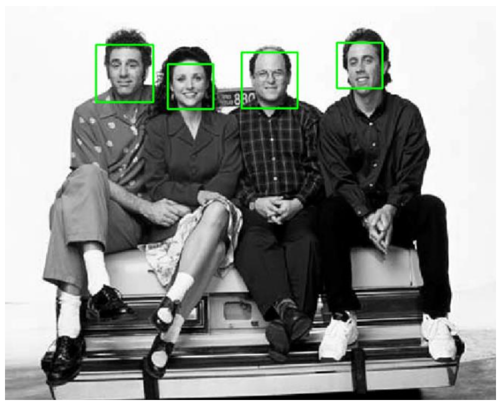
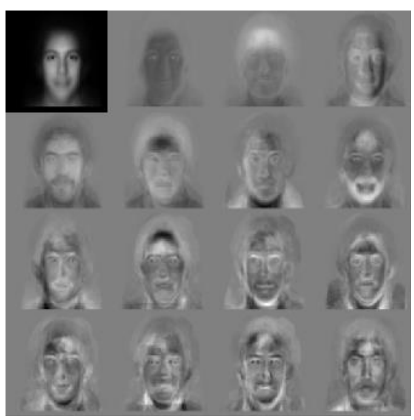
CS4670 / 5670: Computer Vision

Noah Snavely

Lecture 29: Face Detection Revisited



Remember eigenfaces?



- They don't work very well for detection

Issues: speed, features

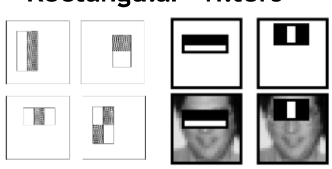
- Case study: Viola Jones face detector
- Exploits two key strategies:
  - simple, super-efficient, but useful features
  - pruning (cascaded classifiers)

- Next few slides adapted Grauman & Liebe's tutorial
  - http://www.vision.ee.ethz.ch/~bleibe/teaching/tutorial-aaai08/
- Also see Paul Viola's talk (video)
  - http://www.cs.washington.edu/education/courses/577/04sp/contents.html#DM

Visual Object Recognition Tutorial

Feature extraction

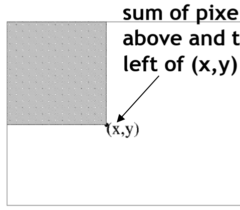
"Rectangular" filters



Feature output is difference between adjacent regions

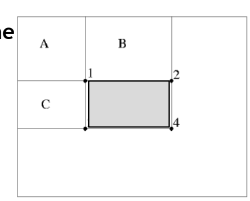
Efficiently computable with integral image: any sum can be computed in constant time

Avoid scaling images → scale features directly for same cost



Value at (x,y) is sum of pixels above and to the left of (x,y)

Integral image



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

Viola & Jones, CVPR 2001

K. Grauman, B. Leibe

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Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

-1	1
1	1

IIR Filter

Weights on Integral Image

Weight on Original Image

34

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

-1	1
1	1

IIR Filter

Weights on Integral Image

Weight on Original Image

34	45

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

Weights on Integral Image

-1	1
1	1

Weight on Original Image

IIR Filter

34	45	78

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

Weights on Integral Image

-1	1
1	1

Weight on Original Image

IIR Filter

34	45	78	81	100	119	137	155	157	181

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

-1	1
1	1

IIR Filter

Weights on Integral Image

Weight on Original Image

34	45	78	81	100	119	137	155	157	181
68	87								

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

-1	1
1	1

IIR Filter

Weights on Integral Image

Weight on Original Image

34	45	78	81	100	119	137	155	157	181
68	87	156							

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

Weights on Integral Image

-1	1
1	1

Weight on Original Image

IIR Filter

34	45	78	81	100	119	137	155	157	181
68	87	156	170	194	224	247	271	288	345

Integral Image

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

Weights on Integral Image

-1	1
1	1

Weight on Original Image

IIR Filter

34	45	78	81	100	119	137	155	157	181
68	87	156	170	194	224	247	271	288	345
85	126	212	230	260	293	321	352	404	479
93	137	238	278	313	347	395	436	500	597
101	152	254	316	370	433	487	548	621	745
117	175	288	367	436	501	580	660	762	896
151	235	377	487	561	632	741	838	944	1088
184	296	468	582	684	776	911	1013	1151	1316
185	315	500	619	748	856	1019	1140	1310	1498
197	340	541	683	825	940	1124	1250	1422	1625

Integral Image

O(N) Operations!
~400 in this case

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

	Sum	Cost	Total Cost
ΣΣ	69	6	6
Integral	69	4	4

34	45	78	81	100	119	137	155	157	181
68	87	156	170	194	224	247	271	288	345
85	126	212	230	260	293	321	352	404	479
93	137	238	278	313	347	395	436	500	597
101	152	254	316	370	433	487	548	621	745
117	175	288	367	436	501	580	660	762	896
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184	296	468	582	684	776	911	1013	1151	1316
185	315	500	619	748	856	1019	1140	1310	1498
197	340	541	683	825	940	1124	1250	1422	1625

Integral Image

ΣΣ: 17+4+6+15+22+5= 69

Integral way: 313+87-194-137= 69

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

	Sum	Cost	Total Cost
ΣΣ	352	24	30
Integral	352	4	8

34	45	78	81	100	119	137	155	157	181
68	87	156	170	194	224	247	271	288	345
85	126	212	230	260	293	321	352	404	479
93	137	238	278	313	347	395	436	500	597
101	152	254	316	370	433	487	548	621	745
117	175	288	367	436	501	580	660	762	896
151	235	377	487	561	632	741	838	944	1088
184	296	468	582	684	776	911	1013	1151	1316
185	315	500	619	748	856	1019	1140	1310	1498
197	340	541	683	825	940	1124	1250	1422	1625

Integral Image

Integral way: 911+156-247-468= 352

Slide courtesy of Andrew Gallagher

Integral Image

34	11	33	3	19	19	18	18	2	24
34	8	36	11	5	11	5	6	15	33
17	22	17	4	6	3	5	7	35	18
8	3	15	22	5	1	20	10	12	22
8	7	1	22	19	29	6	20	9	27
16	7	11	17	15	2	25	19	29	10
34	26	29	31	5	6	30	17	4	10
33	28	30	4	28	21	26	5	32	21
1	18	13	5	27	16	28	19	32	23
12	13	16	23	13	7	21	5	2	15

Original Image

	Sum	Cost	Total Cost
ΣΣ	141	9	39
Integral	141	4	12

34	45	78	81	100	119	137	155	157	181
68	87	156	170	194	224	247	271	288	345
85	126	212	230	260	293	321	352	404	479
93	137	238	278	313	347	395	436	500	597
101	152	254	316	370	433	487	548	621	745
117	175	288	367	436	501	580	660	762	896
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184	296	468	582	684	776	911	1013	1151	1316
185	315	500	619	748	856	1019	1140	1310	1498
197	340	541	683	825	940	1124	1250	1422	1625

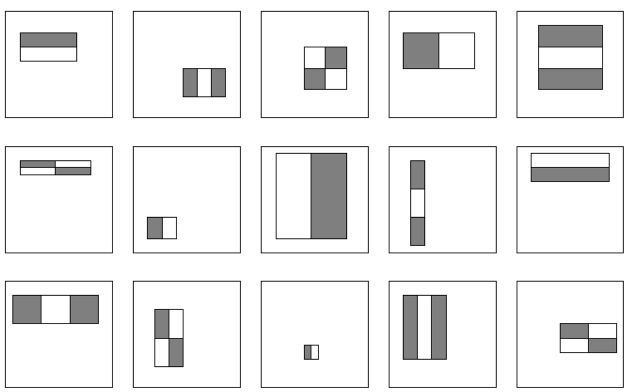
Integral Image

Integral way: 762-621= 141

Slide courtesy of Andrew Gallagher

Visual Object Recognition Tutorial

Large library of filters



Considering all possible filter parameters: position, scale, and type:

180,000+ possible features associated with each 24 x 24 window

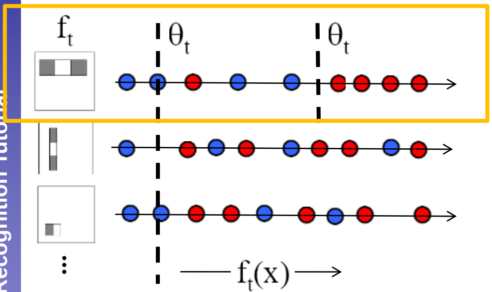
Use AdaBoost both to select the informative features and to form the classifier

Viola & Jones, CVPR 2001

K. Grauman, B. Leibe

AdaBoost for feature+classifier selection

- Want to select the single rectangle feature and threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of *weighted* error.



Outputs of a possible rectangle feature on faces and non-faces.

Resulting weak classifier:

$$h_t(x) = \begin{cases} +1 & \text{if } f_t(x) > \theta_t \\ -1 & \text{otherwise} \end{cases}$$

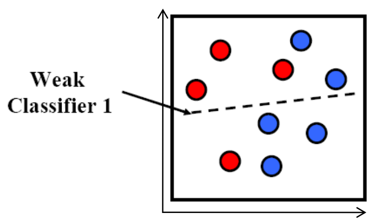
For next round, reweight the examples according to errors, choose another filter/threshold combo.

Viola & Jones, CVPR 2001

K. Grauman, B. Leibe

Visual Object Recognition Tutorial

AdaBoost: Intuition



Consider a 2-d feature space with positive and negative examples.

Each weak classifier splits the training examples with at least 50% accuracy.

Examples misclassified by a previous weak learner are given more emphasis at future rounds.

Figure adapted from Freund and Schapire

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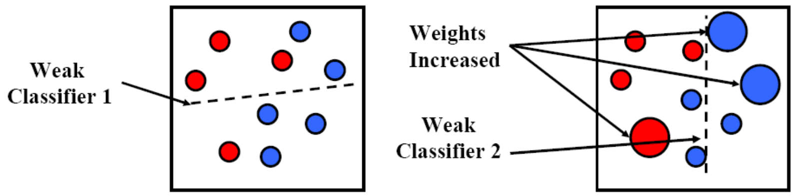
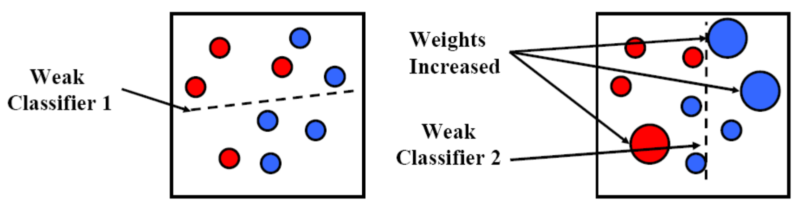
Visual Object Recognition Tutorial

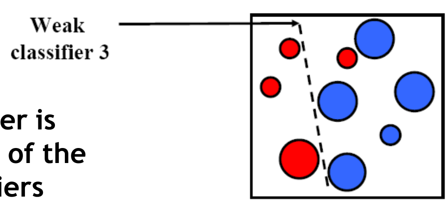
AdaBoost: Intuition



Visual Object Recognition Tutorial

AdaBoost: Intuition



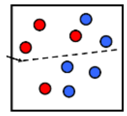


Final classifier is combination of the weak classifiers

- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \, |h_j(x_i) - y_i|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
where $\alpha_t = \log \frac{1}{\beta_t}$

AdaBoost Algorithm

Start with uniform weights on training examples



$\{x_1, \ldots x_n\}$

For T rounds

Evaluate *weighted* error for each feature, pick best.

Re-weight the examples:
Incorrectly classified -> more weight
Correctly classified -> less weight

Final classifier is combination of the weak ones, weighted according to error they had.

an, B. Leibe

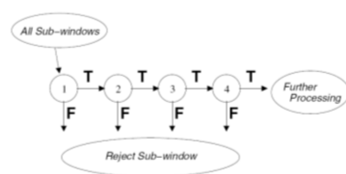
Freund & Schapire 1995

Visual Object Recognition Tutorial

Cascading classifiers for detection

For efficiency, apply less accurate but faster classifiers first to immediately discard windows that clearly appear to be negative; e.g.,

- **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 2001
Rowley et al., PAMI 1998
Viola & Jones, CVPR 2001

K. Grauman, B. Leibe

Figure from Viola & Jones CVPR 2001

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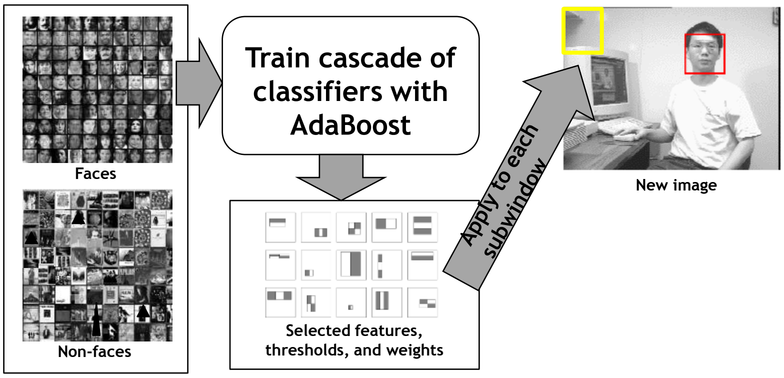
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Summary



- Train with 5K positives, 350M negatives
- Real-time detector using 38 layer cascade
- 6061 features in total throughout layers
- [Implementation available in OpenCV: http://www.intel.com/technology/computing/opencv/]

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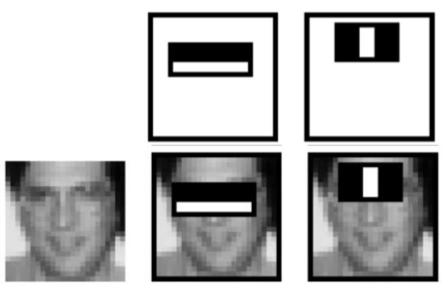
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results



First two features selected

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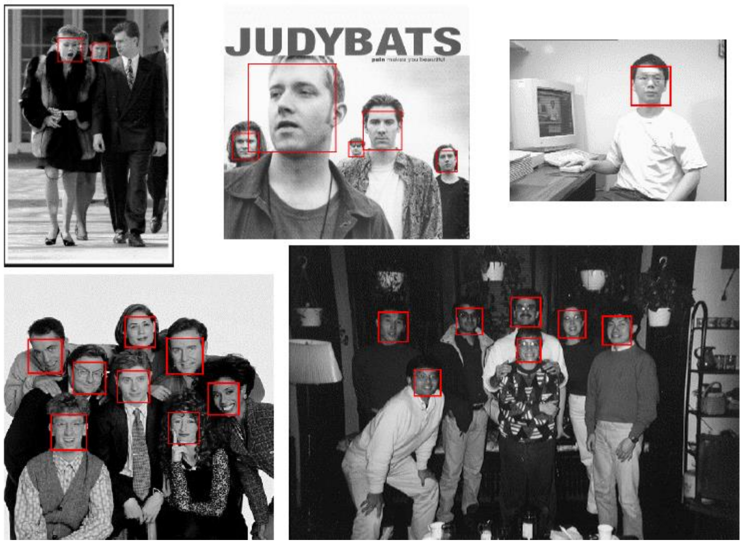
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results



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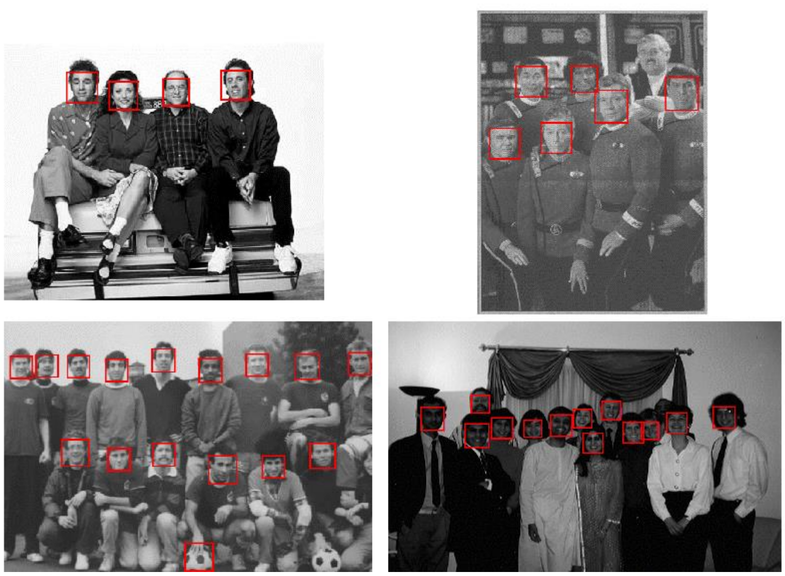
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results



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Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results

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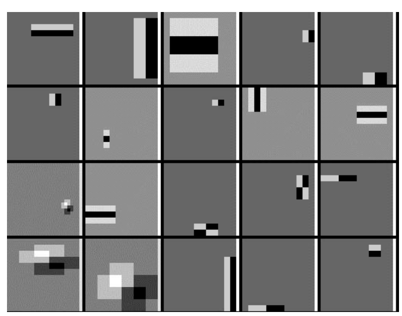
Visual Object Recognition Tutorial

Detecting profile faces?

Detecting profile faces requires training separate detector with profile examples.



K. Grauman, B. Leibe

Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results

Paul

K. Grauman, B. Leibe

Questions?