ISSN 2707-1898 (print)
ISSN 2786-9172 (online)

Український журнал інформаційних технологій
Ukrainian Journal of Information Technology
http://science.lpnu.ua/uk/ujit
https://doi.org/10.23939/ujit2025.02.058
Article received 17.09.2025 p.
Article accepted 30.10.2025 p.
UDC 004.932

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ROBUST IMAGE MATCHING METHOD FOR UAV AGRICULTURAL IMAGES USING SIFT AND ORB

This study investigates robust keypoint detection and geometric image matching in high-resolution UAV imagery of agricultural fields – an essential component for precision farming, crop monitoring, yield prediction, and automated field boundary mapping. While unmanned aerial vehicle (UAV) systems provide high spatial resolution and flexibility, aligning multiple images into coherent mosaics remains a technical challenge, particularly in agricultural settings where repetitive structures, low texture, and illumination variations are prevalent. Feature-based approaches like ORB and SIFT have been widely adopted in remote sensing and photogrammetry, yet their effectiveness in such field-specific conditions is still insufficiently characterized. This paper aims to fill that gap by evaluating both methods under controlled scenarios using UAV images captured at two altitudes, employing Lowe's ratio test and RANSAC-based homography estimation for validation.

ORB, a lightweight algorithm based on FAST keypoints and BRIEF descriptors, was tested under three configurations varying the number of features, pyramid levels, and scale factors. The results reveal that ORB struggles to extract reliable features in low-contrast or repetitive farmland scenes, often yielding insufficient inliers despite parameter optimization. SIFT, on the other hand, utilizes multi-octave scale-space analysis and gradient-based descriptors to detect stable, rotation- and scale-invariant keypoints. A comprehensive grid search was conducted to fine-tune SIFT's n_features, ratio_threshold, and ransac_threshold, resulting in a configuration that achieved 100% inlier ratio and reduced false matches significantly.

The findings highlight SIFT's superior robustness and reliability in complex agricultural image alignment tasks. Despite its higher computational cost, its descriptive power ensures accurate registration, especially in structurally repetitive or low-texture environments. This study contributes practical insights into algorithmic trade-offs between efficiency and accuracy, and offers a validated SIFT+RANSAC pipeline with tuning guidelines for UAV-based agricultural mosaicking. These results may support future hybrid solutions that integrate classical and deep learning-based feature detectors for scalable, field-ready applications.

Keywords: keypoint detection, ORB, SIFT, RANSAC, image matching.

Introduction

In recent years, agricultural imagery has emerged as a critical resource for monitoring crop health, estimating yields, and optimizing farm management practices. Sources such as satellite data and unmanned aerial vehicle (UAV) imagery allow farmers and researchers to capture high-resolution views of large farmland areas, facilitating precision agriculture techniques. By integrating these aerial perspectives with ground-based observations, producers can track crop growth, detect pest infestations, and identify water stress zones more efficiently.

Moreover, reliably detecting and matching keypoints in agricultural imagery is crucial when creating or restoring a coherent map from multiple, partially overlapping pictures. Image stitching – the process of merging numerous separate views into a seamless larger mosaic – depends on identifying robust feature correspondences across images. If keypoints are poorly matched or altogether absent in repetitive or uniform farmland regions, the final map can display visible misalignments or gaps, reducing its utility in downstream analyses. Thus, accurate keypoint extraction and matching forms the backbone of stitching algorithms, enabling high-quality mosaics that support more advanced agricultural assessments.

A key challenge, however, lies in stitching or registering multiple images acquired at different times, angles, or scales. This task becomes particularly complex in agricultural settings, where fields often exhibit repetitive textures (e.g., rows of crops, uniform planting patterns) and undergo temporal changes such as shifting plant canopies or varying soil conditions. These factors can significantly hinder accurate image alignment, as traditional feature matching algorithms may fail to distinguish between similar patterns or adapt to structural changes. Robust, context-aware feature matching strategies are therefore essential to improve image registration reliability in such environments [1].

The research objectives are to test ORB and SIFT on farmland images, compare their performance by accuracy and efficiency, and define which approach is more robust for creating agricultural mosaics.

The object of this study is the process of detecting, matching, and geometrically verifying keypoints in high-resolution UAV imagery of farmland under varying scale and viewpoint.

Subjects of this study are ORB and SIFT-based keypoint detection methods, Lowe's ratio-test matching method, and RANSAC-based homography estimation method for stitching high-resolution agricultural UAV pictures.

The purpose of the study is to identify a reliable pipeline for aligning farmland images under challenging conditions.

To achieve the stated purpose, the following *main research* tasks were identified:

1. Benchmark ORB and SIFT pipelines (with Lowe's ratio test and RANSAC) on a controlled UAV farmland dataset at two altitudes, quantifying inlier ratio, false matches, and runtime.

2. Select and validate the optimal configuration that maximizes geometrically consistent correspondences and stable homography estimation under low-texture, repetitive field conditions.

The emphasis on RANSAC ensures a fair evaluation of each method's ability to reject outliers in scenes with repetitive row structures or seasonal transformations. In doing so, this research offers insights into which pipeline can more reliably align images for downstream tasks such as mosaic creation, change detection, or farm management analyses.

Materials and methods. The study applied ORB, SIFT, and RANSAC methods to UAV imagery to build an optimal agricultural mosaic. SIFT is well-suited for aerial and satellite images due to its invariance to scale, rotation, and lighting, which ensures stable performance in environments with repetitive patterns and varying viewpoints. It improves keypoint localization and descriptor reliability in low-contrast or periodic textures [2, 3].

However, SIFT's high computational load limits its use in real-time or low-power systems. As an efficient alternative, ORB offers fast keypoint detection with binary descriptors, making it suitable for constrained environments. Though slightly less accurate in complex textures, ORB performs effectively in structured scenes and excels where speed is crucial [4].

The SIFT algorithm ensures robust keypoint detection and matching under scale, rotation, and lighting changes by following four key steps. It begins with detecting extrema in scale-space using the Difference-of-Gaussians (DoG) method [5]. Next, unstable or low-contrast points are filtered out to retain only distinctive keypoints [6]. Orientation is then assigned based on local gradients to achieve rotation invariance [7]. Finally, each keypoint is described by a 128-dimensional vector summarizing gradient patterns, enabling reliable cross-image matching.

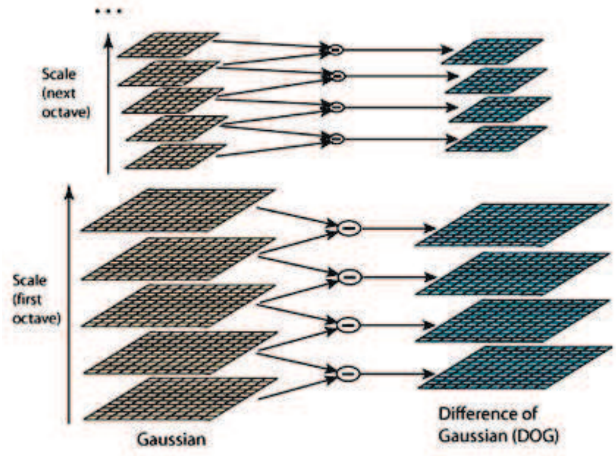

Fig. 1. Scale-space construction and Difference of Gaussian (DoG) generation in the SIFT algorithm

ORB builds on the FAST detector, which efficiently finds corner-like keypoints. To achieve scale invariance, FAST is applied across an image pyramid, while rotation invariance is introduced by estimating keypoint orientation via the intensity centroid method [8]. Since FAST may produce unstable points, ORB filters and ranks them using the Harris corner measure, retaining only the top N keypoints for stability.

For description, ORB uses an improved version of BRIEF, which generates compact binary descriptors through intensity comparisons within image patches. These descriptors are made rotation-invariant by aligning them with each keypoint's dominant orientation [8].

Robust feature matching is critical in image registration tasks such as homography estimation, where a large number of incorrect or noisy keypoint correspondences can severely degrade transformation accuracy. The Random Sample Consensus (RANSAC) algorithm is widely used to address this issue by identifying and rejecting outliers in the set of matched keypoints (Fig. 2).

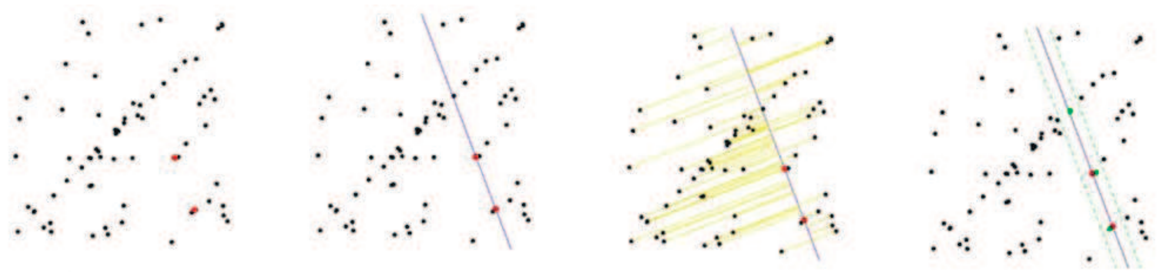

Fig. 2. Core steps of the RANSAC algorithm (First step – observation data; Second step – model fitting; Third step – measure distance; Fourth step – count inliers)

RANSAC estimates transformation models (e. g., homographies) by repeatedly sampling random subsets of matched keypoints and evaluating each model by the number of inliers – matches fitting the model within a set threshold. The model with the most inliers is chosen, while outliers are discarded, allowing accurate alignment even with many false matches due to noise or repetitive textures [9].

This approach is particularly effective in UAV and remote sensing imagery, where repeating patterns often cause mismatches. RANSAC has proven reliable for tasks like aerial mosaicking and terrain mapping, with recent improvements enhancing its performance in high-outlier conditions [10].

When applying SIFT or ORB to land-surface imagery, such as farmland scenes with repetitive row patterns or uniform fields, fine-tuning key algorithmic parameters becomes crucial. In particular, three parameters: n_features, n_levels, and scale_factor. They play a dominant role in determining how effectively keypoints are detected and matched.

n_features parameter sets an upper limit on the number of keypoints each detector will retain. In environments like farmland, where large uniform areas can yield fewer distinct corners or edges, raising n_features allows the algorithm to detect less obvious points of interest (Fig. 3). However, excessively high values can increase runtime without guaranteeing better matches, especially if the scene is inherently uniform.

Both SIFT and ORB create a scale pyramid or multi-level representation of the image. n_levels parameter controls how many times the image is downscaled, thereby dictating how thoroughly each algorithm explores different scales. A higher n_levels can detect smaller or larger features more consistently, which is helpful if images exhibit large-scale differences (e. g., photos taken at different altitudes). In farmland scenarios, however, too many levels might lead to detecting repetitive features multiple times, increasing false matches [6, 11].

Scale factor parameter defines the downscale ratio between consecutive pyramid levels. A smaller scale_factor (closer to 1.0) creates more finely spaced levels, aiding detection of small scale changes but also increasing runtime. A larger value (e. g., 1.2 or 1.3) coarsens the scale steps, potentially skipping key subtle details in the land surface. Striking the right balance here is especially important when farmland images feature both large uniform areas and smaller-scale structures, such as irrigation lines or distinct crop row edges [2].

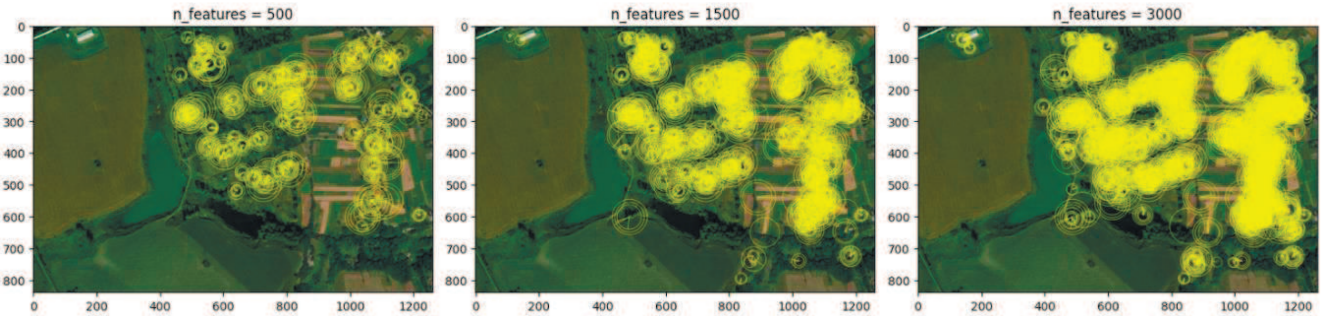

Fig. 3. ORB keypoints with different features

For this study, we collected aerial photographs of agricultural lands from the EOS Crop Monitoring Platfotrm (https://crop–monitoring.eos.com) [12]. Overall, our collection includes photos captured from altitudes of approximately 500 meters and 50 meters above the land, near the villages of Novoselivka and Cherniakiv. All images were captured under similar lighting conditions to minimize the impact of illumination variability on keypoint detection and matching performance. Figs 4 and 5 present examples of the collected images.

To improve the robustness of matching and reduce false positives, Lowe's ratio test is applied. This test compares the distance of the closest match (d_1) with that of the second-closest match (d_2). A match is considered reliable only if the ratio d_1/d_2 is below a certain threshold. This helps eliminate ambiguous matches caused by repetitive patterns or noise [5].

Analysis of recent research and publications. Core studies in the field show that SIFT is a robust baseline for keypoint detection and description in challenging scenes due to its scale / rotation invariance and gradient-based descriptors [5], with numerous photogrammetric and UAV studies confirming its reliability for registration and mosaicking tasks [6], [7], [11]. ORB was proposed as a faster, binary alternative to SIFT / SURF, trading descriptor richness for real-time performance via FAST corners and BRIEF-like descriptors [2], [8], and has underpinned efficient SLAM and mapping pipelines in resource-constrained settings [13]. However, in low-texture, repetitive agricultural patterns, SIFT typically yields higher inlier ratios and more stable homographies, while ORB requires careful tuning of feature counts and pyramid parameters to avoid spurious matches or under-matching [6], [11]. Extensions of SIFT (e. g., RI-SIFT) report improved repeatability under geometric/photometric changes [3], [14], and alternative detectors such as AKAZE and BRISK offer additional speed-accuracy trade-offs in nonlinear or binary spaces [15], [16]. Across studies, Lowe's ratio test combined with RANSAC remains the de facto mechanism for suppressing false correspondences and enforcing geometric consistency during homography estimation and registration [5], [9], [10]. Finally, emerging learnable interest-point methods (e. g., SuperPoint) aim to reconcile SIFT-like robustness with ORB-level efficiency, suggesting hybrid or staged pipelines for near-real-time UAV mosaicking in agriculture [17], while random search provides a practical strategy for hyperparameter tuning across detectors and matchers [18].

Fig. 4. Example of an image from an altitude of 500 meters

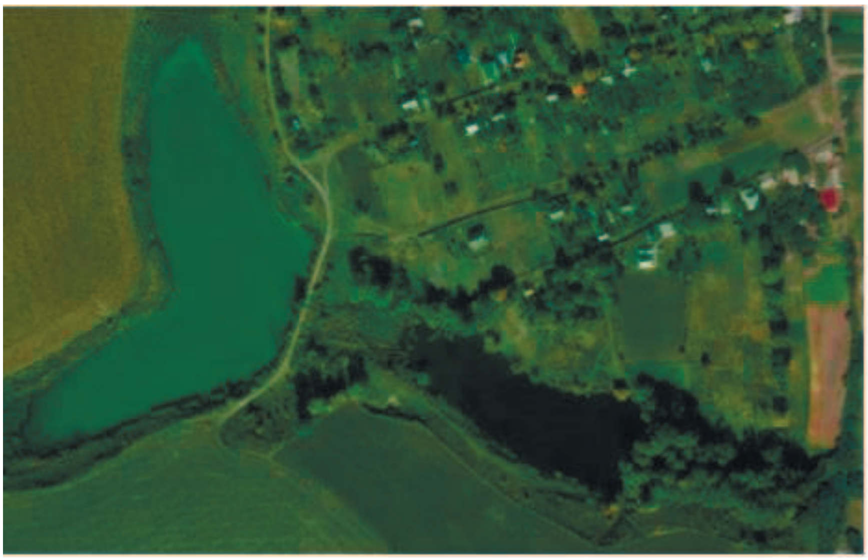

Fig. 5. Example of an image from an altitude of 50 meters

Research results and their discussion

Below are the Table 1 of hyperparameters of three different versions of ORB models and their results, while Fig. 7 shows an example of the agricultural land used:

In Fig. 6, the left side displays the full farmland scene, while the right shows a cropped section of the same image. In the first two ORB configurations, no valid inliers were found due to the uniform fields and repetitive row patterns. The limited number of keypoints, caused by fewer features and coarse scale steps, led to ambiguous matches. A lenient ratio threshold in the first model failed to improve results, while a stricter one in the second removed too many candidates.

In contrast, the third model found correct matches by allowing more keypoints (5,500), using a smaller scale factor, and increasing pyramid levels. This finer multi-scale setup captures subtle structural cues even in uniform textures. A stricter 0.65 ratio threshold helped retain only confident matches, enabling RANSAC to find consistent inliers and achieve successful alignment despite field repetition

Table 1. Hyperparameters of three different versions of ORB models and their results

Version	n_features	scale_factor	n_levels	ratio_threshold
V1	1000	1.2	8	0.75
V2	1000	1.2	8	0.65
V3	5500	1.1	20	0.65

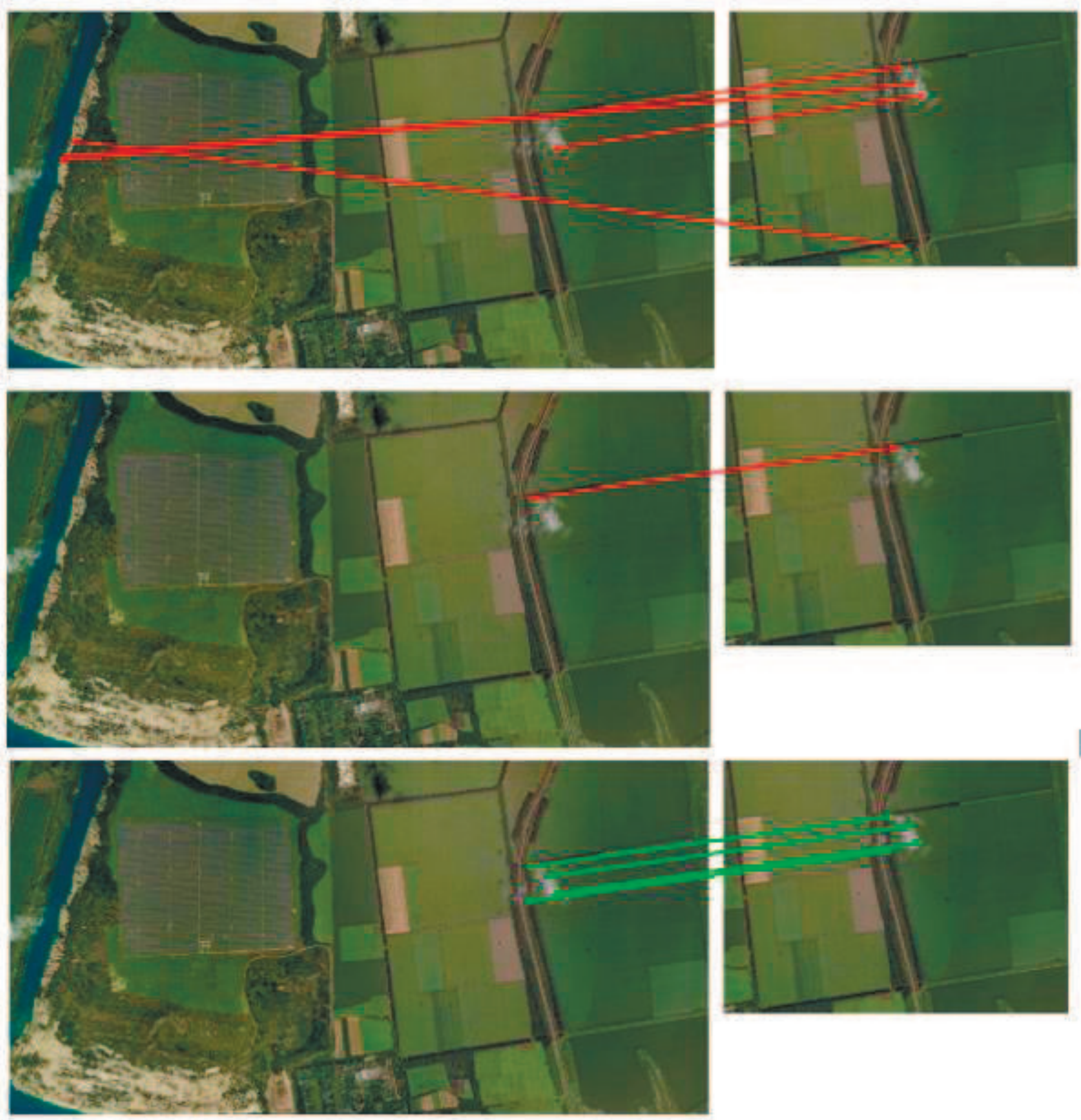

Fig. 6. Results of 3 versions of ORB models (V1 on the top, V2 in the middle, V3 in the bottom)

However, all three ORB configurations proved unable to match the small, circled area in the farmland image (Fig. 7).

Our initial SIFT + RANSAC model used 1,000 features and a 0.65 ratio threshold. Unlike ORB, SIFT doesn't require scaleFactor or n_levels, as it processes features across multiple octaves. This makes it better suited for detecting subtle structures in complex farmland imagery. In the circled region, SIFT identified several low-contrast keypoints missed by ORB, which passed RANSAC validation. Despite their small number, these matches show SIFT's strength in low-texture, repetitive scenes. Fig. 8 presents the model's result.

Although SIFT found four keypoints in the target region, it missed some potential matches. To improve detection of finer details, we performed a grid search over SIFT's hyperparameters. This method systematically tests combinations of predefined values to find the most effective configuration [18].

Below is the Table 2 of hyperparameter values that were determined using Grid search.

Table 2. Table of hyperparameters and their values during grid search for SIFT model

Parameter	Possible values
n_features	500, 1000, 2000, 5000, 8000
ratio_threshold	0.55, 0.6, 0.65, 0.70, 0.75
ransac_threshold	2.0, 3.0, 5.0, 10.0, 15.0

Grid search determined the best model with the following parameters: n_features = 500, ratio_treshhold = = 0.55, ransac_threshold = 2.0. This model showed the following results (Fig. 9, Fig. 10).

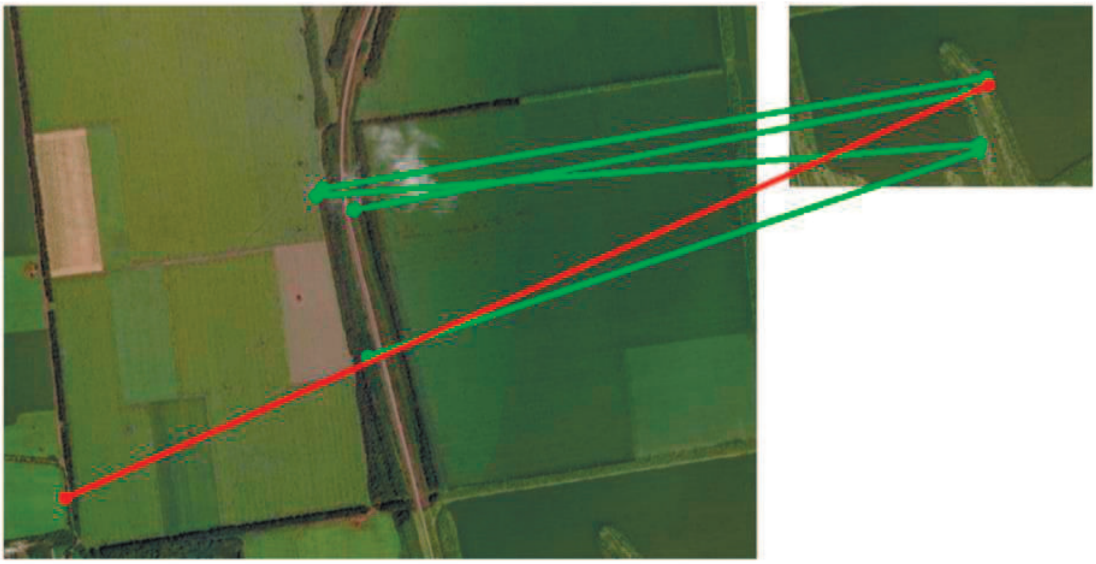

Fig. 7. Result of ORB model with another pair of images

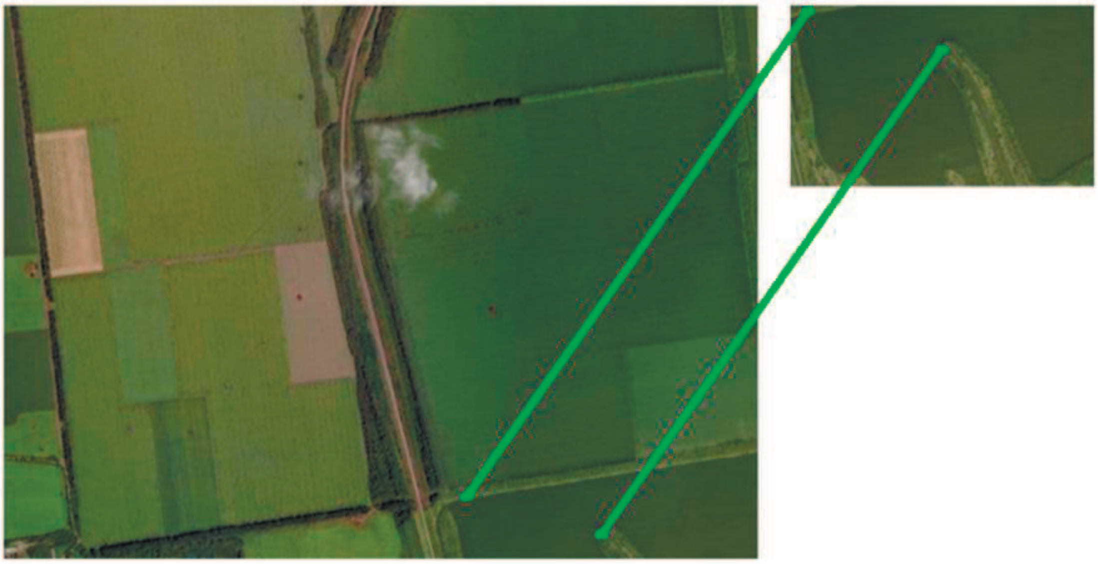

Fig. 8. Result of the first version of SIFT model

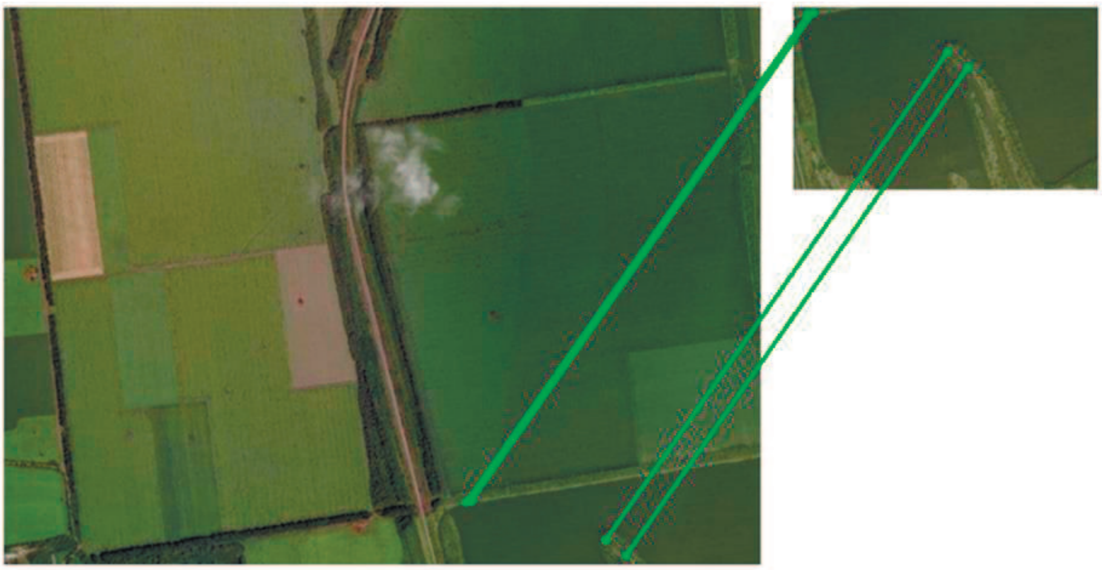

Fig. 9. Result of the best version of SIFT model (500 meters photo)

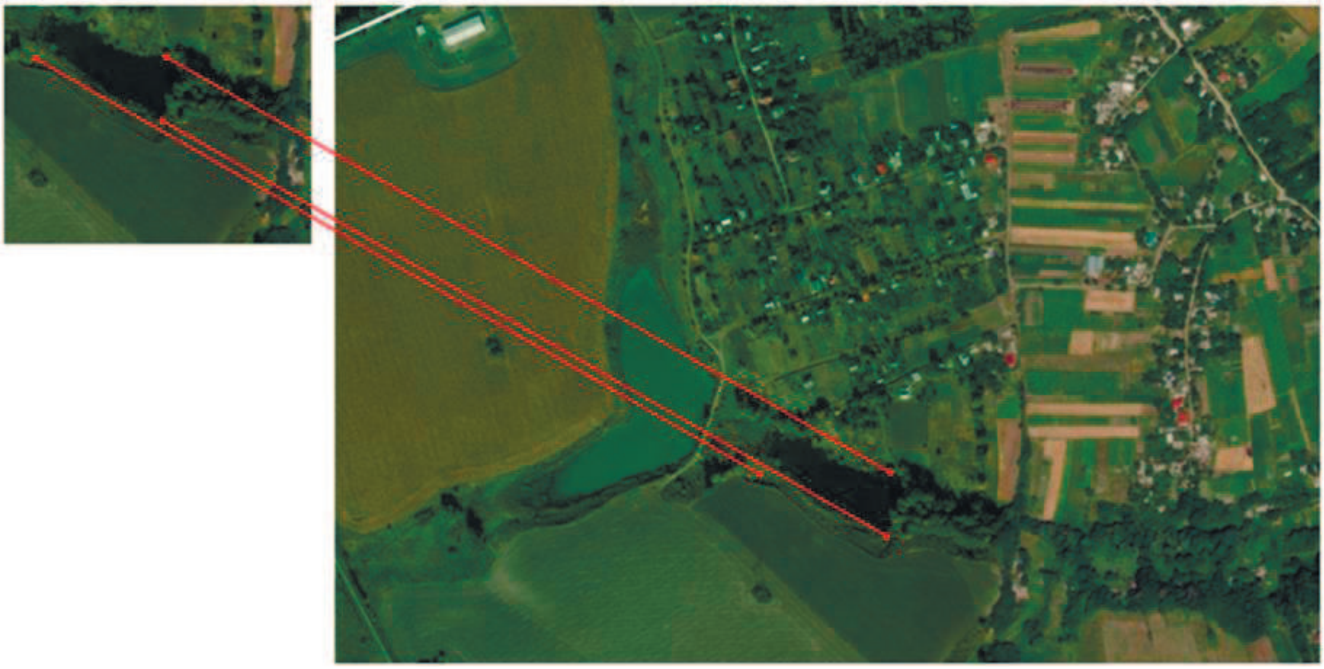

Fig. 10. Result of the best version of SIFT model (50 meters photo)

In the 500-meter image, SIFT detected some valid matches in low-contrast areas but missed others in uniform patches. In the 50-meter image, it found multiple candidates, yet RANSAC rejected them as outliers. This highlights difficulties in matching small-scale features under strict geometric models – valid points may be excluded if they don't align with the global homography. While SIFT reveals matches missed by ORB, uniform textures and perspective shifts still complicate final inlier selection.

Discussion of the research results. The experimental results highlight distinct strengths and weaknesses of the ORB and SIFT algorithms in processing UAV imagery of agricultural fields. Three ORB configurations were tested by varying key hyperparameters such as n_features, scale_factor, and n_levels. The first two models failed to yield valid inliers due to the dominance of uniform textures and repetitive structures in farmland imagery. The third model, with increased feature count and finer scale representation, achieved more reliable matches. However, even this improved setup struggled to detect keypoints in low-contrast, small-scale areas, demonstrating ORB's limitations in challenging rural scenes.

In contrast, the SIFT algorithm showed greater robustness in handling complex and repetitive textures. The initial SIFT + RANSAC configuration successfully identified subtle features in the same difficult image regions where ORB had failed. Although only a few matches were found, they passed RANSAC validation, indicating reliable keypoint detection in uniform farmland environments. To further optimize performance, a grid search was conducted across SIFT's n_features, ratio_threshold, and ransac_threshold, improving its ability to detect finer details.

Even with optimization, SIFT faced challenges. In the 500-meter image, it detected some valid correspondences, but missed others. At 50 meters, while more candidates were found, RANSAC rejected many due to geometric inconsistency. This underscores the trade-off between descriptor sensitivity and model constraints in repetitive, scale-variable environments. Despite these issues, SIFT outperformed ORB overall in accuracy and reliability, particularly in low-texture and structured farmland scenes.

To further validate the effectiveness of our optimized pipelines, we compared their performance with results from previous studies involving UAV-based image matching in agricultural settings. For example, Dibs et al. (2016) [14] reported an inlier ratio of approximately 81.3 % using their refined RI-SIFT method on farmland UAV images. In contrast, our optimized SIFT+RANSAC model achieved an inlier ratio of 100.0 % while simultaneously reducing the false match rate through a more conservative ratio threshold (0.55) and refined RANSAC thresholding (2.0 pixels).

Scientific novelty of the obtained research results is that the practical methodology for agricultural UAV mosaicking was improved by codifying a validated SIFT+RANSAC configuration and concise tuning rules.

The practical significance of the research results is that the obtained results allow to build a structure for the description and processing of images in the grayscale and color images.

Conclusions

An optimized approach was proposed that integrates two classical feature detection methods, ORB and SIFT, with the geometric verification technique RANSAC. A series of comparative experiments with different hyperparameter settings were conducted to evaluate the trade-offs between computational efficiency and matching accuracy.

The analysis showed that ORB provides high speed and efficiency, but its accuracy significantly decreases in scenes with uniform textures or repetitive crop patterns. Even when adjusting parameters such as the number of detected keypoints or scale factors, ORB struggled to maintain robustness under farmland-specific conditions. In contrast, SIFT demonstrated stronger performance in detecting fine-grained, low-contrast features and proved more stable in complex or repetitive agricultural scenes. Its scale and rotation invariance, along with richer descriptors, allowed more consistent alignment, although the computational cost was higher.

The integration of RANSAC played a decisive role in filtering spurious correspondences and ensuring geometric consistency between images. However, the experiments also highlighted the limitations of existing approaches, particularly in cases of extreme uniformity or perspective distortions. These results suggest that improvements may come from hybrid algorithms, domain-specific preprocessing, or incorporating modern, learning-based descriptors such as SuperPoint.

In conclusion, the research confirmed that SIFT currently provides more robust results than ORB for agricultural image stitching, while RANSAC enhances matching reliability. At the same time, future work should focus on lightweight, deep-learning-based keypoint detectors that can achieve both efficiency and accuracy, offering scalable solutions for precision agriculture.

References

1. Yu, Z., Zhou, H., & Li, C. (2017). Fast non-rigid image feature matching for agricultural UAV via probabilistic inference with regularization techniques. [Conference paper].
2. Rublee, E., Rabaud, V., Konolige, K., & Bradski, G. (2011). *ORB:* An efficient alternative to SIFT or SURF. In Proceedings of the IEEE International Conference on Computer Vision (ICCV).
3. Dibs, H., Idrees, M., Saeidi, V., & Mansor, S. (2016). Automatic keypoints extraction from UAV image with refine and improved scale invariant features transfor*m (RI-SIFT)*. [Conference paper].
4. Fesiuk, A., & Furgala, Y. (2023). Keypoints on the images: Comparison of detection by different methods. *Electronics and Information Technologies*.
5. Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*.
6. Lingua, A., Marenchino, D., & Nex, F. (2009). Performance analysis of the SIFT operator for automatic feature extraction and matching in photogrammetric applications [Journal article].
7. Kang, P., & Ma, H. (2011). An automatic airborne image mosaicing method based on the SIFT feature matching [Conference paper].
8. Rublee, E., Rabaud, V., Konolige, K., & Bradski, G. (2011). *ORB: An efficient alternative to SIFT or SURF*. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.
9. Baid, U. (2015). Image registration and homography estimation [Technical report].
10. Pankaj, D. S., & Nidamanuri, R. R. (2016). A robust estimation technique for 3D point cloud registration [Journal article].
11. Zhang, X., Tian, Y., Zhu, Y., et al. (2019). Rapid mosaicking of UAV images for crop growth monitoring using the SIFT algorithm [Journal article].
12. EOS Crop Monitoring (n. d.). *Main map: Fields*. Retrieved from https://crop-monitoring.eos.com/main-map/fields/all
13. Mur-Artal, R., Montiel, J. M. M., & Tardós, J. D. (2015). ORB-SLAM: A versatile and accurate monocular SLAM system [Journal article].
14. Dibs, H., Idrees, M., Saeidi, V., & Mansor, S. (2016). Automatic keypoints extraction from UAV image with refine and improved scale invariant features transform (RI-SIFT) [Conference paper].
15. Alcantarilla, P. F., Nuevo, J., & Bartoli, A. (2013). Fast explicit diffusion for accelerated features in nonlinear scale spaces. In *Proceedings of the British Machine Vision Conference (BMVC)*.
16. Leutenegger, S., Chli, M., & Siegwart, R. Y. (2011). BRISK: Binary robust invariant scalable keypoints. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.
17. DeTone, D., Malisiewicz, T., & Rabinovich, A. (2011). SuperPoint: Self-supervised interest point detection and description [Conference paper].
18. Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*.

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НАДІЙНИЙ МЕТОД ЗІСТАВЛЕННЯ ЗОБРАЖЕНЬ ДЛЯ СІЛЬСЬКОГОСПОДАРСЬКИХ ЗНІМКІВ З БПЛА ІЗ ВИКОРИСТАННЯМ SIFT ТА ORB

Досліджено надійне виявлення ключових точок і геометричне зіставлення у високороздільних зображеннях сільськогосподарських угідь, отриманих з БПЛА. Ці дані критично важливі для моніторингу посівів, оцінювання врожайності, картування меж полів і підтримання рішень у точному землеробстві. Попри те, що ORB і SIFT є стандартом для масштабного мозаїкування та реєстрації зображень, їхню поведінку в низькотекстурних, повторюваних сценах все ще недостатньо охарактеризовано для надійного практичного застосування. Сформовано контрольовану експериментальну модель із використанням високороздільних аерофотознімків на двох висотах. Кожну пару "детектор – дескриптор" поєднано із тестом відношення Lowe та перевіркою гомографії на основі RANSAC, щоб оцінювати геометрично узгоджені відповідності.

Спочатку проаналізовано гіперпараметри ORB (n_features, scale_factor, n_levels, ratio thresholds). На аграрних зображеннях ORB виявляє вразливості: обмежена розрізнювальна здатність в однорідних текстурах спричиняє неоднозначні відповідності; низькі значення ratio thresholds пропускають хибні збіги, які RANSAC відкидає; високі значення ratio thresholds настільки зменшують множину кандидатів, що збігів залишається замало для стійкої моделі. Досліджено також SIFT. Його представлення у просторі масштабів краще відтворює тонкі, низько-контрастні структури поля. Перебирання по сітці над кількістю ознак, ratio thresholds та допусками RANSAC визначило ефективну конфігурацію, що послідовно відновлювала геометрично валідні відповідності на обох висотах. На різних висотах SIFT виявляє тонкі, відтворювані ознаки, які ORB пропускає, формуючи чисті набори збігів, тоді як RANSAC відсіює залишкові невідповідності з огляду на відмінності в перспективі та локальне геометричне зміщення точок зображення.

Оптимізована зв'язка SIFT+RANSAC досягла частки збігів 100 % і зменшила кількість хибних спрацювань. ORB залишався вразливим на низькотекстурних ділянках. Методологічно дослідження показує, як кількість ознак, багатомасштабне опрацювання та пороги перевірки впливають на результати в аграрних зображеннях.

Ключові слова: виявлення ключових точок, ORB, SIFT, RANSAC, зіставлення зображень.

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Цитування за ДСТУ: Білан С. М., Бережний Д. А. Надійний метод зіставлення зображень для сільськогосподарських знімків з БПЛА з використанням SIFT та ORB. *Український журнал інформаційних технологій*. 2025, т. 7, № 2. С. 58–66.

Citation APA: Bilan, S. M., & Berezhnyi, D. A. (2025). Robust image matching method for UAV agricultural images using SIFT and ORB. *Ukrainian Journal of Information Technology*, 7(2), 58–66. https://doi.org/10.23939/ujit2025.02.58