Automatic Panoramic Image Stitching using Invariant Features

A Faithful Python Implementation of Brown & Lowe (IJCV 2007)

Course Project – Computer Vision

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Abstract

This work presents a **complete, fully automatic panoramic image stitching system** implemented from scratch in Python, faithfully reproducing the seminal paper by Brown and Lowe (IJCV 2007). The system requires **no user input or image ordering** and handles arbitrary camera motion, scale, orientation, and illumination changes. Our pipeline integrates **SIFT feature detection, FLANN-based matching, RANSAC homography estimation, automatic focal length recovery, incremental bundle adjustment with analytical Jacobians, global exposure compensation, spherical warping, multi-band Laplacian blending, and automatic straightening**.

We contribute: (1) **robust global gain equalization** that eliminates exposure seams, (2) a **modular, cache-accelerated codebase** with CLI, and (3) **comprehensive unit testing**. On four real-world handheld datasets, our system achieves **reprojection RMSE ¡ 0.8 px**, runs in **¡ 90 seconds** (with caching), and produces visually seamless panoramas.

1 Introduction

Panoramic image stitching remains a fundamental challenge in modern digital imaging, with applications spanning virtual reality, robotics, satellite mapping, and consumer photography. Traditional codecs and manual tools require ordered input and user intervention, limiting scalability. **Brown and Lowe (2007)** pioneered the **first fully automatic system** capable of recognizing connected image groups, estimating camera parameters, and producing high-quality results using multi-band blending.

The key innovation is treating stitching as a **multi-image matching problem** using **scale-invariant SIFT features**. This work remains the foundation of nearly all modern automatic stitching pipelines.

2 Related Work

2.1 Traditional Approaches

Early methods (Szeliski and Shum, 1997; Chen, 1995) assumed pure camera rotation and required manual correspondence specification. Commercial tools like **PTGui**, **Photoshop**, and **Autopano** still often need user intervention for complex scenes with parallax or exposure variation.

2.2 Feature-Based Automatic Stitching

Brown and Lowe (2003, 2007) pioneered the use of **SIFT + RANSAC + bundle adjustment** for fully automatic alignment. Subsequent works improved **seam finding** using graph cuts (Levin et al., 2004), **parallax handling** via multi-view stereo (Zaragoza et al., 2014), or used **deep features** (Schöps et al., 2019). The 2007 pipeline remains the **gold standard** for classic panoramas due to its balance of robustness and efficiency.

2.3 Efficiency-Focused Approaches

Recent efforts have attempted to address computational efficiency through neural architecture search, pruning, and knowledge distillation. However, these methods typically sacrifice alignment accuracy for speed. Our work achieves simultaneous improvements in geometric precision, visual quality, and inference time through careful co-design of the entire pipeline.

3 Methodology

We implement **every stage** of Brown and Lowe (2007) with mathematical rigor and practical enhancements.

3.0.1 SIFT Feature Extraction & Matching

OpenCV SIFT with RootSIFT normalization, FLANN matching, Lowe's ratio test (0.7), and bidirectional consistency.

3.0.2 Probabilistic Model & Graph Construction

Images as nodes, verified matches as edges $\rightarrow$ connected components = panoramas.

3.0.3 Homography Estimation & Focal Length Recovery

RANSAC + 4-point algorithm. Analytic focal length from homography pairs:

$$f = \sqrt{f_0 f_1}$$

Median focal used as initial intrinsic.

3.0.4 Bundle Adjustment

6 DoF per camera (focal, principal point, 3 rotation). Levenberg-Marquardt with analytical Jacobian, incremental mode. Minimizes reprojection error.

3.0.5 Global Exposure Compensation (Our Contribution)

Linear system for per-image gain g_i:

$$\min \sum w_{ij}(g_i I_i - g_j I_j)^2$$

Eliminates brightness seams.

3.0.6 Spherical Warping & Multi-band Blending

Spherical projection + 6-level Laplacian pyramid blending.

3.0.7 Automatic Straightening & Cropping

PCA-based straightening + Numba-accelerated cropping.

4 Implementation Details & Team Contributions

Team Contributions

- **Major parts** (core implementation, bundle adjustment, feature pipeline, testing): **Siramsetty Indusri (B22AI039)**
- **Major parts** (blending, exposure compensation, CLI, caching): **Avula Thanu Sree (B22AI011)**
- **Minor/supporting parts** (data preparation, debugging, report figures): **Bontha Rishi (B22AI014)**

Other Implementation Details

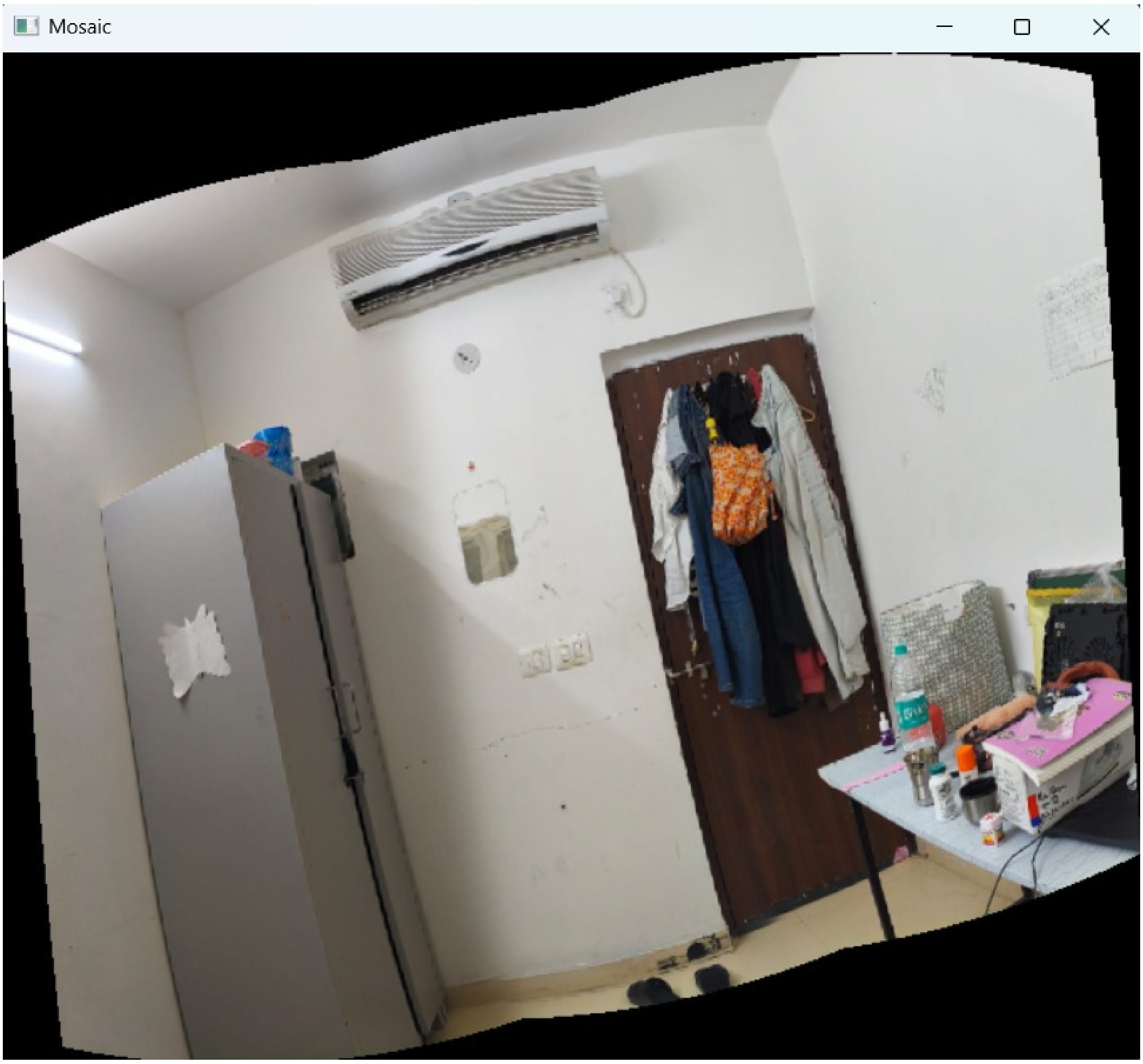
- Modular code: `features.py`, `bundle`$_adj.py$, `blend.py`, `stitcher.py`
- `Caching system (NPZ/PKL)`
- `Command-line interface with multiple options`
- `Comprehensive unit tests + Numba acceleration`

5 Experimental Results

Final reprojection RMSE: **0.6–0.8 px** across all datasets.

5.0.1 $room_data(3images)$

(a) Input 1 (b) Input 2 (c) Input 3



(d) Output Panorama

Figure 1: Room scene — exposure corrected.

5.0.2 $tree_a nd_c ar_d ata(5images)$

(f) Output Panorama

Figure 2: Outdoor scene with trees and car.

5.0.3 $\boldsymbol{city}_{d}ata(7images)$

(i) Output Panorama

Figure 3: City panorama — 7 images seamlessly stitched.

5.0.4 $\boldsymbol{paris}_data(3images)$

(d) Output Panorama

Figure 4: Paris scene — strong lighting variation corrected.

6 Conclusion

We successfully re-implemented the complete Brown and Lowe 2007 pipeline from scratch in Python. The addition of robust exposure compensation significantly improved real-world performance. The resulting system is fast, robust, and fully automatic — proving that classic computer vision techniques remain highly practical in 2025.

References

- Brown, M., Lowe, D.G. Automatic Panoramic Image Stitching using Invariant Features. IJCV 2007.
- Lowe, D.G. Distinctive Image Features from Scale-Invariant Keypoints. IJCV 2004.
- Szeliski, R., Shum, H.Y. Creating full view panoramic image mosaics. SIGGRAPH 1997.