$: "strong" or final classifier
- AdaBoost:
  - Construct a strong classifier as a thresholded linear combination of the weighted weak classifiers:

$$H(\mathbf{x}) = sign\left(\sum_{m=1}^{M} \alpha_m h_m(\mathbf{x})\right)$$

Recap: AdaBoost – Algorithm

1. Initialization: Set $w_n^{(1)} = \frac{1}{N}$ for $n = 1,\ldots,N$.
2. For $m = 1,\ldots,M$ iterations
   a) Train a new weak classifier $h_m(\mathbf{x})$ using the current weighting coefficients $\mathbf{W}^{(m)}$ by minimizing the weighted error function

$$J_m = \sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}) \neq t_n) \qquad I(A) = \begin{cases} 1, & \text{if } A \text{ is true} \\ 0, & \text{else} \end{cases}$$

   b) Estimate the weighted error of this classifier on $\mathbf{X}$:

$$\epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}$$

   c) Calculate a weighting coefficient for $h_m(\mathbf{x})$:

$$\alpha_m = \ln\left\{\frac{1-\epsilon_m}{\epsilon_m}\right\}$$

   d) Update the weighting coefficients:

$$w_n^{(m+1)} = w_n^{(m)} \exp\left\{\alpha_m I(h_m(\mathbf{x}_n) \neq t_n)\right\}$$

From Offline to Online Boosting

- Main issue
  - Computing the weight distribution for the samples.
  - We do not know a priori the difficulty of a sample! (Could already have seen the same sample before...)
- Idea of Online Boosting
  - Estimate the importance of a sample by propagating it through a set of weak classifiers.
  - This can be thought of as modeling the information gain w.r.t. the first n classifiers and code it by the importance weight λ for the n+1 classifier.
  - Proven [Oza]: Given the same training set, Online Boosting converges to the same weak classifiers as Offline Boosting in the limit of $N \to \infty$ iterations.

N. Oza and S. Russell. Online Bagging and Boosting. Artificial Intelligence and Statistics, 2001.

Recap: From Offline to Online Boosting

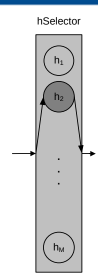
off-line	on-line
Given:	**Given**:
- set of labeled training samples $\mathcal{X} = \{\langle \mathbf{x}_1, y_1\rangle, ..., \langle \mathbf{x}_L, y_L\rangle \mid y_i \pm 1\}$	- ONE labeled training sample $\langle \mathbf{x}, y\rangle \mid y \pm 1$
- weight distribution over them $D_0 = 1/L$	- strong classifier to update
	- initial importance $\lambda = 1$
for n = 1 to N	for n = 1 to N
- train a weak classifier using samples and weight dist. $h_n^{weak}(\mathbf{x}) = \mathcal{L}(\mathcal{X}, D_{n-1})$	- update the weak classifier using samples and importance $h_n^{weak}(\mathbf{x}) = \mathcal{L}(h_n^{weak}, \langle x, y\rangle, \lambda)$
- calculate error e_n	- update error estimation $\hat{e_n}$
- calculate weight $\alpha_n = f(e_n)$	- update weight $\alpha_n = f(\hat{e}_n)$
- update weight dist. D_n	- update importance weight λ
next	next
$h^{strong}(\mathbf{x}) = \text{sign}(\sum_{n=1}^{N} \alpha_n \cdot h_n^{weak}(\mathbf{x}))$	$h^{strong}(\mathbf{x}) = \text{sign}(\sum_{n=1}^{N} \alpha_n \cdot h_n^{weak}(\mathbf{x}))$

Recap: Online Boosting for Feature Selection

- Introducing "Selector"
  - Selects one feature from its local feature pool

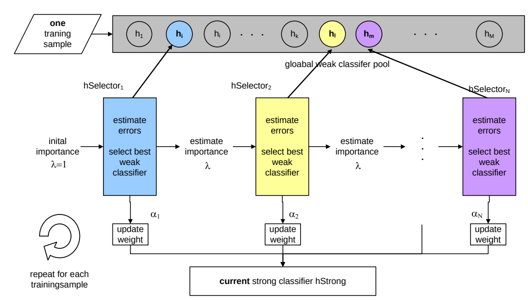
$$\mathcal{H}^{weak} = \{h_1^{weak}, ..., h_M^{weak}\}$$
$$\mathcal{F} = \{f_1, ..., f_M\}$$
$$h^{sel}(\mathbf{x}) = h_m^{weak}(\mathbf{x})$$
$$m = \arg\min_i e_i$$

On-line boosting is performed on the Selectors and not on the weak classifiers directly.

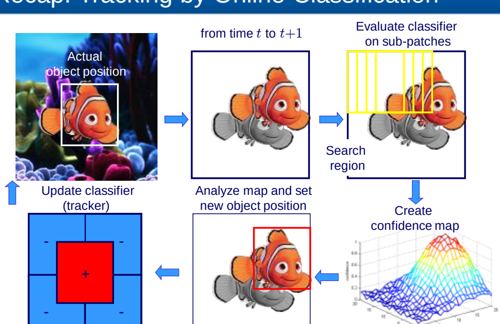


H. Grabner and H. Bischof. On-line boosting and vision. CVPR, 2006.

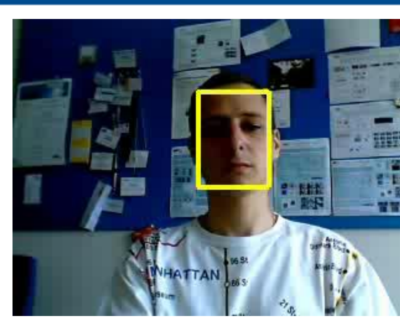
Recap: Direct Feature Selection



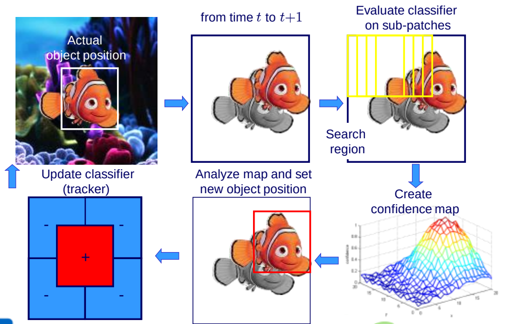
Recap: Tracking by Online Classification



When Does It Fail...



Why Does It Fail?



Slide credit: Helmut Grabner Image source: Disney/Pixar

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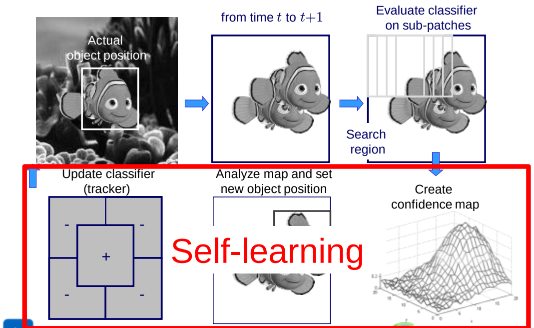
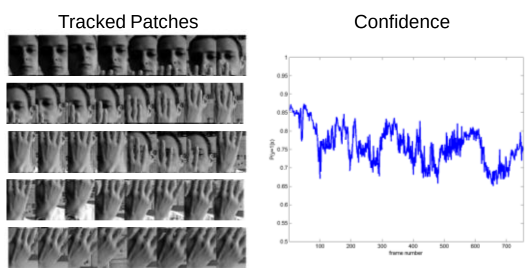


Slide credit: Helmut Grabner Image source: Disney/Pixar

Drifting Due to Self-Learning Policy



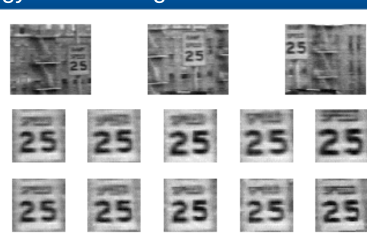
⇒ Not only does it drift, it also remains confident about it!

Slide credit: Helmut Grabner Image source: Grabner et al., ECCV'08

Self-Learning and Drift

- Drift
  - Major problem in all adaptive or self-learning trackers.
  - Difficulty: distinguish “allowed” appearance change due to lighting or viewpoint variation from “unwanted” appearance change due to drifting.
  - Cannot be decided based on the tracker confidence!
    - Since the confidence is always dependent on the learned model
    - Model may already be affected by drift when the confidence is measured.
  - Several approaches have been proposed to address this.

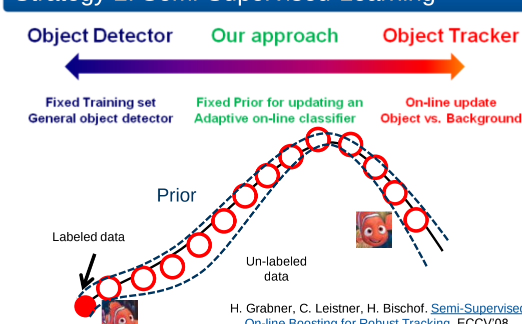
Strategy 1: Match Against Initialization



- Used mostly in low-level trackers (e.g., KLT)
  - Advantage: robustly catches drift
  - Disadvantage: cannot follow appearance changes

J. Shi and C. Tomasi. Good Features to Track. CVPR 1994.

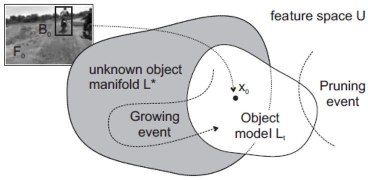
Strategy 2: Semi-Supervised Learning



H. Grabner, C. Leistner, H. Bischof. Semi-Supervised On-line Boosting for Robust Tracking. ECCV'08.

Slide credit: Helmut Grabner

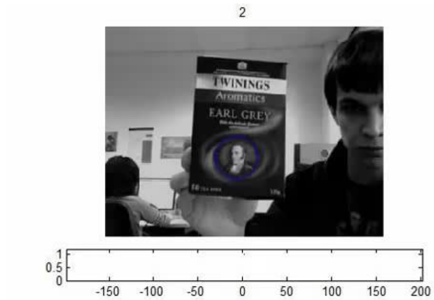
Strategy 3: Using Additional Cues



- Tracking-Learning-Detection
  - Combination of KLT and Tracking-by-Detection
  - Use a KLT tracker as additional cue to generate confident (positive and negative) training examples.
  - Learn an object detector on the fly using Online Random Ferns.

Z. Kalal, K. Mikolajczyk, J. Matas. Tracking-Learning-Detection. PAMI 2011.

TLD Results



Video source: Z. Kalal

Accumulated Training Examples

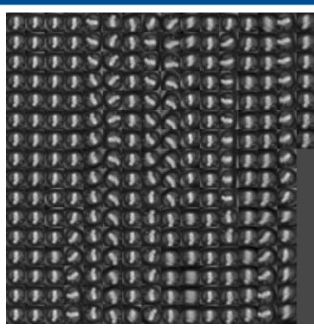
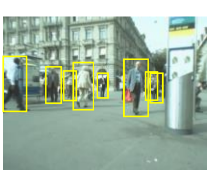


Image source: Z. Kalal

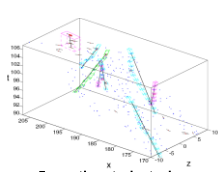
TLD Results

Video source: Z. Kalal

Today: Tracking by Detection



Object detections



Spacetime trajectories

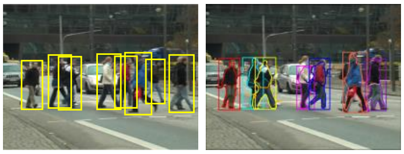
Can we use generic object detection to track people?

Image source: B. Leibe

Topics of This Lecture

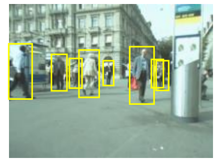
- Tracking by Detection
  - Motivation
  - Recap: Object detection
- SVM based Detectors
  - Recap: HOG
  - DPM
- AdaBoost based Detectors
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN

Detection-Based Tracking

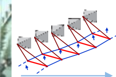


- Main ideas
  - Apply a generic object detector to find objects of a certain class
  - Based on the detections, extract object appearance models
    - Even possible to derive figure-ground segmentations from detection results
  - Link detections into trajectories

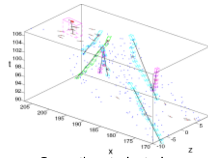
Tracking-by-Detection in 3D



Object detections



3D Camera path estimation



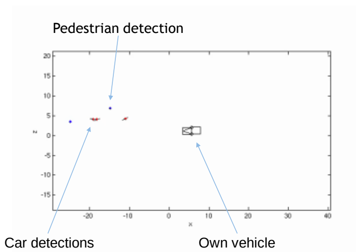
Spacetime trajectories

Simple f/g model:
E.g., elliptical region in detection box

Main Issue:
Data Association
(We'll come to that later…)

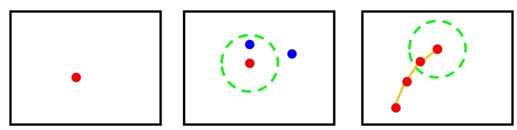
[Leibe, Cornelis, Schindler, Van Gool, PAMI'08]

Spacetime Trajectory Analysis



[Leibe, Cornelis, Schindler, Van Gool, CVPR'07]

Elements of Tracking



- Detection
  - *Where are candidate objects?*

Today's topic

- Data association
  - *Which detection corresponds to which object?*
- Prediction
  - *Where will the tracked object be in the next time step?*

Recap: Sliding-Window Object Detection

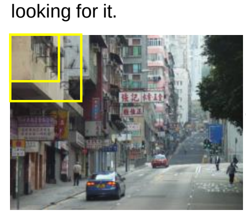
- Basic component: a binary classifier

→ Car/non-car Classifier → No, not a car. / Yes, car.

Slide credit: Kristen Grauman

Recap: Sliding-Window Object Detection

- If object may be in a cluttered scene, slide a window around looking for it.



→

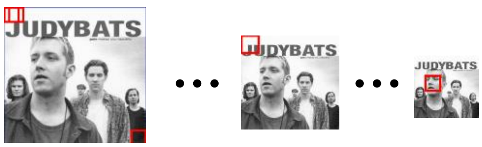
→ Car/non-car Classifier

- Essentially, this is a brute-force approach with many local decisions.

Slide credit: Kristen Grauman

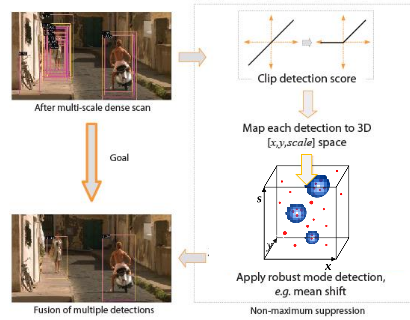
What *is* a Sliding Window Approach?

- Search over space and scale



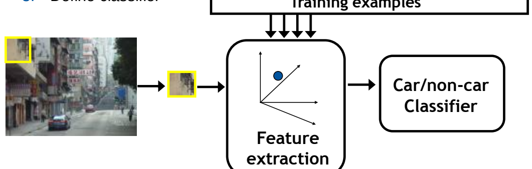
- Detection as subwindow classification problem
- *"In the absence of a more intelligent strategy, any global image classification approach can be converted into a localization approach by using a sliding-window search."*

Recap: Non-Maximum Suppression



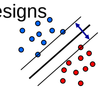
Recap: Sliding-Window Object Detection

- Fleshing out this pipeline a bit more, we need to:
  1. Obtain training data
  2. Define features
  3. Define classifier

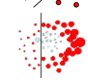


Object Detector Design

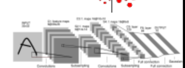
- In practice, the classifier often determines the design.
  - Types of features
  - Speedup strategies
- Today, we'll look at 3 state-of-the-art detector designs
  - Based on SVMs



  - Based on Boosting

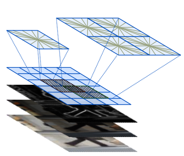


  - Based on CNNs



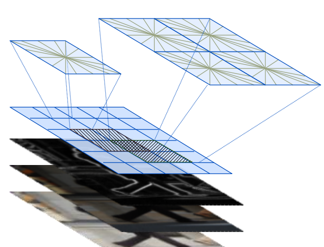
Topics of This Lecture

- Tracking by Detection
  - Motivation
  - Recap: Object detection
- **SVM based Detectors**
  - **Recap: HOG**
  - DPM
- AdaBoost based Detectors
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN



Recap: Histograms of Oriented Gradients (HOG)

- Holistic object representation
  - Localized gradient orientations

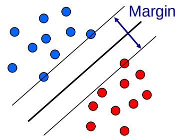


Object/Non-object
↑
Linear SVM
↑
Collect HOGs over detection window
↑
Contrast normalize over overlapping spatial cells
↑
Weighted vote in spatial & orientation cells
↑
Compute gradients
↑
Gamma compression
↑
Image Window

Recap: Support Vector Machine (SVM)

- Basic idea
  - The SVM tries to find a classifier which maximizes the margin between pos. and neg. data points.
  - Up to now: consider linear classifiers

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0$$



- Formulation as a convex optimization problem
  - Find the hyperplane satisfying

$$\underset{\mathbf{w},b}{\arg\min} \frac{1}{2}\|\mathbf{w}\|^2$$

under the constraints

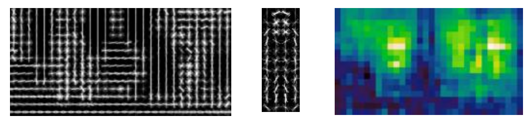
$$t_n(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n + b) \geq 1 \quad \forall n$$

based on training data points $\mathbf{x}_n$ and target values $t_n \in \{-1, 1\}$

Recap: Pedestrian Detection with HOG

- Train a pedestrian template using a linear SVM
- At test time, convolve feature map with template

$$y(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b$$

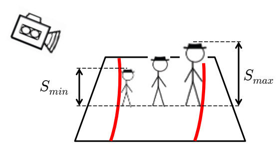


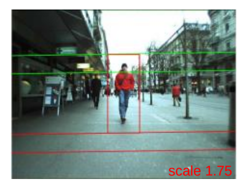
N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Pedestrian detection with HoGs & SVMs

N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Incorporating Ground Plane Constraints





- Efficient integration into detector design (*groundHOG*)
  - Idea: only evaluate geometrically valid detection windows
  - Derivation: Region of interest lies between two parabolas…
  - …that can in most cases be approximated by straight lines.
  - ⇒ *Only touch pixels inside the ROI for all computations.*
  - ⇒ Factor 2-4 speed improvement *on top of all other optimizations*

[P. Sudowe, B. Leibe, ICVS'11]

Real-Time Pedestrian Detection

- Efficient CUDA HOG implementation (equivalent to original HOG code)
- Code made publicly available as open source under GPL

- Run-time comparison:

run-time	1280 × 960		640 × 480	
	cuda	ground	cuda	ground
Laptop GTX 285M	1.6 fps	9.6 fps	7.2 fps	26 fps
Desktop GTX 280	5.5 fps	17.2 fps	22.7 fps	56 fps
Desktop GTX 580	9.8 fps	27.8 fps	41.6 fps	83 fps

⇒ *Detection at video frame rate possible even on laptops with mobile GPUs!*

[P. Sudowe, B. Leibe, ICVS'11]

You Can Try It At Home…

- groundHOG GPU detector code publicly available
  - Highly optimized for speed
  - Can be used with or without ground plane constraints
  - Supports general ROI processing
  - Supports multi-class detection with feature sharing
  - Published under GPL license (other licensing negotiable)

  - http://www.vision.rwth-aachen.de/projects/groundhog

P. Sudowe, B. Leibe, Efficient Use of Geometric Constraints for Sliding Window Object Detection in Video, ICVS 2011

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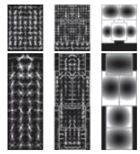
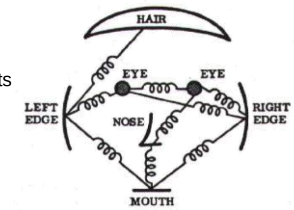


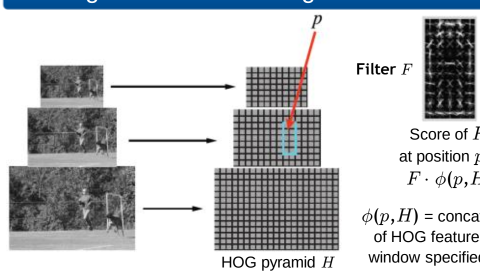
Recap: Part-Based Models

- Pictorial Structures model
  - [Fischler & Elschlager 1973]
- Model has two components
  - Parts
    (2D image fragments)
  - Structure
    (configuration of parts)



- Use in Deformable Part-based Model (DPM)
  - Parts ≡ 5-7 semantically meaningful parts
  - Probabilistic model enabling efficient inference

Starting Point: HOG Sliding-Window Detector

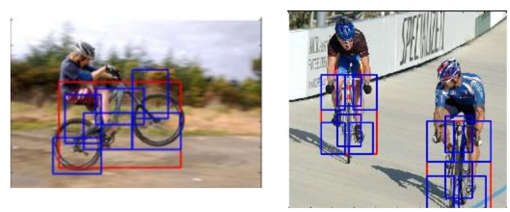


Score of F at position p is $F \cdot \phi(p, H)$

$\phi(p, H)$ = concatenation of HOG features from window specified by p.

- Array of weights for features in window of HOG pyramid
- Score is dot product of filter and vector

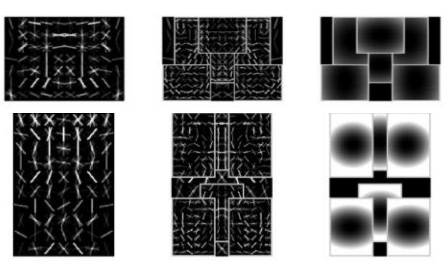
Deformable Part-based Models



- Mixture of deformable part models (Pictorial Structures)
- Each component has global template + deformable parts
- Fully trained from bounding boxes alone

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

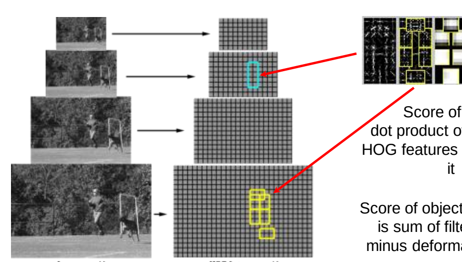
2-Component Bicycle Model



Root filters coarse resolution | Part filters finer resolution | Deformation models

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Object Hypothesis



Score of filter: dot product of filter with HOG features underneath it

Score of object hypothesis is sum of filter scores minus deformation costs

- Multiscale model captures features at two resolutions

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Score of a Hypothesis

$$\text{score}(p_0, \ldots, p_n) = \overbrace{\sum_{i=0}^{n} \underset{\text{filters}}{F_i} \cdot \phi(H, p_i)}^{\text{"data term"}} - \overbrace{\sum_{i=1}^{n} \underset{\text{deformation parameters}}{d_i} \cdot \underset{\text{displacements}}{(dx_i^2, dy_i^2)}}^{\text{"spatial prior"}}$$

$$\text{score}(z) = \beta \cdot \Psi(H, z)$$

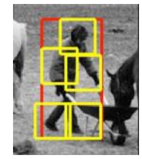
β: concatenation filters and deformation parameters

$\Psi(H, z)$: concatenation of HOG features and part displacement features

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Recognition Model

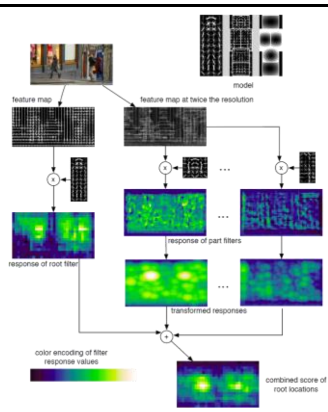
$f_w(x) = w \cdot \Phi(x)$



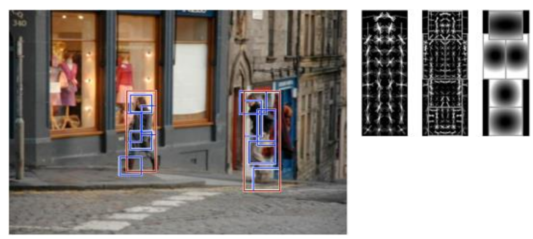
$f_w(x) = \max_z w \cdot \Phi(x, z)$

- Difference to standard HOG model
  - Hidden variable z: vector of part offsets
  - $\Phi(x,z)$: vector of HOG features (from root filter & appropriate part sub-windows) and part offsets

    $\Rightarrow$ Need to optimize over all possible part positions

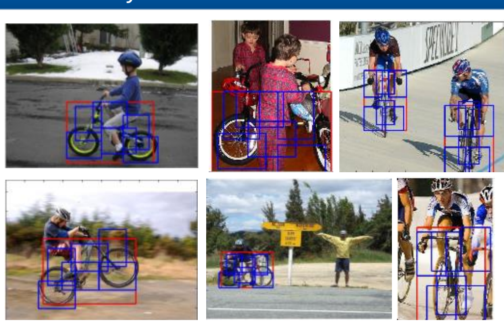


Results: Persons



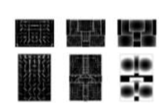
- Results (after non-maximum suppression)
  - ~1s to search all scales

Results: Bicycles



Extensions and Detailed Improvements

- More efficient features
  - Very simplified version of HOG
- Latent part (re-)learning
  - Perform several rounds of training, adapting the annotation bboxes
- Multi-aspect detection
  - Mixture model of different aspects to capture different viewpoints of objects
- Bounding box prediction
  - Infer final detection bounding box from detected part locations
- Multi-resolution models
- Cascaded evaluation



[Felzenszwalb, McAllister, Ramanan, PAMI'10]

You Can Try It At Home…

- Deformable part-based models have been very successful at several recent evaluations.
  ⇒ One of the state-of-the-art approaches in object detection
- Source code and models trained on PASCAL 2006, 2007, and 2008 data are available here:
  http://www.cs.uchicago.edu/~pff/latent

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  - Recap: HOG
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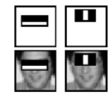
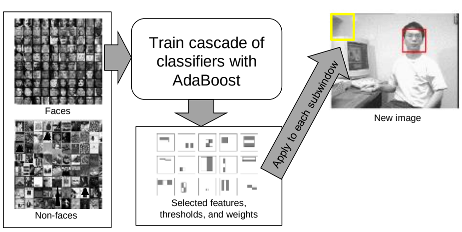
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN



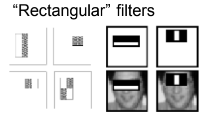
Recap: Viola-Jones Face Detector



- Train with 5K positives, 350M negatives
- Real-time detector using 38 layer cascade (6061 features in final layer)
- [Implementation available in OpenCV: http://sourceforge.net/projects/opencvlibrary/]

Recap: Haar Wavelets

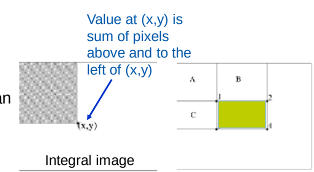
"Rectangular" filters



Feature output is difference between adjacent regions

Efficiently computable with integral image: any sum can be computed in constant time

Avoid scaling images
⇒ Scale features directly for same cost

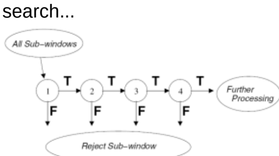


Integral image

$$D = 1 + 4 - (2 + 3)$$
$$= A + (A + B + C + D) - (A + C + A + B)$$
$$= D$$

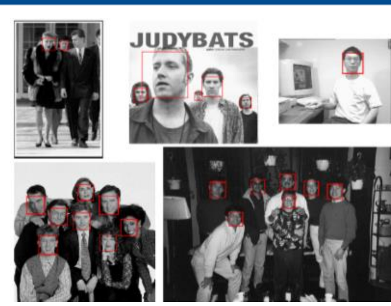
Recap: Cascading Classifiers for Detection

- Even if the filters are fast to compute, each new image has a lot of possible windows to search...
- Idea: Classifier cascade
  - Observation: most image windows are negative and look very different from the searched object class.
  - Filter for promising regions with an initial inexpensive classifier
  - Build a chain of classifiers, choosing cheap ones with low false negative rates early in the chain



[Fleuret & Geman, IJCV'01; Rowley et al., PAMI'98; Viola & Jones, CVPR'01]

Viola-Jones Face Detector: Results



You Can Try It At Home…

- The Viola & Jones detector was a huge success
  - First real-time face detector available
  - Many derivative works and improvements
- C++ implementation available in OpenCV [Lienhart, 2002]
  - http://sourceforge.net/projects/opencvlibrary/
- Matlab wrappers for OpenCV code available, e.g. here
  - http://www.mathworks.com/matlabcentral/fileexchange/19912

P. Viola, M. Jones, Robust Real-Time Face Detection, IJCV, Vol. 57(2), 2004

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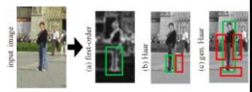
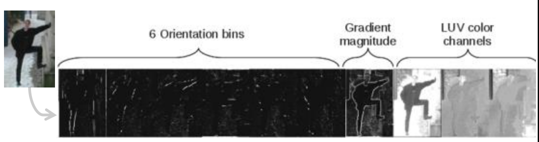


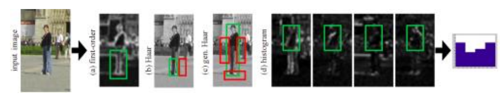
Integral Channel Features



- Generalization of Haar Wavelet idea from Viola-Jones
  - Instead of only considering intensities, also take into account other feature channels (gradient orientations, color, texture).
  - Still efficiently represented as integral images.

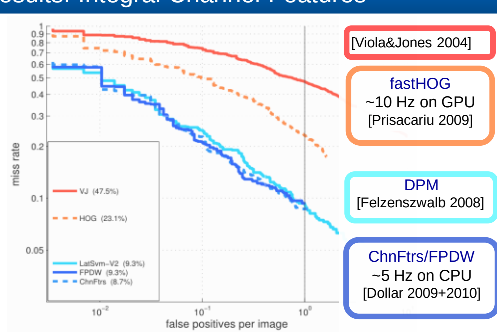
P. Dollar, Z. Tu, P. Perona, S. Belongie. Integral Channel Features, BMVC'09.

Integral Channel Features



- Generalize also block computation
  - 1st order features:
    - Sum of pixels in rectangular region.
  - 2nd-order features:
    - Haar-like difference of sum-over-blocks
  - Generalized Haar:
    - More complex combinations of weighted rectangles
  - Histograms
    - Computed by evaluating local sums on quantized images.

Results: Integral Channel Features



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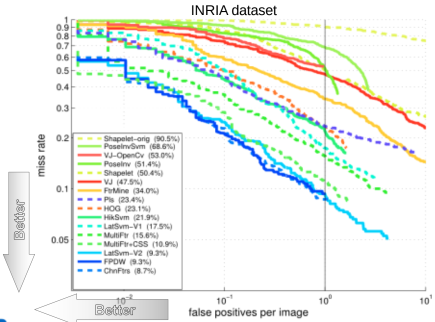
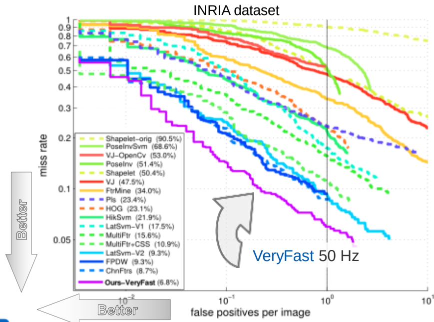
Performance Comparison of Detectors



Performance Comparison of Detectors



Issues for Efficient Detection

- One template cannot detect at multiple scales...

Issues for Efficient Detection

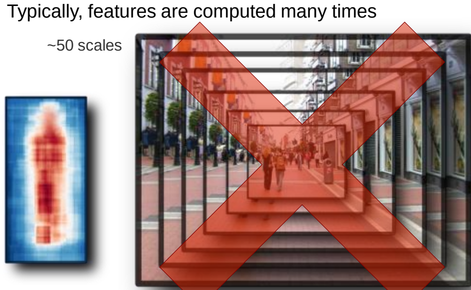
- Typically, features are computed many times

~50 scales

Issues for Efficient Detection

- Typically, features are computed many times

~50 scales



VeryFast Detector

- Idea 1: Invert the relation

1 model,
50 image scales

50 models,
1 image scale

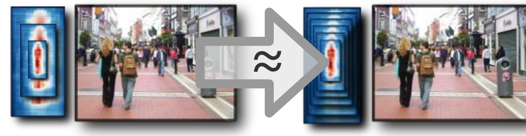
R. Benenson, M. Mathias, R. Timofte, L. Van Gool. Pedestrian Detection at 100 Frames per Second, CVPR'12.

Practical Considerations

- Training and running 1 model/scale is too expensive

VeryFast Detector

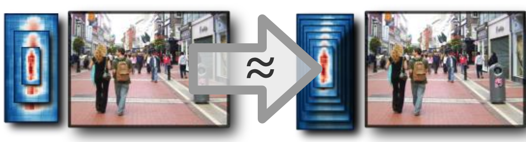
- Idea 2: Reduce training time by feature interpolation



- Shown to be possible for Integral Channel features
  - P. Dollár, S. Belongie, Perona. The Fastest Pedestrian Detector in the West, BMVC 2010.

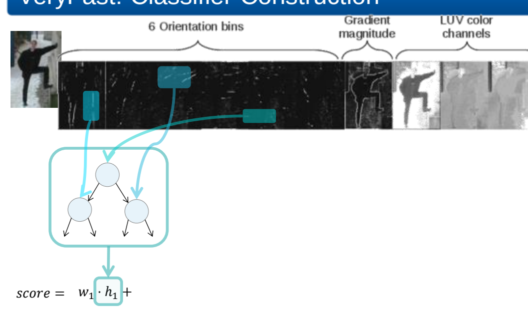
VeryFast Detector

- Effect: Transfer test time computation to training time



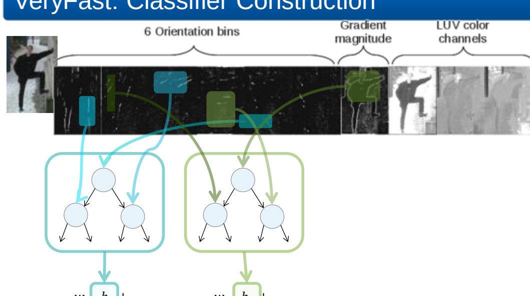
⇒ *Result: 3x reduction in feature computation*

VeryFast: Classifier Construction



- Ensemble of short trees, learned by AdaBoost

VeryFast: Classifier Construction



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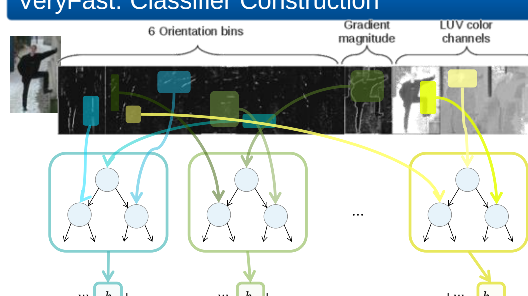
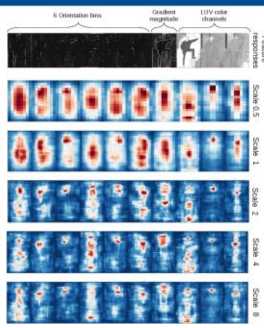


- Ensemble of short trees, learned by AdaBoost

Learned Models



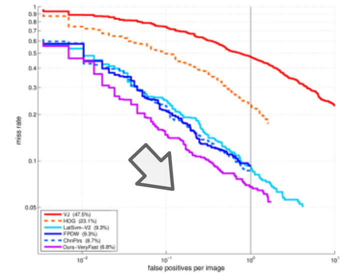
Integral Channel features

Models

⋮

Slide credit: Rodrigo Benenson

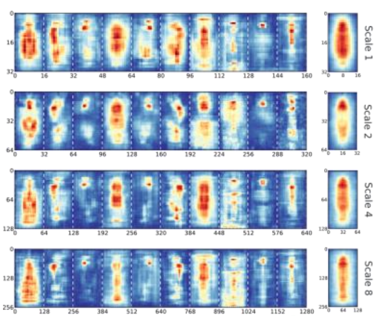
Results



- Detection without resizing improves quality of results

Slide credit: Rodrigo Benenson

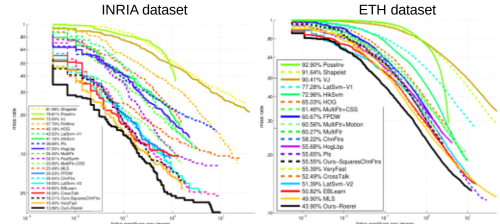
Multi-Scale Models > Single-Scale Model



Slide adapted from Rodrigo Benenson

Comparison to State-of-the-Art

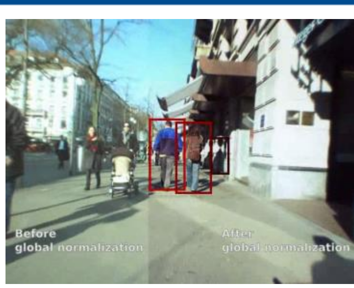
INRIA dataset ETH dataset



- Extension: Roerei detector
  - Detailed evaluation of design space
  - Non-regular pooling regions found to work best.

Slide adapted from Rodrigo Benenson

Roerei Results



R. Benenson, M. Mathias, R. Timofte, L. Van Gool. Seeking the Strongest Rigid Detector. CVPR'13.

Applications: Mobile Robot Navigation

link to the video

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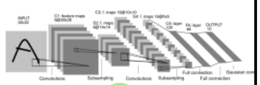
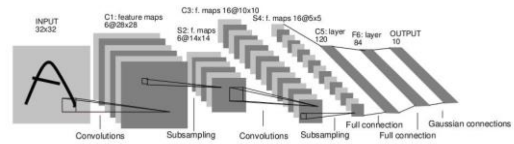


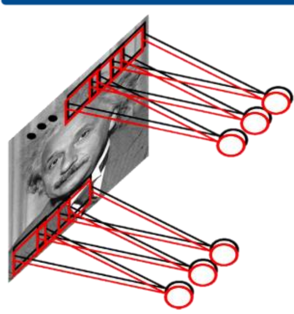
Recap: Convolutional Neural Networks



- Neural network with specialized connectivity structure
  - Stack multiple stages of feature extractors
  - Higher stages compute more global, more invariant features
  - Classification layer at the end

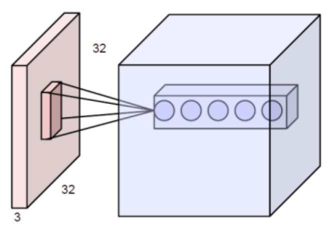
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Recap: Intuition of CNNs

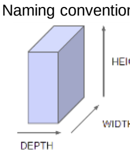


- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels
- Learn *multiple* filters
  - E.g. 1000×1000 image
    100 filters
    10×10 filter size
    ⇒ only 10k parameters
- Result: Response map
  - size: 1000×1000×100
  - Only memory, not params!

Recap: Convolution Layers

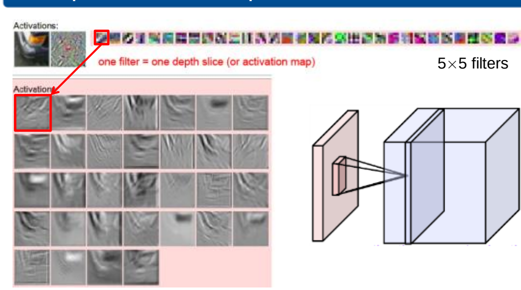


Naming convention:



- All Neural Net activations arranged in 3 dimensions
  - Multiple neurons all looking at the same input region, stacked in depth
  - Form a single [1×1×depth] depth column in output volume.

Recap: Activation Maps



5×5 filters

Activation maps

Recap: Pooling Layers

Single depth slice

x

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

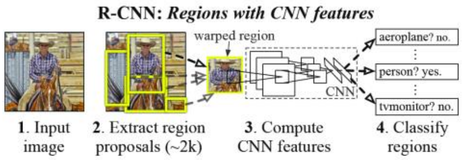
y

max pool with 2x2 filters and stride 2 →

6	8
3	4

- Effect:
  - Make the representation smaller without losing too much information
  - Achieve robustness to translations

R-CNN Detector



- Results on PASCAL VOC Detection benchmark
  - Pre-CNN state of the art: 35.1% mAP [Uijlings et al., 2013]
    33.4% mAP DPM
  - R-CNN: 53.7% mAP

R. Girshick, J. Donahue, T. Darrell, and J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR 2014

You Can Try All of This At Home…

- Detector code is publicly available
  - HOG:
    - Dalal's original implementation: http://www.navneetdalal.com/software/
    - Our CUDA-optimized *groundHOG* code (>80 fps on GTX 580) http://www.mmp.rwth-aachen.de/projects/groundhog
  - DPM:
    - Felzenswalb's original implementation: http://www.cs.uchicago.edu/~pff/latent
  - VeryFast
    - Benenson's original implementation: https://bitbucket.org/rodrigob/doppia/
  - R-CNN
    - Girshick's original implementation: https://github.com/rbgirshick/rcnn