Name: Bhavya Samhitha Mallineni
USC ID: 6580252371
USC Email: mallinen@usc.edu
Submission Date: 03/10/2024

REPORT
HOMEWORK3

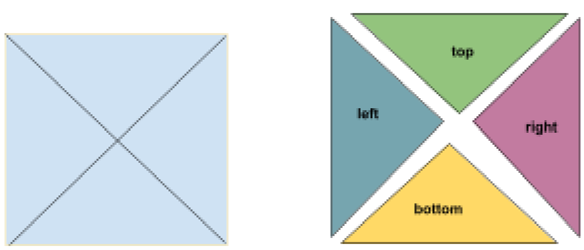
Problem 1: Geometric Image Modification

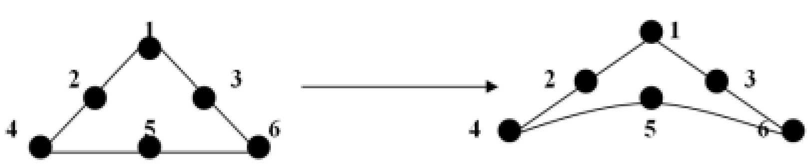
I. Abstract and Motivation :

Geometric transformation in the realm of image processing is a method that alters the positions of pixels while keeping their colors intact. This approach is used for several purposes, including generating unique visual effects, aligning images accurately, and seamlessly blending one image into another.
Spatial warping is achieved by applying a coordinate mapping function to the image pixels, which repositions them according to a predefined mathematical model. The process can stretch, compress, or rotate the image content, effectively changing its appearance while maintaining pixel integrity. Spatial warping is widely used in creating artistic effects, correcting distortions, and simulating different viewpoints, enhancing.

II. Approach and Procedure:

For our problem, we need to perform spatial warping on images of dogs and cats. The goal is to achieve a star-shaped effect, where all images appear to curve towards the center. To accomplish this, I divided each image into four triangles: top, left, right, and bottom. I used this specific mapping function for this process,





$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} a_0 & a_1 & a_2 & a_3 & a_4 & a_5 \\ b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \\ x^2 \\ xy \\ y^2 \end{bmatrix}$$

$$\begin{bmatrix} a_0 & a_1 & a_2 & a_3 & a_4 & a_5 \\ b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix} = \begin{bmatrix} u_0 & u_1 & u_2 & u_3 & u_4 & u_5 \\ v_0 & v_1 & v_2 & v_3 & v_4 & v_5 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ x_0 & x_1 & x_2 & x_3 & x_4 & x_5 \\ y_0 & y_1 & y_2 & y_3 & y_4 & y_5 \\ x_0^2 & x_1^2 & x_2^2 & x_3^2 & x_4^2 & x_5^2 \\ x_0y_0 & x_1y_1 & x_2y_2 & x_3y_3 & x_4y_4 & x_5y_5 \\ y_0^2 & y_1^2 & y_2^2 & y_3^2 & y_4^2 & y_5^2 \end{bmatrix}^{-1}$$

which involved taking the inverse of a matrix to find the coefficients of my quadratic equations. After solving these equations, I mapped the pixels in the output image within each triangle back to the original image using these coefficients. Finally, I calculated the pixel values using bilinear interpolation.
To reconstruct the warped output, we had to warp it back to its original location values.

III. Experimental Results:

Figure 1: Original Cat Image

Figure 2: Cat Image after warping

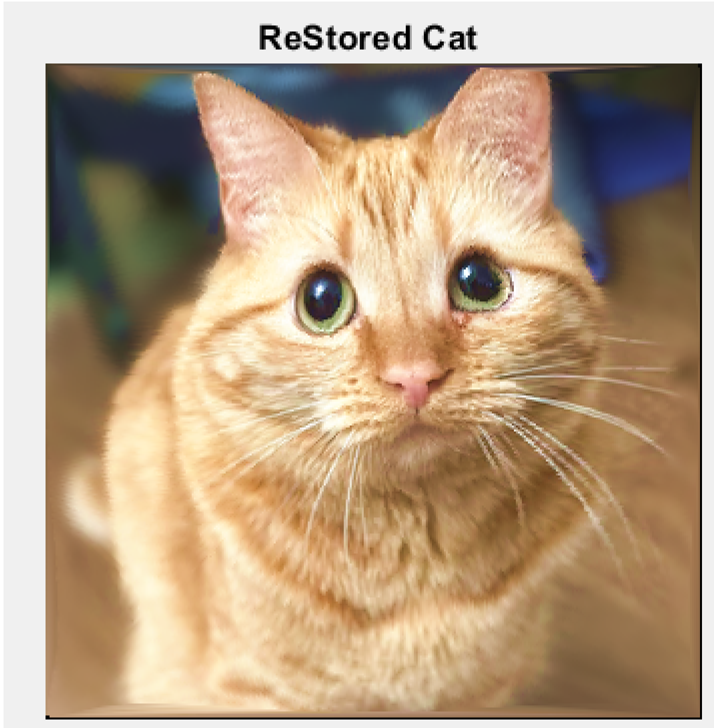


Figure 3: Cat Image after reverse warping

Figure 4: Original Dog Image

Figure 5: Dog Image after warping

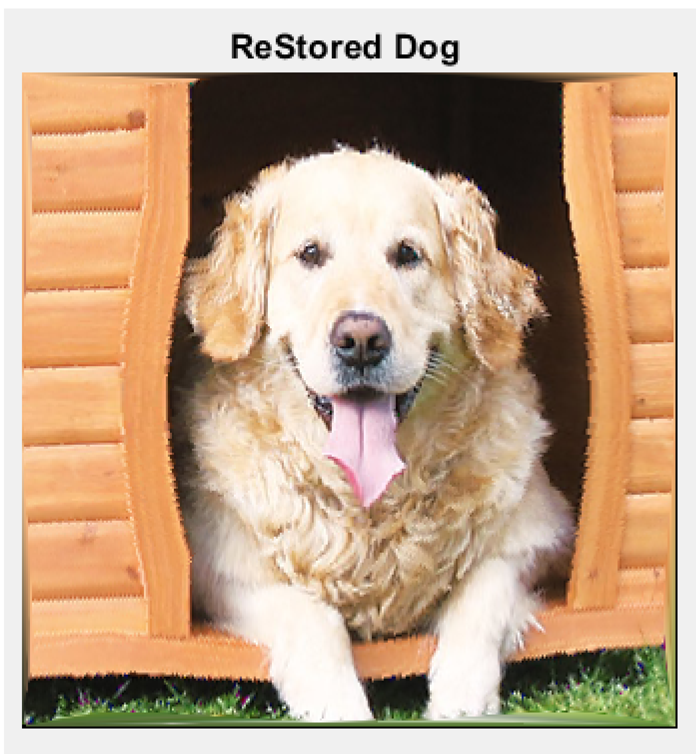


Figure 6: Dog Image after reverse warping

IV. Discussion

1) The results of the spatial warping are above.
2) After applying the reverse spatial warping by interchanging the indices
3) There is definitely a difference in the image quality, as the original image is clearer. The recovered image is taken from a compressed original image, which means that when we are reverting back, we are expanding a small image to a larger one. This will cause a lot of distortion

Problem 2: Homographic Transformation and Image Stitching

V. Abstract and Motivation:

The homography matrix is a transformative tool in computer vision that enables the mapping of points from one plane to another through a projective transformation. This mathematical concept is crucial for various applications, including augmented reality, where it assists in estimating the camera pose from points that lie on the same plane. It's also instrumental in correcting perspectives in images, allowing for adjustments that make the captured scene appear as if viewed from a single, consistent point of view. This correction is essential for tasks like perspective removal, where the goal is to eliminate the distortion caused by the camera angle, making the image look as though it was taken straight on.
Homography finds significant use in image warping, enabling the alteration of the original image shape for various effects or corrections. Perhaps one of its most captivating applications is in panorama stitching. This process involves synthesizing and combining multiple photographs taken from different viewpoints into a seamless single image that represents a unified perspective. By applying the homography matrix, we can effectively align and stitch these images, ensuring that the transition between them is smooth and natural, thereby creating a cohesive panorama that offers a broad, unified view from multiple images.

VI. Approach and Procedure:

Several steps were followed to produce the panorama image, including:

1. Converting all the color images to black and white.
2. Finding the features in each of the left, right, and middle images using SURF (Speeded Up Robust Features) open-source. SURF is a robust local feature

detector and descriptor that is used in computer vision tasks for object recognition, image matching, and classification. It is known for its speed and efficiency, especially in comparison to other feature detectors and descriptors like SIFT.

3. Checking various matching points to see if they exactly match.
4. Selecting 4 points that show similarity.
5. Using the set of 4 points to find the two different homography matrices, one for the left and one for the right. A homography matrix of two points gets a new set of points. Using a single pair of matching points, we can derive two equations. Applying forward mapping on the left and the right, we obtain a new set of points. The black spaces are filled using interpolation.

$$\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} * \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x_2' \\ y_2' \\ w_2' \end{bmatrix}$$

$$x_2 = \frac{x_2'}{w_2'}$$

$$y_2 = \frac{y_2'}{w_2'}$$

$$h_{11}x_1 + h_{12}y_1 + h_{13} = x_2(h_{31}x_1 + h_{32}y_1 + h_{33})$$

$$h_{21}x_1 + h_{22}y_1 + h_{23} = y_2(h_{31}x_1 + h_{32}y_1 + h_{33})$$

VII. Experimental Results:

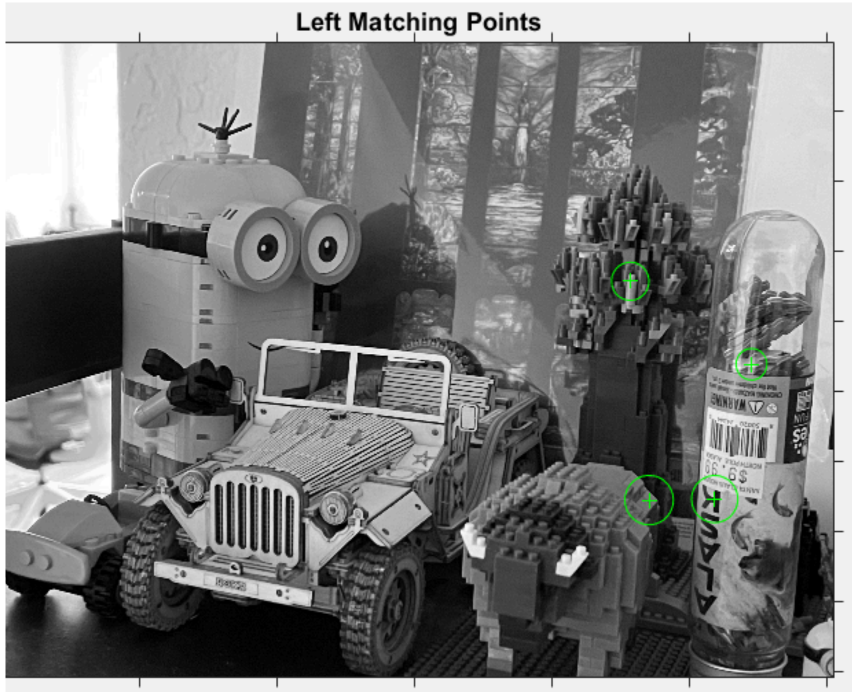


Figure7: left features

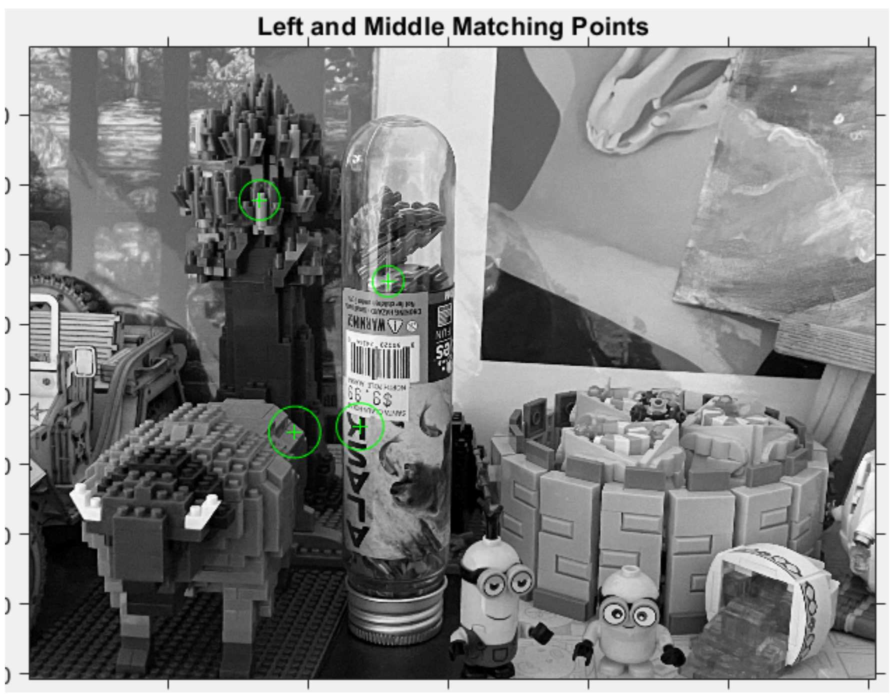


Figure 8: left and middle common features

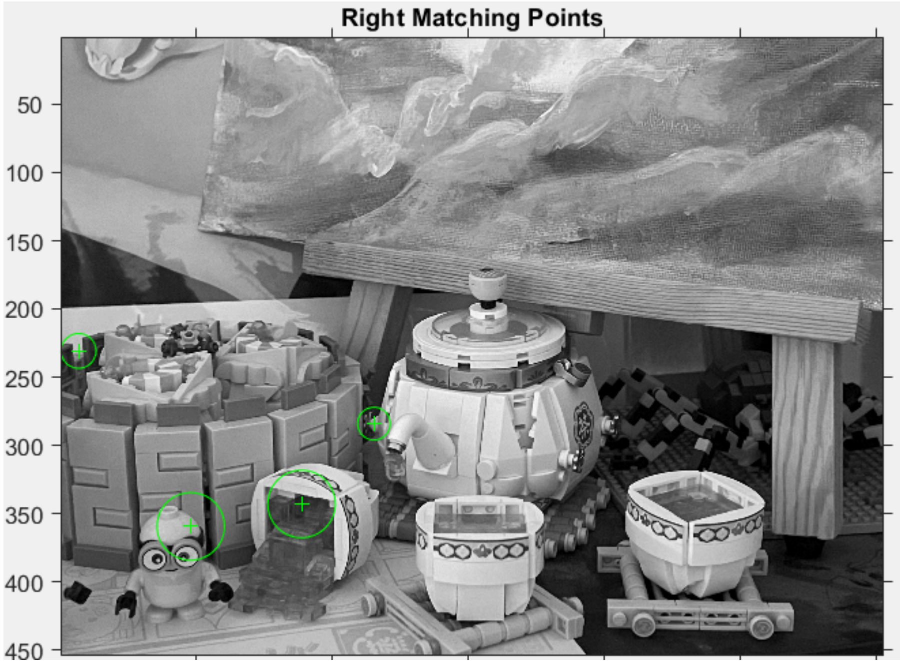


Figure 9: right features

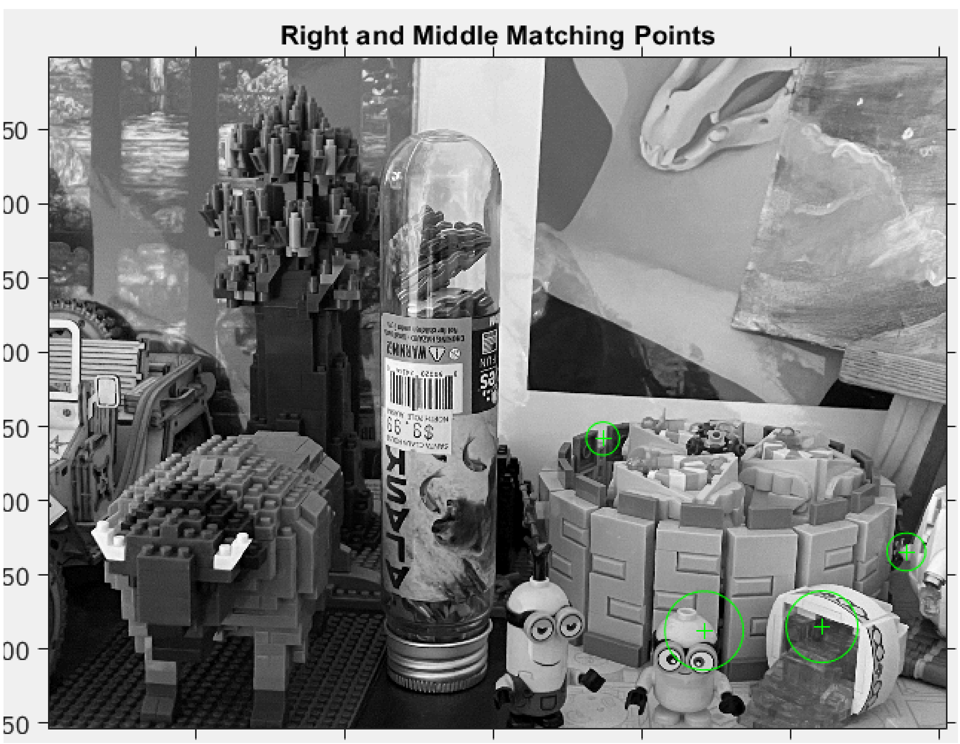


Figure 10: right and middle common features

Figure 11: left and middle common features mapping

Figure 12: right and middle common features mapping

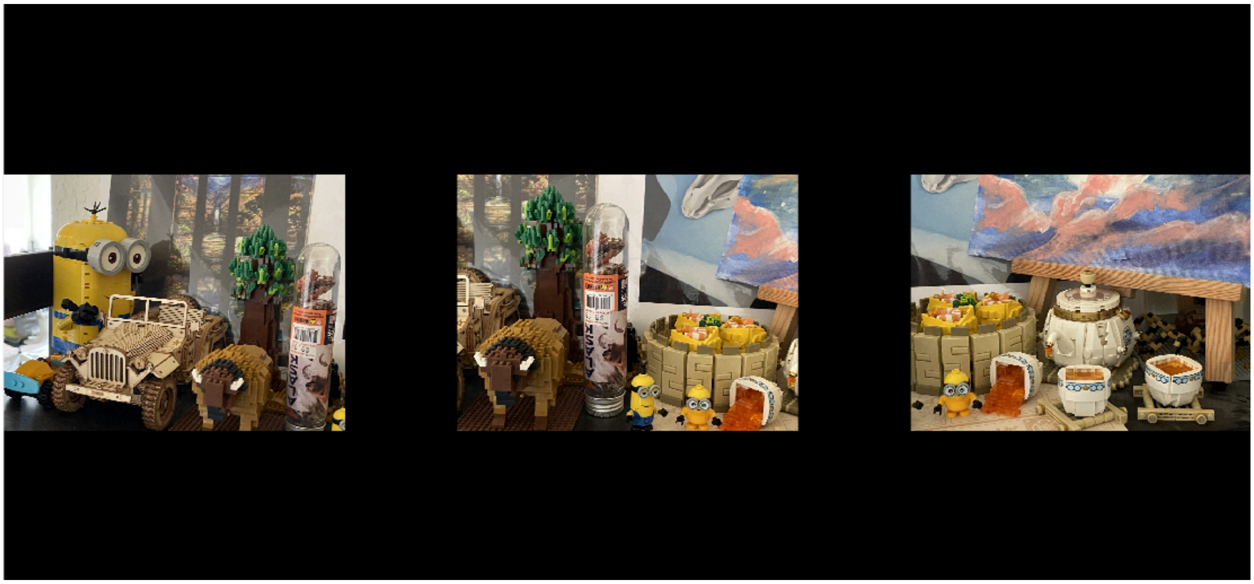


Figure 13: creating a big enough Canvas

Figure 14: After forward mapping of left and right homographic matrix

VIII.

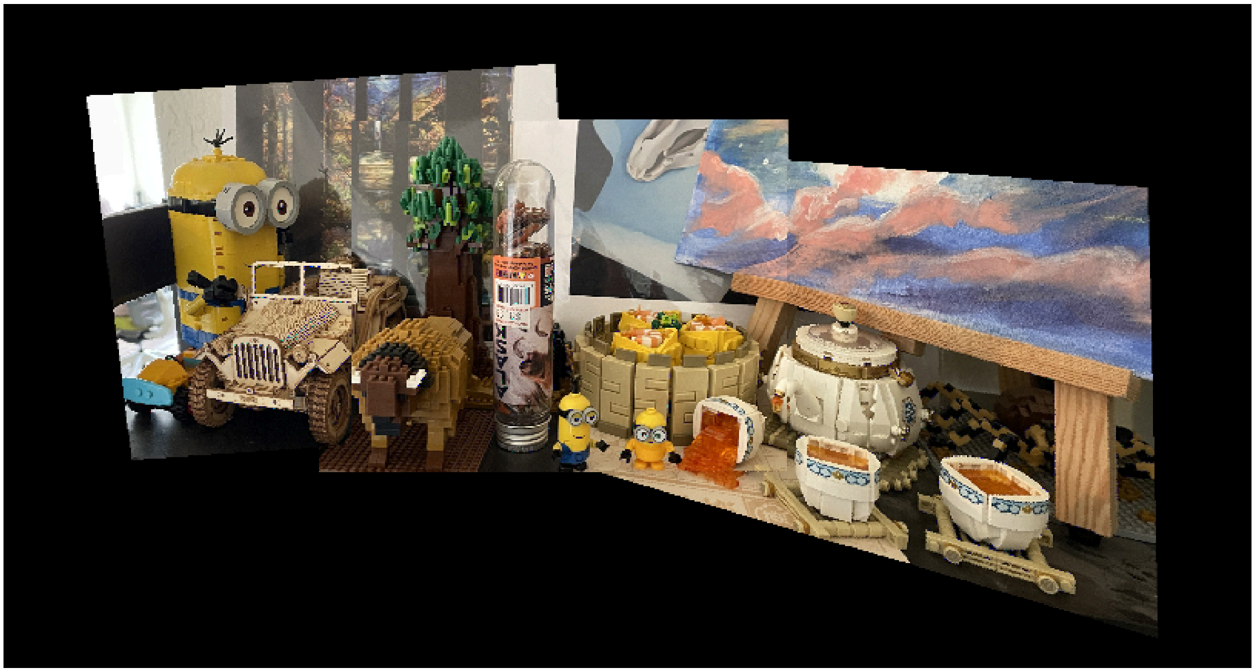


Figure 15: Panorama after interpolation

VIII. Discussion:

The results are shown above

1. Each pair of images must have a minimum of four control points in order to perform a homogeneous transformation. This is due to the fact that every pair of control points yields two equations, and when four pairs are obtained, the eight equations required to solve for the eight unknowns in the matrix in H are obtained.
2. The control points were selected based on feature matching between two consecutive images, which were obtained using the SURF algorithm. I considered various sets of 4 control points and ultimately chose the best 4 that yielded a satisfactory panorama output.SURF (Speeded Up Robust Features) is pivotal for creating panoramas as it efficiently identifies and matches distinctive features across images. This algorithm accelerates the feature detection process and ensures robustness against image transformations. By pinpointing precise control points for alignment, SURF facilitates seamless stitching of images into a cohesive panorama, enhancing visual continuity.

Problem 3: Morphological Processing

IX. Abstract and Motivation

Morphological processes such as thinning, shrinking, and skeletonizing are essential techniques in digital image processing, primarily used for shape manipulation and feature extraction. Thinning reduces the thickness of object boundaries to a single pixel width, effectively simplifying the object's representation while preserving its overall topology and geometry. This process is particularly useful in pattern recognition and OCR (Optical Character Recognition), where the simplified object can be more easily analyzed. Shrinking, on the other hand, systematically reduces objects in a binary image to smaller representations, potentially down to single points, enabling the counting or labeling of disconnected objects in a scene. Skeletonizing, akin to thinning, refines objects to their skeletal backbone, but focuses on retaining the critical structure that represents the shape's essence. This is crucial in medical imaging, biometric recognition, and structural analysis, where understanding the underlying anatomical or structural features is paramount. Each of these processes employs iterative algorithms that apply specific morphological operators, ensuring that the transformation preserves the fundamental attributes of the original image while reducing its complexity for further analysis.

a. Basic Morphological Process and Implementation:

X. Approach and Procedure

Here, we have performed thinning using pattern tables. The steps involved in thinning are as follows:

1. Since the image is in grayscale, we first convert it into binary.
2. We apply the thinning iteratively. In the morphological algorithm, we distinguish between conditional and unconditional patterns.
3. The image is first processed through all the conditional patterns, where it records the matches.
4. These matches are then passed on to the unconditional patterns, where pixel removal occurs.
5. This process continues until convergence, meaning no further pixels can be removed.

XI. Experimental Results

All the original, 20th iterations and the final thinning output.

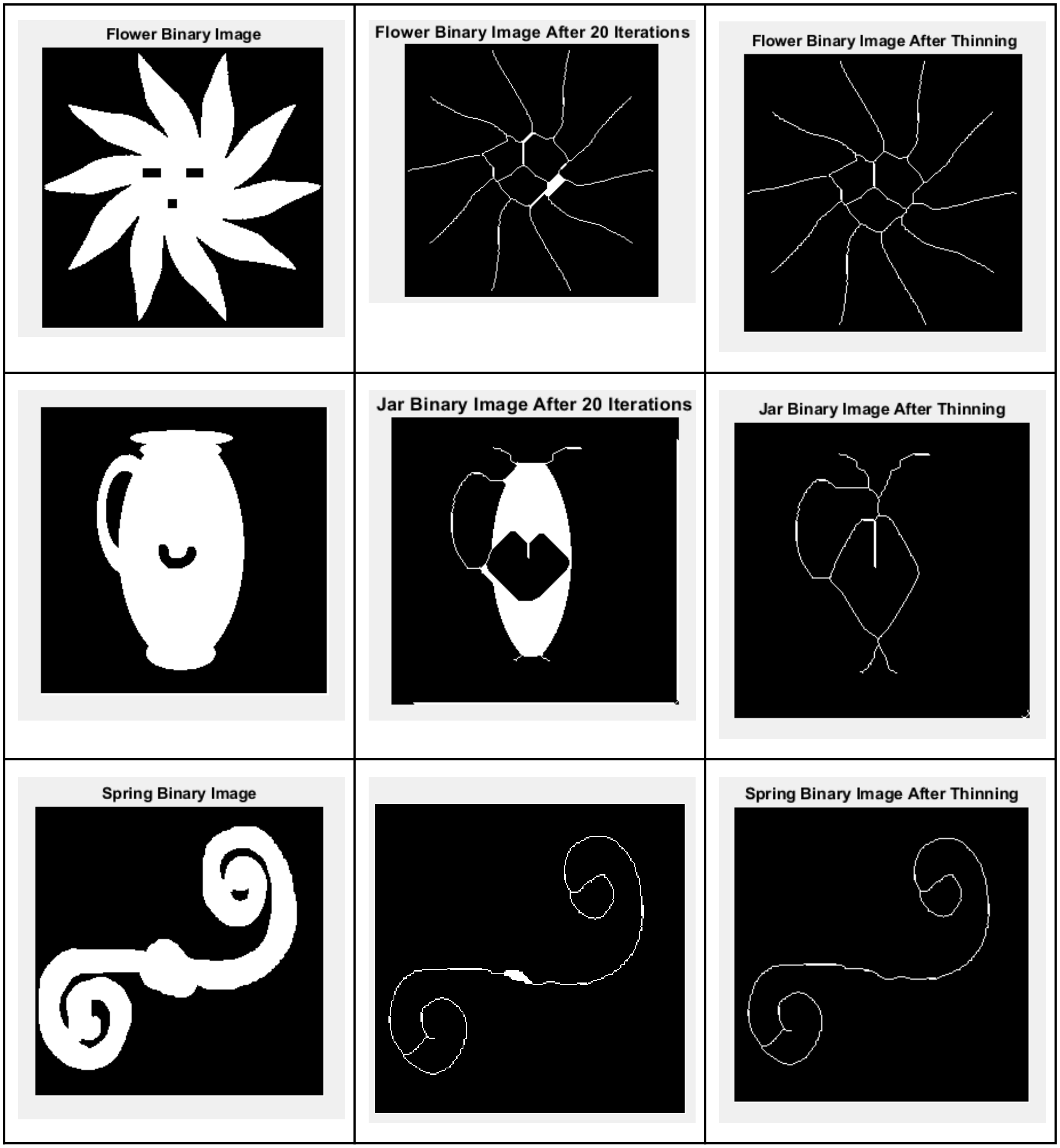


Figure 16: Comparison of different thinning levels

XII. Discussion:

The intermediate thinning images and the final thinned image are obtained. We can observe that thinning happens iteratively, removing each layer one by one. The iterations end when the image is maximally thinned, and it can't be further reduced.

b. Shape Detection and Counting:

XIII. Approach and Procedure:

1. To find the number of black holes, we first inverted the image, making all the black circular holes white. Then, using a shrinking operation, we changed these holes into dots, which were then counted using a simple pattern of [0 0 0, 0 1 0, 0 0 0].
2. After filling the black holes, the image was converted back to its original state, and the shrinking operation was performed again. This time, all areas with white objects became points, and these points were counted using the same method as above.
3. And 4. Here we are using connected components to detect the object shape, where The binary image is scanned to identify pixels that belong to the foreground. When a foreground pixel is found, it is checked against its neighbors (adjacent pixels) to determine if it is part of a new object or an existing one. Each identified foreground pixel is assigned a label. If a pixel is part of an existing object (connected to other foreground pixels already encountered), it receives the same label as those connected components. If it is the first pixel of a new object, it is given a new label. The process ensures that all pixels belonging to the same object have the same label.Once all objects have been labeled, their properties can be analyzed. This can include the number of pixels (area), perimeter (boundary length), and shape descriptors like circularity.

XIV. Experimental Results:

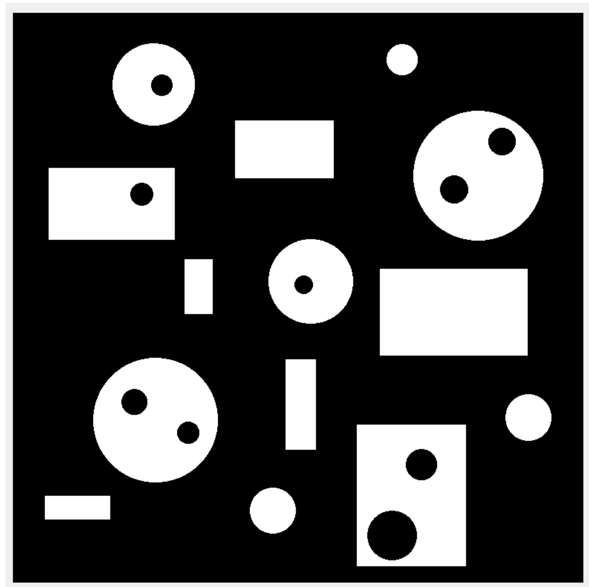


Figure 17: original Image

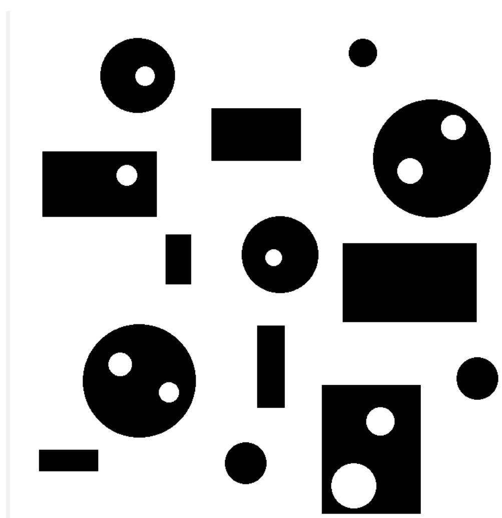


Figure 18: inverted image

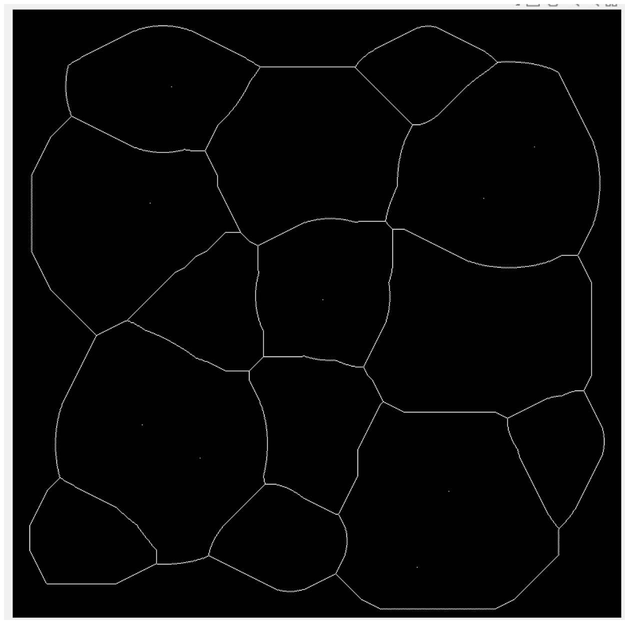


Figure 19: Shrinked Image

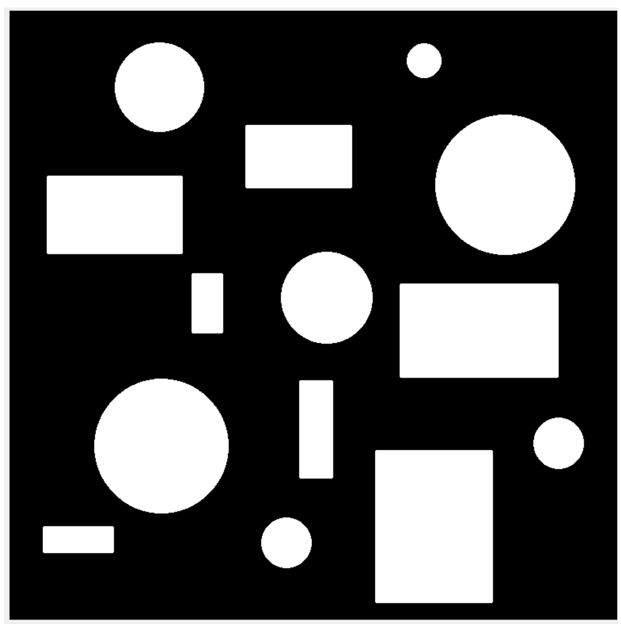


Figure 20: Black holes filled image

XV. Discussion:

Finally we got all the correct counts using morphological processing

```
Number of black dots: 9
Number of white objects: 14
Number of Rectangles: 7
Number of Circles: 7
```

Figure 21: Final output counts

C. Object Segmentation and Analysis:

XVI. Approach and Procedure:

To accurately count the total number of beans in the images, a series of pre-processing steps is employed. Initially, the color images are converted to grayscale to simplify the subsequent analysis. Following this, the grayscale images undergo further processing to eliminate noise and emphasize the object edges, facilitating easier object detection. The Canny edge detection algorithm is applied for this purpose, which effectively identifies the edges of the beans while minimizing background interference. Subsequently, using connected components analysis, the number of distinct objects, representing individual beans, is determined. Leveraging the labeled components and the corresponding bean counts, the area of each bean is computed and compared. This comparison aids in distinguishing between different types of beans and provides valuable insights into their distribution and characteristics within the images.

XVII: Experimental Results :

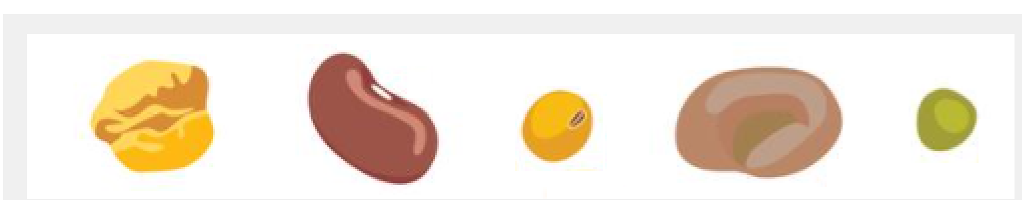


Figure 22: Original Beans image

Figure 23: Canny Edge Detected

```
Number of beans: 5
```

XVII: Discussion :

Position of the Bean	Area of the bean
5	402
3	411
2	1062
1	1354
4	1714

From the morphological processing we could detect the object and get the areas of the beans.