

# Readme

This the notebook is for Li Bin Song's MM805 Assignment.

The source code is located at [github](#). Or you can unzip the zip from eclass.

## Requirement to run this notebook

The commands shows here are based on Linux(Ubuntu)

1. Python 3.8
2. Setup Python virtual environment

```
python3.8 -m venv .venv  
. .venv/bin/activate  
pip install --upgrade pip
```

3. Install required packages `pip install -r requirements.txt`
4. Open `report.ipynb` , select python kernel and run

## Q1. (40 points) Feature extraction and matching

### 1a. Harris Corner Point detection

The feature I implemented is Harris corner point. The logic is based on [wikipedia](#)

Answer:

The key function is `get_harris_points` , the detail code can be found in `assignment_code.py` ane extra function `display_corner_points` is written for display finding point on image as red point.

The main logic are:

1. convert image to grayscale color

2. calculate Ix, ly spatial derivative
3. structure Matrix A
4. Harris response calculation(calcualte Det(A) and Trace(A))
5. Based on the response choose corner points

In [ ]:

```
import numpy as np
import cv2
from pprint import pprint
from scipy import ndimage
from skimage.feature import corner_peaks
from scipy import signal

def imfilter(I, filter)->np.ndarray:
    # I_f = ndimage.filters.correlate(I, weights=filter, mode='constant')
    I_ = signal.convolve2d(I, filter, boundary='symm', mode='same')
    return I_

def harris_corner_points(I, k=0.05,top_n_points = 5000):

    # check image and convert to gray and normalize
    if len(I.shape) == 3 and I.shape[2] == 3:
        I = cv2.cvtColor(I, cv2.COLOR_BGR2GRAY)
    if I.max() > 1.0:
        I = I / 255.0

    # Step 1 calcualte Axx, Axy and Ayy

    # Step 1.1 calculate Ix, Iy
    # apply soble filter for quick calculation
    filter_x = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]]) / \
        8.0 # sobel filter for x derivative
    filter_y = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]]) / \
        8.0 # sobel filter for y derivative

    Ix = imfilter(I, filter_x)
    Iy = imfilter(I, filter_y)
    Ixx = Ix * Ix
    Iyy = Iy * Iy
    Ixy = Ix * Iy
```

```
window = np.ones((3, 3))

Axx = imfilter(Ixx, window)
Axy = imfilter(Ixy, window)
Ayy = imfilter(Iyy, window)

# Step 2 calculate response
# determinant
detA = Axx * Ayy - Axy ** 2
# trace
traceA = Axx + Ayy
# response
response = detA - k * traceA ** 2

# step 3. Get points location(x,y)
# points = corner_peaks(response,min_distance=4)
points = get_coordinate(response,top_n_points,I.shape)

return points

def get_coordinate(response, alpha, image_shape):
    # sort with flatten mode
    sortedIndex = np.argsort(response, axis=None)[::-1]

    # maxIndexes are index of flatten array
    maxIndexes = sortedIndex[0:alpha]

    # generate points coordinates
    # consider image as coordinate in place m x n
    # each point coordinate is (m', n')
    # m' * n + n' = flattened index
    m = image_shape[0]
    n = image_shape[1]

    points = np.zeros((2, alpha), dtype=np.int32)
    x = np.floor(maxIndexes/n)
    y = np.mod(maxIndexes, n)
    points[0, :] = x
    points[1, :] = y
    points = points.T

    return points

def display_corner_points(org_img:np.ndarray, points, output_name):
    bool_arr = np.zeros(org_img.shape[:2], dtype=np.int8)
```

```
bool_arr = np.bool8(bool_arr)

# pprint(bool_arr)
for (x,y) in points:
    bool_arr[x,y] = True

# pprint(bool_arr)
org_img[bool_arr]=[0,255,0]
cv2.imwrite(output_name, org_img)
```

In [ ]:

```
# showing result
import matplotlib.pyplot as plt

image_name = "data/carmel/carmel-00.png"
image = cv2.imread(image_name, cv2.IMREAD_GRAYSCALE)
plt.figure(figsize=(20, 15))
plt.imshow(image, cmap='gray', vmin=0, vmax=255)
plt.title("original")
plt.show()

image_folder = "./data/carmel"
for i in range(10):
    I = cv2.imread(f"{image_folder}/carmel-0{i}.png")
    gray = cv2.cvtColor(I, cv2.COLOR_BGR2GRAY)
    gray = gray / 255.0
    points = harris_corner_points(gray,top_n_points=50000)
    output_name = f"./output/a_harris_output.jpg"
    display_corner_points(I,points,output_name)
    image2 = cv2.imread(output_name)
    image2 = cv2.cvtColor(image2,cv2.COLOR_BGR2RGB)
    plt.figure(figsize=(20,15))
    plt.imshow(image2)
    plt.title(f"Image with Harris Points: {i}")
    plt.show()
```

original



Image with Harris Points: 0



Image with Harris Points: 1



Image with Harris Points: 2

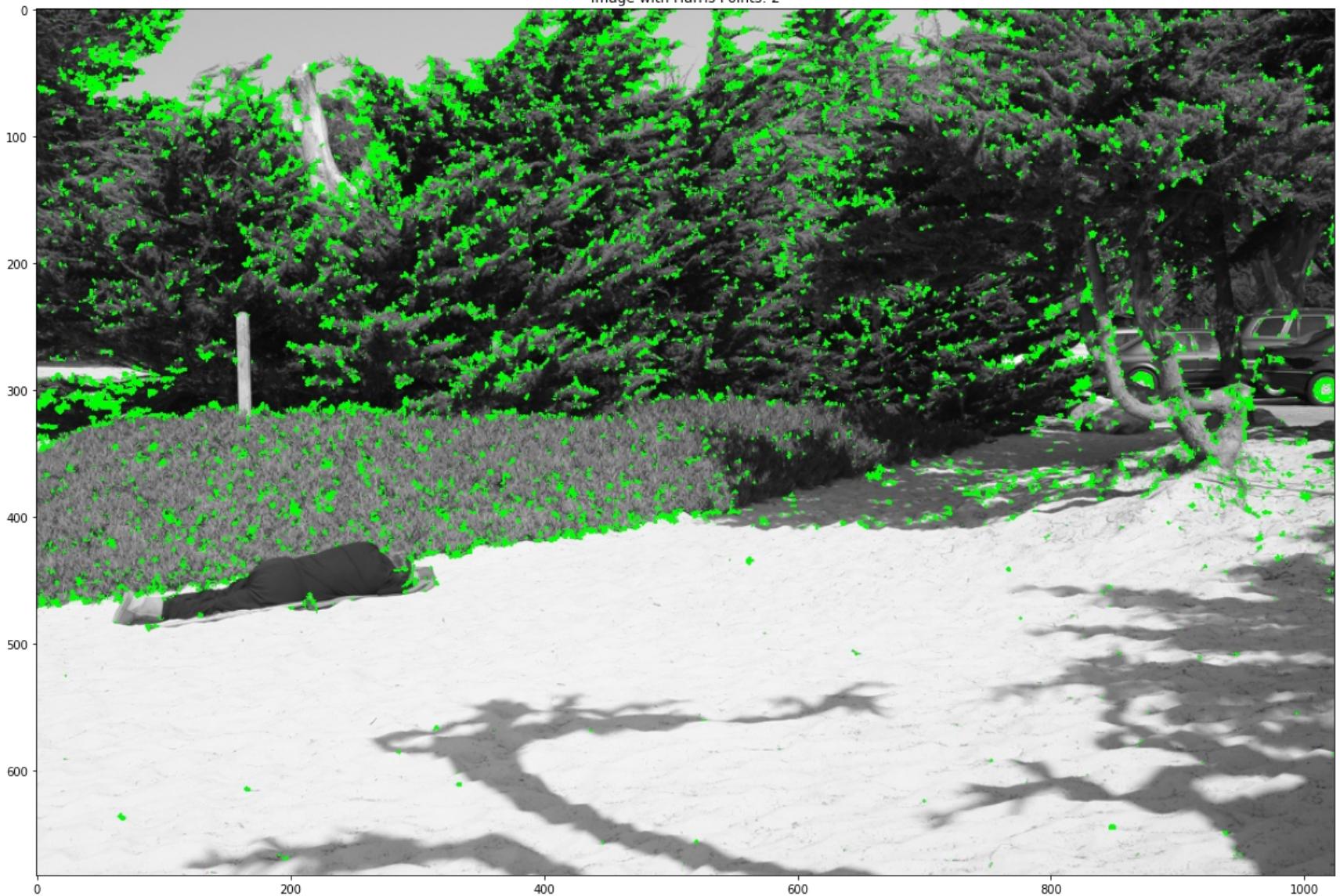


Image with Harris Points: 3

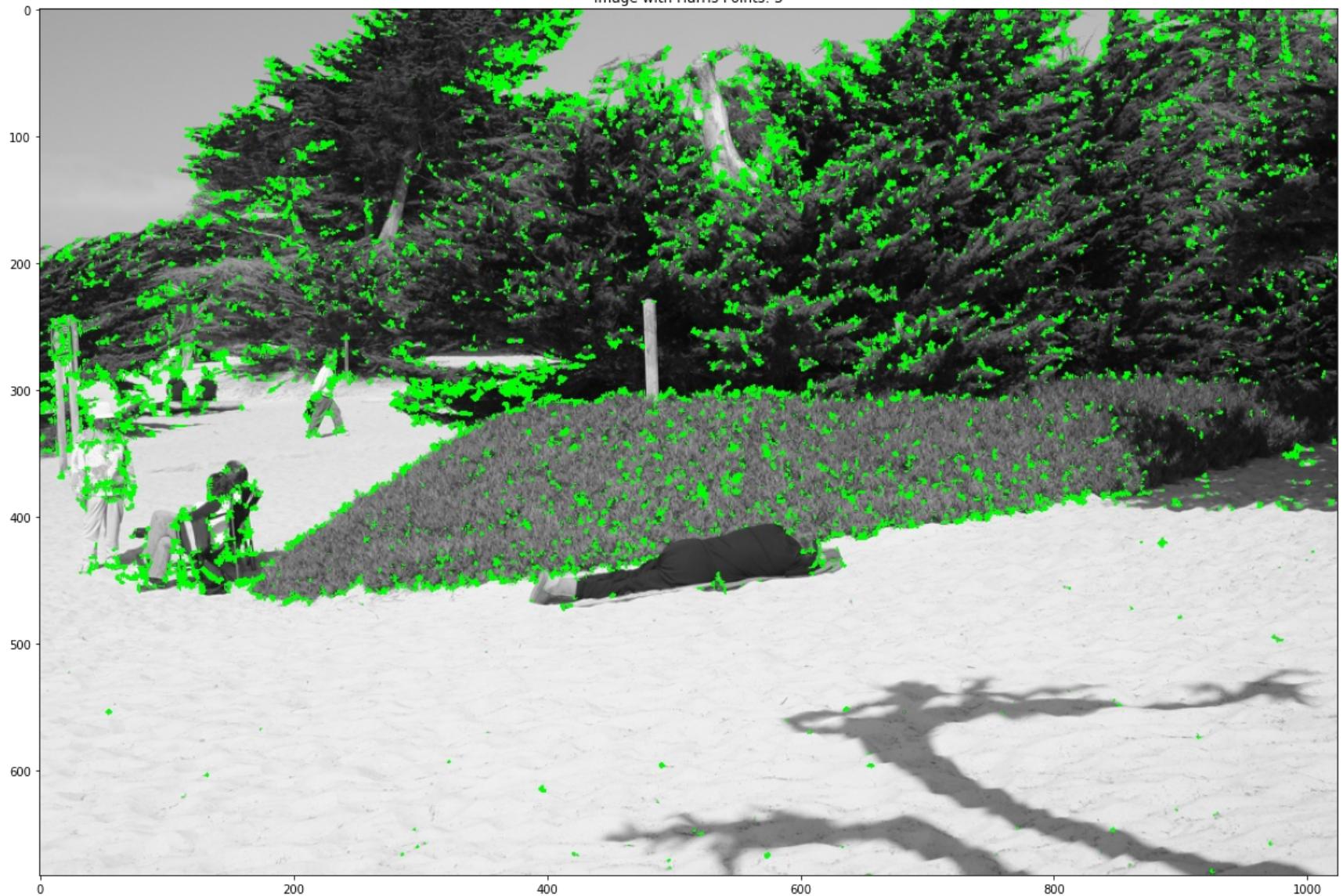


Image with Harris Points: 4

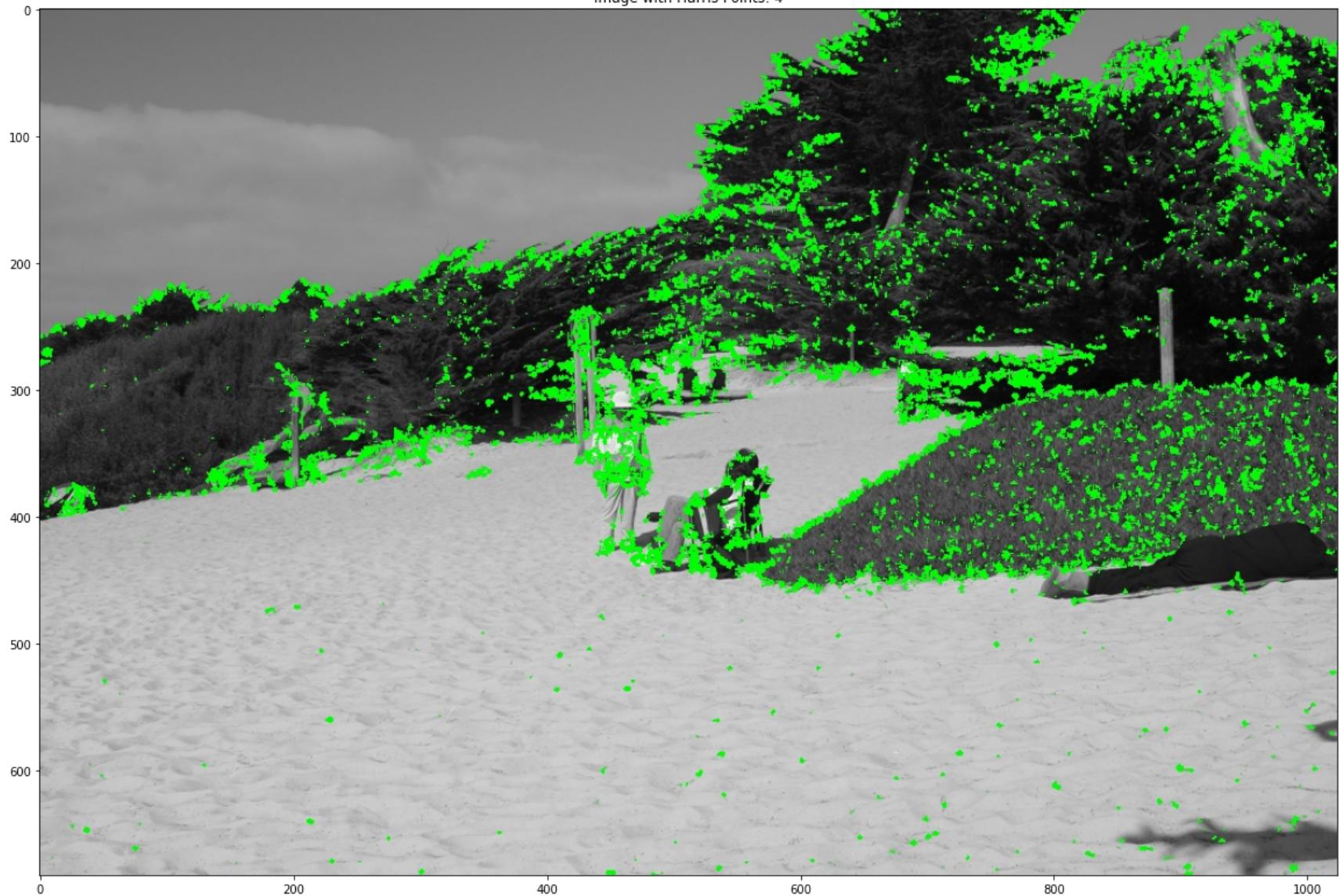


Image with Harris Points: 5

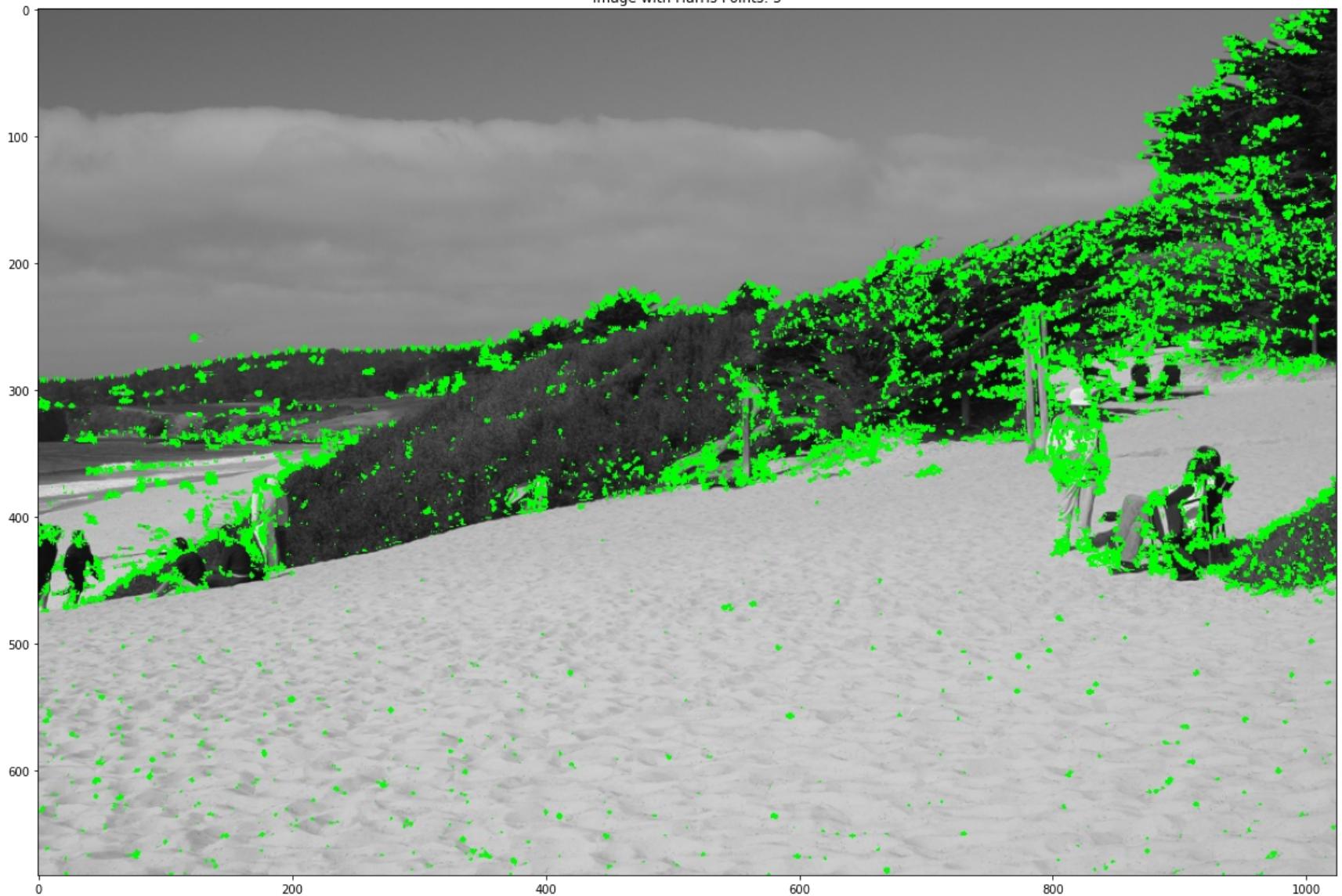


Image with Harris Points: 6



Image with Harris Points: 7



Image with Harris Points: 8



Image with Harris Points: 9



## 1B. Feature Matching

Question: Implement a simple feature matching by using two feature descriptors of your choice (you can use the available feature descriptors in OpenCV or Matlab). Compare the two feature descriptors and the matching results on a few different images.

Answer:

The matching function is usign K near neighbour algorithm. The function accept descriptor name and display the result.

The first descriptor ORB feature descriptor and the second one is SIFT feature descriptor.

The SIFT gives better result. From the output you can see SIFT detects more good key points.

Accredit: the ploting function has refereced some logic from opencv example code.

In [ ]:

```
import numpy as np
import cv2
from pprint import pprint
from scipy import ndimage
from skimage.feature import corner_peaks
from sklearn.metrics import pairwise_distances
import matplotlib.pyplot as plt

def knn_match(img1,img2,descriptor='sift',show_limit=100):
    '''Only support sift and orb as descriptor'''

    # Initiate SIFT detector
    if descriptor == 'sift':
        sift = cv2.SIFT_create()
        # find the keypoints and descriptors with SIFT
        # descriptors are 128 dimention histogram,
        # to compare descriptors using Knn
        kp1, des1 = sift.detectAndCompute(img1,None)
        kp2, des2 = sift.detectAndCompute(img2,None)
    elif descriptor == 'orb':
        # Initiate ORB detector
        orb = cv2.ORB_create()
        # find the keypoints and descriptors with ORB
        kp1, des1 = orb.detectAndCompute(img1,None)
        kp2, des2 = orb.detectAndCompute(img2,None)
    else:
        print(f"Unsupported descriptor {descriptor}")
        return

    # KNN match
    k = 2
    m = des1.shape[0]
    n = des2.shape[0]

    matches = list()
```

```
dis_list = pairwise_distances(des1,des2,metric='euclidean')
for i in range(m):
    d_list = list()
    arr = dis_list[i,:]
    arr = np.argsort(arr, axis=0)[0:k]
    for j in range(k):
        idx_j = arr[j]
        d = cv2.DMatch()
        d.distance = dis_list[i,idx_j]
        d.imgIdx = 0
        d.queryIdx = i
        d.trainIdx = idx_j
        d_list.append(d)

    # add to matches
    matches.append(d_list)

matches = np.array(matches)
r1 = matches.shape[0]

good = []
dis_values = list()
for m,n in matches:
    if m.distance < 0.75*n.distance:
        good.append([m])
        dis_values.append(m.distance)

r2 = len(good)
print(f"Descriptor {descriptor} detects {r1} points and {r2} points are good.")

# sort good
sorted_idx = np.argsort(dis_values)[:show_limit]
good_show = []
for idx in sorted_idx:
    good_show.append(good[idx])

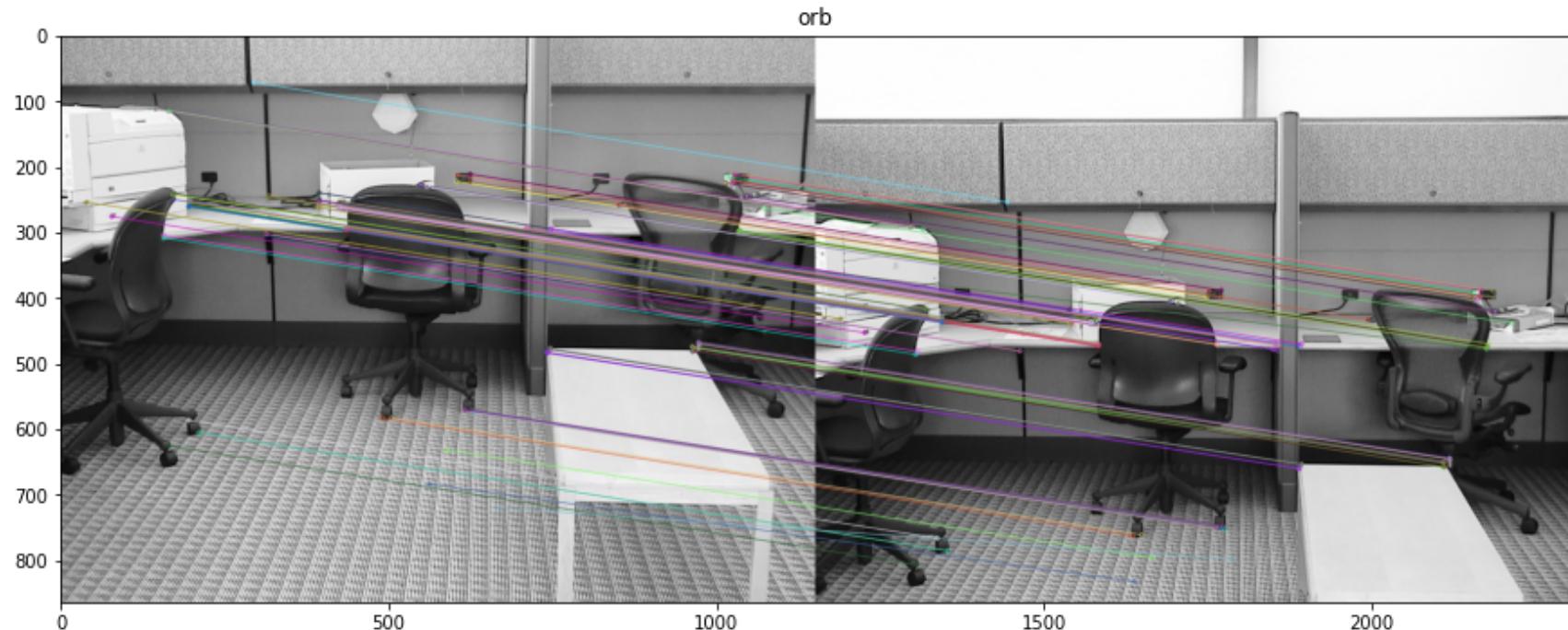
# Display result on plot
img3 = cv2.drawMatchesKnn(img1,kp1,img2,kp2,good_show,None,flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POINTS)
plt.figure(figsize=(15, 10))
plt.imshow(img3)
plt.title(descriptor)
plt.show()
```

```
In [ ]: # img_name1 = './data/office/office-00.png'
# img_name2 = './data/office/office-01.png'

images = [
    './data/office/office-00.png',
    './data/office/office-01.png',
    './data/shanghai/shanghai-00.png',
    './data/shanghai/shanghai-01.png',
    './data/carmel/carmel-00.png',
    './data/carmel/carmel-01.png',
]

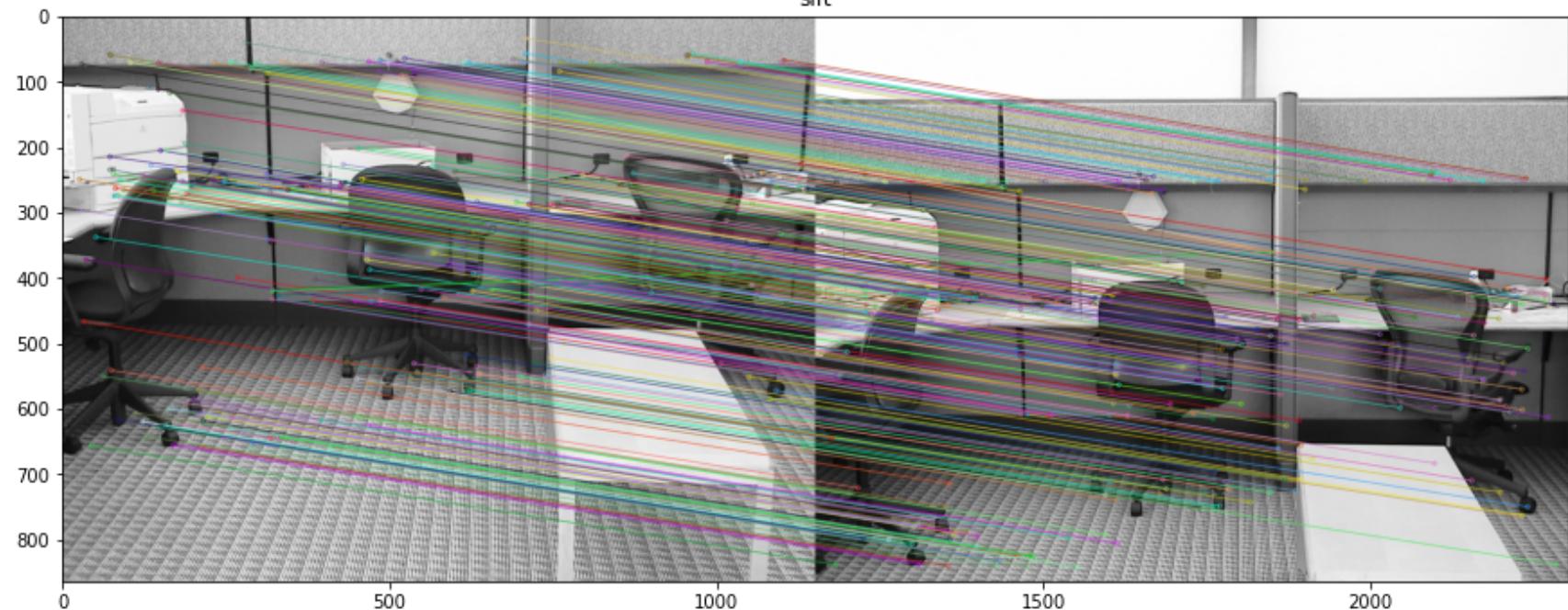
n = len(images)//2
for i in range(n):
    img1 = cv2.imread(images[2*i],cv2.IMREAD_GRAYSCALE)           # queryImage
    img2 = cv2.imread(images[2*i + 1],cv2.IMREAD_GRAYSCALE) # trainImage
    knn_match(img1,img2,'orb',300)
    knn_match(img1,img2,'sift',300)
```

Descriptor orb detects 500 points and 132 points are good.



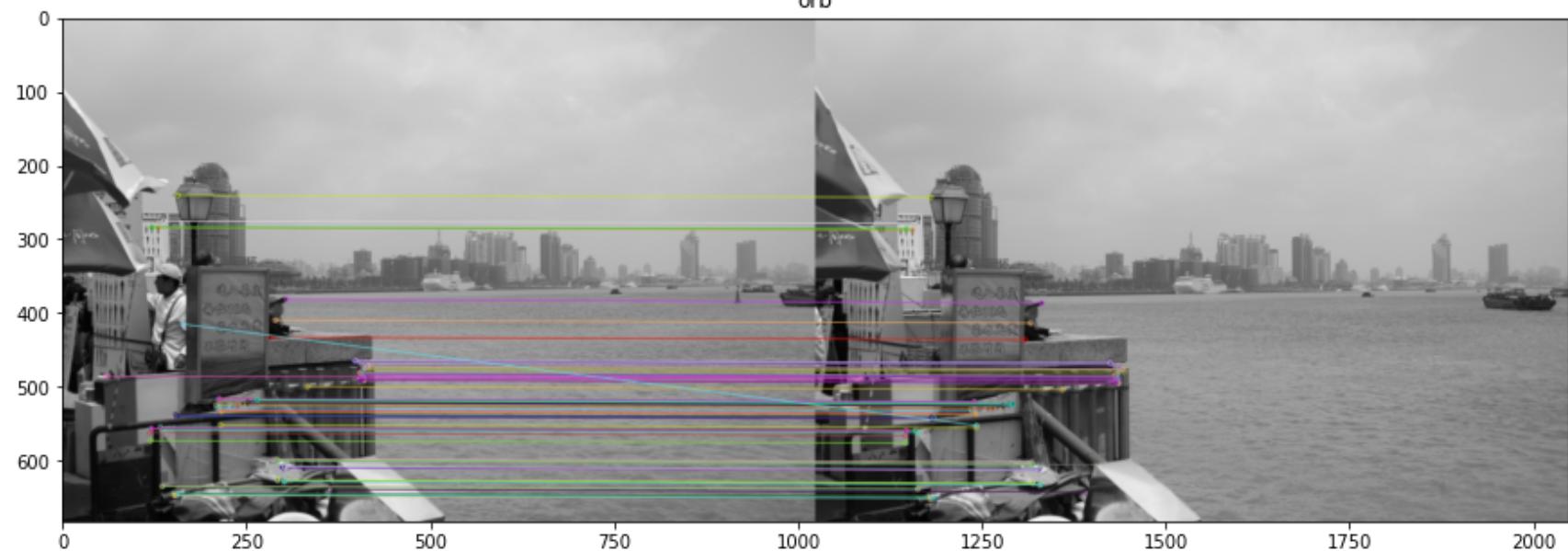
Descriptor sift detects 8726 points and 883 points are good.

sift



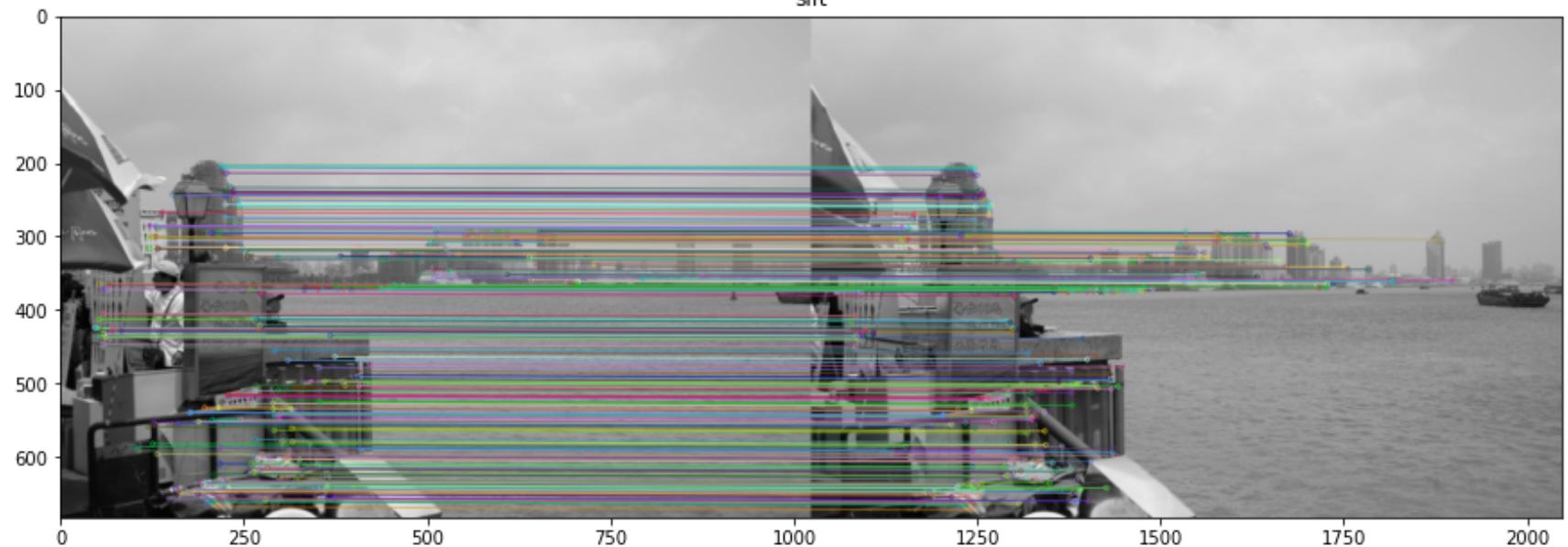
Descriptor orb detects 500 points and 76 points are good.

orb



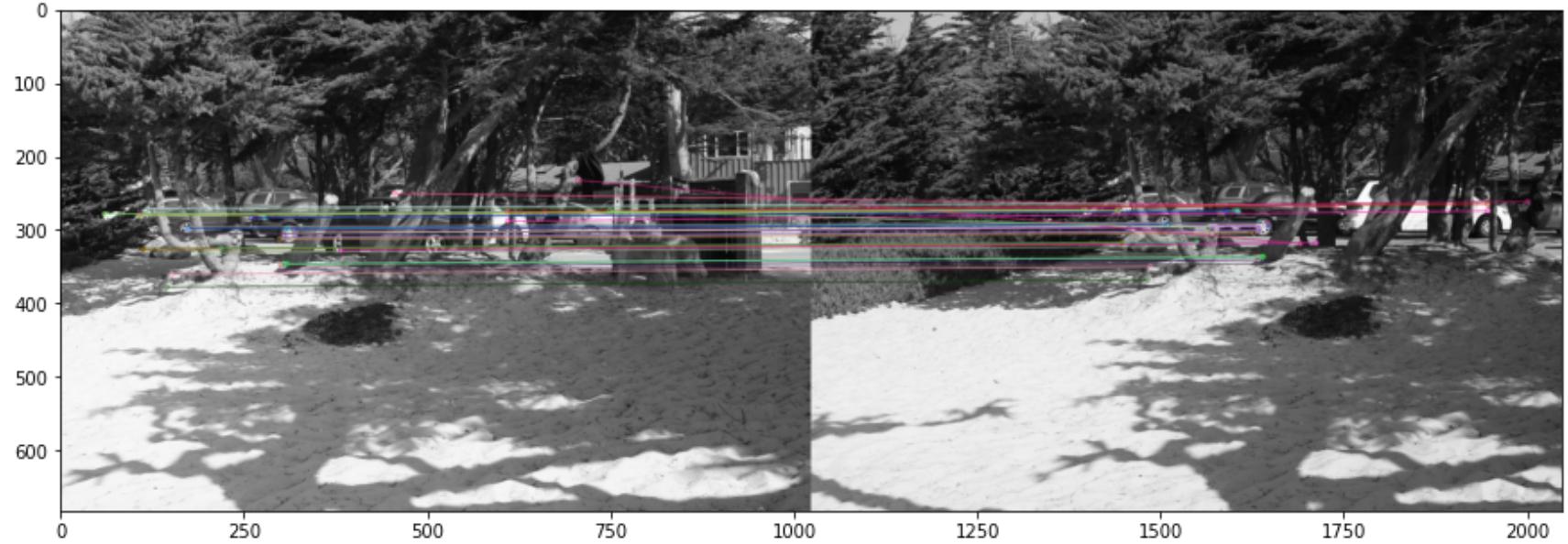
Descriptor sift detects 1659 points and 851 points are good.

sift

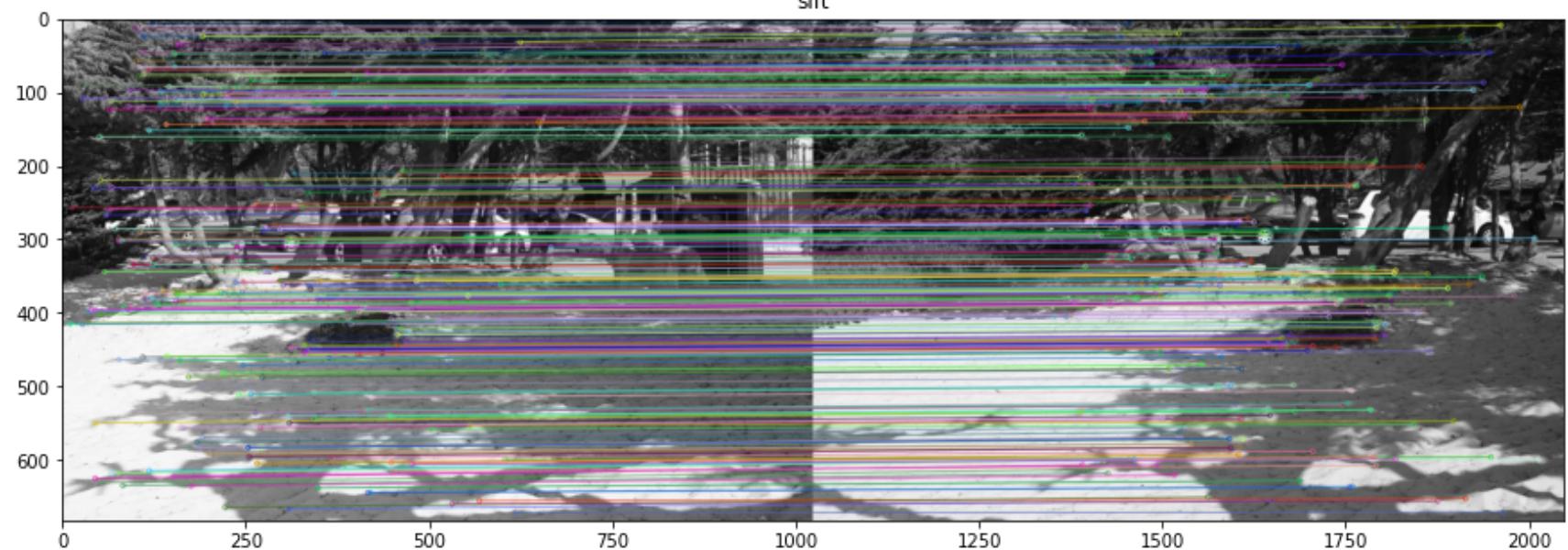


Descriptor orb detects 500 points and 40 points are good.

orb



Descriptor sift detects 6963 points and 2184 points are good.



## 1C Feature tracking

Question: (10 points) Instead of finding feature points independently in multiple images and then matching them, find features in the first image of a video or image sequence and then re-locate the corresponding points in the next frames using search and gradient descent (Shi and Tomasi 1994). When the number of tracked points drops below a threshold or new regions in the image become visible, find additional points to track.

Answer:

The code is included below, here are some comments to guide you through.

function `get_pre_points` will generate good features to track

function `get_new_points` will search new frame based on `pre_points`

function `feature_match_by_tracking` is main function, the input is image folder, which includes video frames download from internet. This can be changed to mp4, but for testing purpose some images frames are good enough. In this function, there is a logic

```
if m < min_threshold:
    # todo recalculate points
    # recalculate pre_points
```

```

        print(f"good points is lower than {min_threshold}, recalculating...")
        (pre_points, kp1) = get_pre_points(pre_gray,n)
        (new_points,kp2,matches) = get_new_points(pre_gray,new_gray,pre_points)
    
```

This logic will check good points left, if it is lower than threshold, will re-retrieve pre\_points from good features to track.

The output shows current frame index, good features left information and matching lines between the previous frame and current frame. The frame 36 shows the result it triggered the re-retrieve pre\_points action.

In [ ]:

```

import numpy as np
import cv2 as cv
from matplotlib import pyplot as plt
from imutils import paths

def get_pre_points(pre_gray,n):
    pre_points = cv2.goodFeaturesToTrack(pre_gray,n,0.01,10)
    pre_points = np.array(pre_points,dtype='float32')
    kp1 = list()
    for j in range(n):
        d = cv2.KeyPoint()
        d.pt = pre_points[j][0]
        d.size = 31.0
        kp1.append(d)
    return(pre_points,kp1)

def get_new_points(pre_gray,new_gray,pre_points):
    new_points, status, err = cv2.calcOpticalFlowPyrLK(pre_gray,
    new_gray,pre_points,None,maxLevel=2)

    n = pre_points.shape[0]
    # show matching
    # convert format to keypoints
    kp2 = list()
    matches = list()
    for j in range(n):
        good = status[j,0]

        d = cv2.KeyPoint()
        d.pt = new_points[j,0]
        d.size = 31
        kp2.append(d)

        if good != 0:
            matches.append((kp1[j],kp2[j]))
    
```

```
m = cv2.DMatch()
m.queryIdx = j
m.trainIdx = j
matches.append(m)

return (new_points,kp2,matches)

def feature_match_by_tracking(image_folder,points_show=50,min_threshold=40):
    print("[INFO] loading images...")
    imagePaths = sorted(list(paths.list_images(image_folder)))
    images = []

        # images to stitch list
    for imagePath in imagePaths:
        image = cv2.imread(imagePath)
        images.append(image)

    # it can be changed to read mp4 if needed
    n = 100
    pre_img = images[0]
    pre_gray = cv2.cvtColor(pre_img,cv2.COLOR_BGR2GRAY)
    (pre_points, kp1) = get_pre_points(pre_gray,n)

    for i in range(1,len(images)):
        new_img = images[i]
        new_gray = cv2.cvtColor(new_img,cv2.COLOR_BGR2GRAY)

        (new_points,kp2,matches) = get_new_points(pre_gray,new_gray,pre_points)
        m = len(matches)

        print(f"frame {i}: good points {m}")

        if m < min_threshold:
            # todo recalculate points
            # recalculate pre_points
            print(f"good points is lower than {min_threshold}, recalculating...")
            (pre_points, kp1) = get_pre_points(pre_gray,n)
            (new_points,kp2,matches) = get_new_points(pre_gray,new_gray,pre_points)

    img3 = cv2.drawMatches(pre_img,kp1,new_img,kp2,
                          matches[:points_show], None,flags=cv2.DrawMatchesFlags_NOT_DRAW_SINGLE_POINTS)

    plt.figure(figsize=(15, 10))
    plt.imshow(img3)
```

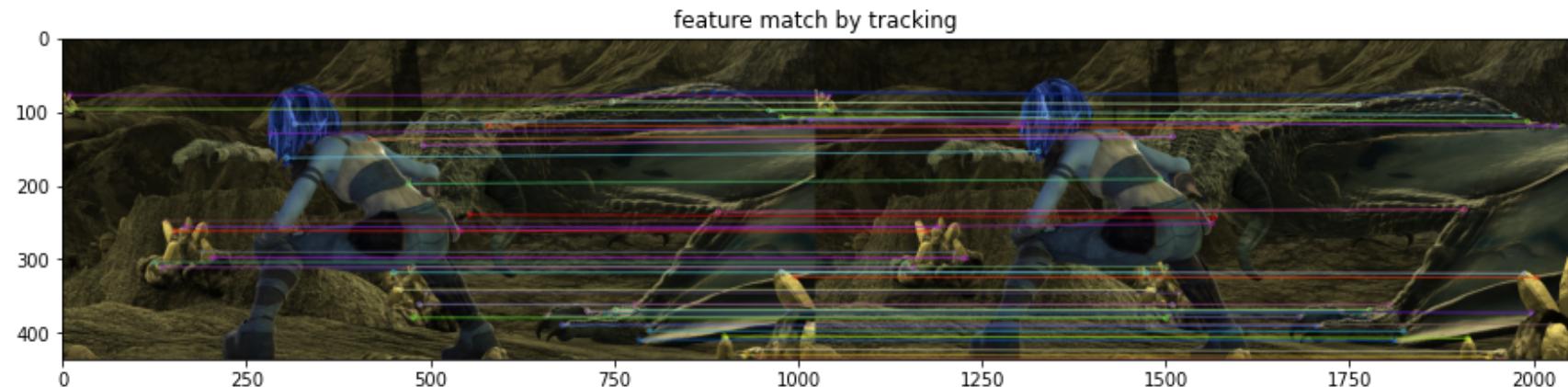
```
plt.title('feature match by tracking')
plt.show()

pre_img = new_img.copy()
pre_points = new_points.copy()
pre_gray = new_gray.copy()
kp1 = kp2.copy()

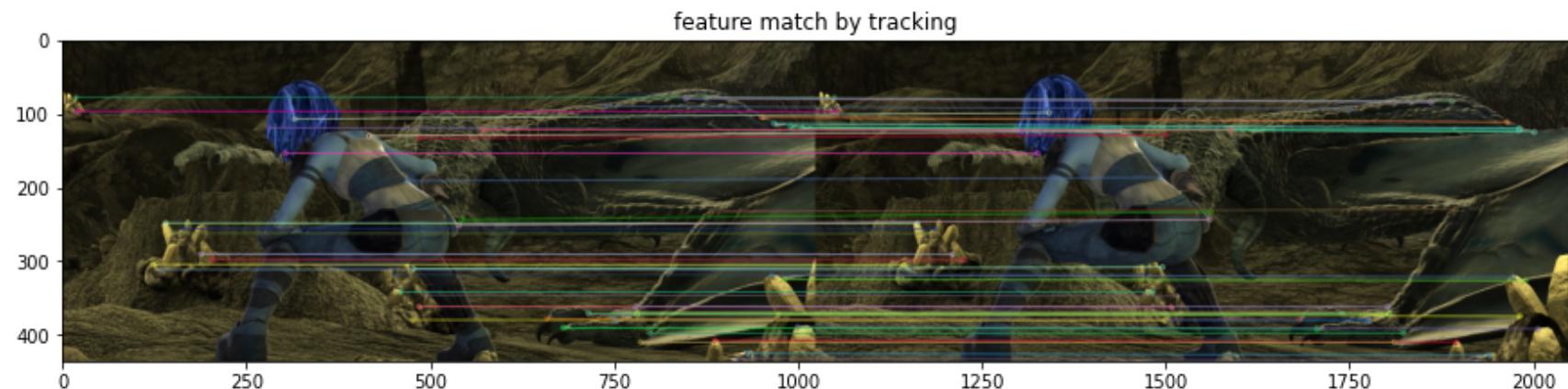
image_folder = './data/cave_3'
feature_match_by_tracking(image_folder,50,40)
```

[INFO] loading images...

frame 1: good points 100

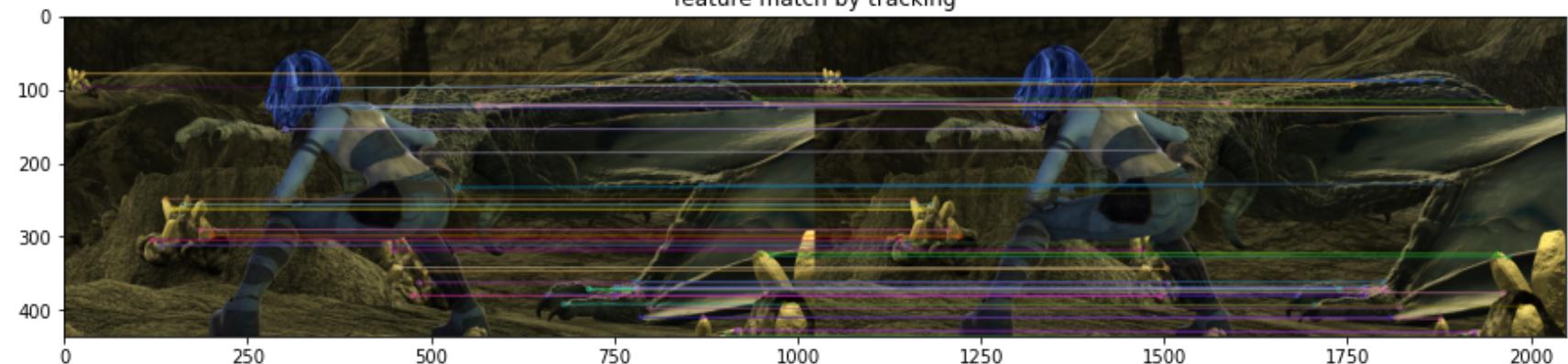


frame 2: good points 100



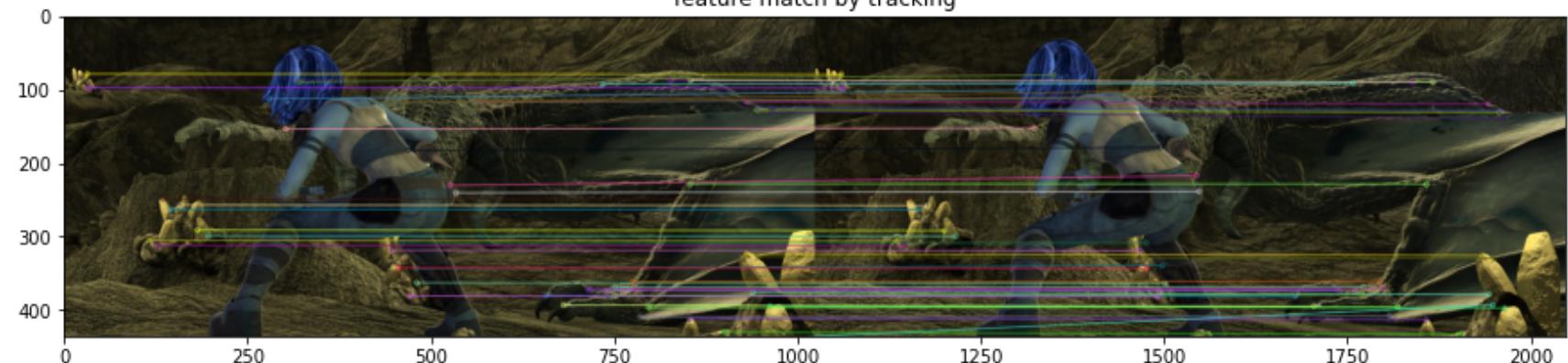
frame 3: good points 100

## feature match by tracking



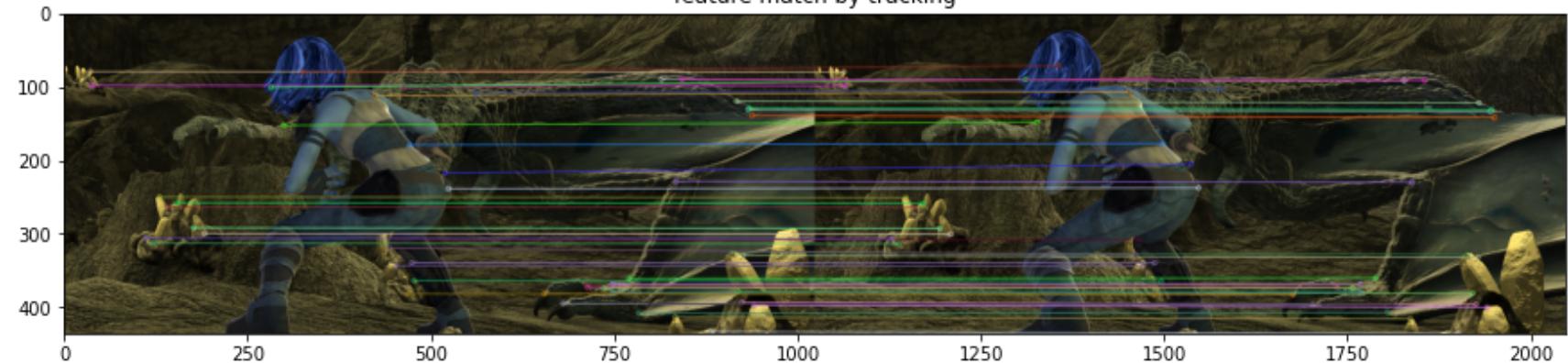
frame 4: good points 100

## feature match by tracking



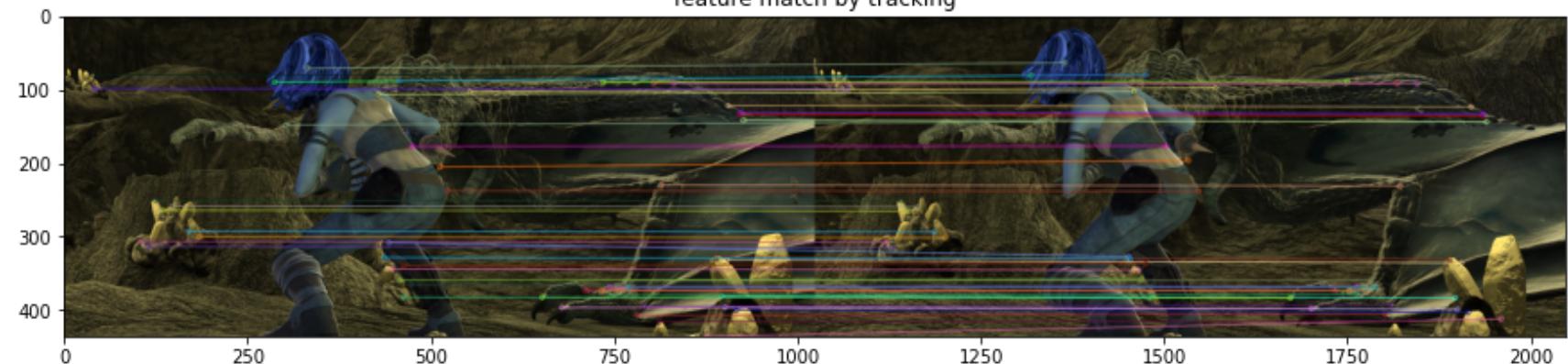
frame 5: good points 100

## feature match by tracking



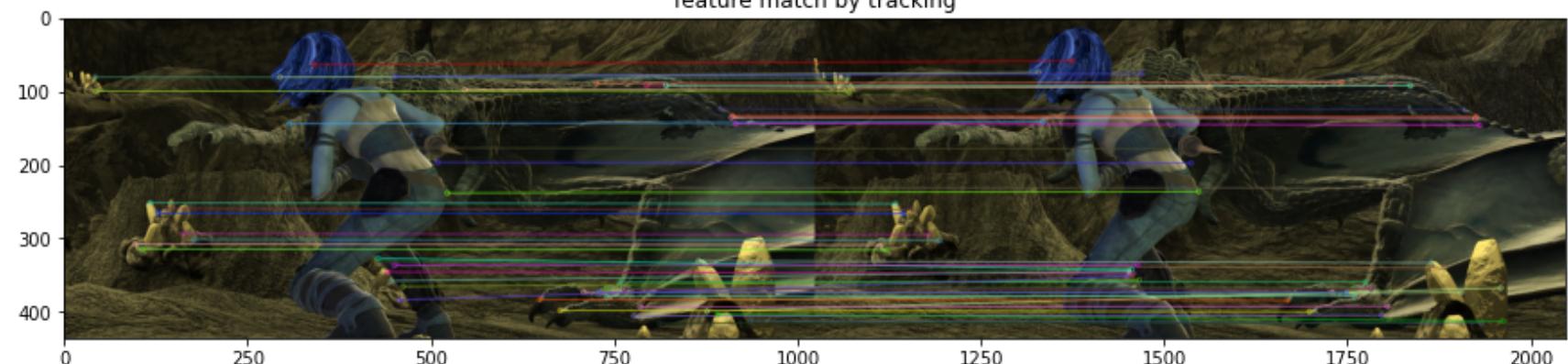
frame 6: good points 99

## feature match by tracking



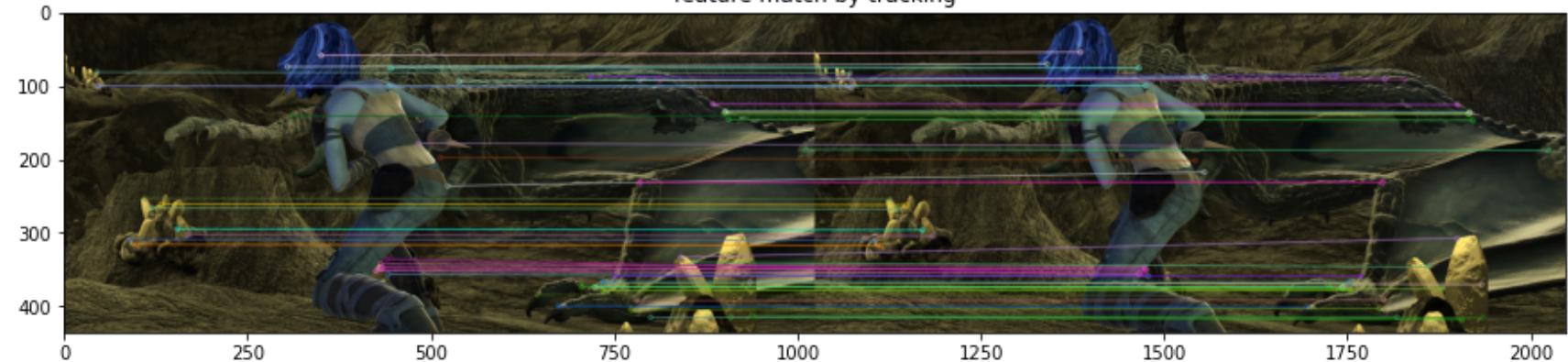
frame 7: good points 98

## feature match by tracking



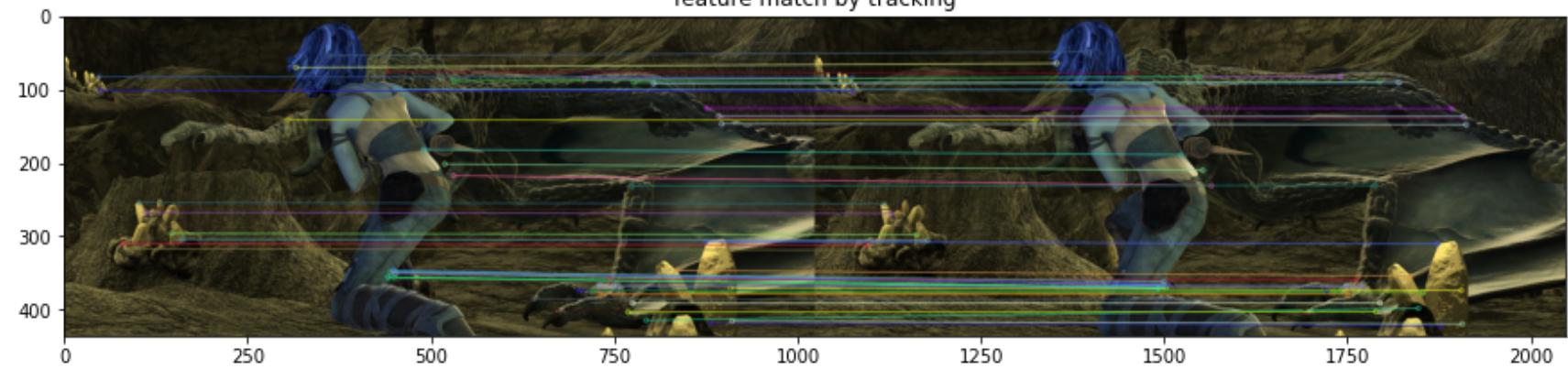
frame 8: good points 98

## feature match by tracking



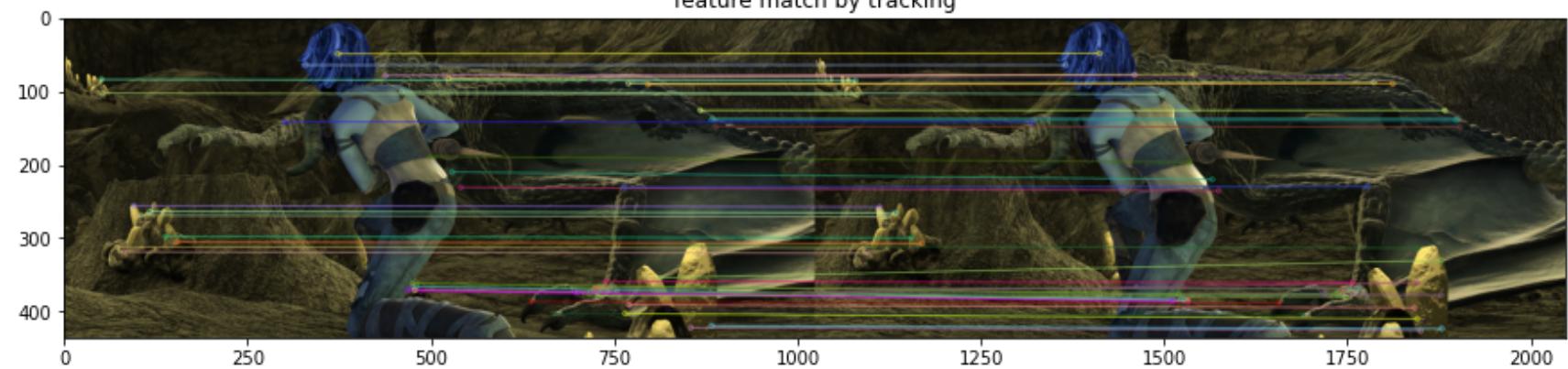
frame 9: good points 97

## feature match by tracking



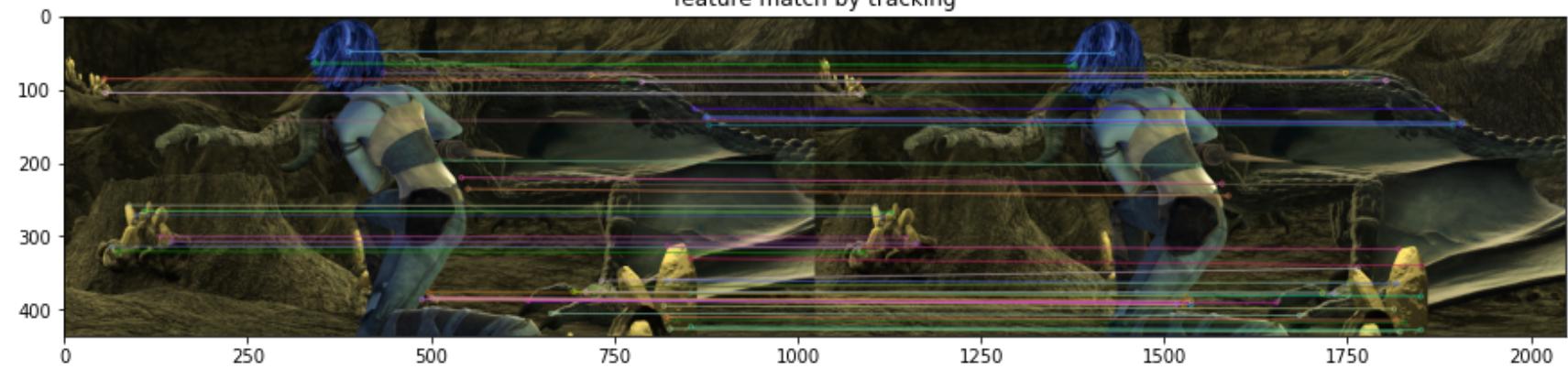
frame 10: good points 97

## feature match by tracking



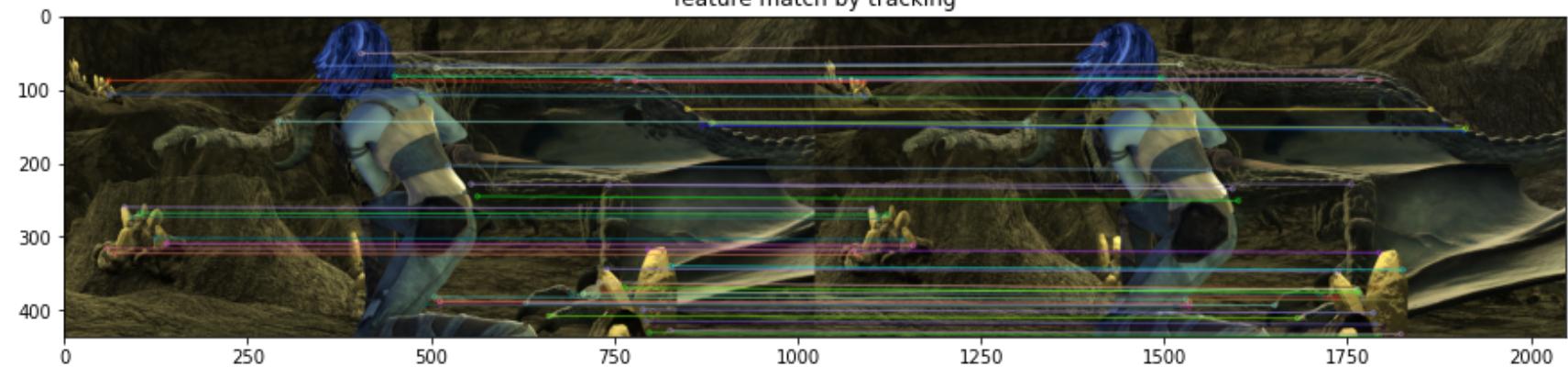
frame 11: good points 97

## feature match by tracking



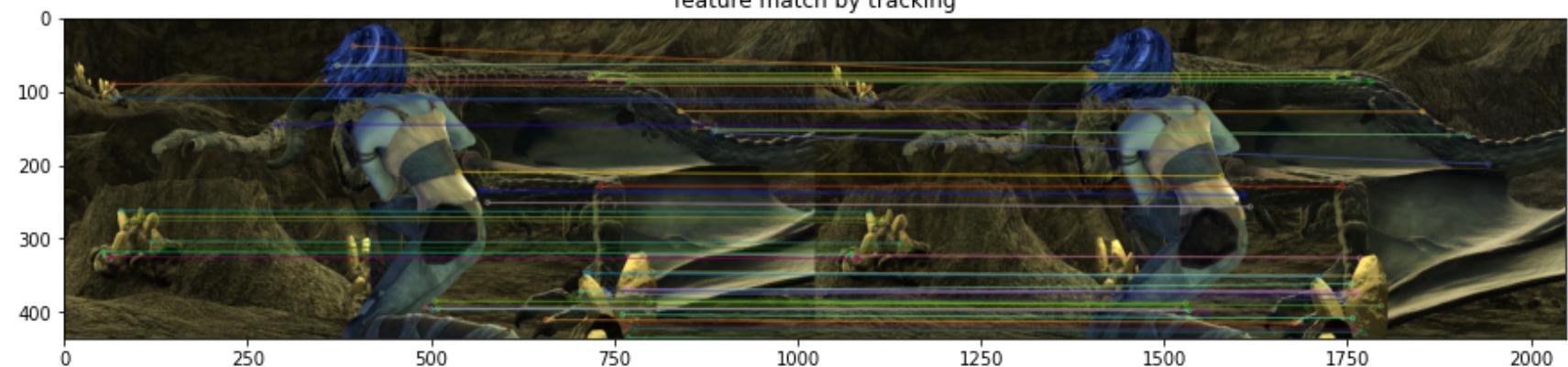
frame 12: good points 97

## feature match by tracking



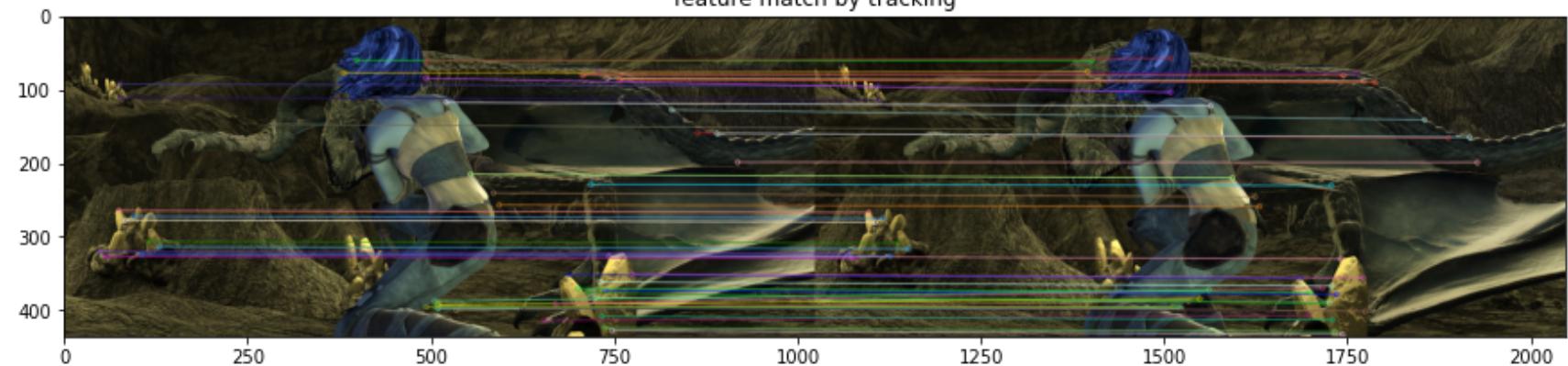
frame 13: good points 96

## feature match by tracking



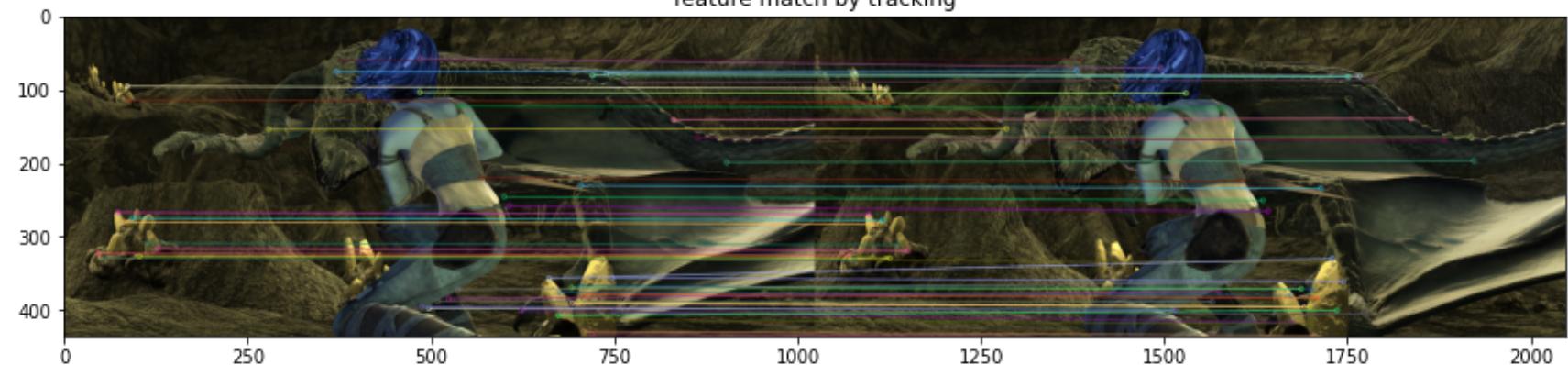
frame 14: good points 94

## feature match by tracking



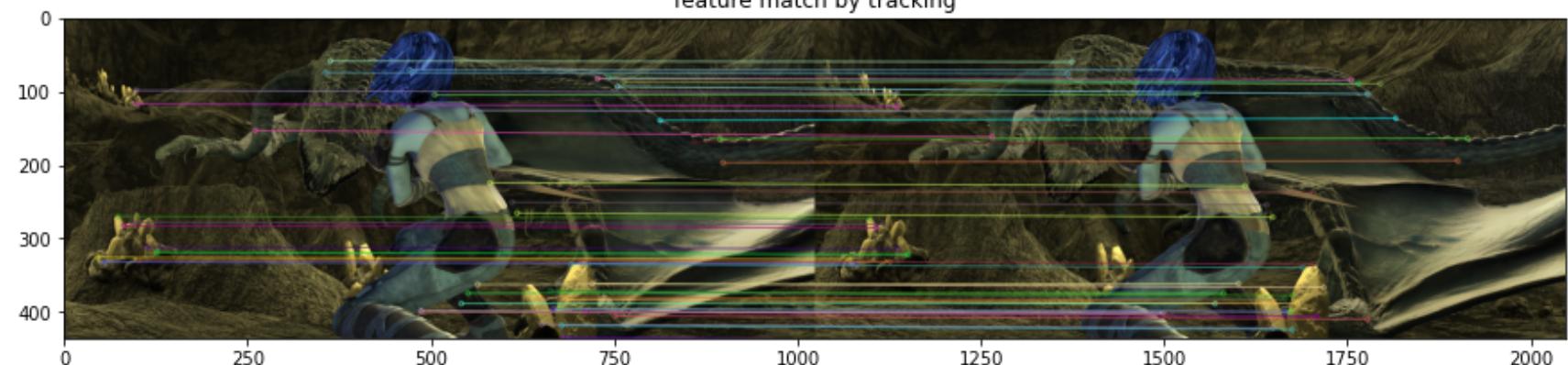
frame 15: good points 94

## feature match by tracking



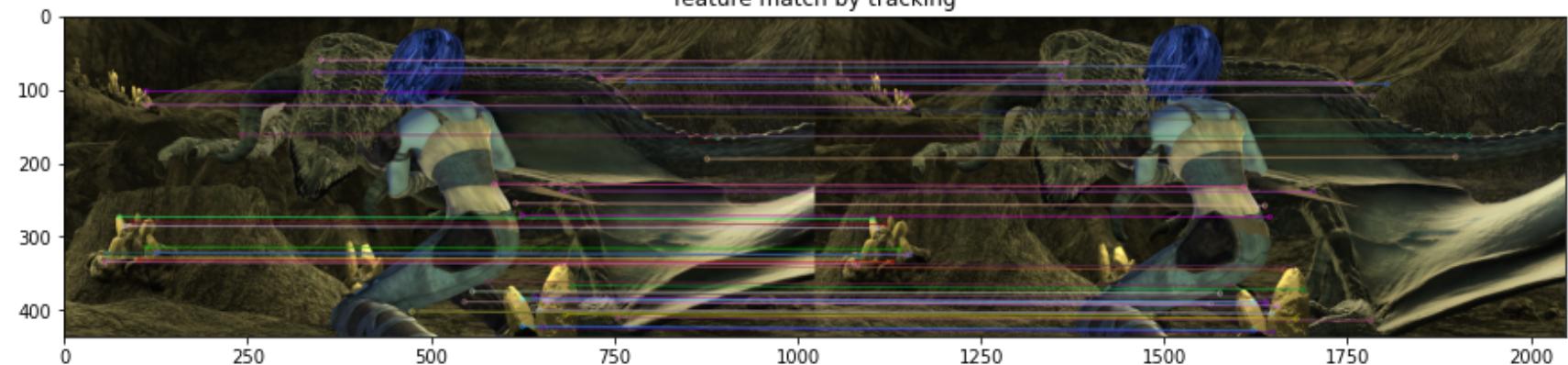
frame 16: good points 93

## feature match by tracking



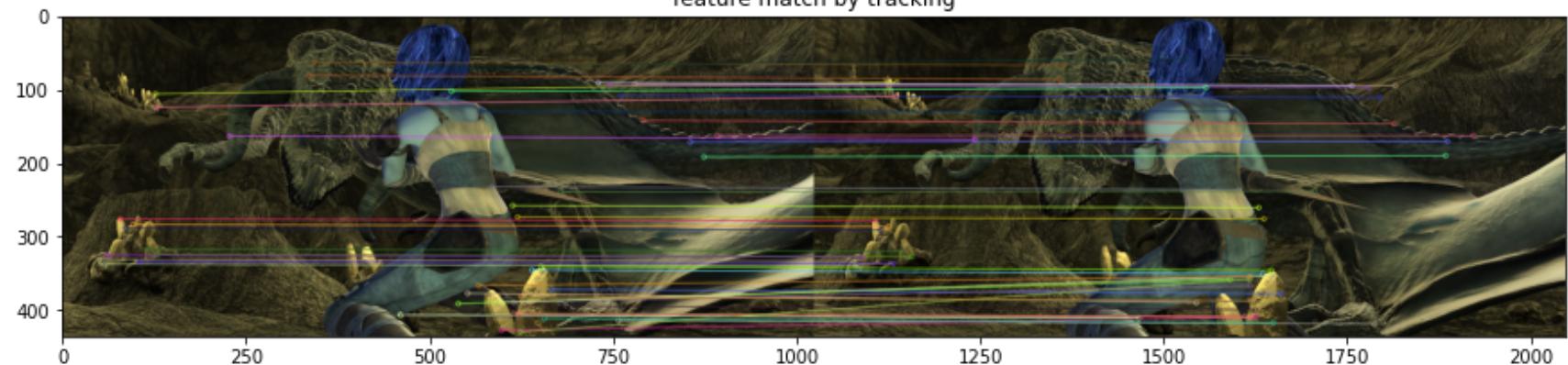
frame 17: good points 91

## feature match by tracking



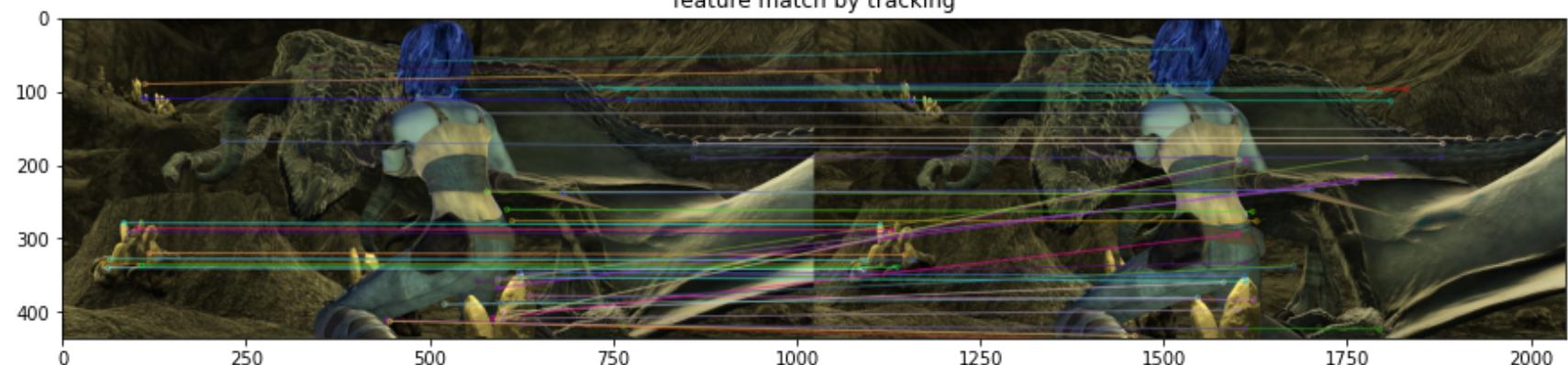
frame 18: good points 90

## feature match by tracking



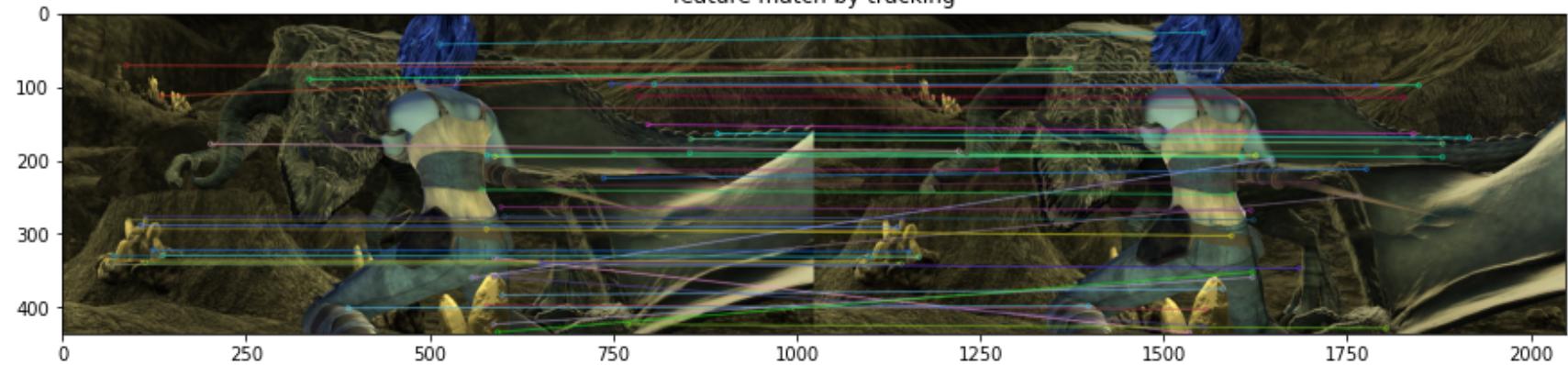
frame 19: good points 89

## feature match by tracking



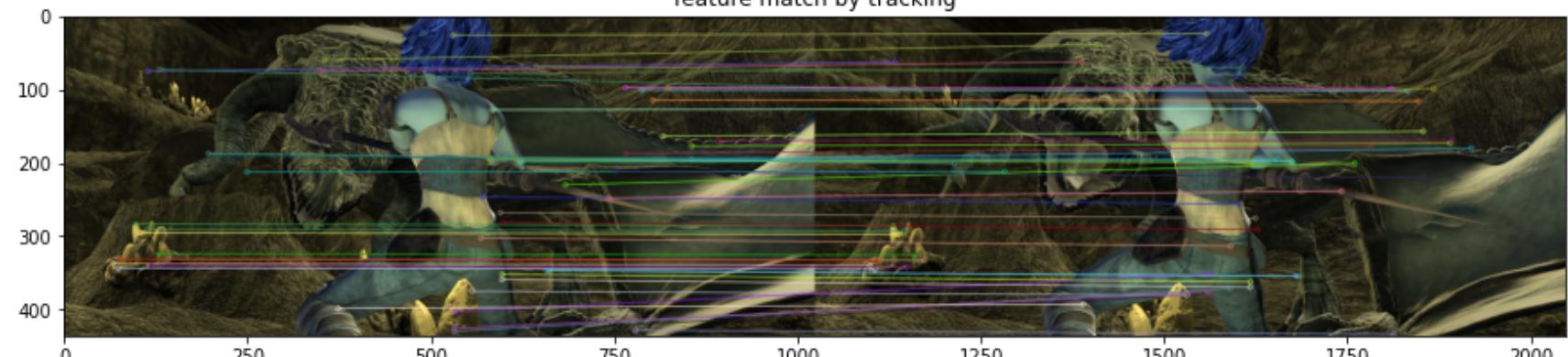
frame 20: good points 86

## feature match by tracking



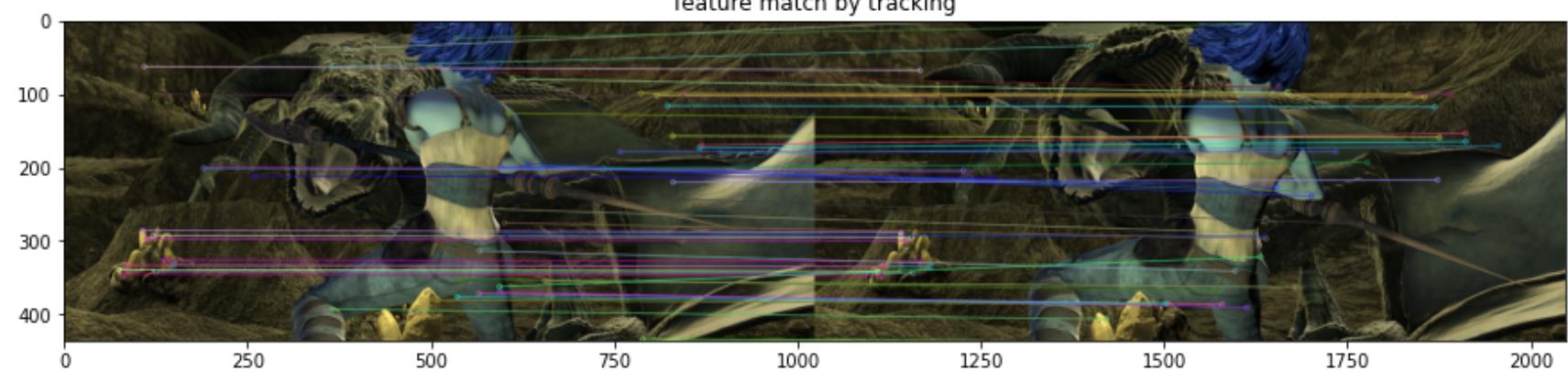
frame 21: good points 86

## feature match by tracking



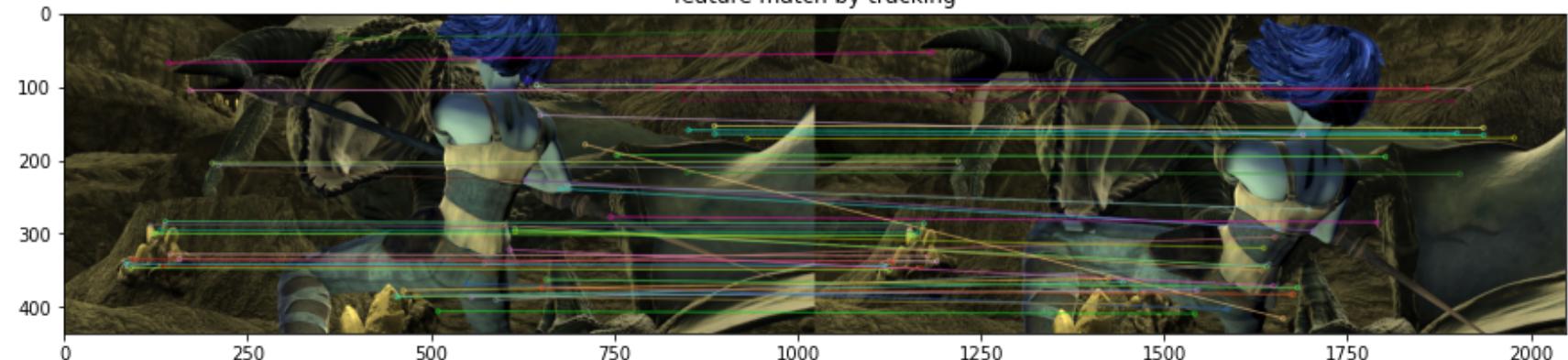
frame 22: good points 86

## feature match by tracking



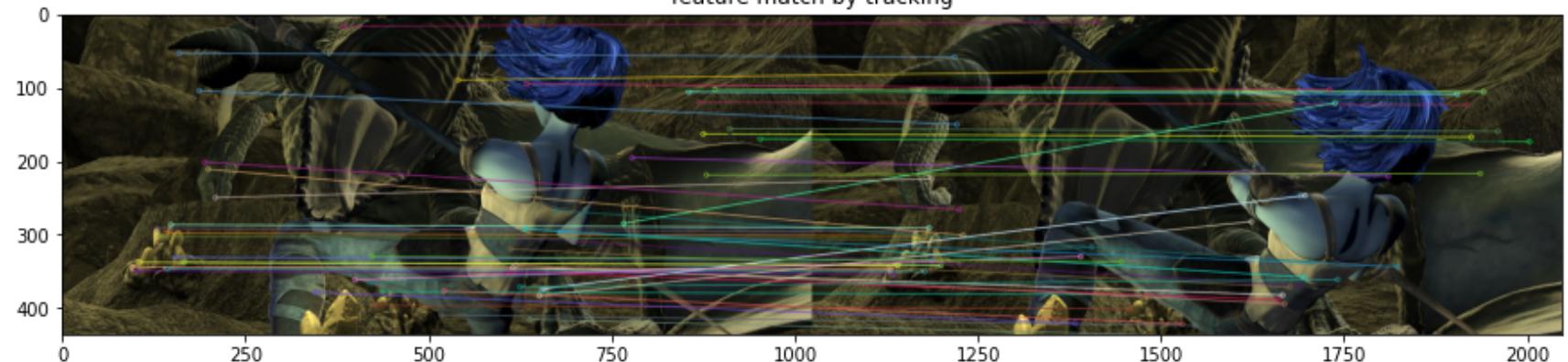
frame 23: good points 82

## feature match by tracking



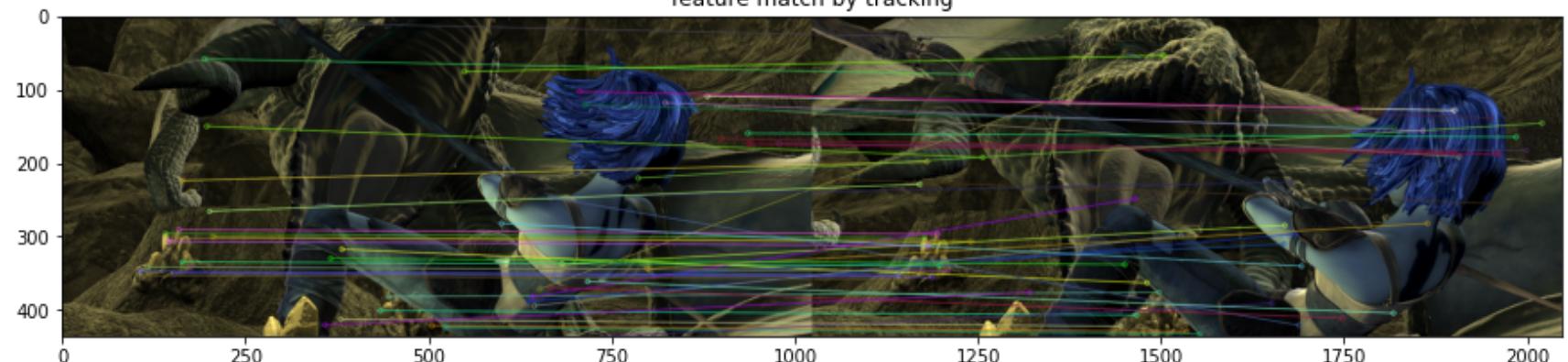
frame 24: good points 79

## feature match by tracking



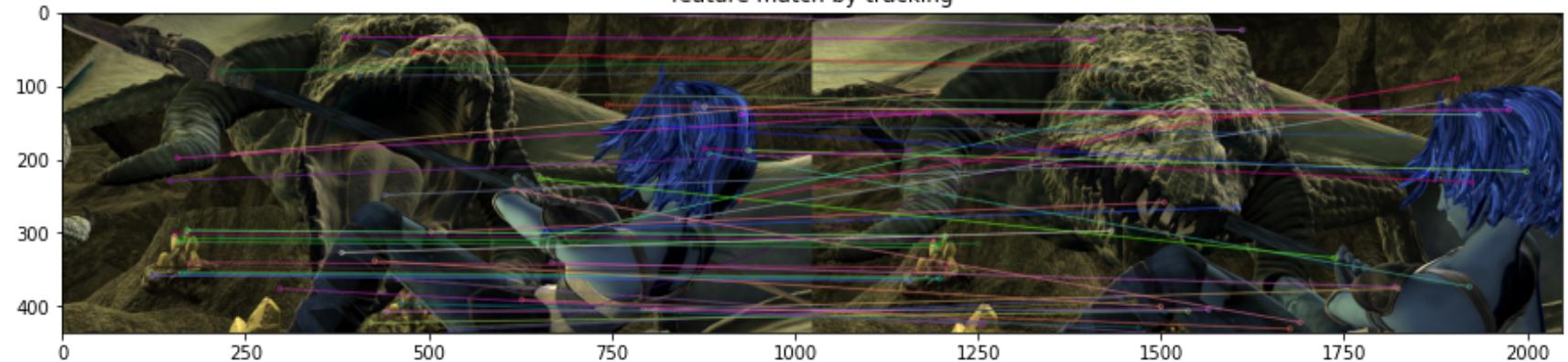
frame 25: good points 75

## feature match by tracking



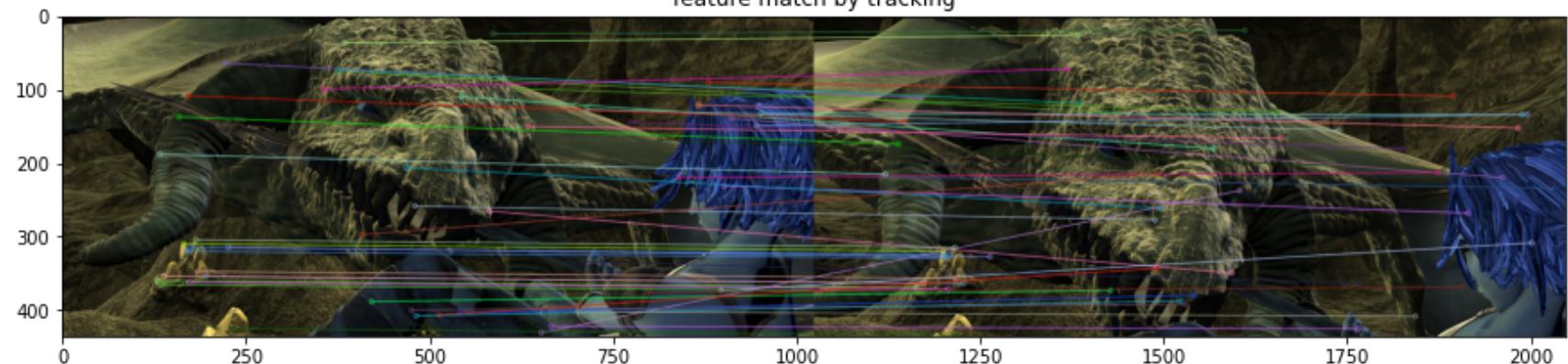
frame 26: good points 66

## feature match by tracking



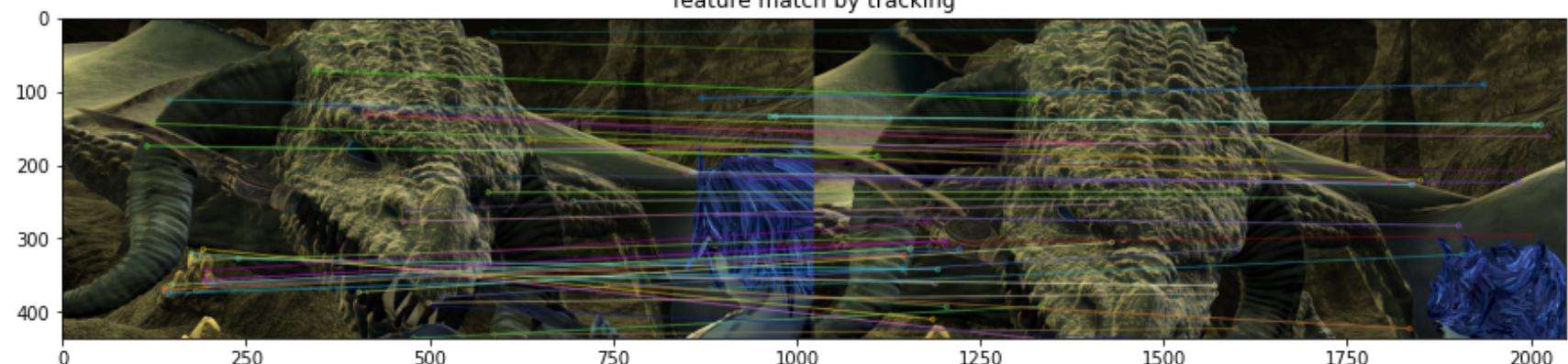
frame 27: good points 62

## feature match by tracking



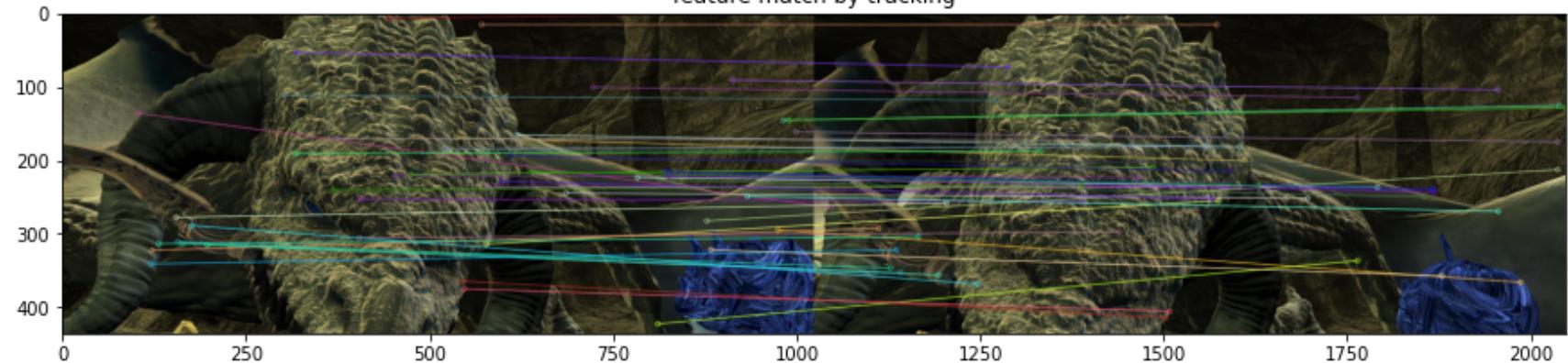
frame 28: good points 59

## feature match by tracking



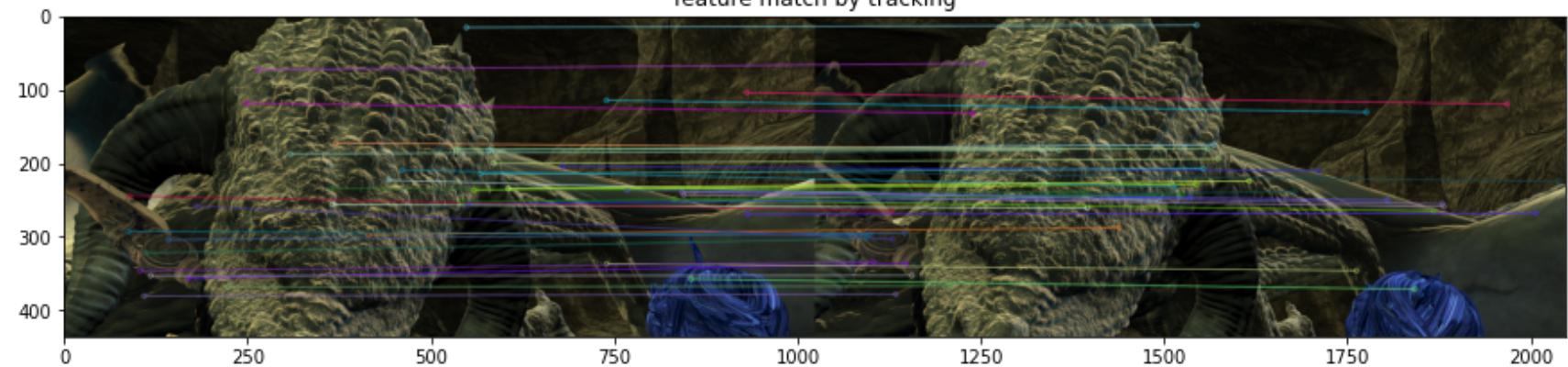
frame 29: good points 46

## feature match by tracking



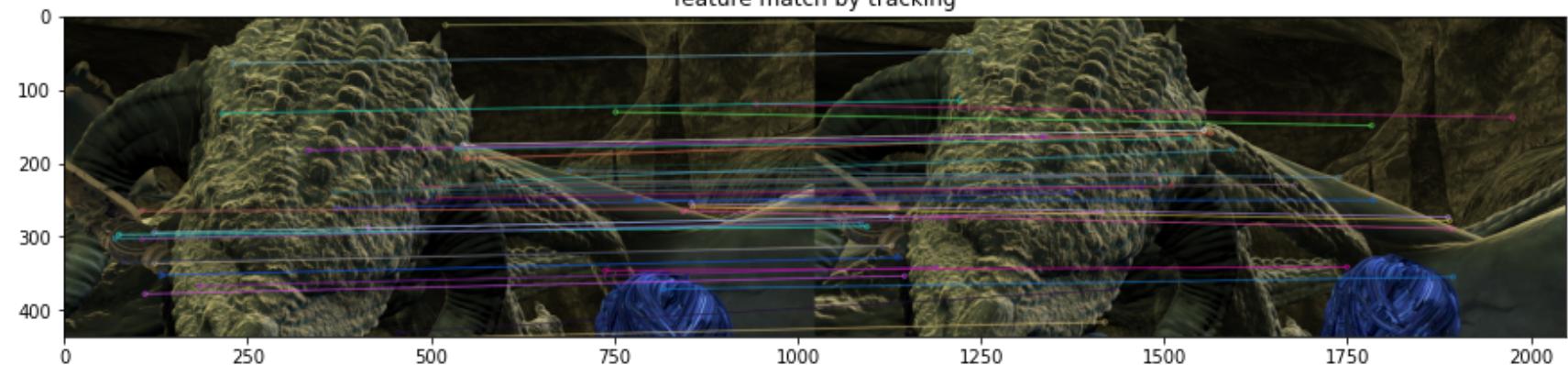
frame 30: good points 40

## feature match by tracking



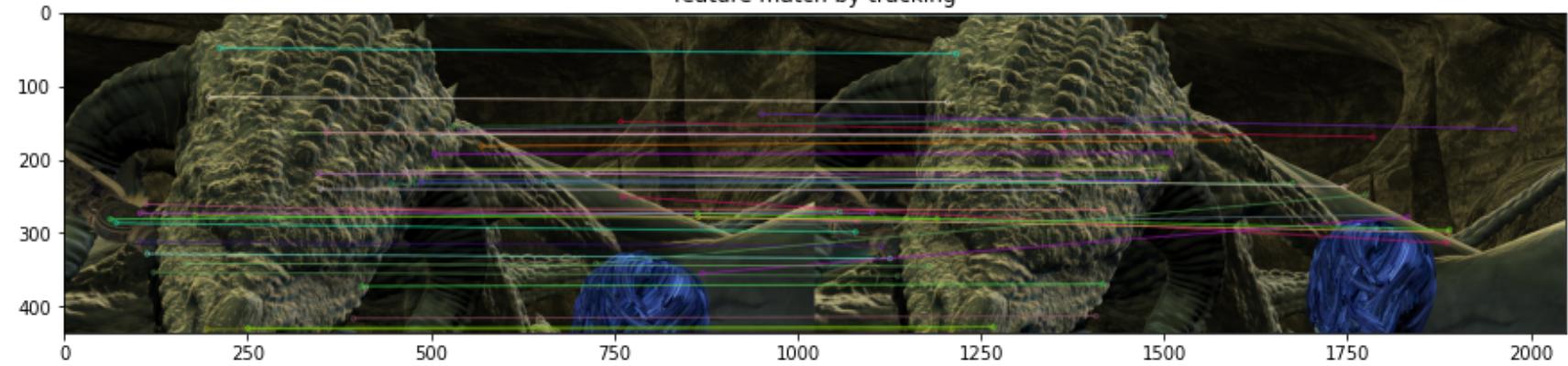
frame 31: good points 40

## feature match by tracking



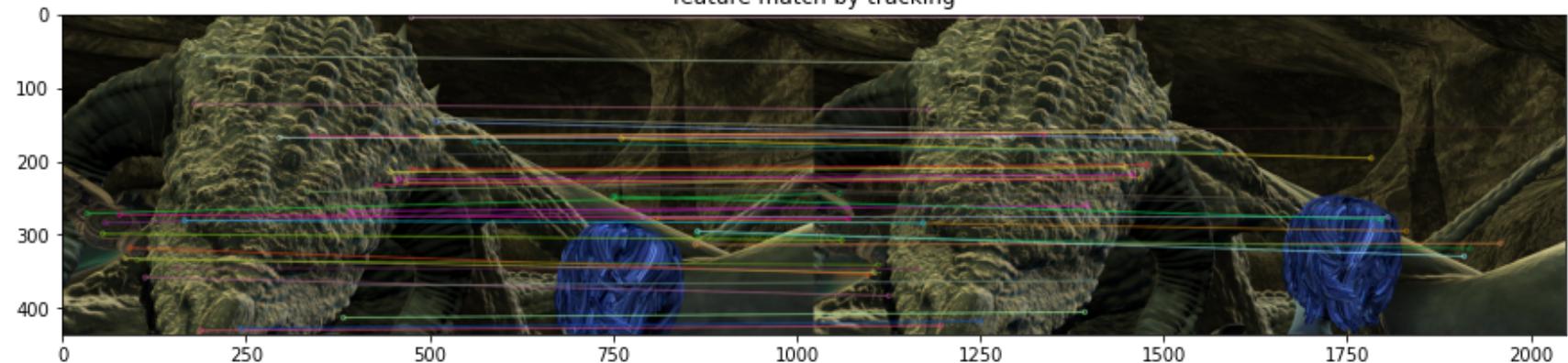
frame 32: good points 42

## feature match by tracking



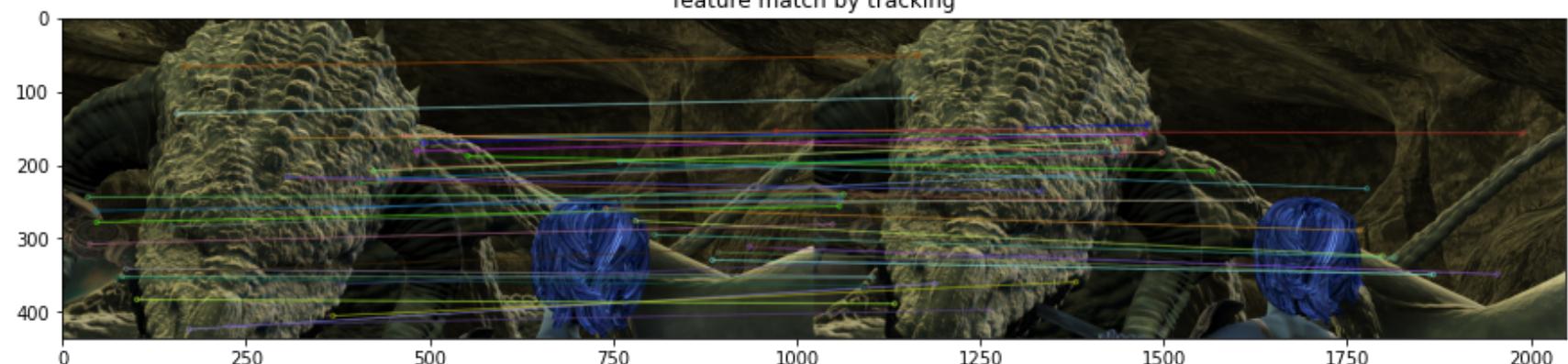
frame 33: good points 42

## feature match by tracking



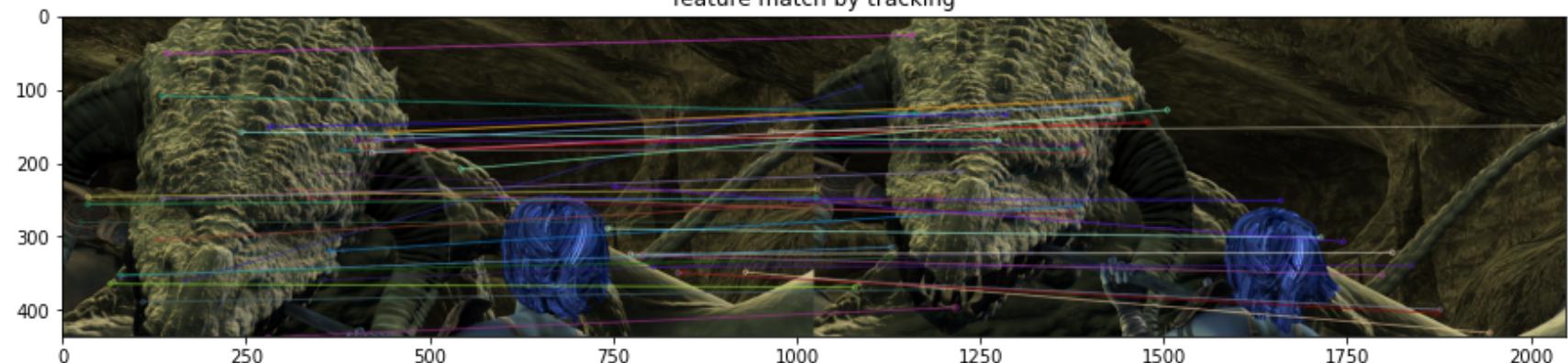
frame 34: good points 41

## feature match by tracking



frame 35: good points 40

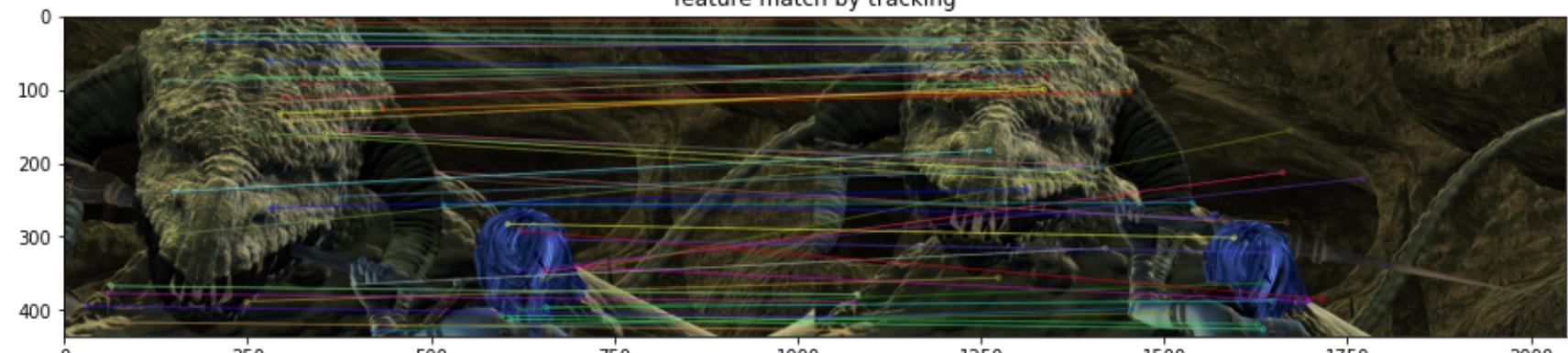
## feature match by tracking



frame 36: good points 38

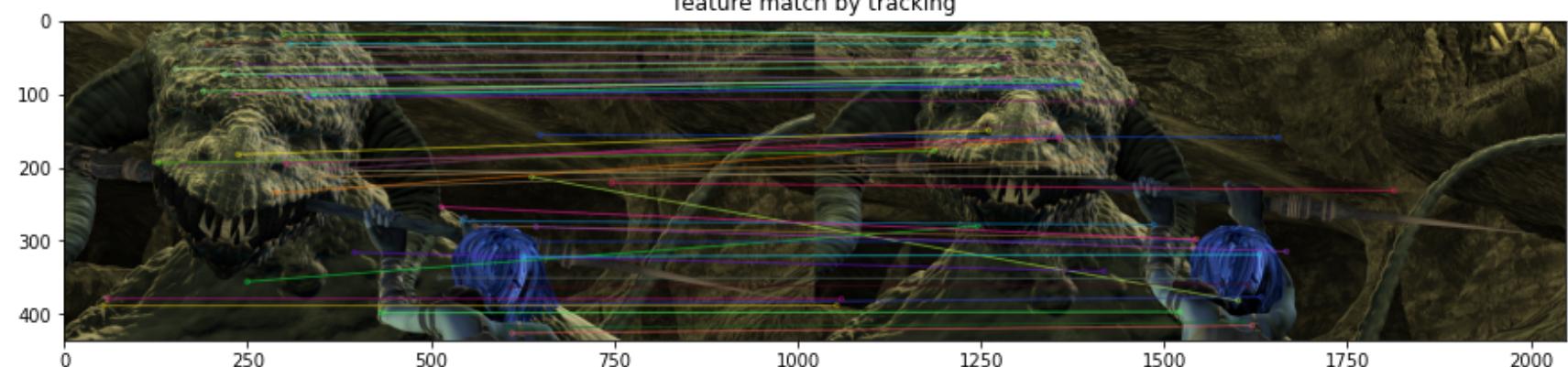
good points is lower than 40, recalculating...

## feature match by tracking



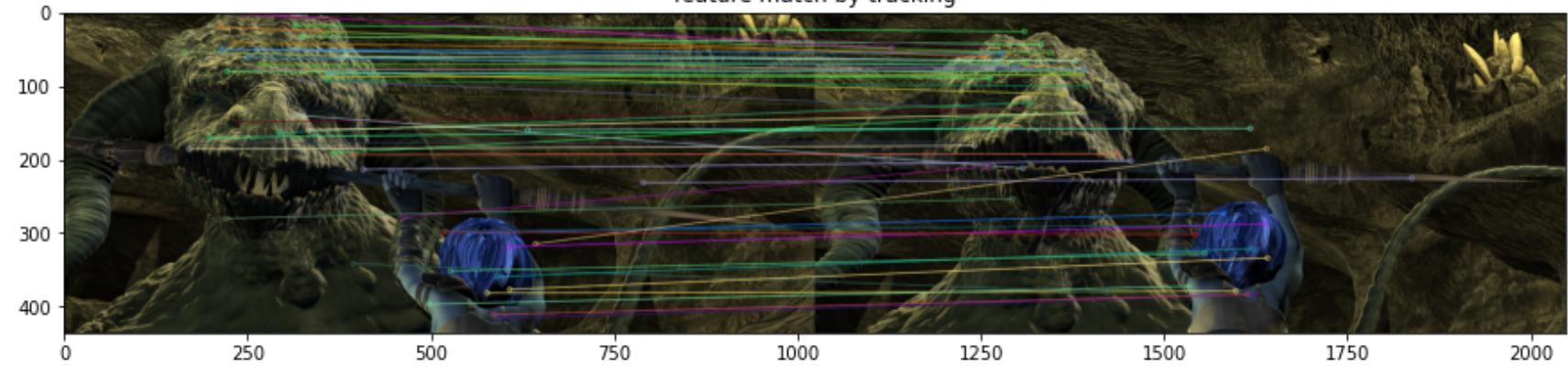
frame 37: good points 90

## feature match by tracking



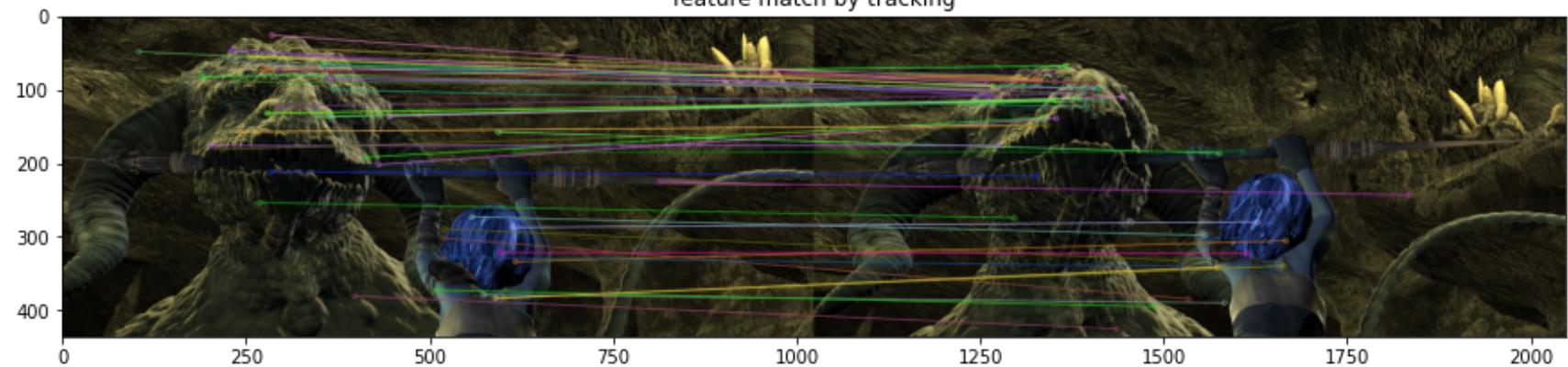
frame 38: good points 87

## feature match by tracking



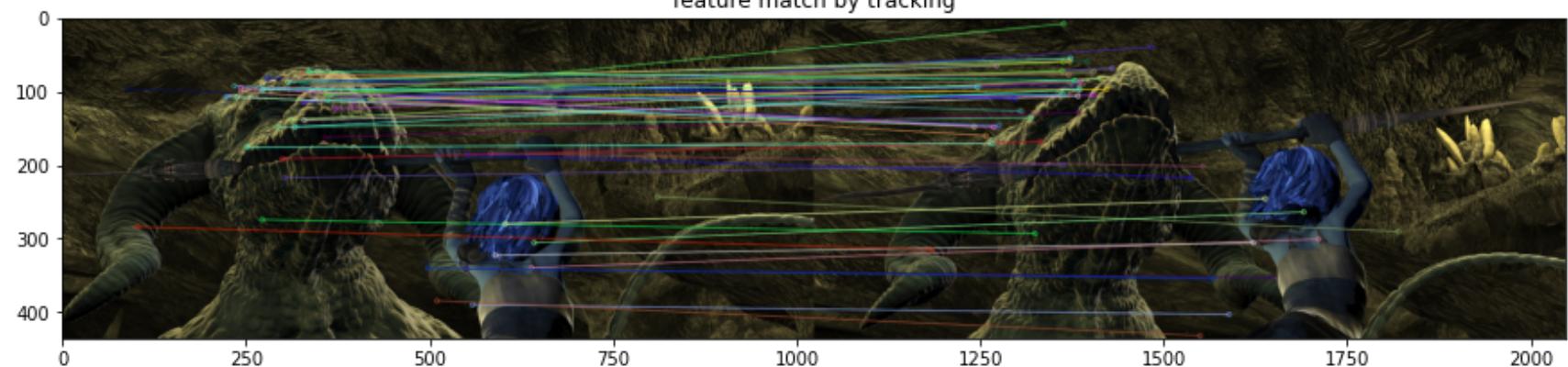
frame 39: good points 87

## feature match by tracking



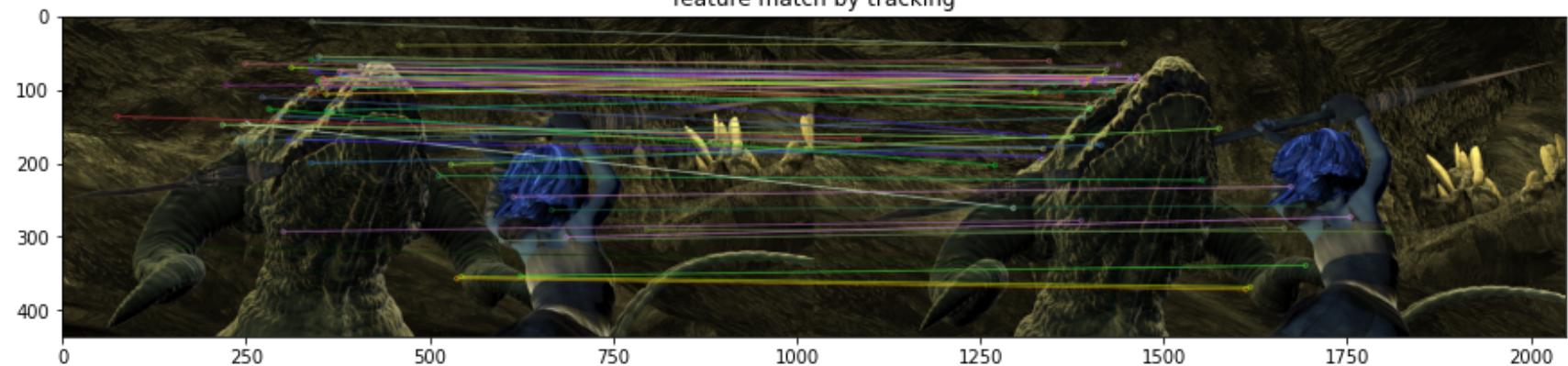
frame 40: good points 78

## feature match by tracking



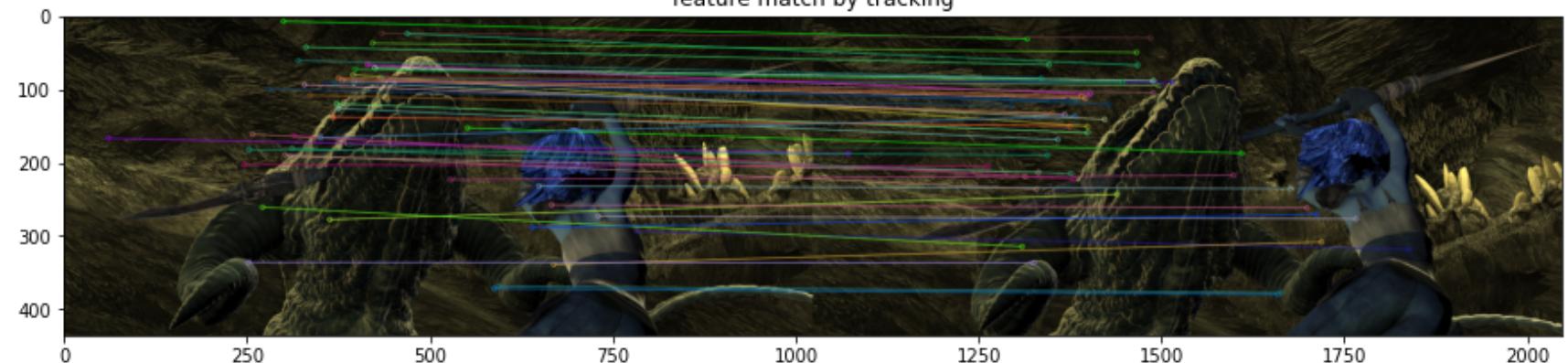
frame 41: good points 75

## feature match by tracking



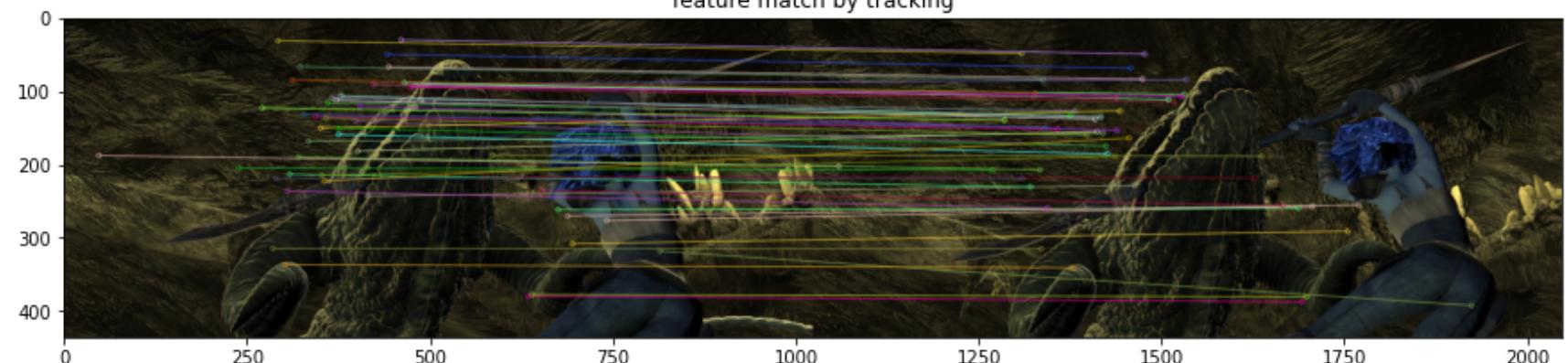
frame 42: good points 79

## feature match by tracking



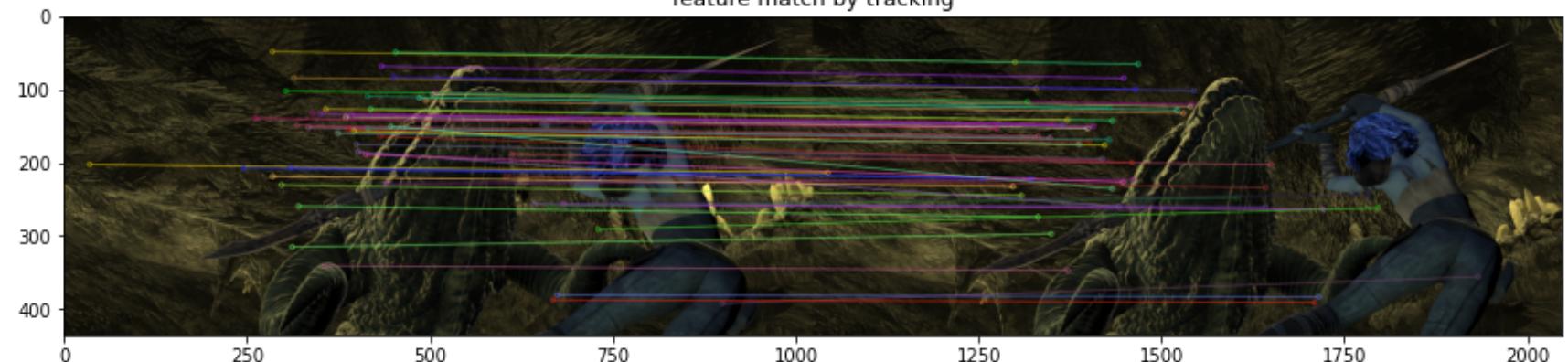
frame 43: good points 80

## feature match by tracking



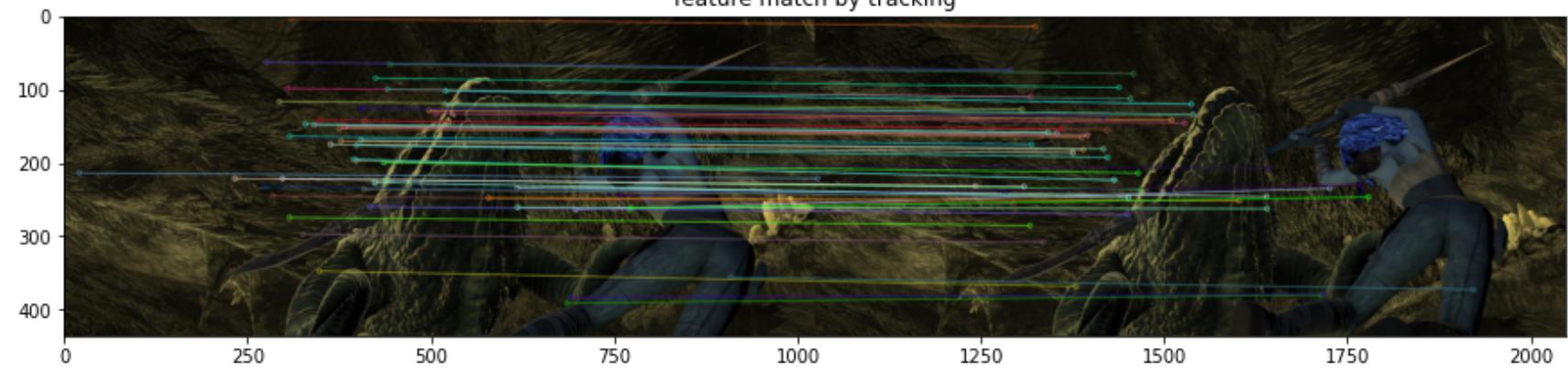
frame 44: good points 80

## feature match by tracking



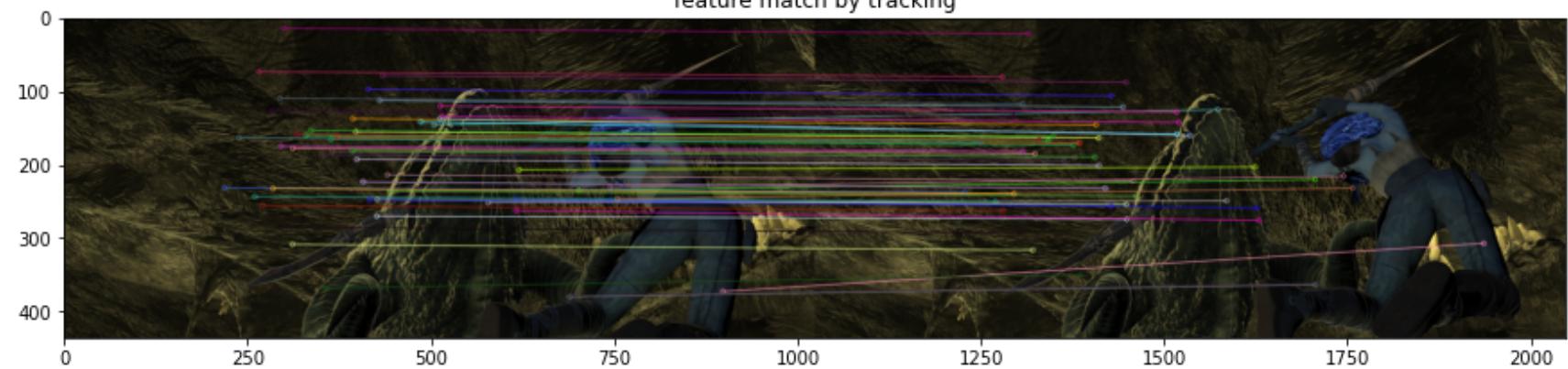
frame 45: good points 81

## feature match by tracking



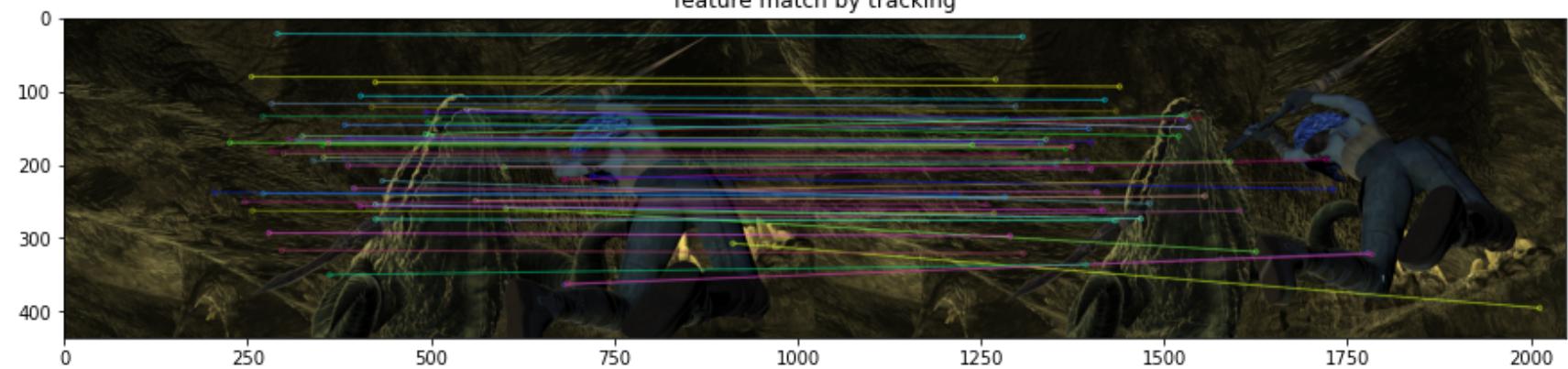
frame 46: good points 80

## feature match by tracking

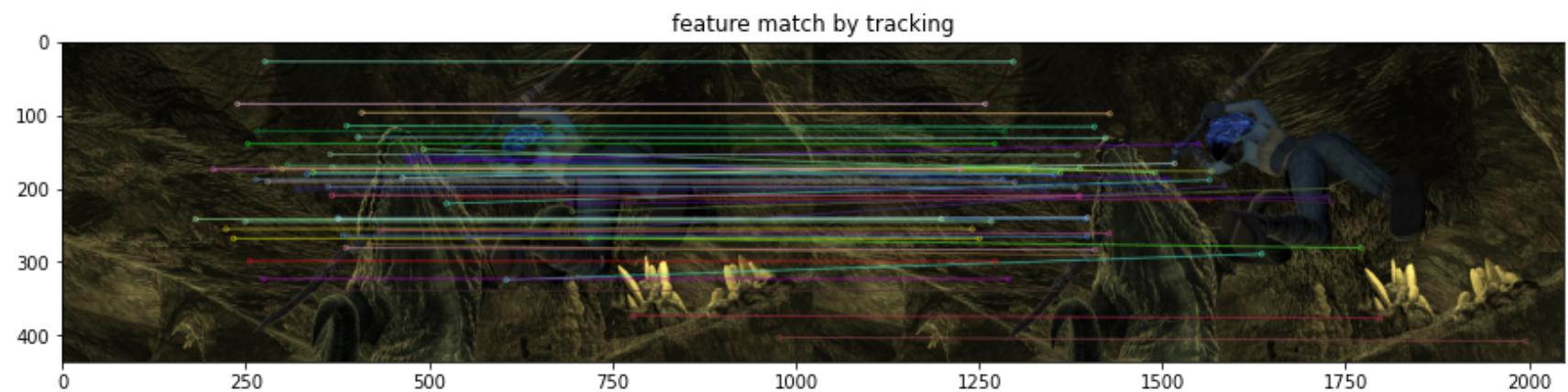
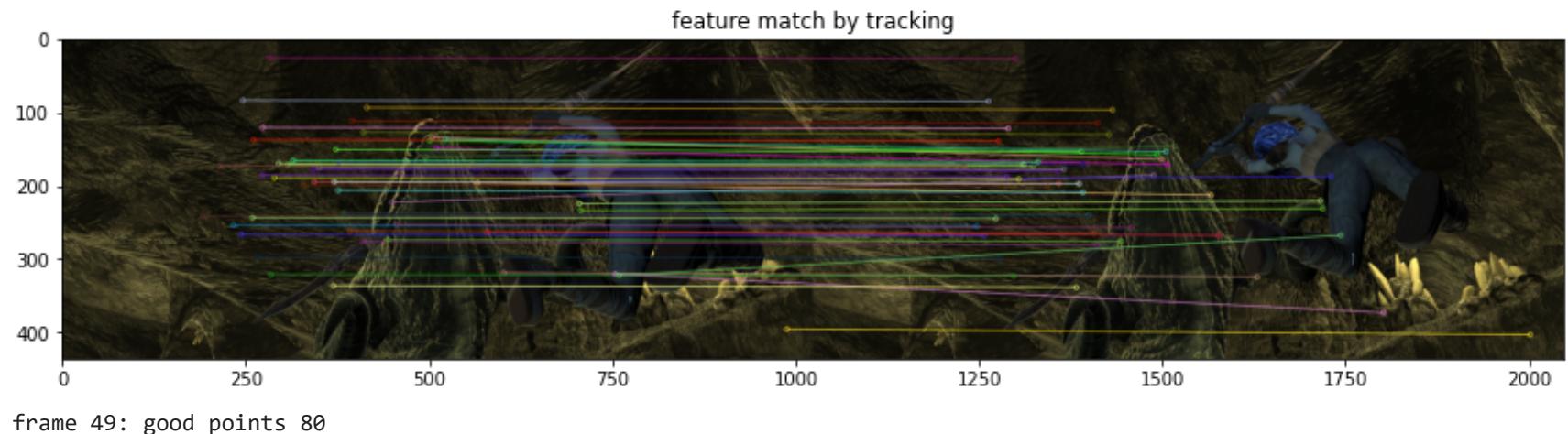


frame 47: good points 80

## feature match by tracking



frame 48: good points 80



## Question 2

Q2. (40 points) Optical flow: (use the motion sequences available at <https://vision.middlebury.edu/flow> or <http://sintel.is.tue.mpg.de>)

Compute optical flow (spline-based or per-pixel) between two images, using one or more of the techniques described in the lecture.

- (15 points) Implement the Lucas-Kanade algorithm (your code).
- (25 points) Visualize the optical flow in two video sequences, provide some examples where Lucas-Kanade fails. Explain the reason in each case.

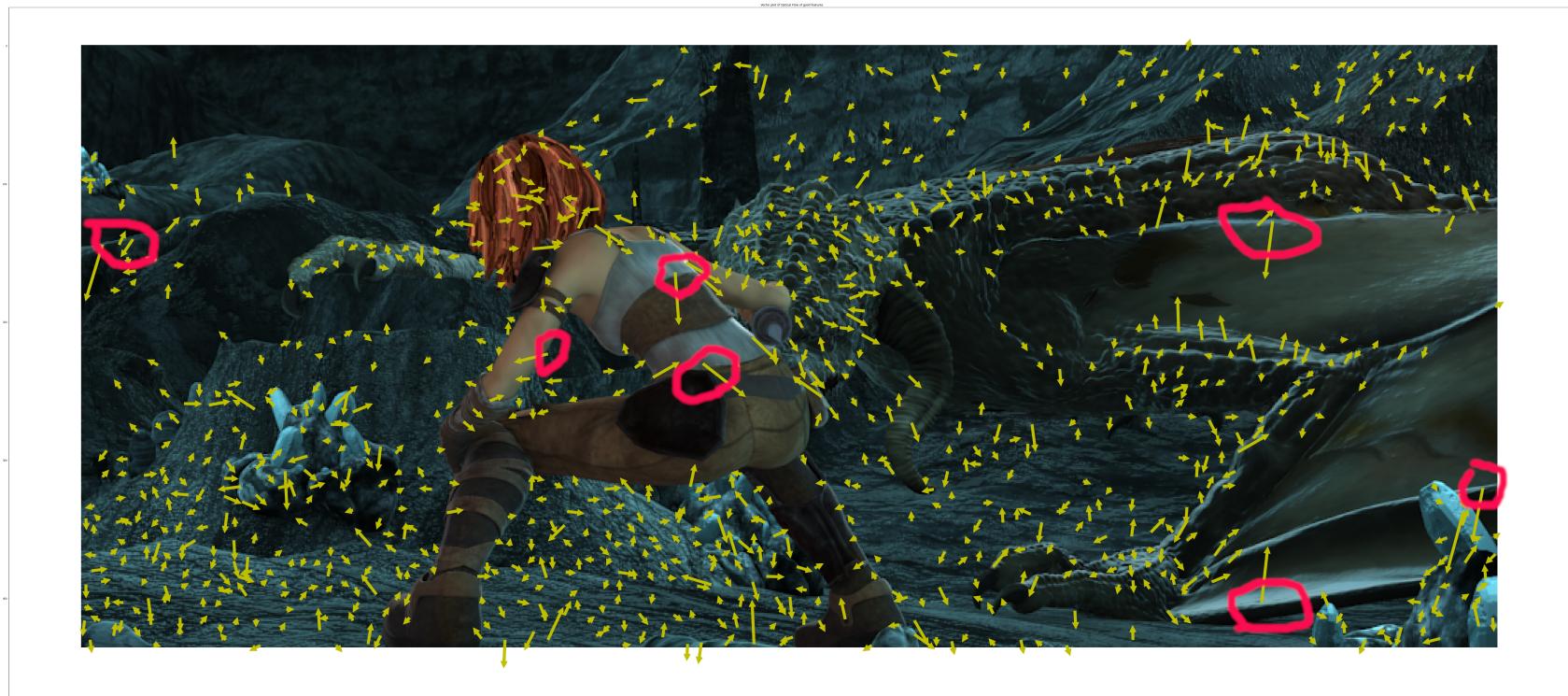
Answer:

- function LK\_OpticalFlow implement Lucas-Kande algorithm.

b. function `display_optical_flow` shows 5 images(processed 6 frames) as the result. The output number can be adjusted in code.

The examples where Lucas-Kanade fails is shown in figure 1. The main reason is because of aperture problem. And this problem can be fixed by adding pyramid function to calculate optical flow for each level.

figure 1



The algorithm may fail if the movement is too big, or the light intensity change too much. But it does not show the failure on this example frame, because it did not run into the condition.

In [ ]:

```
import numpy as np
import cv2 as cv
from matplotlib import pyplot as plt
from imutils import paths

#2a Lucas-Kanade optical flow, return u, v (dx,dy)
def LK_OpticalFlow(gray1,gray2,win_size=(3,3)):
    ...
    This function implements the LK optical flow without pyramid or consider as level 1 pyramid.
    ...
```

```
# 1. apply Gaussian filter to smooth the image in order to remove noise
I1 = cv2.GaussianBlur(gray1, win_size, 0)
I2 = cv2.GaussianBlur(gray2, win_size, 0)
m,n = win_size
m = m//2
n = n//2

# Calculate Ix, Iy, It
# The filter multiple 1/4 for average result
filter_x = np.array([[-1,1],[-1,1]]) * 0.25
filter_y = np.array([[1,-1],[1,1]]) * 0.25
filter_t1 = np.array([[1,1],[1,1]]) * 0.25
filter_t2 = np.array([[1,1],[1,1]]) * -1 * 0.25

Ix = signal.convolve2d(I1,filter_x,'same') + signal.convolve2d(I2,filter_x,'same')
Iy = signal.convolve2d(I1,filter_y,'same') + signal.convolve2d(I2,filter_y,'same')
It = signal.convolve2d(I1,filter_t1,'same') + signal.convolve2d(I2,filter_t2,'same')

# retrieve good features to track
points = cv2.goodFeaturesToTrack(I1,1000, 0.01,10)
points = np.int0(points)

#init u, v
u = np.zeros(gray1.shape)
v = np.zeros(gray1.shape)

# todo:
# Calculating the u and v arrays for the good features obtained n the previous step.
kp = list()
status = list()
err = list()
for p in points:
    # nparray image format is h, w(y,x)
    y,x = p.ravel()

    # calculating the derivatives for the neighbouring pixels
    # windows size mxn

    IX = Ix[x-m:x+m+1,y-n:y+n+1].flatten()
    IY = Iy[x-m:x+m+1,y-n:y+n+1].flatten()
    IT = It[x-m:x+m+1,y-n:y+n+1].flatten()

    # Resolve minimum Least squares equation
    # x = inverse(At dot A) dot (At dot b)
```

```
# np.concatenate((IX,IY),axis=1)
At = np.matrix((IX,IY))
A = np.matrix.transpose(At)
A = np.array(A)
At = np.array(At)
b = np.transpose(np.array(IT))

At_dot_A = np.dot(At,A)
A_inv = np.linalg.pinv(At_dot_A)
B = np.dot(At,b)

X = np.dot(A_inv,B)
u[x,y] = X[0]
v[x,y] = X[1]
if X[0] != 0 or X[1] != 0:
    status.append(1)
else:
    status.append(0)
kp.append(p)
kp.append(0)

# print(f"({x,y}): {X[0]}, {X[1]}")

return (u, v, points, status, err)

# 2b Visualize result
def display_opitical_flow(image_folder, show_n=10, threshold = 0.5):
    imagePaths = sorted(list(paths.list_images(image_folder)))
    images = []

    # images to stitch list
    for imagePath in imagePaths:
        image = cv2.imread(imagePath)
        images.append(image)

    img1 = images[0]
    gray1 = cv2.cvtColor(img1,cv2.COLOR_BGR2GRAY)
    n = min(len(images),show_n)+1
    for i in range(1,n):
        img2 = images[i]
        gray2 = cv2.cvtColor(img2,cv2.COLOR_BGR2GRAY)
        (u, v, points, status, err) = LK_OpticalFlow(gray1,gray2, win_size=(3,3))

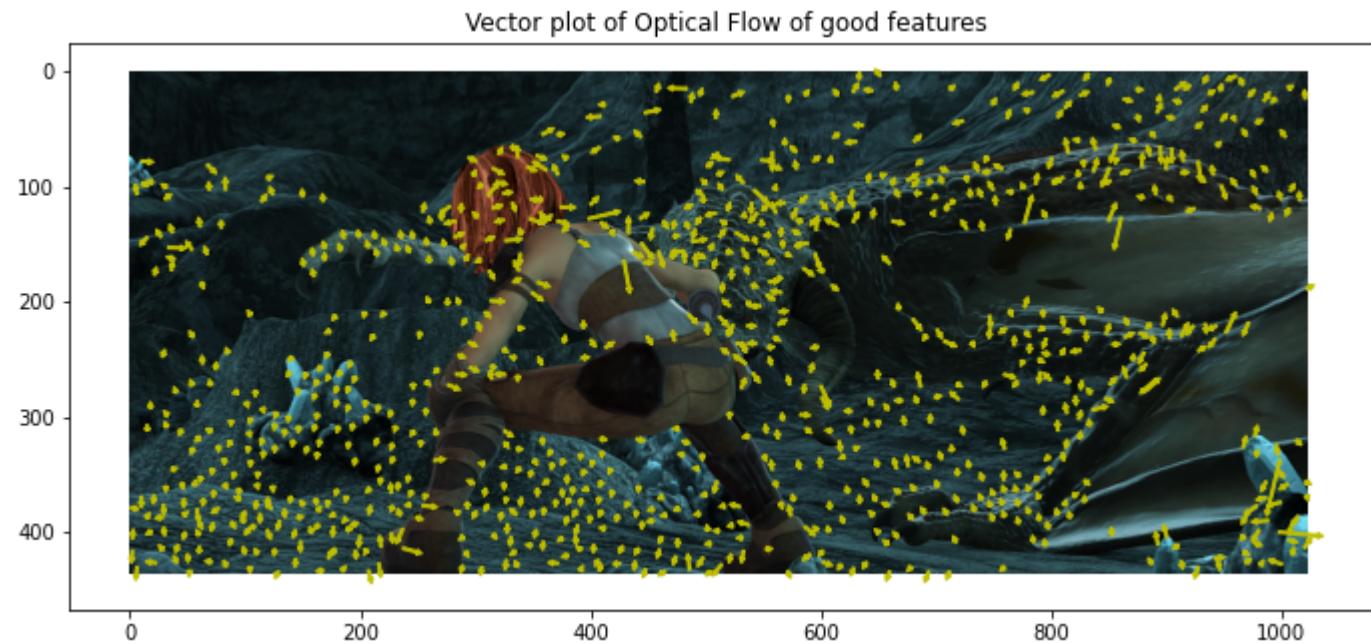
    # display result
```

```
img = cv2.cvtColor(img1, cv2.COLOR_BGR2RGB)
plt.figure(figsize=(40,30))
plt.subplot(1,3,3)
plt.title('Vector plot of Optical Flow of good features')
plt.imshow(img)
for i in range(len(points)):
    p = points[i]
    y,x = p.ravel()
    # only show points value > threshold
    if status[i] == 1 and (abs(u[x,y])>threshold or abs(v[x,y])>threshold):
        plt.arrow(y,x, v[x,y], u[x,y], width=2, head_width = 5, head_length = 5, color = 'y')

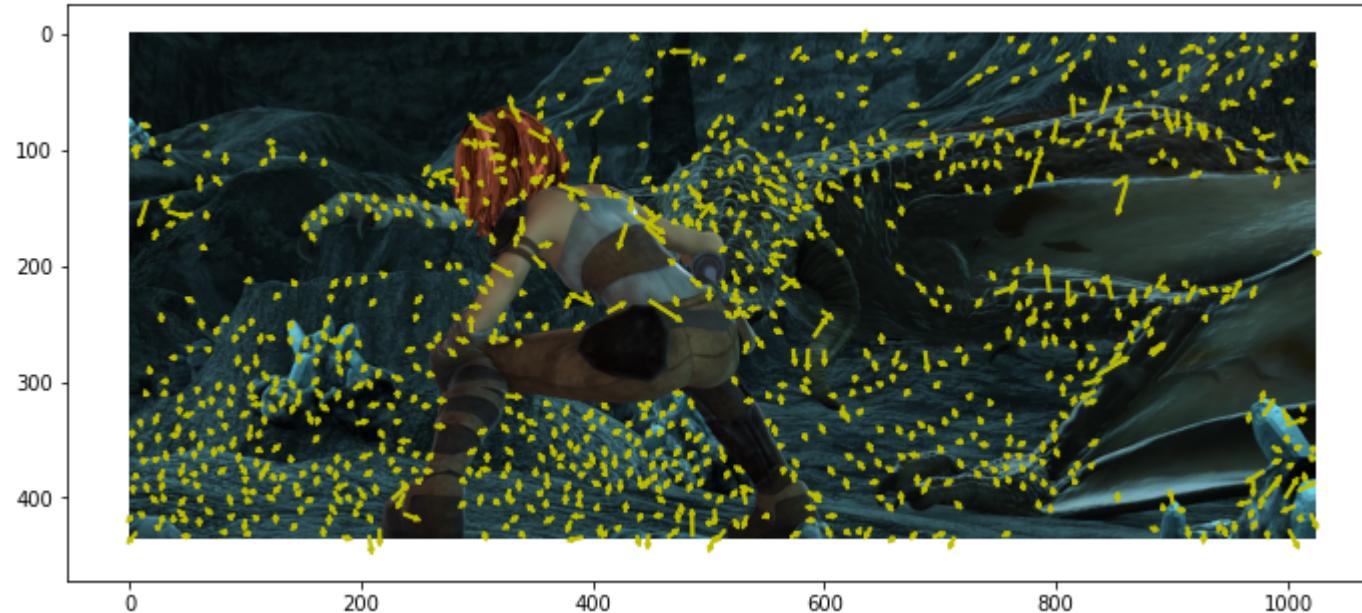
plt.show()

img1 = img1
gray1 = gray1

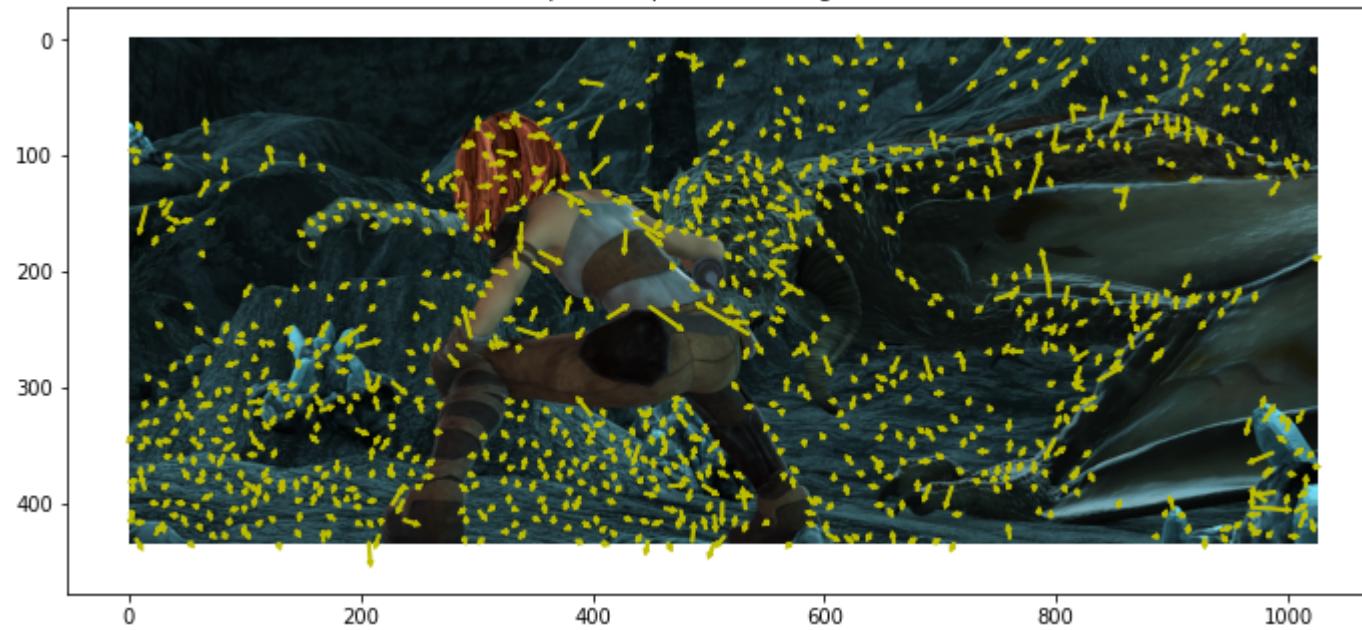
# 2 Results
image_folder = "./data/cave_3"
display_optical_flow(image_folder,5,0.5)
```



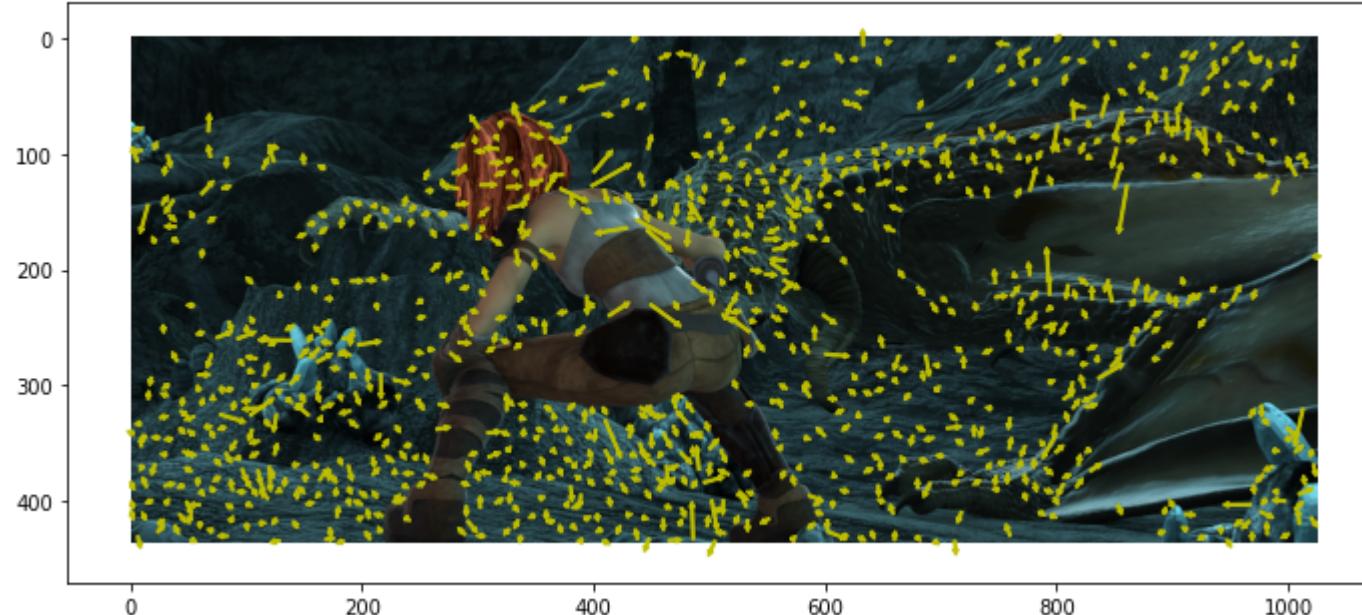
Vector plot of Optical Flow of good features



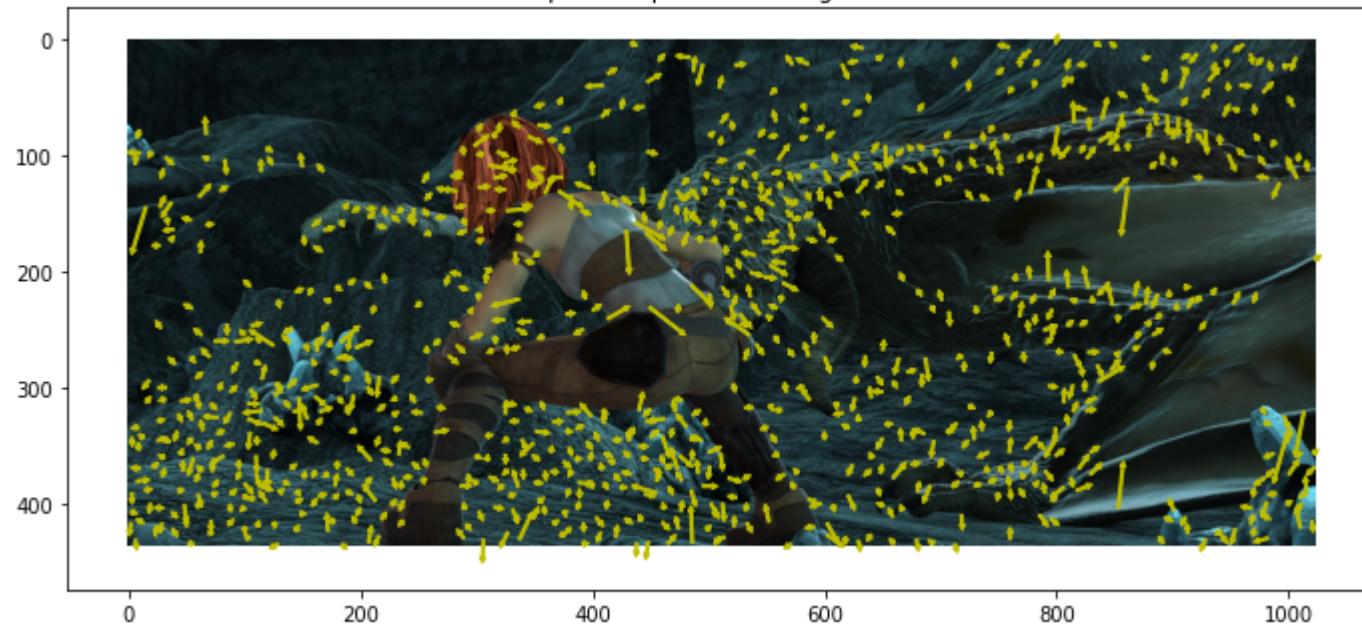
Vector plot of Optical Flow of good features



Vector plot of Optical Flow of good features



Vector plot of Optical Flow of good features



### Q3. (20 points) Head detection:

You are asked to implement an algorithm that can detect head in images and videos. The algorithm should detect head regardless of viewing direction of the camera. What is your suggestion? Try to eliminate false positives as much as you can.

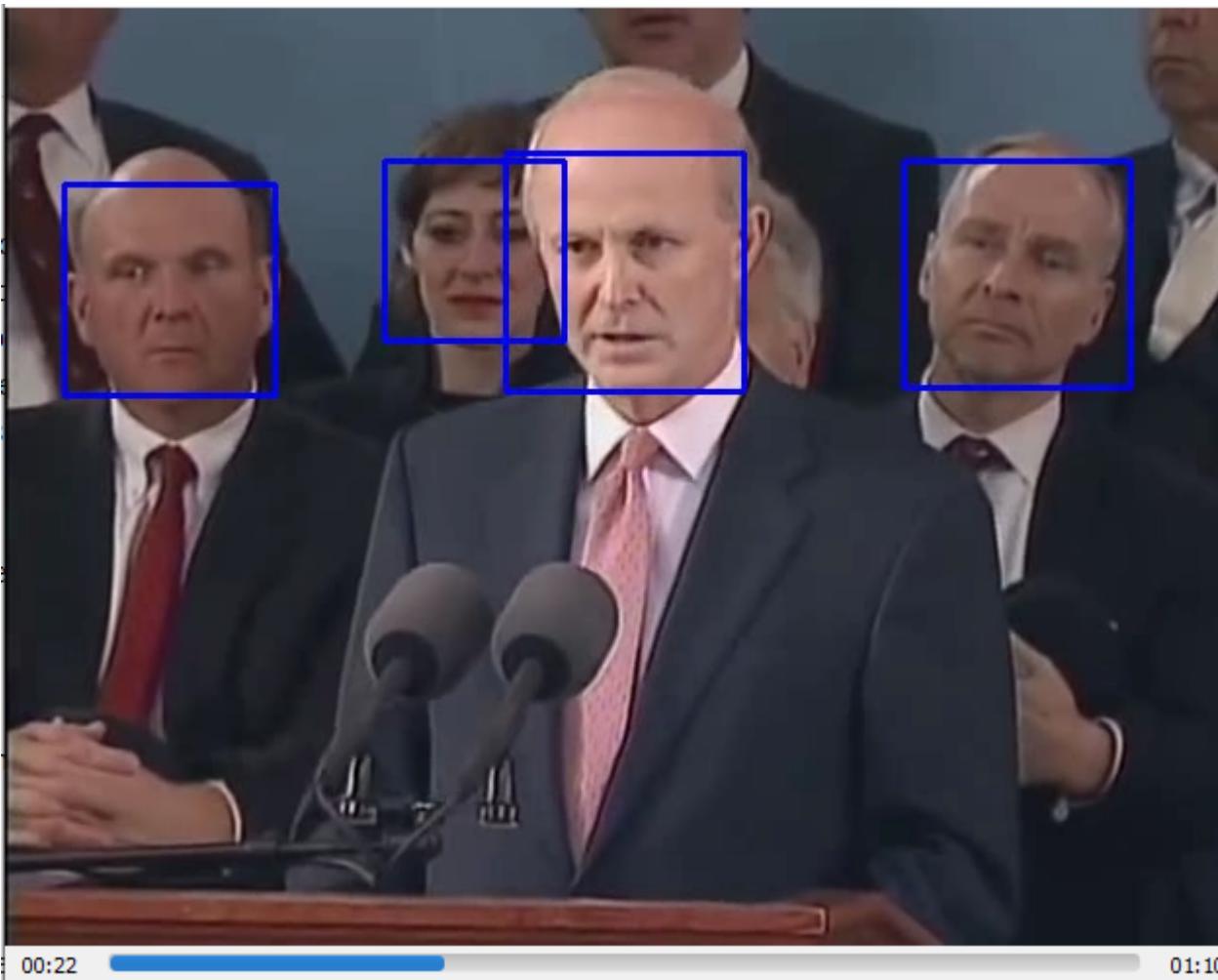
## Answer

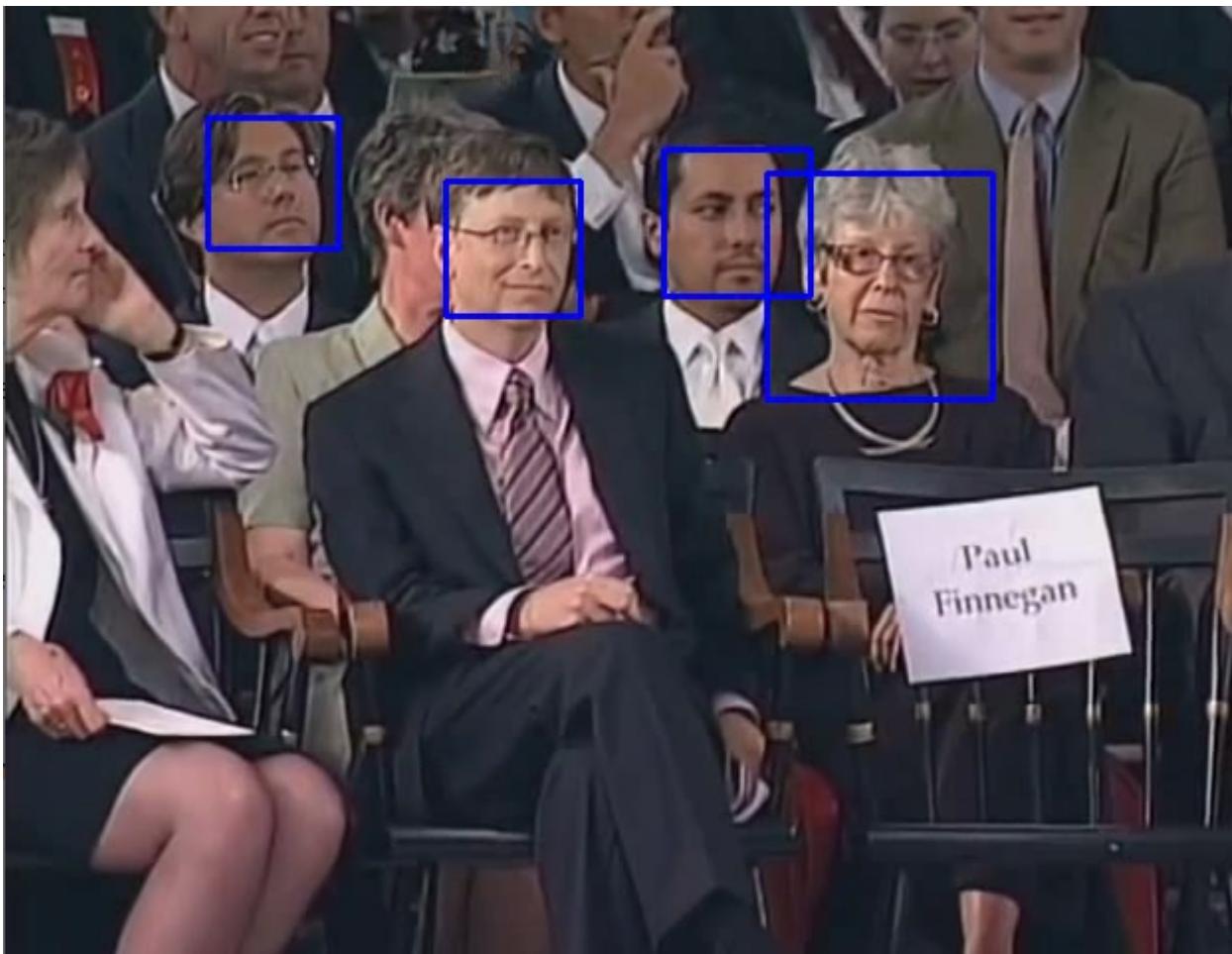
1) The first option I thought about is to contour detection. The assumption is that the head is oval shape. If I can get contour first, then I can filter oval shape and I will get the head mask. I wrote a test program to detect the contour by using `CV2.findContours`. The code is in `head.py` and the function name is `contour_detect`. But the result does not work well, because the intensity are changing in the video and it could not easily get contour of a head. I gave up this option. 2) The next option I used is `Haar cascade object detection` method. Haar feature-based cascade classifiers is proposed by Paul Viola and Michael Jones in their paper, "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001. There are three types of Harr features are defined and the whole process requires a training in order to do object detection. In the code I am using pre-trained `haarcascade_frontalface_default.xml` features for the detection. The code is shown in next python code cell.

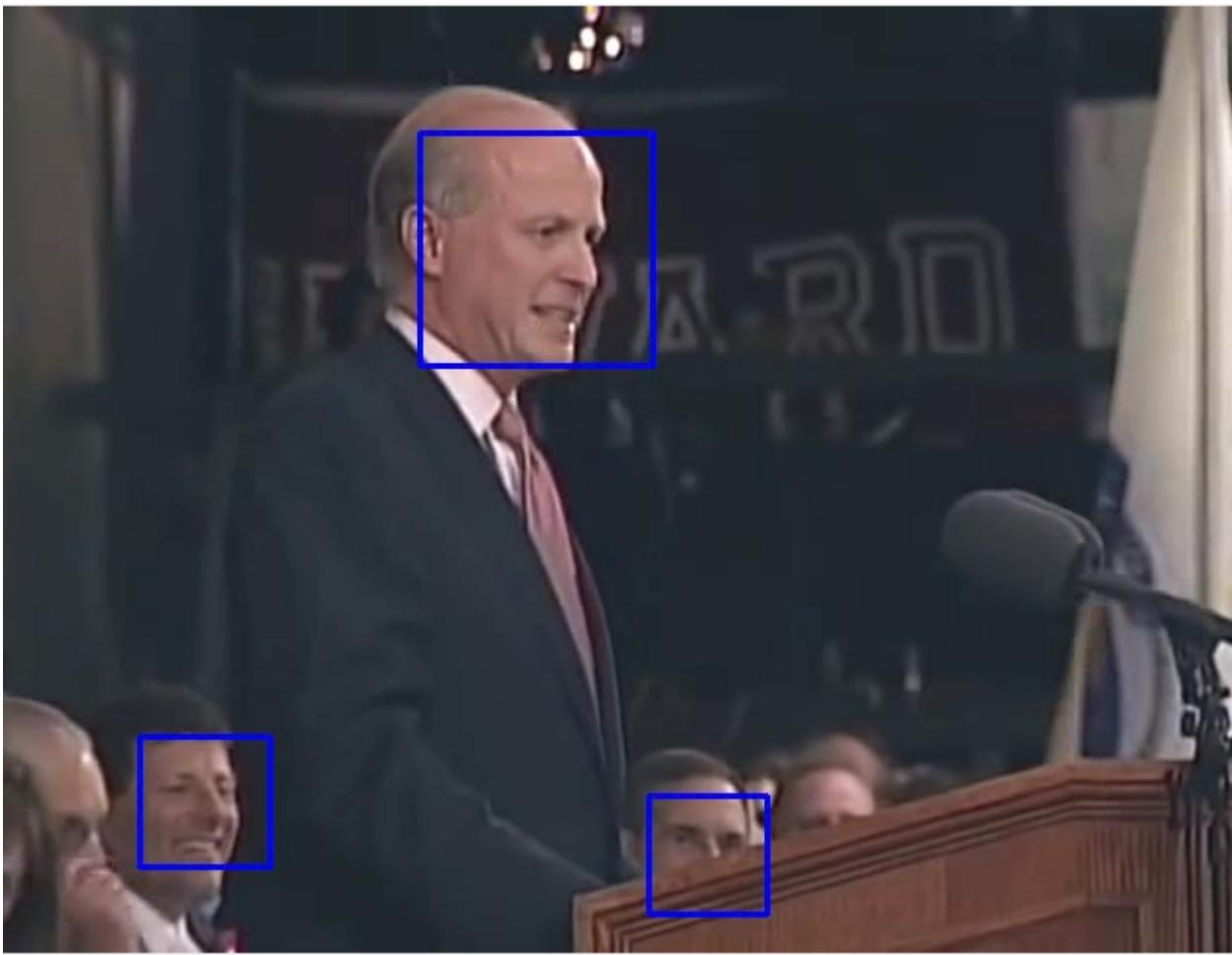
## Result 1

1) The result from default parameters can be watched from [Youtube](#). The url is <https://youtu.be/EjcGXcOtiMw>.

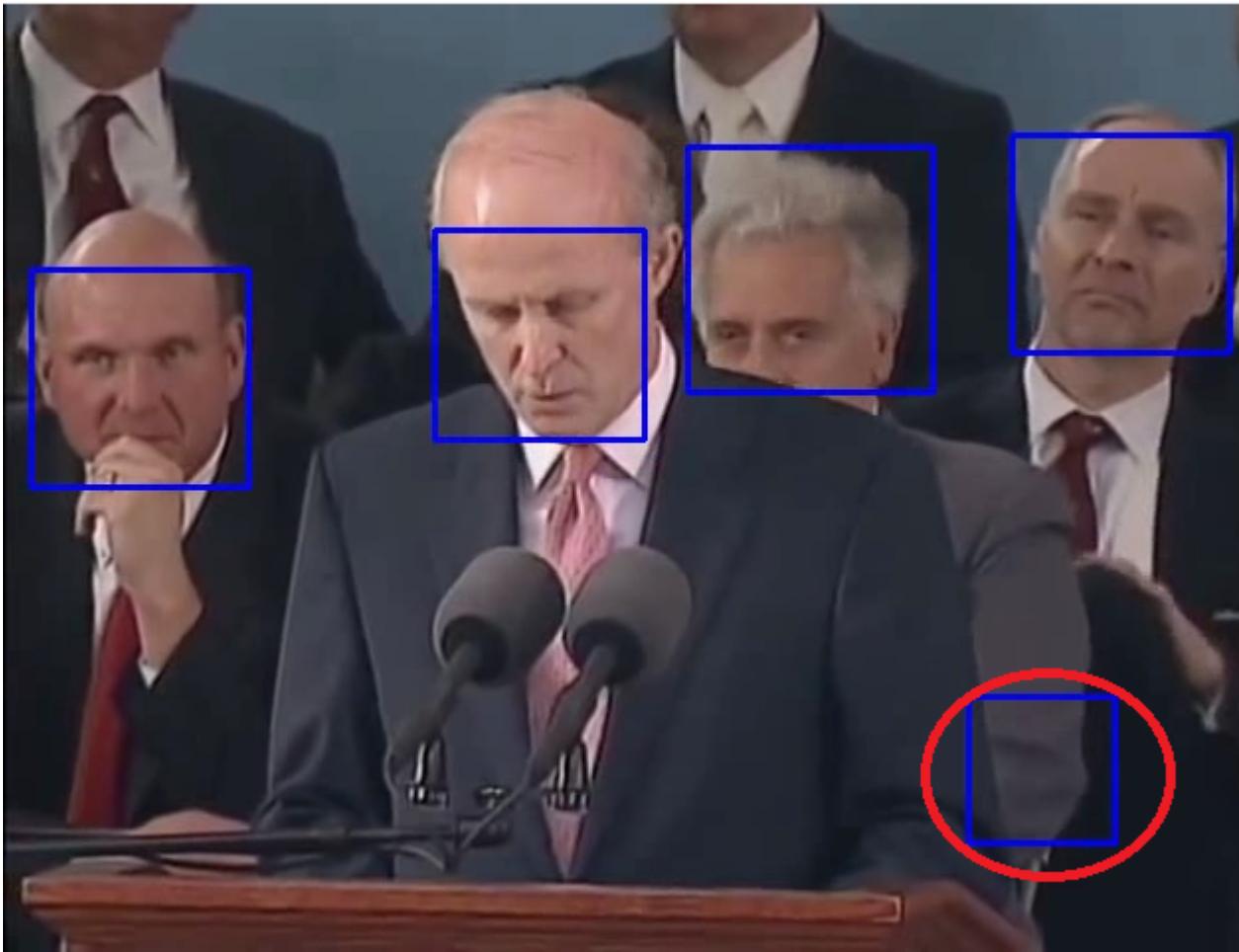
True Positive results:







False Positive results:





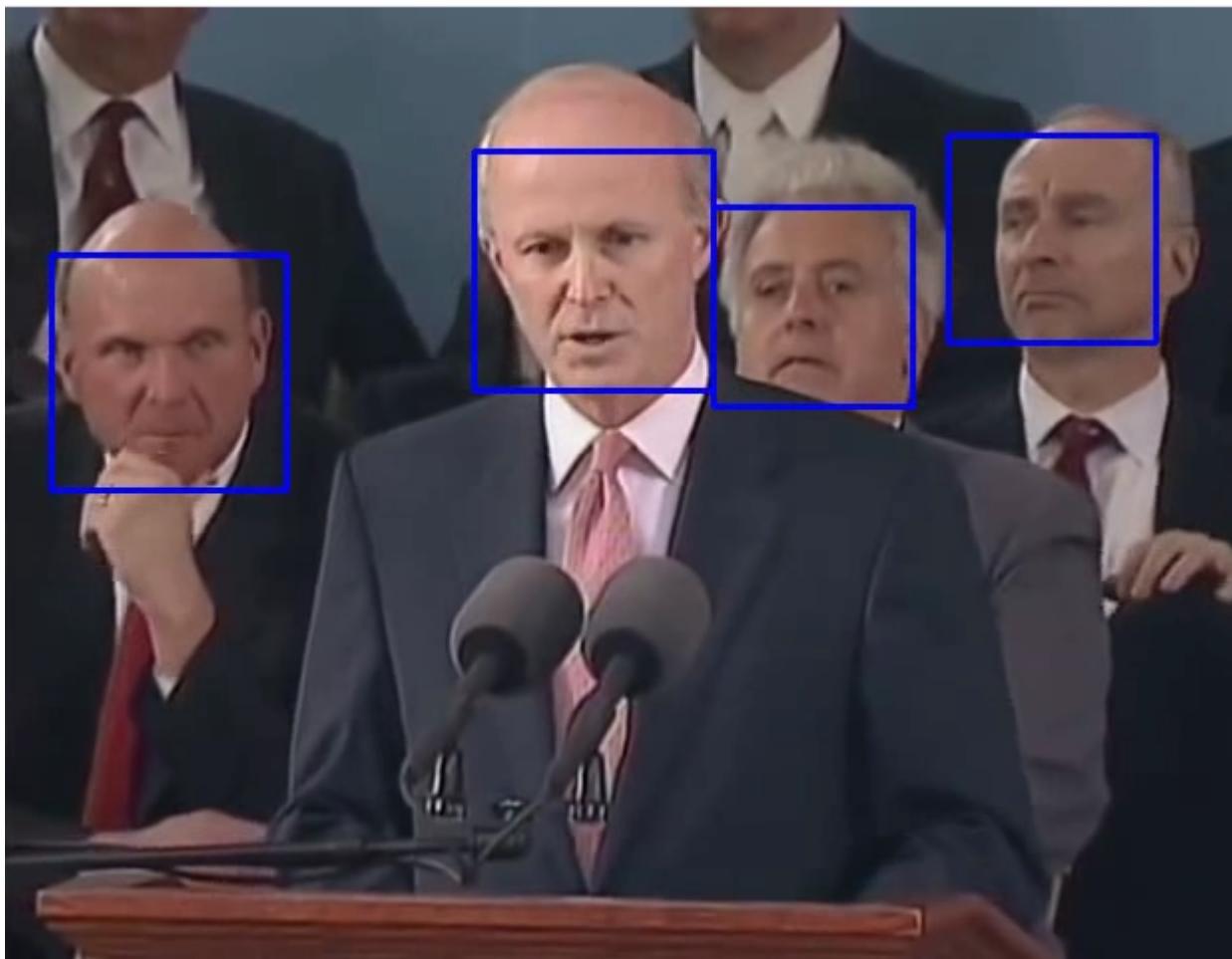
## Reduce false positive

After testing there are a few things impact on false positive results.

- 1) Harr features are capturing features changes patterns. For example, left eye, nose, right eye has a pattern darker,bright, darker. These patterns together represents the object features. In our case it is face,part of head. This is fundamental assumptions and it will happen if any pattern matches with the trained classifier.
- 2) There are two parameters used in detecting stage, scaleFactor=1.1 and minNeighbors=3. The minNeighbors impacts false positive and scaleFactor impact both searching performance and false positive result. After tuned, the minNeighbors is set to 5(default 3) and scaleFactor is set to 1.3(default 1.1).
- 3) Another behavior is that the image size,

also has impact on the searching performance and false positive. In my code I resize the frame size to 1/3 of original to acquire better performance and lower false positive.

The video can be seen from [YouTube](#) and the url is <https://youtu.be/-FnyaVMCaUk>. And two screenshots is shown here.





## Q3 Code

To run the code please make sure you have the video files comes with this project. The video file is under data folder.

In [ ]:

```
import numpy as np
import cv2

# org video is from https://www.youtube.com/watch?v=zPx5N6Lh3sw&t=1276s
# ffmpeg -i BillGates.mp4 -ss 00:00:05 -t 00:10:00 -async 1 cut.mp4
# ffmpeg -i cut.mp4 -vf scale=320:240 small.mp4

def harr_cascade_detect(harr_cascade,frame):
```

```
# detection, inside the detection the frame data is changed with
# bounding box and returned
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
a = 2
gray = cv2.resize(gray, dsize=(0, 0), fx=1/a, fy=1/a)
heads = harr_cascade.detectMultiScale(gray,scaleFactor=1.3,minNeighbors=5)

for (x,y,w,h) in heads:
    cv2.rectangle(frame,(a*x,a*y),(a*x+a*w,a*y+a*h),(255,0,0),2)

return frame

def harr_cascade_mp4():
    xml = 'haarcascade_frontalface_default.xml'
    # xml = 'haarcascade_upperbody.xml'

    harr_cascade = cv2.CascadeClassifier(f'./data/cv2/{xml}')
    video_name = "cut1.mp4"
    # cut2 does not work.
    vid_capture = cv2.VideoCapture(f'./data/{video_name}')

    if (vid_capture.isOpened() == False):
        print("Error opening the video file")
        return

    # get video meta info
    fps = vid_capture.get(5)
    frame_count = vid_capture.get(7)
    frame_width = int(vid_capture.get(3))
    frame_height = int(vid_capture.get(4))
    frame_size = (frame_width,frame_height)
    # fps = 20
    print(f"Video Info:")
    print(f"width:{frame_width} height:{frame_height} FPS: {fps} Count: {frame_count}")

    # output to mp4
    output = cv2.VideoWriter(f'./data/output_{video_name}', \
        cv2.VideoWriter_fourcc(*'mp4v'), fps, frame_size)

    while(vid_capture.isOpened()):
        # vid_capture.read() methods returns a tuple, first element is a bool
        # and the second is frame
        ret, frame = vid_capture.read()
        if ret == True:
```

```
# detection, inside the detection the frame data is changed with
# bounding box and returned
frame = harr_cascade_detect(harr_cascade,frame)
# frame = contour_detect(frame)

cv2.imshow('Frame',frame)
output.write(frame)

# press q to quit
key = cv2.waitKey(20)
if key == ord('q'):
    break
else:
    break

vid_capture.release()
output.release()
cv2.destroyAllWindows()

harr_casscade_mp4()
```

Video Info:

width:632 height:480 FPS: 29.97002997002997 Count: 5005.0