

# OpenCV Python Tutorial For Beginners (10 hrs)

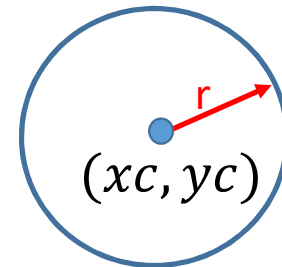
<https://www.youtube.com/watch?v=N81PCpADwKQ&t=27645s>

<https://www.youtube.com/watch?v=kdLM6A0d2vc&list=PLS1Qu1Wo1RIa7D106skqDQ-JZ1GGHKK-K>



### 34. Circle Detection using OpenCV Hough Circle Transform

$$(x - x_c)^2 + (y - y_c)^2 = r^2$$



```
circles=cv.HoughCircles( image, method, dp, minDist[, circles[, param1[, param2[,  
minRadius[, maxRadius]]]]])
```

**image** 8-bit, single-channel, grayscale input image.

**circles** Output vector of found circles.

**method** Detection method, see HoughModes. Currently, the only implemented method is HOUGH\_GRADIENT

**dp** Inverse ratio of the accumulator resolution to the image resolution.

**minDist** Minimum distance between the centers of the detected circles.

**param1** First method-specific parameter. In case of HOUGH\_GRADIENT , it is the higher threshold of the two passed to the Canny edge detector (the lower one is twice smaller).

**param2** Second method-specific parameter. In case of HOUGH\_GRADIENT , it is the accumulator threshold for the circle centers at the detection stage.

**minRadius** Minimum circle radius.

**maxRadius** Maximum circle radius. If  $\leq 0$ , uses the maximum image dimension. If  $< 0$ , returns centers without finding the radius.

**cv.HoughCircles** (image, circles, method, dp, minDist, param1 = 100, param2 = 100, minRadius = 0, maxRadius = 0)

Parameters:

**image** 8-bit, single-channel, **grayscale** input image.

**circles** output vector of found circles(cv.CV\_32FC3 type). Each vector is encoded as a 3-element **floating-point** vector (**x, y, radius**) .

**method** detection method (see cv.HoughModes). Currently, the only implemented method is HOUGH\_GRADIENT

**dp** inverse ratio of the accumulator resolution to the image resolution. For example, if  $dp = 1$  , the accumulator has the same resolution as the input image. If  $dp = 2$  , the accumulator has half as big width and height.

**minDist** minimum distance between the centers of the detected circles. If the parameter is too small, multiple neighbor circles may be falsely detected in addition to a true one. If it is too large, some circles may be missed.

**cv.HoughCircles** (image, circles, method, dp, minDist, param1 = 100, param2 = 100, minRadius = 0, maxRadius = 0)

Parameters:

**Param1** first method-specific parameter. In case of HOUGH\_GRADIENT , it is the higher threshold of the two passed to the **Canny edge detector** (the lower one is twice smaller).

**Param2** second method-specific parameter. In case of HOUGH\_GRADIENT , it is the accumulator threshold for the circle centers at the detection stage. The smaller it is, the more false circles may be detected. Circles, corresponding to the larger accumulator values, will be returned first.

**minRadius** minimum circle radius.

**maxRadius** maximum circle radius.

`cv.HoughCircles` (image, circles, method, dp, minDist, param1 = 100, param2 = 100, minRadius = 0, maxRadius = 0)

ex40.py

13 circles

```
8 import numpy as np
9 import cv2 as cv
10 img = cv.imread('smarties.png')
11 output = img.copy()
12 gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
13 gray = cv.medianBlur(gray, 5)
14 circles = cv.HoughCircles(gray, cv.HOUGH_GRADIENT, 1, 20,
15                             param1=50, param2=30, minRadius=0, maxRadius=0)
16 detected_circles = np.uint16(np.around(circles)) # (1, 13, 3)
17 for (x, y, r) in detected_circles[0, :]:
18     cv.circle(output, (x, y), r, (0, 0, 0), 3) # black circles
19     cv.circle(output, (x, y), 2, (0, 255, 255), 3) # yellow centers
20
21 cv.imshow('output', output)
22 cv.waitKey(0)
23 cv.destroyAllWindows()
```

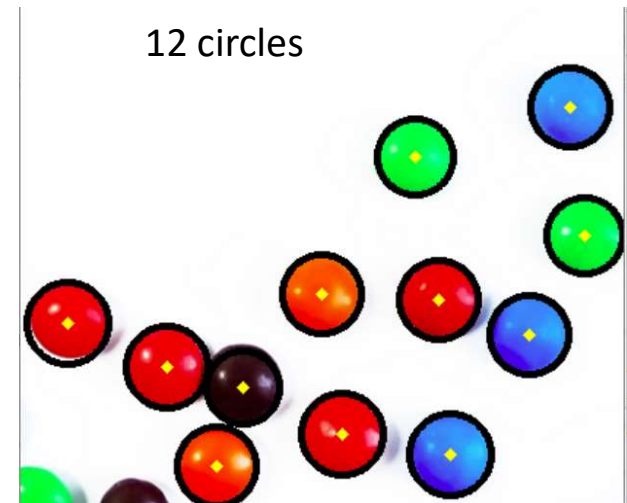
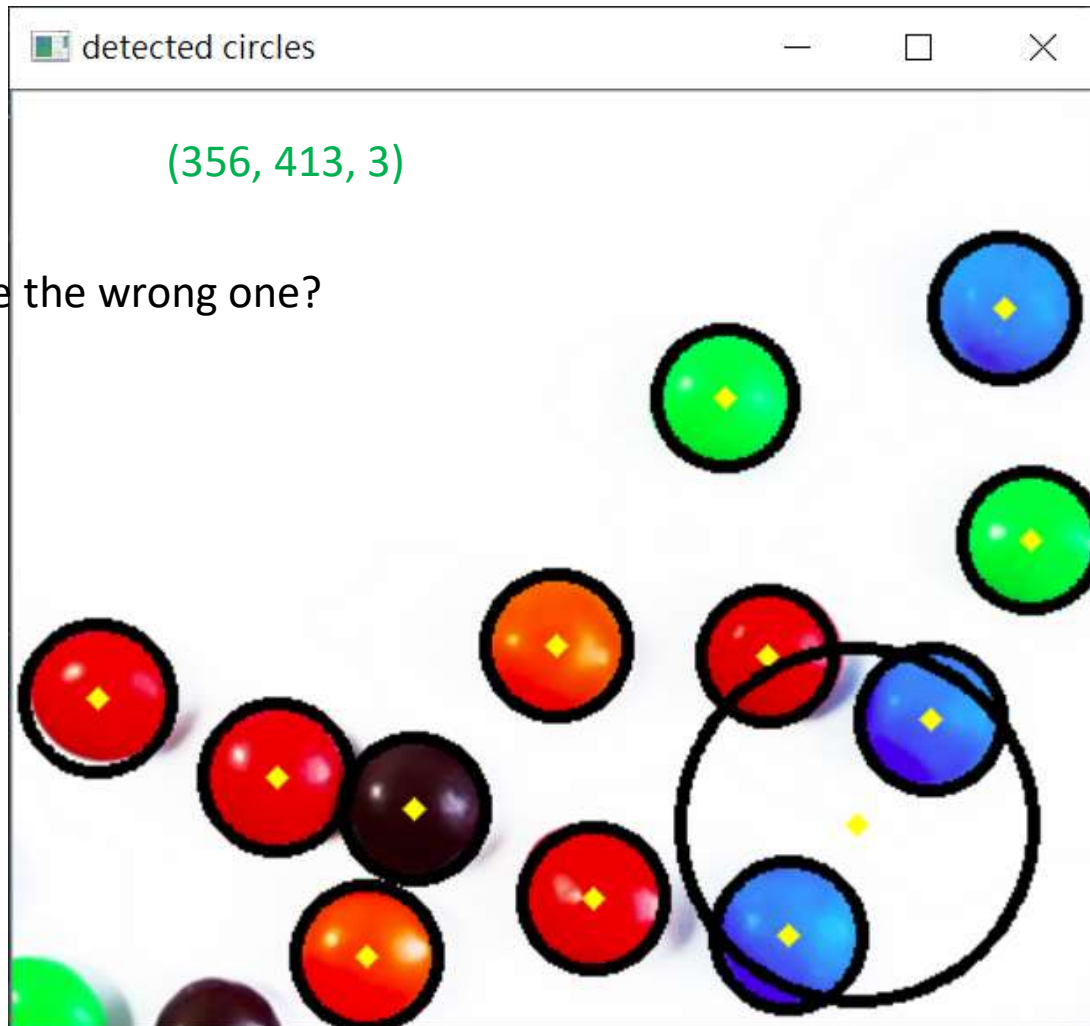
circles: array([[ [376.5, 81.5, 26.6], ..., [320.5, 278.5, 67.4] ]], dtype=float32) Shape (1, 13, 3)  
                  x,          y,          r



13 circles  
accuracy?

(12/13 accuracy)

Q: how to eliminate the wrong one?



## 35 (36). Face (+Eyes) Detection using Haar Cascade Classifiers

匈牙利數學家Alfred Haar

<https://github.com/opencv/opencv/tree/master/data/haarcascades> to download

`haarcascade_frontalface_alt.xml` (pretrained face detector)

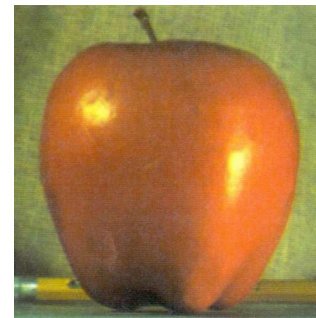
`haarcascade_eye_tree_eyeglasses.xml` (pretrained eye detector)

Object Detection using **Haar feature-based cascade classifiers** is an effective object detection method proposed by Paul Viola and Michael Jones in their paper, "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001. It is a **machine learning** based approach where a cascade function is trained from a lot of positive (image of face) and negative images (image without face).

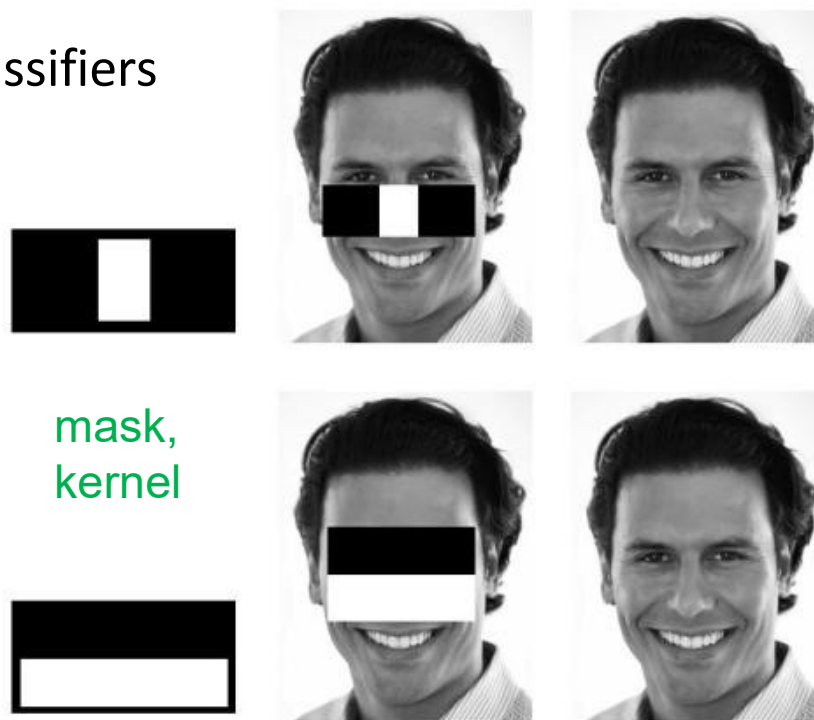
positive



negative



## Haar **feature-based** cascade classifiers



## Haar feature-based **cascade classifiers**

每一個基本的Haar-like特徵就是一個弱分類器，**Cascade Classifier**透過數個強分類器的組合（**級聯**），將每一張輸入的圖片依次通各個強分類器，前面的強分類器相對簡單，其包含的弱分類器也較少，後面的強分類器逐級複雜，只有通過前面的強分類檢測後的圖片才能進入後面的強分類器進行檢測，所以前面幾級的分類器已經過濾掉大部分不合格的圖片，只有通過了所有強分類器檢測的才是正確辨識出的圖片。

<https://chtseng.wordpress.com/2018/06/15/opencv-cascade-object-detection/>



(pretrained model)

```
face_cascade = cv2.CascadeClassifier('haarcascade_frontalface_alt.xml')
```

```
face_cascade.detectMultiScale
```

```
faces = face_cascade.detectMultiScale(image[, scaleFactor[, minNeighbors[, flags[, minSize[,  
maxSize]]]])
```

## Parameters

**image** Matrix of the type CV\_8U containing an image where objects are detected.

**objects**

Vector of rectangles where each rectangle contains the detected object, the rectangles may be partially outside the original image.  
(n, 4): x, y, w, h

**scaleFactor** Parameter specifying how much the image size is reduced at each image scale.

**minNeighbors** Parameter specifying how many neighbors each candidate rectangle should have to retain it.

**flags** Parameter with the same meaning for an old cascade as in the function cvHaarDetectObjects. It is not used for a new cascade.

**minSize** Minimum possible object size. Objects smaller than that are ignored. (w, h)

**maxSize** Maximum possible object size. Objects larger than that are ignored. If `maxSize == minSize` model is evaluated on single scale.

```
objects = cv.CascadeClassifier.detectMultiScale( image, scaleFactor,  
minNeighbors )
```

*image* Matrix of the type CV\_8U containing an image where objects are detected.

*objects* Vector of rectangles where each rectangle contains the detected object, the rectangles may be partially outside the original image.

*scaleFactor* Parameter specifying how much the image size is reduced at each image scale.

*minNeighbors* Parameter specifying how many neighbors each candidate rectangle should have to retain it.

ex41.py

faces.shape  
Out[20]: (1, 4)      array([[243, 123, 247, 247]], dtype=int32)

```
8  import cv2
9
10 face_cascade = cv2.CascadeClassifier('haarcascade_frontalface_alt.xml')
11 eye_cascade = cv2.CascadeClassifier('haarcascade_eye_tree_eyeglasses.xml')
12 # Read the input image
13 #img = cv2.imread('test.png')
14 cap = cv2.VideoCapture(0) #'test.mp4')
15
16 while cap.isOpened():
17     _, img = cap.read()
18
19     gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
20     faces = face_cascade.detectMultiScale(gray, 1.1, 3) # default (1.1, 3)
21
22     for (x, y , w ,h) in faces:
23         cv2.rectangle(img, (x,y), (x+w, y+h), (255, 0 , 0), 3) # blue
```



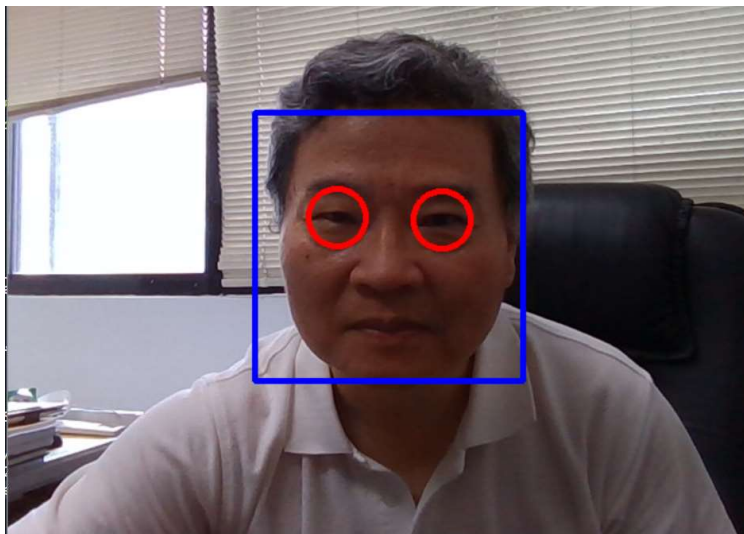
ex41.py

eyes.shape  
Out[32]: (2, 4)

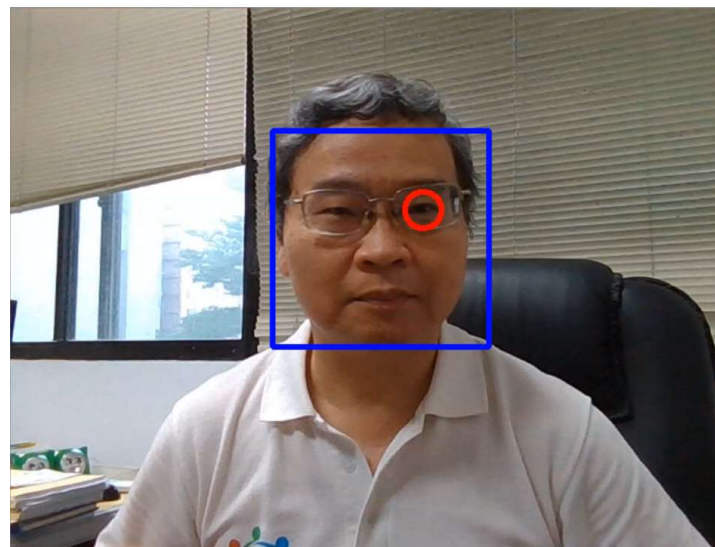
array([[ 45, 57, 55, 55],  
 [149, 60, 55, 55]], dtype=int32)

```
25     faceROI = gray[y:y+h,x:x+w]
26     #-- In each face, detect eyes
27     eyes = eye_cascade.detectMultiScale(faceROI, 1.1, 3)
28     for (x2,y2,w2,h2) in eyes:
29         eye_center = (x + x2 + w2//2, y + y2 + h2//2)
30         radius = int(round((w2 + h2)*0.25))
31         frame = cv2.circle(img, eye_center, radius, (0, 0, 255 ), 3) #red
32
33     # Display the output
34     cv2.imshow('img', img)
35     if cv2.waitKey(1) & 0xFF == ord('q'):
36         break
37
38 cap.release()
39 cv2.destroyAllWindows()
```

```
faces.shape  
Out[20]: (1, 4)
```



```
eyes.shape  
Out[32]: (2, 4)
```

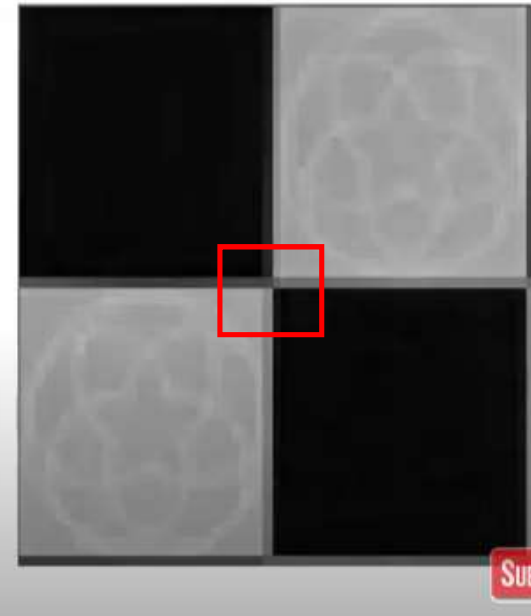




## 37. Detect Corners with Harris Corner Detector

# Harris Corner Detector

1. determine which windows produce very large variations in intensity when moved in both X and Y directions.
2. With each such window found, a score  $R$  is computed.
3. After applying a threshold to this score, important corners are selected & marked.



Chris Harris and Mike Stephens (1988). "A Combined Corner and Edge Detector". *Alvey Vision Conference*. **15**.

# Harris Corner Detector

1. determine which windows produce very large variations in intensity when moved in both X and Y directions.

$$E(u, v) = \sum_{x,y} \underbrace{w(x, y)}_{\text{window function}} \underbrace{[I(x + u, y + v) - I(x, y)]}_{\text{shifted intensity} - \text{intensity}}^2$$

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

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

# Harris Corner Detector

2. With each such window found, a score  $R$  is computed.

$$R = \det(M) - k(\text{trace}(M))^2$$

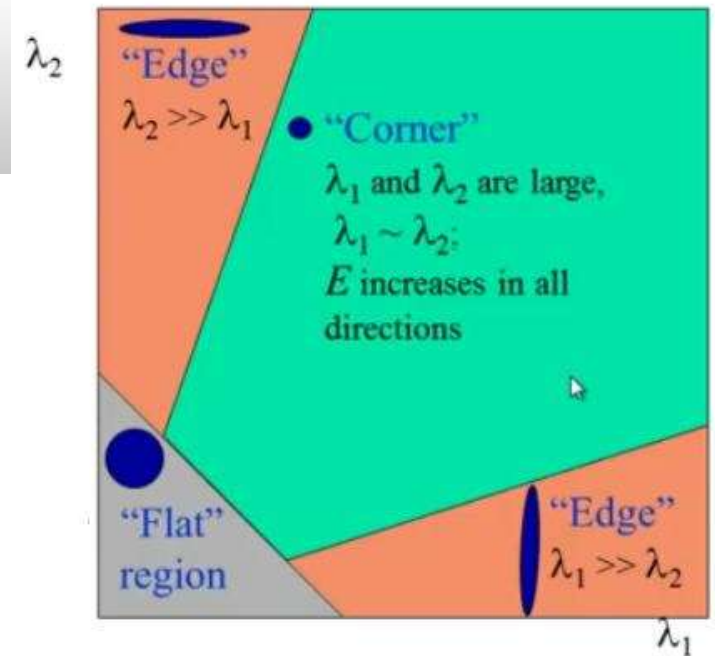
where  $R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$

- $\det(M) = \lambda_1 \lambda_2$
- $\text{trace}(M) = \lambda_1 + \lambda_2$
- $\lambda_1$  and  $\lambda_2$  are the eigen values of  $M$

# Harris Corner Detector

3. After applying a threshold to this score, important corners are selected & marked.

1.  $|R|$  is small, which happens when  $\lambda_1$  and  $\lambda_2$  are small, the region is flat.
2.  $R < 0$ , which happens when  $\lambda_1 \gg \lambda_2$  or vice versa, the region is edge.
3.  $R$  is large, which happens when  $\lambda_1$  and  $\lambda_2$  are large and  $\lambda_1 \sim \lambda_2$ , the region is a corner.





```
dst = cv.cornerHarris(img, 2, 3, 0.04)
```

*img* - Input image, it should be grayscale and float32 type.  
*blockSize* - It is the size of neighbourhood considered for corner detection  
*ksize* - Aperture parameter of Sobel derivative used.  
*k* - Harris detector free parameter in the equation.

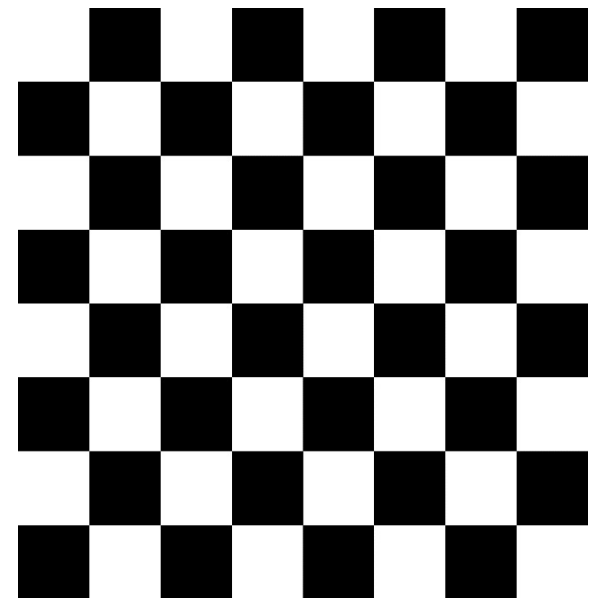
```
dst=cv2.dilate(src, kernel[, dst[, anchor[, iterations[, borderType[, borderValue]]]])  
cv2.dilate(img,kernel,iterations = 1)
```



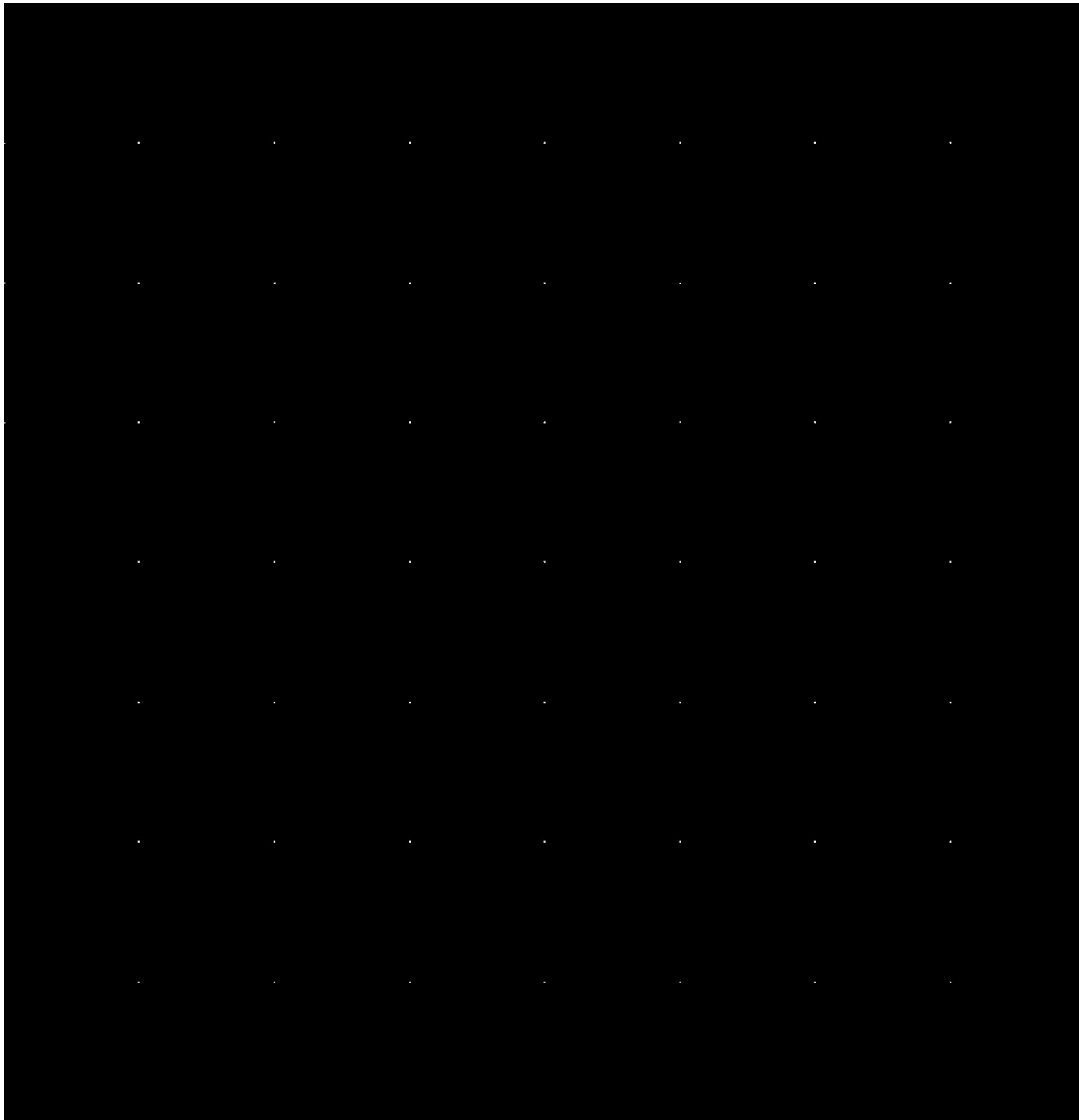
```
8 import numpy as np
9 import cv2 as cv
10
11 img = cv.imread('blox.jpg') #chessboard.png') # (3723, 3595, 3)
12 cv.imshow('img', img)
13
14 gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
15 gray = np.float32(gray)
16
17 dst1 = cv.cornerHarris(gray, 2, 3, 0.04) # (3723, 3595)
18 #result is dilated for marking the corners, not important
19 dst = cv.dilate(dst1, None)
20
21 cv.imshow('dst', dst)
22
23 img[dst > 0.01 * dst.max()] = [0, 0, 255] # red
24
25 cv.imshow('corner', img)
26
27 if cv.waitKey(0) & 0xff == 27:
28     cv.destroyAllWindows()
29
30 # cv.imwrite('corner.png',img)
```

ex42.py

chessboard.png



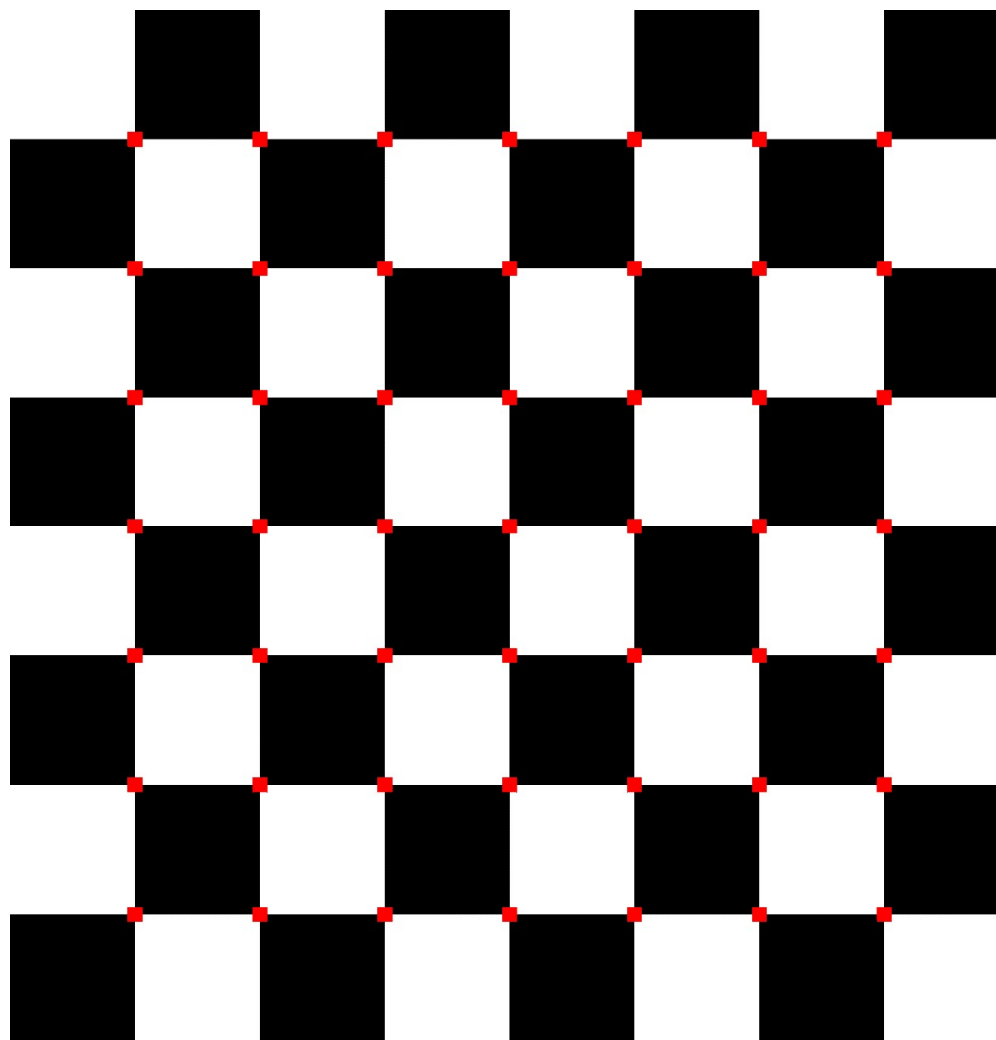
cv2.cornerHarris



■ corner



cv.cornerHarris(gray, 50, 3, 0.04)



## 38. Detect Corners with Shi Tomasi Corner Detector

J. Shi and C. Tomasi. [Good Features to Track](#),. 9th IEEE Conference on Computer Vision and Pattern Recognition. Springer. June 1994.

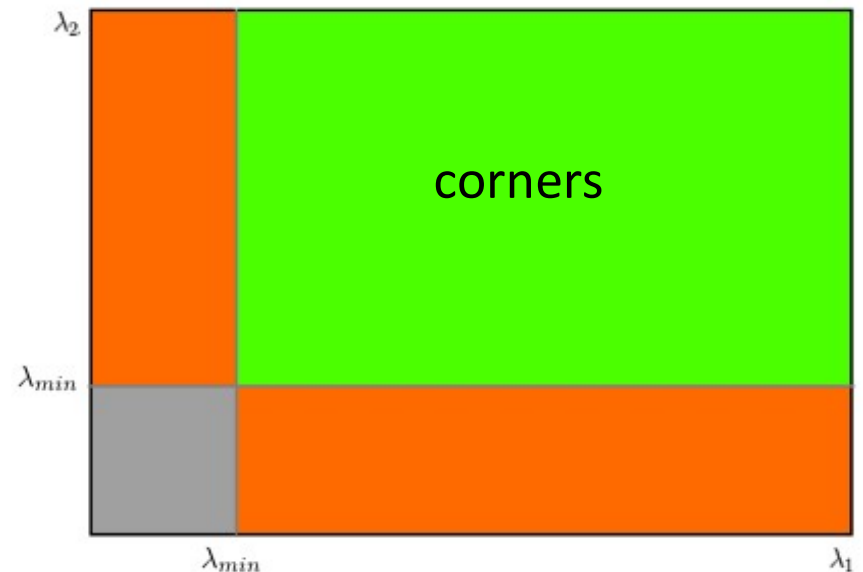
The scoring function in Harris Corner Detector was given by:

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

Instead of this, Shi-Tomasi proposed:

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

$$R_{threshold} = \lambda_{min}$$



```
corners = cv2.goodFeaturesToTrack(gray, 100, 0.01, 10)
```

**cv2.goodFeaturesToTrack()**.

It finds N strongest corners in the image by Shi-Tomasi method (or Harris Corner Detection, if you specify it).

As usual, image should be a **grayscale** image. **gray**

Then you specify **number of corners** you want to find. **100**

Then you specify the **quality level**, which is a value between 0-1, which denotes the minimum quality of corner below which everyone is rejected. **0.01**

Then we provide the **minimum euclidean distance** between corners detected. **10**

numpy.int0 這個其實就是numpy.int64



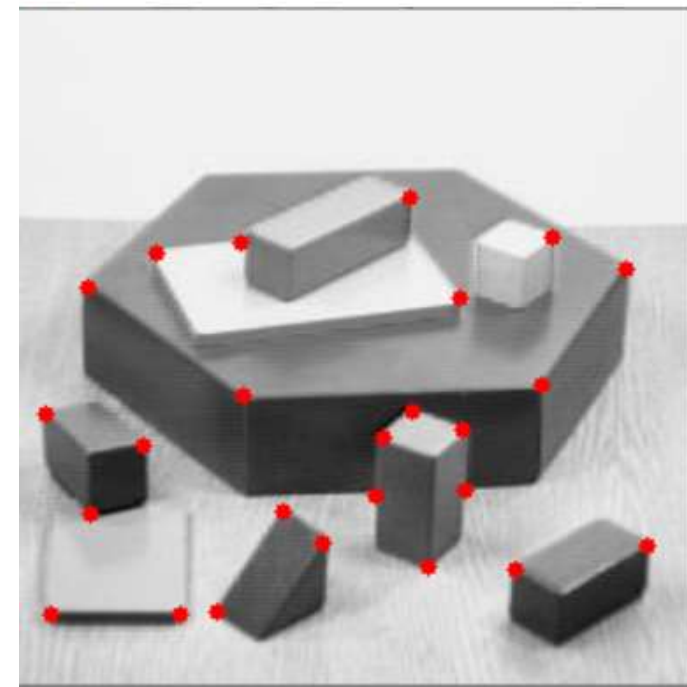
## ex43.py

```
7  import numpy as np
8  import cv2 as cv
9
10 img = cv.imread('blox.jpg')
11
12 gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
13
14 corners = cv.goodFeaturesToTrack(gray, 25, 0.01, 10)
15
16 corners = np.int0(corners) # (25, 1, 2)
17
18 for i in corners:          # i.shape = (1,2)
19     x, y = i.ravel()       # i.ravel().shape = (2,)
20     cv.circle(img, (x, y), 3, [0, 0, 255], -1) # red
21
22 cv.imshow('Shi-Tomasi Corner Detector', img)
23
24 if cv.waitKey(0) & 0xff == 27:
25     cv.destroyAllWindows()
```

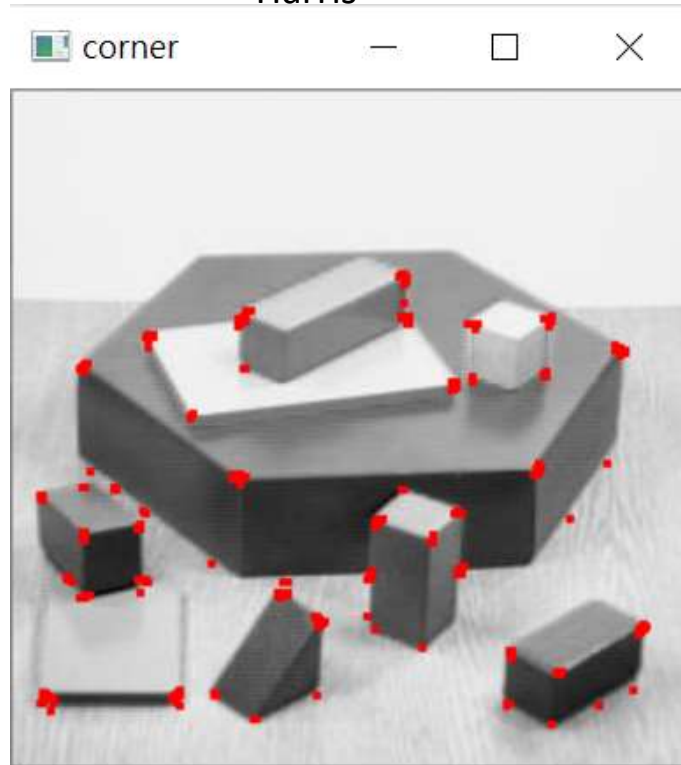
i= [[155 211]]

i.ravel() = [155 211]

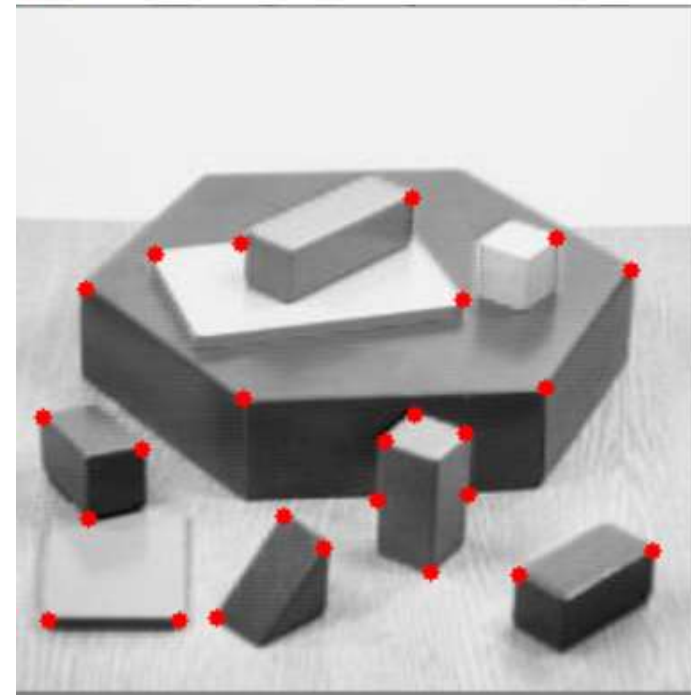
Shi-Tomasi Corner Detector



## Harris

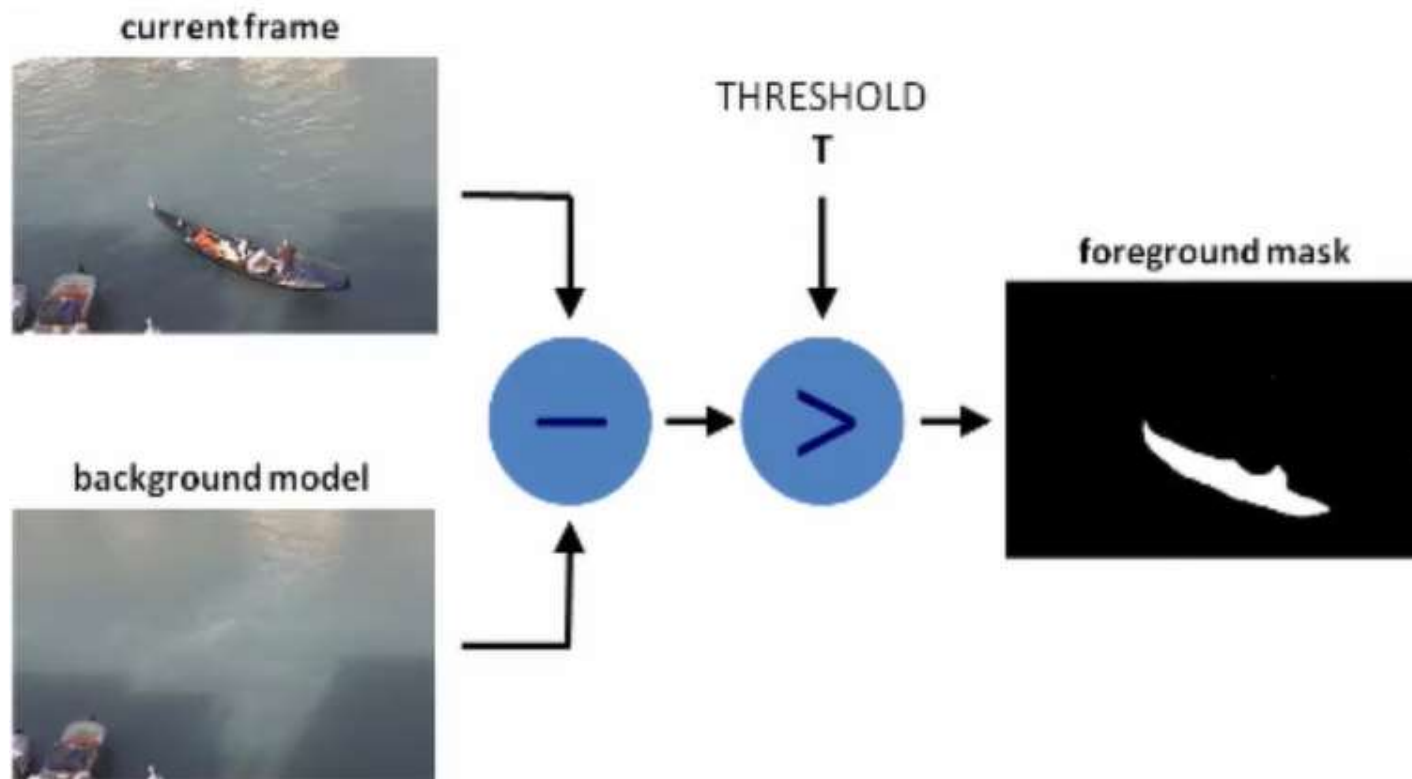


## Shi-Tomasi Corner Detector



## 39. How to Use Background Subtraction Methods

To detect moving objects in a static scene.



Optical flow ?

## 1. Gaussian Mixture-based Background/Foreground Segmentation Algorithm

```
retval=cv.createBackgroundSubtractorMOG2([, history[, varThreshold[, detectShadows]]])
```

Parameters 500 16, True

**history** Length of the history.

**varThreshold** Threshold on the squared Mahalanobis distance between the pixel and the model to decide whether a pixel is well described by the background model. This parameter does not affect the background update.

**detectShadows** If true, the algorithm will detect shadows and mark them. It decreases the speed a bit, so if you do not need this feature, set the parameter to false. default = True

## 2. K-nearest neighbours - based Background/Foreground Segmentation Algorithm

```
retval=cv.createBackgroundSubtractorKNN([, history[, dist2Threshold[, detectShadows]]])
```

Parameters 500 400.0, True

**history** Length of the history.

**dist2Threshold** Threshold on the squared distance between the pixel and the sample to decide whether a pixel is close to that sample. This parameter does not affect the background update.

**detectShadows** If true, the algorithm will detect shadows and mark them. It decreases the speed a bit, so if you do not need this feature, set the parameter to false. default = True

## Member functions:

### `createBackgroundSubtractorMOG2.apply`

Computes a foreground mask

```
cv.BackgroundSubtractorMOG2.apply(image[, fgmask[, learningRate]])
```

`image` Next video frame. Floating point frame will be used without scaling and should be in range [0,255].

`fgmask` The output foreground mask as an **8-bit binary image**.

`learningRate` The value between 0 and 1 that indicates how fast the background model is learnt.

**Negative parameter value** makes the algorithm to use some automatically chosen learning rate.

0 means that the background model is not updated at all,

1 means that the background model is completely reinitialized from the last frame.

### `createBackgroundSubtractorMOG2.getHistory()`

Returns the number of last frames that affect the background model.

....

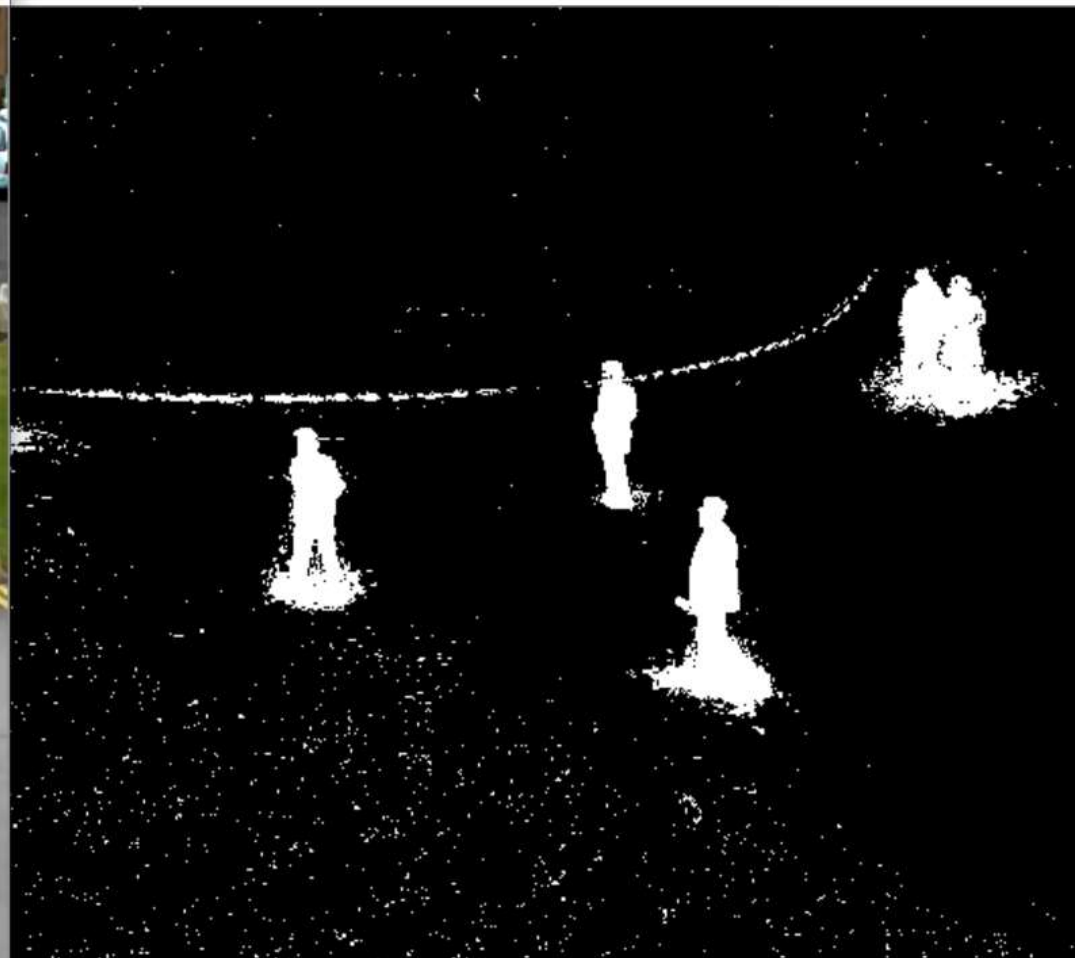
....



## ex44.py

```
8 import cv2 as cv
9
10 cap = cv.VideoCapture('vtest.avi')
11 #cap = cv.VideoCapture(0)
12
13 fgbg = cv.createBackgroundSubtractorMOG2(detectShadows=False) #shadow shown in gray
14 #fgbg = cv.createBackgroundSubtractorKNN(detectShadows=False)
15
16 while True:
17     ret, frame = cap.read()
18     if frame is None:
19         break
20
21     fgmask = fgbg.apply(frame) #The output foreground mask as an 8-bit binary image
22
23     cv.imshow('Frame', frame)
24     cv.imshow('FG MASK Frame', fgmask)
25
26     keyboard = cv.waitKey(30)
27     if keyboard == 113 or keyboard == 27: # 'q' or 'esc'
28         print(fgbg.getHistory())
29         break
30 cap.release()
31 cv.destroyAllWindows()
```

No shadows



Try `detectShadows` and `cap = cv.VideoCapture(0)`

## 40. Mean Shift Object Tracking

Video used : [https://www.bogotobogo.com/python/OpenCV\\_Python/images/mean\\_shift\\_tracking/slow\\_traffic\\_small.mp4](https://www.bogotobogo.com/python/OpenCV_Python/images/mean_shift_tracking/slow_traffic_small.mp4)

In OpenCV, for HSV color space

hue range is [0,179], saturation range is [0,255], and value range is [0,255].

Object Tracking using color thresholding (顏色二值化)

ex45.py

```
green = np.uint8([[[0,255,0 ]]]) #(1,1,3)
hsv_green = cv.cvtColor(green,cv.COLOR_BGR2HSV)
print( hsv_green )
# [[[ 60 255 255]]]

lower_green = np.array([50,100,100])
upper_green = np.array([70,255,255])
                    h   s   v
```



```
import numpy as np
```

```
import cv2 as cv
```

```
17 lower_green = np.array([50,100,100])
```

```
18 upper_green = np.array([70,255,255])
```

```
19
```

```
20 cap = cv.VideoCapture('slow_traffic_small.mp4')
```

```
21
```

```
22 while(1):
```

```
23     # Take each frame
```

```
24     ret, frame = cap.read()
```

```
25     if ret == True:
```

```
26         # Convert BGR to HSV
```

```
27         hsv = cv.cvtColor(frame, cv.COLOR_BGR2HSV)
```

```
28         # Threshold the HSV image to get only green colors
```

```
29         mask = cv.inRange(hsv, lower_green, upper_green)
```

```
30         # Bitwise-AND mask and original image
```

```
31         res = cv.bitwise_and(frame,frame, mask= mask)
```

```
32         cv.imshow('frame',frame)
```

```
33         cv.imshow('mask',mask)
```

```
34         cv.imshow('res',res)
```

```
35         k = cv.waitKey(30) & 0xff
```

```
36         if k == 27:      # esc
```

```
37             break
```

```
38     else:
```

```
39         break
```

```
40
```

```
41 cap.release()
```

```
42 cv.destroyAllWindows()
```

ex45.py

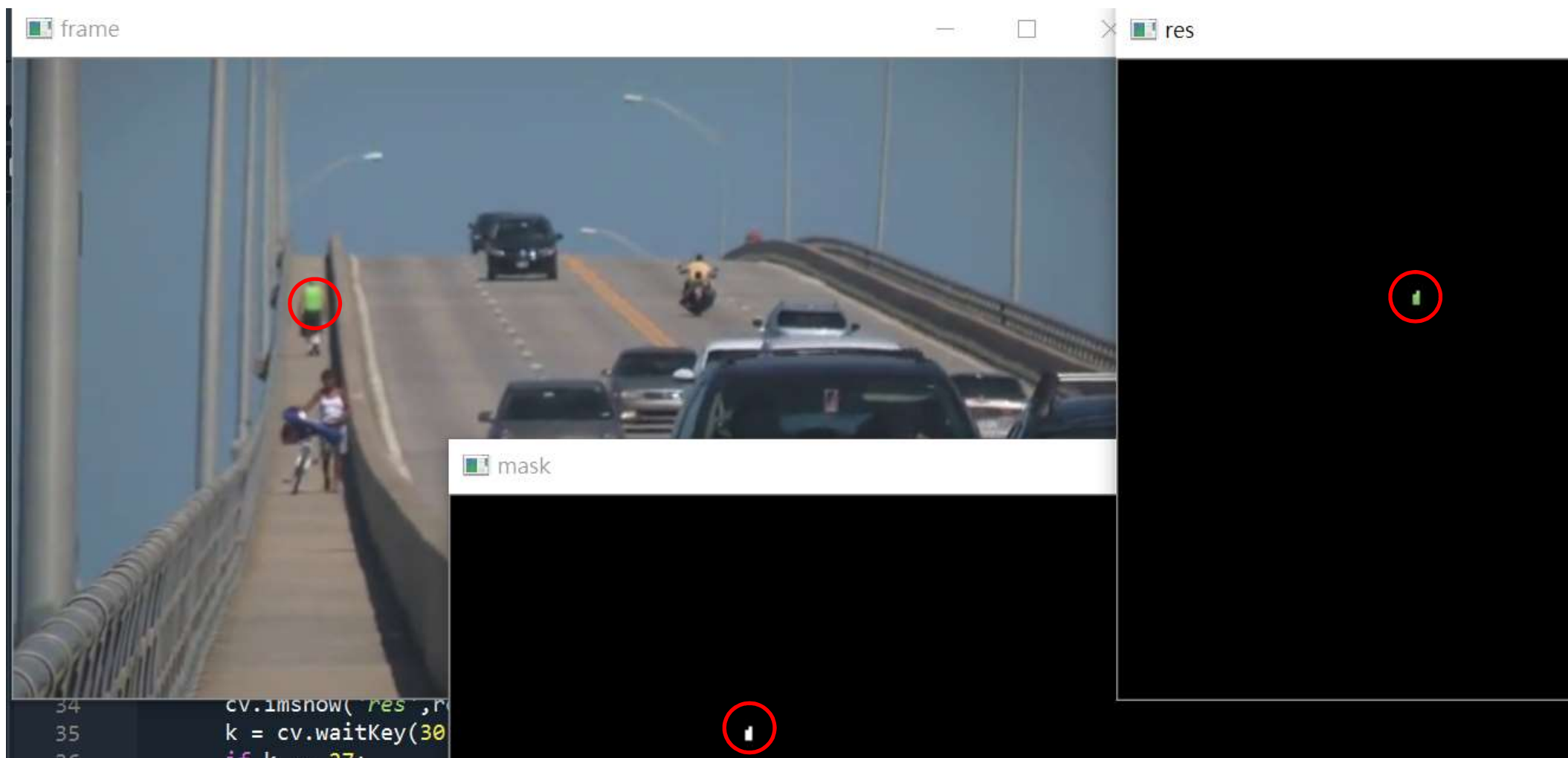
dst=cv.inRange(src, lowerb, upperb[, dst])

Checks if array elements lie between the elements of two other arrays.

dst (I) is set to 255 (all 1 -bits) if src (I) is within the specified 1D, 2D, 3D, ... box and 0 otherwise.

255 (decimal): 1 1 1 1 1 1 1 1 (binary)





mask

res

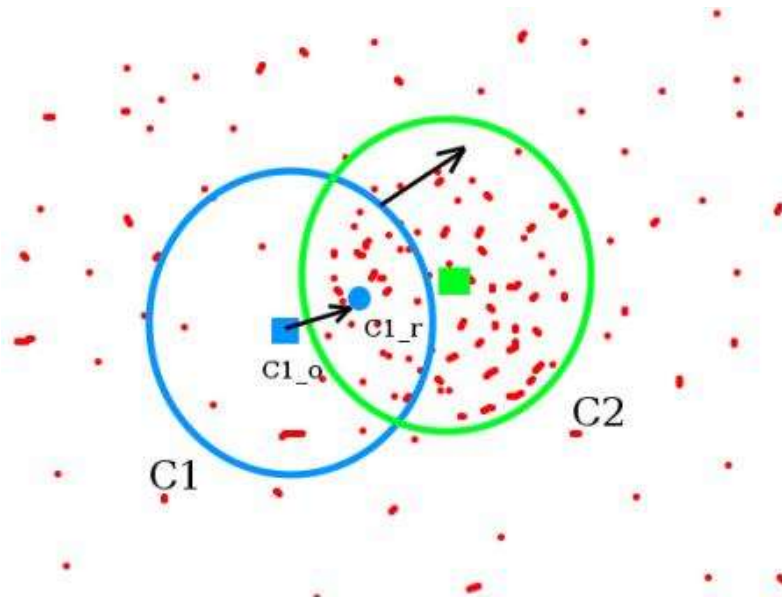
frame

```
34 cv.imshow('res', r)
35 k = cv.waitKey(30)
36 if k == 27:
```

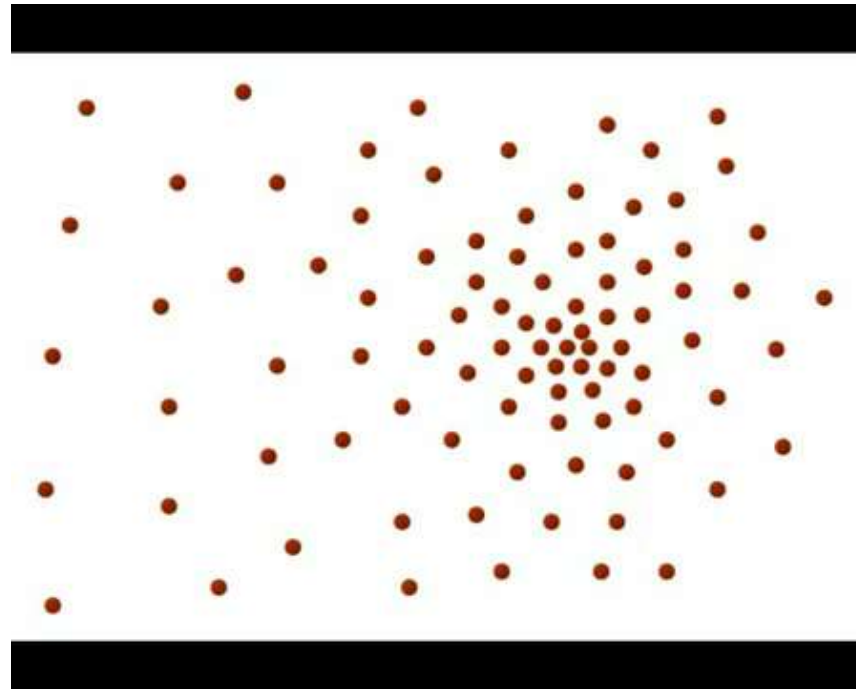
## 40. Mean Shift Object Tracking

[https://docs.opencv.org/3.4/d7/d00/tutorial\\_meanshift.html](https://docs.opencv.org/3.4/d7/d00/tutorial_meanshift.html)

We will learn about the **Meanshift** and **Camshift** algorithms to track objects in videos.

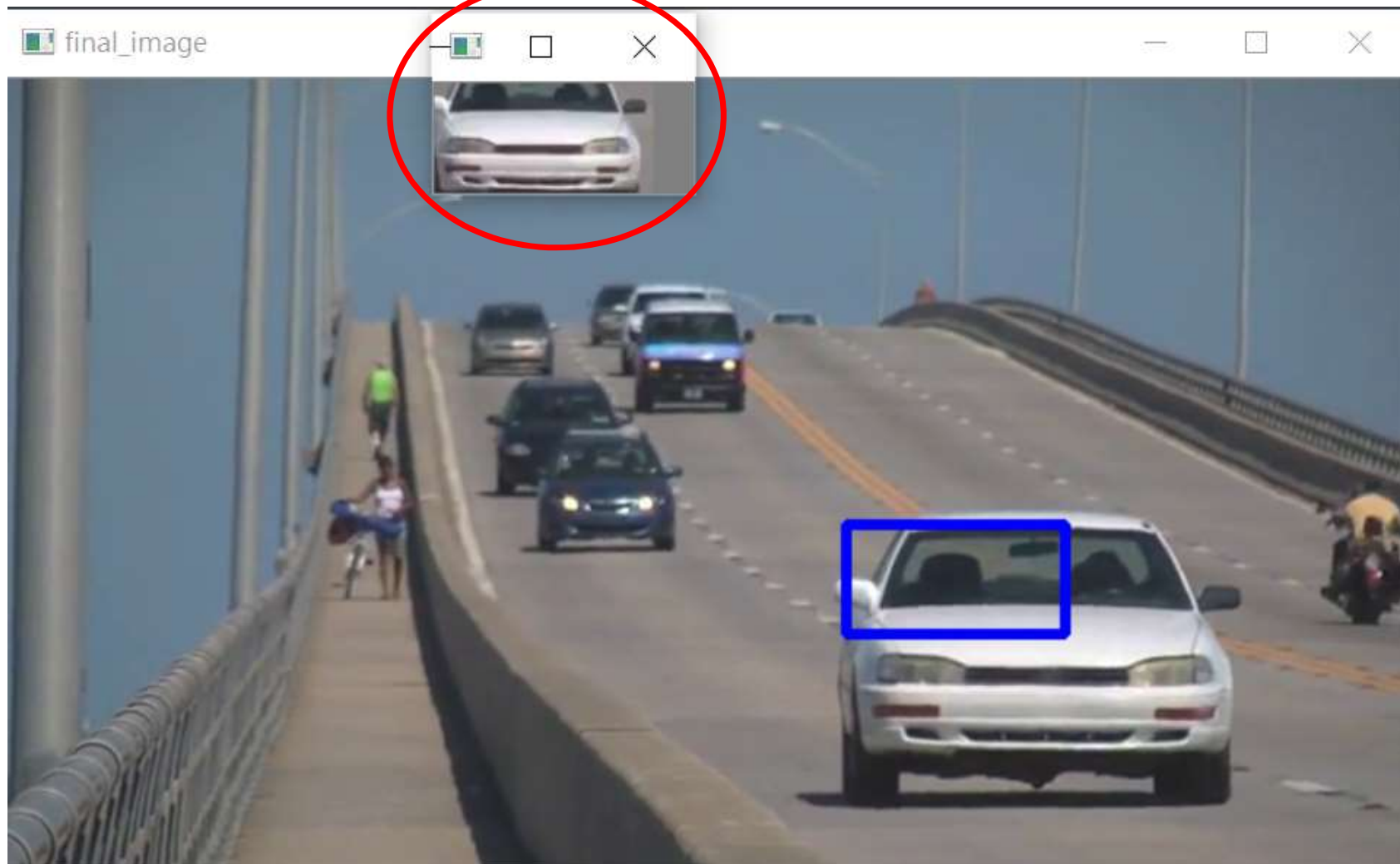


## Meanshift





ROI



To use **meanshift** in OpenCV:

first we need to setup the **target (ROI)**,

find its **histogram** so that we can **backproject** the target on each frame for calculation of meanshift.

We also need to provide an **initial location** of window.

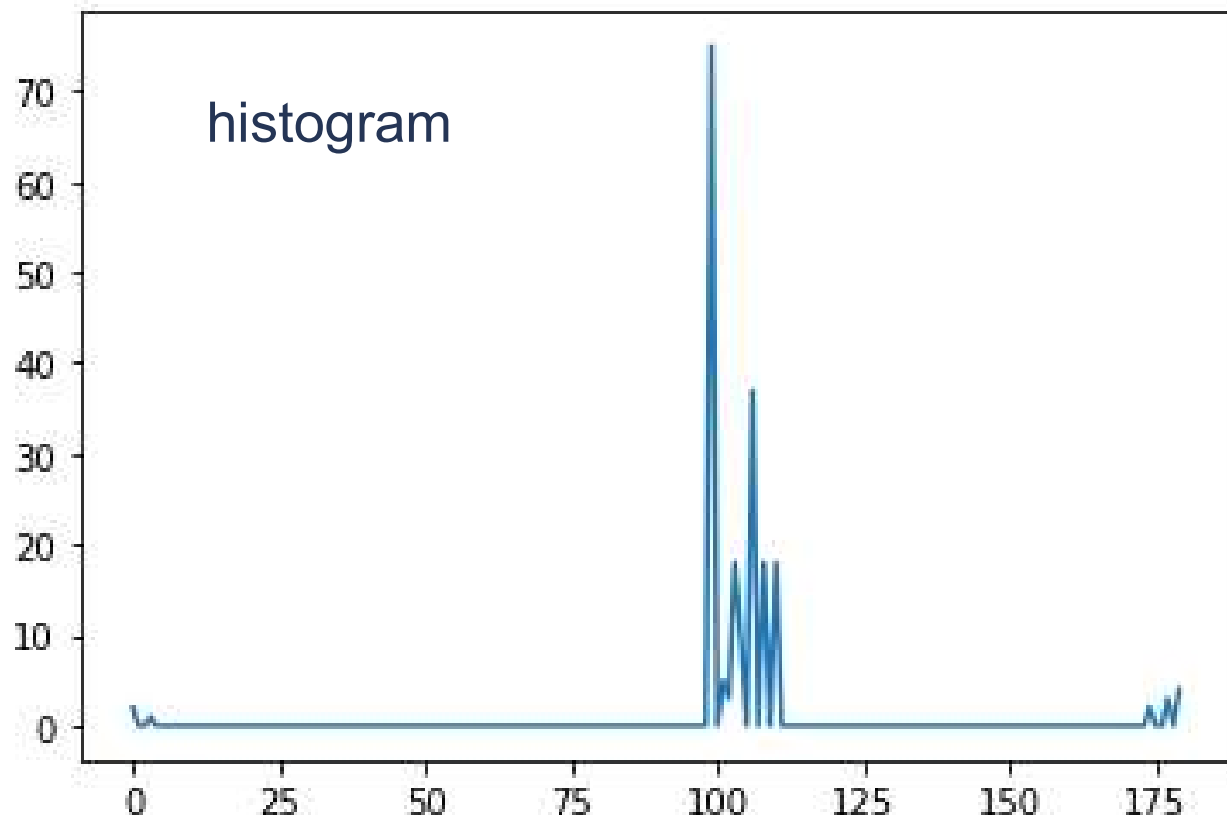
For histogram, only **Hue** is considered here. Also, to avoid false values due to low light, low light values are discarded using **cv.inRange()** function.

```
channel
cv2.calcHist([src], [0], None, [histSize], [histRange])
roi_hist = cv.calcHist([hsv_roi], [0], mask, [180], [0, 180]) # shape (180,1)

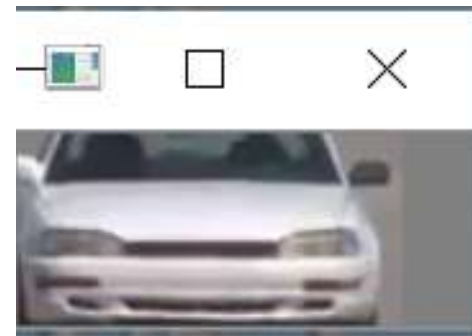
dst=cv.normalize(src, dst[, alpha[, beta[, norm_type[, dtype[, mask]]]]])
cv.normalize(roi_hist, roi_hist, 0, 255, cv.NORM_MINMAX)
```

**alpha, beta** : the lower and upper range boundary in case of the range normalization

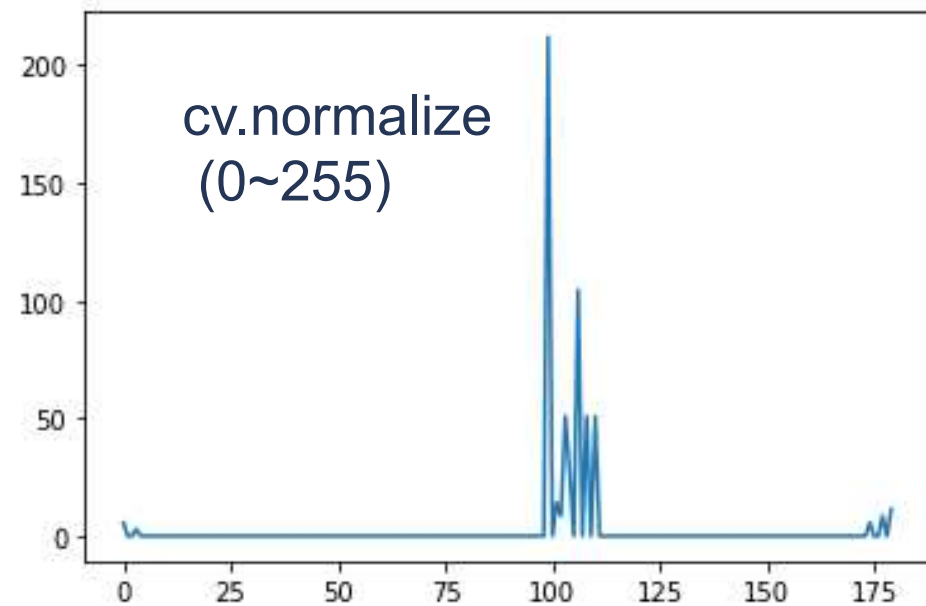
histogram



Hue



ROI (shape (50, 100))



cv.normalize  
(0~255)

The class defining termination criteria for iterative algorithms

**cv.TERM\_CRITERIA\_EPS** - stop the algorithm iteration if specified accuracy, *epsilon*, is reached.

**cv.TERM\_CRITERIA\_COUNT** - the maximum number of iterations at which the iterative algorithm stops

```
term_crit = ( cv.TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT, 10, 1) # tuple (3,10,1)
```

termination criteria, either **10 iterations** or move by at least **1 pt**

### Back Projection:

- Back Projection is a way of recording how well the pixels of a given image fit the distribution of pixels in a histogram model.
- To make it simpler: For Back Projection, you calculate the histogram model of a feature and then use it to find this feature in an image.

```
dst=cv.calcBackProject(images, channels, hist, ranges, scale[, dst])
```

Let's say you have gotten a skin histogram (Hue-Saturation) based on the image below. The histogram besides is going to be our *model histogram* (which we know represents a sample of skin tonality). You applied some mask to capture only the histogram of the skin area:



Now, let's imagine that you get another hand image (Test Image) like the one below: (with its respective histogram)





- What we want to do is to use our *model histogram* (that we know represents a skin tonality) to detect skin areas in our Test Image. Here are the steps
  1. In each pixel of our Test Image (i.e.  $p(i, j)$ ), collect the data and find the correspondent bin location for that pixel (i.e.  $(h_{i,j}, s_{i,j})$ ).
  2. Lookup the *model histogram* in the correspondent bin -  $(h_{i,j}, s_{i,j})$  - and read the bin value.
  3. Store this bin value in a new image (*BackProjection*). Also, you may consider to normalize the *model histogram* first, so the output for the Test Image can be visible for you.
  4. Applying the steps above, we get the following BackProjection image for our Test Image:



5. In terms of statistics, the values stored in *BackProjection* represent the *probability* that a pixel in *Test Image* belongs to a skin area, based on the *model histogram* that we use. For instance in our Test image, the brighter areas are more probable to be skin area (as they actually are), whereas the darker areas have less probability (notice that these "dark" areas belong to surfaces that have some shadow on it, which in turns affects the detection).

`dst=cv.calcBackProject(images, channels, hist, ranges, scale[, dst])`

- images** Source arrays. They all should have the same depth, CV\_8U, CV\_16U or CV\_32F , and the same size. Each of them can have an arbitrary number of channels.
- nimages** Number of source images.
- channels** The list of channels used to compute the back projection. The number of channels must match the histogram dimensionality. The first array channels are numerated from 0 to images[0].channels()-1 , the second array channels are counted from images[0].channels() to images[0].channels() + images[1].channels()-1, and so on.
- hist** Input histogram that can be dense or sparse.
- backProject** Destination back projection array that is a single-channel array of the same size and depth as images[0] .
- ranges** Array of arrays of the histogram bin boundaries in each dimension. See [calcHist](#) .
- scale** Optional scale factor for the output back projection.
- uniform** Flag indicating whether the histogram is uniform or not (see above).

`dst = cv.calcBackProject([hsv], [0], roi_hist, [0, 180], 1)`

```
retval, window = cv.meanShift(problImage, window, criteria)
```

**problImage** Back projection of the object histogram. See calcBackProject for details.

**window** Initial search window.

**criteria** Stop criteria for the iterative search algorithm. returns : Number of iterations CAMSHIFT took to converge. The function implements the iterative object search algorithm. It takes the input back projection of an object and the initial position. The mass center in window of the back projection image is computed and the search window center shifts to the mass center. The procedure is repeated until the specified number of iterations criteria.maxCount is done or until the window center shifts by less than criteria.epsilon. The algorithm is used inside CamShift and, unlike CamShift , the search window size or orientation do not change during the search. You can simply pass the output of calcBackProject to this function. But better results can be obtained if you pre-filter the back projection and remove the noise. For example, you can do this by retrieving connected components with findContours , throwing away contours with small area ( contourArea ), and rendering the remaining contours with drawContours.



ex46.py

```
8 import numpy as np
9 import cv2 as cv
10 import matplotlib.pyplot as plt
11
12 cap = cv.VideoCapture('slow_traffic_small.mp4')
13 # take first frame of the video
14 ret, frame = cap.read()
15
16 # setup initial location of window
17 x, y, width, height = 300, 200, 100, 50
18 track_window = (x, y, width, height)
19 # set up the ROI for tracking
20 roi = frame[y:y+height, x : x+width]
21 hsv_roi = cv.cvtColor(roi, cv.COLOR_BGR2HSV)
22
23 mask = cv.inRange(hsv_roi, np.array((0., 60., 32.)), np.array((180., 255., 255)))
24 # mask.shape = (50, 100)
25 roi_hist = cv.calcHist([hsv_roi], [0], mask, [180], [0, 180]) # shape (180,1)
26 plt.plot(roi_hist)
27 cv.normalize(roi_hist, roi_hist, 0, 255, cv.NORM_MINMAX)
28
29 # Setup the termination criteria, either 10 iteration or move by atleast 1 pt
30 term_crit = ( cv.TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT, 10, 1) # tuple (3,10,1)
31 cv.imshow('roi',roi)
```

## ex46.py

```
33 while(1):
34     ret, frame = cap.read()
35     if ret == True:
36
37         hsv = cv.cvtColor(frame, cv.COLOR_BGR2HSV)
38         dst = cv.calcBackProject([hsv], [0], roi_hist, [0, 180], 1) #(360, 640)
39         # apply meanshift to get the new location
40         ret, track_window = cv.meanShift(dst, track_window, term_crit)
41         # Draw it on image
42         x,y,w,h = track_window
43         final_image = cv.rectangle(frame, (x,y), (x+w, y+h), 255, 3)
44
45         cv.imshow('dst', dst)
46         cv.imshow('final_image', final_image)
47         k = cv.waitKey(30) & 0xff
48         if k == 27:    # esc
49             break
50     else:
51         break
52
53 cap.release()
54 cv.destroyAllWindows()
```



dst



## 41. Object Tracking Camshift Method

**CAMshift** (**C**ontinuously **A**daptive **M**ean**s**hift) published by Gary Bradsky in his paper "Computer Vision Face Tracking for Use in a Perceptual User Interface" in 1998.

The **meanshift problem** is that the **window** always has **the same size** whether the car is very far or very close to the camera. That is not good. We need to adapt the window size with **size** and **rotation** of the target.

It applies meanshift first. Once meanshift converges, it updates the size of the window as,  $s = 2 \times \sqrt{\frac{M_{00}}{256}}$ .

It also calculates the **orientation** of the best fitting **ellipse** to it. Again it applies the meanshift with new scaled search window and previous window location. The process continues until the required accuracy is met.



Mean shift window  
initialization

```
ret, track_window = cv.CamShift(dst, track_window, term_crit) # ret= ((x, y), (w, h),  $\theta$ )
```

```
pts = cv.boxPoints(ret) #查找旋轉矩形的4個頂點, shape=(4,2)
```

```
((415.0, 226.5), (52.80326461791992, 166.11111450195312), 87.1136474609375)  
(331, 199, 168, 55) ( center (x,y), (width, height), angle of rotation )  
[[330.72034 204.31413]  
 [496.62073 195.9496 ]  
 [499.27966 248.68587]  
 [333.37927 257.0504 ]]
```

非填充多邊形：**polylines()**

```
# cv2.polylines(img, [pts], isClosed, color[, thickness[, lineType[, shift]]])
```

# img – 要畫的圖片

# pts – 多邊形的頂點

# isClosed – 是否閉合線段

# color – 顏色

# thickness – 線段寬度

ex47.py

```
8 import numpy as np
9 import cv2 as cv
10 cap = cv.VideoCapture('slow_traffic_small.mp4')
11 # take first frame of the video
12 ret, frame = cap.read()
13 # setup initial location of window
14 x, y, width, height = 300, 200, 100, 50
15 track_window = (x, y, width, height)
16 # set up the ROI for tracking
17 roi = frame[y:y+height, x : x+width]
18 hsv_roi = cv.cvtColor(roi, cv.COLOR_BGR2HSV)
19 mask = cv.inRange(hsv_roi, np.array((0., 60., 32.)), np.array((180., 255., 255)))
20 roi_hist = cv.calcHist([hsv_roi], [0], mask, [180], [0, 180])
21 cv.normalize(roi_hist, roi_hist, 0, 255, cv.NORM_MINMAX)
22 # Setup the termination criteria, either 10 iteration or move by atleast 1 pt
23 term_crit = ( cv.TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT, 10, 1)
24 cv.imshow('roi',roi)
```

ex47.py

```
25 while(1):
26     ret, frame = cap.read()
27     if ret == True:
28
29         hsv = cv.cvtColor(frame, cv.COLOR_BGR2HSV)
30         dst = cv.calcBackProject([hsv], [0], roi_hist, [0, 180], 1)
31         # apply camshift to get the new location
32         ret, track_window = cv.CamShift(dst, track_window, term_crit)
33         #print(ret)
34         #print(track_window)
35         # Draw it on image
36         pts = cv.boxPoints(ret)
37         print(pts)
38         pts = np.int0(pts)
39         final_image = cv.polylines(frame, [pts], True, (0, 255, 0), 2)
40                                     # green
41         cv.imshow('dst', dst)
42         cv.imshow('final_image', final_image)
43         k = cv.waitKey(30) & 0xff
44         if k == 27:
45             break
46     else:
47         break
48
49 cap.release()
50 cv.destroyAllWindows()
```



## CAMshift Object Tracking

ex47.py



## PyTesseract: Python Optical Character Recognition | Using Tesseract OCR with Python

In this video we will talk about PyTesseract. Python-tesseract is an **optical character recognition (OCR)** tool for python. That is, it will recognize and “read” the text embedded in images.

**Image to Text with Python - pytesseract.**



### Installing Tesseract

1. Download **tesseract-ocr-setup-3.02.02.exe** and install <https://tesseract-ocr.github.io/tessdoc/Downloads.html>
2. pip install pytesseract
3. Include this line in python script  
`pytesseract.pytesseract.tesseract_cmd = r'C:\Program Files (x86)\Tesseract-OCR\tesseract'`

A comprehensive guide to OCR with Tesseract, OpenCV and Python

<https://nanonets.com/blog/ocr-with-tesseract/>

ex48.py

```
8  import pytesseract
9  import cv2 as cv
10
11  img = cv.imread('plate.jfif')
12  cv.imshow('car plate',img)
13
14  pytesseract.pytesseract.tesseract_cmd = r'C:\Program Files (x86)\Tesseract-OCR\tesseract'
15
16  # get grayscale image
17  def get_grayscale(image):
18      return cv.cvtColor(image, cv.COLOR_BGR2GRAY)
19
20  # noise removal
21  def remove_noise(image):
22      return cv.medianBlur(image,5)
23
24  # thresholding
25  def thresholding(image):
26      return cv.threshold(image, 0, 255, cv.THRESH_BINARY + cv.THRESH_OTSU)[1] # [1] = image
```

ex48.py

```
28     gray = get_grayscale(img)
29     thresh = thresholding(gray)
30     blur = remove_noise(thresh)
31
32     text = pytesseract.image_to_string(img)
33     print(text)
34
35     if cv.waitKey(0) & 0xff == 27:
36         cv.destroyAllWindows()
```



ex48.py

image



v\iv~9999j

grayscale



VW9999

thresh



VW9999

blur



vvv~9999