

Project 4: Panoramas

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I. P 4.1: SPHERICAL REPROJECTION

This part of the code, we are using blender to generate images. The images that I have generated using blender with different focal lengths are listed below.

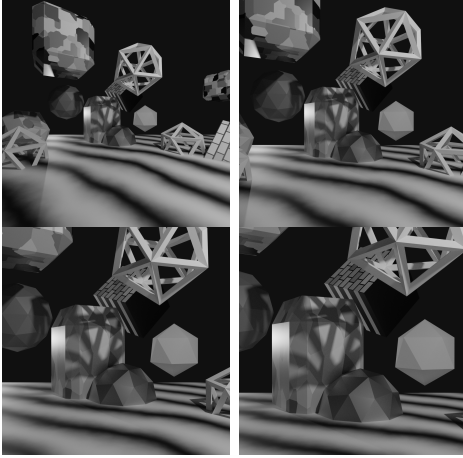


Fig. 1. Blender Images

We basically take 1 image and generate 4 different images with different focal lengths. We are making a panorama by reprojecting the images onto sphere by editing the reproject_image_to_sphere. By researching lecture slides, as asked in the jupyter lab, I got the formula from the slides which is displayed below. To convert the spherical coordinates, you have to find the unit vector for x, y, z.

$$x = \sin\theta \cos\phi$$

$$y = \sin\phi$$

$$z = \cos\theta \sin\phi$$

To project images into a plane, the equation of x is $f * x/z$ and y is $f * y/z$.

We can re-project the images onto a sphere

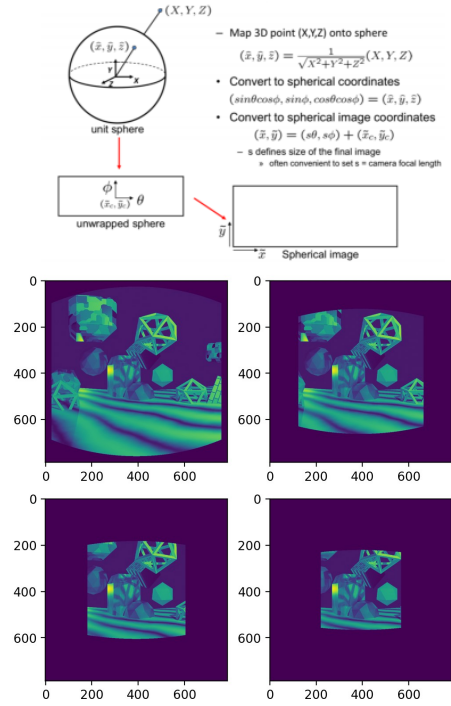


Fig. 2. The Re-projection

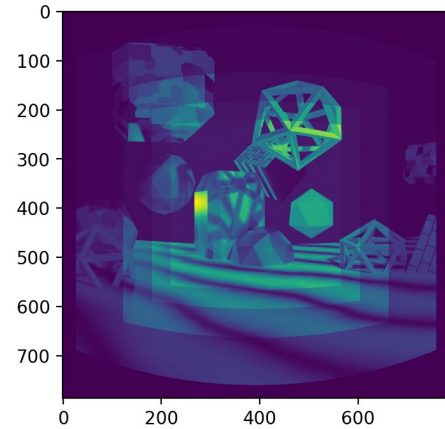


Fig. 3. Panorama

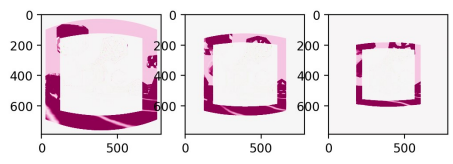


Fig. 4. Difference

II. P 4.2: PANORMA STITCHING

After generating all the images and re-projecting it into a sphere, you can see the panorama image generated below. By following the thorough explanation on the slides about how to stitch images together to generate a mosaic, I first found the corresponding features in a pair of image. We did feature matching in earlier projects, so the first step similar to that previous project.

In step 2, I computed the transformation between the images through the command, `cv.warpPerspective`, to move the images in place and by following step 3, I warped the images on top of each other so image 1 will overlay on image 2. Finally, I went ahead to blend the images, so we will not have a visual difference between the matching of the images. In shorter terms, the image will look smooth.

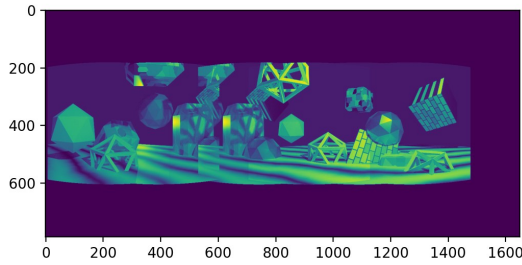


Fig. 5. Combined Image Panorama

III. P4.3.1 PROJECTING INTO IMAGE SPACE

The goal of 4.3.1 is to basically go over computing image-space point from a 3D point in a scene and the known camera matrices. We are going to apply the `get_projected_point` function on these two images. What we are going to do is detect the edges of the cubes as you can see below.

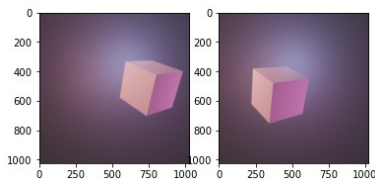


Fig. 6. Image A and B cubes

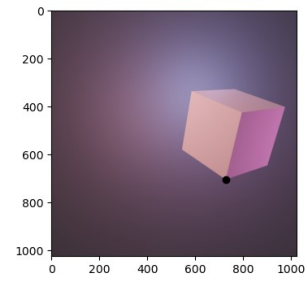


Fig. 7. Image A

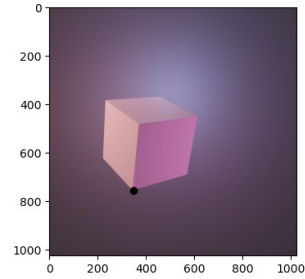


Fig. 8. Image B

A. Question: What are the camera matrices p_a and p_b ? I will accept either the final matrix, or the matrix written in terms of its component matrices (the intrinsic and extrinsic matrices), as long as these are defined.

Matrix P_a is below

$$\begin{bmatrix} 1.13780e+03 & 0.00000e+00 & 5.12000e+02 & 2.56000e+03 \\ 0.00000e+00 & 1.13780e+03 & 5.12000e+02 & 2.33244e+03 \\ 0.00000e+00 & 0.00000e+00 & 1.00000e+00 & 5.00000e+00 \end{bmatrix}$$

Matrix P_b is written below

$$\begin{bmatrix} 1.1378e+03 & 0.0000e+00 & 5.1200e+02 & 8.5330e+02 \\ 0.0000e+00 & 1.1378e+03 & 5.1200e+02 & 2.5600e+03 \\ 0.0000e+00 & 0.0000e+00 & 1.0000e+00 & 5.0000e+00 \end{bmatrix}$$

IV. P4.3.2 DETERMINING THE SIZE OF THE CUBE

In section 4.3.2, we will triangulate a point from two correspondences and the steps to do so is given in the slides. First I am picking the two corners of the cube and randomly making an educated guess regarding its x, y image coordinates for both the images, a and b. As you can see, I have also added the code snippet for the section to help better understand my explanation and gain full credit. Using Image A and Image B, and the variety of coordinated generated from the two images, you can see that we are sort of detecting the edges of the cube similar to what we did in previous project.

A. Question: What is the side length of the cube shown in the two images above?

The side length of the cube shown in the two images below is 1.1536955839418352.

$$\begin{bmatrix} 1.77195723 & 0.81604985 & 0.15646519 \\ 1.91903588 & -0.24615024 & -0.28324128 \end{bmatrix}$$

```

def find_path
  # Create a vector of ImagePoints[] from triangulation to compute 3D point from the 2D image coordinates from the different cameras
  img_pts = ImagePoints[]
  Ap = P[]
  Ap1 = P[]
  Ap2 = P[]
  # Note: The following rows from camera matrices to be used in A matrix
  Ap = Ap1
  Ap = Ap2
  Ap = Ap1
  Ap = Ap2
  A = np.zeros((3,3))
  b = np.zeros(3)
  A[0,0] = np.dot(ImagePoints[0], Ap0)
  A[0,1] = np.dot(ImagePoints[0], Ap1)
  A[0,2] = np.dot(ImagePoints[0], Ap2)
  A[1,0] = np.dot(ImagePoints[1], Ap0)
  A[1,1] = np.dot(ImagePoints[1], Ap1)
  A[1,2] = np.dot(ImagePoints[1], Ap2)
  A[2,0] = np.dot(ImagePoints[2], Ap0)
  A[2,1] = np.dot(ImagePoints[2], Ap1)
  A[2,2] = np.dot(ImagePoints[2], Ap2)
  # Solve system of linear system using numpy.linalg.lstsq(A,b)
  # Compute 3D coordinate by taking eigenvalue with smallest eigenvalue of A
  b = eigenvals(A, np.array(eigen_values))
  b = b[b[0]]
  return b
end def

def find_pts
  img_pts = ImagePoints[]
  img_pts1 = ImagePoints[]
  img_pts2 = ImagePoints[]
  # Usually selected 2D image points
  img_pts1 = ImagePoints[]
  img_pts2 = ImagePoints[]
  img_pts3 = ImagePoints[]
  # Solve system of linear system using numpy.linalg.lstsq(A,b)
  point_3D = np.array([img_pts[0], img_pts[1], img_pts[2]])
  # Find 3D point of first 3D point selected
  point_3D = point_3D
  # Solve system of linear system using numpy.linalg.lstsq(A,b)
  point_3D = np.array([img_pts1[0], img_pts1[1], img_pts1[2]])
  # Find 3D point of second 3D point selected
  point_3D = point_3D
  # Solve system of linear system using numpy.linalg.lstsq(A,b)
  point_3D = np.array([img_pts2[0], img_pts2[1], img_pts2[2]])
  # Find 3D point of third 3D point selected
  point_3D = point_3D
  # Compute side length of cube
  distance12 = math.sqrt((point_3D[0] - point_3D[1])**2 + (point_3D[1] - point_3D[2])**2 + (point_3D[2] - point_3D[3])**2)
  distance13 = math.sqrt((point_3D[0] - point_3D[2])**2 + (point_3D[1] - point_3D[3])**2 + (point_3D[2] - point_3D[0])**2)
  distance23 = math.sqrt((point_3D[1] - point_3D[2])**2 + (point_3D[2] - point_3D[3])**2 + (point_3D[3] - point_3D[0])**2)
  return (distance12, distance13, distance23)
end def

```

Fig. 9. 4.3.2 Code

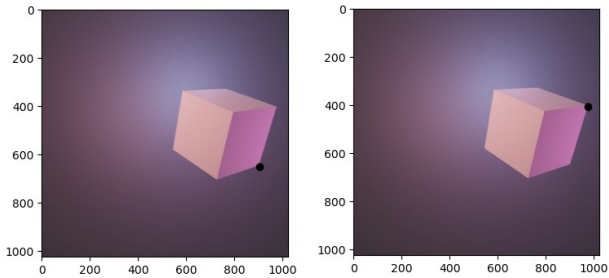


Fig. 10. Image A Point 1 and 2

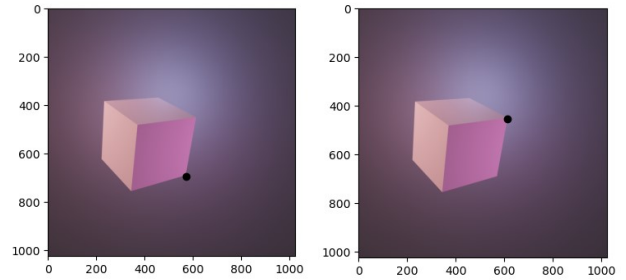


Fig. 11. Image B Point 1 and 2

V. P 4.4: STEREO PATCH MATCHING

Using the patch match stereo, I am going to detect the features matches in the art image given to me in this section. This will create a depth map of the images.

A. *Question: The possible feature matches in the second image are along the epipolar line. Since the images are properly rectified, what is the epipolar line in the second image corresponding to coordinate (x_a, y_a) in the first image?*

To answer the question, I would first like to explain what epipolar line is which can be defined as the lines intersecting at the epipolar plane and the two image planes. Epipolar lines have such a property that they intersect the baseline at the respective epipoles in the image plane. If your two image planes are parallel to each other then the epipoles are located at infinity and the epipolar lines will be parallel to the x axis of each image plane. Therefore, if the image is rectified, the epipolar line will be parallel on the x and y coordinate in the first image.

B. Question: The left few columns of both depth maps is quite noisy and inaccurate. Give an explanation for why this is the case?

If you look closely, you can see that the depth map is being shifted towards the left by a few pixels. This is the main reason why the columns within the image of both, the ssd and ncc, image are quite noisy and inaccurate on the left.

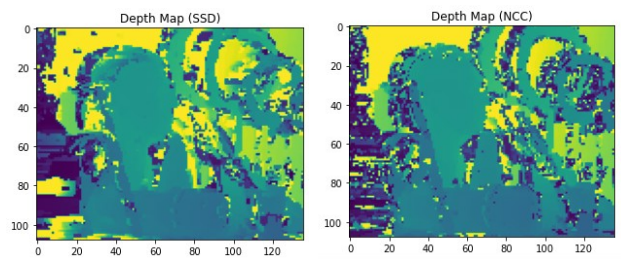


Fig. 12. Depth Map