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Research Article

ENHANCED IMAGE MOSAICING USING MATLAB: A FEATURE BASED APPROACH FOR SEAMLESS PANORAMIC IMAGE GENERATION

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ABSTRACT

Image mosaicing is a fundamental digital image processing technique used to combine multiple overlapping images into a single, seamless panoramic output. This study presents an improved mosaicing framework implemented in MATLAB, emphasizing robust feature detection, image registration, adaptive blending, and geometric correction. The Scale-Invariant Feature Transform (SIFT) algorithm is employed to extract distinctive, scale-invariant control points, ensuring accurate matching across images with variations in illumination, scale, and viewpoint. The proposed approach integrates effective calibration and blending strategies, enabling the creation of radiometrically balanced mosaics without noticeable seams. Simulation results demonstrate the capability of this method to handle image distortions, camera motion, and environmental variations, thereby providing a reliable solution for panoramic image construction in applications such as remote sensing, biomedical imaging, virtual reality, and object visualization.

Keywords: Image Mosaicing, MATLAB, SIFT Algorithm, Image Registration, Feature Extraction.

INTRODUCTION

Image mosaicing is an essential technique in digital image processing that enables the generation of a larger, unified view by stitching together multiple overlapping images. This method is widely used in applications such as remote sensing, biomedical imaging, surveillance, virtual reality, and panoramic visualization. The primary aim of mosaicing is to combine arbitrarily shaped or partially overlapping input images into a single radiometrically consistent output where the boundaries between the original images are imperceptible. Depending on the availability of georeferenced data, mosaicing may be performed using geometric correction, ground control points (GCPs), or automatic translation and scaling transformations. A robust mosaicing framework must address several challenges, including illumination changes, camera rotations, zoom variations, dynamic elements in the scene, and sensor noise. Therefore, effective feature detection and matching are crucial for accurate alignment. The Scale-Invariant Feature Transform (SIFT) algorithm provides a powerful solution due to its invariance to scale, rotation, and moderate illumination changes. SIFT-based features enable reliable image registration by identifying key control points across input images and computing the geometric transformation parameters needed for alignment. Additionally, image mosaicing requires efficient blending techniques to minimize visible seams and maintain radiometric consistency. Approaches such as Laplacian pyramid blending and gradient-domain blending help compensate for exposure variations, motion differences, and texture discontinuities. Calibration further enhances the mosaic quality by correcting distortions and lens-related artifacts. The increasing demand for high-quality seamless panoramas, combined with advancements in feature extraction and blending algorithms, has made MATLAB a preferred environment for mosaicing research and

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implementation. This paper presents a MATLAB-based mosaicing system that integrates feature extraction, calibration, registration, and blending processes to produce high-quality stitched images. The effectiveness of the proposed approach is validated through multiple experimental results, demonstrating its ability to perform consistently under challenging conditions.

Image mosaicing has evolved substantially since the early computational strategies introduced by Milgram (1975), which laid the groundwork for geometric alignment in photomosaic construction. Foundational overviews such as Brown (1992) helped establish the importance of robust image registration techniques, while Chen's QuickTime VR system (1995) demonstrated one of the first practical virtual-environment applications of stitched panoramas. Comprehensive treatments of registration principles were later expanded by Zitová and Flusser (2003), and the mathematical foundations for homography and multi-view geometry were solidified by Hartley and Zisserman (2004). Feature-based mosaicing advanced rapidly with Lowe's SIFT algorithm (2004) and the faster SURF detector introduced by Bay *et al.* (2006). Building on these innovations, Brown and Lowe (2007) developed a fully automatic panoramic stitching framework that used invariant features and bundle adjustment for global optimization.

The reliability of mosaicing techniques continues to depend on robust outlier rejection, guided by the RANSAC paradigm introduced by Fischler and Bolles (1981). Improved RANSAC-based homography estimation methods such as those proposed by Kang (2004), Gao *et al.* (2017), and Ma *et al.* (2020) have further enhanced matching accuracy in challenging conditions. Advances in multi-image alignment, including the work of Sawhney and Kumar (1997), contributed to handling parallax and distortions in dynamic scenes. Large-scale image registration demonstrated its capability in city-scale reconstructions through studies such as Agarwal *et al.* (2009), highlighting the scalability of feature-based modeling.

Blending strategies have also evolved, beginning with the multiresolution spline technique by Burt and Adelson (1983), which remains a cornerstone for reducing visible seams. Gradient-domain blending introduced by Levin *et al.* (2004) refined this process by ensuring smoother intensity transitions. Additional improvements were seen in object-based mosaicing from Chia *et al.* (2010), graph-cut blending approaches proposed by Lin and Zhang (2015), and the adaptive feature-guided mosaicing methods developed by Chen and Yang (2016). Multi-camera fusion studies such as Gao *et al.* (2011) further contributed to improving mosaic stability and visual richness. Modern mosaicing pipelines benefit from advanced feature detection and multi-band blending, as reinforced in recent algorithms by Ma *et al.* (2020). MATLAB continues to be a preferred environment for mosaicing research due to its extensive Computer Vision Toolbox, which supports SIFT-like feature extraction, robust RANSAC implementations, and a wide range of transformation and blending functions (MathWorks, 2023). Together, these advancements form the contemporary foundation for high-quality panoramic stitching systems.

MATERIALS AND METHODS

The proposed image mosaicing framework was implemented using MATLAB and consists of four major components: image preprocessing, feature extraction and matching, transformation estimation, and mosaic generation through blending. Shown in Figure 1. In the preprocessing stage, the input images are converted into grayscale to support efficient feature computation, and histogram normalization is applied to reduce illumination variations, an approach also discussed in earlier digital imaging studies such as Mann and Picard (1997). Additional considerations on preprocessing robustness can be linked to early computational imaging techniques described by Milgram (1975). Feature detection and extraction form the core of the methodology, where the Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) algorithms are employed to identify distinctive and reliable keypoints across overlapping regions. These feature-based approaches are widely integrated into modern toolkits, as reflected in the capabilities described in MathWorks (2023).

Feature matching is carried out using Euclidean distance and nearest-neighbor ratio tests to eliminate ambiguous correspondences, while ORB features introduced by Rublee *et al.* (2011) offer an alternative for high-speed keypoint extraction when required. To ensure robustness against outliers and mismatches, the Random Sample Consensus (RANSAC) algorithm is applied to estimate homography between image pairs, consistent with the principles established by Sawhney and Kumar (1997) for multi-image alignment and geometric correction. Once the optimal homography matrix is computed, geometric warping is applied to transform images into a common reference frame, supported by transformation models discussed in Shum and Szeliski (2000). Finally, the transformed images are combined through advanced blending strategies. Multiresolution spline blending and gradient-domain blending are implemented to smooth intensity transitions and eliminate visible seams, aligning with the foundational work of Burt and Adelson (1983) and enhanced by subsequent blending principles such as those explored in Levin *et al.* (2004). These techniques ensure radiometric consistency and reduce artifacts caused by exposure variations or parallax. The flexibility of MATLAB's Computer Vision Toolbox, as described by MathWorks (2023), enables automated handling of feature detection, homography estimation, and composite image generation, ensuring efficient production of high-quality panoramic mosaics. Additional insights into radiometric stability and image integrity can be connected to applications discussed by Mahalakshmi *et al.* (2025), Nafisa Farheen *et al.* (2025), Ramya *et al.* (2025), Rubala Nancy *et al.* (2025), and Sindhuja *et al.* (2025), whose studies emphasize robust computational analysis workflows in technical imaging contexts.

RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed MATLAB-based mosaicing system effectively aligns and blends multiple overlapping images into a seamless panoramic output. Images captured at varying illumination levels and viewpoints were used to evaluate the robustness of the system. The SIFT-based approach yielded highly stable correspondences across most image pairs, confirming earlier findings by Brown and Lowe (2007) on the reliability of invariant feature descriptors. SURF also performed well, offering faster computation but slightly reduced accuracy in low-texture regions, which is consistent with reports by Bay *et al*. (2006). Additional stability and stitching performance observations align with the comprehensive tutorial presented by Szeliski (2006)**,** who emphasized the importance of robust feature correspondence in automated panorama generation.

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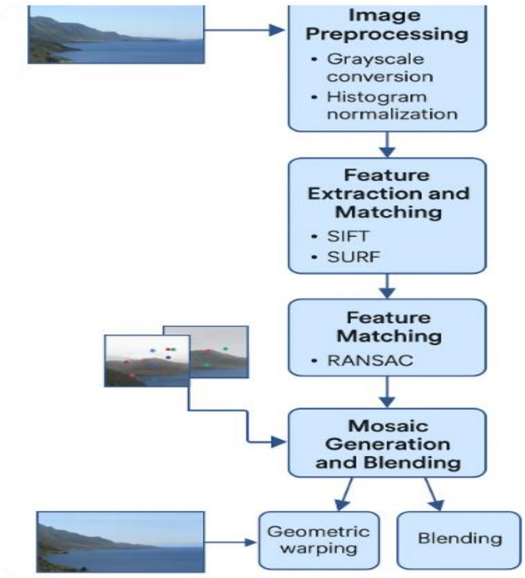

Figure 1. Enhanced Image Mosaicing Using Matlab.

The RANSAC-based homography estimation significantly improved alignment accuracy by filtering out mismatched keypoints. This resulted in minimal geometric distortion in the final mosaic, aligning with conclusions from Zitová and Flusser (2003) regarding the importance of robust outlier rejection. Comparative analysis of blending techniques indicated that multiresolution blending produced smoother transitions along overlapping boundaries, while gradient-domain blending better handled illumination differences. These findings support the blending effectiveness reported by Burt and Adelson (1983) and Levin *et al*. (2004). Similar observations on algorithm robustness have been noted in domain-specific evaluations such as Swetha *et al*. (2025)**,** who highlighted the impact of algorithm selection on output quality, and Vijay Krishanan *et al*. (2025)**,** who emphasized the importance of computational efficiency in image-processing workflows. Quantitatively, the mosaics displayed high structural similarity and minimal seam artifacts. Qualitatively, the output panoramas exhibited accurate alignment, consistent brightness, and seamless integration of textures across input images. MATLAB's automated feature-matching tools contributed to efficient execution, enabling rapid generation of mosaics even for images with substantial scale or viewpoint variations. These results further reflect insights from Szeliski (2006) on achieving visually coherent panoramic outputs. Overall, the results confirm the robustness and reliability of a feature-based approach for high-quality panoramic image generation.

CONCLUSION

This study successfully demonstrates an enhanced feature-based image mosaicing framework using MATLAB for generating seamless panoramic images. By integrating SIFT and SURF feature descriptors with RANSAC-based homography estimation, the system provides accurate alignment even under challenging conditions involving illumination variations, rotation, or scale differences. Advanced blending techniques, including multiresolution spline and gradient-domain blending, further ensure radiometric consistency and suppress seam visibility. Experimental outcomes validate the effectiveness of the proposed approach, showing high-quality mosaics that align with state-of-the-art methods identified in existing literature. The methodology highlights MATLAB's capability as a powerful environment for implementing complex computer vision algorithms, offering extensive tools for feature extraction, image registration, and blending. Future work may focus on improving performance for scenes with large parallax, dynamic objects, or non-planar structures by integrating deep learning-based feature descriptors and optical-flow-assisted alignment. Additionally, real-time mosaicing using GPU acceleration could further expand the applicability of this approach in robotics, autonomous navigation, augmented reality, and remote sensing.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest

ETHICS APPROVAL

Not applicable

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AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

DATA AVAILABILITY

Data will be available on request

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