

EE655: Computer Vision & Deep Learning

Lecture 05

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Lecture Outline

Haar Features



Harris Corner Detection

Shi-Tomasi Corner Detector

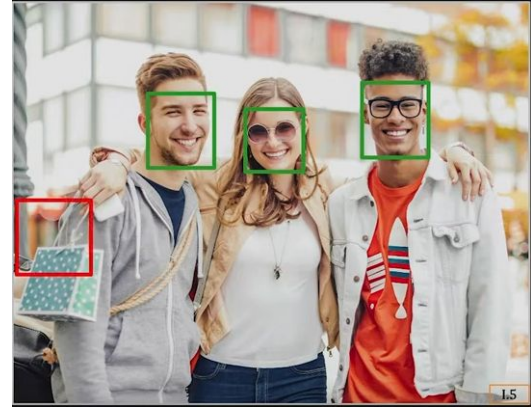
How can we use features for face detection



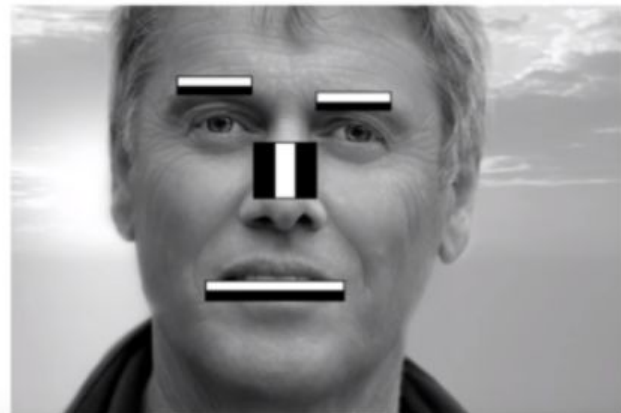
Start with a window,
with roughly the size
of the face we are
looking for



Keep moving it and
extract features



Use a classifier to
identify if the features
extracted represent a
face



WE CAN REPRESENT THE MOST RELEVANT FEATURES WITH HAAR-FEATURES !!!

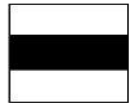
Features



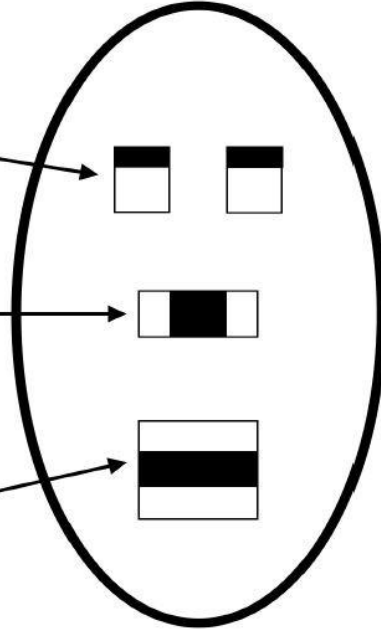
Eyes



Nose



Mouth



A Theoretical
Face Model

Haar Features

Set of Correlation Responses to Haar Filters



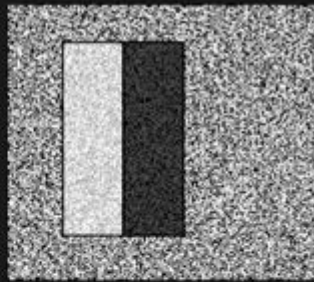
Input Image

$$\begin{bmatrix} \begin{array}{|c|c|} \hline \text{white} & \text{black} \\ \hline \end{array} & H_A \\ \begin{array}{|c|c|} \hline \text{black} & \text{white} \\ \hline \end{array} & H_B \\ \begin{array}{|c|c|} \hline \text{white} & \text{white} \\ \hline \end{array} & H_C \\ \begin{array}{|c|c|} \hline \text{white} & \text{black} \\ \hline \end{array} & H_D \\ \vdots & \end{bmatrix} \otimes = \begin{bmatrix} V_A[i,j] \\ V_B[i,j] \\ V_C[i,j] \\ V_D[i,j] \\ \vdots \end{bmatrix}$$

Need to perform correlation with these 2-valued Haar filters (1 or -1)



$$V_A = 64$$



$$V_A \approx 0$$



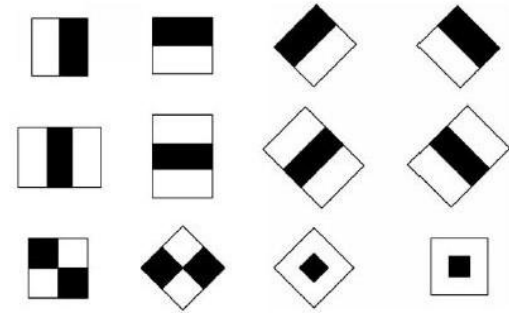
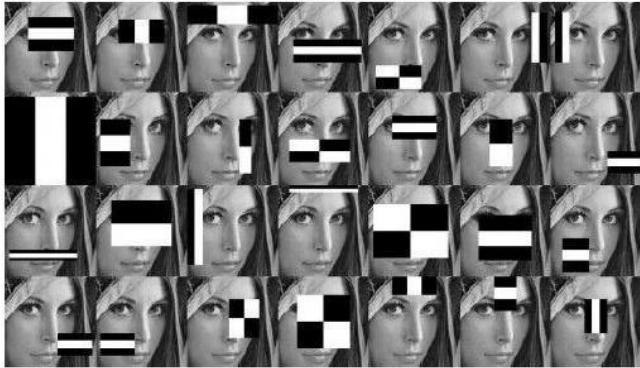
$$V_A = 16$$



$$V_A = -127$$

Haar features

- Face detection

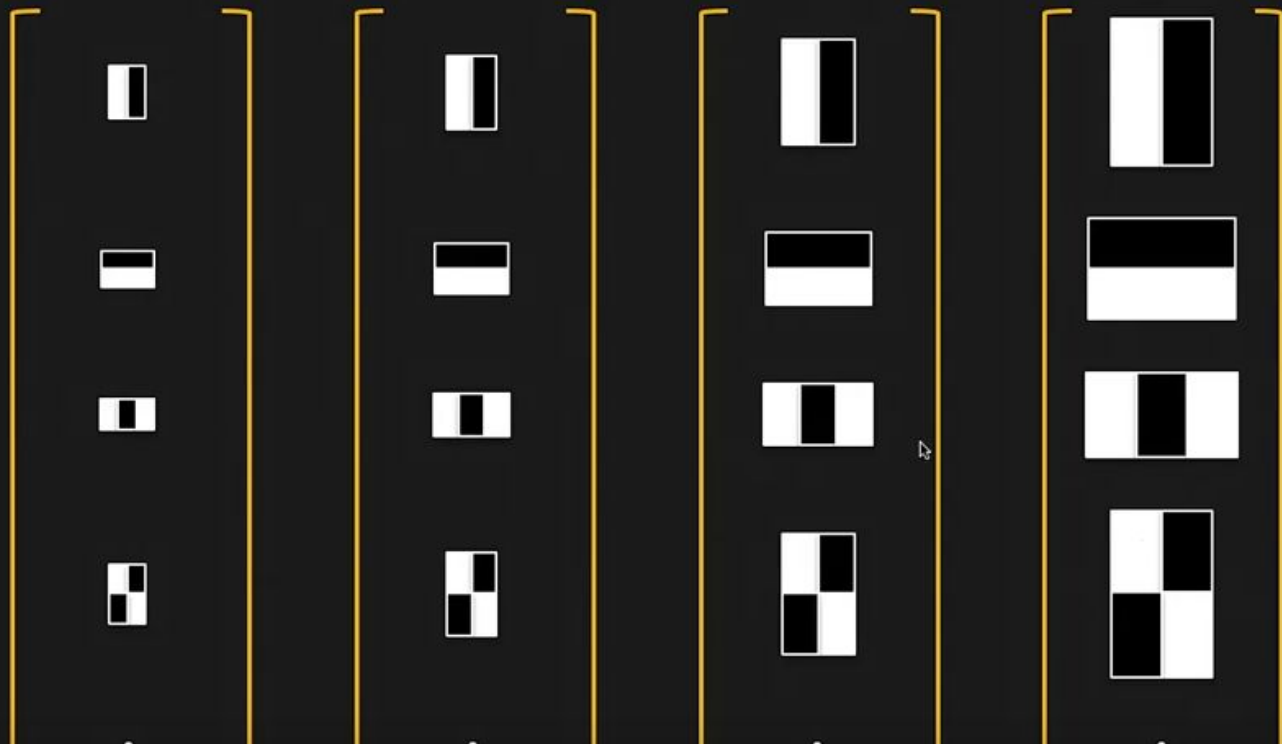


Haar filters

$$\text{Haar feature: } f(x, y) = \sum I(R_{\text{white}}) - \sum I(R_{\text{black}})$$

Detecting Faces of Different Size

Compute Haar Features at different scales to detect faces of different sizes.



For each window:



Extract
Features



$\begin{bmatrix} \mathbf{f} \end{bmatrix}$

Match
Face Model



Yes / No

Computing A Haar Feature



H_A

White = 1, Black = -1

Response to Filter H_A at location (i, j) :

$$V_A[i, j] = \sum_m \sum_n I[m - i, n - j] H_A[m, n]$$

$$V_A[i, j] = \sum (\text{pixel intensities in white area}) \\ - \sum (\text{pixels intensities in black area})$$

And it needs to be
done efficiently

Integral Image

A table that holds the sum of all pixel values to the left and top of a given pixel, **inclusive**.

98	110	121	125	122	129
99	110	120	116	116	129
97	109	124	111	123	134
98	112	132	108	123	133
97	113	147	108	125	142
95	111	168	122	130	137
96	104	172	130	126	130

Image *I*

98	208	329	454	576	705
197	417	658	899	1137	1395
294	623	988	1340	1701	2093
392	833	1330	1790	2274	2799
489	1043	1687	2255	2864	3531
584	1249	2061	2751	3490	4294
680	1449	2433	3253	4118	5052

Integral Image *II*

Integral Image concept is introduced to do it efficiently

98	110	121	125	122	129
99	110	120	116	116	129
97	109	124	111	123	134
98	112	132	108	123	133
97	113	147	108	125	142
95	111	168	122	130	137
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Image I

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Integral Image II

98	110	121	125	122	129
99	110	120	116	116	129
97	109	124	111	123	134
98	112	132	108	123	133
97	113	147	108	125	142
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Integral Image II

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Image I

98	208	329	454	576	705
$R \rightarrow$ 197	417	658	899	1137	\leftarrow 1395 Q
294	623	988	1340	1701	2093
392	833	1330	1790	2274	2799
489	1043	1687	2255	2864	3531
$S \rightarrow$ 584	1249	2061	2751	3490	\leftarrow 4294 P
680	1449	2433	3253	4118	5052

Integral Image II

$$\begin{aligned}
 Sum &= II_P - II_Q - II_S + II_R \\
 &= 3490 - 1137 - 1249 + 417 = 1521
 \end{aligned}$$

Computational Cost: Only 3 additions

Haar Response using Integral Image

98	110	121	125	122	129
99	110	120	116	116	129
97	109	124	111	123	134
98	112	132	108	123	133
97	113	147	108	125	142
95	111	168	122	130	137
96	104	172	130	126	130

Image I

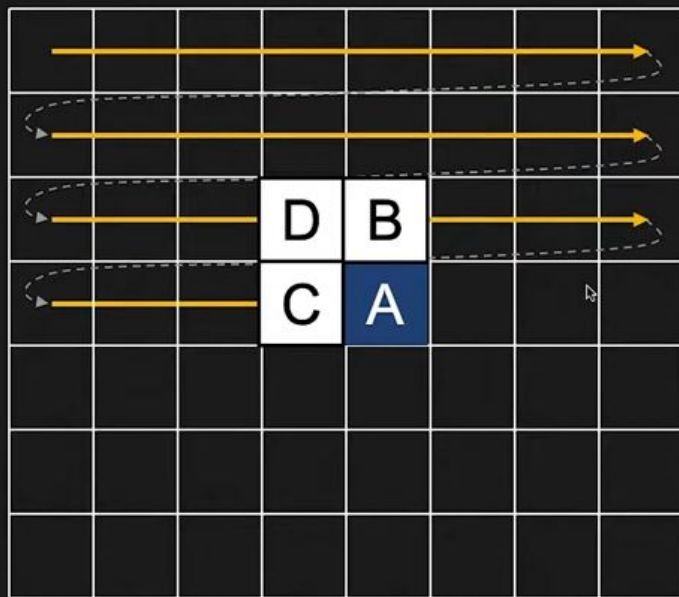
R	98	208	329	454	576	705	T
	197	417	658	899	1137	1395	Q
	294	623	988	1340	1701	2093	
	392	833	1330	1790	2274	2799	
	489	1043	1687	2255	2864	3531	
S	584	1249	2061	2751	3490	4294	P
O	680	1449	2433	3253	4118	5052	

Integral Image II

$$\begin{aligned}
 V_A &= \sum(\text{pixel intensities in white}) - \sum(\text{pixel intensities in black}) \\
 &= (II_O - II_T + II_R - II_S) - (II_P - II_Q + II_T - II_O)
 \end{aligned}$$

Computational Cost: Only 7 additions

Computing Integral Image



Raster
Scanning

Let I_A and II_A be the values of Image and Integral Image, respectively, at pixel A.

$$II_A = II_B + II_C - II_D + I_A$$

Lecture Outline

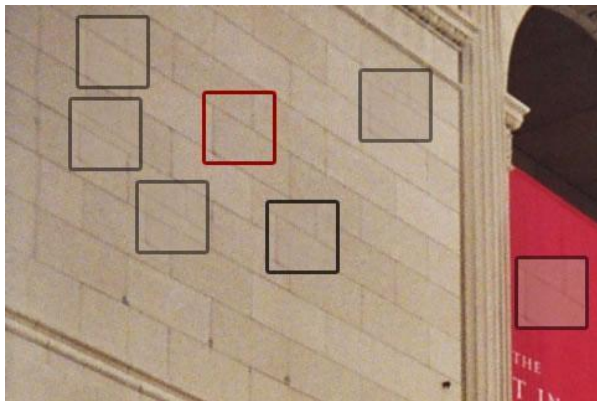
Haar Features

Harris Corner Detection



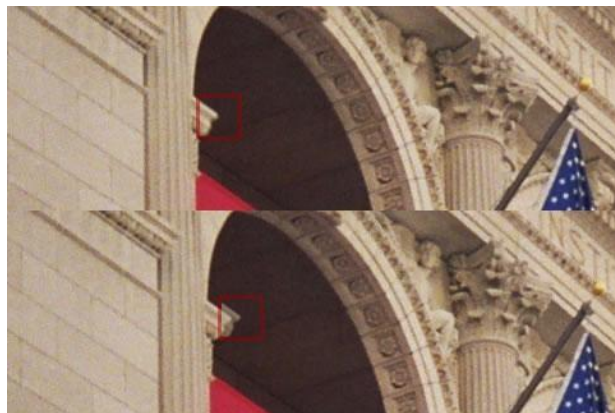
Shi-Tomasi Corner Detector

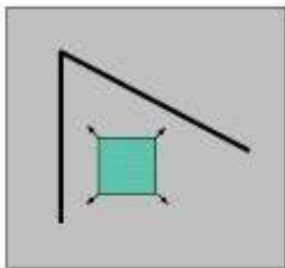
Harris Corner Detection



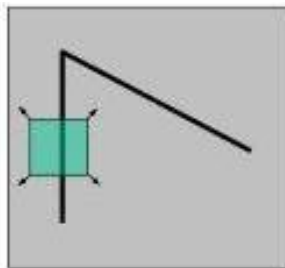
Slightly shifting windows of homogeneous regions doesn't change the window content.

In contrast, Slightly shifting windows of corners change the window content very much.

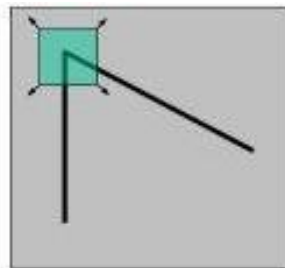




"flat" region:
no change in all
directions



"edge":
no change along the
edge direction



"corner":
significant change in
all directions

Mathematical Formulation

$$f(\Delta x, \Delta y) = \sum_{(x_k, y_k) \in W} (I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y))^2$$

$I(x + \Delta x, y + \Delta y)$ can be approximated by a [Taylor expansion](#). Let I_x and I_y be the partial [derivatives](#) of I , such that

$$I(x + \Delta x, y + \Delta y) \approx I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y$$

This produces the approximation

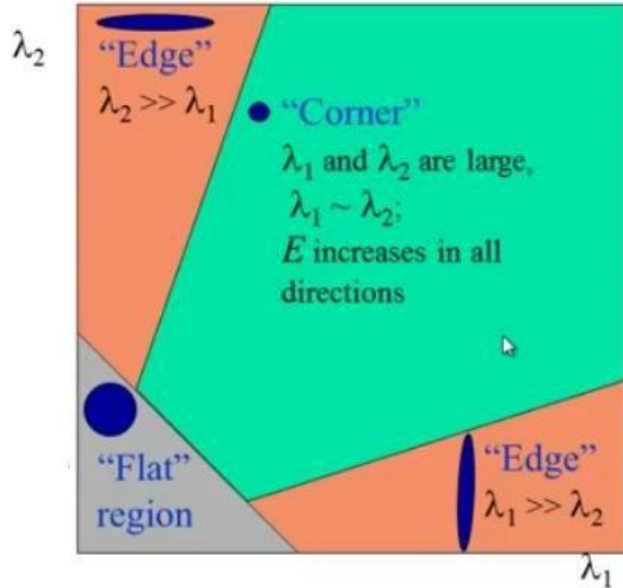
$$f(\Delta x, \Delta y) \approx \sum_{(x, y) \in W} (I_x(x, y)\Delta x + I_y(x, y)\Delta y)^2,$$

which can be written in matrix form:

$$f(\Delta x, \Delta y) \approx \begin{pmatrix} \Delta x & \Delta y \end{pmatrix} M \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix},$$

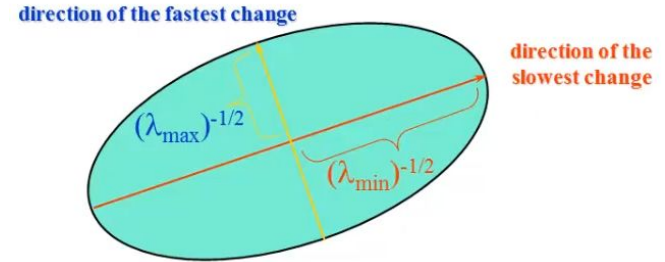
where M is the [structure tensor](#),

$$M = \sum_{(x, y) \in W} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \sum_{(x, y) \in W} I_x^2 & \sum_{(x, y) \in W} I_x I_y \\ \sum_{(x, y) \in W} I_x I_y & \sum_{(x, y) \in W} I_y^2 \end{bmatrix}$$



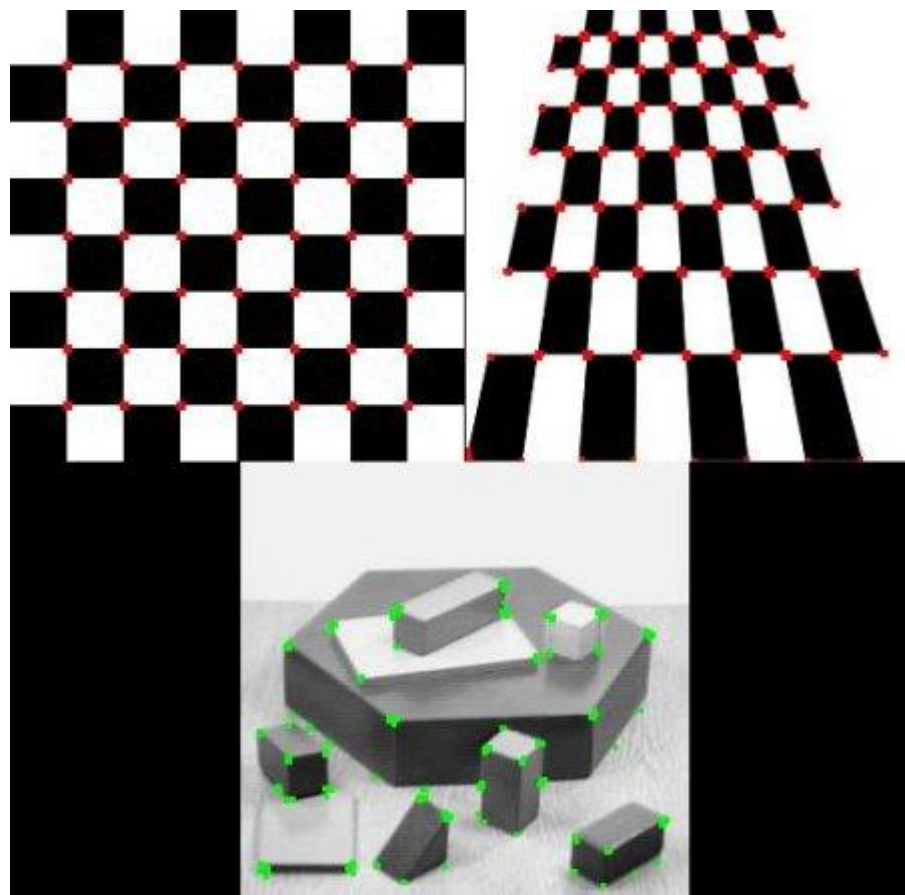
Note:
 $E=f(dx,dy)$

- $f(dx,dy)$ is an equation of ellipse.
- M can be viewed as a covariance matrix.
- The eigenvectors of M represent the principal directions of gradient variation.
- The eigenvalues represent the magnitude of variation in those directions.



$$R = \lambda_1 \lambda_2 - k \cdot (\lambda_1 + \lambda_2)^2 = \det(M) - k \cdot \text{tr}(M)^2$$

where k is an empirically determined constant; $k \in [0.04, 0.06]$



Lecture Outline

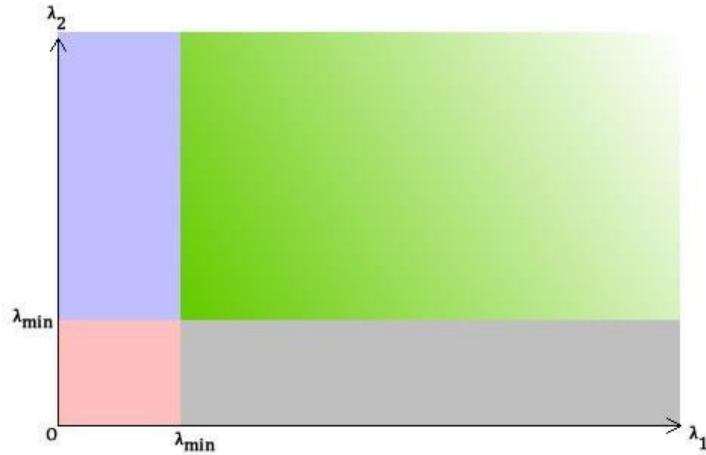
Haar Features

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Shi-Tomasi Corner Detector



Shi-Tomasi Corner Detector



$$R = \min(\lambda_1, \lambda_2)$$

