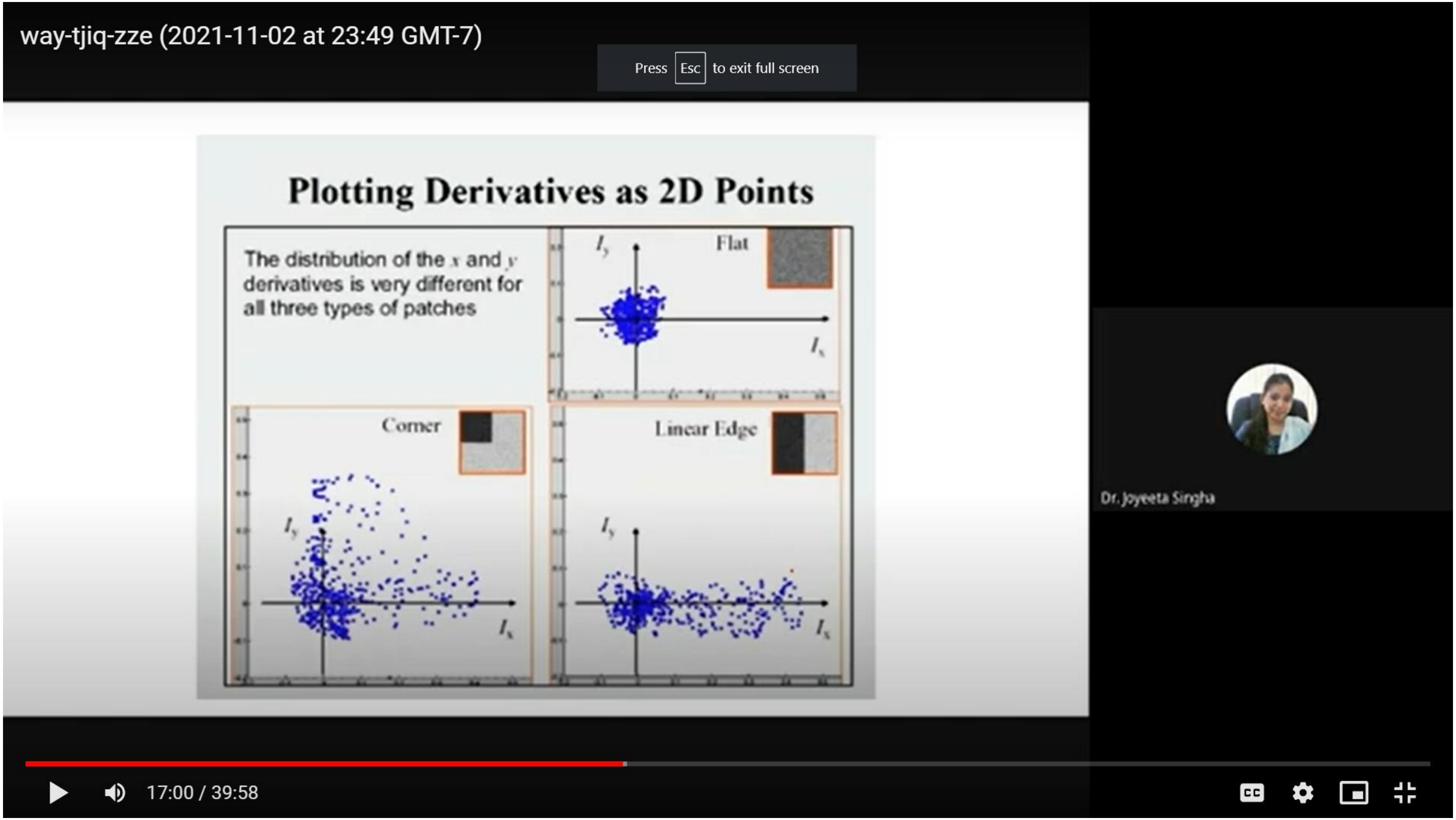
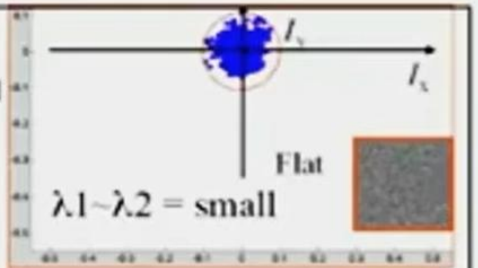
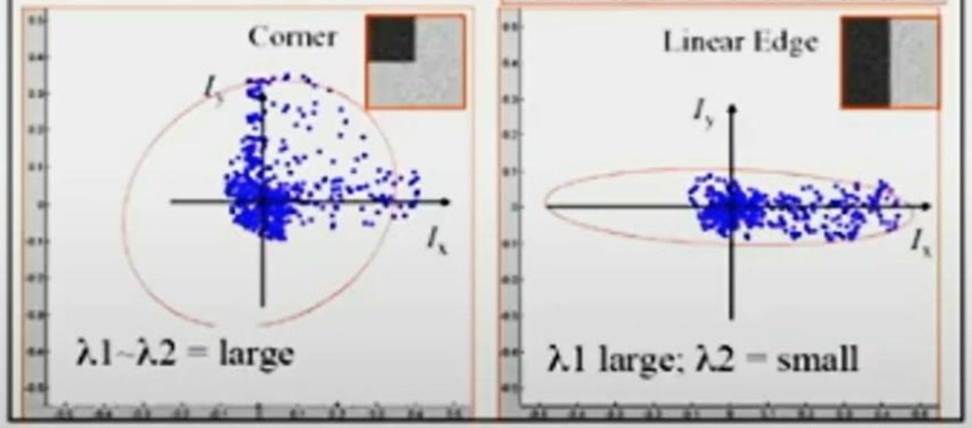

way-tjiq-zze (2021-11-02 at 23:49 GMT-7)
Press Esc to exit full screen
Plotting Derivatives as 2D Points
The distribution of the x and y derivatives is very different for all three types of patches
Flat
Corner
Linear Edge
I_y
I_x
Dr. Joyeeta Singha
17:00 / 39:58

Fitting Ellipse to each Set of Points

The distribution of x and y derivatives can be characterized by the shape and size of the principal component ellipse





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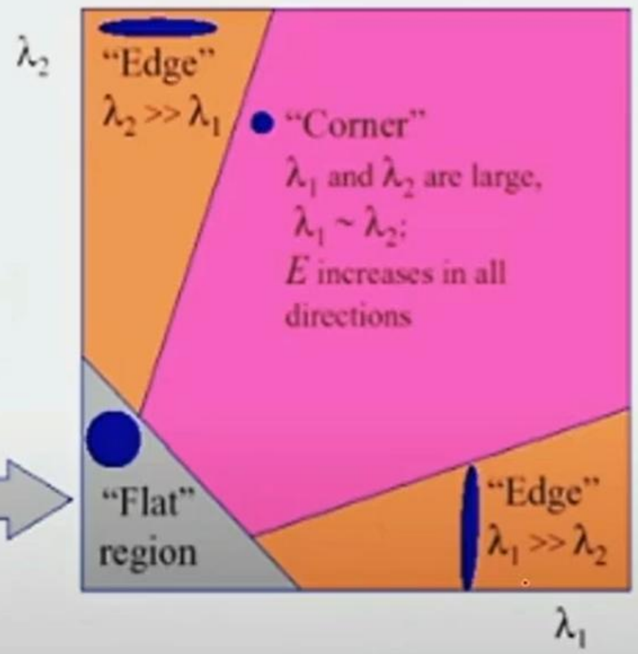
Classification via Eigenvalues

Classification of image points using eigenvalues of M:



λ_1 and λ_2 are small;
E is almost constant in all directions

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Corner Response Measure

Measure of corner response:

$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

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

Windowing function - computing a weighted sum (simplest case, w=1)

Note: these are just products of components of the gradient, Ix, Iy

$$\det M = \lambda_1 \lambda_2$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

(k is an empirically determined constant; k = 0.04 - 0.06)

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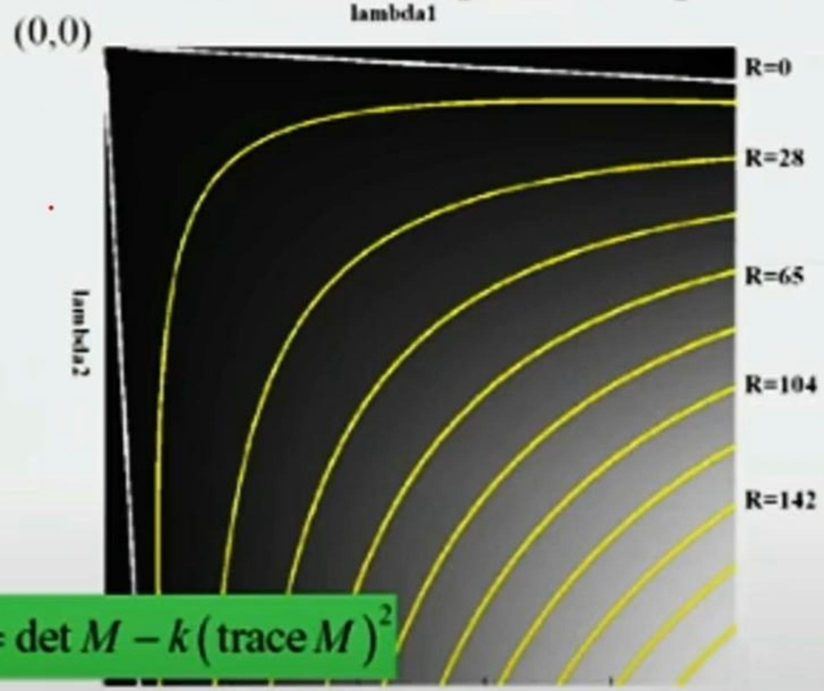
Corner Response Map



$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

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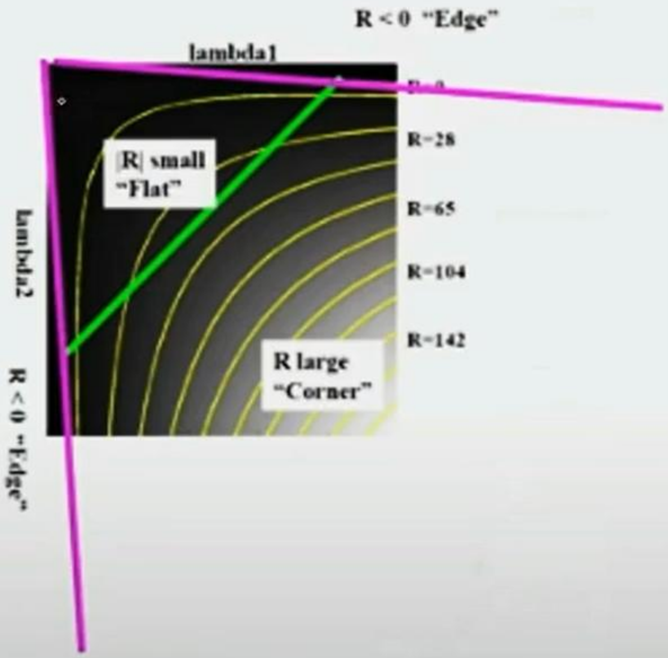
Corner Response Map

- *R* depends only on eigenvalues of M
- *R* is large for a corner
- *R* is negative with large magnitude for an edge
- $|R|$ is small for a flat region

$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

$$\det M = \lambda_1 \lambda_2$$

$$\operatorname{trace} M = \lambda_1 + \lambda_2$$



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Corner Response Example

Threshold: > 10000
(corners)

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Harris Detector: Workflow

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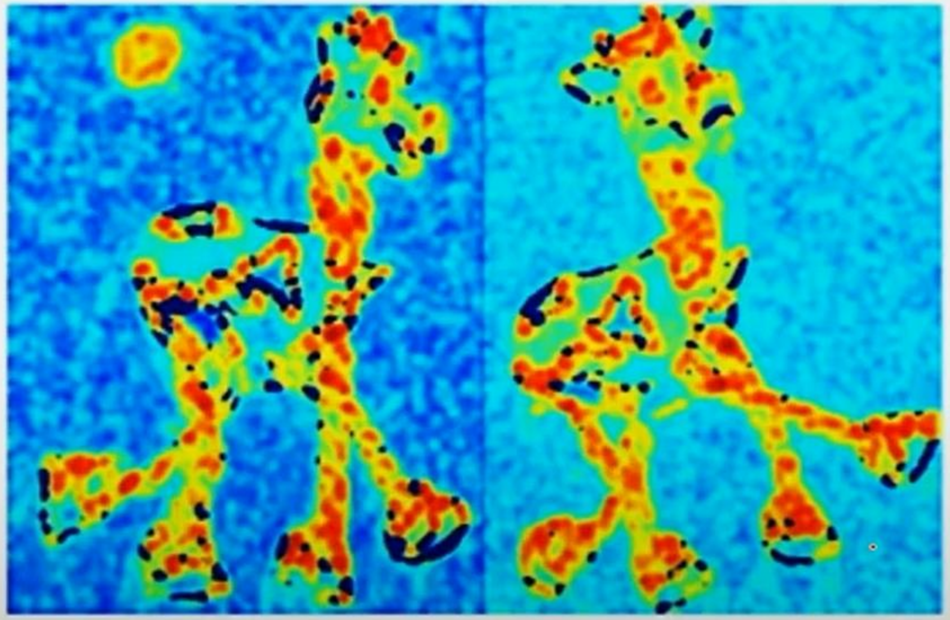
Harris Detector: Workflow

Compute corner response R



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Harris Detector: Workflow

Find points with large corner response: $R >$ threshold

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Harris Detector: Workflow

Take only the points of local maxima of R

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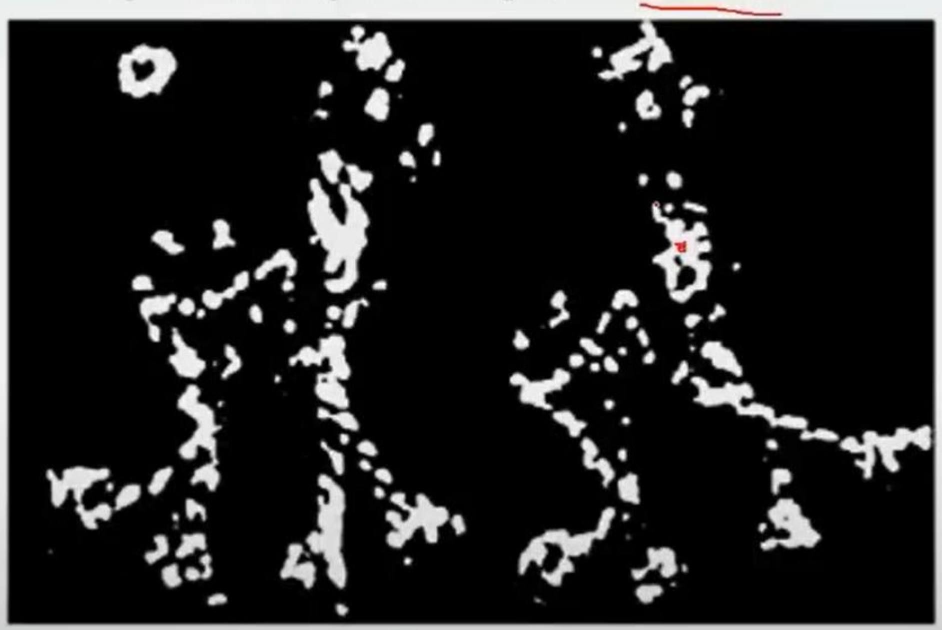
Harris Detector: Workflow

Find points with large corner response: $R>$threshold



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Harris Detector: Summary

- Average intensity change in direction $[u,v]$ can be expressed as a bilinear form:

$$E(u,v) \cong [u,v] \quad M \begin{bmatrix} u \\ v \end{bmatrix}$$

- Describe a point in terms of eigenvalues of M: *measure of corner response*

$$R = \lambda_1 \lambda_2 - k\left(\lambda_1 + \lambda_2\right)^2$$

- A good (corner) point should have a *large intensity change* in *all directions*, i.e. R should be large positive

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Histograms of Oriented Gradients (HoG)

- **Histogram of Oriented Gradients (HOG)** are feature descriptors used in computer vision and image processing for the purpose of object detection.

- The technique counts occurrences of gradient orientation in localized portions of an image.

- Local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions

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- Gradient-based feature descriptor developed for people detection
  - Authors: Dalal&Triggs
  - Global descriptor for the complete body
- Very high-dimensional
  - Typically ~4000 dimensions

Very promising results on challenging data sets

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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

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Gradient computation:

- Use Sobel / any other edge detection masks.

- Gradient:

$$\text{Magnitude}: \ |\Delta f| = \sqrt{G_x^2 + G_y^2}$$

$$\text{Orientation}: \ \theta = \arctan\left(\frac{G_y}{G_x}\right)$$

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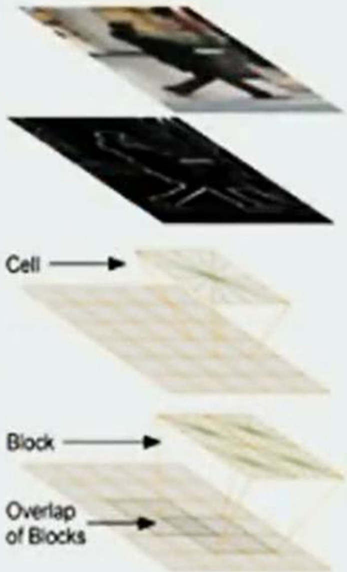
Orientation binning:

- For a 64x128 image,
- Divide the image into 16x16 blocks of 50% overlap.
- 7x15=105 blocks in total
- Each block should consist of 2x2 cells with size 8x8.
- Quantize the gradient orientation into 9 bins
- The vote is the gradient magnitude
- Interpolate votes bi-linearly between neighboring bin center



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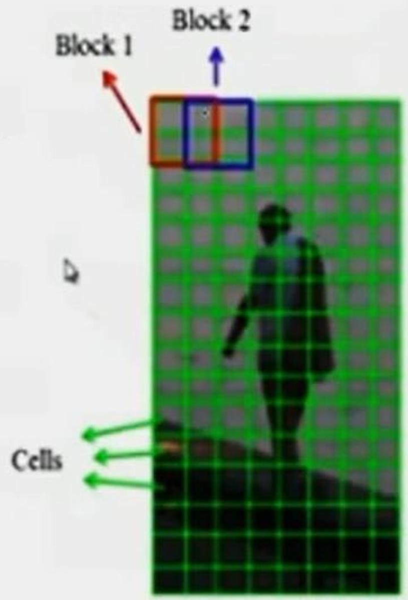
Blocks, Cells

- 16x16 blocks of 50% overlap.
  - 7x15=105 blocks in total
- Each block should consist of 2x2 cells with size 8x8.



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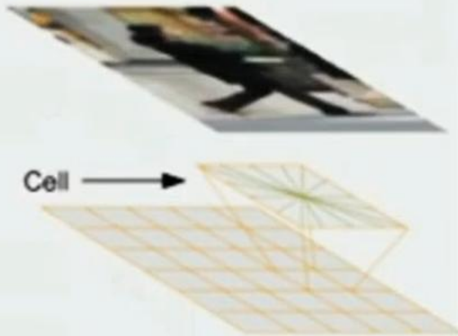
Cell histograms

- 9 bins for gradient orientations

  0-180 degrees (Unsigned gradient Orientation)



- Each bin voted with gradient magnitudes

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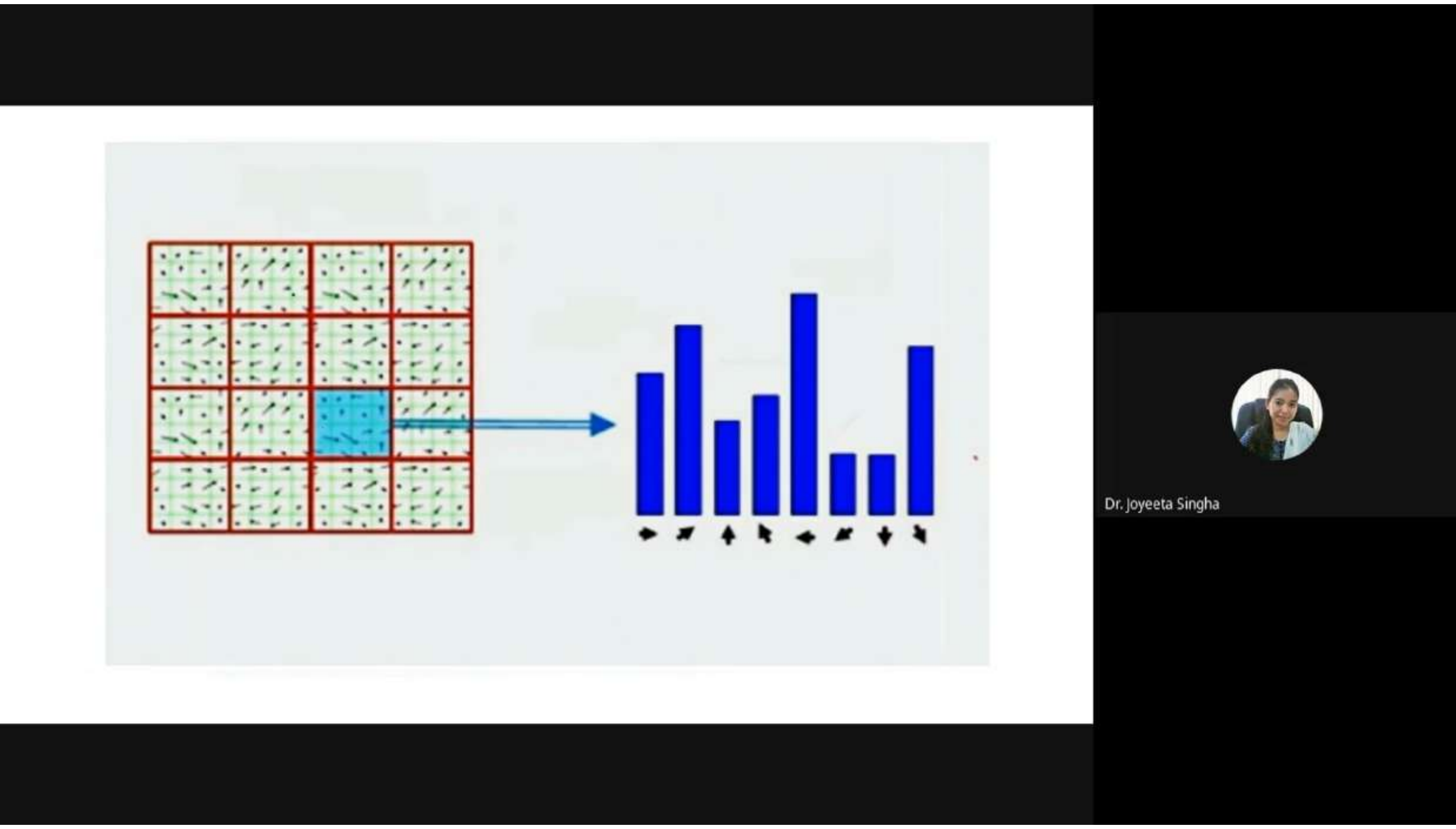
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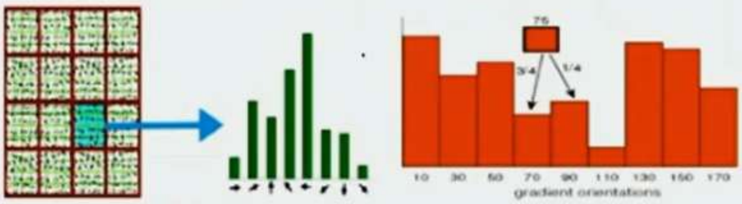
Histogram interpolation example

$\theta = 75^\circ$

- Distance to bin centers
  - Bin 70 -> 5 degress
  - Bin 90 -> 15 degrees

The ratios of belongingness

- Ratios: 5/20=1/4, 15/20=3/4



(a) (b)

Histogram of oriented gradients: (a) cell histogram and (b) orientation binning.

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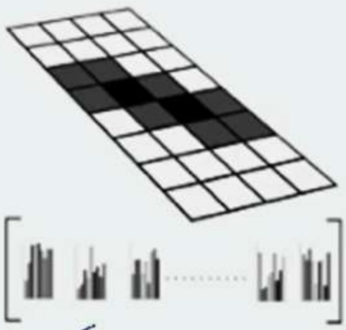
Concatenation of descriptor blocks:

- The cell histograms are then concatenated to form a feature vector.
- The histograms obtained from overlapping blocks of 2X2 cells are concatenated into a 1-D feature vector of dimension 105 X 2 X 2 X 9 = 3780.



Concatenated feature vector.

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Block normalization:

Let v be the non-normalized vector containing all histograms in a given block

Dalal and Triggs explored different methods for block normalization

L_2-norm: $f = \frac{v}{\|v\|_2}$

L_1-norm: $f = \frac{v}{\|v\|_1}$

L_1-square root $f = \sqrt{\frac{v}{\|v\|_1}}$

In addition, the scheme L_2-Hysteresis can be computed by first taking the L_2-norm, clipping the result, and then renormalizing.

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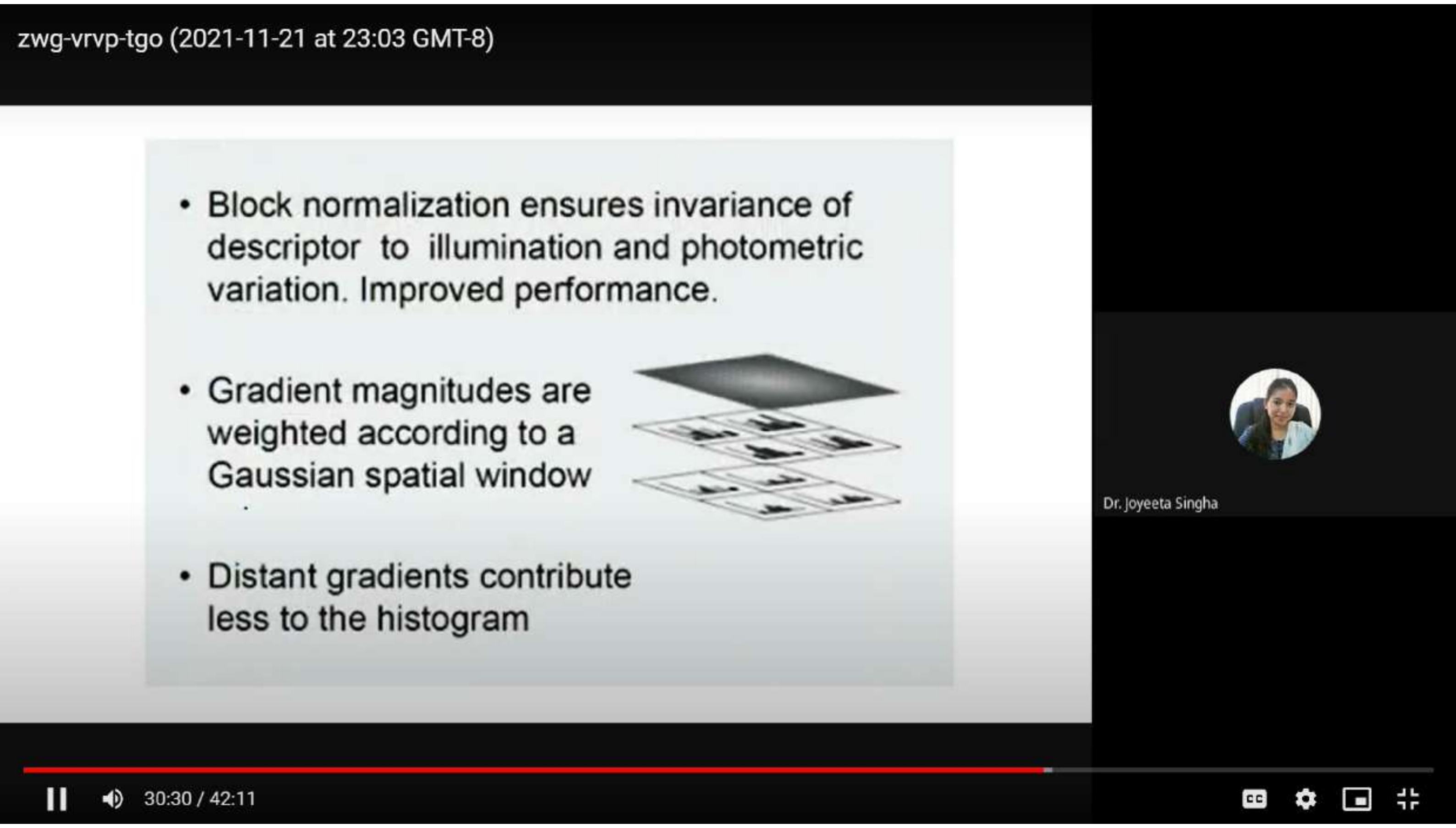
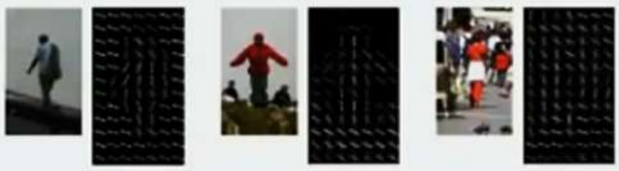

zwg-vrvp-tgo (2021-11-21 at 23:03 GMT-8)
• Block normalization ensures invariance of descriptor to illumination and photometric variation. Improved performance.
• Gradient magnitudes are weighted according to a Gaussian spatial window
• Distant gradients contribute less to the histogram
Dr. Joyeeta Singha
30:30 / 42:11

Final descriptor:

- Concatenation of Blocks

Visualization:



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(a) (b)

(a) Cameraman image and (b) HOG

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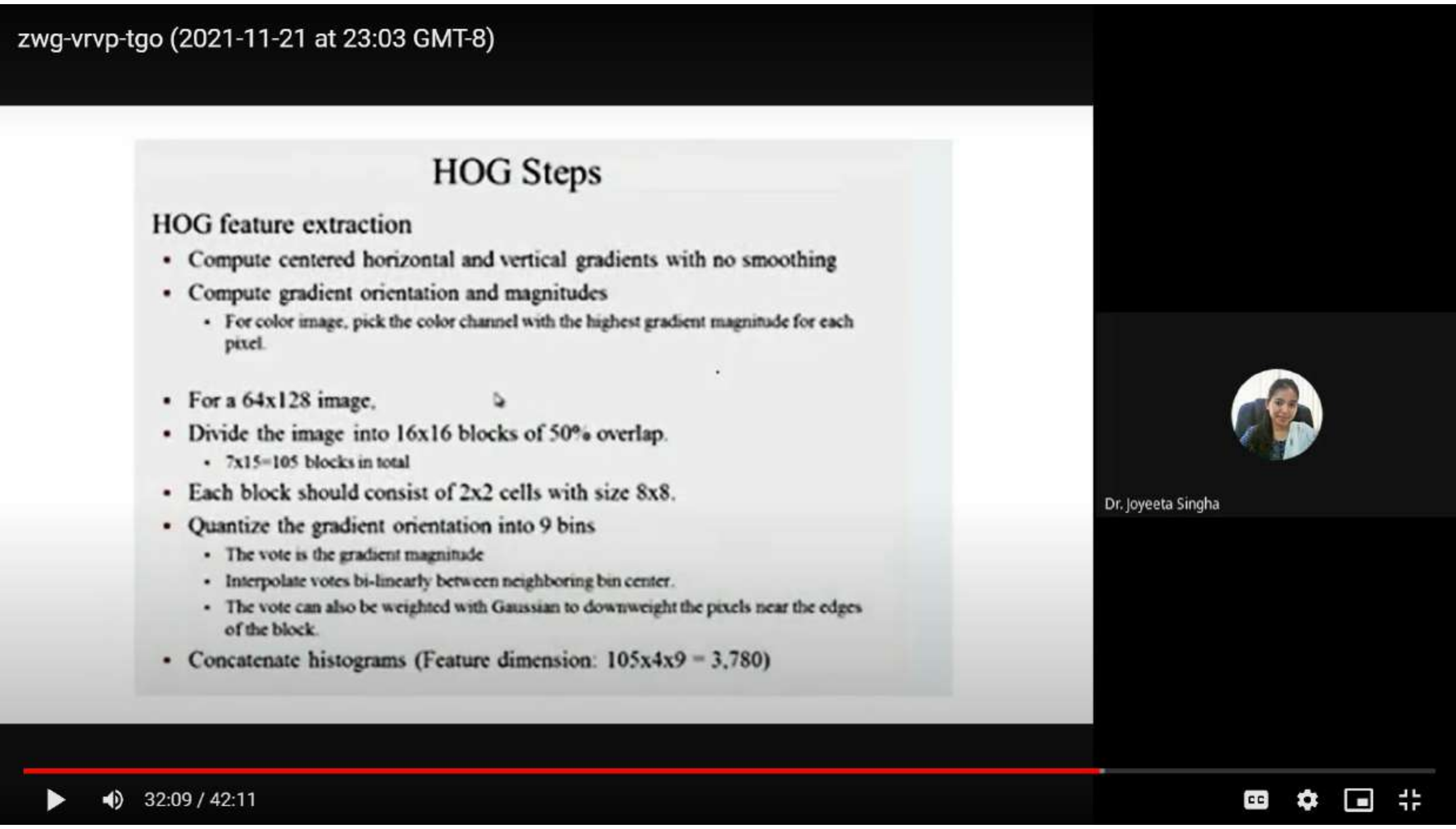
zwg-vrvp-tgo (2021-11-21 at 23:03 GMT-8)
HOG Steps
HOG feature extraction
• Compute centered horizontal and vertical gradients with no smoothing
• Compute gradient orientation and magnitudes
• For color image, pick the color channel with the highest gradient magnitude for each pixel.
• For a 64x128 image,
• Divide the image into 16x16 blocks of 50% overlap.
• 7x15=105 blocks in total
• Each block should consist of 2x2 cells with size 8x8.
• Quantize the gradient orientation into 9 bins
• The vote is the gradient magnitude
• Interpolate votes bi-linearly between neighboring bin center.
• The vote can also be weighted with Gaussian to downweight the pixels near the edges of the block.
• Concatenate histograms (Feature dimension: 105x4x9 = 3,780)
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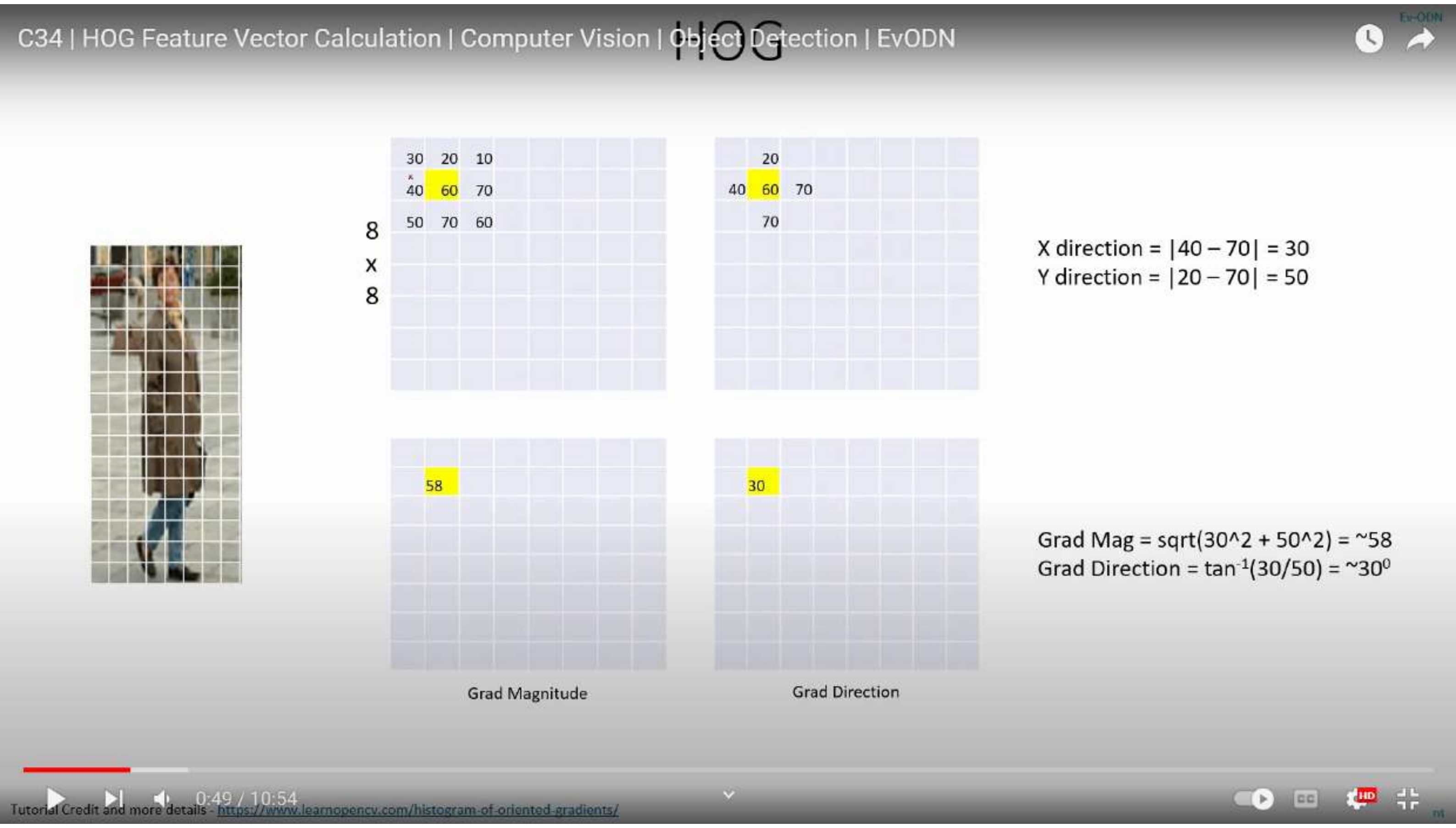
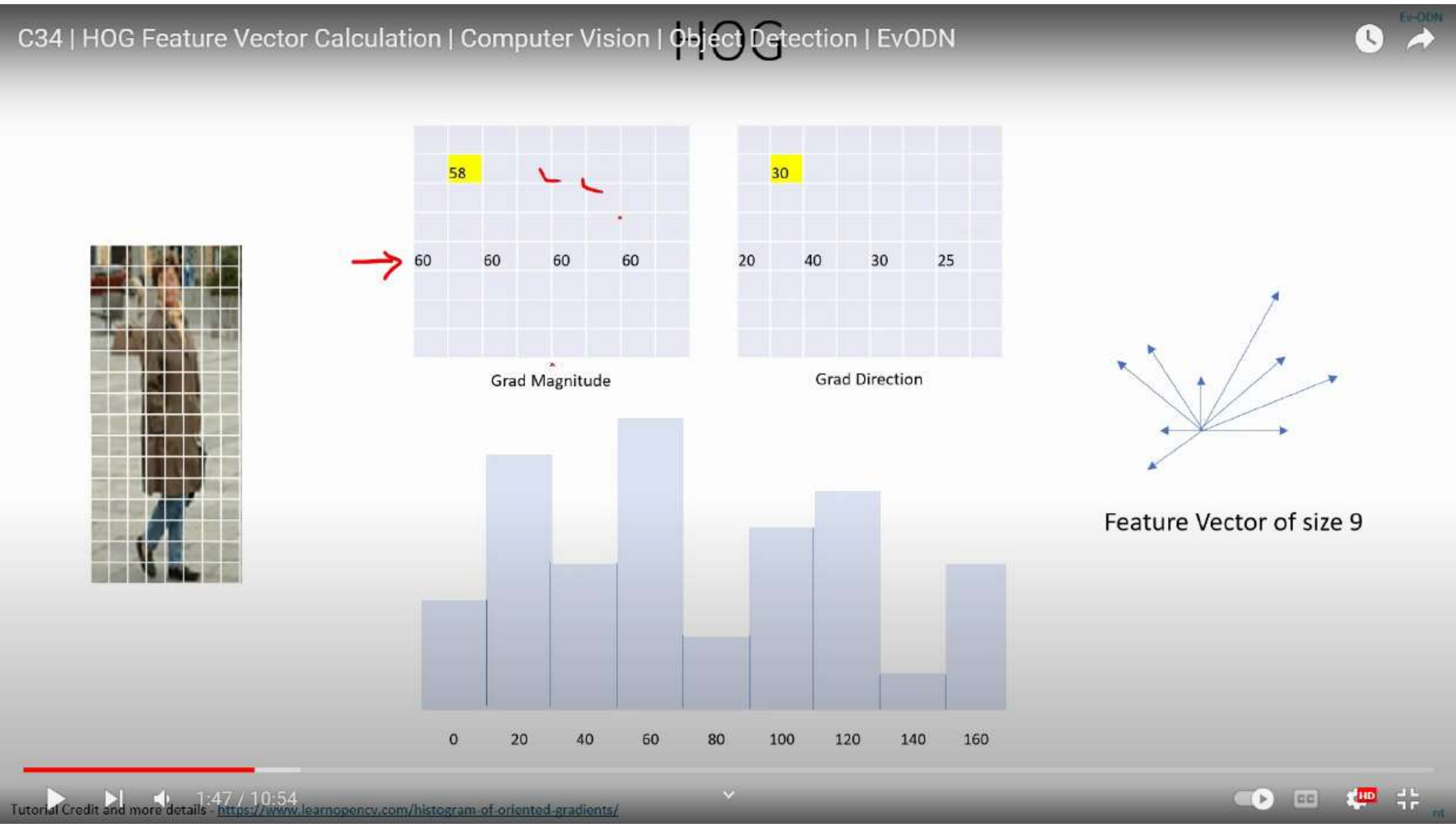
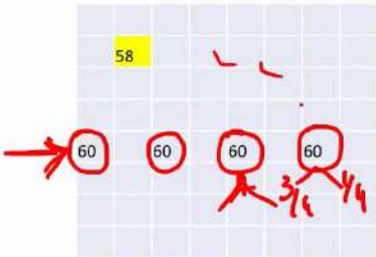
32:09 / 42:11

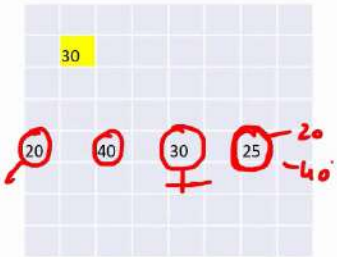

C34 | HOG Feature Vector Calculation | Computer Vision | Object Detection | EvODN
HOG
8 x 8
30 20 10
40 60 70
50 70 60
20
40 60 70
70
58
30
X direction = |40 – 70| = 30
Y direction = |20 – 70| = 50
Grad Mag = sqrt(30^2 + 50^2) = ~58
Grad Direction = tan-1(30/50) = ~30°
Grad Magnitude
Grad Direction
0:49 / 10:54
Tutorial Credit and more details - https://www.learnopencv.com/histogram-of-oriented-gradients/


C34 | HOG Feature Vector Calculation | Computer Vision | Object Detection | EvODN
HOG
58
60 60 60 60
Grad Magnitude
30
20 40 30 25
Grad Direction
0 20 40 60 80 100 120 140 160
Feature Vector of size 9
1:47 / 10:54
Tutorial Credit and more details - https://www.learnopencv.com/histogram-of-oriented-gradients/

HOG

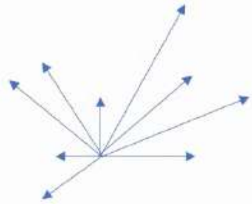


Grad Magnitude

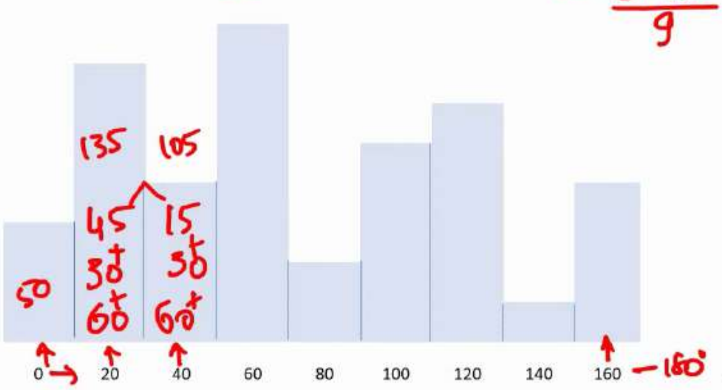


Grad Direction

$\frac{0-180^\circ}{9}$



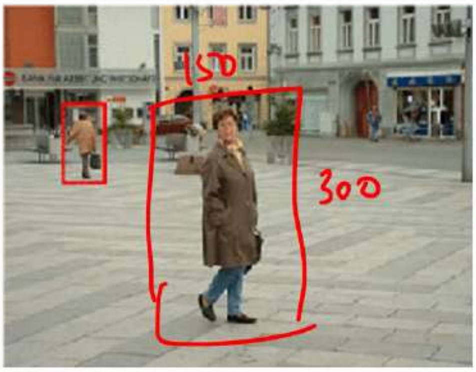
Feature Vector of size 9



FV = [50, 135, 105, - . .] 9

Tutorial Credit and more details - https://www.learnopencv.com/histogram-of-oriented-gradients/

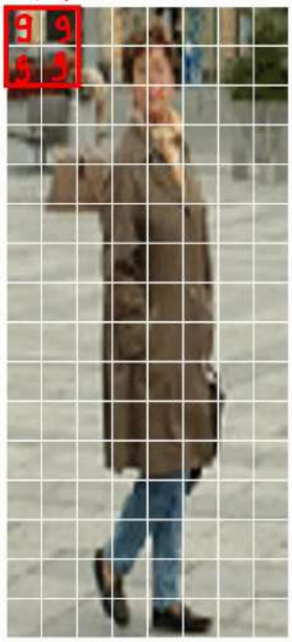
HOG Feature Vector



64x128

8

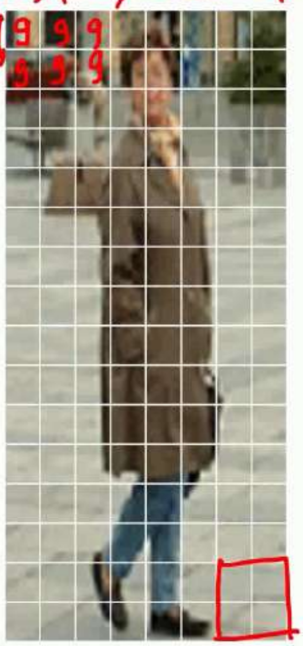
8



8x16 7*15*36 = 3780

HOG Feature Vector

64x128



$\boxed{2,4}$ $\sqrt{2^2+4^2} = 4.472$

$\frac{2}{4.472}, \frac{4}{4.472} = 0.44, 0.89$

$\boxed{4,8}$ $\sqrt{4^2+8^2} = 8.944$

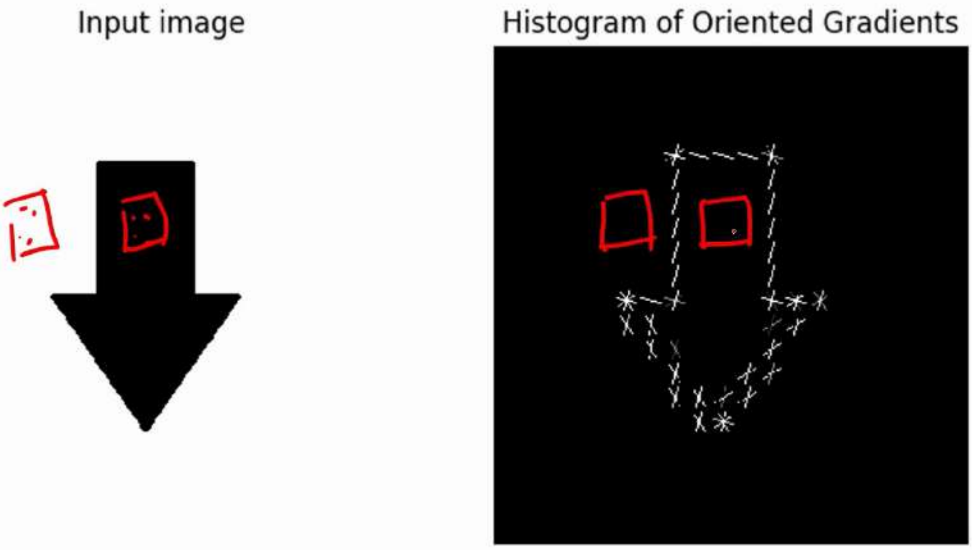
$\frac{4}{8.944}, \frac{8}{8.944} = 0.4472, 0.8944$

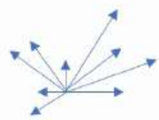
8x16

7x15

7*15*36 = 3780 } 150x300 = 45,000

HOG - Example



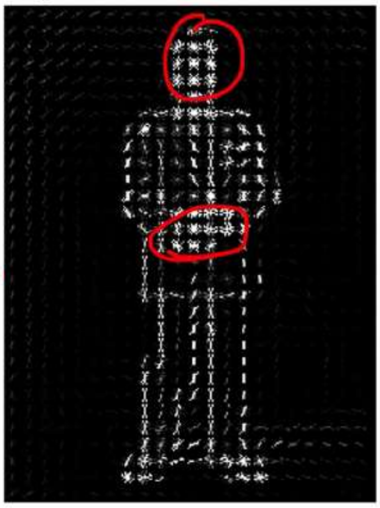


HOG generated using skimage: http://scikit-image.org/docs/dev/auto_examples/features_detection/plot_hog.html

HOG - Example

Input image

Histogram of Oriented Gradients



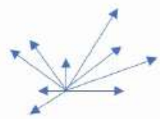
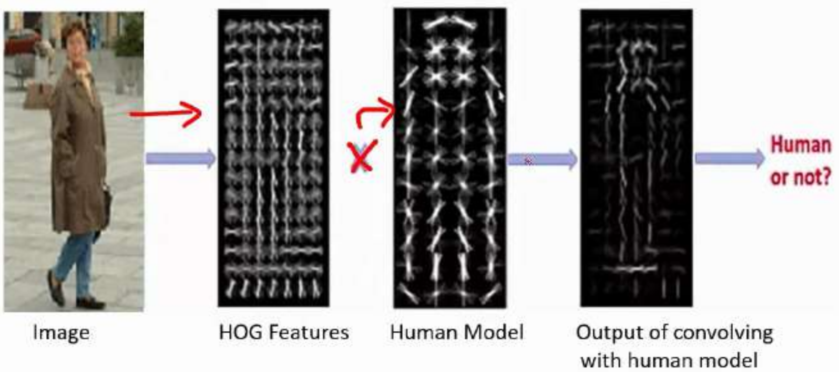


Image Credit - https://en.wikipedia.org/wiki/File:05_Sebastian_Maniscalco_1251f.jpg
HOG generated using skimage: http://scikit-image.org/docs/dev/auto_examples/features_detection/plot_hog.html

Object Detection with HOG+SVM



Histograms of Oriented Gradients for Human Detection
Navneet Dalal and Bill Triggs

Slide credit: https://www.youtube.com/watch?v=2DihVLm8v38
Dalal & Triggs Detector: https://lear.inrialpes.fr/people/triggs/pubs/Dalal-cvpr05.pdf