Assignment 1 Report

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Using OpenCV and Python for image detection, segmentation and stitching.

Link to GitHub Repo:

https://github.com/NikitaKiran/VR_Assignment1_NikitaKiran_IMT2022028

Installation and Setup

Step 1: Install Dependencies

Install the required Python packages:

```
pip install opencv-python numpy matplotlib
```

Step 2: Prepare Input Images

- Place the input image for **coin detection** (`coin_detection_input.jpg`) inside the `inputs/` folder.
- Place the three images for **image stitching** (`1.jpg`, `2.jpg`, `3.jpg`) inside `inputs/panorama_inputs1/`.

Step 3: Running the Code

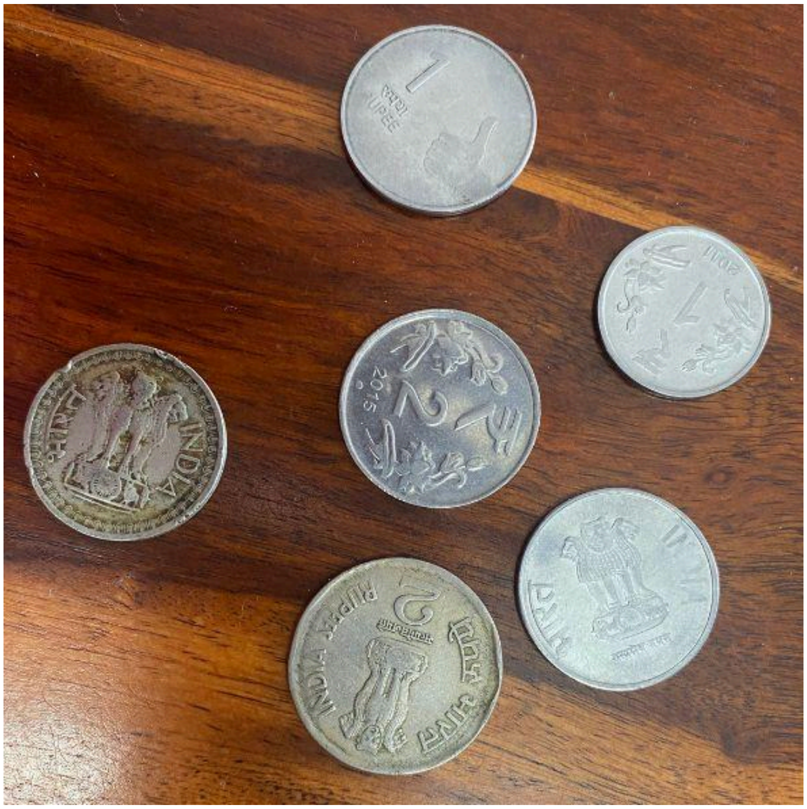
1. After ensuring the images are in the correct path and the dependencies are installed, navigate to the project directory in the terminal.
2. Run the code for Part 1 by executing the following command:
   ```
   python coin_detection.py
   ```
3. Run the code for Part 2 by executing the following command:
   ```
   python image_stitching.py
   ```

Step 4: Viewing Outputs

- The outputs for coin detection are saved in `coin_detection_outputs/`
- The outputs for image stitching are saved in `panorama_outputs1/`

Coin Detection and Segmentation

Input Image:



Methodology

1. ***Preprocessing***:
   - The input image is first converted to grayscale for easier processing.
   - A **Gaussian Blur** is applied to reduce noise.

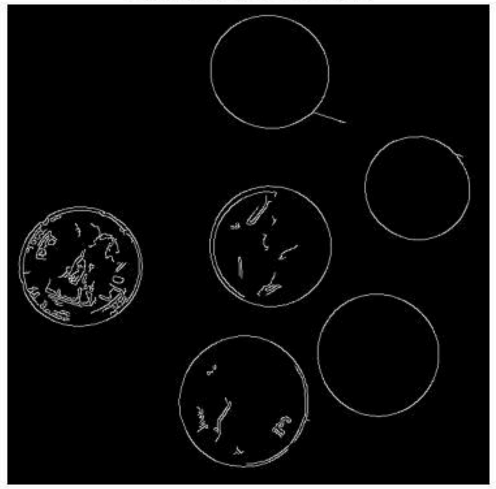
2. ***Edge Detection & Contour Detection***:
   - **Canny Edge Detection** is used to identify object edges.
   - **Morphological closing operation** is done to close small gaps in edges.
   - Contours are extracted using `cv2.findContours()`.

3. ***Segmentation & Counting***:
   - Small contours are filtered out on the basis of area.
   - A mask is obtained for each contour.
   - The mask is applied on the original image to segment out the coin.
   - A bounding box is drawn around the coin and the individual coins are cropped and displayed separately.
   - The total number of detected coins are displayed.

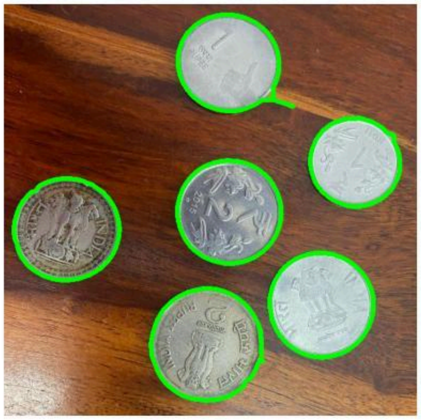
Results

1. **Edge Detection & Outlining:**

   – Coins in the image are successfully detected and highlighted with contours.



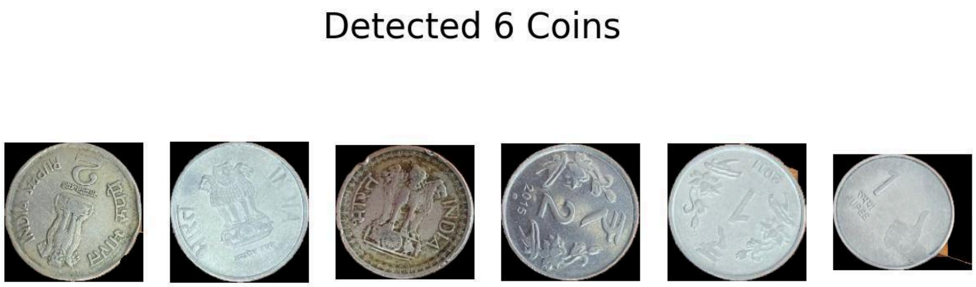
Canny Edge Detection

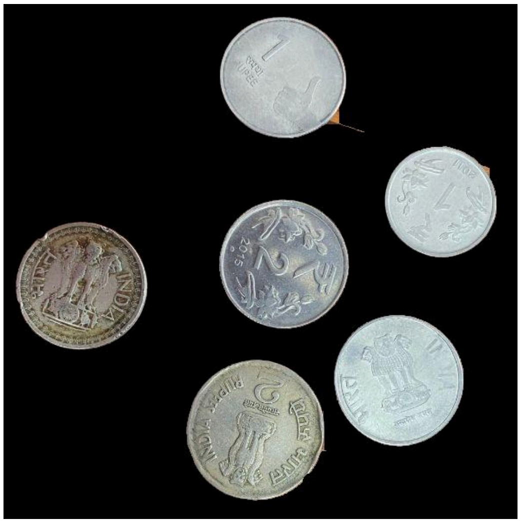


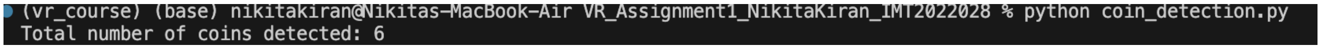
Detected Coins

2. **Segmentation and Counting:**

   – Each coin is **accurately isolated**.
   – Filtering out invalid contours helps avoid incorrect segmentation.
   – The total number of coins is correctly displayed.







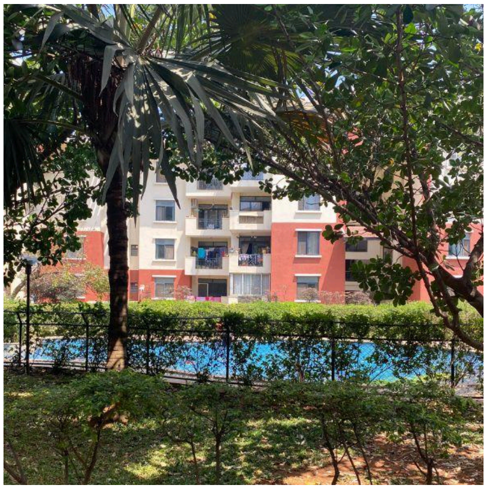
```
(vr_course) (base) nikitakiran@Nikitas-MacBook-Air VR_Assignment1_NikitaKiran_IMT2022028 % python coin_detection.py
Total number of coins detected: 6
```

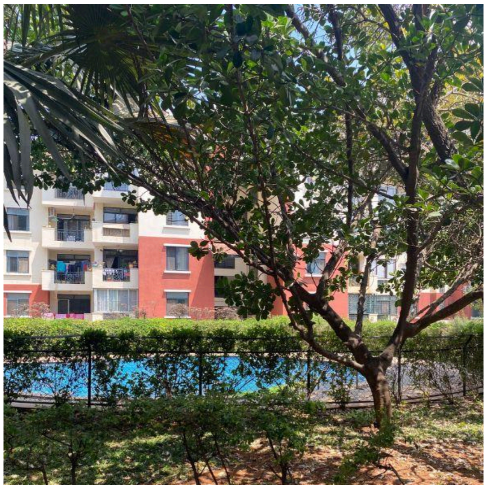
Observations and Experiment Details

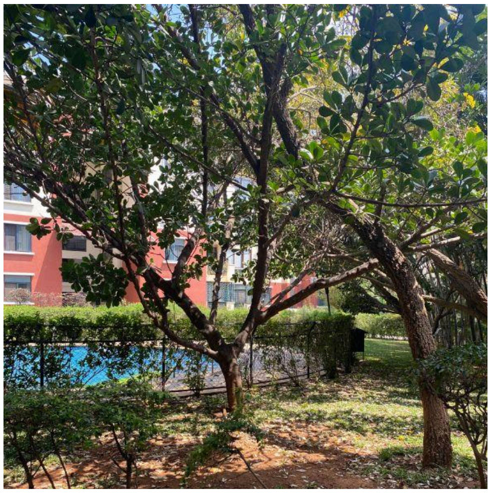
- **Gaussian Blur** significantly improved edge detection by reducing background noise. However the size of the kernel played a very important role. While using a very small kernel, noise still remained and the edge detection had many unnecessary edges. However if the kernel used was very large, blurring was too much and many coin edges were undetected.
- **Threshold values for Canny edge detection**: After experimenting with several different values, the best output was obtained when the lower and upper thresholds were in a ratio of around 1:3.
- Without the **morphological closing operation**, a few of the coin edges were broken and resulted in incomplete contours.
- **Filtering out smaller contours** ensured that many invalid contours were not wrongly counted as coins.

Image Stitching for Panorama Creation

Input Images:







Methodology

1. Keypoint Detection

I used the **SIFT** feature detector to identify key points in each of the overlapping images. SIFT is invariant to rotation and scale, making it suitable for feature detection in image stitching.

2. Feature Matching

The **Brute-Force Matcher (BFMatcher)** was used to match key points between consecutive images. Lowe's ratio test was used to ensure only good matches were retained. The ratio test compares the distance of the closest match to the distance of the second closest match. If the ratio of these distances is below a certain threshold (0.75), the match is considered good.

3. Homography Transformation

To align overlapping images accurately, a **homography matrix** was computed using **RANSAC (Random Sample Consensus)**. This transformation maps corresponding key points between image pairs, ensuring proper **perspective correction** and minimizing alignment errors caused by outliers.

4. Image Warping and Stitching

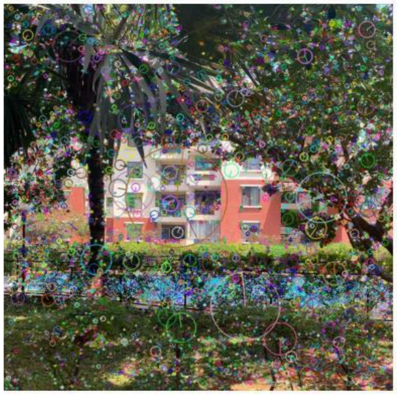
Each image was **warped** using the estimated homography matrix, transforming it into the reference frame of the previous image in the sequence. The warped images were then **stitched together** using **linear blending**, ensuring a smooth transition between overlapping regions. This prevents visible seams.

5. Cropping

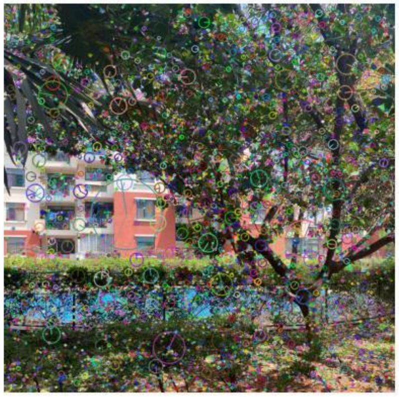
To remove black regions introduced by warping, thresholding followed by bounding box detection and cropping was used, ensuring the final panorama had no unnecessary black spaces.

Results

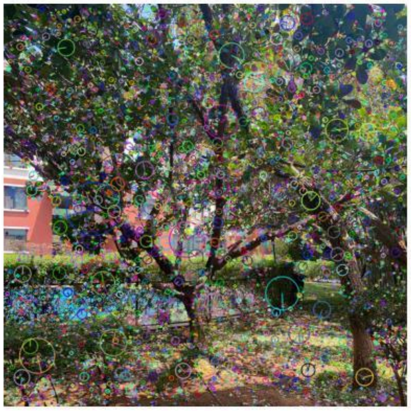
Key Points Visualization:



keypoints1

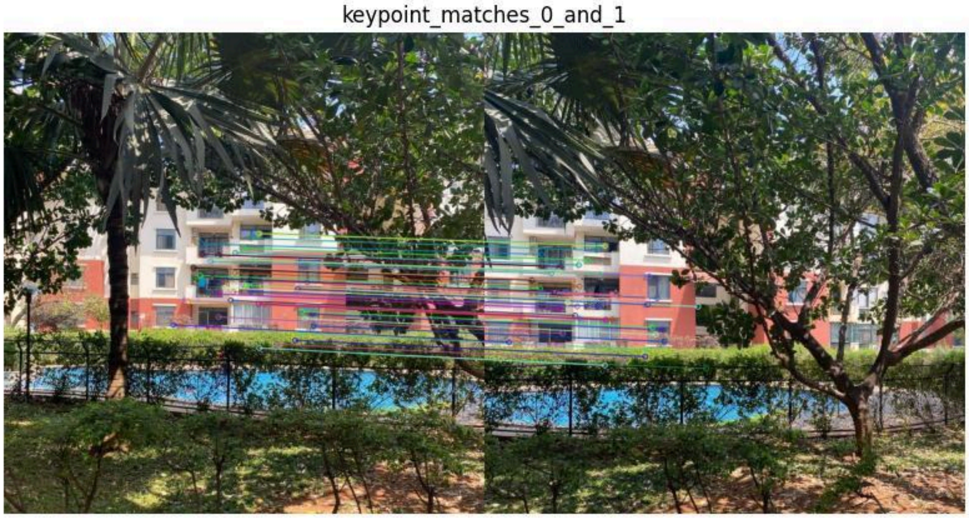


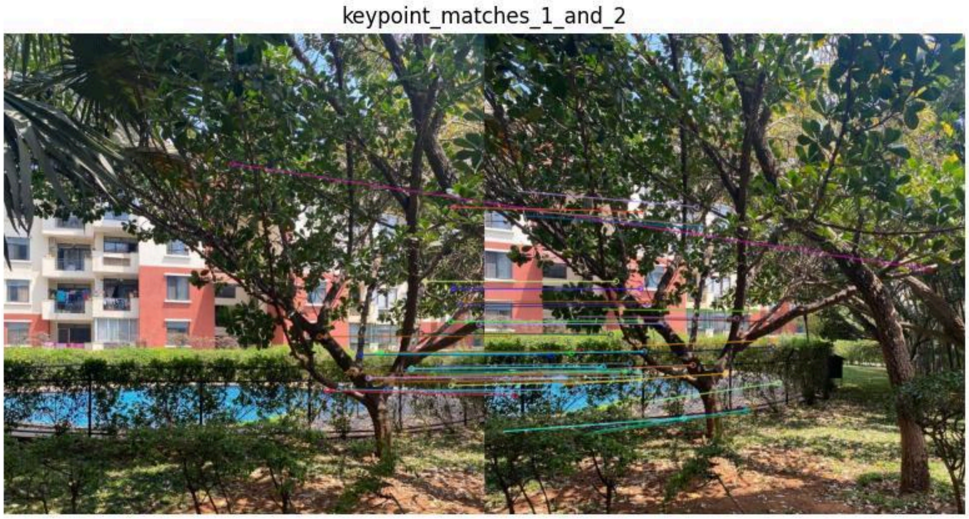
keypoints2



keypoints3

Visualisation of 50 best matches

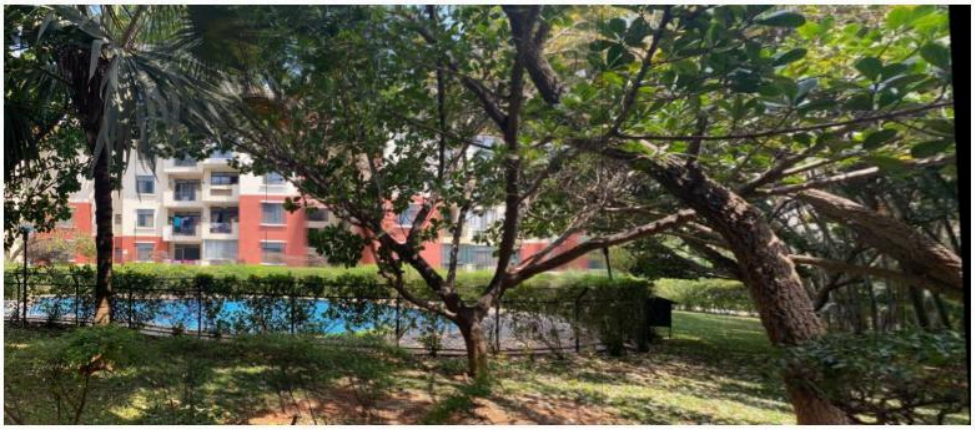




Final Stitched Panorama

The stitched image, obtained after key point detection, feature matching, homography transformation, warping and blending.

final-panorama



Observations and Experiment Details

- Most of the key points were correctly matched in the images. However there were a few outlier matches.
- The RANSAC-based homography estimation was able to handle outlier matches.
- Stitching the images together without blending resulted in seams. Thus I used linear blending to ensure the images were stitched together seamlessly.
- Without cropping, black regions were present at the edges of the image. Thus cropping was needed to remove them.