# PRACTICAL NO: 1

**Aim: Perform Geometric transformation.**

**Theory:**

**Geometric Transformations:**

Geometric transformation is a fundamental technique used in image processing that involves manipulating the spatial arrangement of pixels in an image. It is used to modify the geometric properties of an image, such as its size, shape, position, and orientation.

OpenCV provides two transformation functions, cv2.warpAffine and cv2.warpPerspective, with which you can have all kinds of transformations. cv2.warpAffine takes a 2x3 transformation matrix while cv2.warpPerspective takes a 3x3 transformation matrix as input.

**OpenCV:**

OpenCV (Open Source Computer Vision Library) is an open-source computer vision and machine learning software library. Initially developed by Intel, it provides a comprehensive suite of tools and algorithms for image processing, computer vision, and machine learning tasks. OpenCV supports various programming languages, including Python, C++, Java, and MATLAB, making it highly versatile for developers. Its applications range from real-time image and video processing to complex tasks like object detection, facial recognition, and motion tracking. To perform the following practical we need to install the module.

**Installation:**

Step 1: Open command prompt by typing "cmd" in the Start menu and hitting Enter.

Step 2: I n the command prompt or terminal, type the following command:

pip install opencv-python

```
:\Users\Admin>pip install opencv-python
ollecting opencv-python
  Downloading opencv_python-4.9.0.80-cp37-abi3-win_amd64.whl.metadata (20 kB)
equirement already satisfied: numpy>=1.21.2 in c:\users\admin\appdata\local\programs\python\python312\lib\site-packages
(from opencv-python) (1.26.4)
ownloading opencv_python-4.9.0.80-cp37-abi3-win_amd64.whl (38.6 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 38.6/38.6 MB 427.6 kB/s eta 0:00:00
nstalling collected packages: opencv-python
uccessfully installed opencv-python-4.9.0.80

:\Users\Admin>
```

## a. Translation:

Translation is the shifting of object's location. If you know the shift in (x,y) direction, let it be , you can create the transformation matrix **M** as follows:

$$M = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix}$$

You can take make it into a Numpy array of type np.float32 and pass it into **cv2.warpAffine()** function. See below example for a shift of (100,50):

**Warning:**

Third argument of the cv2.warpAffine() function is the size of the output image, which should be in the form of (width, height). Remember width = number of columns, and height = number of rows.

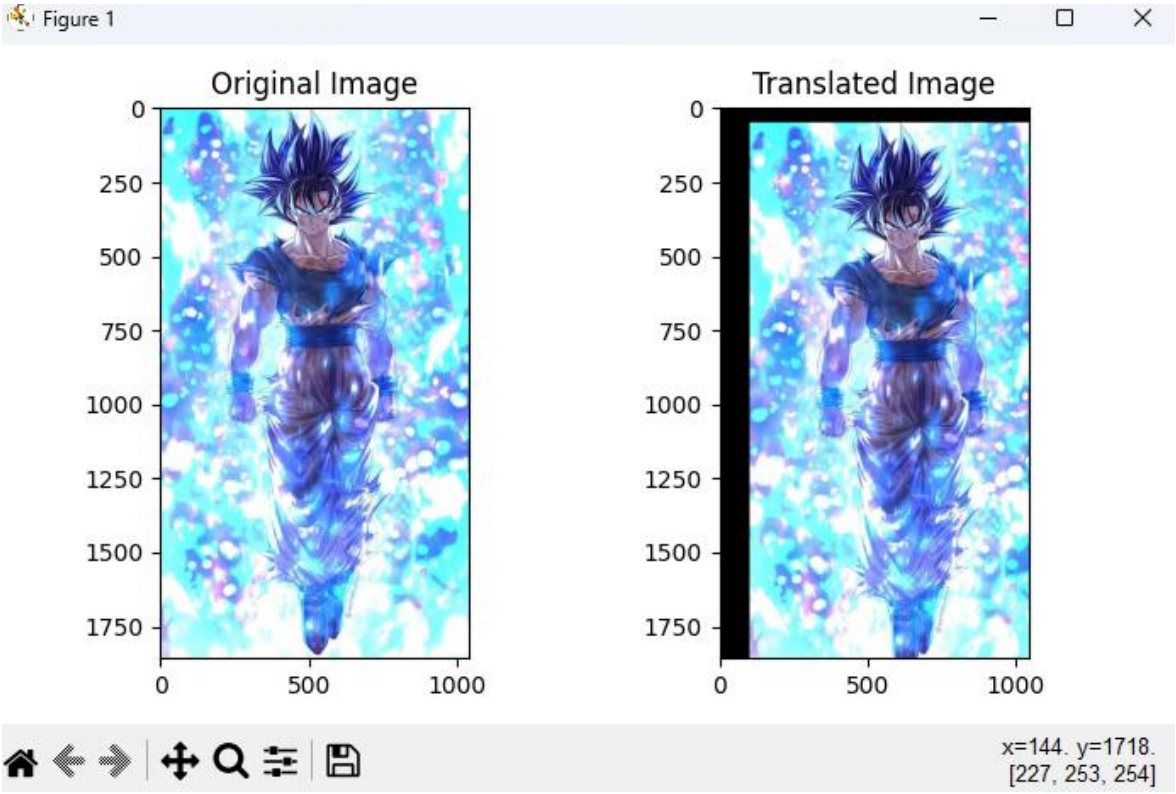
**Code:**

Prac1a.py - C:\MScITPracs\OpenCV\Prac1a.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://MScITPracs//OpenCV//BatmanArkhamKnight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

M = np.float32([[1,0,100],[0,1,50]])

dst = cv2.warpAffine(img_rgb, M, (cols,rows))

fig, axs = plt.subplots(1,2, figsize=(7,4))

axs[0].imshow(img_rgb)
axs[0].set_title("Original Image")

axs[1].imshow(dst)
axs[1].set_title("Translated Image")

plt.tight_layout()
plt.show()
```

**Output:**




## Scaling

Scaling is just resizing of the image. OpenCV comes with a function cv2.resize() for this purpose. The size of the image can be specified manually, or you can specify the scaling factor. Different interpolation methods are used. Preferable interpolation methods are cv2.INTER_AREA for shrinking and cv2.INTER_CUBIC (slow) & cv2.INTER_LINEAR for zooming. By default, interpolation method used is cv2.INTER_LINEAR for all resizing purposes. You can resize an input image either of following methods:

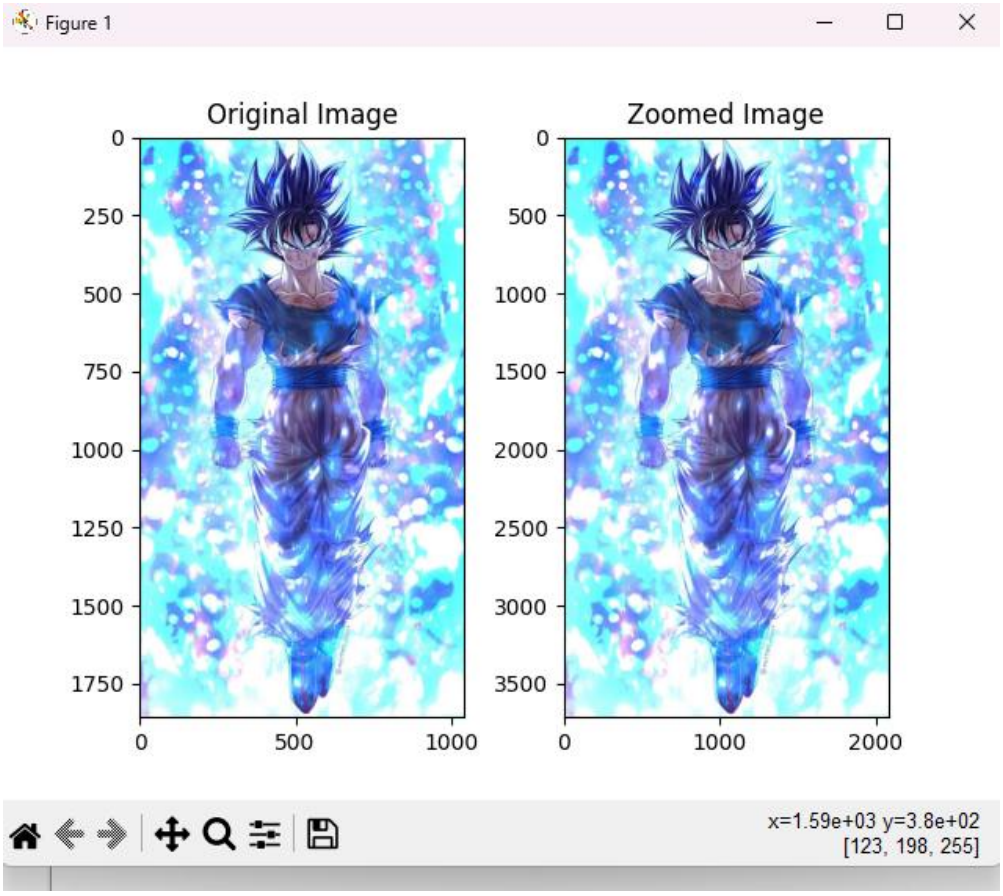
## b. Code: #Zooming

Prac1b.py - C:\MScITPracs\OpenCV\Prac1b.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://MScITPracs//OpenCV//BatmanArkhamKnight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

resize_img = cv2.resize(img_rgb,(0,0), fx=2, fy=2, interpolation=cv2.INTER_CUBIC)

plt.subplot(121), plt.imshow(img_rgb), plt.title('Original Image')
plt.subplot(122), plt.imshow(resize_img), plt.title('Zoomed Image')
plt.show()
```

Output:



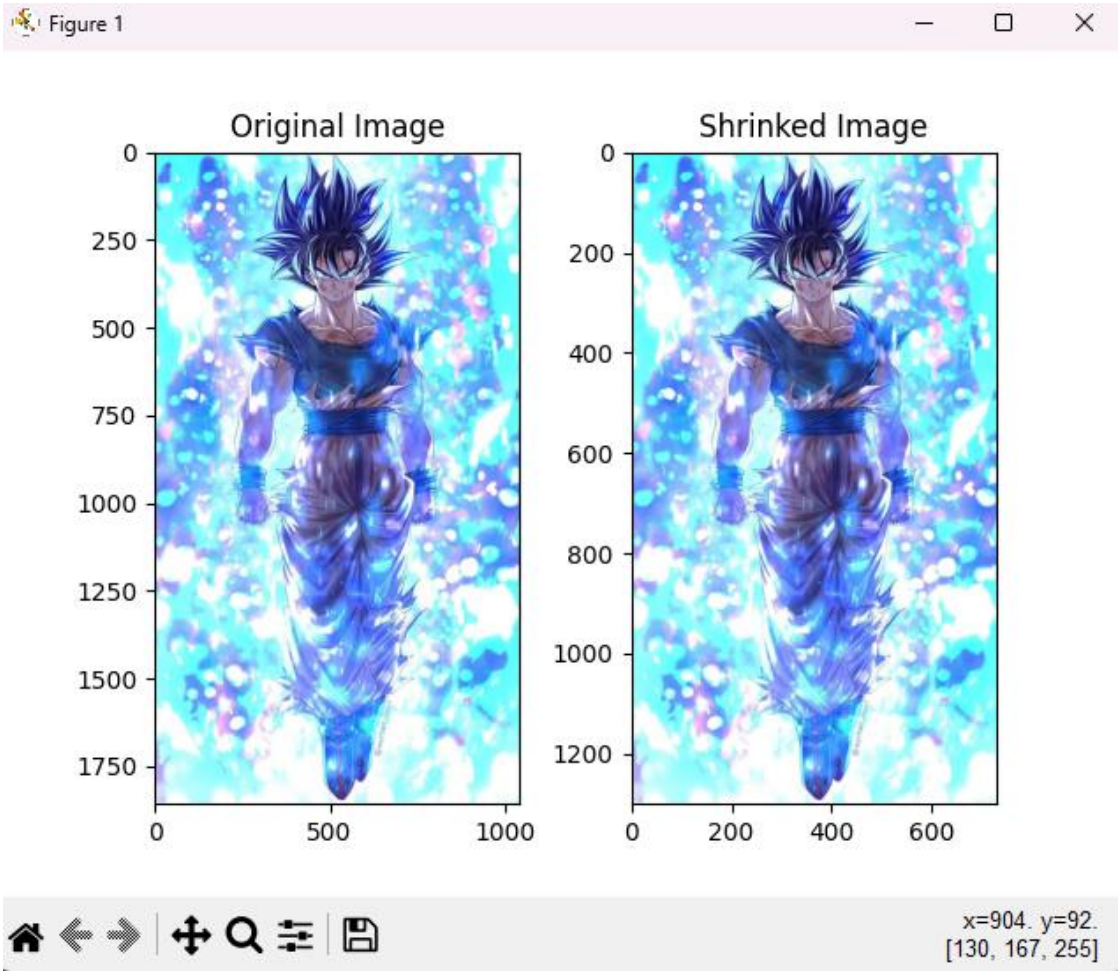
## c. Code: #Shrinking

Prac1c.py - C:\MScITPracs\OpenCV\Prac1c.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://MScITPracs//OpenCV//BatmanArkhamKnight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

resize_img = cv2.resize(img_rgb,(0,0), fx=0.7, fy=0.7, interpolation=cv2.INTER_AREA)

plt.subplot(121), plt.imshow(img_rgb), plt.title('Original Image')
plt.subplot(122), plt.imshow(resize_img), plt.title('Shrinked Image')
plt.show()
```

Output:



**d. Rotation:**

Rotation of an image for an angle is achieved by the transformation matrix of the form

$$M = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix}$$

But OpenCV provides scaled rotation with adjustable center of rotation so that you can rotate at any location you prefer. Modified transformation matrix is given
by

$$\begin{bmatrix} \alpha & \beta & (1-\alpha)\cdot center.x - \beta \cdot center.y \\ -\beta & \alpha & \beta \cdot center.x + (1-\alpha)\cdot center.y \end{bmatrix}$$

where:

$$\alpha = scale \cdot \cos\theta,$$
$$\beta = scale \cdot \sin\theta$$

To find this transformation matrix, OpenCV provides a function, **cv2.getRotationMatrix2D**. Check below example which rotates the image by 90 degree with respect to center without any scaling.

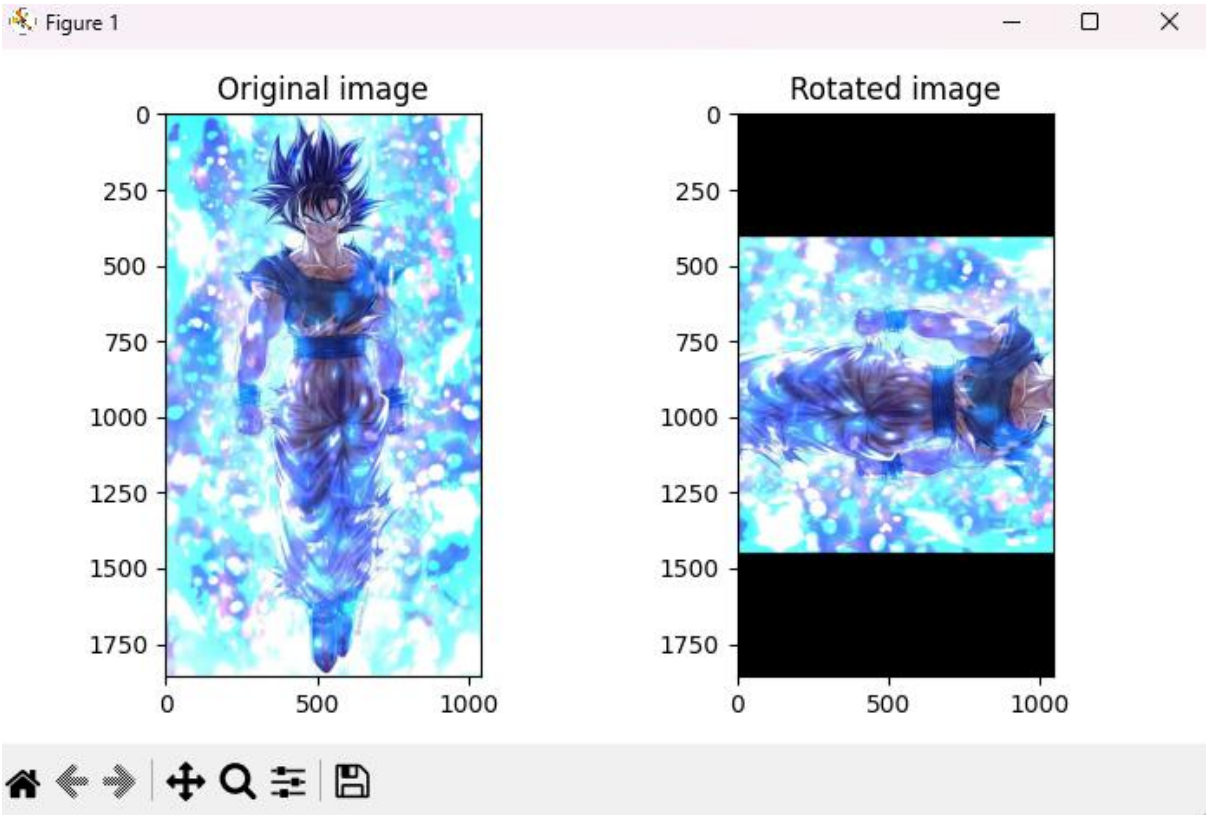
# Code:

Prac1d.py - C:\MScITPracs\OpenCV\Prac1d.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://MScITPracs//OpenCV//BatmanArkhamKnight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

center = (cols // 2, rows // 2)
angle = -90
scale = 1

rotation_matrix = cv2.getRotationMatrix2D(center, angle, scale)

rotated_image = cv2.warpAffine(img_rgb, rotation_matrix, (cols,rows))

fig, axs = plt.subplots(1,2,figsize=(7, 4))

axs[0].imshow(img_rgb)
axs[0].set_title("Original image")

axs[1].imshow(rotated_image)
axs[1].set_title("Rotated image")

plt.tight_layout()
plt.show()
```

# Output:



## e. Affine Transformation

In affine transformation, all parallel lines in the original image will still be parallel

in the output image. To find the transformation matrix, we need three points from

input image and their corresponding locations in output image.

Then cv2.getAffineTransform will create a 2x3 matrix which is to be passed

to cv2.warpAffine.

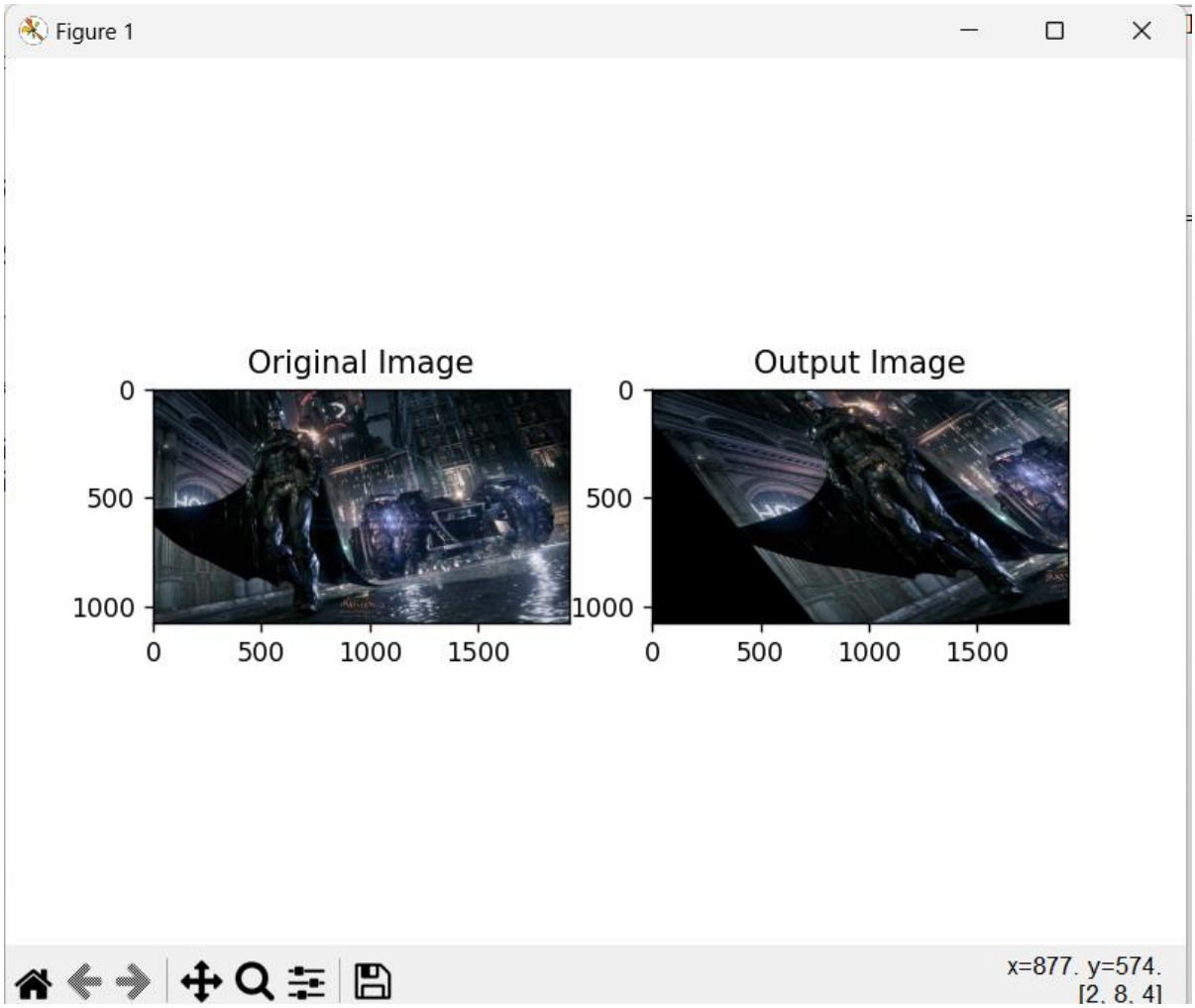
**Code:**

Prac1e.py - C:\MScITPracs\OpenCV\Prac1e.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://MScITPracs//OpenCV//BatmanArkhamKnight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

pts1 = np.float32([[50,50],[200,50],[50,200]])

pts2 = np.float32([[20,90],[200,50],[150,250]])

M = cv2.getAffineTransform(pts1, pts2)

dst = cv2.warpAffine(img_rgb,M,(cols,rows))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

**Output:**




## f. Perspective Transformation

For perspective transformation, you need a 3x3 transformation matrix. Straight lines will remain straight even after the transformation. To find this transformation matrix, you need 4 points on the input image and corresponding points on the output image. Among these 4 points, 3 of them should not be collinear. Then transformation matrix can be found by the function **cv2.getPerspectiveTransform**. Then apply **cv2.warpPerspective** with this 3x3 transformation matrix.

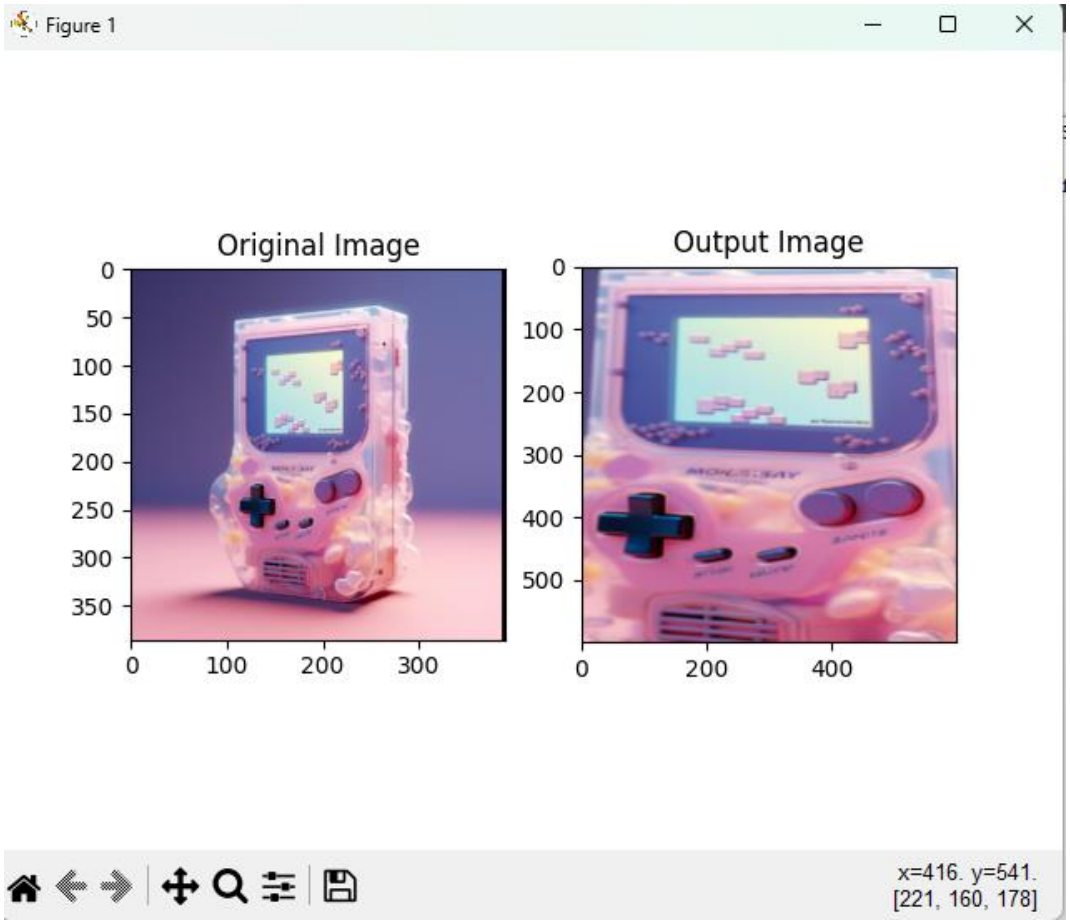
## Code:

Prac1f.py - C:\MScITPracs\OpenCV\Prac1f.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('D://Part1Msc//CV//GameBoyy.png')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

pts1 = np.float32([[100,51],[260,37],[110,325], [250,320]])

pts2 = np.float32([[0,0],[600,0],[0,600], [600,600]])

M = cv2.getPerspectiveTransform(pts1, pts2)

dst = cv2.warpPerspective(img_rgb,M,(600,600))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

## Output:



## Shearing:

Image shearing is a geometric transformation that skews an image along one or both axes i.e x or y axis.

- To shear an image using OpenCV, we need to create a transformation matrix. This matrix is a 2×3 matrix that specifies the amount of shearing in each direction.
- The cv2.warpAffine() function is used to apply a transformation matrix to an image. It takes the following arguments:
    - The image to be transformed.
    - The transformation matrix.
    - The output image size.
- The shearing parameters are specified in the transformation matrix as the shearX shearY elements. The shearX element specifies the amount of shearing in the x-axis, while the shearY element specifies the amount of shearing in the y-axis.

## g. Image Shearing in X-Axis:

While the shearing image is on the x-axis, the boundaries of the image that are parallel to the x-axis keep their location, and the edges parallel to the y-axis change their place depending on the shearing factor.

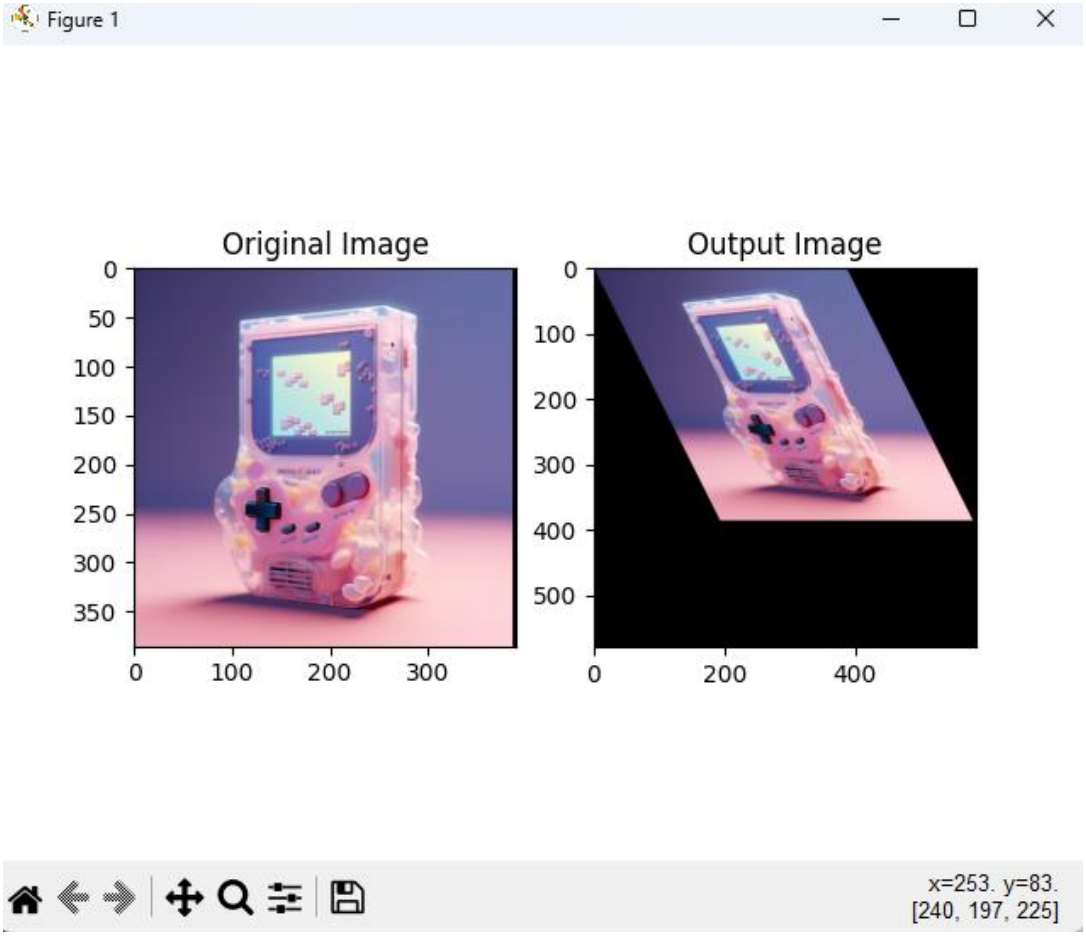
**Code:**

*Prac1ShearX.py - C:\MScITPracs\OpenCV\Prac1ShearX.py (3.11.6)*

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('D://Part1Msc//CV//GameBoyy.png')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

#For Image Shearing in X*axis
M = np.float32([[1, 0.5, 0], [0, 1, 0], [0, 0, 1]])

dst = cv2.warpPerspective(img_rgb, M,
                          (int(cols*1.5),
                          int(rows*1.5)))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

## Output:



## h. Image Shearing in Y-Axis

When shearing is done in the y-axis direction, the boundaries of the image that are parallel to the y-axis keep their location, and the edges parallel to the x-axis change their place depending on the shearing factor.

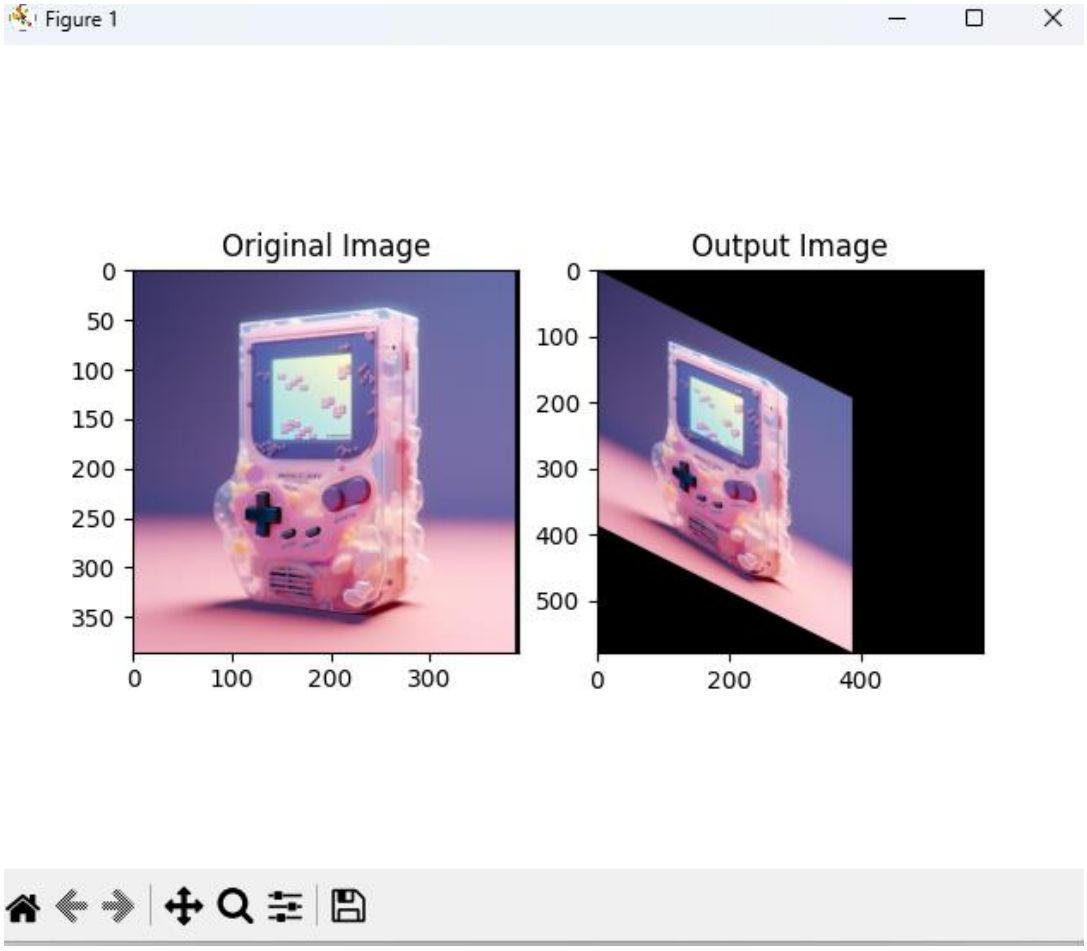
**Code:**

Prac1ShearX.py - C:\MScITPracs\OpenCV\Prac1ShearX.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('D://Part1Msc//CV//GameBoyy.png')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape


#For Image Shearing in Y axis
#M = np.float32([[1, 0, 0], [0.5, 1, 0], [0, 0, 1]])

dst = cv2.warpPerspective(img_rgb, M,
                          (int(cols*1.5),
                          int(rows*1.5)))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

**Output:**




## i. Cropping:

Cropping is the removal of unwanted outer areas from an image.

OpenCV loads the image as a NumPy array, we can crop the image simply by indexing the array, in our case, we choose to get 200 pixels from 100 to 300 on both axes.

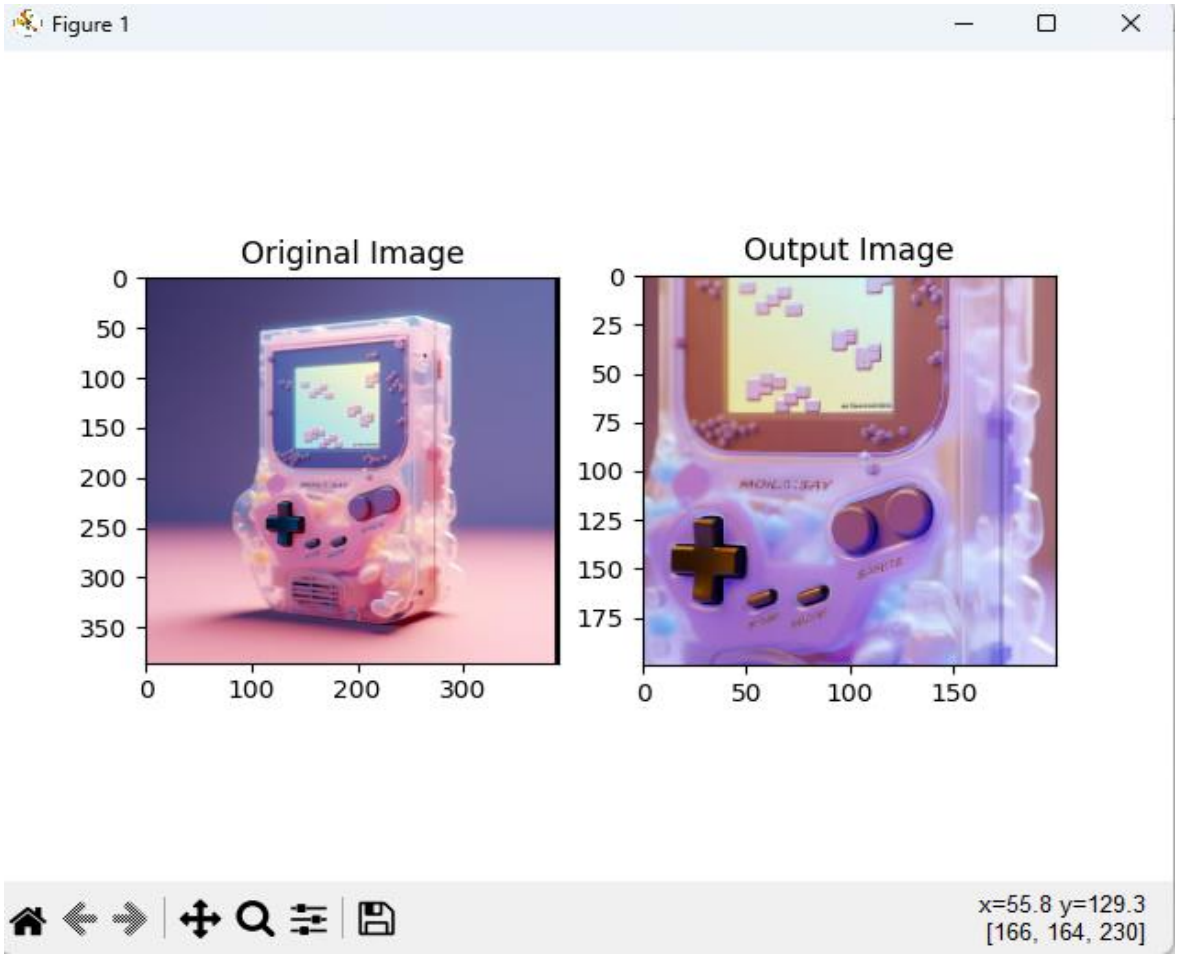
**Code:**

Prac1Cropped.py - C:\MScITPracs\OpenCV\Prac1Cropped.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('D://Part1Msc//CV//GameBoyy.png')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape


#We choose to get 200 pixels from 100 to 300 on both axes.
dst = img[100:300, 100:300]

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

## Output:



## j. Image Reflection:

In computer vision or image processing, image translation is the rectilinear shift of an image from one location to another, so the shifting of an object is called translation. In other words, translation is the shifting of an object's location.

### Vertically:

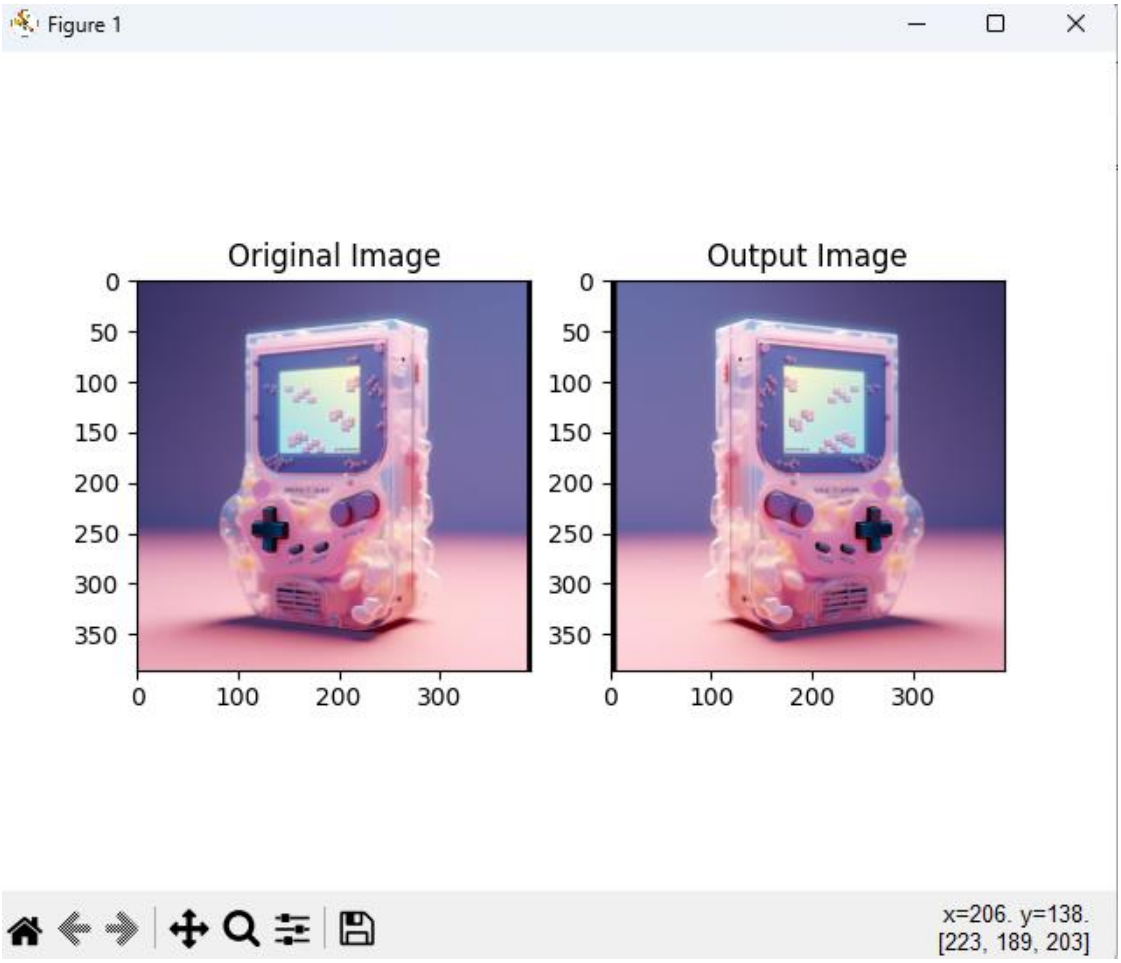
### Code:

Prac1Reflected.py - C:\MScITPracs\OpenCV\Prac1Reflected.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://Practicals//OpenCV//Batman Arkham Knight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

#To flip vertically
M = np.float32([[-1,0,cols],[0,1,0],[0,0,1]])

dst = cv2.warpPerspective(img_rgb,M,(cols,rows))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

### Output:




## Horizontally:

## Code:

*Prac1Reflected.py - C:\MScITPracs\OpenCV\Prac1Reflected.py (3.11.6)*

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

img = cv2.imread('C://Practicals//OpenCV//Batman Arkham Knight.jpg')

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

rows, cols, channels = img_rgb.shape

#To flip horizontally
M = np.float32([[1, 0, 0], [0, -1, rows],[0,  0, 1]])

dst = cv2.warpPerspective(img_rgb,M,(cols,rows))

plt.subplot(121),plt.imshow(img_rgb), plt.title("Original Image")
plt.subplot(122),plt.imshow(dst), plt.title("Output Image")
plt.show()
```

## Output:

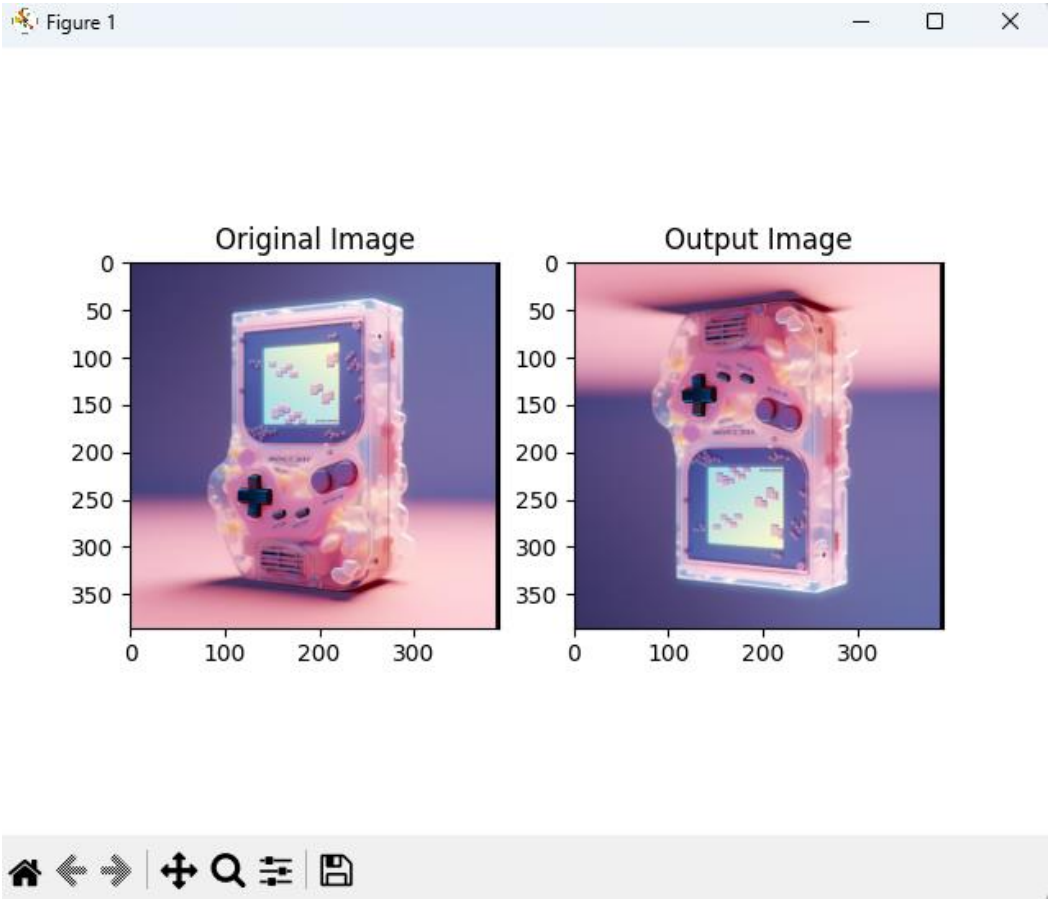


Figure 1
Original Image
Output Image
0
50
100
150
200
250
300
350
0
100
200
300

# PRACTICAL NO: 2

**Aim: Perform Image Stitching.**

**Theory:**

**Image stitching** is the process of combining multiple overlapping images to create a seamless, high-resolution output image. This technique is commonly used to create panoramic images, virtual tours, and even some medical imaging applications.

Image stitching involves several steps:

1. **Feature detection:** Identifying and extracting unique features (e.g., corners, edges) from each input image. Compute the SIFT-key points and descriptors for both the images.

2. **Feature matching:** Finding correspondences between features in the overlapping regions of the input images. Compute distances between every descriptor in one image and every descriptor in the other image. Select the top 'm' matches for each descriptor of an image.

**3. Homography estimation:** Estimating the transformation (e.g., rotation, scaling, translation) that aligns the input images. Run RANSAC to estimate homography

**4. Warping:** Applying the estimated transformation to the input images. Warp to align for stitching

**5. Blending:** Combining the warped images into a single seamless output image. Now stitch them together

Explanation of Code:

Firstly, we have to find out the features matching in both the images. These best matched features act as the basis for stitching.

We extract the key points and sift descriptors for both the images as follows:

```
sift = cv2.SIFT_create()
# find the keypoints and descriptors with SIFT
kp1, des1 = sift.detectAndCompute(img1,None)
kp2, des2 = sift.detectAndCompute(img2,None)
```

kp1 and kp2 are keypoints, des1 and des2 are the descriptors of the respective images.

Now, the obtained descriptors in one image are to be recognized in the image too. We do that as follows:

```
bf = cv2.BFMatcher()
matches = bf.knnMatch(des1,des2, k=2)
```

The BFMatcher() matches the features which are more similar. When we set parameter k=2, we are asking the knnMatcher to give out 2 best matches for each descriptor.

**'matches'** is a list of list, where each sub-list consists of 'k' objects.

Often in images, there are tremendous chances where the features may be existing in many places of the image. This may mislead us to use trivial features for our experiment. So we filter out through all the matches to obtain the best ones. So we apply ratio test using the

top 2 matches obtained above. We consider a match if the ratio defined below is predominantly greater than the specified ratio.

```
# Apply ratio test
good = []
for m in matches:
if m[0].distance < 0.5*m[1].distance:
good.append(m)
matches = np.asarray(good)
```

It's time to align the images now. As you know that a homography matrix is needed to perform the transformation, and the homography matrix requires at least 4 matches, we do the following.

```
if len(matches[:,0]) >= 4:
src = np.float32([ kp1[m.queryIdx].pt for m in matches[:,0]
]).reshape(-1,1,2)
dst = np.float32([ kp2[m.trainIdx].pt for m in matches[:,0]
]).reshape(-1,1,2)H, masked = cv2.findHomography(src, dst,
cv2.RANSAC, 5.0)
#print H
else:
raise AssertionError("Can't find enough keypoints.")
```

And finally comes the last part, stitching of the images. Now that we found the homography for transformation, we can now proceed to warp and stitch them together:

```
dst = cv2.warpPerspective(img_,H,(img.shape[1] + img_.shape[1],
img.shape[0]))
plt.subplot(122),plt.imshow(dst),plt.title('Warped Image')
plt.show()
plt.figure()
dst[0:img.shape[0], 0:img.shape[1]] = img
cv2.imwrite('output.jpg',dst)
plt.imshow(dst)
plt.show()
```

We get warped image plotted using matplotlib to well visualize the warping.

Code:

Prac2.py - C:\MScITPracs\OpenCV\Prac2.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from random import randrange

img_ = cv2.imread("C://MScITPracs//OpenCV//uttower_right.JPG")
img1 = cv2.cvtColor(img_, cv2.COLOR_BGR2GRAY)

img = cv2.imread("C://MScITPracs//OpenCV//uttower_left.JPG")
img2 = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

sift=cv2.SIFT_create()

kp1, des1 = sift.detectAndCompute(img1,None)
kp2, des2 = sift.detectAndCompute(img2,None)


bf= cv2.BFMatcher()
matches = bf.knnMatch(des1,des2,k=2)

good=[]
for m in matches:
    if m[0].distance < 0.5*m[1].distance:
        good.append(m)
matches = np.asarray(good)

if len(matches[:,0]) >=4:
    src  = np.float32([kp1[m.queryIdx].pt for m in matches[:,0] ]).reshape(-1,1,2)
    dst = np.float32([kp2[m.trainIdx].pt for m in matches[:,0] ]).reshape(-1,1,2)

    H, masked = cv2.findHomography(src, dst, cv2.RANSAC, 5.0)
    print(H)

else:
    raise AssertionError("Cannor find enough key points.")
```

```
else:
    raise AssertionError("Cannor find enough key points.")

dst = cv2.warpPerspective(img_,H, (img.shape[1] + img_.shape[1], img.shape[0]))
plt.subplot(122),plt.imshow(dst), plt.title("Wraped Image")
plt.show()
plt.figure()
dst[0:img.shape[0], 0:img.shape[1]] = img
cv2.imwrite("Resultant_stiched_panaroma.jpg",dst)
plt.imshow(dst)
plt.show()
```

Input:

## Output:

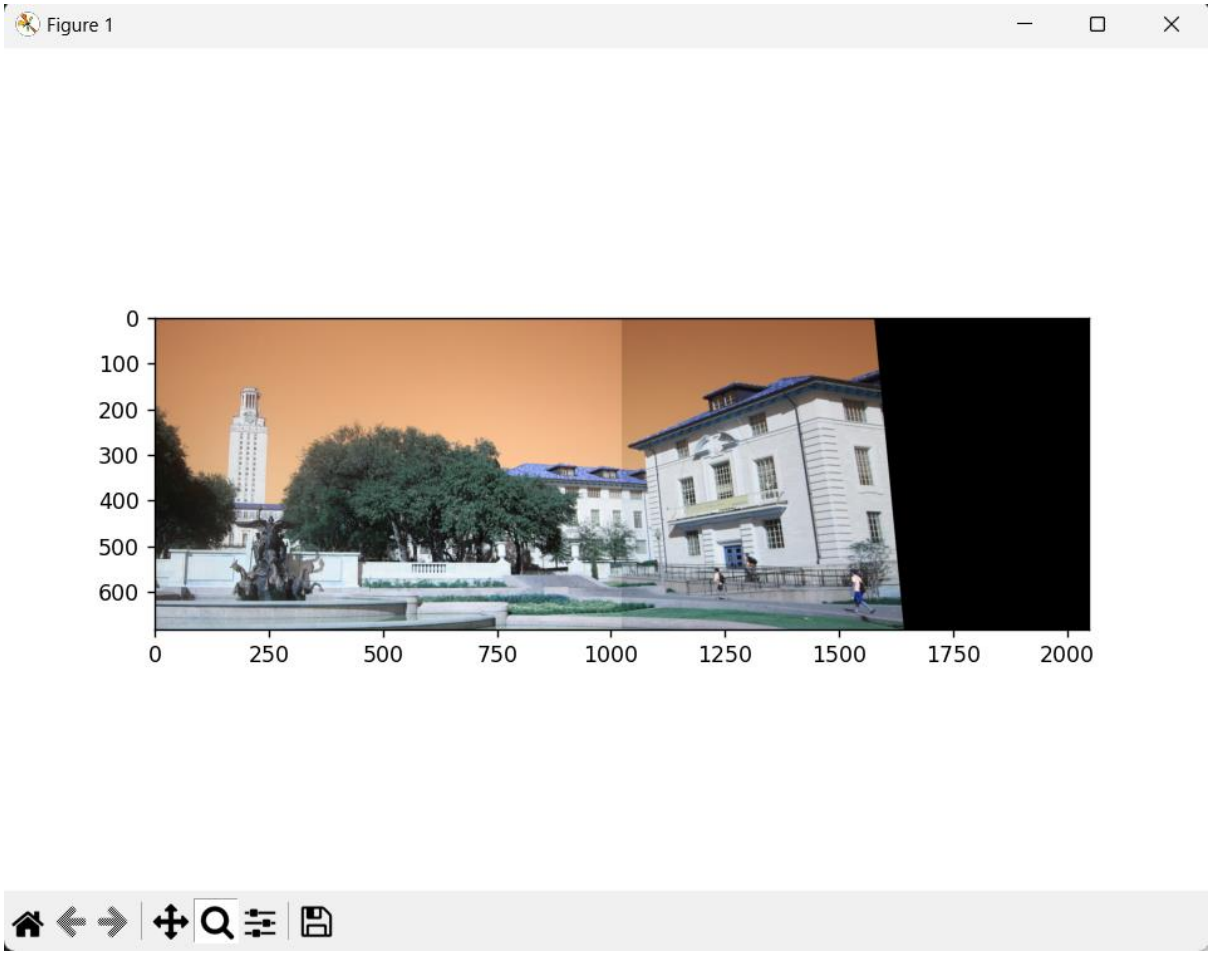


Figure 1
0
100
200
300
400
500
600
0
250
500
750
1000
1250
1500
1750
2000

# PRACTICAL NO: 3

**Aim: Perform Camera Calibration**

**Theory:**

A camera is an integral part of several domains like robotics, space exploration, etc camera is playing a major role. It helps to capture each and every moment and helpful for many analyses. In order to use the camera as a visual sensor, we should know the parameters of the camera. Camera Calibration is nothing but estimating the parameters of a camera, parameters about the camera are required to determine an accurate relationship between a 3D point in the real world and its corresponding 2D projection (pixel) in the image captured by that calibrated camera.

We need to consider both internal parameters like focal length, optical center, and radial distortion coefficients of the lens etc., and external parameters like rotation and translation of the camera with respect to some real world coordinate system.

Camera Calibration can be done in a step-by-step approach:

Step 1: First define real world coordinates of 3D points using known size of checkerboard pattern.

Step 2: Different viewpoints of check-board image is captured.

Step 3: findChessboardCorners() is a method in OpenCV and used to find pixel coordinates (u, v) for each 3D point in different images

Step 4: Then calibrateCamera() method is used to find camera parameters.

Similarly, tangential distortion occurs because the image-taking lense is not aligned perfectly parallel to the imaging plane. So, some areas in the image may look nearer than expected. The amount of tangential distortion can be represented as below:

$$x_{distorted} = x + [2p_1xy + p_2(r^2 + 2x^2)] y_{distorted} = y + [p_1(r^2 + 2y^2) + 2p_2xy]$$

In short, we need to find five parameters, known as distortion coefficients given by:

$$Distortion\ coefficients = (k_1 \quad k_2 \quad p_1 \quad p_2 \quad k_3)$$

It will take our calculated (threedpoints, twodpoints, grayColor.shape[::-1], None, None) as parameters and returns list having elements as Camera matrix, Distortion coefficient, Rotation Vectors, and Translation Vectors.

$$camera\ matrix = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

Camera Matrix helps to transform 3D objects points to 2D image points and the Distortion Coefficient returns the position of the camera in the world, with the values of Rotation and Translation vectors.

Code:

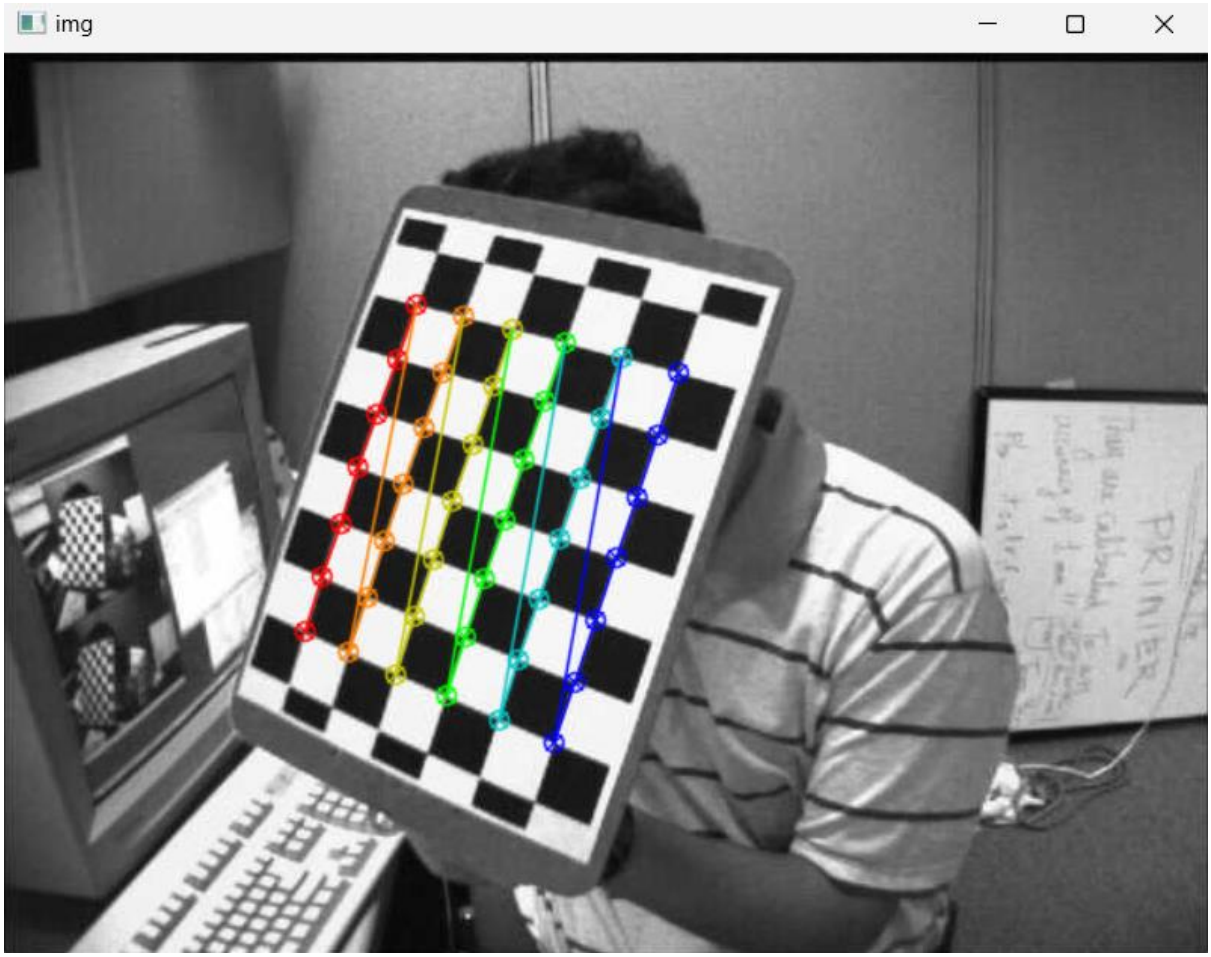
Camera_Calliberation.py - C:\MScITPracs\OpenCV\Prac3\Camera_Calliberation.py (3.11.6)

File Edit Format Run Options Window Help

```
import numpy as np
import cv2 as cv
import glob

criteria = (cv.TERM_CRITERIA_EPS + cv.TERM_CRITERIA_MAX_ITER, 30, 0.001)

objp = np.zeros((6*7,3), np.float32)
objp[:,:2] = np.mgrid[0:7,0:6].T.reshape(-1,2)

objpoints = []
imgpoints = []

images = glob.glob('*.jpg')

for fname in images:
    img = cv.imread(fname)
    gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    ret, corners = cv.findChessboardCorners(gray,(7,6), None)

    if ret == True:
        objpoints.append(objp)
        corners2 = cv.cornerSubPix(gray,corners,(11,11), (-1,-1), criteria)
        imgpoints.append(corners2)
        cv.drawChessboardCorners(img, (7,6), corners2, ret)
        cv.imshow('img', img)
        cv.waitKey(500)
cv.destroyAllWindows()
ret, mtx, dist, rvec, tvecs = cv.calibrateCamera(objpoints, imgpoints, gray.shape[::-1],None,None)
print("Camera matrix: ")
print(mtx)
print("dist: ")
print(dist)
print("rvecs: ")
print(rvec)
print("tvecs: ")
print(tvecs)
```

```
print("tvecs: ")
print(tvecs)

img=cv.imread('left08.jpg')
h,w = img.shape[:2]
newcameramtx, roi = cv.getOptimalNewCameraMatrix(mtx,dist,(w,h),1,(w,h))


dst = cv.undistort(img,mtx,dist,None, newcameramtx)

x,y,w,h = roi
dst = dst[y:y+h, x:x+w]
cv.imwrite('calibresult.png',dst)
```

Output:



# Practical No: 4

**Aim: Perform the following:**

a. **Face detection**
b. **Object detection**
c. **Pedestrian detection**
d. **Face recognition**

**Theory:**

**a. Face detection**

**Face detection** involves identifying a person's face in an image or video. This is done by analyzing the visual input to determine whether a person's facial features are present.

Since human faces are so diverse, face detection models typically need to be trained on large amounts of input data for them to be accurate. The training dataset must contain a sufficient representation of people who come from different backgrounds, genders, and cultures.

These algorithms also need to be fed many training samples comprising different lighting, angles, and orientations to make correct predictions in real-world scenarios.

These nuances make face detection a non-trivial, time-consuming task that requires hours of model training and millions of data samples.

The OpenCV package comes with pre-trained models for face detection, which means that we don't have to train an algorithm from scratch. More specifically, the library employs a machine learning approach called Haar cascade to identify objects in visual data.

Face detection approach called Haar Cascade for face detection using OpenCV and Python.

**Intro to Haar Cascade Classifiers**

This method was first introduced in the paper Rapid Object Detection Using a Boosted Cascade of Simple Features, written by Paul Viola and Michael Jones.

The idea behind this technique involves using a cascade of classifiers to detect different features in an image. These classifiers are then combined into one

strong classifier that can accurately distinguish between samples that contain a human face from those that don't.

The Haar Cascade classifier that is built into OpenCV has already been trained on a large dataset of human faces, so no further training is required. We just need to load the classifier from the library and use it to perform face detection on an input image.

**Installing OpenCV for Python**

To install the OpenCV library, simply open your command prompt or terminal window and run the following command:

pip install opencv-python

**OpenCV for Face Detection in Images**

We will build a detector to identify the human face in a photo. Make sure to save the picture to your working directory and rename it to input_image before coding along.

**Step 1: Import the OpenCV Package**

Now, let's import OpenCV and enter the input image path with the following lines of code:

import cv2

imagePath = 'input_image.jpg'

**Step 2: Read the Image**

Then, we need to read the image with OpenCV's imread() function:

img = cv2.imread(imagePath)

This will load the image from the specified file path and return it in the form of a Numpy array.

Print the dimensions of this array:

print(img.shape)

(4000, 2667, 3)

Notice that this is a 3-dimensional array. The array's values represent the picture's height, width, and channels respectively. Since this is a color image, there are three channels used to depict it - blue, green, and red (BGR).

Note that while the conventional sequence used to represent images is RGB (Red, Blue, Green), the OpenCV library uses the opposite layout (Blue, Green, Red).

**Step 3: Convert the Image to Grayscale**

To improve computational efficiency, we first need to convert this image to grayscale before performing face detection on it:

gray_image = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

**Step 4: Load the Classifier**

Let's load the pre-trained Haar Cascade classifier that is built into OpenCV:

face_classifier = cv2.CascadeClassifier( cv2.data.haarcascades + "haarcascade_frontalface_default.xml" )

Notice that we are using a file called haarcascade_frontalface_default.xml. This classifier is designed specifically for detecting frontal faces in visual input.

https://github.com/opencv/opencv/tree/master/data/haarcascades

OpenCV also provides other pre-trained models to detect different objects within an image - such as a person's eyes, smile, upper body, and even a vehicle's license plate.

**Step 5: Perform the Face Detection**

We can now perform face detection on the grayscale image using the classifier we just loaded:

face = face_classifier.detectMultiScale(

gray_image, scaleFactor=1.1, minNeighbors=5, minSize=(40, 40)

)

Let's break down the methods and parameters specified in the above code:

**detectMultiScale():**

The detectMultiScale() method is used to identify faces of different sizes in the input image.

**grey_image:**

The first parameter in this method is called grey_image, which is the grayscale image we created previously.

**scaleFactor:**

This parameter is used to scale down the size of the input image to make it easier for the algorithm to detect larger faces. In this case, we have specified a scale factor of 1.1, indicating that we want to reduce the image size by 10%.

**minNeighbors:**

The cascade classifier applies a sliding window through the image to detect faces in it. You can think of these windows as rectangles.

Initially, the classifier will capture a large number of false positives. These are eliminated using the minNeighbors parameter, which specifies the number of neighboring rectangles that need to be identified for an object to be considered a valid detection.

To summarize, passing a small value like 0 or 1 to this parameter would result in a high number of false positives, whereas a large number could lead to losing out on many true positives.

The trick here is to find a tradeoff that allows us to eliminate false positives while also accurately identifying true positives.

**minSize:**

Finally, the minSize parameter sets the minimum size of the object to be detected. The model will ignore faces that are smaller than the minimum size specified.

**Step 6: Drawing a Bounding Box**

Now that the model has detected the faces within the image, let's run the following lines of code to create a bounding box around these faces:

```
for (x, y, w, h) in face:

cv2.rectangle(img, (x, y), (x + w, y + h), (0, 255, 0), 4)
```

The face variable is an array with four values: the x and y axis in which the faces were detected, and their width and height. The above code iterates over the identified faces and creates a bounding box that spans across these measurements.

The parameter 0,255,0 represents the color of the bounding box, which is green, and 4 indicates its thickness.

### Step 7: Displaying the Image

To display the image with the detected faces, we first need to convert the image from the BGR format to RGB:

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

Use the Matplotlib library to display the image:

import matplotlib.pyplot as plt

plt.figure(figsize=(20,10))

plt.imshow(img_rgb)

plt.show()

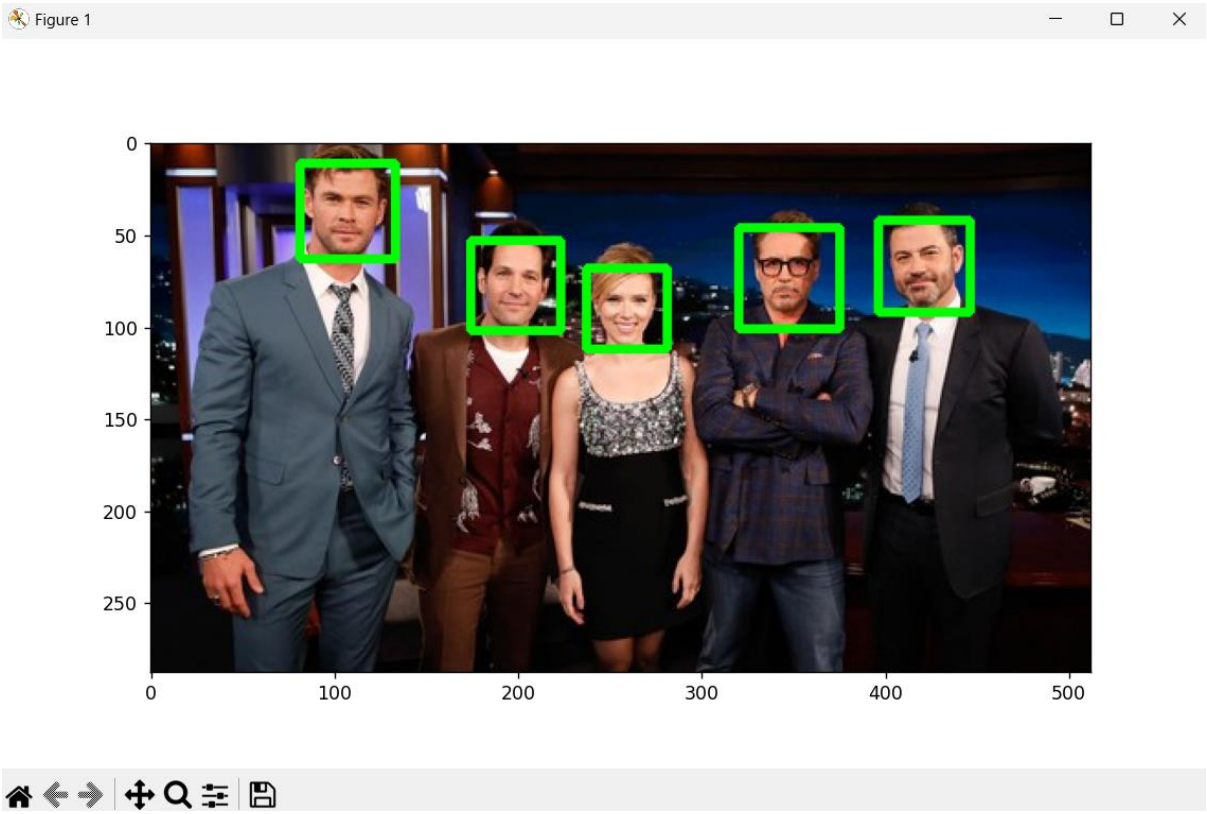
### Code:

Prac4a.py - C:/MScITPracs/OpenCV/Prac4a.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt

imagePath = 'C://MScITPracs//OpenCV//avengers.jpg'

img = cv2.imread(imagePath)

print(img.shape)

gray_image = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

face_classifier = cv2.CascadeClassifier(cv2.data.haarcascades + "haarcascade_frontalface_default.xml")

face = face_classifier.detectMultiScale(gray_image, scaleFactor=1.1, minNeighbors=5, minSize=(40, 40))

for (x, y, w, h) in face:
    cv2.rectangle(img, (x, y), (x + w, y + h), (0, 255, 0), 4)

img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

plt.figure(figsize=(20, 10))

plt.imshow(img_rgb)
plt.show()
```

Output:



# Practical No: 4

**Aim: Perform the following:**

**a. Face detection**

**b. Object detection**

**c. Pedestrian detection**

**d. Face recognition**

**Theory:**

**b. Object detection**

Object detection is a computer technology related to computer vision and image processing that deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos.

**Haar cascade:**

Basically, the Haar cascade technique is an approach based on machine learning where we use a lot of positive and negative images to train the classifier to classify between the images. Haar cascade classifiers are considered as the effective way to do object detection with the OpenCV library.

**Positive images:** These are the images that contain the objects which we want to be identified from the classifier.

**Negative Images**: These are the images that do not contain any object that we want to be detected by the classifier, and these can be images of everything else.

**Requirements for object detection with Python OpenCV:**

**1. Install OpenCV-Python Library**

**2. Install matplotlib library**

**3. An Image with Stop Sign.**

**4. An xml file "Stop_data.xml" to detect stop sign board.**

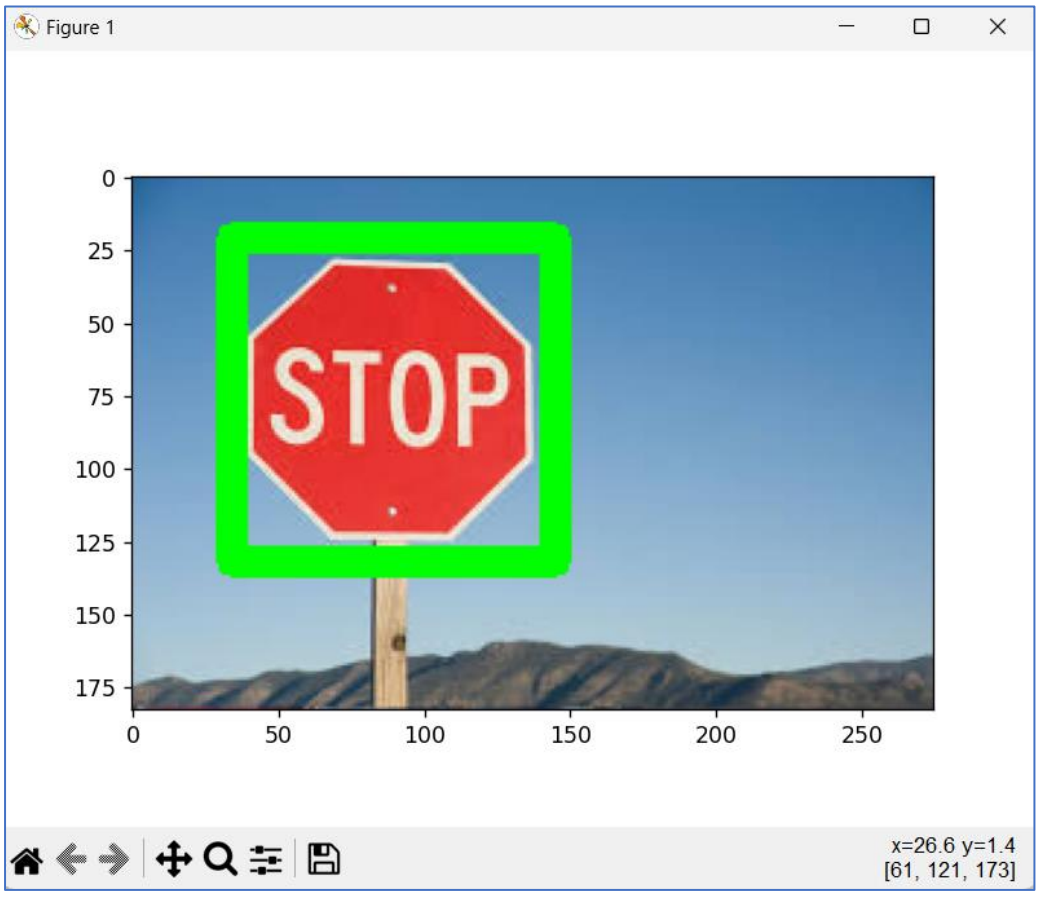
## Code:

prac4b1.py - C:/MScITPracs/OpenCV/Prac 4/prac4b1.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import matplotlib.pyplot as plt

imaging = cv2.imread("C://MScITPracs//OpenCV//Prac 4//prac4ba.jpg")
imaging_gray = cv2.cvtColor(imaging, cv2.COLOR_BGR2GRAY)
imaging_rgb = cv2.cvtColor(imaging, cv2.COLOR_BGR2RGB)

xml_data = cv2.CascadeClassifier('stop_data.xml')
detecting = xml_data.detectMultiScale(imaging_gray, minSize=(30, 30))

amountDetecting = len(detecting)
if amountDetecting != 0:
    for (a, b, width, height) in detecting:
        cv2.rectangle(imaging_rgb, (a, b), (a + height, b + width), (0, 275, 0), 9)

plt.imshow(imaging_rgb)
plt.show()
```

## Output:



https://medium.com/@vipulgote4/guide-to-make-custom-haar-cascade-xml-file-for-object-detection-with-opencv-6932e22c3f0e

## Line Detection in OpenCV

Line detection is a fundamental operation in computer vision, often used for object detection, feature extraction, and image analysis. OpenCV provides several methods to detect lines in images, with the Hough Line Transform being the most popular. Here's a detailed explanation of line detection using the Hough Line Transform in OpenCV.

## Theory: Hough Line Transform

The Hough Line Transform is a technique to detect lines in an image. It works by transforming points in the image space into a parameter space where lines can be more easily detected. This is based on the fact that a line can be represented in various ways, but the most common parameterization in the Hough Transform is:

$\rho = x\cos(\theta) + y\sin(\theta)$

ρ=xcos(θ)+ysin(θ)

Where:

ρ is the distance from the origin to the line.

θ is the angle of the line.

The Hough Transform converts each point in the image into a sinusoidal curve in the ρ−θ space. The intersections of these curves in the parameter space correspond to potential lines in the image space.

## Steps for Line Detection

### a. Convert the image to grayscale:

Line detection usually works on grayscale images.

### b. Edge detection:

Detect edges in the image using edge detection techniques like Canny edge detector.

**c. Hough Line Transform:**

Apply the Hough Line Transform to detect lines in the edge-detected image.

**d. Draw the detected lines:**

Visualize the detected lines on the original image.

**Explanation of the Code**

**a. Loading and Converting the Image:**

- The image is loaded using cv2.imread.
- It is then converted to grayscale using cv2.cvtColor.

**b. Edge Detection:**

- The cv2.Canny function is used to detect edges in the grayscale image. This function requires two threshold values (50 and 150 in this example) and an aperture size for the Sobel operator (3 here).

**c. Hough Line Transform:**

- cv2.HoughLines is used to detect lines in the edge-detected image. The function parameters include the edge-detected image, the resolution of the parameter $\rho$ (here 1 pixel), the resolution of the parameter $\theta$ (here np.pi / 180 radians), and the threshold (200 here), which determines the minimum number of intersections needed to detect a line.

**d. Drawing the Detected Lines:**

- The detected lines are drawn on the original image using cv2.line.
- The endpoints of the lines are calculated using the $\rho$ and $\theta$ values returned by the Hough Transform.

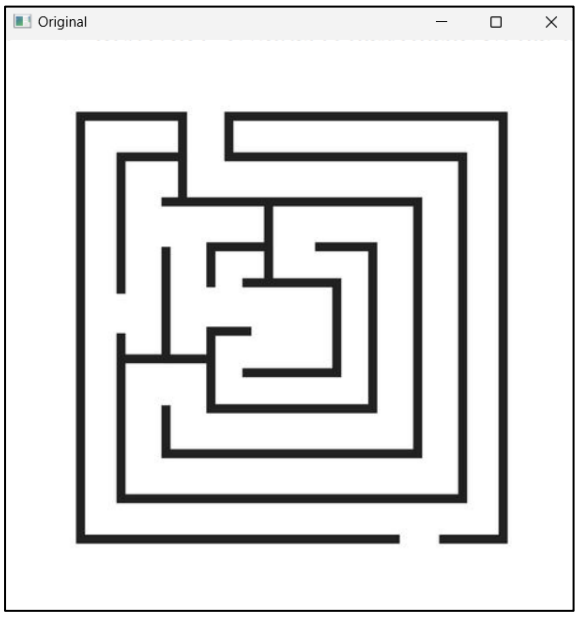
## Code:

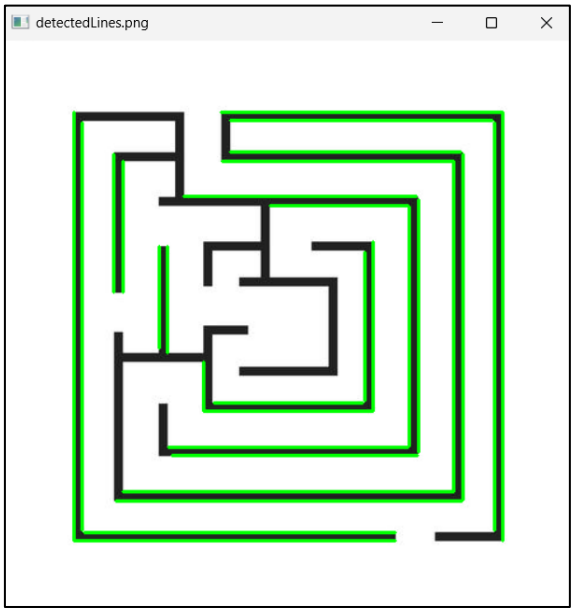
prac4b2.py - C:/MScITPracs/OpenCV/Prac 4/prac4b2.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import numpy as np

image = cv2.imread('C://MScITPracs//OpenCV//Prac 4//Lines.jpg')
cv2.imshow('Original', image)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
edges = cv2.Canny(gray, 50, 150, apertureSize=3)

lines_list = []
lines = cv2.HoughLinesP(
    edges,
    rho=1,
    theta=np.pi / 180,
    threshold=100,
    minLineLength=3,
    maxLineGap=5
)

for points in lines:
    x1, y1, x2, y2 = points[0]
    cv2.line(image, (x1, y1), (x2, y2), (0, 255, 0), 2)
    lines_list.append([(x1, y1), (x2, y2)])

cv2.imshow('detectedLines.png', image)
```

## Output:



## Hough transform

• Finds circles in a grayscale image using the Hough transform.

• The function finds circles in a grayscale image using a modification of the Hough transform.

```
void cv::HoughCircles ( InputArray  image,
                        OutputArray circles,
                        int         method,
                        double      dp,
                        double      minDist,
                        double      param1 = 100 ,
                        double      param2 = 100 ,
                        int         minRadius = 0 ,
                        int         maxRadius = 0
                      )
```

• Usually the function detects the centers of circles well. However, it may fail to find correct radii.

• You can assist to the function by specifying the radius range ( minRadius and maxRadius ) if you know it.

• Or, in the case of HOUGH_GRADIENT method you may set maxRadius to a negative number to return centers only without radius search, and find the correct radius using an additional procedure.

• It also helps to smooth image a bit unless it's already soft. For example, GaussianBlur() with 7x7 kernel and 1.5x1.5 sigma or similar blurring may help.

**Parameters**

| | |
|---|---|
| **image** | 8-bit, single-channel, grayscale input image. |
| **circles** | Output vector of found circles. Each vector is encoded as 3 or 4 element floating-point vector $(x, y, radius)$ or $(x, y, radius, votes)$ . |
| **method** | Detection method, see **HoughModes**. The available methods are **HOUGH_GRADIENT** and **HOUGH_GRADIENT_ALT**. |
| **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. For **HOUGH_GRADIENT_ALT** the recommended value is dp=1.5, unless some small very circles need to be detected. |
| **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. |
| **param1** | First method-specific parameter. In case of **HOUGH_GRADIENT** and **HOUGH_GRADIENT_ALT**, it is the higher threshold of the two passed to the Canny edge detector (the lower one is twice smaller). Note that **HOUGH_GRADIENT_ALT** uses **Scharr** algorithm to compute image derivatives, so the threshold value shough normally be higher, such as 300 or normally exposed and contrasty images. |
| **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. In the case of **HOUGH_GRADIENT_ALT** algorithm, this is the circle "perfectness" measure. The closer it to 1, the better shaped circles algorithm selects. In most cases 0.9 should be fine. If you want get better detection of small circles, you may decrease it to 0.85, 0.8 or even less. But then also try to limit the search range [minRadius, maxRadius] to avoid many false circles. |
| **minRadius** | Minimum circle radius. |
| **maxRadius** | Maximum circle radius. If <= 0, uses the maximum image dimension. If < 0, **HOUGH_GRADIENT** returns centers without finding the radius. **HOUGH_GRADIENT_ALT** always computes circle radiuses. |

What is Hough accumulator?

• The Hough transform algorithm uses an array, called an accumulator, to detect the existence of a line y = mx + b. The dimension of the accumulator is equal to the number of unknown parameters of the Hough transform problem.

## Overview of np.around()

Basically, `np.around()` is NumPy's function to round floats (decimal numbers) or integers. It takes three arguments:

1. The first mandatory argument is the number you want to round
2. `decimals` - optional argument, the number of decimal places you want to round to
3. `out` - optional argument, where to output

By default np.around() will round the given number to a the nearest whole number and return the rounded value:

```
>>> np.around(5)
5

>>> np.around(5.11212)
5.0

>>> np.around(9.11212)
9.0

>>> np.around(9.5)
10.0
```

**OpenCV-Python** is a library of Python bindings designed to solve computer vision problems. cv2.circle() method is used to draw a circle on any image. The syntax of cv2.circle() method is:

**Syntax:**

```
cv2.circle(image, center_coordinates, radius, color, thickness)
```

**Parameters:**

- **image:** It is the image on which the circle is to be drawn.
- **center_coordinates:** It is the center coordinates of the circle. The coordinates are represented as tuples of two values i.e. (**X** coordinate value, **Y** coordinate value).
- **radius:** It is the radius of the circle.
- **color:** It is the color of the borderline of a circle to be drawn. For **BGR**, we pass a tuple. eg: (255, 0, 0) for blue color.
- **thickness:** It is the thickness of the circle border line in **px**. Thickness of **-1 px** will fill the circle shape by the specified color.

**Return Value:** It returns an image

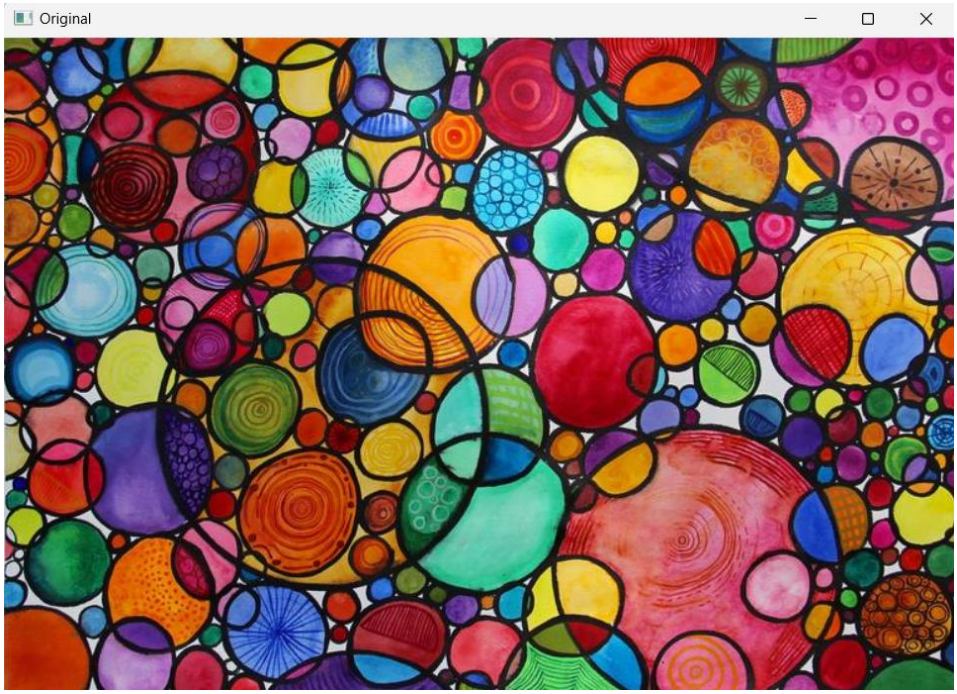
## Code:

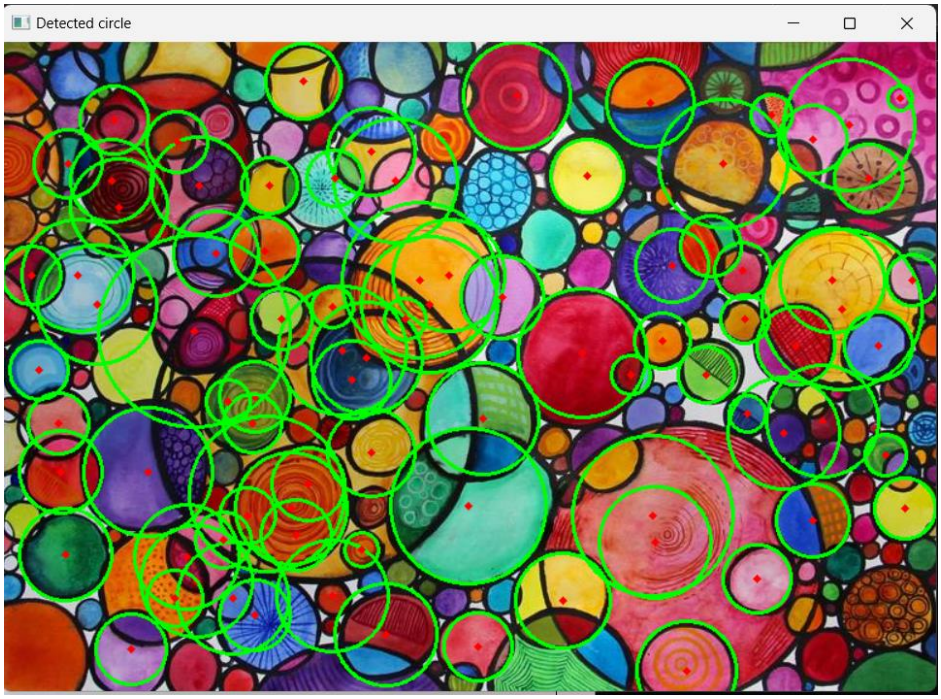
Pract_4b(3).py - C:\MScITPracs\OpenCV\Prac 4\Pract_4b(3).py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import numpy as np

img = cv2.imread('shapes.jpg')
cv2.imshow('Original',img)

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
gray_blurred = cv2.blur(gray,(3,3))
detected_circles = cv2.HoughCircles(gray_blurred, cv2.HOUGH_GRADIENT,1,20,param1 = 1(

if detected_circles is not None:
    detected_circles = np.uint16(np.around(detected_circles))
    for pt in detected_circles[0,:]:
        a,b,r = pt[0],pt[1],pt[2]
        cv2.circle(img,(a,b),r,(0,255,0),2)
        cv2.circle(img,(a,b),1,(0,0,255),3)
    cv2.imshow('Detected circle',img)
```

## Output:



# PRACTICAL NO: 4

**Aim: Perform the following:**

**a. Face detection**

**b. Object detection**

**c. Pedestrian detection**

**d. Face recognition**

**Theory:**

**c. Pedestrian detection**

Pedestrian detection is a very important area of research because it can enhance the functionality of a pedestrian protection system in Self Driving Cars. We can extract features like head, two arms, two legs, etc, from an image of a human body and pass them to train a machine learning model. After training, the model can be used to detect and track humans in images and video streams. However, OpenCV has a built-in method to detect pedestrians. It has a pre-trained HOG(Histogram of Oriented Gradients) + Linear SVM model to detect pedestrians in images and video streams.

**Histogram of Oriented Gradients**

This algorithm checks directly surrounding pixels of every single pixel. The goal is to check how darker is the current pixel compared to the surrounding pixels. The algorithm draws and arrows showing the direction of the image getting darker. It repeats the process for each and every pixel in the image. At last, every pixel would be replaced by an arrow, these arrows are called Gradients. These gradients show the flow of light from light to dark. By using these gradients algorithms perform further analysis.

**Requirements**

**1. opencv-python**

**2. imutils**

```
Command Prompt
Microsoft Windows [Version 10.0.22631.3593]
(c) Microsoft Corporation. All rights reserved.

C:\Users\Om Solanki>pip install imutils
Collecting imutils
  Downloading imutils-0.5.4.tar.gz (17 kB)
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
Building wheels for collected packages: imutils
  Building wheel for imutils (pyproject.toml) ... done
  Created wheel for imutils: filename=imutils-0.5.4-py3-none-any.whl size=25855 sha256=607c4ea0
69d51596dfbed14b78a090408e6a744
  Stored in directory: c:\users\om solanki\appdata\local\pip\cache\wheels\31\d0\2c\87ce38f60528
10e908d449f16
Successfully built imutils
Installing collected packages: imutils
Successfully installed imutils-0.5.4

[notice] A new release of pip is available: 23.3.2 -> 24.0
[notice] To update, run: python.exe -m pip install --upgrade pip

C:\Users\Om Solanki>
```

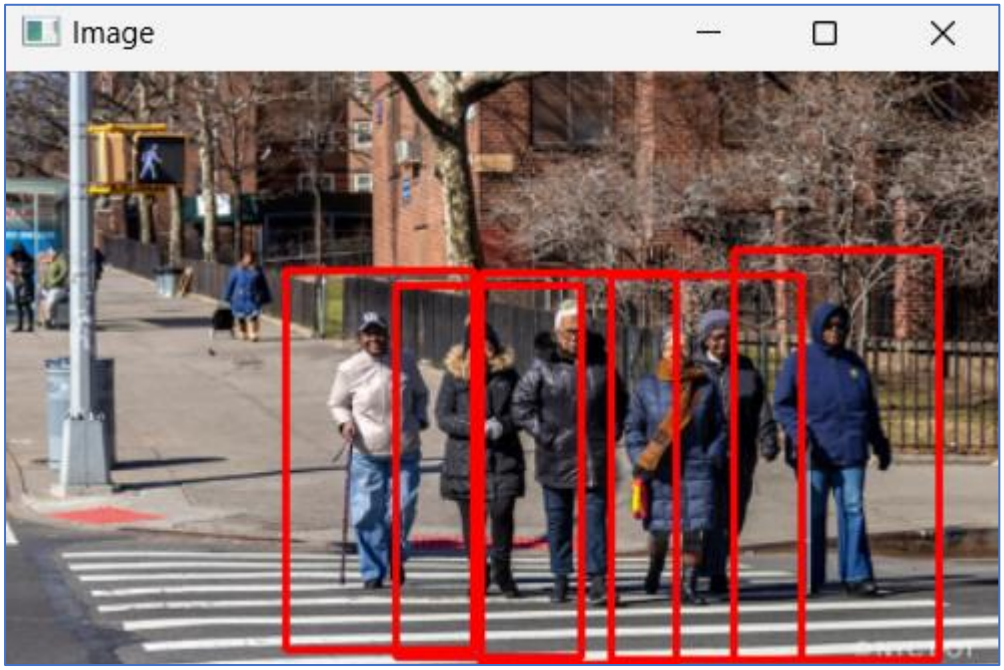
## Code:

Pract_4c.py - C:/MScITPracs/OpenCV/Prac 4/Pract_4c.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import imutils

# Initializing the HOG person detector
hog = cv2.HOGDescriptor()
hog.setSVMDetector(cv2.HOGDescriptor_getDefaultPeopleDetector())

# Reading the Image
image = cv2.imread('beats.png')

# Resizing the Image
image = imutils.resize(image, width=min(400, image.shape[1]))

# Detecting all the regions in the Image that have pedestrians inside it
(regions, _) = hog.detectMultiScale(
    image,
    winStride=(4, 4),
    padding=(4, 4),
    scale=1.05
)

# Drawing the regions in the Image
for (x, y, w, h) in regions:
    cv2.rectangle(image, (x, y), (x + w, y + h), (0, 0, 255), 2)

# Showing the output Image
cv2.imshow("Image", image)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

## Output:



# PRACTICAL NO: 4

**Aim: Perform the following:**

**a. Face detection**

**b. Object detection**

**c. Pedestrian detection**

**d. Face recognition**

**Theory:**

**d. Face recognition**

Face recognition is different from face detection. In face detection, we had only detected the location of human faces, and we recognized the identity of faces in the face recognition task. In this article, we are going to build a face recognition system using python with the help of face recognition library.

There are many algorithms available in the market for face recognition. This broad computer vision challenge is detecting faces from videos and pictures. Many applications can be built on top of recognition systems. Many big companies are adopting recognition systems for their security and authentication purposes.

Use Cases of Recognition Systems

Face recognition systems are widely used in the modern era, and many new innovative systems are built on top of recognition systems.

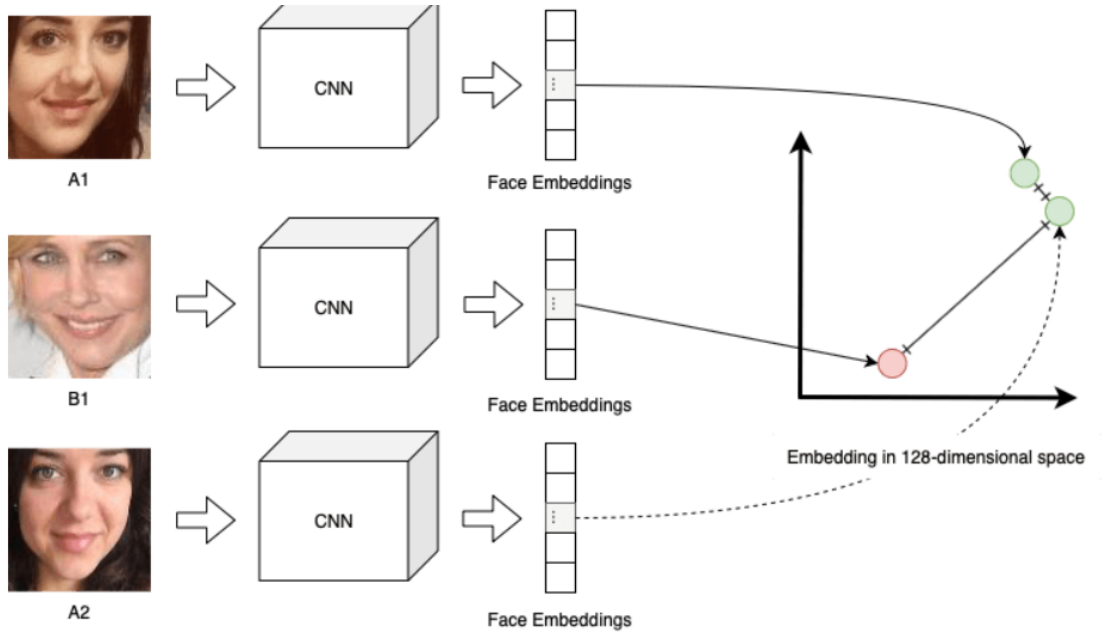
**There are a few used cases :**

- Finding Missing Person
- Identifying accounts on social media
- Recognizing Drivers in Cars
- School Attendance System

Several methods and algorithms implement facial recognition systems depending on the performance and accuracy.

Steps Involved in Face Recognition

1. **Face Detection**: Locate the face, note the coordinates of each face locate,d and draw a bounding box around every faces.
2. **Face Alignments**. Normalize the faces in order to attain fast training.
3. **Feature Extraction**. Local feature extraction from facial pictures for training, this step is performed differently by different algorithms.
4. **Face Recognition**. Match the input face with one or more known faces in our dataset.




Implementation

Implementing a face recognition system using python. Implementing a Deep learning-based face recognition system using the face_recognition library.

**Step 1: Setting Face Recognition Libraries**

In order to install the face recognition library, we need to first install the dlib.

**dlib :** It is a modern C++ toolkit that contains ML-related algorithms and tools.

```
# installing dlib
pip install dlib
```

```
C:\Users\Om Solanki>pip install dlib-19.24.1-cp311-cp311-win_amd64.whl
Processing c:\users\om solanki\dlib-19.24.1-cp311-cp311-win_amd64.whl
Installing collected packages: dlib
Successfully installed dlib-19.24.1

[notice] A new release of pip is available: 23.3.2 -> 24.0
[notice] To update, run: python.exe -m pip install --upgrade pip

C:\Users\Om Solanki>
```

**face recognition** The actual face recognition library can be installed after dlib.

```
# installing face recognition
pip install face recognition
```

**Opencv** for some image pre-processing

```
# installing opencv
pip install opencv
```

**Note**: Sometimes installing dlib throws error in that case install install the C++ development toolkit using vs_code community .

**Importing Libraries**

```
import cv2
import numpy as np
import face_recognition
```

**Step 2: Loading Image**

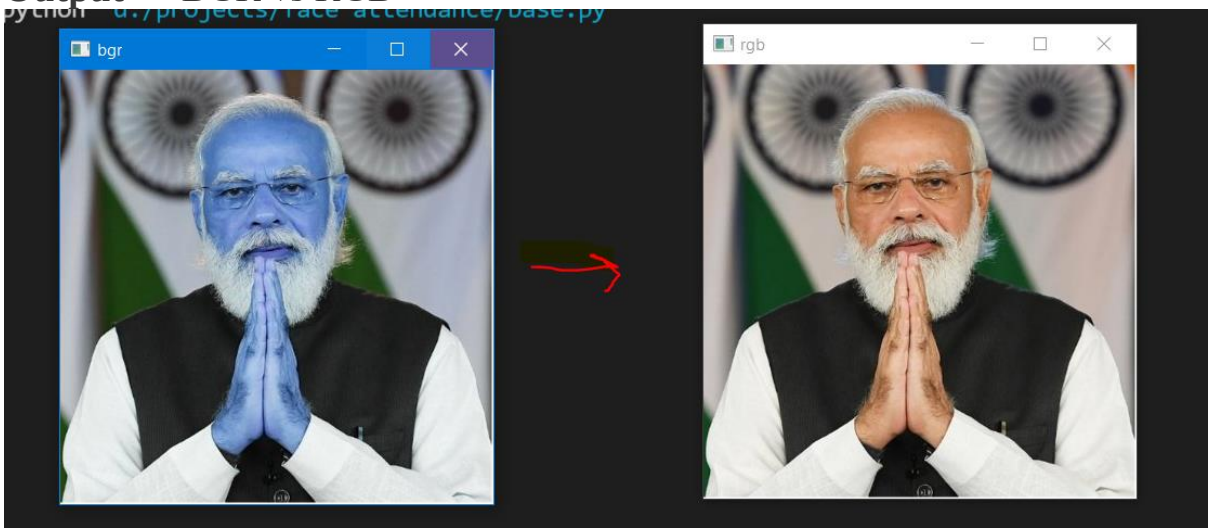
We are done with installing and importing the libraries. It's time to load some sample images to the face_recognition library. Here is the link for the same.

The library face_recognition supports only the BGR format of images. While printing the output image we should convert it into RGB using OpenCV.

**Face_recognition** Loads images only in BGR format.

```
import cv2
import numpy as np
import face_recognition
img_bgr = face_recognition.load_image_file('student_images/modi.jpg')
img_rgb = cv2.cvtColor(img_bgr,cv2.COLOR_BGR2RGB)
cv2.imshow('bgr', img_bgr)
cv2.imshow('rgb', img_rgb)
cv2.waitKey
```

**Output** → BGR vs RGB

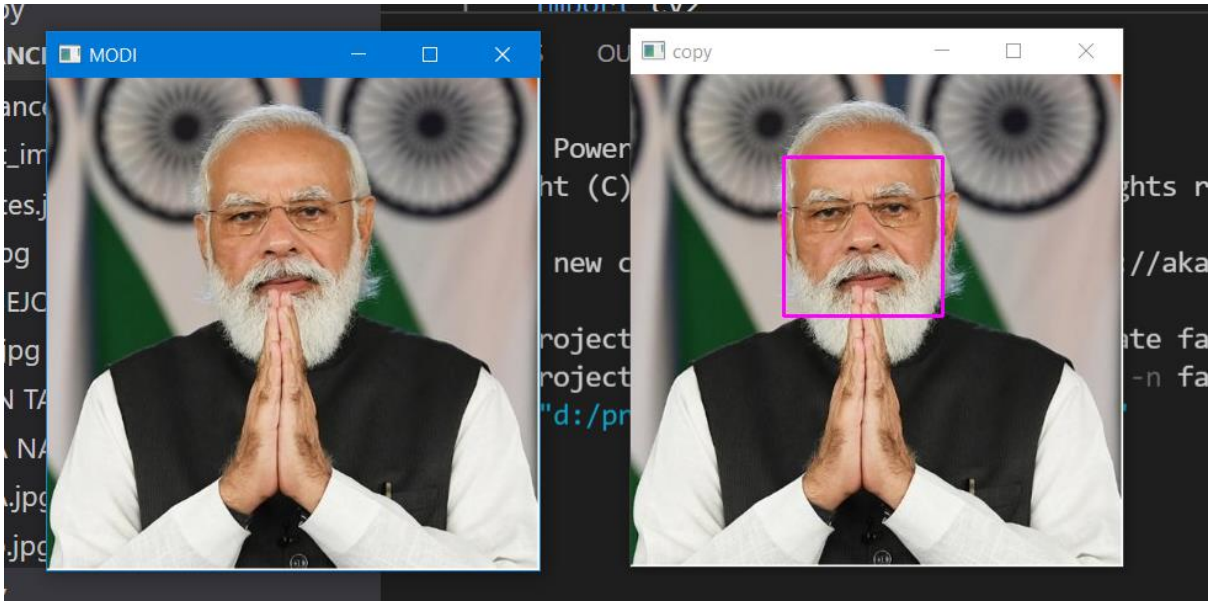



**Step 3: Detecting and Locating Faces**

The library face_recognitioncan quickly locate faces on its own, we don't need to use haar_cascade and other techniques.

```
img_modi=face_recognition.load_image_file('student_images/modi.jpg')
img_modi_rgb = cv2.cvtColor(img_modi,cv2.COLOR_BGR2RGB)
#--------- Detecting Face -------
face = face_recognition.face_locations(img_modi_rgb)[0]
copy = img_modi_rgb.copy()
# ------ Drawing bounding boxes around Faces-------------------------
cv2.rectangle(copy, (face[3], face[0]),(face[1], face[2]), (255,0,255), 2)
cv2.imshow('copy', copy)
cv2.imshow('MODI',img_modi_rgb)
cv2.waitKey(0)
```

**Output**




**Step 4: Sample Image Recognition**

The library face_recognition is based on deep learning, it supports single-shot learning which means it needs a single picture to train itself to detect a person.

```
img_modi = face_recognition.load_image_file('student_images/modi.jpg')
img_modi = cv2.cvtColor(img_modi,cv2.COLOR_BGR2RGB)

#------to find the face location
face = face_recognition.face_locations(img_modi)[0]

#--Converting image into encodings
train_encode = face_recognition.face_encodings(img_modi)[0]

#----- lets test an image
test = face_recognition.load_image_file('student_images/modi2.jpg')
test = cv2.cvtColor(test, cv2.COLOR_BGR2RGB)
test_encode = face_recognition.face_encodings(test)[0]
print(face_recognition.compare_faces([train_encode],test_encode))
cv2.rectangle(img_modi, (face[3], face[0]),(face[1], face[2]), (255,0,255), 1)
cv2.imshow('img_modi', img_modi)
cv2.waitKey(0)
```

- **face_recognition.face_encodings(imgelon)[0]** →Returns encoding of passed Image.
- **face_recognition.compare_faces([train_encode],test_encode)** → Takes a list of trained encodings and a test encoding of the unknown Image. It returns True if both test encoding has a match in train encoding; otherwise, it returns. False.

## Understand the Working of Face Recognition

1. We pass the person's picture to the model and their name.
2. The model takes every picture, converts them into some numerical encoding, and stores them in a list and all the labels(names of persons) in another list.
3. In the Prediction Phase when we pass a picture of an unknown person recognition model converts the unfamiliar person's Image into encoding.
4. After converting an unknown person's Image into encoding, it tries to find the most similar encoding based on the distance parameter. The store encoding with the least distance from the encoding of an unknown person will be the closest match.
5. After getting the closest match encoding, we take the index of that encoding from that list and use indexing. We find the detected person's name.

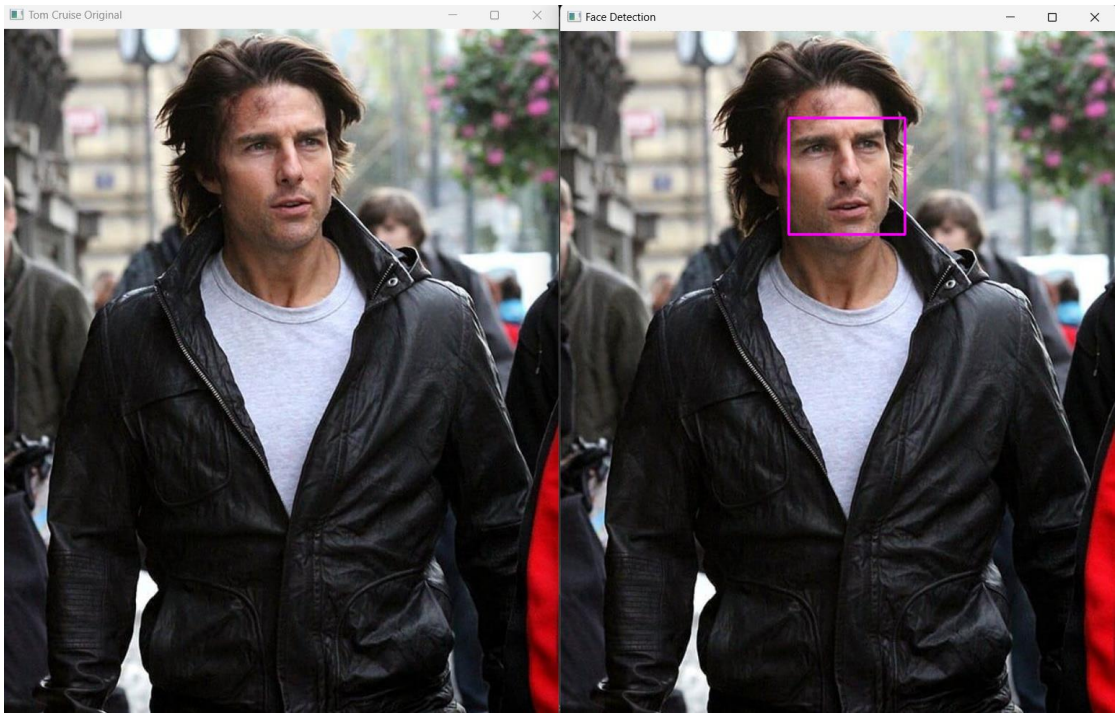
## Code:

*Pract_4d.py - C:/MScITPracs/OpenCV/Prac 4/Pract_4d.py (3.11.6)*

File Edit Format Run Options Window Help

```
import cv2
import numpy as np
import face_recognition
img_bgr = face_recognition.load_image_file('tomc.jpg')
img_rgb = cv2.cvtColor(img_bgr,cv2.COLOR_BGR2RGB)
cv2.imshow('bgr', img_bgr)
cv2.imshow('rgb', img_rgb)
cv2.waitKey
img_modi=face_recognition.load_image_file('tomc.jpg')
img_modi_rgb = cv2.cvtColor(img_modi,cv2.COLOR_BGR2RGB)
#--------- Detecting Face -------
face = face_recognition.face_locations(img_modi_rgb)[0]
copy = img_modi_rgb.copy()
# ------ Drawing bounding boxes around Faces-------------------------
cv2.rectangle(copy, (face[3], face[0]),(face[1], face[2]), (255,0,255), 2)
cv2.imshow('Face Detection', copy)
cv2.imshow('Tom Cruise Original',img_modi_rgb)
cv2.waitKey(0)
img_modi = face_recognition.load_image_file('tomc.jpg')
img_modi = cv2.cvtColor(img_modi,cv2.COLOR_BGR2RGB)

#------to find the face location
face = face_recognition.face_locations(img_modi)[0]

#--Converting image into encodings
train_encode = face_recognition.face_encodings(img_modi)[0]

#----- lets test an image
test = face_recognition.load_image_file('tomc2.jpg')
test = cv2.cvtColor(test, cv2.COLOR_BGR2RGB)
test_encode = face_recognition.face_encodings(test)[0]
print(face_recognition.compare_faces([train_encode],test_encode))
cv2.rectangle(img_modi, (face[3], face[0]),(face[1], face[2]), (255,0,255), 1)
cv2.imshow('img_tomC', img_modi)
cv2.waitKey(0)
```

# Output:



# PRACTICAL NO: 5

**Aim: Implement object detection and tracking from video.**

**Theory:**

**Object detection** is the detection on every single frame and frame after frame.

**Object tracking** does frame-by-frame tracking but keeps the history of where the object is at a time after time

**1. Importing Libraries and Modules:**

import cv2:

Imports the OpenCV library used for computer vision tasks.

from tracker import *:

Imports all functions and classes from a tracker module, which likely contains the implementation of the EuclideanDistTracker.

**2. Creating Objects and Initializing Video Capture:**

tracker = EuclideanDistTracker():

Instantiates the Euclidean Distance Tracker.

cap = cv2.VideoCapture("highway.mp4"):

Initializes video capture with the video file "highway.mp4".

**3. Object Detection Initialization:**

object_detector = cv2.createBackgroundSubtractorMOG2(history=100, varThreshold=40):

Initializes a background subtractor with MOG2 method to differentiate between foreground (moving objects) and the background.

Background subtraction (BS) is a common and widely used technique for generating a foreground mask (namely, a binary image containing the pixels belonging to moving objects in the scene) by using static cameras.

As the name suggests, BS calculates the foreground mask performing a subtraction between the current frame and a background model, containing the static part of the scene or, more in general, everything that can be considered as background given the characteristics of the observed scene.

## Code:

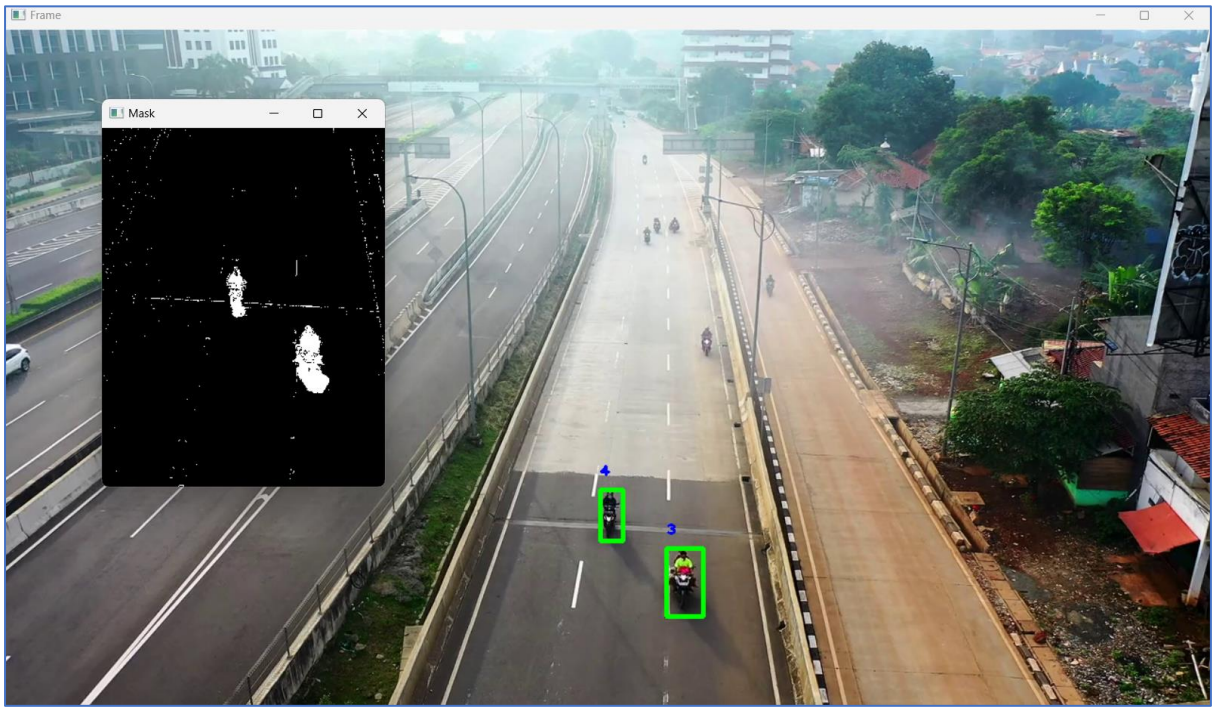
prac 5a.py - C:\MScITPracs\OpenCV\OpenCV\CV\prac 5a.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
from tracker import *

tracker = EuclideanDistTracker()

cap = cv2.VideoCapture("highway.mp4")

object_detector = cv2.createBackgroundSubtractorMOG2(history=100, varThreshold=40)

while True:
    ret, frame = cap.read()
    height, width, _ = frame.shape
    print(height, width)

    roi = frame[340: 720, 500:800]

    mask = object_detector.apply(roi)
    _,mask = cv2.threshold(mask, 254, 255, cv2.THRESH_BINARY)
    contours, _ = cv2.findContours(mask, cv2.RETR_TREE, cv2.CHAIN_APPROX_SIMPLE)

    detections=[]

    for cnt in contours:
        area = cv2.contourArea(cnt)
        if area > 100:
            x,y,w,h = cv2.boundingRect(cnt)
            cv2.rectangle(roi, (x,y), (x+w, y+h), (0,255,0), 2)
            detections.append([x,y,w,h])

    boxes_ids = tracker.update(detections)
    for box_id in boxes_ids:
        x,y,w,h , id=box_id
        cv2.putText(roi, str(id), (x, y-15), cv2.FONT_HERSHEY_PLAIN, 1, (255,0,0),2)
        cv2.rectangle(roi, (x,y), (x+w, y+h),(0,255,0),3)
```

```
    cv2.imshow("Roi",roi)
    cv2.imshow("Frame", frame)
    cv2.imshow("Mask", mask)

    key = cv2.waitKey(30)
    if key ==27:
        break

cap.release()
cv2.destroyAllWindows()
```

## Output:



# PRACTICAL NO: 5

**Aim: Implement object detection and tracking from video.**

**Theory:**

**B] Count number of Faces using Python**

We will use image processing to detect and count the number of faces. We are not supposed to get all the features of the face. Instead, the objective is to obtain the bounding box through some methods i.e. coordinates of the face in the image, depending on different areas covered by the number of the coordinates, number faces that will be computed.

**Required libraries:**

 **OpenCV** library in python is a computer vision library, mostly used for image processing, video processing, and analysis, facial recognition and detection, etc.

 **Dlib** library in python contains the pre-trained facial landmark detector, that is used to detect the (x, y) coordinates that map to facial structures on the face.

 **Numpy** is a general-purpose array-processing package. It provides a high-performance multidimensional array object and tools for working with these arrays.

**Code:**

5b.py - C:\MScITPracs\OpenCV\OpenCV\CV\5b.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import numpy as np
import dlib

cap = cv2.VideoCapture("Faces1.mp4")

detector = dlib.get_frontal_face_detector()

while True:

    ret, frame = cap.read()
    frame = cv2.flip(frame, 1)

    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = detector(gray)

    i=0
    for face in faces:
        x, y = face.left(),face.top()
        x1, y1 = face.right(), face.bottom()
        cv2.rectangle(frame, (x,y), (x1,y1), (0,255,0),2)
        i=i+1
        cv2.putText(frame, 'face num'+str(i), (x-10,y-10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0,0,255),3)
        print(face, i)

    frame = cv2.resize(frame,(1000,500))
    cv2.imshow('frame', frame)

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

cap.release()
cv2.destroyAllWindows()
```

## Output:

# PRACTICAL NO: 5

**Aim: Implement object detection and tracking from video.**

**Theory:**

**C] Object Tracking**

This detection method works only to track two identical objects, so for example if we want to find the cover of a book among many other books, if we want to compare two pictures.

I'm going to take the cover of a book from google and then I will try to detect the same book on my hand.


Book Cover

**How do we match the images of the Book?**

What approach are we going to use to detect the book that I'm holding on my hand, once we already have the image of the cover (the image above)?


Book detection

**First, we're going to use the Feature matching approach**, that I've already explained in this post.

We load the image of the book (queryimage), and then we load the camera.

```
import cv2
import numpy as np
img = cv2.imread("ultimo_sopravvissuto.jpg", cv2.IMREAD_GRAYSCALE) # queryiamge
cap = cv2.VideoCapture(0)
```

We then load the SIFT algorythm (or another feature detection algorythm).
On **line 8** we get the keypoints and descriptors of the Queryimage.
On **line 12** we load the flann algorythm which we are going to use to find the matching features.

```
# Features
sift = cv2.xfeatures2d.SIFT_create()
kp_image, desc_image = sift.detectAndCompute(img, None)
# Feature matching
index_params = dict(algorithm=0, trees=5)
search_params = dict()
flann = cv2.FlannBasedMatcher(index_params, search_params)
```

Then we **detect the features and descriptors of the frame** (train image) from the webcam, and we compare them with the ones of the query image.

```
_, frame = cap.read()
grayframe = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY) # trainimage
kp_grayframe, desc_grayframe = sift.detectAndCompute(grayframe, None)
matches = flann.knnMatch(desc_image, desc_grayframe, k=2)
good_points = []
for m, n in matches:
if m.distance < 0.6 * n.distance:
good_points.append(m)
```

And we get this result:


Feature matching

**How do we detect the Book and its Homography?**

Once we have the matches between queryimage and trainimage, most of the work is done.
What we only need to do is to **find its homography, so the object with its perspective**. For example as you can notice in the video tutorial, when I move the book in different angle, its perspective changes.

To get the homography, we need first to obtain the matrix and we do it with the function findHomography.

```
query_pts = np.float32([kp_image[m.queryIdx].pt for m in
good_points]).reshape(-1, 1, 2)
train_pts = np.float32([kp_grayframe[m.trainIdx].pt for m in
good_points]).reshape(-1, 1, 2)
matrix, mask = cv2.findHomography(query_pts, train_pts, cv2.RANSAC, 5.0)
matches_mask = mask.ravel().tolist()
```

Finally we do the perspective transform using the points and the matrix.

```
# Perspective transform
h, w = img.shape
pts = np.float32([[0, 0], [0, h], [w, h], [w, 0]]).reshape(-1, 1, 2)
dst = cv2.perspectiveTransform(pts, matrix)
```

And at the end we can **show the result on the screen**.

```
homography = cv2.polylines(frame, [np.int32(dst)], True, (255, 0, 0), 3)
cv2.imshow("Homography", homography)
```


Homography

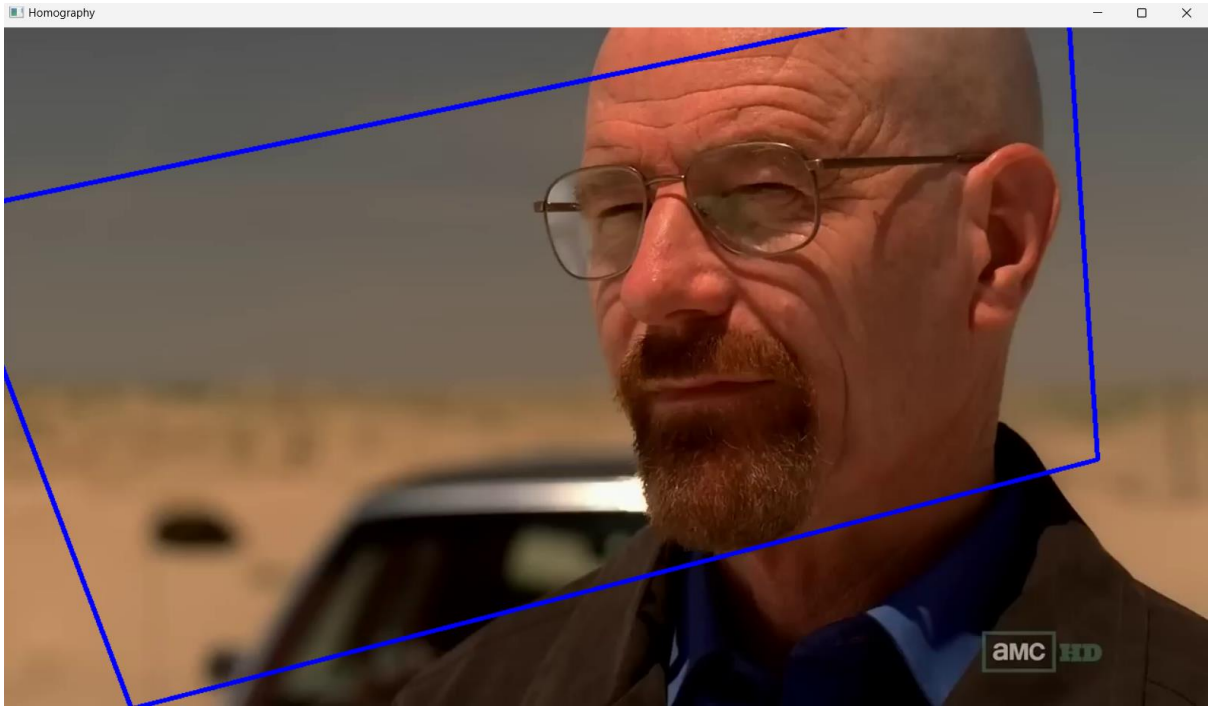
**Code:**

5c.py - C:\MScITPracs\OpenCV\OpenCV\CV\5c.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import numpy as np

img = cv2.imread("MyName.png", cv2.IMREAD_GRAYSCALE)
cap = cv2.VideoCapture("Say My Name.mp4")

sift = cv2.SIFT_create()
kp_image, desc_image = sift.detectAndCompute(img, None)

index_params = dict(algorithm=0, trees=5)
search_params = dict()
flann = cv2.FlannBasedMatcher(index_params, search_params)
_, frame = cap.read()
grayframe = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
kp_grayframe, desc_grayframe = sift.detectAndCompute(grayframe, None)
matches = flann.knnMatch(desc_image, desc_grayframe, k=2)
good_points = []
for m, n in matches:
    if m.distance < 0.6 * n.distance:
        good_points.append(m)
query_pts = np.float32([kp_image[m.queryIdx].pt for m in good_points]).reshape(-1, 1, 2)
train_pts = np.float32([kp_grayframe[m.trainIdx].pt for m in good_points]).reshape(-1, 1, 2)
matrix, mask = cv2.findHomography(query_pts, train_pts, cv2.RANSAC, 5.0)
matches_mask = mask.ravel().tolist()

h, w = img.shape
pts = np.float32([[0, 0], [0, h], [w, h], [w, 0]]).reshape(-1, 1, 2)
dst = cv2.perspectiveTransform(pts, matrix)
homography = cv2.polylines(frame, [np.int32(dst)], True, (255, 0, 0), 3)
cv2.imshow("Homography", homography)
```

## Output:



# PRACTICAL NO: 6

**Aim: Perform Colorization.**

**Theory:**

We'll create a program to convert a black & white image i.e grayscale image to a colour image. We're going to use the **Caffe colourization model** for this program. And you should be familiar with basic OpenCV functions and uses like reading an image or how to load a pre-trained model using dnn module etc.

The procedure that we'll follow to implement the program:

**Steps:**

1. Load the model and the **convolution/kernel points**
2. Read and preprocess the image
3. Generate model predictions using the **L channel** from our input Image
4. Use the output -> **ab channel** to create a resulting image

*What is the L channel and ab channel?* Basically like **RGB** colour space, there is something similar, known as **Lab colour space**. And this is the basis on which our program is based. Let's discuss what it is briefly:

**What is Lab Colour Space?**

Like RGB, lab colour has 3 channels L, a, and b. But here instead of pixel values, these have different significances i.e :

- **L-channel:** light intensity
- **a channel:** green-red encoding
- **b channel:** blue-red encoding

And In our program, we'll use the L channel of our image as input to our model to predict ab channel values and then rejoin it with the L channel to generate our final image.

Automatic colorization of photos using deep neural networks is a technology that can add color to black and white photos without the need for manual coloring. This technology uses deep neural networks that have been trained on

large datasets of color images to learn the relationship between luminance and color, which can then be used to predict the color channels of grayscale images. This technique has many applications, including restoring old photos and enhancing the visual appeal of images.

## Background

Before the advent of computer technology, adding color to a black-and-white photograph was a manual and time-consuming process that required skilled artists. With the introduction of automated colorization methods, the process became quicker but often inaccurate and still required manual intervention.

Deep neural networks are a type of machine learning algorithm inspired by the human brain, and they have made it possible to automatically colorize black-and-white photographs with high accuracy and speed. These networks are trained on large datasets of color images and use what they learned to generate plausible colorizations for grayscale images. Using deep neural networks for automatic colorization has many practical applications, such as restoring old photographs, enhancing medical images, and creating realistic 3D models from 2D images.

## To implement it, follow the below steps.

1. We need to import some libraries that will be used in our implementation.

```
import numpy as np
```

```
import cv2
```

2. These are variables used in the code for the automatic colorization of photos using a deep neural network. “PROTOTXT” is a file that contains the network architecture, “POINTS” is a file that stores color space information, and “MODEL” is a pre-trained model file that contains the learned weights of the neural network.

```
PROTOTXT = &quot;colorization_deploy_v2.prototxt&quot;
```

```
POINTS = &quot;pts_in_hull.npy&quot;
```

```
MODEL = &quot;colorization_release_v2.caffemodel&quot;
```

3. These lines of code load the pre-trained colorization model and the corresponding points used for color mapping into the program. The model and

points are stored in files, which are read and loaded into the program using the OpenCV library and the numpy library, respectively.

```
net = cv2.dnn.readNetFromCaffe(PROTOTXT, MODEL)

pts = np.load(POINTS)
```

4. This code sets up the pre-trained neural network by obtaining the layer IDs for class8 and conv8. It then reshapes the "pts" variable to match the dimensions of the layers and sets the layer blobs to the reshaped "pts" array and a 313×1 array filled with the scalar value of

2.606.

```
class8 = net.getLayerId(&amp;quot;class8_ab&amp;quot;)

conv8 = net.getLayerId(&amp;quot;conv8_313_rh&amp;quot;)

pts = pts.transpose().reshape(2, 313, 1, 1)

net.getLayer(class8).blobs =
[pts.astype(&amp;quot;float32&amp;quot;)]

net.getLayer(conv8).blobs = [np.full([1, 313], 2.606,
dtype=&amp;quot;float32&amp;quot;)]
```

5. The code reads an image file named "flower.jpg" using OpenCV and scales the pixel values to a range between 0 and 1. The image is then converted from BGR to LAB color space using cv2.cvtColor(). Finally, the image is resized to 224×224 pixels using cv2.resize().

```
image = cv2.imread(&amp;quot;flower.jpg&amp;quot;)

scaled = image.astype(&amp;quot;float32&amp;quot;) / 255.0

lab = cv2.cvtColor(scaled, cv2.COLOR_BGR2LAB)

resized = cv2.resize(lab, (224, 224))
```

6. In this code, the L channel of the resized LAB image is extracted using cv2.split(), and then its pixel values are subtracted by 50.

```
L = cv2.split(resized)[0]

L -= 50
```

7. The grayscale image "L" is fed into the pre-trained neural network using the setInput function to produce an output array "ab". The output array is reshaped and resized to match the dimensions of the original image.

```
net.setInput(cv2.dnn.blobFromImage(L))
ab = net.forward()[0, :, :, :].transpose((1, 2, 0))
ab = cv2.resize(ab, (image.shape[1], image.shape[0]))
```

8. This code separates the L channel from a given LAB color image using OpenCV's "cv2.split" function.

```
L = cv2.split(lab)[0]
```

9. In this code, the colorized image is obtained by concatenating the L channel of the LAB color space with the predicted AB channels, converting the image back to the BGR color space, clipping the pixel values to lie between 0 and 1, and finally scaling the pixel values to the range of 0 to 255.

```
colorized = np.concatenate((L[:, :, np.newaxis], ab),
axis=2)
colorized = cv2.cvtColor(colorized, cv2.COLOR_LAB2BGR)
colorized = np.clip(colorized, 0, 1)
colorized = (255 * colorized).astype(&amp;quot;uint8&amp;quot;)
```

10. This code creates a window with a name, resizes it to match the size of the original image, and displays the colorized image in the window.

```
window_name = &amp;quot;Colorized Image By PythonGeeks&amp;quot;
cv2.namedWindow(window_name, cv2.WINDOW_NORMAL)
cv2.resizeWindow(window_name, image.shape[1],
image.shape[0])
cv2.imshow(window_name, colorized)
```

11. The code creates a window to display the original image with a specified name and size using OpenCV functions namedWindow and resizeWindow. Then, it shows the original image in the window using the imshow function.

```
cv2.namedWindow(&amp;quot;Original Image By PythonGeeks&amp;quot;,
cv2.WINDOW_NORMAL)
```

```
cv2.resizeWindow(&amp;quot;Original Image By
PythonGeeks&amp;quot;, image.shape[1], image.shape[0])

cv2.imshow(&amp;quot;Original Image By PythonGeeks&amp;quot;,
image)
```

12. This program waits indefinitely until a key is pressed. Argument 0 specifies that the program should wait indefinitely.

```
cv2.waitKey(0)
```

## Conclusion

Automated colorization using deep neural networks is a technique that uses pre-trained neural networks to automatically add color to grayscale images. This method is useful for image and video editing, restoration of historical media, and improving accessibility for individuals with visual impairments. The process involves converting the grayscale image to the LAB color space, predicting the color channels using the neural network, and merging them with the grayscale image to produce the final colorized image. Advancements in deep learning algorithms and large-scale datasets will likely lead to further advancements in this field.

## Code:

prac6.py - C:/MScITPracs/OpenCV/OpenCV/CV/prac6.py (3.11.6)

File Edit Format Run Options Window Help

```
import numpy as np
import cv2
from cv2 import dnn

# Model file paths
proto_file = 'colorization_deploy_v2.prototxt'
model_file = 'colorization_release_v2.caffemodel'
hull_pts = 'pts_in_hull.npy'
img_path = 'ansel_adams2.jpg'

# Reading the model parameters
net = dnn.readNetFromCaffe(proto_file, model_file)
kernel = np.load(hull_pts)

# Reading and preprocessing image
img = cv2.imread(img_path)
scaled = img.astype("float32") / 255.0
lab_img = cv2.cvtColor(scaled, cv2.COLOR_BGR2LAB)

# Add the cluster centers as 1x1 convolutions to the model
class8 = net.getLayerId("class8_ab")
conv8 = net.getLayerId("conv8_313_rh")
pts = kernel.transpose().reshape(2, 313, 1, 1)
net.getLayer(class8).blobs = [pts.astype("float32")]
net.getLayer(conv8).blobs = [np.full([1, 313], 2.606, dtype="float32")]

# Resize the image for the network
resized = cv2.resize(lab_img, (224, 224))

# Split the L channel
L = cv2.split(resized)[0]

# Mean subtraction
L -= 50
```

```
# Mean subtraction
L -= 50

# Predicting the ab channels from the input L channel
net.setInput(cv2.dnn.blobFromImage(L))
ab_channel = net.forward()[0, :, :, :].transpose((1, 2, 0))

# Resize the predicted 'ab' volume to the same dimensions as our input image
ab_channel = cv2.resize(ab_channel, (img.shape[1], img.shape[0]))

# Take the L channel from the image
L = cv2.split(lab_img)[0]

# Join the L channel with predicted ab channel
colorized = np.concatenate((L[:, :, np.newaxis], ab_channel), axis=2)

# Convert the image from Lab to BGR
colorized = cv2.cvtColor(colorized, cv2.COLOR_LAB2BGR)
colorized = np.clip(colorized, 0, 1)

# Change the image to 0-255 range and convert it from float32 to uint8
colorized = (255 * colorized).astype("uint8")

# Resize the images and show them together
img = cv2.resize(img, (640, 640))
colorized = cv2.resize(colorized, (640, 640))
result = cv2.hconcat([img, colorized])

cv2.imshow("Grayscale -> Colour", result)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

## Output:

# PRACTICAL NO: 7

**Aim: Perform Text Detection and Recognition.**

**Theory:**

**Required Installations:**

pip install opencv-python

pip install pytesseract

```
C:\Users\Om Solanki>pip install pytesseract
Collecting pytesseract
  Downloading pytesseract-0.3.10-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: packaging>=21.3 in c:\users\om solanki\appdata\local\programs\python\python311\lib\s
ackages (from pytesseract) (23.2)
Requirement already satisfied: Pillow>=8.0.0 in c:\users\om solanki\appdata\local\programs\python\python311\lib\sit
kages (from pytesseract) (10.1.0)
Downloading pytesseract-0.3.10-py3-none-any.whl (14 kB)
Installing collected packages: pytesseract
Successfully installed pytesseract-0.3.10

[notice] A new release of pip is available: 23.3.2 -> 24.0
[notice] To update, run: python.exe -m pip install --upgrade pip
```

Follow the instructions given in below Link:

https://builtin.com/articles/python-tesseract

OpenCV package is used to read an image and perform certain image processing techniques. Python-tesseract is a wrapper for Google's Tesseract-OCR Engine which is used to recognize text from images.

Python-tesseract is an optical character recognition (OCR) tool for python. That is, it will recognize and "read" the text embedded in images.

Python-tesseract is a wrapper for Google's Tesseract-OCR Engine. It is also useful as a stand-alone invocation script to tesseract, as it can read all image types supported by the Pillow and Leptonica imaging libraries, including jpeg, png, gif, bmp, tiff, and others. Additionally, if used as a script, Python-tesseract will print the recognized text instead of writing it to a file.

**Approach:**

After the necessary imports, a sample image is read using the imread function of opencv.

**Applying image processing for the image:**

The colorspace of the image is first changed and stored in a variable. For color conversion we use the function cv2.cvtColor(input_image, flag). The second

parameter flag determines the type of conversion. We can chose among cv2.COLOR_BGR2GRAY and cv2.COLOR_BGR2HSV. cv2.COLOR_BGR2GRAY helps us to convert an RGB image to gray scale image and cv2.COLOR_BGR2HSV is used to convert an RGB image to HSV

(Hue, Saturation, Value) color-space image. Here, we use cv2.COLOR_BGR2GRAY. A threshold is applied to the converted image using cv2.threshold function.

There are 3 types of thresholding:

1. Simple Thresholding

2. Adaptive Thresholding

3. Otsu's Binarization

For more information on thresholding, refer Thresholding techniques using OpenCV.

cv2.threshold() has 4 parameters, first parameter being the color-space changed image, followed by the minimum threshold value, the maximum threshold value and the type of thresholding that needs to be applied.

**To get a rectangular structure:**

cv2.getStructuringElement() is used to define a structural element like elliptical, circular, rectangular etc. Here, we use the rectangular structural element (cv2.MORPH_RECT). cv2.getStructuringElement takes an extra size of the kernel parameter. A bigger kernel would make group larger blocks of texts together. After choosing the correct kernel, dilation is applied to the image with cv2.dilate function. Dilation makes the groups of text to be detected more accurately since it dilates (expands) a text block.

**Finding Contours:**

cv2.findContours() is used to find contours in the dilated image. There are three arguments in cv.findContours(): the source image, the contour retrieval mode and the contour approximation method.

This function returns contours and hierarchy. Contours is a python list of all the contours in the image. Each contour is a Numpy array of (x, y) coordinates of boundary points in the object. Contours are typically used to find a white object from a black background. All the above image processing techniques are applied so that the Contours can detect the boundary edges of the blocks of text

of the image. A text file is opened in write mode and flushed. This text file is opened to save the text from the output of the OCR.

## Applying OCR:

Loop through each contour and take the x and y coordinates and the width and height using the function cv2.boundingRect(). Then draw a rectangle in the image using the function cv2.rectangle() with the help of obtained x and y coordinates and the width and height. There are 5 parameters in the cv2.rectangle(), the first parameter specifies the input image, followed by the x and y coordinates (starting coordinates of the rectangle), the ending coordinates of the rectangle which is (x+w, y+h), the boundary color for the rectangle in RGB value and the size of the boundary. Now crop the rectangular region and then pass it to the tesseract to extract the text from the image. Then we open the created text file in append mode to append the obtained text and close the file.

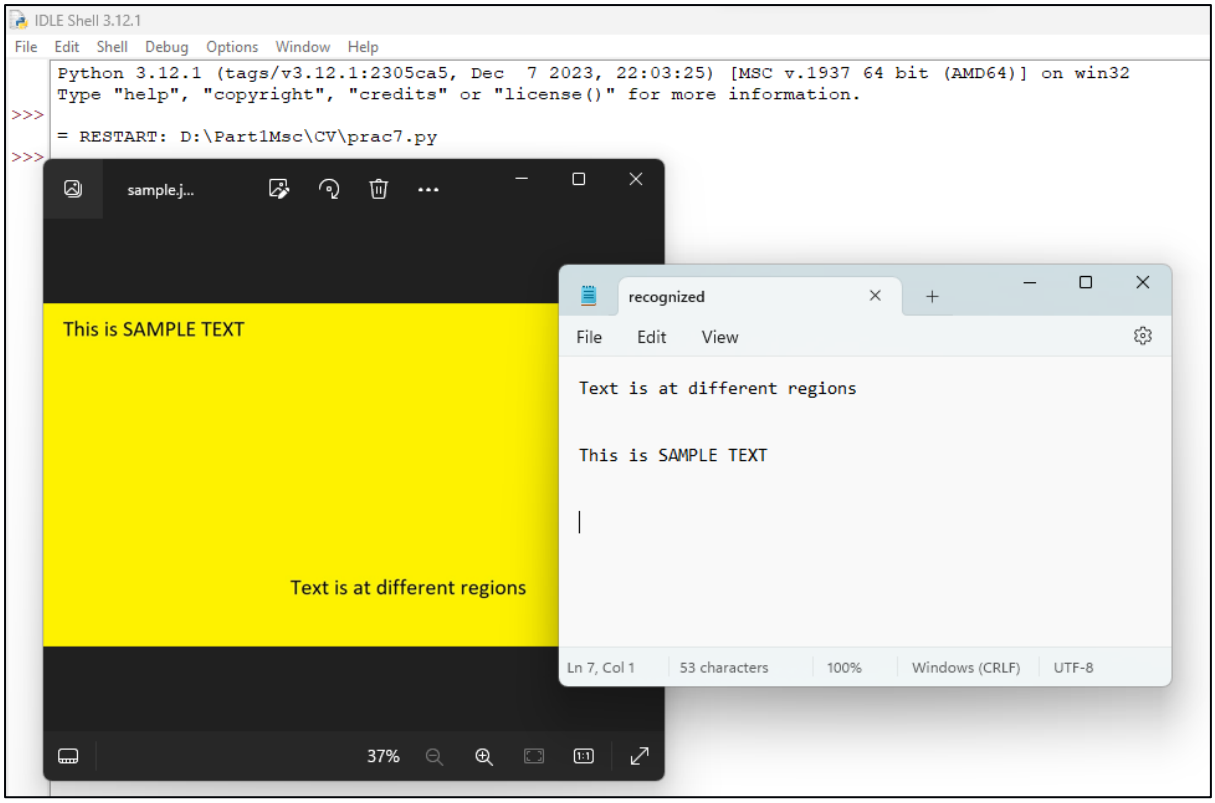
## Code:

prac7.py - C:\MScITPracs\OpenCV\OpenCV\CV\prac7.py (3.11.6)

File Edit Format Run Options Window Help

```
import cv2
import pytesseract

pytesseract.pytesseract.tesseract_cmd = 'C:\\Program Files\\Tesseract-OCR\\tesseract.exe'

img = cv2.imread('sample.jpg')

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

ret, thresh1 = cv2.threshold(gray, 0, 255, cv2.THRESH_OTSU | cv2.THRESH_BINARY_INV)

rect_kernel = cv2.getStructuringElement(cv2.MORPH_RECT,(18,18))

dilation= cv2.dilate(thresh1, rect_kernel, iterations = 1)


contours, hierarchy = cv2.findContours(dilation,cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NONE)

im2 = img.copy()

file = open('recognized.txt','w+')
file.write("")
file.close()

for cnt in contours:
    x,y,w,h = cv2.boundingRect(cnt)
    rect = cv2.rectangle(im2, (x,y), (x+w,y+h), (0,255,0),2)
    cropped = im2[y:y+h,x:x+w]

    file = open('recognized.txt','a')
    text = pytesseract.image_to_string(cropped)
    file.write(text)
    file.write("\n")

    file.close()
```

## Output:


IDLE Shell 3.12.1
File Edit Shell Debug Options Window Help
Python 3.12.1 (tags/v3.12.1:2305ca5, Dec 7 2023, 22:03:25) [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: D:\Part1Msc\CV\prac7.py
>>>
sample.j...
This is SAMPLE TEXT
Text is at different regions
37%
recognized
File Edit View
Text is at different regions
This is SAMPLE TEXT
Ln 7, Col 1
53 characters
100%
Windows (CRLF)
UTF-8

# Practical No: 8

**Aim: Construct 3D model from Images.**

**Theory:**

Transforming a 2D image into a 3D environment requires depth estimation, which can be a difficult operation depending on the amount of precision and information required. OpenCV supports a variety of depth estimation approaches, including stereo vision and depth from focus/defocus.

**In this practical we'll see a basic technique utilizing stereovision:**

**Transform a 2D image into a 3D space using OpenCV**

Transforming a 2D image into a 3D space using OpenCV refers to the process of converting a two-dimensional image into a three-dimensional spatial representation using the Open Source Computer Vision Library (OpenCV). This transformation involves inferring the depth information from the 2D image, typically through techniques such as stereo vision, depth estimation, or other computer vision algorithms, to create a 3D model with depth perception. This process enables various applications such as 3D reconstruction, depth sensing, and augmented reality.

**Importance of transformations of a 2D image into a 3D space**

Transforming 2D images into 3D space becomes crucial in various fields due to its numerous applications and benefits:

**Depth Perception:** We are able to detect depth by transforming 2D pictures into 3D space. This makes it possible to use augmented reality, object recognition, and scene understanding.

**3D Reconstruction:** Converting 2D photos into 3D space makes it easier to recreate 3D scenes, which is crucial in industries like robotics, computer vision, and the preservation of cultural assets.

**Stereo Vision:** Stereo vision depends on converting 2D images into 3D space. It entails taking pictures from various angles and calculating depth from the difference between matching spots. It is employed in 3D modeling, autonomous navigation, and depth sensing, among other applications.

**Medical Imaging:** Improved visualization, diagnosis, and treatment planning are possible in medical imaging when 2D medical scans—such as CT or MRI scans—are converted into 3D space.

**Virtual Reality and Simulation:** In virtual reality, simulation, and gaming, realistic 3D worlds must be constructed from 2D photos or video. This requires translating 2D visuals into 3D space.

**How you get a 3D image from a 2D?**

In conventional photography, you can either utilize a mirror and attach a camera to it to create an immediate 3D effect, or you can take a shot, step to your right (or left), and then shoot another, ensuring that all components from the first photo are present in the second.

However, if you just move a 2D picture left by 10 pixels, nothing changes. This is because you are shifting the entire environment, and no 3D information is saved.

Instead, there must be a bigger shift distance between the foreground and backdrop. In other words, the farthest point distant from the lens remains motionless while the nearest point moves.

**How is this related to using a 2D image to create a 3D image?**

We need a method to move the pixels since an picture becomes three-dimensional when the foreground moves more than the background. Fortunately, a technique known as depth detection exists that generates what is known as a depth map.

Now remember that this is only an estimate. Furthermore, it won't reach every nook and corner. All that depth detection does is use cues like shadows, haze, and depth of focus to determine if an object is in the forefront or background.

We can instruct a program on how far to move pixels now that we have a depth map.

**Approach:**

- **Obtain Stereo Images:** Take or obtain two pictures of the same scene taken from two separate perspectives.

- **Stereo Calibration:** For precise depth estimation, ascertain each camera's intrinsic and extrinsic properties.

- **Rectification:** To make matching easier, make sure corresponding spots in stereo pictures line up on the same scanlines.

- **Stereo matching:** Use methods such as block matching or SGBM to find correspondences between corrected stereo pictures.

- **Disparity**: Calculate the disparity by dividing the horizontal locations of corresponding points by their pixels.

- **Depth Estimation:** Using camera settings and stereo geometry,

convert disparity map to depth map.

- 3D Reconstruction: Using the depth map as a guide, reconstruct the scene's three dimensions.

**Implementations of a 2D image into a 3D space Transformations**

using OpenCV

Input image:

- cube 1
- cube 2

Code steps:

- First we have imported the required libraries.
  - PIL (Python Imaging Library), which is used to work with images
  - numpy is used for numerical computations

Then we have defined a function named `shift_image` that takes three parameters: `img`, `depth_img`, and `shift_amount`. `img` is the base image that will be shifted, `depth_img` is the depth map providing depth information for the shift, and `shift_amount`specifies the maximum amount of horizontal shift allowed.

- After that we have converted the input images (`img` and `depth_img`) into arrays using NumPy for further processing.

- The base image (img) is converted to RGBA format to ensure it has an alpha channel, while the depth image (depth_img) is converted to grayscale (`L`) to ensure it contains only one channel representing depth values.
- Then calculates the shift amounts based on the depth values obtained from the depth image. It scales the depth values to the range [0, 1] and then multiplies it by the `shift_amount`. The result is then converted to integers using `astype(int)`.
- Then initializes an array (`shifted_data`) with the same shape as the base image (`data`) filled with zeros. This array will store the shifted image data.
- The nested loops iterate over the elements of the `deltas` array to perform the shift operation. For each pixel position (x, y) in the base image, the corresponding shift amount `dx` is applied horizontally. If the resulting position (x + dx, y) is within the bounds of the image, the pixel value at (x, y) in the base image is copied to (x + dx, y) in the shifted image.
- Image.fromarray converts the shifted image data (`shifted_data`) back to a PIL Image object. The data is converted to np.uint8 type before creating the image.
- Then we read the images from our local files and applied to the newly created functions.
- shifted_img.show will plot the newly transformed image

**Limitations of OpenCV to 2D image into a 3D space image tranformations**

The process of simulating a 3D effect by shifting pixels based on depth information has several limitations also:

- **Simplified Depth Representation:** Since the depth map is a grayscale picture, intricate depth fluctuations might not be properly captured.

  It Only moves pixels horizontally, assuming that all depth fluctuations are horizontal. This assumption might not hold true in scenarios found in the actual world.

- **Uniform Shift Amount:** Unrealistic effects may result from the linear connection between depth and pixel shift, which may not adequately reflect real-world depth perception.
- **Limited Depth Cues:** It does not use other depth cues such as perspective distortion or occlusion, instead depending solely on the parallax effect.
- **Boundary Artifacts:** Boundary artifacts may arise from the disregard of pixels that have been pushed outside the limits of the picture.
- **Dependency on Parameter:** The shift amount parameter that is selected has a significant impact on the 3D effect's quality.

- **Limited Application Scope:** Although it works well for basic 3D effects, it might not be accurate enough for complex 3D activities like medical imaging or augmented reality.

## Code:

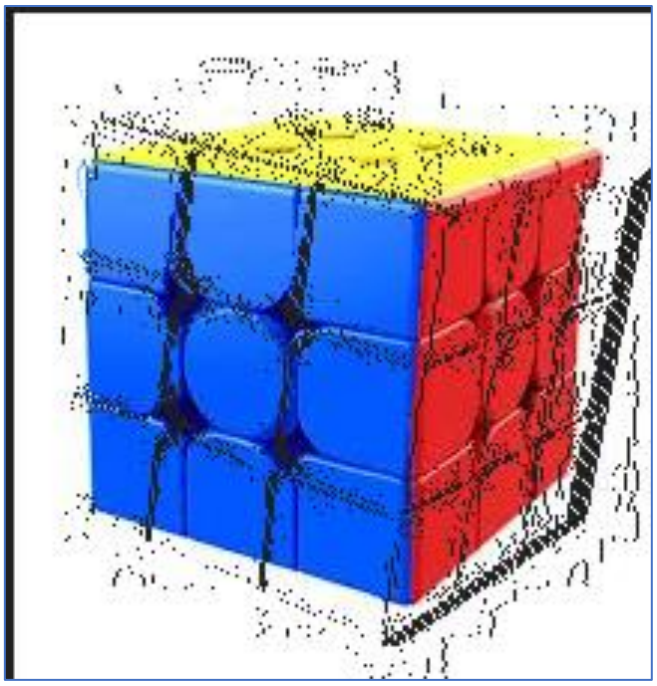
prac8.py - C:/MScITPracs/OpenCV/OpenCV/CV/prac8.py (3.11.6)

File Edit Format Run Options Window Help

```
from PIL import Image
import numpy as np
import os

def shift_image(img, depth_img, shift_amount=10):
    # Ensure base image has alpha
    img = img.convert("RGBA")
    data = np.array(img)

    # Ensure depth image is grayscale (for single value)
    depth_img = depth_img.convert("L")
    depth_data = np.array(depth_img)

    # Calculate deltas for shifting
    deltas = ((depth_data / 255.0) * float(shift_amount)).astype(int)

    # Create the transparent resulting image with the same shape as the original image
    shifted_data = np.zeros_like(data)
    height, width, _ = data.shape

    # Shift the image pixels based on depth data
    for y, row in enumerate(deltas):
        for x, dx in enumerate(row):
            if x + dx < width and x + dx >= 0:
                shifted_data[y, x + dx] = data[y, x]

    # Convert the pixel data to an image
    shifted_image = Image.fromarray(shifted_data.astype(np.uint8))
    return shifted_image

# Load the images
img = Image.open("cubel.jpeg")
depth_img = Image.open("cube2.jpeg")

# Shift the image based on depth image
shifted_img = shift_image(img, depth_img, shift_amount=10)
```

```
# Load the images
img = Image.open("cubel.jpeg")
depth_img = Image.open("cube2.jpeg")

# Shift the image based on depth image
shifted_img = shift_image(img, depth_img, shift_amount=10)

# Show the shifted image
shifted_img.show()
```

## Output:



# PRACTICAL NO: 9

## Aim: Perform Feature extraction using RANSAC.

## Theory:

Image registration is a digital image processing technique that helps us align different images of the same scene. For instance, one may click the picture of a book from various angles. Below are a few instances that show the diversity of camera angles.

Now, we may want to "align" a particular image to the same angle as a reference image. In the images above, one may consider the first image to be an "ideal" cover photo, while the second and third images do not serve well for book cover photo purposes. The image registration algorithm helps us align the second and third pictures to the same plane as the first one.

### How does image registration work?

Alignment can be looked at as a simple coordinate transform. The algorithm works as follows:

- Convert both images to grayscale.
- Match features from the image to be aligned, to the reference image and store the coordinates of the corresponding key points. Keypoints are simply the selected few points that are used to compute the transform (generally points that stand out), and descriptors are histograms of the image gradients to characterize the appearance of a keypoint. In this post, we use ORB (Oriented FAST and Rotated BRIEF) implementation in the OpenCV library, which provides us with both key points as well as their associated descriptors.
- Match the key points between the two images. In this post, we use BFMatcher, which is a brute force matcher. BFMatcher.match() retrieves the best match, while BFMatcher.knnMatch() retrieves top K matches, where K is specified by the user.
- Pick the top matches, and remove the noisy matches.
- Find the homomorphy transform.
- Apply this transform to the original unaligned image to get the output image.

### Applications of Image Registration –

Some of the useful applications of image registration include:

- Stitching various scenes (which may or may not have the same camera alignment) together to form a continuous panoramic shot.
- Aligning camera images of documents to a standard alignment

to create realistic scanned documents.

- Aligning medical images for better observation and analysis.

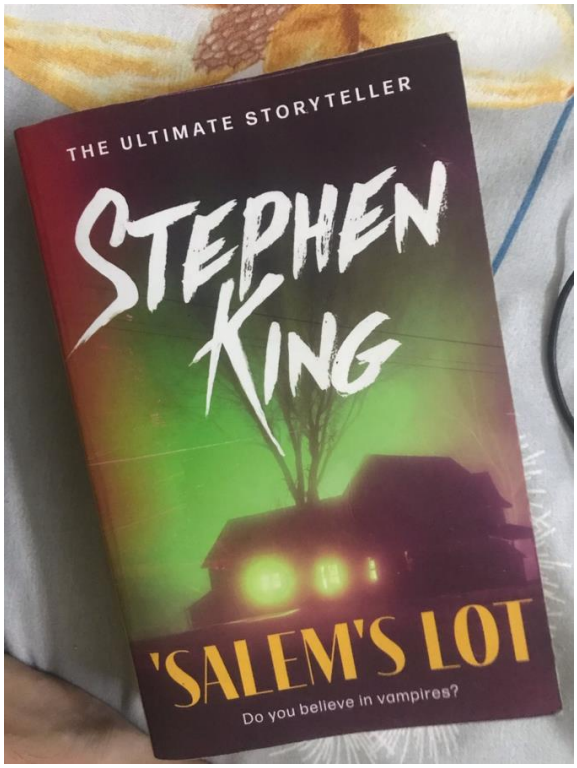
## Code:

Prac9.py - C:/MScITPracs/OpenCV/OpenCV/CV/Prac9.py (3.11.6)

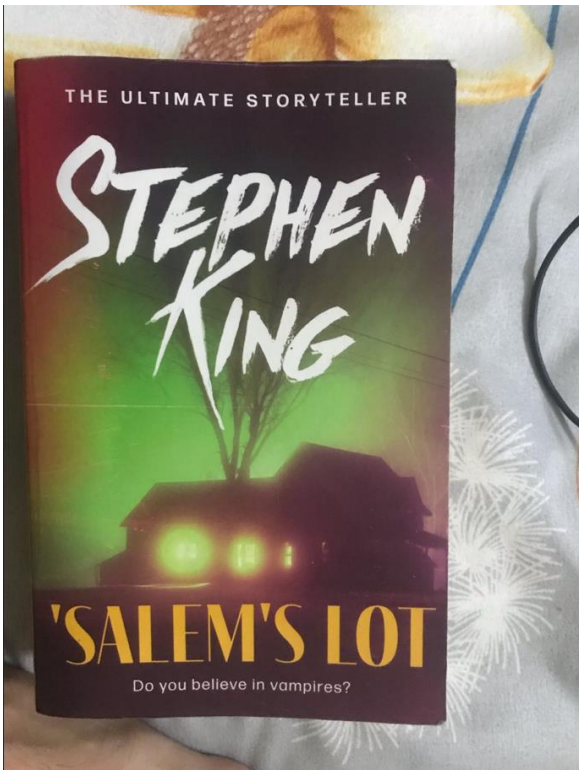
File Edit Format Run Options Window Help

```
import cv2
import numpy as np

img1_color = cv2.imread("slant.jpeg")
img2_color = cv2.imread("straight.jpeg")

img1 = cv2.cvtColor(img1_color, cv2.COLOR_BGR2GRAY)
img2 = cv2.cvtColor(img2_color, cv2.COLOR_BGR2GRAY)
height, width = img2.shape

orb_detector = cv2.ORB_create(5000)

kp1, d1 = orb_detector.detectAndCompute(img1, None)
kp2, d2 = orb_detector.detectAndCompute(img2, None)

matcher = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True)

matches = matcher.match(d1, d2)

matches = sorted(matches, key = lambda x:x.distance)

matches = matches[:int(len(matches)*0.9)]
no_of_matches = len(matches)

p1 = np.zeros((no_of_matches,2))
p2 = np.zeros((no_of_matches,2))

for i in range(len(matches)):
    p1[i, :] = kp1[matches[i].queryIdx].pt
    p2[i, :] = kp2[matches[i].trainIdx].pt

homography, mask = cv2.findHomography(p1, p2, cv2.RANSAC)

transformed_img = cv2.warpPerspective(img1_color, homography, (width, height))

cv2.imwrite('output.jpg',transformed_img)
```

**Input:**




**Slant.jpeg**




**Straight.jpeg**

**Output:**