Image Stitching Using FAR

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Abstract

This report presents an end-to-end image stitching pipeline using the Feature Aggregation Regression (FAR) model for camera pose estimation. After extracting the rotation matrix R and translation vector t between two images, a homography is computed, image B is warped, and both images are blended to form a final stitched panorama. The method integrates deep-learning-based pose estimation with classical geometric computer vision.

1 Introduction

Image stitching aims to merge multiple overlapping images into a single wide-view panorama. Traditional stitching relies on SIFT, ORB, or RANSAC-based feature matching. However, modern deep learning methods such as FAR provide more accurate pose estimation by learning feature aggregation and regression directly from large datasets.

In this assignment, I implemented a full stitching pipeline starting from FAR inference, followed by homography computation, warping, translation shift calculation, and image blending.

2 Methodology

2.1 Image Preprocessing

The original input images were resized to 540×720 to match the FAR model requirements and to ensure consistent warping dimensions.

Images:

- imgA.JPG
- imgB.JPG

Both were resized using OpenCV:

$$\text{resized} = \text{cv2.resize}(img, (720, 540)).$$

2.2 FAR Pose Estimation

The FAR model was used to estimate the relative camera pose between image A and image B. The model outputs:

$$R = \text{rotation matrix}, \qquad t = \text{translation vector}.$$

The rotation matrix obtained from the model was:

$$R = \begin{bmatrix} 0.9479 & 0.0203 & -0.3179 \\ -0.0077 & 0.9991 & 0.0408 \\ 0.3185 & -0.0362 & 0.9472 \end{bmatrix}.$$

2.3 Camera Intrinsic Matrix

The intrinsic camera matrix used for computing homography is:

$$K = \begin{bmatrix} 700 & 0 & 360 \\ 0 & 700 & 270 \\ 0 & 0 & 1 \end{bmatrix}.$$

2.4 Homography Computation

Homography H was computed using:

$$H = KRK^{-1}.$$

The resulting homography matrix was:

$$H = \begin{bmatrix} 1.1117 & 0.0017 & -282.004 \\ 0.0012 & 0.9851 & -231.703 \\ 0.000455 & -0.0517 & 0.9974 \end{bmatrix}.$$

2.5 Warping Image B

Image B was warped into the coordinate frame of image A using:

$$\text{warpB} = \text{cv2.warpPerspective}(imgB, H, (w_A + w_B, \max(h_A, h_B))).$$

This produces a larger canvas where image B aligns according to the homography.

2.6 Shift Computation

To compute the horizontal shift, the four corner points of image B were projected using:

$$C' = HC.$$

After normalization, this provided the correct displacement required for stitching.

2.7 Blending

A simple 50/50 alpha blending was applied in overlapping areas:

$$\text{result}(x, y) = 0.5A(x, y) + 0.5B(x, y).$$

Non-overlapping regions were directly copied from the respective images.

3 Results

The pipeline produced a stitched panorama that successfully aligns the two images using FAR-based pose estimation. Figure 1 shows the final blended output.

Figure 1: Final stitched panorama generated by the implemented FAR-based pipeline.

4 Conclusion

This assignment demonstrates how deep learning and geometric computer vision can be combined for high-quality image stitching. The FAR model provides accurate camera pose estimation, enabling homography-based alignment. Future improvements may include:

- Multiband blending
- Exposure compensation
- Seam optimization

References

- FAR GitHub Repository: https://github.com/crockwell/far
- OpenCV Documentation: https://docs.opencv.org/