A Comparative Study of Image Mosaicking using CNN-based Homography and Algorithmic Analysis

Bharat Mahesh, Aditya Pawar, Qusai Kader, Yashraj Deshmukh
Department of Computer Engineering
K.J. Somaiya College of Engineering
India

Abstract

Image mosaicing is a fundamental technique for creating seamless panoramic views, with applications ranging from photography to satellite mapping. This research focuses on advancing image mosaicing algorithms, particularly for high resolution and aerial images. The project evaluates existing algorithms, addresses variability in aerial data, and explores feature extraction techniques. A key contribution is the integration of Convolutional Neural Networks (CNNs) for homography estimation, enhancing mosaicing accuracy and efficiency. Additionally, feature extraction algorithms such as Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) are investigated. The proposed automated framework aims to scale efficiently, minimize resource consumption, and adapt to diverse aerial contexts. This paper presents a comparative analysis of image stitching algorithms, highlighting the effectiveness of CNN based homography estimation and feature extraction algorithms in improving mosaicing accuracy and seamlessness.

Keywords: Image Mosaicing, Convolutional Neural Networks, SIFT, SURF, Homography Estimation, Feature Extraction,

1. Introduction

Image mosaicking, the process of seamlessly stitching multiple images together to create a panoramic view, has emerged as a pivotal component in modern imaging applications. By transcending the constraints of individual image frames, mosaicking enables broader fields of view, heightened detail, and superior visual consistency. This technique addresses critical limitations inherent in traditional imaging, particularly in scenarios requiring comprehensive visual coverage. From surveillance and landscape photography to medical imaging and satellite mapping, image mosaicking plays a transformative role by providing extended and more detailed perspectives that were previously unattainable with isolated images. The significance of image mosaicking lies in its ability to meet the growing demand for comprehensive visual representation across diverse domains.

Conventional imaging techniques often fall short when tasked with capturing expansive scenes or maintaining intricate details, particularly in challenging contexts such as panoramic landscapes, real-time surveillance, and medical diagnostics. The process of image mosaicking bridges these gaps by integrating multiple images into a unified, seamless output, offering a more holistic and detailed visual narrative. In the realm of surveillance and security, image mosaicking proves invaluable by enhancing situational awareness through the provision of an uninterrupted, wide-angle view of monitored areas. This capability is essential for informed decision-making in environments where a fragmented view could lead to oversight or delayed responses. Similarly, in photography, mosaicking opens creative avenues, enabling the construction of stunning panoramic images that capture the grandeur of natural landscapes, cityscapes, and architectural marvels, thereby enriching the storytelling potential of visual media. Medical imaging is another field that benefits immensely from this technology. By assembling detailed and cohesive visuals from segmented medical scans, image mosaicking aids in more accurate diagnoses, allowing healthcare professionals to examine complex anatomical structures with greater clarity. Likewise, industries such as satellite mapping and geospatial analysis rely heavily on mosaicking to generate high-resolution, expansive maps that are critical for environmental monitoring, urban development, and disaster management. This project is motivated by the increasing reliance on high-quality, comprehensive visual data in modern applications. The focus is on addressing the unique challenges posed by high-resolution and aerial imagery, where issues such as variability in lighting, perspective, and resolution are prevalent. To achieve this, the project involves assessing and refining established image mosaicking algorithms, with a particular emphasis on their application in aerial contexts. The scope of this endeavor includes the evaluation of existing algorithms, the development of advanced correction methods to address variability in aerial data, and the exploration of state-of-the-art feature extraction techniques to enhance alignment and stitching accuracy.

 | DOI: 10.20533/ijmip.2042.4647.2024.0072

Additionally, automation strategies are investigated to optimize the handling of high-resolution imagery, ensuring efficiency in resource consumption and scalability for large-scale applications. By tailoring these methodologies to minimize distortions and maximize output quality, the project aims to contribute significantly to application-driven domains such as environmental analysis and urban planning. Ultimately, this project aspires to develop an automated and robust framework specifically designed for aerial image mosaicking. The objectives include achieving scalability, resource efficiency, and accuracy in generating high-quality mosaics while ensuring adaptability to diverse aerial imaging scenarios. By addressing the technical and application-specific challenges of image mosaicking, this work seeks to advance the field and establish new benchmarks for visual representation in modern imaging technologies.

The Need for Mosaicing

Image mosaicing is a technique used to stitch together multiple images to create a seamless and panoramic view. It is essential in modern imaging applications due to the limitations of individual images, especially in scenarios requiring a broader field of view, enhanced detail, and visual consistency. Applications span diverse fields such as surveillance, landscape photography, medical imaging, and satellite mapping. By combining images seamlessly, mosaicing provides an extended and more detailed perspective, overcoming challenges such as parallax effects and lighting inconsistencies.

The need for image mosaicing has grown with the increasing demand for high-resolution visual data across various industries. In surveillance, mosaicing enables the construction of wide-area monitoring systems that improve situational awareness and security response. Landscape photography benefits from mosaicing by allowing photographers to capture and represent vast natural scenes that would otherwise be constrained by the frame of a single image. In medical imaging, mosaicing plays a vital role in constructing comprehensive visuals from smaller scans, aiding in accurate diagnosis and treatment planning. Satellite mapping and geospatial analysis rely heavily on mosaicing to generate expansive and detailed maps, critical for applications such as urban planning, disaster management, and environmental monitoring. By addressing the limitations of conventional imaging methods, mosaicing serves as a transformative tool for capturing and interpreting complex visual environments.

Challenges in Mosaicing

Despite its benefits, image mosaicing faces several challenges. One major challenge is the variation in image scale, orientation, and lighting conditions, which can lead to visible seams and distortions in the final mosaic. Another challenge is the presence of moving objects or changes in the scene between image captures, which can disrupt the stitching process. Additionally, mosaicing high-resolution or aerial images poses challenges due to the large amount of data involved and the need for precise alignment to avoid distortions.

Our Approach

To address the challenges in image mosaicing, several solutions have been proposed. One approach is to use feature-based algorithms such as Scale-Invariant Feature Transform (SIFT) or Speeded Up Robust Features (SURF) to detect and match key points in images, allowing for accurate alignment and stitching. Another approach is to use advanced blending techniques to seamlessly merge images, reducing visible seams. Additionally, the use of Convolutional Neural Networks (CNNs) for homography estimation can improve the accuracy and efficiency of the mosaicing process, particularly in handling variations in scale and orientation. Automated correction methods can also be employed to compensate for changes in lighting conditions or scene variations between image captures, ensuring a more consistent and accurate final mosaic.

Scope and Objectives

This research project aims to advance the field of image mosaicking by focusing on the specific challenges presented by high-resolution and aerial imagery. The project will involve a thorough evaluation and comparison of existing image stitching algorithms to determine their effectiveness in handling these types of images. By enhancing and customizing these algorithms, the goal is to optimize the accuracy of image stitching while minimizing distortions and ensuring a seamless blend between images. One key aspect of the research will be addressing challenges related to satellite and aerial image data, such as variations in illumination and differences between sensors, through the implementation of radiometric and geometric correction methods. Additionally, the project will involve the development of feature extraction techniques tailored for specific applications, such as environmental analysis or urban planning, using the resulting mosaics. Through these efforts, the project seeks to contribute to the advancement of image mosaicking technology, particularly in fields where high-resolution and aerial imagery play a crucial role.

2. Literature Review

Image mosaicking, the process of stitching multiple images together to create a seamless composite, is vital in fields such as surveillance, landscape photography, and satellite mapping. With the increasing availability of high-resolution and aerial imagery, the need for effective mosaicking algorithms has become more pronounced. This literature survey examines research papers that contribute to the advancement of image mosaicking, focusing on algorithm optimization, automation, seam-line detection, and registration methods.

One of the key challenges in image mosaicking is the efficient matching of features across images. The paper titled” SIFT optimization and automation for matching images from multiple temporal sources” addresses this by optimizing the SIFT algorithm. The study highlights the efficacy of SIFT in aerial image analysis and emphasizes the importance of parameter tuning [1]. It also discusses the challenges faced in video recording and the successful use of image intervals for quality metadata. By optimizing and automating the SIFT algorithm, this research contributes to improving the accuracy and efficiency of feature matching in image mosaicking.

Another significant challenge in image mosaicking is the detection of seamlines, which are the boundaries between stitched images. The paper titled” Automatic Seam-Line Detection in UAV Remote Sensing Image Mosaicking by Use of Graph Cuts” by authors introduces a method for automatic seam-line detection using graph cuts. The study introduces a global optical flow field to improve UAV image mosaicking, addressing challenges such as geometric displacement and projection errors [2]. By integrating optical flow and graph cuts, the proposed method outperforms existing algorithms in determining seamlines, contributing to more accurate and seamless image mosaics.

The paper titled” An optimization method for registration and mosaicking of remote sensing images” focuses on optimizing the registration and mosaicking process of remote sensing images. The study proposes a weighted optimization approach to reduce alignment errors, particularly in areas of interest [3]. Experimental results demonstrate the achievement of sub-pixel precision in mosaicked images, highlighting the effectiveness of the proposed method in improving the accuracy of image mosaicking.

In the context of crop growth monitoring using UAV images, the paper by authors titled” Rapid Mosaicking of Unmanned Aerial Vehicle (UAV) Images for Crop Growth Monitoring Using the SIFT Algorithm” presents a rapid mosaicking method based on the Scale-Invariant Feature Transform (SIFT) algorithm [4]. The study dynamically sets contrast thresholds in the difference of Gaussian scale-space, optimizing the number of matched feature point pairs and increasing mosaicking efficiency. By integrating the Random Sample Consensus (RANSAC) algorithm, the proposed method eliminates the influence of mismatched point pairs, improving mosaicking accuracy.

Furthermore, the paper by authors titled” Automatic Satellite Image Stitching Based on Speeded Up Robust Feature” demonstrates image stitching using the Speeded Up Robust Feature (SURF) algorithm [5]. The study uses affine transformation for aligning input images to the mosaic frame and alpha blending for making the mosaic image smooth. Experimental results show the efficiency of the SURF algorithm in detecting and matching features in images at different scales, contributing to seamless image blending in mosaicking.

In addition,” Blurry Satellite Images of Palestine and Israel Make Rebuilding Harder” discusses the challenges posed by low-resolution satellite imagery in critical applications such as rebuilding efforts [6]. The research underscores the importance of high-resolution images for accurate and effective mosaicking.

The paper by Chaozhen and colleagues titled” Deep learning algorithm for feature matching of cross modality remote sensing images” explores the application of deep learning in feature matching, enhancing accuracy and efficiency [7]. This study contributes to the growing body of research focusing on the use of advanced machine learning techniques in improving image mosaicking processes.

Moreover, the work of Lowe et al. in” Fast Approximate Nearest Neighbors with Automatic Algorithm Configuration” provides insights into the development of algorithms that can adaptively configure themselves to improve the performance of feature matching in image mosaicking [8]. This approach is particularly beneficial in handling the variability and complexity of high-resolution aerial images.

An important contribution is from Brown and Lowe, who in their paper” Automatic Panoramic Image Stitching using Invariant Features” demonstrate the use of invariant features for panoramic image stitching [9]. This method significantly improves the robustness and accuracy of the stitching process, making it highly applicable to aerial and satellite imagery.

The paper by Yi et al., titled” Seamless Mosaicking of UAV-Based Push-Broom Hyperspectral Images for Environment Monitoring,” highlights the use of push-broom hyperspectral images for environment monitoring [10]. The study presents a seamless mosaicking approach that enhances the quality and continuity of hyperspectral data, crucial for accurate environmental analysis.

Finally, the research titled” An Algorithm for Remote Sensing Image Mosaic Based on Valid Area” introduces a novel algorithm that focuses on the valid areas of remote sensing images to improve the efficiency and accuracy of the mosaicking process [11]. This method is particularly effective in dealing with the challenges posed by large and complex datasets. In summary, these research papers contribute significantly to advancing image mosaicking technology by addressing key challenges and proposing innovative solutions. The optimization and automation of algorithms like SIFT and SURF, along with the development of new seam-line detection methods and the application of deep learning techniques, are crucial steps towards improving the accuracy and efficiency of image mosaicking, particularly in handling high-resolution and aerial images (see Figure 1).

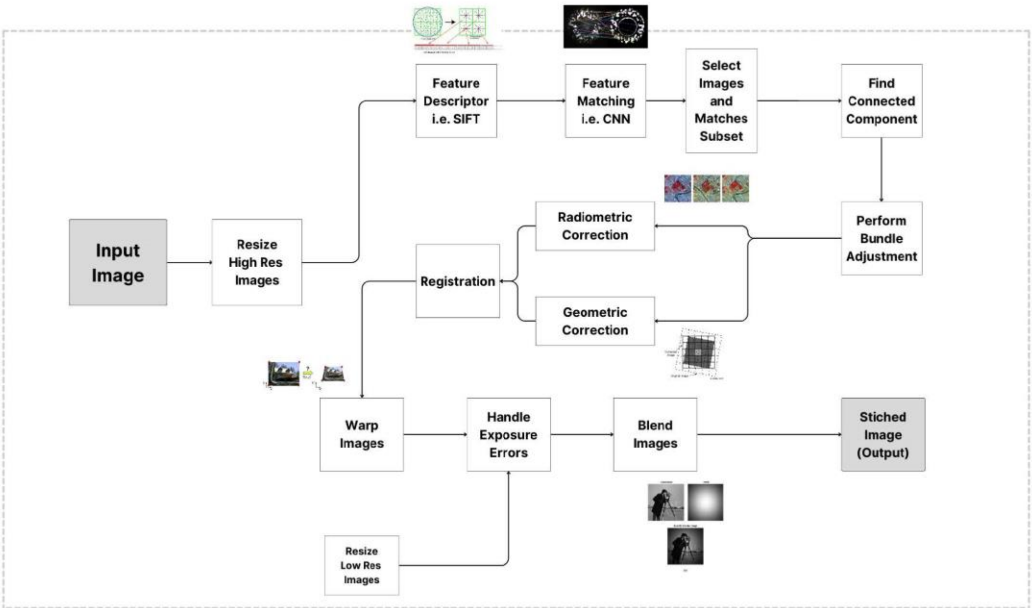

Figure 1. HLD of Image Mosaicing Pipeline

3. Methodology

Data Collection

For our project, we leveraged the Draper satellite imagery dataset, which is openly accessible on Kaggle [12]. This dataset comprises an extensive collection of high-resolution aerial photographs, totaling over one thousand images, all taken in southern California. These photographs were captured from an aircraft and are intended to closely resemble satellite imagery, providing a valuable resource for a variety of remote sensing applications. The dataset's high resolution and aerial perspective make it particularly suitable for exploring the challenges associated with image mosaicking, including alignment, feature extraction, and handling scale variations.

The dataset is structured in a unique way to facilitate diverse analytical approaches. Images are grouped into sets of five, each sharing a common setId, which serves as a grouping identifier. Notably, each image within a set was captured on a different day, ensuring temporal diversity. However, these images were not necessarily taken at consistent times, introducing potential variations in lighting and atmospheric conditions. Despite covering roughly the same geographical area, the images within a set are not perfectly aligned, making them ideal for testing and evaluating mosaicking algorithms. The images follow a naming convention based on their setId and day (e.g., setId-day), with the training set preserving the correct chronological order of days, while the test set has a scrambled order, adding an additional layer of complexity for alignment tasks.

In our implementation, we selected 11 images from this dataset to create a focused subset that captures a diverse range of geographical locations, landscapes, and features. This selection was made to ensure that the data represents various challenges encountered in real-world mosaicking scenarios, such as variations in terrain, vegetation, and urban environments. The selected images were then divided into two halves, with a deliberate 40% overlap between them. This overlap is critical for the stitching process, as it provides common reference points for alignment and feature matching, ensuring that the resulting mosaic is seamless and visually coherent.

To further investigate the impact of scale differences on the stitching process, we applied deliberate manipulations to the scales of the image halves. While one half was kept at its original resolution, the other half was resized to three different scales: 80%, 50%, and 30% of its original size. This approach introduces varying levels of scale disparity, simulating real-world scenarios where images captured by different sensors or at different altitudes may exhibit significant size variations. By analyzing the performance of mosaicking algorithms under these conditions, we aim to gain insights into their robustness and adaptability to scale differences.

Additionally, the dataset allowed us to explore the effects of other variables, such as illumination changes and perspective shifts, on the mosaicking process. For instance, temporal variations between images within the same set often result in changes in lighting and shadows, presenting a unique challenge for achieving seamless alignment. We also considered factors such as edge artifacts and noise, which are common in high-resolution imagery and can significantly affect the quality of the final mosaic.

By using this dataset and implementing these specific experimental parameters, we created a challenging yet realistic testing ground for evaluating and comparing different image mosaicking algorithms. This comprehensive approach enables us to assess the algorithms ’capabilities in handling scale differences, alignment challenges, and varying image qualities. The results of these evaluations provide valuable insights into the strengths and limitations of current mosaicking techniques, paving the way for advancements in the field and offering practical solutions for real-world applications.

Experimental Setup

In our comparative analysis focused on identifying the most effective algorithm for mosaicking aerial images, we employed a variety of approaches. Our primary choice was the Scale-Invariant Feature Transform (SIFT) algorithm [9] for feature detection, complemented by the Fast Library for Approximate Nearest Neighbors (FLANN) for efficient feature matching. This combination was selected to leverage SIFT’s ability to detect scale-invariant key points, coupled with FLANN’s speed and accuracy in matching these key points, thereby enhancing the overall robustness of the mosaicing process.

As an alternative approach, we utilized the Oriented FAST and Rotated BRIEF (ORB) [14] feature detector along with a Brute Force matcher. ORB is known for its computational efficiency and effectiveness in real-time applications, making it suitable for key point detection in our mosaicking process. The brute force matching technique was employed for descriptor matching, providing a simpler yet effective approach to feature matching.

For the third method, we combined the strengths of both SIFT and Harris corner detection. While SIFT provided scale and rotation invariant key points, Harris corner detection contributed localized corner features. This fusion aimed to capitalize on the benefits of corner localization offered by Harris and the robustness of SIFT against scale and rotation variations, potentially enhancing the accuracy of feature detection and matching.

The fourth method introduced a novel approach using a Convolutional Neural Network (CNN)for feature matching and key point detection. This method, as proposed and implemented in the paper” Deep learning algorithm for feature matching of cross-modality remote sensing images,” [7] aimed to explore the efficiency of a transfer learning approach to image mosaicking compared to traditional algorithms like SIFT and ORB. By leveraging the capabilities of CNNs in learning complex patterns and features [13], we sought to evaluate its potential in improving the accuracy and efficiency of image mosaicking processes.

All methods were implemented on a 64-bit Windows platform, ensuring consistency in the hardware specifications across the different approaches, thereby allowing for a fair and objective comparison of their performance.

4. Results

Experimental Comparison

Table 1. Average SSIM and MSE scores for all four approaches, at various percentage of compression of second image being stitched.

Table 1. Average SSIM and MSE scores

Approach	Percentage compression of second image	Average SSIM	Average MSE
SIFT	80	0.990360938	4.869058655
	50	0.9755981818	13.648579
	30	0.9471579091	32.13819909
ORB and BFM	80	0.9538214378	67.66724495
	50	0.9177236364	86.38458182
	30	0.9848477432	9.96239969
Harris Corner and SIFT	80	0.9848477432	9.96239969
	50	0.9538214378	67.66724495
	30	0.9538214378	67.66724495
CNN	80	0.6646240574	466.3396799
	50	0.6894784545	482.2485455
	30	0.5851952727	757.7848664

In our analysis of the performance of different mosaicking algorithms, we focused on comparing the number of features matched, the Structural Similarity Index (SSIM) score, and the Mean Squared Error (MSE) across 11 stitched images created using four different approaches. Each stitched image was created using a pair of images, one uncompressed and the other compressed to 80%, 50%, and 30% of its original size, allowing us to assess algorithm performance under varying levels of image compression.

One of the key observations from our analysis is the significant decrease in the number of features detected as the level of compression increases. This trend was consistent across all approaches, but the magnitude of the decrease varied. For example, when using the SIFT+FLANN matcher approach, the number of features detected in a specific image (set4 1) dropped from 7535 at 80% compression to 2089 at 30% compression. In comparison, the ORB+BFM approach [14] showed a decrease from 193 to 161 features, and the CNN approach exhibited a decrease from 3488 to 3136 features for the same image and compression ratios.

In general, the SIFT-based approaches experienced a more significant reduction in the number of features detected compared to other approaches. Specifically, the average percentage reduction in the number of features detected for all images was 103.157% for SIFT+FLANN and 154.128% for SIFT+Harris Corner at 80% and 30% compression levels. In contrast, the ORB+BFM approach showed a much lower reduction of only 20.964%, and the CNN-based approach demonstrated a reduction of 13.536%. These results highlight the varying performance of different mosaicking algorithms under different levels of image compression. While SIFT-based approaches are known for their robustness, especially in handling scale and rotation variations, they may be more sensitive to image compression. On the other hand, approaches like ORB+BFM and CNN demonstrate more resilience to compression, suggesting their potential for more efficient feature matching and key point detection in compressed images.

Interpretation Of Results

Table 2. Percentage change in parameters when stitching images with one image uncompressed and the second image at 80pc and 30pc compression.

Table 2. Percentage change in parameters

Approach	Change in number of features detected	Average difference in SSIM	Average difference in MSE
SIFT	-103.157	-4.474	145.782
ORB	-20.964	-3.875	75.557
Harris Corner+SIFT	-154.128	-4.514	117.561
CNN	117.561	-16.831	57.990

The results of our analysis provide valuable insights into the performance of different mosaicking algorithms under varying levels of image compression. The SSIM score, or Structural Similarity Index, is a metric used to measure the similarity between two images. A higher SSIM score indicates a greater similarity between the images, suggesting a better quality of the stitched image. On the other hand, the Mean Squared Error (MSE) measures the average squared difference between the original and reconstructed images. A lower MSE indicates a better-quality reconstruction.

For the SIFT+FLANN approach, we observed a significant decrease in the average SSIM score from 0.990 at 80% compression to 0.947 at 30% compression. This indicates a noticeable loss in image quality as the level of compression increases. The average percentage change in the SSIM score was 4.474%, highlighting the sensitivity of this approach to compression artifacts. Additionally, the average MSE increased substantially from 4.869 to 32.138, indicating a higher level of distortion in the reconstructed images.

Similarly, the Harris Corner+SIFT approach [15] showed a similar trend, with a decrease in the average SSIM score and an increase in the average MSE as the compression level increased. This suggests that this approach is also sensitive to compression artifacts, leading to a decrease in image quality and an increase in distortion.

In contrast, the ORB+BFM approach demonstrated a relatively smaller decrease in the average SSIM score and a smaller increase in the average MSE compared to the SIFT-based approaches [15]. This indicates that ORB+BFM is more robust to image compression, resulting in better image quality and lower distortion in the reconstructed images.

5. Conclusions

The CNN-based approach showed the highest change in the average SSIM score, with a decrease of 16.831% from 80% to 30% compression. However, the change in the average MSE was relatively lower compared to the other approaches. This suggests that while the CNN approach may result in a greater loss of image quality compared to the other approaches, it may still be able to maintain a lower level of distortion in the reconstructed images.

Overall, the SSIM score and MSE are crucial metrics for evaluating the quality of stitched images, providing valuable insights into the performance of different mosaicking algorithms under varying levels of image compression.

6. References

[1] Castillo-Carrión, S., and Guerrero-Ginel, J.-E. (May 2017). SIFT optimization and automation for matching images from multiple temporal sources. International Journal of Applied Earth Observation and Geoinformation, 57, 113–122. DOI: 10.1016/j.jag.2016.12.017.

[2] Li, M., Li, D., Guo, B., Li, L., Wu, T., and Zhang, W. (August 2018). Automatic seam-line detection in UAV

remote sensing image mosaicking by use of graph cuts. ISPRS International Journal of Geo-information, 7(9), 361. DOI: 10.3390/ijgi7090361.

[3] Chen, J., Feng, H., Pan, K., Xu, Z., and Li, Q. (January 2014). An optimization method for registration and mosaicking of remote sensing images. Optik, 125(2), 697–703. DOI: 10.1016/j.ijleo.2013.07.034.

[4] Zhao, J., et al. (May 2019). Rapid mosaicking of unmanned aerial vehicles (UAV) images for crop growth monitoring using the SIFT algorithm. Remote Sensing, 11(10), 1226. DOI: 10.3390/rs11101226.

[5] Megha, V., and Rajkumar, K. K. (September 24, 2021). Automatic satellite image stitching based on speeded up robust feature. IEEE Conference Publication – IEEE Xplore. https://ieeexplore.ieee.org/document/9670954 (Acc-ess Date: 12 December 2024).

[6] Romero, L. Blurry satellite images of Palestine and Israel make rebuilding harder. Wired. Available at: https://www.wired.com/story/blurrysatellite-images-palestine-israel-make-rebuilding-harder/ (Access Date: 12 Decem-ber 2024).

[7] Chaozhen, L. A. N., Wanjie, L. U., Junming, Y. U., and Qing, X. U. (March 2021). Deep learning algorithm for feature matching of cross-modality remote sensing images. Acta Geodaetica et Cartographica Sinica, 50(2), 189. DOI: 10.11947/j.AGCS.2021.20200048.

[8] Muja, M., Lowe, D., Gunjala, G., and Zhang, J. (2009). FAST approximate nearest neighbors with automatic algorithm configuration. Available at: (Access Date: 07 December 2023).

[9] Brown, M., and Lowe, D. G. (December 2006). Automatic panoramic image stitching using invariant features. International Journal of Computer Vision, 74(1), 59–73. DOI: 10.1007/s11263-006-0002-3.

[10] Yi, L., Chen, J. M., Zhang, G., Xu, X., Ming, X., and Guo, W. (January 2021). Seamless mosaicking of UAV-based push-broom hyperspectral images for environment monitoring. Remote Sensing, 13(22), 4720. DOI: 10.3390/rs13224720.

[11] An algorithm for remote sensing image mosaic based on valid area. IEEE Conference Publication – IEEE Xplore. Available at: https://ieeexplore.ieee.org (Access Date: 07 December 2023).

[12] Draper satellite image chronology. Kaggle.com. Available at: https://www.kaggle.com/competitions/draper-satellite-image-chronology/data (Access Date: 12 Decembe-r 2024).

[13] Niblick, D., and Kak, A. Homography estimation with convolutional neural networks under conditions of variance. Available at: (Access Date: 7 December 2023).

[14] Rublee, E., Rabaud, V., Konolige, K., and Bradski, G. (November 1, 2011). ORB: An efficient alternative to SIFT or SURF. IEEE Xplore. https://ieeexplore.ieee.org/docume-nt/6126544 (Access Date: 7 December 2023).

[15] Image stitching based on optimized SIFT algorithm. IEEE Conference Publication – IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/10170989 (Access Date: 07 December 2023).