

PURDUE UNIVERSITY

ECE 661 COMPUTER VISION

HOMEWORK 3

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TASK 1.1 : POINT-TO-POINT CORRESPONDENCE METHOD

The task for the first part of the question is to remove distortion using a Point-to-Point Correspondence approach. For this we use the approach we adopted in the solution for homework 2 of this course.

SOLUTION

From the program's perspective, we can split the task into these separate tasks:

1. Write code to easily pick the four coordinates which collectively form the region of interest (ROI) in the image.
2. Form ROI using the given world plane measurements.
3. Calculate point-to-point homography using the two corresponding ROIs
4. Use the newly found mapping to determine new pixel value for the resulting image.

Once we know the broad tasks at hand, we can work on the logic for each part. The first task, then, would be to calculate the homography. Let the point **A** on the worl plane **PQRS** be denoted by the HC representation $(x,y,1)$. That is to say that the point **A** has the coordinates (x,y) in the physical plane **PQRS**. Let the corresponding point **B** on the image plane **ABCD** be denoted by the HC representation $(x',y',1)$. That is to say that the point **B** has the coordinates (x',y') in the physical image plane **ABCD**. We can say that for a particular homography **H** there exists the relation $AH=B$. Let us consider the general homography matrix representation:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} = 1 \end{bmatrix}$$

The last element is 1 because the homography matrix is homogeneous and non singular. By taking it as 1, we make sure the last row does not become $(0,0,0)$ and also the ratio is maintained. So by taking it as 1 we preserve the information. From the equation $AH=B$ we get:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$$

Solving the above equation we get the following three equations:

$$\begin{aligned} a_{11}x + a_{12}y + a_{13} &= x' \\ a_{21}x + a_{22}y + a_{23} &= y' \\ a_{31}x + a_{32}y + 1 &= 1 \end{aligned}$$

Dividing the first equation by 1 on both sides we get:

$$\frac{a_{11}x + a_{12}y + a_{13}}{1} = \frac{x'}{1}$$

This can be written as:

$$\frac{a_{11}x + a_{12}y + a_{13}}{a_{31}x + a_{32}y + 1} = \frac{x'}{1}$$

Because

$$a_{31}x + a_{32}y + a_{33} = 1$$

Similarly for the second equation we get:

$$\frac{a_{21}x + a_{22}y + a_{23}}{a_{31}x + a_{32}y + 1} = \frac{y'}{1}$$

After simplification we get the following two equations to solve:

$$a_{11}x + a_{12}y + a_{13} = a_{31}xx' + a_{32}yx' + x'$$

$$a_{21}x + a_{22}y + a_{23} = a_{31}xy' + a_{32}yy' + y'$$

These can be written in the form:

$$x' = a_{11}x + a_{12}y + a_{13} - a_{31}xx' - a_{32}yx'$$

$$y' = a_{21}x + a_{22}y + a_{23} - a_{31}xy' - a_{32}yy'$$

A system with 8 unknowns needs at least 8 equations to solve. Let us take three more pairs of equations which describe the correspondence between the pair of points (x_1, y_1) and (x'_1, y'_1) , (x_2, y_2) and (x'_2, y'_2) , (x_3, y_3) and (x'_3, y'_3) .

Thus, we now have a total of 8 equations representing the correspondence between the points (x, y) and (x', y') , (x_1, y_1) and (x'_1, y'_1) , (x_2, y_2) and (x'_2, y'_2) , (x_3, y_3) and (x'_3, y'_3) . Writing the 8 equations in matrix form:

$$\begin{bmatrix} x & y & 1 & 0 & 0 & 0 & -xx' & yx' \\ 0 & 0 & 0 & x & y & 1 & -xy' & yy' \\ x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x'_1 & y_1x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y'_1 & y_1y'_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2x'_2 & y_2x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2y'_2 & y_2y'_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3x'_3 & y_3x'_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3y'_3 & y_3y'_3 \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{21} \\ a_{22} \\ a_{23} \\ a_{31} \\ a_{32} \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ x'_3 \\ y'_3 \end{bmatrix}$$

By solving the above equation for the values of the H matrix we can then rearrange the terms to arrive at the final 3X3 H matrix:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix}$$

Once we have a way to map the pixels, all that is left is to find the actual pixel value for each newly mapped pixel. We know that each pixel has to be located at a specific integer coordinate value. For any point A located at (x, y) in the physical plane, we know that:

$$x, y \in \text{Integers}$$

For any point A (x, y) on the physical world plane **PQRS** we can find the corresponding coordinate on the image plane **ABCD** : B (x', y') using the relation:

$$AH = B$$

Unlike the previous solution (in homework 2), we use the inverse homography because we are mapping points from the image plane to the world plane. Therefore the final relation we are looking at is:

$$A = H^{-1}B$$

Note that we form the ROIs for the world image plane using the given measurements. The given measurements are in centimeters. For the purpose of this solution we assume that each pixel measures one centimeter in both height width. Therefore the ROI of the world image is formed in the following way:

- Point one = (0,0)
- Point two = (width,0)
- Point three = (0,height)
- Point four = (width,height)

WEIGHTED PIXEL VALUES

This was presented in the solution for homework 2. I am writing it here again because it is relevant for our solution for homework 3.

Once we find the mapping between the world image plane and the source image plane, we get the coordinates of the pixels whose pixel values we need to form the newly transformed image. It is highly likely that the resulting (x',y') value will be float values and not Integer values. But we cannot use the float value coordinates because such a location does not exist on the image plane **ABCD**. Consequently we cannot get the pixel value of such a point. A workaround for this is to find the weighted pixel value of the point using the pixel values of the surrounding pixels as reference values.

Consider four pixels

$$p_1, p_2, p_3, p_4$$

. The pixel values are

$$pv_1, pv_2, pv_3, pv_4$$

The pixels are such that they form a square around the point (x',y'). That is to say that these four pixels are four of the closest pixels around point B (x',y') that form a square. Therefore, the coordinates of the pixels would be:

$$\begin{aligned} p_1 &: (\text{floor}(x'), \text{floor}(y')) \\ p_2 &: (\text{floor}(x'), \text{ceil}(y')) \\ p_3 &: (\text{ceil}(x'), \text{ceil}(y')) \\ p_4 &: (\text{ceil}(x'), \text{floor}(y')) \end{aligned}$$

Where floor() function floors the value of x' or y' to the highest Integer value less than x' or y'. Ceil function ceils the value of x' or y' to the lowest Integer value higher than x' or y'. Next, let us take

$$dist_1, dist_2, dist_3, dist_4$$

as the distance between the pixels

$$p_1, p_2, p_3, p_4$$

from the point B at (x',y'). Then the weighted pixel value of the coordinate (x',y') is given by the equation:

$$pv_{(x',y')} = \frac{dist_1(pv_1) + dist_2(pv_2) + dist_3(pv_3) + dist_4(pv_4)}{dist_1 + dist_2 + dist_3 + dist_4}$$

Now, we can say that for every point **A** at (x,y) on the plane **PQRS** we have corresponding point **B** on the plane **ABCD** whose pixel value is

$$pv_{(x',y')}$$

We then construct the new image pixel by pixel. If, the calculated (x',y') lies outside the plane **ABCD** then we assign a RGB value of [0,0,0] to that pixel (black). Else we calculate the weighted pixel value at (x',y') and use that value for the new pixel in the result image.

TASK 1.2 - TWO-STEP METHOD

The two step approach we need to take involves the following tasks:

- **Task a :** Remove projective distortion using the vanishing line method. By removing projective distortion, we mean that we eliminate all the converging lines in the image which are supposed to be parallel in the world plane. We do this by mapping the vanishing line back to the line at infinity.

$$l_{vl} \rightarrow l_{\infty}$$

- **Task b :** Remove affine distortion using the cosine theta method. By removing the affine distortion we mean that we eliminate the angles between the parallel lines and make them orthogonal - just like how they are in the world image (reality). We use the known relation:

$$\cos(\theta) = \frac{L^T C_{\infty}^* M}{\sqrt{(L^T C_{\infty}^* L)(M^T C_{\infty}^* M)}}$$

TASK 1.2.A - REMOVING PROJECTIVE DISTORTION

To map the vanishing line back to the line at infinity, we first need to figure out a method to represent the vanishing line in equation. For this, we will need a total of two unique pairs of lines which strictly form two unique pairs of parallel lines in the real world. Because of projective distortion, we know that the original parallel lines in the real world will appear to be converging at a point (known as the vanishing point). Therefore, two such pairs will converge at two unique vanishing points. By knowing the two vanishing points, we have essentially found the vanishing line as all vanishing points have to lie on the vanishing line.

Let us consider two points p_1 and p_2 which lie on a line l_1 in the image. We get the equation of the line l_1 using the relation:

$$l_1 = p_1 X p_2$$

Similarly for two such points p_3 and p_4 on a 'seemingly' parallel line l_2 we get the line using the relation:

$$l_2 = p_3 X p_4$$

The lines l_1 and l_2 converge at a point known as the vanishing point vp_1 then we have:

$$vp_1 = l_1 X l_2$$

The same can be applied to a set of four more points which lie on a pair (two each) of parallel lines (unique pair) l_3 and l_4 to get the second vanishing point vp_2 . Where we have the relation:

$$vp_2 = l_3 X l_4$$

Therefore, we can finally get the vanishing line representation using the relation:

$$l_{vl} = vp_1 X vp_2$$

If vl_1 , vl_2 and vl_3 are the parameters that represent the vanishing line l_{vl} then we have the homography matrix H which maps the vanishing line back to the line at infinity given by:

$$H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ vl_1 & vl_2 & vl_3 \end{bmatrix}$$

Where we have $l_{vl} = [vl_1 \ vl_2 \ vl_3]^T$

By obtaining the H matrix as shown above, we create an image with no projective distortion. Of course, we will need to use the inverse H matrix H^{-1} because we are mapping from the image plane to the world plane.

TASK 1.2.B - REMOVING AFFINE DISTORTION

Once we remove the projective distortion from the image, we know that we have restored parallelism in the image. That is to say that we have effectively mapped the vanishing line back to the line at infinity. Now, we are left with parallel lines but their angles are distorted. This means that there is affine distortion in the image. Orthogonal expansion leads to affine distortion. Our task, by removing affine distortion, is to restore the orthogonality of the scene in the image. We do this by using the cosine theta method. By using the earlier mentioned relation:

$$\cos(\theta) = \frac{L^T C_\infty^* M}{\sqrt{(L^T C_\infty^* L)(M^T C_\infty^* M)}}$$

We, in essence, trace our steps back to find the homography by setting the θ value = 90 degrees. Therefore, we have $\cos(90) = 0$ and hence the equation becomes:

$$\frac{L^T C_\infty^* M}{\sqrt{(L^T C_\infty^* L)(M^T C_\infty^* M)}} = 0$$

We know that for an affine homography H , the conic transforms in the following way:

$$C_\infty^{*' *} = H C_\infty^* H^T$$

It is reasonable to say that in the cos equation, the numerator is equal to 0 since $\cos(\theta) = 0$. Therefore, we have:

$$L^T C_\infty^{*' *} M' = 0$$

Using the transform relation for the conic, we get:

$$L^T H C_\infty^* H^T M' = 0$$

Using the following relations:

$$C_\infty^* = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

and

$$H = \begin{bmatrix} A & 0 \\ 0 & 1 \end{bmatrix}$$

Also let us take the parameters of the line L as [a b c] and the parameters of the line M as [d e f]. Using the above relations, we simplify the equations to get:

$$HC_{\infty}^* H^T = \begin{bmatrix} AA^T & 0 \\ 0 & 0 \end{bmatrix}$$

The complete equation becomes:

$$[a \ b \ c] \begin{bmatrix} AA^T & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} d \\ e \\ f \end{bmatrix} = 0$$

We will need to denote AA^T as matrix S which is

$$S = \begin{bmatrix} s_a & s_b \\ s_b & s_c = 1 \end{bmatrix}$$

Note that s_c is 1 because the information is in the ratios. Division by 1 preserves the information as it preserves the ratio. Using that, we simplify the equation to get the following equation to solve:

$$s_a ad + s_b (ae + bd) + be = 0$$

The above equation has two variables: s_a and s_b . Therefore, we will need two equations, at least, to solve them. Hence, we will need to select two unique pairs of orthogonal lines. Using the two equations, we can calculate the matrix S. We know that $S = AA^T$. Since A is non-singular and positive definite, we can recover A by a SVD operation (singular value decomposition) where $A = VDV^T$. From the lecture notes, we will be able to justify that:

$$S = V \begin{bmatrix} \lambda_1^2 & 0 \\ 0 & \lambda_2^2 \end{bmatrix} V^T$$

Using this, we compute for A to finally form the matrix H which is:

$$H = \begin{bmatrix} A & 0 \\ 0 & 1 \end{bmatrix}$$

We transform the image using this homography multiplied with the projective homography. The coordinates used to calculate the orthogonal lines for this are first calculated based on how they were transformed when we applied projective homography to transform the image.

TASK 1.3 ONE STEP APPROACH

The one step approach makes use of the fact that the dual degenerate conic is represented in the form:

$$C_{\infty}' = \begin{bmatrix} a & b/2 & d/2 \\ b/2 & c & e/2 \\ d/2 & e/2 & f=1 \end{bmatrix}$$

Note that we have chosen to set the value of f as 1 because the information is in the ratios and by setting it to one, we preserve the ratio and hence the information. We now have the following variables to solve for: a, b, c, d, e . A total of 5 variables. Therefore, we will need to identify five orthogonal line pairs to solve for these 5 variables using the equation:

$$L^T C_{\infty}^{*'} M' = 0$$

Further, we find the combined homography by a similar SVD operation of $C_{\infty}^{*'} \text{ where the homography matrix } H \text{ is given by:}$

$$H = \begin{bmatrix} A & 0 \\ v^T & 1 \end{bmatrix}$$

The method is the same as mentioned in the two step method. Here:

$$S = AA^T$$

further,

$$S = \begin{bmatrix} a & b/2 \\ b/2 & c \end{bmatrix}$$

Once we estimate the homography matrix H , we transform the image to get rid of both the projective and affine distortion in one go.

RESULTS

The input images have been annotated with the points I used as inputs for the code. The yellow lines represent the points I used for the two step method and the one step method. The red lines represent the points I used for the Point-to-Point Correspondence method. We assume that one pixel is 1 cm for all purposes of this code. The measurements of the world plane are as follows:

- Input 1: Width 75cm, Height 85cm
- Input 2: Width 84cm, Height 74cm
- Input 3: Width 55cm, Height 36cm; I took only one of the three given measurements
- Input 4: Width 3.6cm, Height 3.6cm; For the purpose of scaling, I scaled it by a factor of 10
- Input 5: Width 40cm, Height 30cm;

REGARDING VECTORIZATION: In my source code I have clearly pointed out TWO instances where I have tried to implement some sort of vectorization to avoid the nested for loops. Both the attempts worked well. But the second instance consumed a lot of RAM. In the end I was forced to use the nested for loops to get the best results. But my code still has the functions where the vectorization attempts were made.

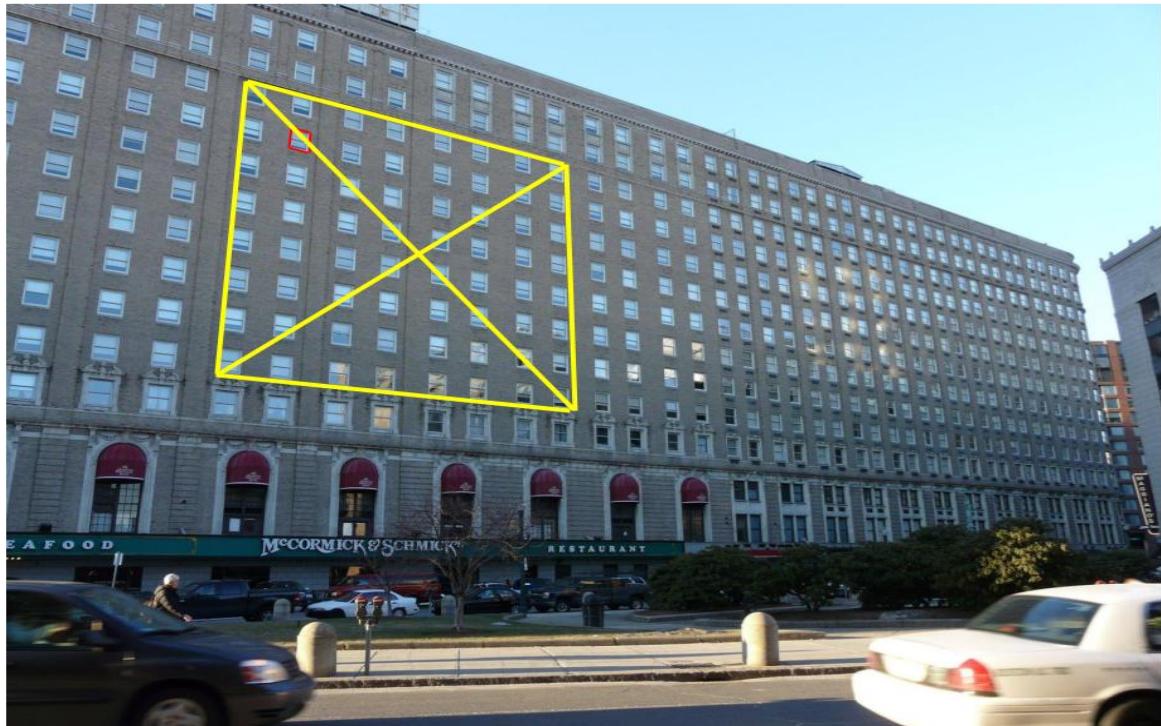


Figure 1: Input Image



Figure 2: Point to Point Correspondence Method



Figure 3: Two Step Method - Removing Projective Distortion Alone



Figure 4: Two Step Method - Removing both Projective and Affine Distortion



Figure 5: One Step Method - Removing both Projective and Affine Distortion



Figure 6: Input Image

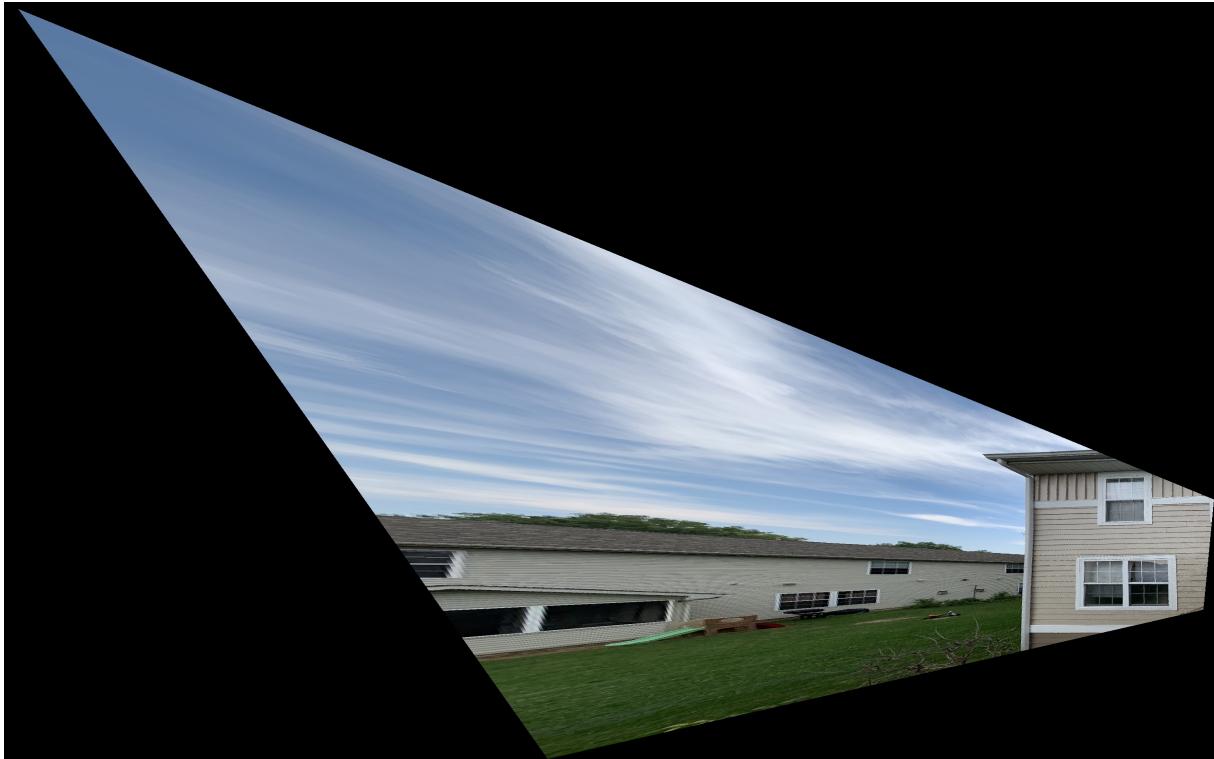


Figure 7: Point to Point Correspondence Method

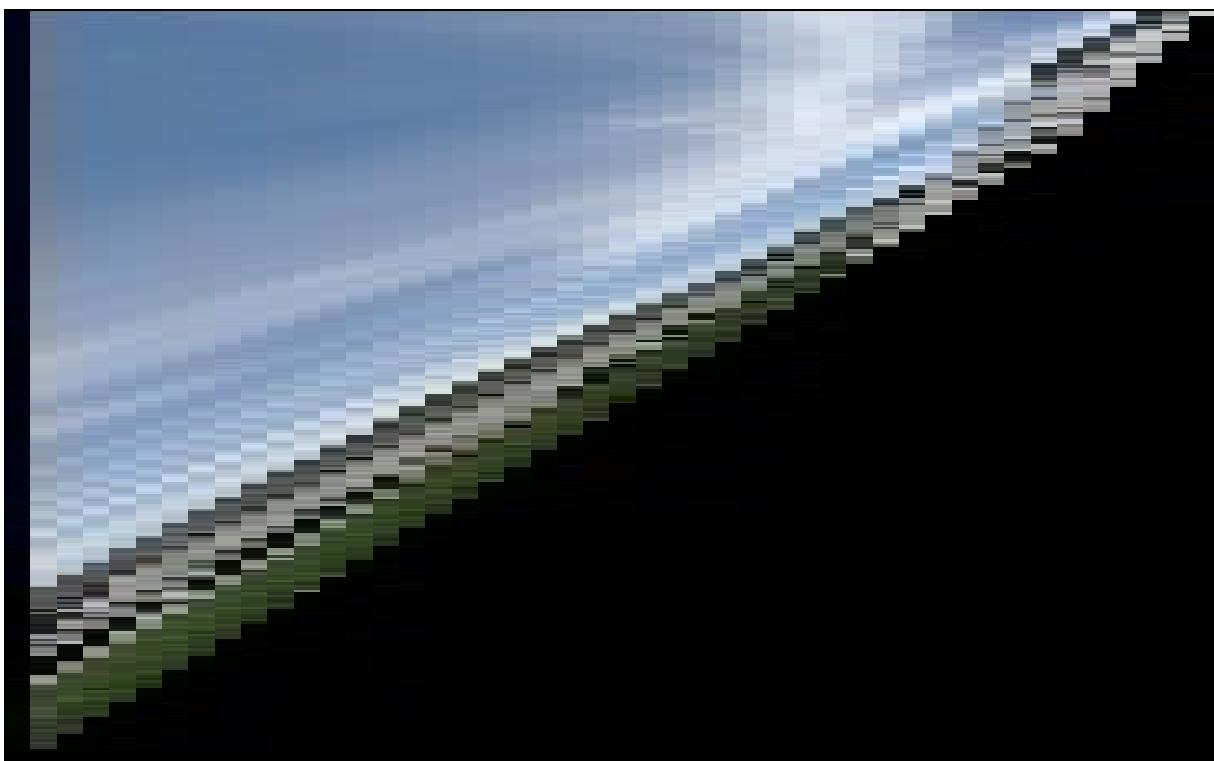


Figure 8: Two Step Method - Removing Projective Distortion Alone

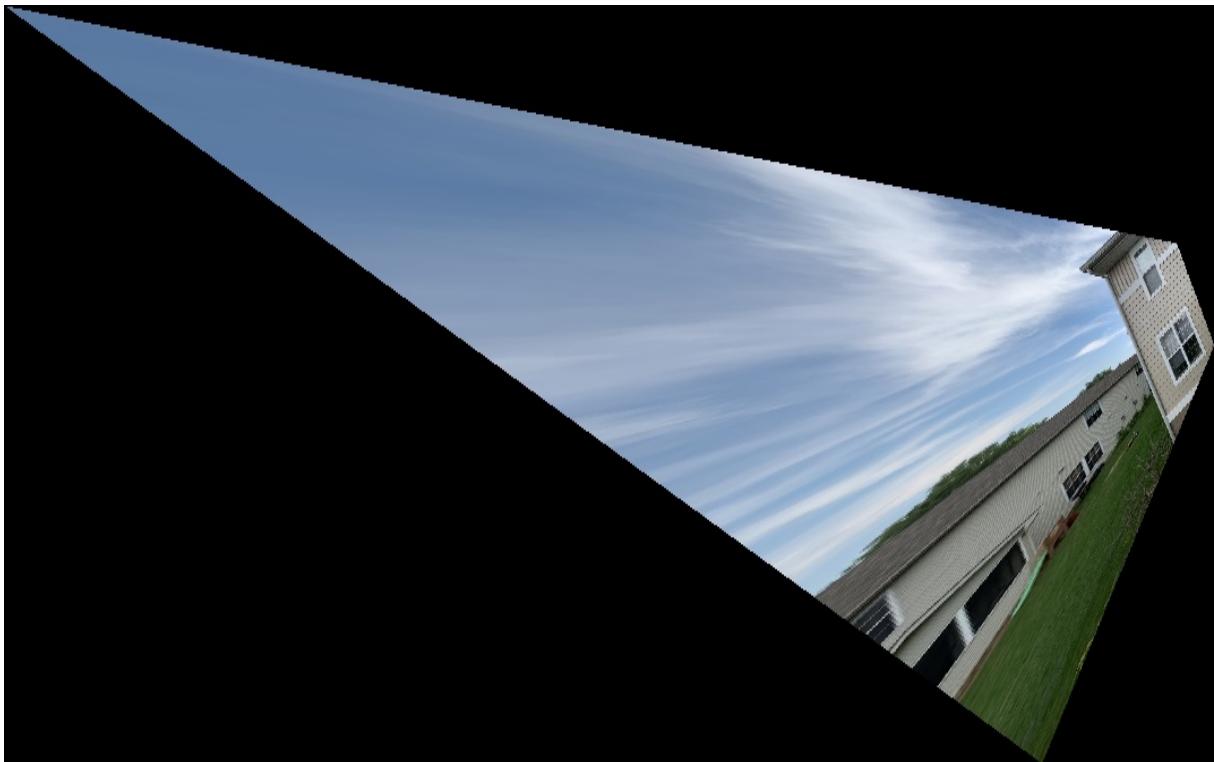


Figure 9: Two Step Method - Removing both Projective and Affine Distortion

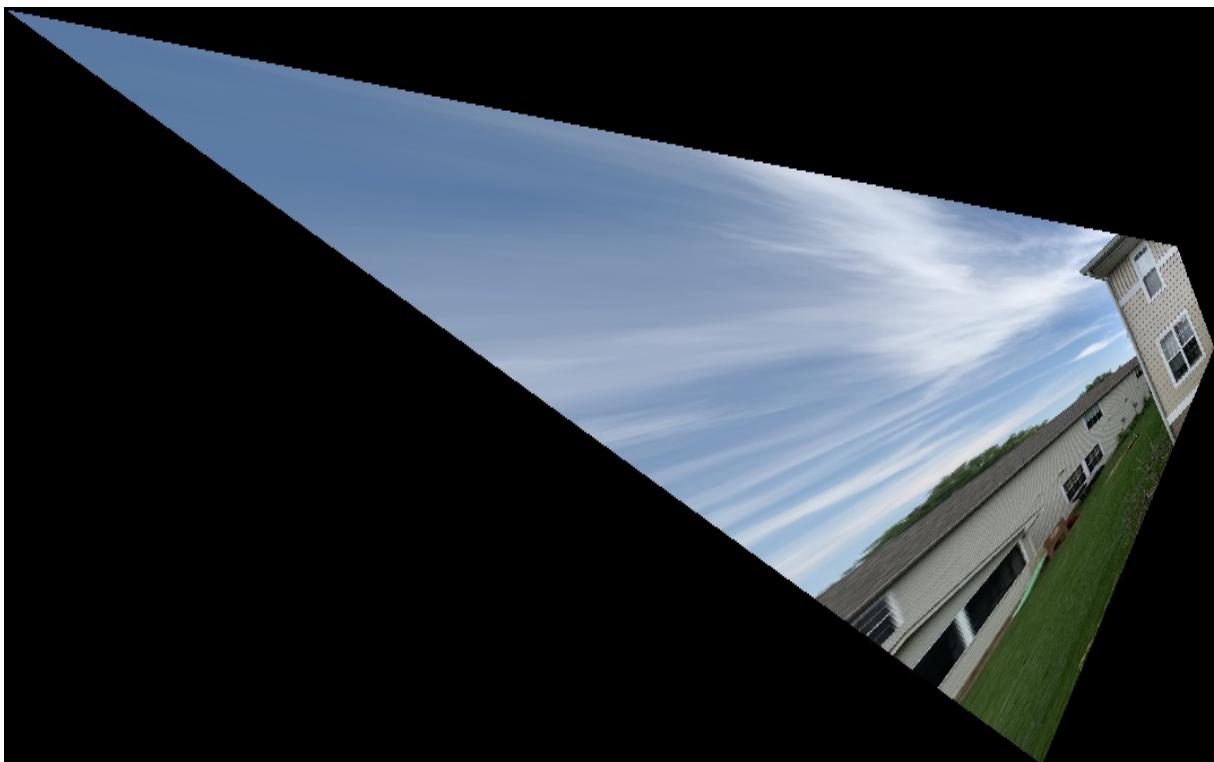


Figure 10: One Step Method - Removing both Projective and Affine Distortion

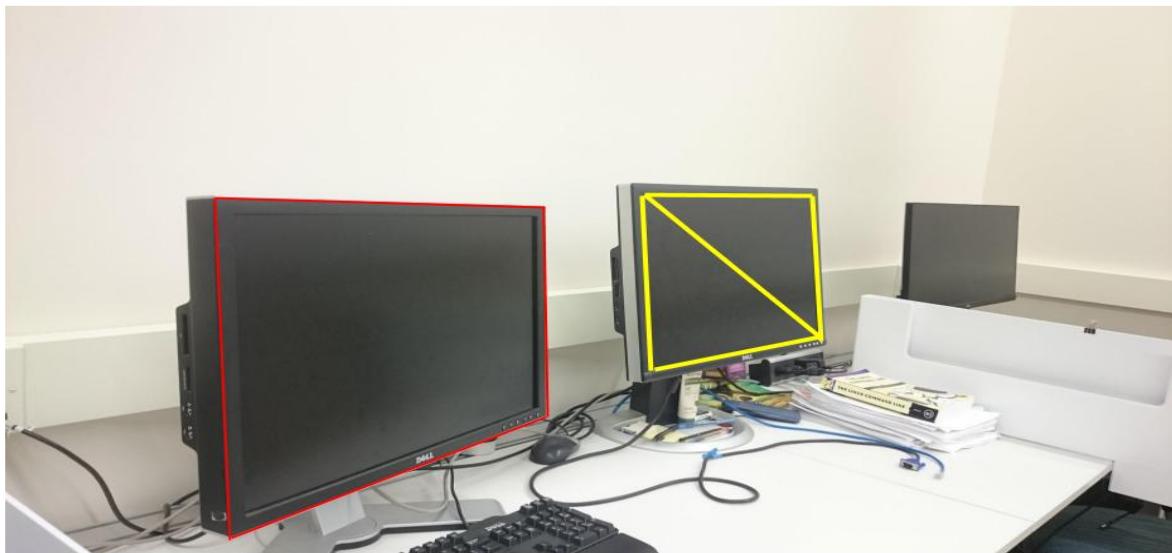


Figure 11: Input Image

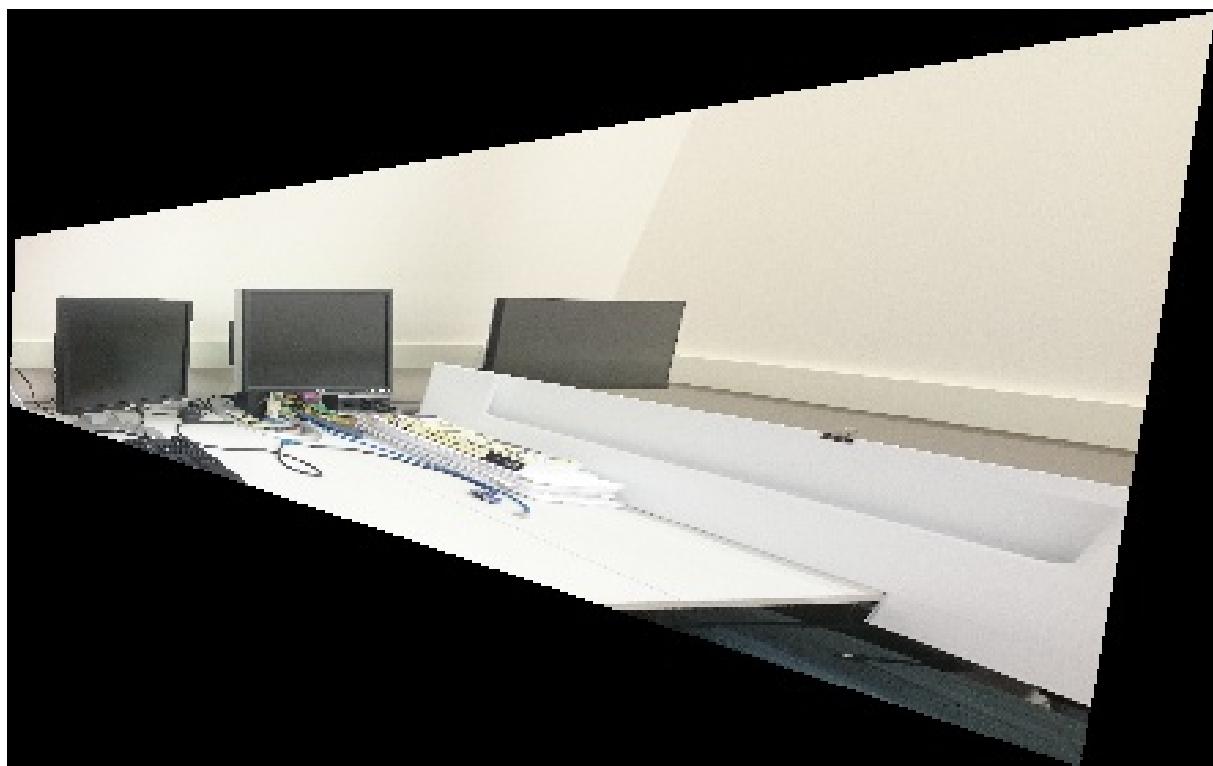


Figure 12: Point to Point Correspondence Method



Figure 13: Two Step Method - Removing Projective Distortion Alone

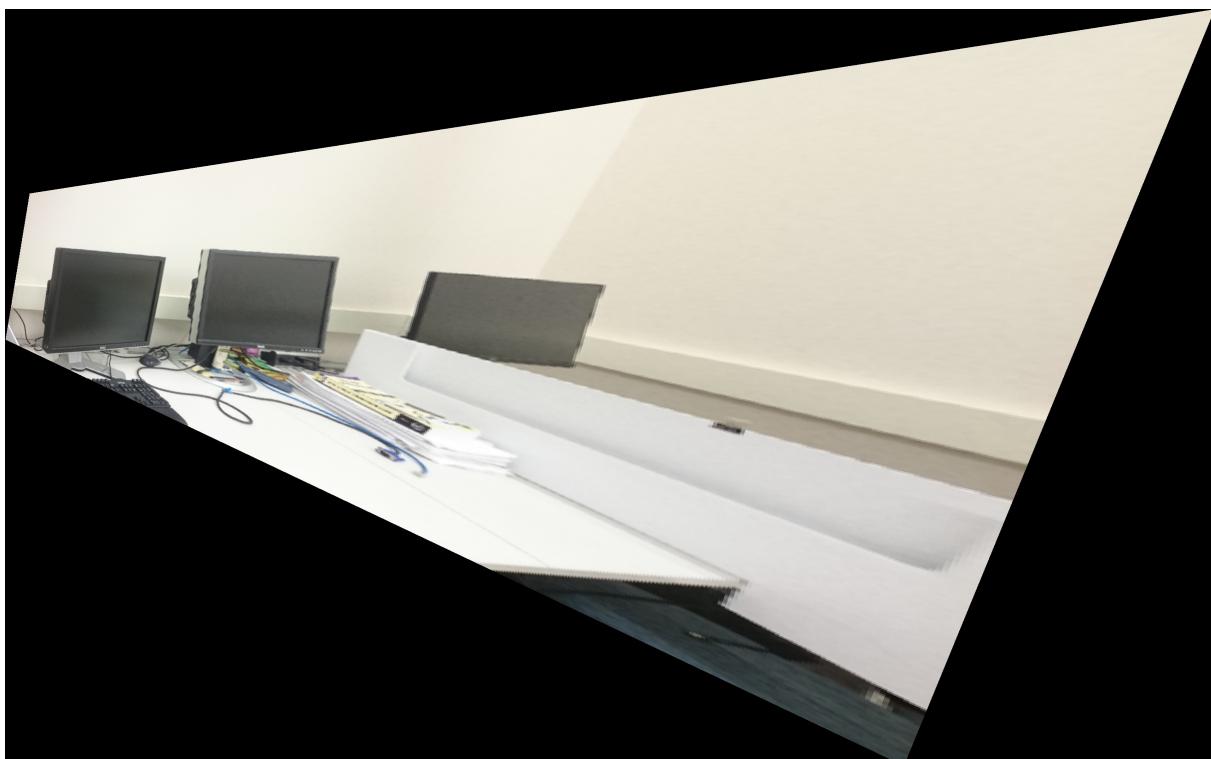


Figure 14: Two Step Method - Removing both Projective and Affine Distortion

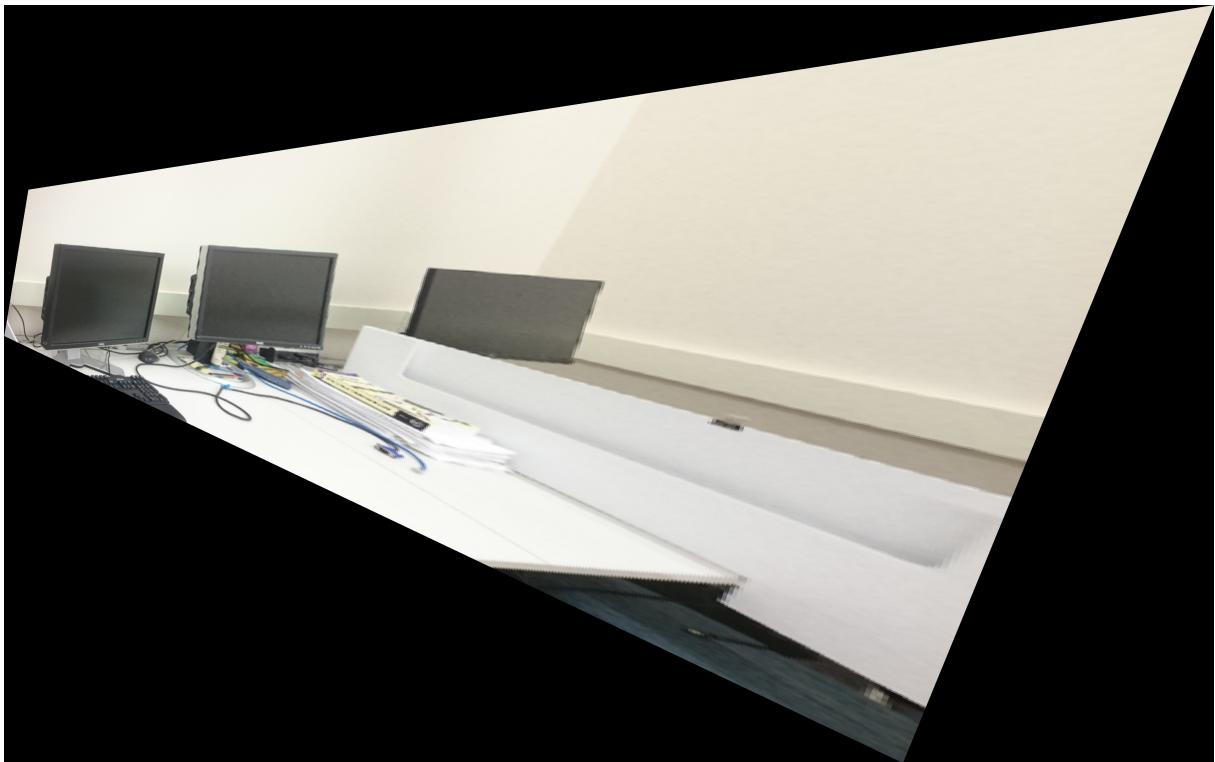


Figure 15: One Step Method - Removing both Projective and Affine Distortion

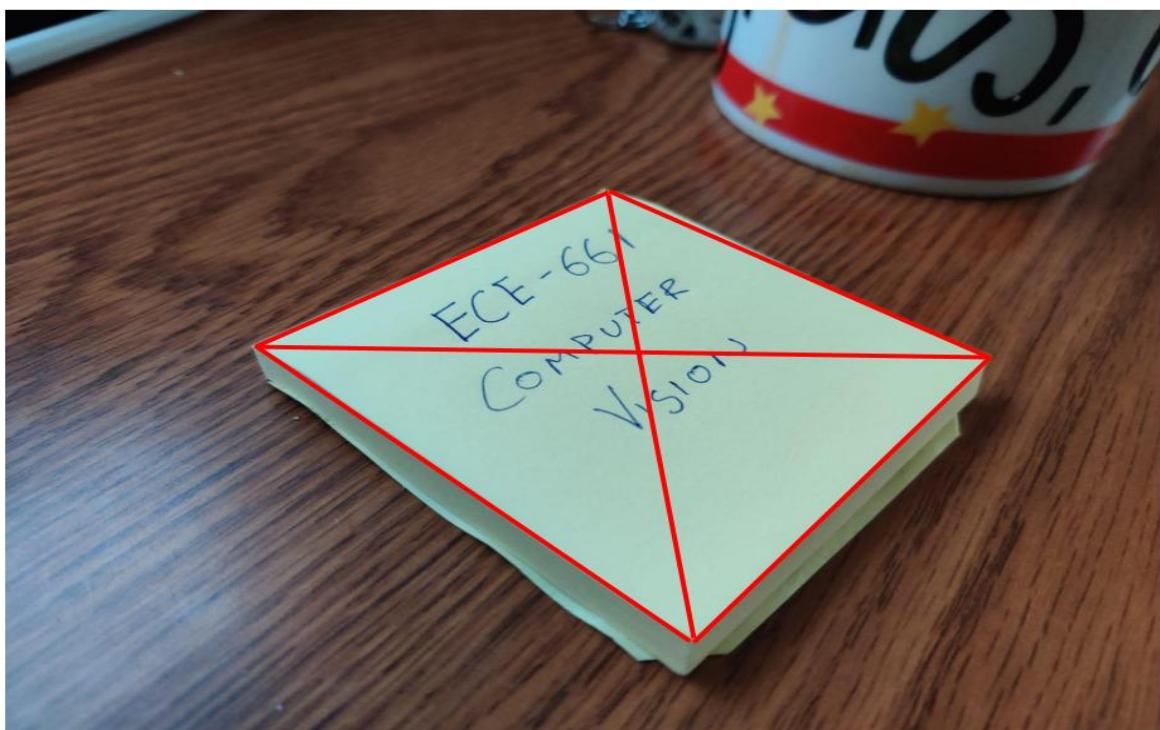


Figure 16: Input Image

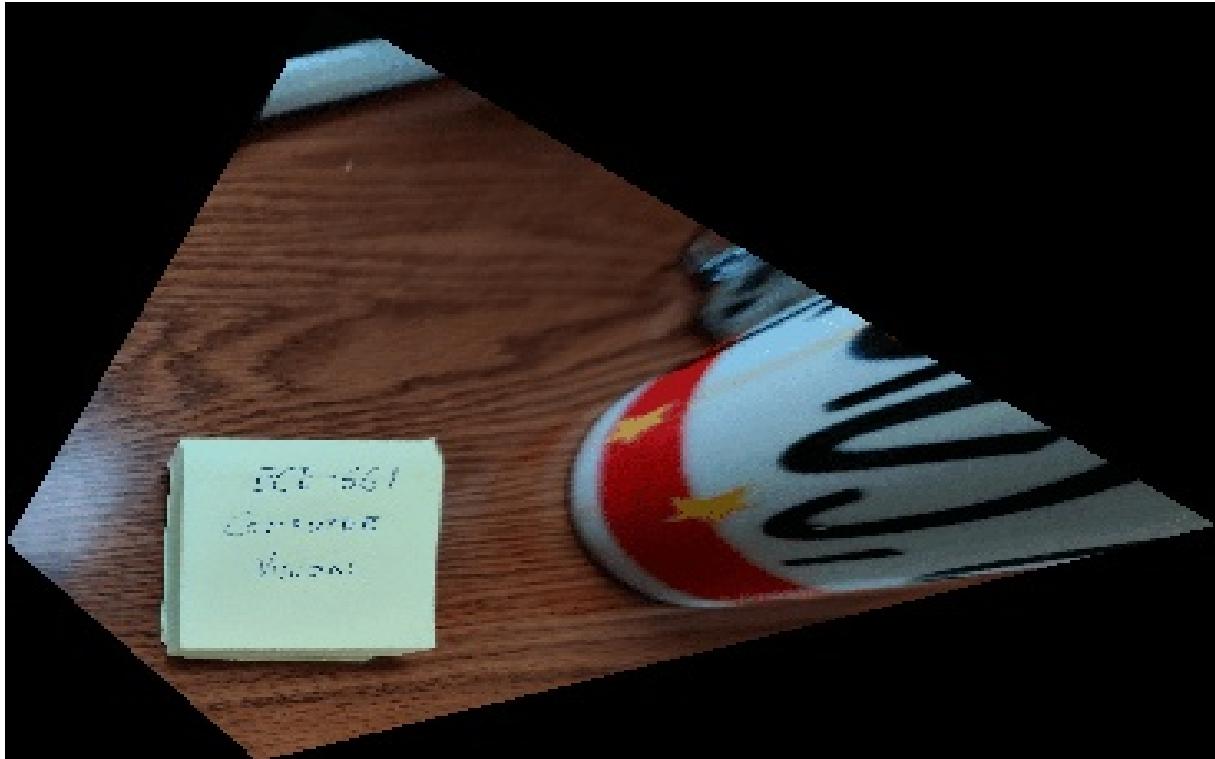


Figure 17: Point to Point Correspondence Method

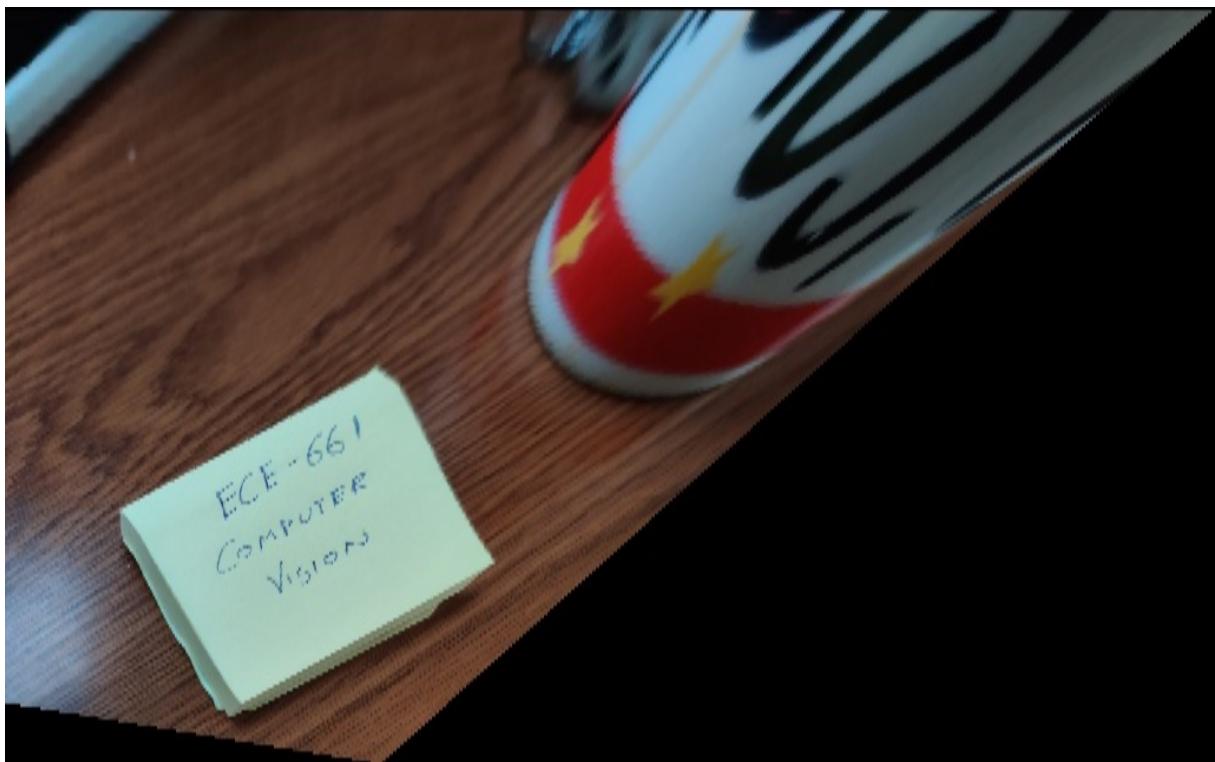


Figure 18: Two Step Method - Removing Projective Distortion Alone

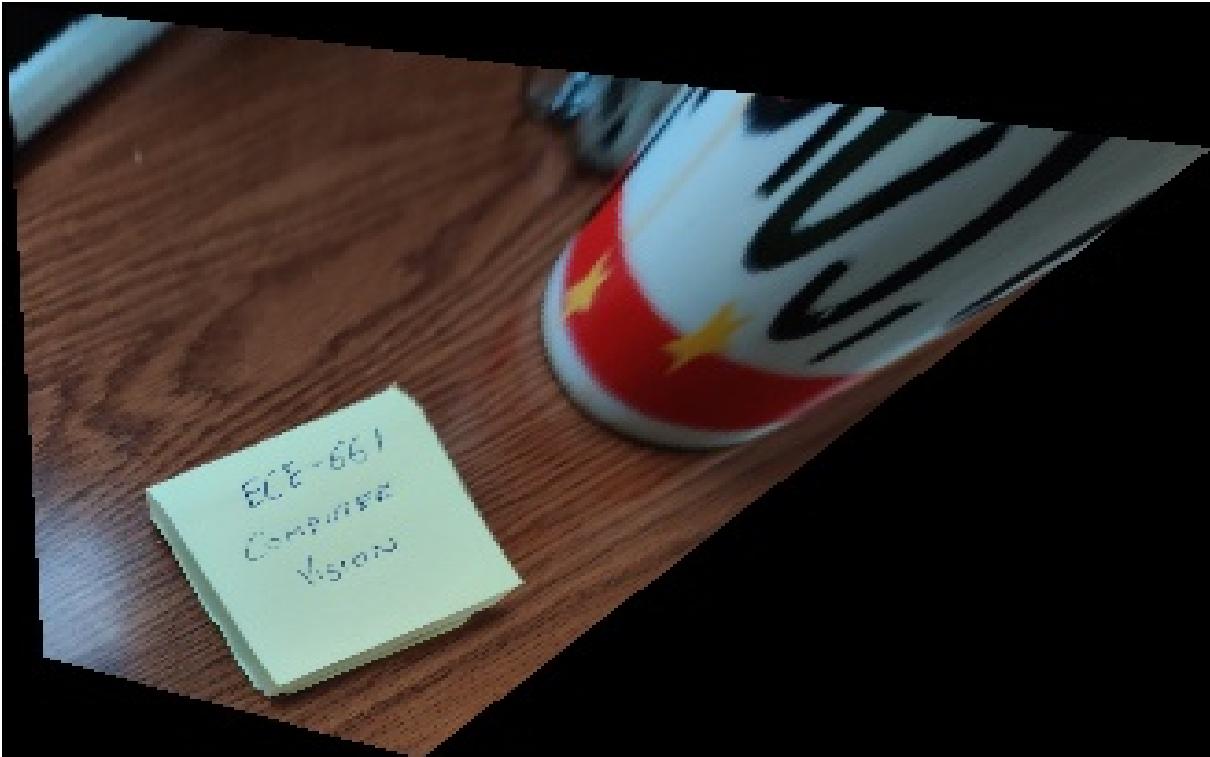


Figure 19: Two Step Method - Removing both Projective and Affine Distortion

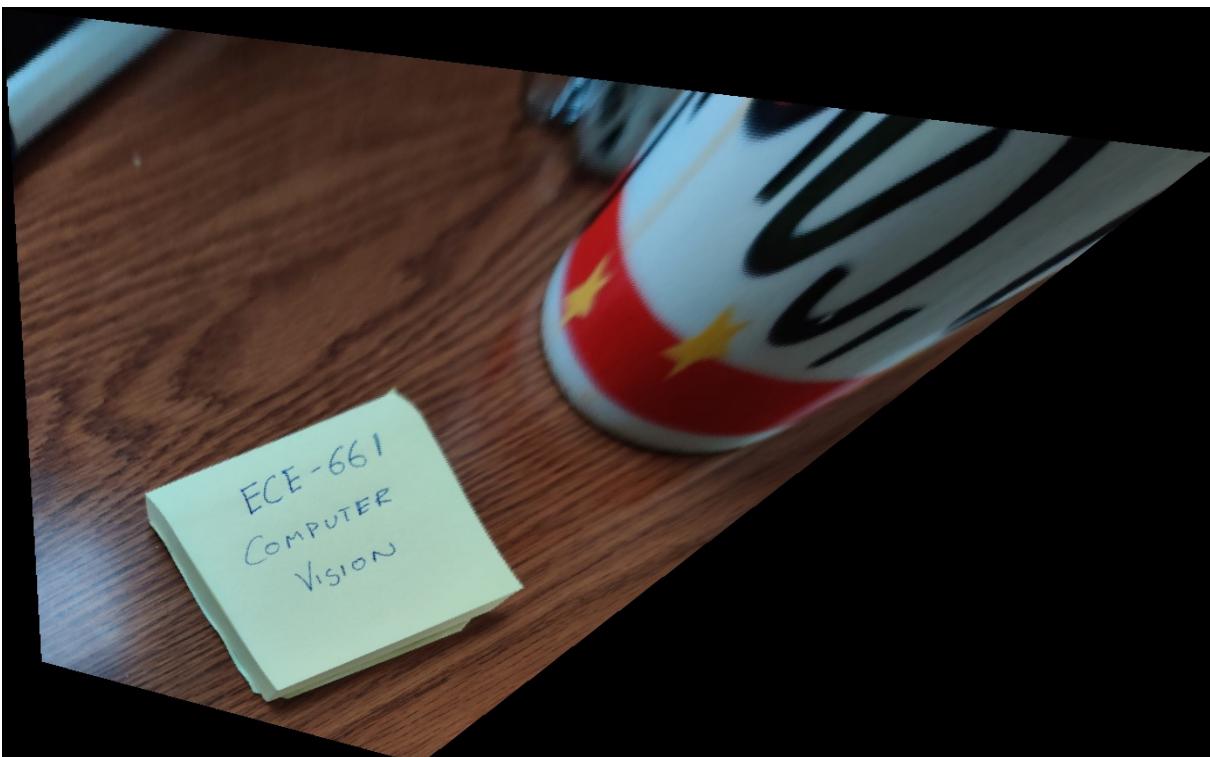


Figure 20: One Step Method - Removing both Projective and Affine Distortion



Figure 21: Input Image

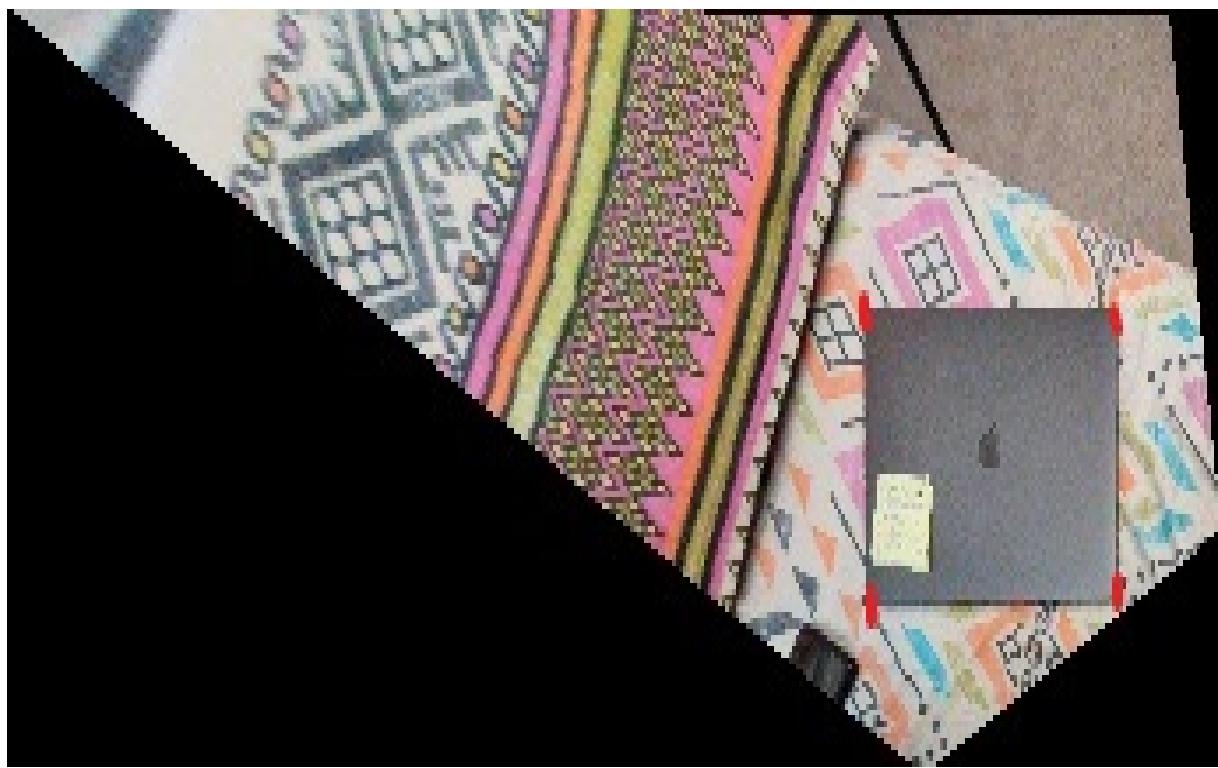


Figure 22: Point to Point Correspondence Method

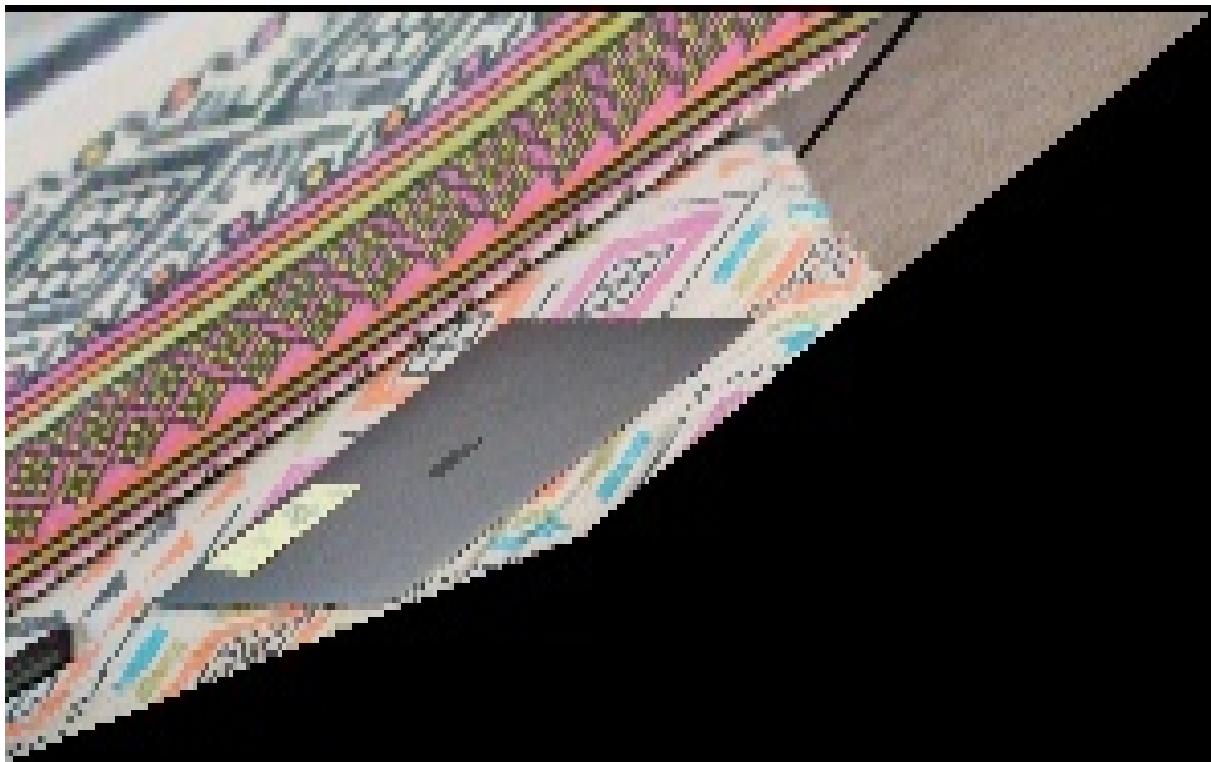


Figure 23: Two Step Method - Removing Projective Distortion Alone

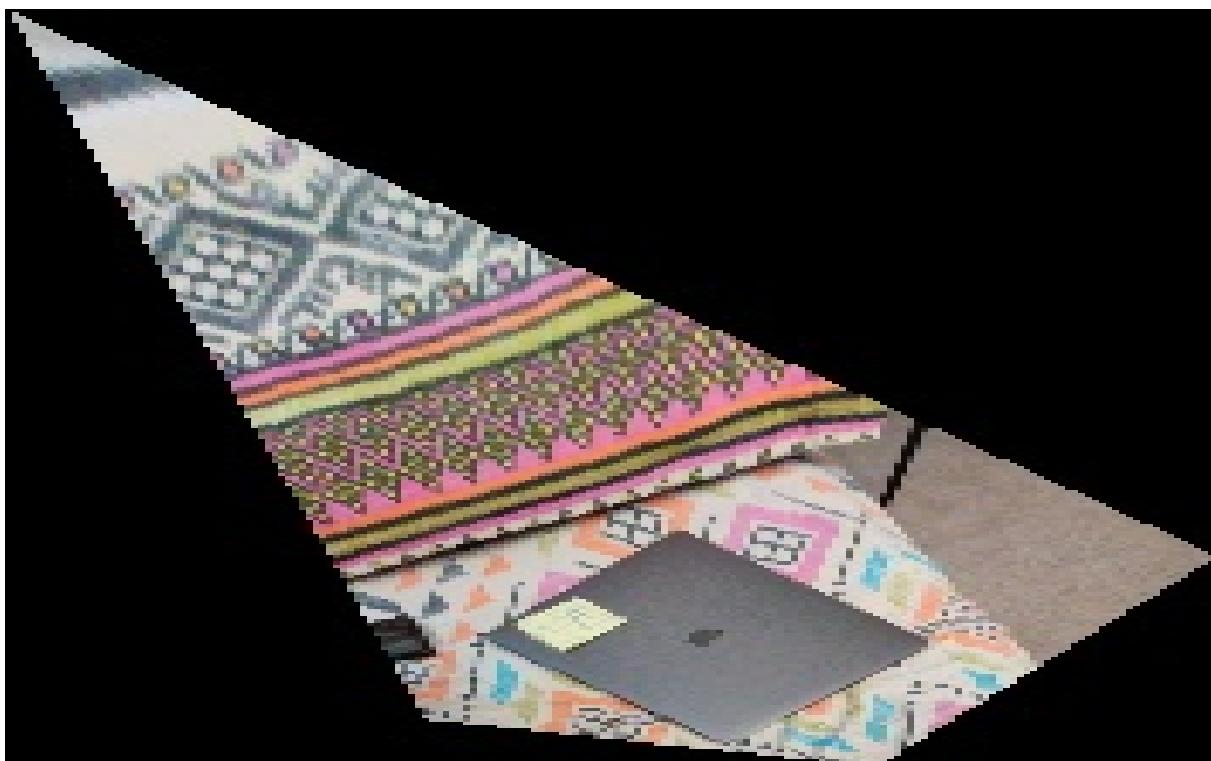


Figure 24: Two Step Method - Removing both Projective and Affine Distortion

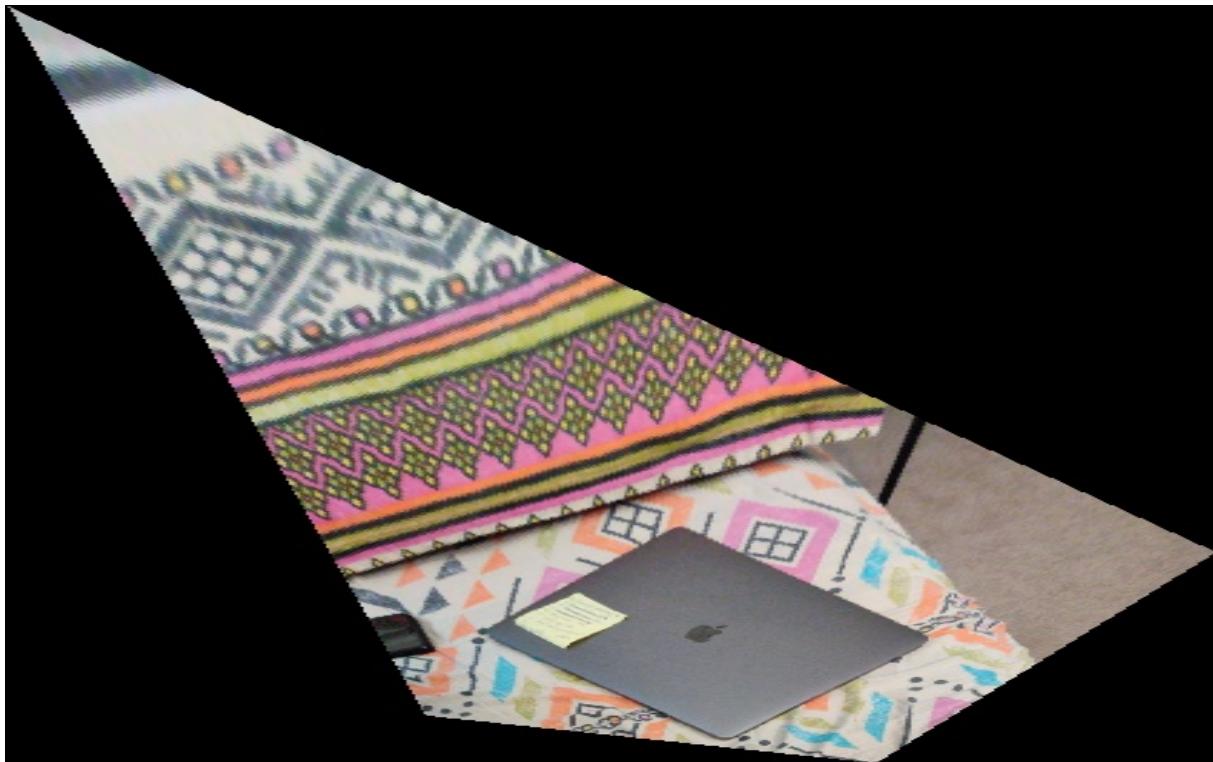


Figure 25: One Step Method - Removing both Projective and Affine Distortion
SOURCE CODE

```
1 """
2 Computer Vision - Purdue University - Homework 3
3
4 Author : Arjun Kramadhati Gopi, MS-Computer & Information
      Technology, Purdue University .
5 Date: September 21, 2020
6
7
8 [TO RUN CODE]: python3 removeDistortion.py
9 The code displays the pictures. The user will have to select the
      ROI points manually in the PQRS fashion.
10 P ----- Q
11 |           |
12 |           |
13 |           |
14 R ----- S
15
16 Output:
17     [jpg]: [Transformed images]
18 """
19
20 import cv2 as cv
21 import math
22 import numpy as np
23 import time
24
```

```
25
26 class removeDistortion:
27
28     def __init__(self,image_addresses):
29
30         self.image_addresses = image_addresses
31         self.image_one = cv.imread(image_addresses[0])
32         self.image_one = cv.resize(self.image_one,(int(self.
33             image_one.shape[1]*0.5),int(self.image_one.shape
34             [0]*0.5)))
35         self.image_two = cv.imread(image_addresses[1])
36         # self.image_two = cv.resize(self.image_two,(int(self.
37             image_two.shape[1]*0.3),int(self.image_two.shape
38             [0]*0.3)))
39         self.image_three = cv.imread(image_addresses[2])
40         self.image_three = cv.resize(self.image_three,(int(self.
41             image_three.shape[1]*0.2),int(self.image_three.shape
42             [0]*0.2)))
43         self.images = [self.image_one,self.image_two,self.
44             image_three]
45         self.image_sizes = [(self.image_one.shape[0],self.
46             image_one.shape[1]),(self.image_two.shape[0],self.
47             image_two.shape[1]),(self.image_three.shape[0],self.
48             image_three.shape[1])]
49         self.image_sizes_corner_points_HC= []
50
51     def createImageCornerPointRepresentations(self):
52         """
53             [summary] This function creates HC representations of the
54                 corner points of the given original input images.
55         """
56         templist = []
57         for size in self.image_sizes:
58             templist.append(np.asarray([0.0,0.0,1.0]))
59             templist.append(np.asarray([float(size[1])
60                 -1.0,0.0,1.0]))
61             templist.append(np.asarray([0.0,float(size[0])
62                 -1.0,1.0]))
```

```
60         templist.append(np.asarray([float(size[1])-1.0, float(
61             size[0])-1.0, 1.0]))
62         self.image_sizes_corner_points_HC.append(templist)
63         templist = []
64
65     def append_points(self, event, x, y, flags, param):
66         """
67             [This function is called every time the mouse left button
68             is clicked - It records the (x,y) coordinates of the
69             click location]
70
71         """
72
73
74     def getROIFromUser(self):
75         """
76             [This function is responsible for taking the regions of
77             interests from the user for all the 4 pictures in
78             order]
79
80         """
81         self.roiList = []
82         cv.namedWindow('Select ROI')
83
84         cv.setMouseCallback('Select ROI', self.append_points)
85         for i in range(3):
86             while(True):
87                 cv.imshow('Select ROI', self.images[i])
88                 k = cv.waitKey(1) & 0xFF
89                 if cv.waitKey(1) & 0xFF == ord('q'):
90                     break
91
92             self.roiList.append(self.roiCoordinates)
93
94             self.roiCoordinates = []
95
96     def weightedPixelValue(self, rangecoordinates, objectQueue):
97         """
98             [This function calculates the weighted pixel value at the
99             given coordinate in the target image]
100
101            Args:
102                rangecoordinates ([list]): [This is the coordinate of
103                    the pixel in the target image]
104                objectQueue ([int]): [This is the index number of the
105                    list which has the coordinates of the roi for the
106                    Object picture]
```

```
104     Returns:  
105         [list]: [Weighted pixel value - RGB value]  
106     """  
107  
108     pointOne = (int(np.floor(rangecoordinates[1])),int(np.  
109         floor(rangecoordinates[0])))  
110     pointTwo = (int(np.floor(rangecoordinates[1])),int(np.  
111         ceil(rangecoordinates[0])))  
112     pointThree = (int(np.ceil(rangecoordinates[1])),int(np.  
113         ceil(rangecoordinates[0])))  
114     pointFour = (int(np.ceil(rangecoordinates[1])),int(np.  
115         floor(rangecoordinates[0])))  
116  
117     pixelValueAtOne = self.images[objectQueue][pointOne[0]][  
118         pointOne[1]]  
119     pixelValueAtTwo = self.images[objectQueue][pointTwo[0]][  
120         pointTwo[1]]  
121     pixelValueAtThree = self.images[objectQueue][pointThree  
122         [0]][pointThree[1]]  
123     pixelValueAtFour = self.images[objectQueue][pointFour  
124         [0]][pointFour[1]]  
125  
126     weightAtOne = 1/np.linalg.norm(pixelValueAtOne -  
127         rangecoordinates)  
128     weightAtTwo = 1/np.linalg.norm(pixelValueAtTwo -  
129         rangecoordinates)  
130     weightAtThree = 1/np.linalg.norm(pixelValueAtThree -  
131         rangecoordinates)  
132     weightAtFour = 1/np.linalg.norm(pixelValueAtFour -  
133         rangecoordinates)  
134  
135     return ((weightAtOne*pixelValueAtOne) + (weightAtTwo*  
136         pixelValueAtTwo) + (weightAtThree*pixelValueAtThree) +  
137         (weightAtFour*pixelValueAtFour))/(weightAtFour +  
138         weightAtThree+weightAtTwo+weightAtOne)
```



```
139  
140     def createBlankImageArray(self,queueHomography,queueImage):  
141         """[summary]  
142             This function is called to create the blank image. The  
143                 blank image is formed of an array - np.zeros. The size  
144                     of the blank image is calculated  
145             based on the homography matrix which is being used. The  
146                 original corner points are used to calculate the new  
147                     corner points in the new image.  
148  
149             Args:  
150                 queueHomography ([int]): [Index of the homography  
151                     matrix being used to calculate the new image size]  
152                 queueImage ([int]): [Index of the image in the list  
153                     being used]  
154  
155             Returns:
```

```
136         [numpy array]: [np.zeros of the size equal to the new
137             image size]
138         [int]: [Returns the xmin value of the new image - The
139             least x value amongst the four transformed corner
140             points]
141         [int]: [Returns the ymin value of the new image - The
142             least y value amongst the four transformed corner
143             points]
144         """
145
146     templist = []
147     templistX = []
148     templistY = []
149     #print(self.image_sizes_corner_points_HC[queueImage])
150     #print(self.homographies[queueHomography][0])
151     for i in range(4):
152         templist.append(np.dot(self.homographies[
153             queueHomography], self.image_sizes_corner_points_HC
154             [queueImage][i]))
155     #print(templist)
156
157     for i, element in enumerate(templist):
158         templist[i] = element / element[2]
159     for element in templist:
160         templistX.append(element[0])
161         templistY.append(element[1])
162
163     breadth = int(math.ceil(max(templistX))) - int(math.floor(
164         min(templistX)))
165     height = int(math.ceil(max(templistY))) - int(math.floor(
166         min(templistY)))
167
168     return np.zeros((height, breadth, 3)), int(math.floor(min(
169         templistX))), int(math.floor(min(templistY)))
170
171
172     def createImage(self, queueHomography, queueImage):
173         """[summary]
174         This function is the function which creates the final
175             result image. This function has the traditional but
176             slow nested for loop approach to build the image.
177         It begins by first getting the blank image of the size of
178             the new image from the createBlankImageArray function
179             above.
180
181         Args:
182             queueHomography ([int]): [Index of the homography
183                 matrix being used to calculate the new image size]
184             queueImage ([int]): [Index of the image in the list
185                 being used]
186
187         Returns:
```

```
173         [numpy ndarray]: [Returns the final resultant image
174                         in numpy.ndarray form.]
175     """
176     print("Processing...")
177     resultImg, xmin, ymin = self.createBlankImageArray(
178         queueHomography, queueImage)
179
180     for column in range(0, resultImg.shape[0]):
181         for row in range(0, resultImg.shape[1]):
182             print("processing" + str(column) + " out of " +
183                   str(resultImg.shape[0]))
184             rangecoordinates = np.dot(self.homographies[
185                 queueHomography+1], (float(row+xmin), float(
186                 column+ymin), 1.0))
187             rangecoordinates = rangecoordinates/
188             rangecoordinates[2]
189
190             if ((rangecoordinates[0]>0) and (rangecoordinates
191                 [0]<self.image_sizes[queueImage][1]-1)) and ((
192                 rangecoordinates[1]>0) and (rangecoordinates
193                 [1]<self.image_sizes[queueImage][0]-1)):
194                 resultImg[column][row] = self.
195                 weightedPixelValue(rangecoordinates,
196                     queueImage)
197             else:
198                 resultImg[column][row] = [0,0,0]
199
200     return resultImg
201
202     def createImageVectorised(self, queueHomography, queueImage):
203         """
204             [summary]
205             ----- Attempt #1 -----
206
207             Vectorised numpy operation
208
209             -----
210
211             This function is the function which creates the final
212                 result image. This was the first attempt towards
213                 writing a fully vectorised numpy pythonic operation.
214             Here, I first arrange the coordinates of each pixel in a
215                 vertical stack (Line 205 - 207). Then I add xmin and y
216                 min vallues to each of the X values and Y values.
217             Then I add a third row of just ones to make them into
218                 individual 3X1 vectors. Using these stacked vectors of
219                 individual pixel coordinates, I perform a vector
220                 multiplication with the homograhy matrix H. I do this
221                 using the '@' operator. The resulting matrix has the
222                 corresponding pixel coordinates of the source image.
223             I extract the pixel values of each of these coordinates
224                 using a nested for loop. Basically, I was able to
225                 avoid the matrix multiplication being written inside
226                 the
```

```
204         nected for loop. I was able to get stable outputs much
205         quicker - 40% faster.
206
207     Args:
208         queueHomography ([int]): [Index of the homography
209             matrix being used to calculate the new image size]
210         queueImage ([int]): [Index of the image in the list
211             being used]
212
213     Returns:
214         [numpy ndarray]: [Returns the final resultant image
215             in numpy.ndarray form.]
216     """
217
218     print("processing...")
219     resultImg,xmin,ymin = self.createBlankImageArray(
220         queueHomography,queueImage)
221     column, row = np.mgrid[0:resultImg.shape[0],0:resultImg.
222         shape[1]]
223     vector = np.vstack((column.ravel(),row.ravel()))
224     row = vector[1] + xmin
225     column = vector[0] + ymin
226     ones = np.ones(len(row))
227     vector = np.array([column,row,ones])
228     s=time.time()
229     resultvector = self.homographies[queueHomography+1]
230         @vector
231     e=time.time()
232     print("timetake",e-s)
233     resultvector = resultvector/resultvector[2]
234     # resultvector = resultvector[:2,:]
235     for column in range(0,resultImg.shape[0]):
236         for row in range(0,resultImg.shape[1]):
237             print("processing" + str(column) + " out of " +
238                 str(resultImg.shape[0]))
239
240             rangecoordinates=np.array([resultvector[1][(
241                 column*resultImg.shape[1])+row],resultvector
242                 [0][(column*resultImg.shape[1])+row],
243                 resultvector[2][(column*resultImg.shape[1])+
244                     row]])
245
246             if ((rangecoordinates[0]>0) and (rangecoordinates
247                 [0]<self.image_sizes[queueImage][1]-1)) and ((
248                 rangecoordinates[1]>0) and (rangecoordinates
249                 [1]<self.image_sizes[queueImage][0]-1)):
250                 resultImg[column][row] = self.
251                     weightedPixelValue(rangecoordinates,
252                         queueImage)
253             else:
254                 resultImg[column][row] = [255.0,255.0,255.0]
255
256     return resultImg
```

```
240
241
242
243
244     def buildImage(self,queueHomography,queueImage,row,column):
245         """[summary]
246             ----- Attempt #2 -----
247
248             Vectorised numpy operation
249
250             -----
251
252             This function is the function which creates the final
253                 result image. This was the second attempt towards
254                 writing a fully vectorised numpy pythonic operation.
255             This function is pretty much the same as the createImage
256                 function. The ket difference here is that this
257                 function does not have the nester for loop.
258             Instead, I vectorise this entire function using the numpy
259                 vectorise operation. Using this entire function as a
260                 vector, I was able to successfully vectorise the
261                 whole image building process.
262
263             Args:
264                 queueHomography ([int]): [Index of the homography
265                     matrix being used to calculate the new image size]
266                 queueImage ([int]): [Index of the image in the list
267                     being used]
268                 row ([int]): [Row value of the pixel being
269                     considered]
270                 column ([int]): [Column value of the pixel being
271                     considered]
272
273             Returns:
274                 Does not return any value. It just updates the global
275                     image variable (self.resultImg).
276
277
278             rangecoordinates = np.matmul(self.homographies[
279                 queueHomography+1],(float(row+self.xmin),float(column+
280                     self.ymin),1.0))
281             rangecoordinates = rangecoordinates/rangecoordinates/[2]
282             if ((rangecoordinates[0]>0) and (rangecoordinates[0]<self
283                 .image_sizes[queueImage][1]-1)) and ((rangecoordinates
284                 [1]>0) and (rangecoordinates[1]<self.image_sizes[
285                     queueImage][0]-1)):
286                 pointOne = (int(np.floor(rangecoordinates[1])),int(np
287                     .floor(rangecoordinates[0])))
288                 pointTwo = (int(np.floor(rangecoordinates[1])),int(np
289                     .ceil(rangecoordinates[0])))
290                 pointThree = (int(np.ceil(rangecoordinates[1])),int(
291                     np.ceil(rangecoordinates[0])))
```

```
274         pointFour = (int(np.ceil(rangecoordinates[1])),int(np
275                         .floor(rangecoordinates[0])))
276
276     pixelValueAtOne = self.images[queueImage][pointOne
277         [0]][pointOne[1]]
277     pixelValueAtTwo = self.images[queueImage][pointTwo
278         [0]][pointTwo[1]]
278     pixelValueAtThree = self.images[queueImage][
279         pointThree[0]][pointThree[1]]
279     pixelValueAtFour = self.images[queueImage][pointFour
280         [0]][pointFour[1]]
280
281     weightAtOne = 1/np.linalg.norm(pixelValueAtOne -
281         rangecoordinates)
282     weightAtTwo = 1/np.linalg.norm(pixelValueAtTwo -
282         rangecoordinates)
283     weightAtThree = 1/np.linalg.norm(pixelValueAtThree -
283         rangecoordinates)
284     weightAtFour = 1/np.linalg.norm(pixelValueAtFour -
284         rangecoordinates)
285
286     self.resultImg[column][row] = ((weightAtOne*
286         pixelValueAtOne) + (weightAtTwo*pixelValueAtTwo) +
287         (weightAtThree*pixelValueAtThree) + (weightAtFour
287         *pixelValueAtFour))/(weightAtFour+weightAtThree+
288         weightAtTwo+weightAtOne)
288
289 else:
289
290     self.resultImg[column][row] = [255.0,255.0,255.0]
290
291 def vectoriseOperations(self,queueHomography,queueImage):
292     """[summary]
293     ----- Attempt #2 Continued -----
294
295     Vectorised numpy operation
296
297     -----
298
299     This function is the extension of the above function -
300         buildImage. This is the function which vectorises the
301         entire buildImage function.
302     In this function, I stack a list which contains all the
303         pixel coordinates in the blank image. I feed this
304         entire list to the vectorised function.
305     This was a successful vectorisation operation however the
306         RAM utilization peaked to a hundred percent. The
307         laptop froze and I could not run this further.
308
309     Args:
310         queueHomography ([int]): [Index of the homography
311             matrix being used to calculate the new image size]
312         queueImage ([int]): [Index of the image in the list
313             being used]
```

```
306
307     Returns:
308         [numpy ndarray]: [Returns the final resultant image
309             in numpy.ndarray form.]
310
311         """
312         self.resultImg, self.xmin, self.ymin = self.
313             createBlankImageArray(queueHomography, queueImage)
314         length = self.resultImg.shape[0]*self.resultImg.shape[1]
315         queueHomography = [queueHomography]*length
316         queueImage = [queueImage]*length
317         vectoriseOperation = np.vectorize(self.buildImage)
318         row, column = np.mgrid[0:self.resultImg.shape[1], 0:self.
319             resultImg.shape[0]]
320         point = np.vstack((row.ravel(), column.ravel()))
321         row = point[0]
322         column = point[1]
323         #print(point)
324         print("processing...")
325         vectoriseOperation(queueHomography, queueImage, row, column)
326         return self.resultImg
327
328
329     def objectMatrixFunction(self, queue):
330
331         """
332             [We construct the B Matrix with dimension 8X1]
333
334             Args:
335                 queue ([int]): [This is the index number of the list
336                     which has the coordinates of the roi for the
337                     object picture]
338
339             """
340             self.objectMatrix = np.zeros((8,1))
341
342             for i in range(len(self.roiRealWorld[queue])):
343                 self.objectMatrix[(2*i)][0] = self.roiRealWorld[queue
344                     ][i][0]
345                 self.objectMatrix[(2*i)+1][0] = self.roiRealWorld[
346                     queue][i][1]
347
348             def parameterMatrixFunction(self, queue, objectQueue):
349
350                 """
351                     [We construct the A Matrix with dimension 8X8 and then we
352                     calculate the inverse of A matrix needed for the
353                     homography calculation]
354
355                     Args:
356                         queue ([int]): [This is the index number of the list
357                             which has the coordinates of the roi for the
358                             destination picture]
```

```
348         objectQueue ([int]): [This is the index number of the
349             list which has the coordinates of the roi for the
350             Object picture]
351
352     """
353     self.parameterMatrix=np.zeros((8,8))
354
355     for i in range(4):
356         self.parameterMatrix[2*i][0] = self.roiList[queue][i][0]
357         self.parameterMatrix[2*i][1] = self.roiList[queue][i][1]
358         self.parameterMatrix[2*i][2] = 1.0
359         self.parameterMatrix[2*i][3] = 0.0
360         self.parameterMatrix[2*i][4] = 0.0
361         self.parameterMatrix[2*i][5] = 0.0
362         self.parameterMatrix[2*i][6] = (-1)*(self.roiList[
363             queue][i][0])*(self.roiRealWorld[objectQueue][i][0])
364         self.parameterMatrix[2*i][7] = (-1)*(self.roiList[
365             queue][i][1])*(self.roiRealWorld[objectQueue][i][0])
366         self.parameterMatrix[(2*i) + 1][0] = 0.0
367         self.parameterMatrix[(2*i) + 1][1] = 0.0
368         self.parameterMatrix[(2*i) + 1][2] = 0.0
369         self.parameterMatrix[(2*i) + 1][3] = self.roiList[
370             queue][i][0]
371         self.parameterMatrix[(2*i) + 1][4] = self.roiList[
372             queue][i][1]
373         self.parameterMatrix[(2*i) + 1][5] = 1.0
374         self.parameterMatrix[(2*i) + 1][6] = (-1)*(self.
375             roiList[queue][i][0])*(self.roiRealWorld[
376                 objectQueue][i][1])
377         self.parameterMatrix[(2*i) + 1][7] = (-1)*(self.
378             roiList[queue][i][1])*(self.roiRealWorld[
379                 objectQueue][i][1])
380
381         self.parameterMatrixI = np.linalg.pinv(self.
382             parameterMatrix)
383
384     def calculateHomography(self):
385         """
386         [We calculate the homography matrix here. Once we have
387             the values of the matrix, we rearrange them into a 3X3
388             matrix.]
389
390         """
391         homographyI = np.matmul(self.parameterMatrixI ,self.
392             objectMatrix)
393         homography = np.zeros((3,3))
394
395         homography [0][0]= homographyI [0]
396         homography [0][1]= homographyI [1]
397         homography [0][2]= homographyI [2]
```

```
383     homography [1] [0]= homographyI [3]
384     homography [1] [1]= homographyI [4]
385     homography [1] [2]= homographyI [5]
386     homography [2] [0]= homographyI [6]
387     homography [2] [1]= homographyI [7]
388     homography [2] [2]= 1.0
389     self.homographies.append(homography)
390     homography = np.linalg.pinv(homography)
391     homography = homography/homography [2] [2]
392     self.homographies.append(homography)
393
394
395
396     def projectiveDistortionHomography(self,queueImage):
397         """[summary]
398             Calculate the homography matrix to eliminate projective
399                 distortion
400
401             Args:
402                 queueImage ([int]): [Index of the image in the list
403                                 being used]
404
405             Calculates the Homography matrix and appends it to the
406                 global homography list.
407             """
408
409             vanishingPointOne = np.cross(np.cross(self.roiList[
410                 queueImage][0],self.roiList[queueImage][1]),np.cross(
411                 self.roiList[queueImage][2],self.roiList[queueImage
412                 ][3]))
413             vanishingPointTwo = np.cross(np.cross(self.roiList[
414                 queueImage][0],self.roiList[queueImage][2]),np.cross(
415                 self.roiList[queueImage][1],self.roiList[queueImage
416                 ][3]))
417
418             vanishingLine = np.cross((vanishingPointOne/
419                 vanishingPointOne [2]),(vanishingPointTwo/
420                 vanishingPointTwo [2]))
421
422             projectiveDHomography = np.zeros((3,3))
423             projectiveDHomography [2] = vanishingLine/vanishingLine [2]
424             projectiveDHomography [0] [0] = 1
425             projectiveDHomography [1] [1] = 1
426             self.homographies.append(projectiveDHomography)
427             inverseH = np.linalg.pinv(projectiveDHomography)
428             self.homographies.append(inverseH/inverseH [2] [2])
429
430
431
432     def affineDistortionHomography(self,queueImage):
433         """[summary]
434             Calculate the homography matrix to eliminate affine
435                 distortion
```

```
424
425     Args:
426         queueImage ([int]): [Index of the image in the list
427                           being used]
428
429             Calculates the Homography matrix and appends it to the
430             global homography list.
431
432             """
433             templist = []
434             temppoints = []
435
436             for i in range(4):
437                 tempvalue = np.dot(self.homographies[0],self.roiList[
438                     queueImage][i])
439                 tempvalue = tempvalue/tempvalue[2]
440                 temppoints.append(tempvalue)
441
442             print(temppoints)
443             ortholinePairOne = np.cross(temppoints[0],temppoints[1])
444             ortholinePairTwo = np.cross(temppoints[0],temppoints[2])
445             ortholinePairThree = np.cross(temppoints[0],temppoints
446                 [3])
447             ortholinePairFour = np.cross(temppoints[1],temppoints[2])
448             templist.append(ortholinePairOne)
449             templist.append(ortholinePairTwo)
450             templist.append(ortholinePairThree)
451             templist.append(ortholinePairFour)
452
453             for i,element in enumerate(templist):
454                 #print(element)
455                 #print(element[2])
456                 templist[i] = element;element[2]
457
458             matrixAT = []
459             matrixAT.append([templist[0][0]*templist[1][0],templist
460                 [0][0]*templist[1][1]+templist[0][1]*templist[1][0]])
461             matrixAT.append([templist[2][0]*templist[3][0],templist
462                 [2][0]*templist[3][1]+templist[2][1]*templist[3][0]])
463             matrixAT = np.asarray(matrixAT)
464             matrixAT = np.linalg.pinv(matrixAT)
465             matrixA = []
466             matrixA.append([-templist[0][1]*templist[1][1]])
467             matrixA.append([-templist[2][1]*templist[3][1]])
468             matrixA = np.asarray(matrixA)
469
470             matrixS = np.dot(matrixAT,matrixA)
471             matrixSRearranged = np.zeros((2,2))
472
473             matrixSRearranged[0][0] = matrixS[0]
474             matrixSRearranged[0][1] = matrixS[1]
475             matrixSRearranged[1][0] = matrixS[1]
476             matrixSRearranged[1][1] = 1
```

```
471     v, lambdamatrix, q = np.linalg.svd(matrixSRearranged)
472
473     lambdaValue = np.sqrt(np.diag(lambdamatrix))
474     Hmatrix = np.dot(np.dot(v, lambdaValue), v.transpose())
475
476     affineHomography=np.zeros((3,3))
477     affineHomography[0][0] = Hmatrix[0][0]
478     affineHomography[0][1] = Hmatrix[0][1]
479     affineHomography[1][0] = Hmatrix[1][0]
480     affineHomography[1][1] = Hmatrix[1][1]
481     affineHomography[2][2] = 1
482
483
484     inverseH = np.linalg.pinv(affineHomography)
485     inverseH = np.dot(inverseH, self.homographies[0])
486     self.homographies.append(inverseH)
487     inverseH = np.linalg.pinv(inverseH)
488     self.homographies.append(inverseH/inverseH[2][2])
489
490     def oneStepDistortionHomography(self, queueImage):
491         """[summary]
492             Calculate the homography matrix to eliminate both
493                 projective and affine distortion
494
495         Args:
496             queueImage ([int]): [Index of the image in the list
497                 being used]
498
499             Calculates the Homography matrix and appends it to the
500                 global homography list.
501
502             """
503             matrixA=[]
504             matrixAT = []
505             templist=[]
506             templist.append(np.cross(self.roiList[queueImage][0], self
507                 .roiList[queueImage][1]))
508             templist.append(np.cross(self.roiList[queueImage][1], self
509                 .roiList[queueImage][3]))
510             templist.append(np.cross(self.roiList[queueImage][1], self
511                 .roiList[queueImage][3]))
512             templist.append(np.cross(self.roiList[queueImage][3], self
513                 .roiList[queueImage][2]))
514             templist.append(np.cross(self.roiList[queueImage][3], self
515                 .roiList[queueImage][2]))
516             templist.append(np.cross(self.roiList[queueImage][2], self
517                 .roiList[queueImage][0]))
518             templist.append(np.cross(self.roiList[queueImage][2], self
519                 .roiList[queueImage][0]))
520             templist.append(np.cross(self.roiList[queueImage][0], self
521                 .roiList[queueImage][1]))
522             templist.append(np.cross(self.roiList[queueImage][0], self
523                 .roiList[queueImage][3]))
524             templist.append(np.cross(self.roiList[queueImage][1], self
525                 .roiList[queueImage][3]))
```

```
    .roiList[queueImage][2]))  
512  
513     for i,element in enumerate(templist):  
514         templist[i] = element/element[2]  
515  
516     for i in range(0,10,2):  
517         matrixAT.append([templist[i][0]*templist[i+1][0],(  
518             templist[i][0]*templist[i+1][1]+templist[i][1]*  
519             templist[i+1][0])/2,templist[i][1]*templist[i+1][1],(  
520             templist[i][0]*templist[i+1][2]+templist[i][2]*  
521             templist[i+1][0])/2,(templist[i][1]*templist[i+1][2]+  
522             templist[i][2]*templist[i+1][1])/2])  
523     matrixA.append([-templist[i][2]*templist[i+1][2]])  
524  
525     matrixAT = np.asarray(matrixAT)  
526     matrixA = np.asarray(matrixA)  
527     matrixS = np.dot(np.linalg.pinv(matrixAT),matrixA)  
528     matrixS = matrixS/np.max(matrixS)  
529  
530     matrixSRearranged = np.zeros((2,2))  
531     matrixSRearranged[0][0] = matrixS[0]  
532     matrixSRearranged[0][1] = matrixS[1] * 0.5  
533     matrixSRearranged[1][0] = matrixS[1] * 0.5  
534     matrixSRearranged[1][1] = matrixS[2]  
535     matrixST = np.array([matrixS[3]*0.5,matrixS[4]*0.5])  
536     v,lambdamatrix,q = np.linalg.svd(matrixSRearranged)  
537     lambdavalue = np.sqrt(np.diag(lambdamatrix))  
538     Hmatrix = np.dot(np.dot(v,lambdavalue),v.transpose())  
539     Vmatrix = np.dot(np.linalg.pinv(Hmatrix),matrixST)  
540  
541     onestepHomography = np.zeros((3,3))  
542     onestepHomography[0][0] = Hmatrix[0][0]  
543     onestepHomography[0][1] = Hmatrix[0][1]  
544     onestepHomography[1][0] = Hmatrix[1][0]  
545     onestepHomography[1][1] = Hmatrix[1][1]  
546     onestepHomography[2][0] = Vmatrix[0]  
547     onestepHomography[2][1] = Vmatrix[1]  
548     onestepHomography[2][2]=1  
549  
550  
551  
552  
553  
554 if __name__ == "__main__":  
555     """  
556     The code begins here. Make sure the input image paths are  
557     properly inserted.
```

```
558
559     """
560
561     tester = removeDistortion(['hw3_Task1_Images/Images/1.jpg','
562                               hw3_Task1_Images/Images/2.jpg','hw3_Task1_Images/Images/3.
563                               jpg'])
564     tester.getROIFromUser()
565     for i in range(0,3):
566         tester.objectMatrixFunction(i)
567         tester.parameterMatrixFunction(i,i)
568         tester.calculateHomography()
569         resultImg = tester.createImage(0,i)
570         cv.imwrite("ptp"+str(i)+".jpg",resultImg)
571
572     tester.getROIFromUser()
573
574     for i in range(0,3):
575         tester.projectiveDistortionHomography(i)
576         resultImg = tester.createImage(0,i)
577         # resultImg = tester.createImageVectorised(0,0)
578         cv.imwrite('1'+str(i)+'.jpg',resultImg)
579         tester.affineDistortionHomography(i)
580         resultImg = tester.createImage(2,i)
581         cv.imwrite('2'+str(i)+'.jpg',resultImg)
582         tester.oneStepDistortionHomography(i)
583         resultImg = tester.createImage(4,i)
584         cv.imwrite('3'+str(i)+'.jpg',resultImg)
585
586 ##### Custom Input Images#####
587
588     tester = removeDistortion(['hw3_Task1_Images/Images/sn.jpg','
589                               hw3_Task1_Images/Images/laptop.jpg'])
590     tester.getROIFromUser()
591     for i in range(0,2):
592         tester.objectMatrixFunction(i)
593         tester.parameterMatrixFunction(i,i)
594         tester.calculateHomography()
595         resultImg = tester.createImage(0,i)
596         cv.imwrite("ptp"+str(i)+".jpg",resultImg)
597
598     tester.getROIFromUser()
599
600     for i in range(0,2):
601         tester.projectiveDistortionHomography(i)
602         resultImg = tester.createImage(0,i)
603         # resultImg = tester.createImageVectorised(0,0)
604         cv.imwrite('1'+str(i)+'.jpg',resultImg)
605         tester.affineDistortionHomography(i)
606         resultImg = tester.createImage(2,i)
607         cv.imwrite('2'+str(i)+'.jpg',resultImg)
608         tester.oneStepDistortionHomography(i)
609         resultImg = tester.createImage(4,i)
610         cv.imwrite('3'+str(i)+'.jpg',resultImg)
```