EAI Endorsed Transactions
on Scalable Information Systems
Research Article EAI.EU

Optimization of image mosaic in weak texture scene by region localization and geometric enhancement strategy

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Abstract

INTRODUCTION: In industrial production and equipment manufacturing, there's a strong practical need to create wide-angle panoramic images through image stitching for comprehensive visual monitoring, but actually deploying it still comes with challenges. However, traditional SIFT-based image registration methods often struggle in low-texture scenes because the feature points are sparse and unevenly distributed, which can easily cause mismatches in non-overlapping areas and lead to registration errors or failures.
OBJECTIVES: This article introduces a new image stitching framework based on SIFT, aimed at improving the quality and accuracy of image stitching in low-texture scenes.
METHODS: We first use a template matching method based on normalized cross-correlation to locate overlapping areas between images, which helps effectively reduce the interference from non-overlapping features and improves the reliability of feature extraction and matching. When the overlapping area mostly consists of weak texture regions, we add a feature matching simulation that uses successfully matched key points to extend extra geometric constraints in the overlap to better link the images.
RESULTS: The experimental results show that the proposed method performs well when stitching images with large areas of weak textures, significantly improving both registration accuracy and overall stitching quality.
CONCLUSION: The proposed method has been initially tested in several challenging scenarios like low light, strong backlighting, and infrared, showing its potential for robust image stitching in low-texture environments.

Keywords: Weak texture, SIFT algorithm, Feature point matches, Feature point expansion, Image registration, Image fusion

Received on 13 August 2026, accepted on 13 October 2026, published on 09 November 2026

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doi: 10.4108/eetsis.14495

1. Introduction

Image mosaic is a technology that seamlessly integrates multiple partially overlapped images into a panoramic image with wide field of view and high resolution. It has been one of the key technologies in the field of computer vision and image processing for a long time [1-4]. This technology is indispensable in many applications, including immersive virtual reality, enhanced remote sensing analysis [5-7], panoramic photography and biomedical imaging. The whole process mainly depends on two key stages: image registration and image fusion. The traditional feature-based stitching process usually follows the following sequence: feature point extraction, feature point matching, geometric transformation matrix calculation, image fusion. Although these methods have good robustness in texture rich scenes, they face significant challenges in weak texture environments. Such scenes usually show uniform color gradient, smooth surface or lack of obvious edges [5], [8-10]. In manufacturing

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scenarios, there are also similar challenges with weak texture stitching. For areas with weak textures, like metal processing surfaces or components with uniform coatings, traditional stitching methods struggle to find enough reliable matching points, making it hard to get enough coverage to fully image the target area [11,12]. Even though the experimental data in this article wasn't collected from real manufacturing scenarios, the challenges addressed are pretty typical for this kind of application. Under these challenging conditions, even the traditional SIFT feature detector [13], which is scale-invariant and affine-robust, often can't detect enough feature points that are both plentiful and reliably noticeable.

The scarcity of feature points directly leads to the problem of insufficient number or low quality of feature points matches, which seriously affects the calculation of subsequent transformation matrix, and ultimately leads to insufficient registration accuracy and even mosaic failure. In order to solve the challenge of insufficient matching relationship of feature points in weak texture scenes, this paper proposes a feature-based image mosaic algorithm framework for weak texture scenes. Our core innovation lies in the improvement of the traditional image mosaic workflow: expanding the traditional five step process to a new seven step process: determining the overlapping area of the image to be spliced, feature point extraction, feature point matching, feature point matching simulation, variable computing homography transformation matrix, image registration and image fusion. Among them, "feature point matching simulation" is the key innovation step of this algorithm framework. We use the spatial relationship of the initial reliable matching points to reasonably propagate the geometrically consistent pseudo feature point matching to the unmatched region, so as to provide an interpretable correspondence in the texture missing region. This can effectively alleviate the fundamental limitation of sparse feature point matching in sparse texture regions and provide a robust basis for accurate geometric transformation estimation. In our proposed framework, we have achieved two specific innovations: Guided overlap region estimation: by combining sliding window template matching and normalized cross-correlation [14,15], we robustly determine the overlap region between image pairs before dense feature processing. This initial coarse alignment step focuses feature extraction and matching on relevant regions, significantly reduces the computational load, and minimizes the interference of misleading features in non-overlapping regions. Feature propagation for enhanced matching: after obtaining reliable correspondence in the estimated overlapping region based on SIFT and robust ratio test [16], our novel feature propagation mechanism simulates geometrically reasonable pseudo correspondence in sparse or unmatched texture regions. This actively enhances the geometric constraints between images and can transform the problem into a form that can be robustly solved by ransac [17] even when there are few initial matching points. To sum up, the contributions of this paper are as follows:

novel algorithm framework: we propose the first feature-based mosaic process that takes "feature point matching simulation" as the core step, and expand the traditional image mosaic framework from five steps to seven steps, which is designed specifically to solve the fundamental limitation of insufficient feature correspondence in weak texture scenes.

The core mechanism of robustness: (1) template matching is used for coarse matching of the effective region of feature point extraction of the image to be stitched, which can effectively avoid the interference of non-overlapping regions; (2) A geometric feature propagation mechanism can reasonably generate pseudo correspondence even when the initial matching points are extremely scarce, so as to achieve reliable transformation estimation.

Cross-Scenario Validation: Comprehensive experimental evidence shows that this algorithm performs remarkably robustly and effectively in real images with very weak texture overlap across various imaging modes, without needing retraining. This proves its practical value across different fields.

2. Related work

Image stitching technology has long relied on the classic "feature detection and matching" steps, yet this process faces fundamental challenges in weak-texture scenarios. To clearly define the innovative positioning of this paper, this section systematically reviews and analyzes two mainstream weak-texture stitching technical approaches and their inherent limitations: traditional methods based on handcrafted features and data-driven methods based on deep learning. A comparative overview of the traditional versus the improved workflow is provided in Figure 1.

2.1 Traditional Feature Methods and Their Challenges in Weak Texture Scenes

The feature-based method represented by sift [13] and its improved variants is the classic paradigm of image mosaic. As shown in the upper part of Figure 1, the standard process usually includes four core steps: feature point extraction, feature matching, geometric transformation estimation and image fusion. SIFT algorithm achieves good invariance to scale, rotation and illumination changes by constructing scale space and gradient direction histogram [13]. In the matching stage, the nearest neighbor search combined with ratio test [16] is often used to obtain the initial correspondence, and robust estimators such as ransac [17] are used to estimate the correct geometric model from the matching with noise [18]. Image fusion usually uses weighted average [2] or multi-resolution algorithm to transition the overlapping area of the image to be stitched.

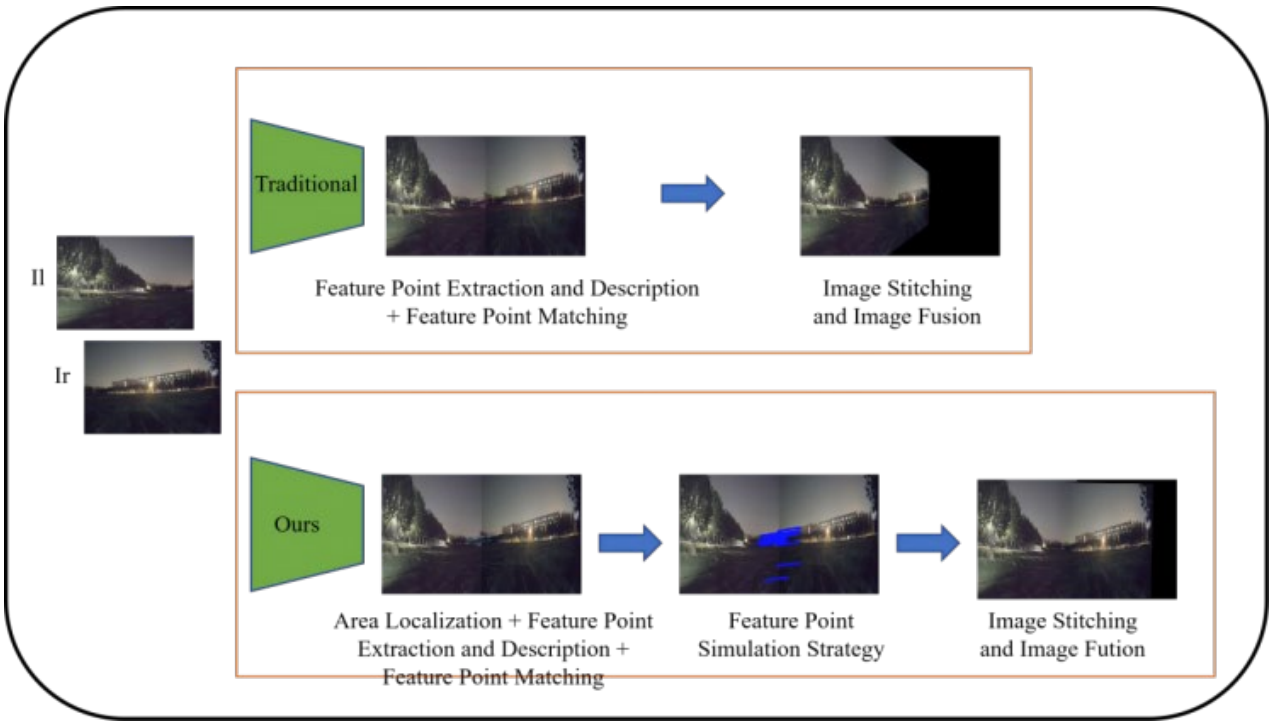


Figure 1. Comparison Between Traditional and Ours Image Stitching Algorithms

Even though this approach performs well on images rich in texture, its strength really depends on the number and distribution of detected feature points. In areas with weak texture, the lacking gradient info means you get very few feature points [9,19]. This will lead to a chain reaction: sparse and unreliable initial matching makes subsequent algorithms unable to estimate the correct transformation model due to insufficient number of correct feature point matching pairs, resulting in registration failure [17]. Therefore, the fundamental limitation of the traditional feature method is that its traditional framework design passively relies on the inherent texture information of the image and cannot deal with the scene where the feature itself is scarce.

2.2 Data Driven Deep Learning Method and Its Limitations

The stitching method based on deep learning has become an effective alternative to the traditional feature-based method. This kind of method directly learns geometric transformation or pixel level correspondence through convolutional neural network [20], avoiding the limitations of traditional feature extraction. However, in weak texture scenes, its effectiveness is still limited by the following three aspects:

Strong dependence on training data: the deep learning model still depends on the data set of handmade features or expensive labels, and it is very difficult to obtain sufficient and diversified real annotation data in weak texture scenes. It has not completely got rid of the dependence on "high-quality supervision information".

The ability of scene generalization is limited: the performance of the model on the weak texture types not covered by the training set is significantly reduced, and there is a significant generalization gap.

High requirements for computing resources: generally, the resources of embedded devices are limited, and it is difficult to realize real-time splicing on devices with limited computing power.

Therefore, in the task of weak texture image mosaic with scarce data and high efficiency requirements, the current standard deep learning method still faces great challenges.

3. Proposed Stitching Method for Weak-Texture Scenes

This section details our proposed framework, whose novel workflow is depicted in Figure 1. Part 3-A first introduces an improved SIFT for adaptively locating key feature regions in the images, thereby reducing the interference of non-overlapping areas in feature point extraction. Subsequently, the SIFT algorithm is applied within the identified overlap region to obtain a high-confidence sparse initial matching set. Part 3-B focuses on another core innovation of this work—a feature matching pair simulation strategy based on morphological dilation. This strategy is capable of synthesizing a large-scale, high-precision dense matching pair set from the aforementioned sparse matching set. Finally, the global transformation

matrix is robustly estimated from the synthesized matches using the RANSAC algorithm.

3.1 Feature Extraction and Description

We use template matching [15] to precisely locate feature point extraction in the overlapping area, reducing feature point extraction errors. The matching measure is defined as the Normalized Cross-Correlation (NCC) [14]:

$$NCC(I,T)=\frac{\sum_{x,y}(I(x,y)-\bar{I})-\bar{I}(T(x,y)-\bar{T})}{\sqrt{\sum_{x,y}(I(x,y)-\bar{I})^2}*\sqrt{\sum_{x,y}(T(x,y)-\bar{T})^2}} \quad (1)$$

In Equation (1), where $\bar{I}$ and $\bar{T}$ are the means of image I and template T. An NCC value closer to 1 indicates a better match. Algorithm Steps:

a) Input Data: Get two images: left I_1 and right I_2.

b) Image Preprocessing: Correct and scale images for matching at the same scale.

c) Set Template Region: Extract multiple template regions from the left image I_1. Select areas near the right edge as templates. Template size ranges from [minWidth, maxWidth].

d) Template Matching: Match template T by sliding it over the right imageI_2. Use OpenCV's cv::matchTemplate function to compute similarity at each position, yielding result map R.

e) Find Best Match: In R, find the point $(x_{best}, y_{best})$with the highest similarity, as expressed in Equation (2).

$$(x_{best}, y_{best}) = \arg\max_{x,y}(x,y) \quad (2)$$

f) Determine Overlap Region: Based on (x, y) and template size, define the overlap region's position $R_{overlap}$, as Expressed in Equation (3).

$$R_{overlap} = \mathrm{Re}\,ct(x_{best}, y_{best}, widthOfT, heightOfT) \quad (3)$$

g) Subsequent Feature Extraction: Extract feature points only within the overlap region identified by template matching.

Once the overlap region $R_{overlap}$ is determined, we apply the Scale-Invariant Feature Transform algorithm [13] within it for feature point extraction and description.

However, in scenes with weak textures, the initial set of SIFT feature points p obtained from the overlapping area R is often extremely sparse, as shown in Figure 3. This scarcity leads to an insufficient number of initial matching points, making it hard to provide enough constraints for a robust estimation of the global transformation matrix.

Therefore, in our framework, these sparse but reliable feature point matching is the core part of our mosaic framework. In the next section, we will introduce our proposed feature matching diffusion simulation strategy in detail. This strategy uses these existing feature matching simulations to generate a more reasonable set of matching points, providing sufficient matching points for solving the global transformation matrix.

3.2 Image Feature Point Simulation

Our method is different from traditional feature point interpolation, mesh deformation, or motion propagation methods. Those methods predict correspondences in unmatched areas by estimating unknown feature responses or building global topological relationships, but the feature simulation strategy we propose doesn't do any estimation or interpolation. On the contrary, it's based on a simple yet effective geometric prior that explicitly spreads the geometric offsets of reliable initial matching points to their local neighborhoods: the spatial mapping relationship is roughly consistent within the local neighborhood of reliable matching points. Traditional interpolation and deformation methods rely on plenty of texture information or a globally consistent deformation model, but when feature points are extremely sparse, neither works. In contrast, our method directly generates simulated matching points from the spatial relationships of high-confidence matches, without any extra estimation or global optimization. This way, even when the initial matches are very limited, it can still provide more reliable geometric constraints for estimating the homography matrix.

Let the initial set of reliable matching point pairs obtained in the overlapping region in Section 3.1 be, as expressed in Equation (4).

$$S = \{(p^i, p_i^{'})\}_{i=1}^{k} \quad (4)$$

Where pi and pi 'are the feature point coordinates of the reference image and the image to be stitched, respectively. We use morphological dilation [21] to diffuse initial matching point pairs within overlapping regions. To this end, we propose a feature simulation strategy based on morphological dilation, which generates a large number of geometrically consistent simulated feature matching point pairs in sparse S.

Formally, define the feature point sets of the two images as expressed in Equation (5) and (6).

$$A = \{p_i = (x_i, y_i) \in R^2\}_{i-1}^{n} \quad (5)$$

$$A^{'} = \{p_j^{'} = (x_j^{'}, y_j^{'}) \in R^2\}_{j-1}^{m} \quad (6)$$

Where n and m are the total number of feature points extracted from the two images, respectively. Define a circular structural element with a radius of r, as expressed in Equation (7).

$$Br = \{(dx, dy) \in R^2 \mid dx^2 + dy^2 \le r^2\} \quad (7)$$

For any point P, its expanding neighborhood as expressed in Equation (8).

$$Br(p_i) = \{p_i + q \mid q \in Br\} \tag{8}$$

Our core assumption is that the spatial mapping relationship is approximately consistent within the local neighborhood of the initial matching point (p_i, p_i'). We set the neighborhood radius r to 3 pixels, which was determined as a trade-off between "generating enough simulated matching points" and "maintaining local geometric consistency," and this value matches the typical 1 to 2 pixel error in feature localization observed in experiments.When the number of initial reliable matching points is very limited, simulated matching points can serve as additional geometric constraints, allowing RANSAC to estimate a valid homography matrix even when the initial matches are sparse. This has been verified in all test scenarios.

Therefore, for any pixel q within the pi domain in the reference image, we select pixels $q' = p_i' + (q - p_i)$ with the same relative offset in the corresponding neighborhood $B_r(p_i')$ of the image to be stitched and denote (q, q') as a pair of simulated matching points. Traverse all initial matching points in S and all pixels within their neighborhoods to obtain complete geometric consistency of simulated matching point pairs, as expressed in Equation (9).

$$\widetilde{S} = \bigcup_{(p_i, p_i') \in S} \{(q, q') \mid \in B_r(p_i), q' \in B_r(p_i'), q - p_i = q' - p_i'\} \tag{9}$$

This geometry contains all simulated matching pairs generated through neighborhood dilation. These points are close to the original matching pairs in space, ensuring geometric consistency. The feature point simulation diagram is shown in Figure 2.

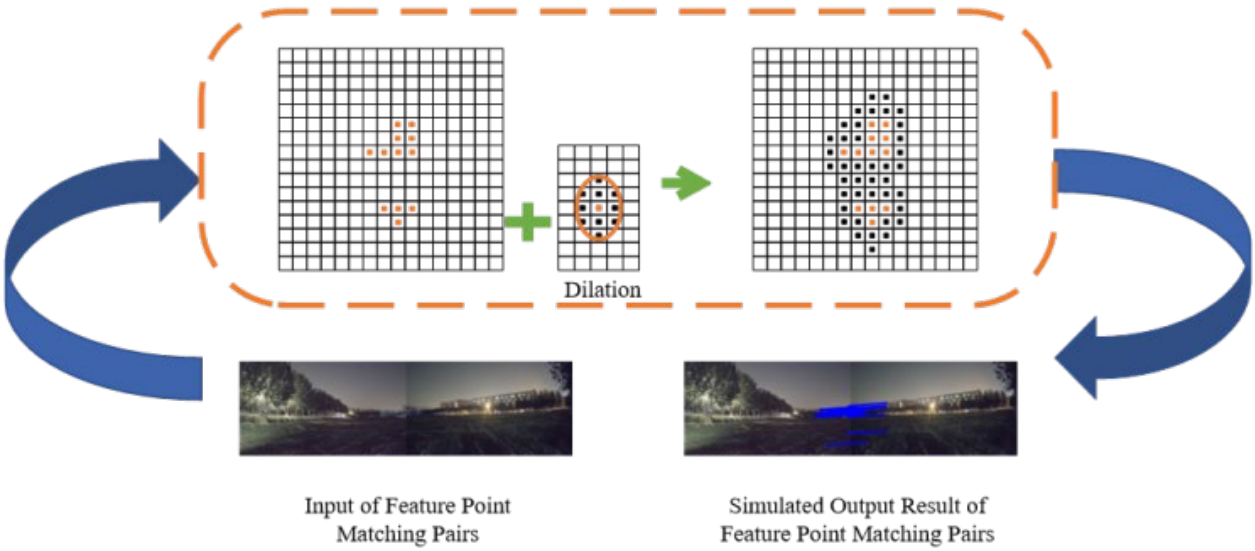


Figure 2. Simulate more feature point matching pairs based on the existing ones

4. Experiment

To check how well the proposed method works, we tested multiple sets of image pairs in three scenarios: thermal images with a resolution of 384×288, nighttime images with a resolution of 1920×1080, and low-texture visible light images with a resolution of 2448×2048.Because traditional methods like SIFT and RANSAC often can't calculate a valid homography matrix in low-texture scenes, making it impossible to generate stitched images for quantitative evaluation, the success of stitching is assessed qualitatively.In all the tested image pairs, this method successfully generated valid homography matrices and got the correct stitching results, while SIFT RANSAC failed in most cases, and ICE also failed in several challenging scenarios.

Across all experiments, a fixed set of parameters was employed to validate the algorithm's strong generalization capability in weak-texture scenarios, highlighting its out-of-the-box applicability in practice.

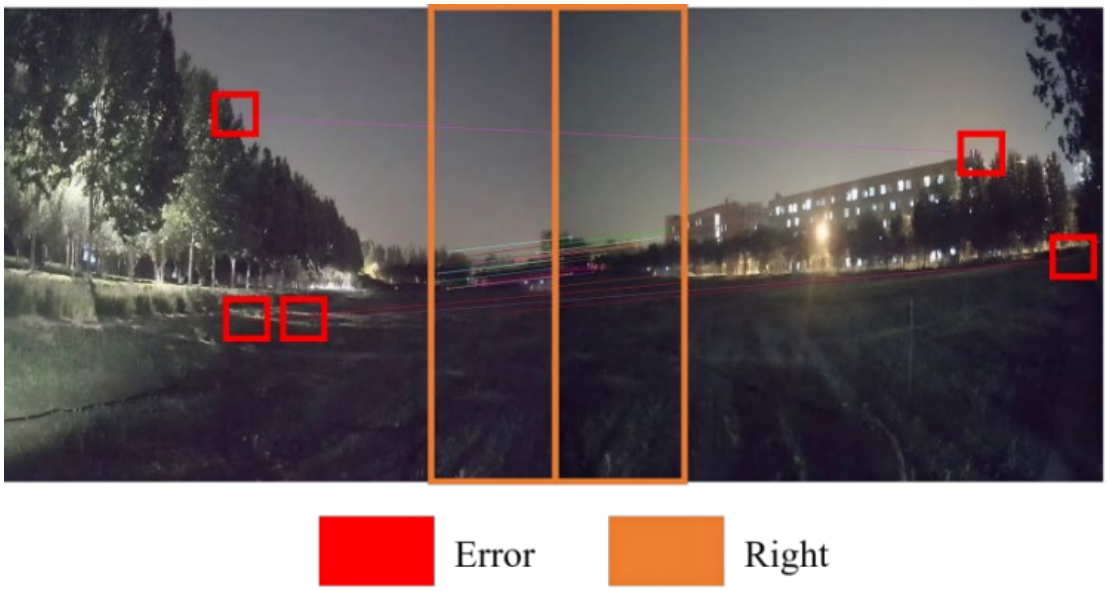


Figure 3. Feature point matching

For the RANSAC algorithm, setting the inlier threshold directly affects how much the model can tolerate wrong matches. The method we proposed consistently maintains a stable matching success rate and isn't sensitive to the exact choice of the inlier threshold, so it's pretty robust. We eventually chose 3.0 pixels as the default value, based on the recommended 2.0–5.0 pixel range from reference [15] and considering the typical 1–2-pixel feature localization error at our experimental image resolution.

We compared our algorithm's performance in different low-texture scenarios with Microsoft Image Composite Editor (ICE) and SIFT + RANSAC [13] through image stitching experiments. As previously discussed, feature point extraction without regional constraints can lead to numerous mismatches from non-overlapping areas, especially between overlapping and non-overlapping regions, and between non-overlapping regions themselves, as shown in Figure 3.

Figure 4 presents comparative results under extreme scenarios involving thermal imaging and visible light. The first row showcases experimental materials consisting of thermal imaging data with a resolution of 384×288. The second and third rows display visible light images with extreme weak textures, captured at a resolution of 2448×2048. Each column corresponds to a successive algorithmic improvement, arranged as follows: SIFT, SIFT+RC (Region Constrained), SIFT+GE (Geometry Enhancement), and SIFT+RC+GE.

It can be seen from the first three columns that the basic performance of sift+rc and sift+ge based on SIFT still maintains good effect on the whole. However, when the original sift method is not good, sift+RC and sift+Ge are difficult to achieve the desired results. The last column presents the results of our proposed complete framework, which can achieve effective and even better stitching in all kinds of extremely weak texture scenes, successfully handle the challenge of insufficient feature matching, and show strong robustness.

Figure 5 shows thermal images at 384x288 resolution. Each column displays results from ICE, SIFT + RANSAC, and our method. ICE barely stitches the first row but looks unnatural, and completely fails in the second and third rows, swapping left and right images. SIFT + RANSAC roughly stitches the first and third rows but with noticeable rotation, causing unnatural results. Our method, shown in the last column, significantly reduces post - stitching rotation.

Figure 6 compares the stitching results of 1920x1080 night - time images. ICE delivers a natural stitch with minor incoherence. In SIFT + RANSAC, the left and right images are misaligned, causing incoherence, and there's obvious ghosting due to significant rotation. Conversely, our method effectively reduces the impact of parallax errors and perspective distortions.

Figure 7 compares the stitching results of 2448x2048 images in extremely low - texture visible light scenes. The first - row images to be stitched have minimal overlap, and the right image is over 90% pure - sky. Only 11 feature point pairs were successfully matched. The ICE results were obtained in Structured panorama mode; in Simple panorama mode, it would be as incorrect as SIFT + RANSAC, with complete registration failure. Our method performs well on both image sets, effectively solving the homography matrix computation problem caused by insufficient feature point pairs in weakly textured scenes [9].In scenes with weak textures, feature points are extremely sparse, and SIFT RANSAC often can't compute a valid homography matrix, causing the stitching to fail completely.The framework proposed in this article successfully generated valid homography matrices and achieved correct stitching results in all test scenarios. This

qualitative comparison proves that our method is effective in overcoming the fundamental limitations of traditional feature-based stitching.

The main challenges and specific characteristics mentioned in this article are summarized as follows. In thermal images with a resolution of 384×288, the main challenges are low signal-to-noise ratio, low contrast, and severe texture loss. Template matching based on NCC helps to focus feature extraction on the overlapping regions, reducing interference from non-overlapping regions. The feature simulation mechanism propagates reliable matching points to generate additional geometric constraints, allowing RANSAC to estimate an effective homography matrix even when the initial matching points are very sparse. In nighttime images with a resolution of 1920×1080, the main challenges are insufficient lighting, noise, and low visibility. The proposed method benefits from the extraction of regional constraint features and geometric enhancement, thus compensating for the lack of reliable features. In visible light images with a resolution of 2448×2048 under strong backlight and low texture, the main challenges are local overexposure and large areas of texture loss. Regional positioning processing can restrict feature matching within valid areas, and simulated matching points can provide sufficient data for global alignment. The method in this paper can still achieve successful stitching in these challenging scenarios.

Limitations and Future Work. The method proposed in this paper can still work effectively even when the number of initial reliable matching points is very limited. However, like all feature-based stitching methods, it requires at least a small number of reliable initial matching points to generate simulated matching points and estimate an effective homography matrix. If there are fewer than 4 reliable matching pairs in the overlapping area, this method cannot produce an effective stitching result. Future work will explore integrating this framework with deep learning to handle such extreme situations.

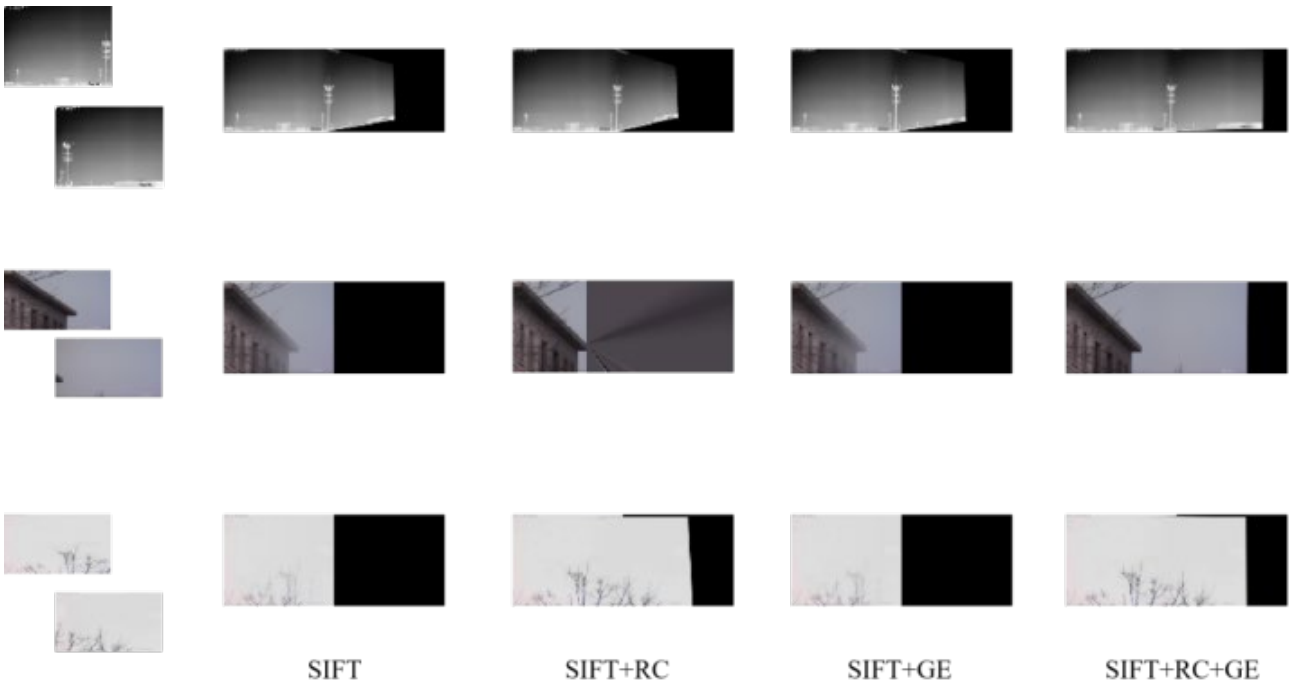


Figure 4. Cross-Modal Datasets: Thermal and Visible Imagery

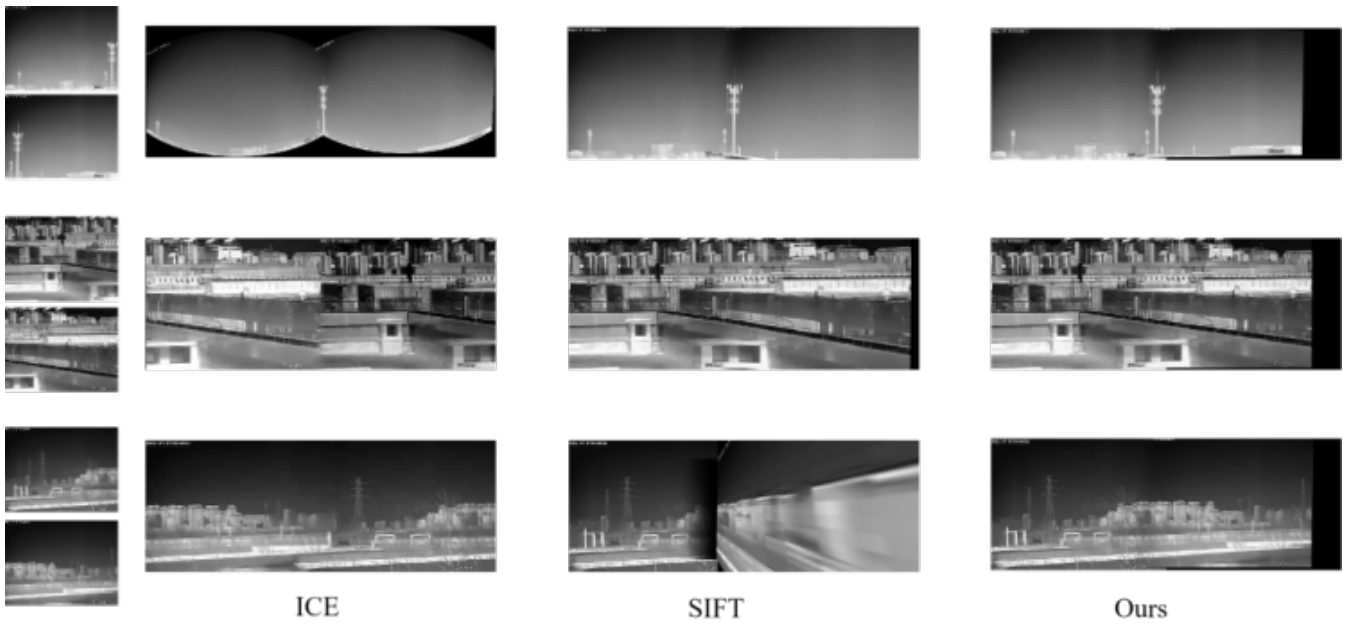


Figure 5. Image stitching for thermographic images with a resolution of 384x288



Figure 6. Image stitching for nighttime images with a resolution of 1920x1080

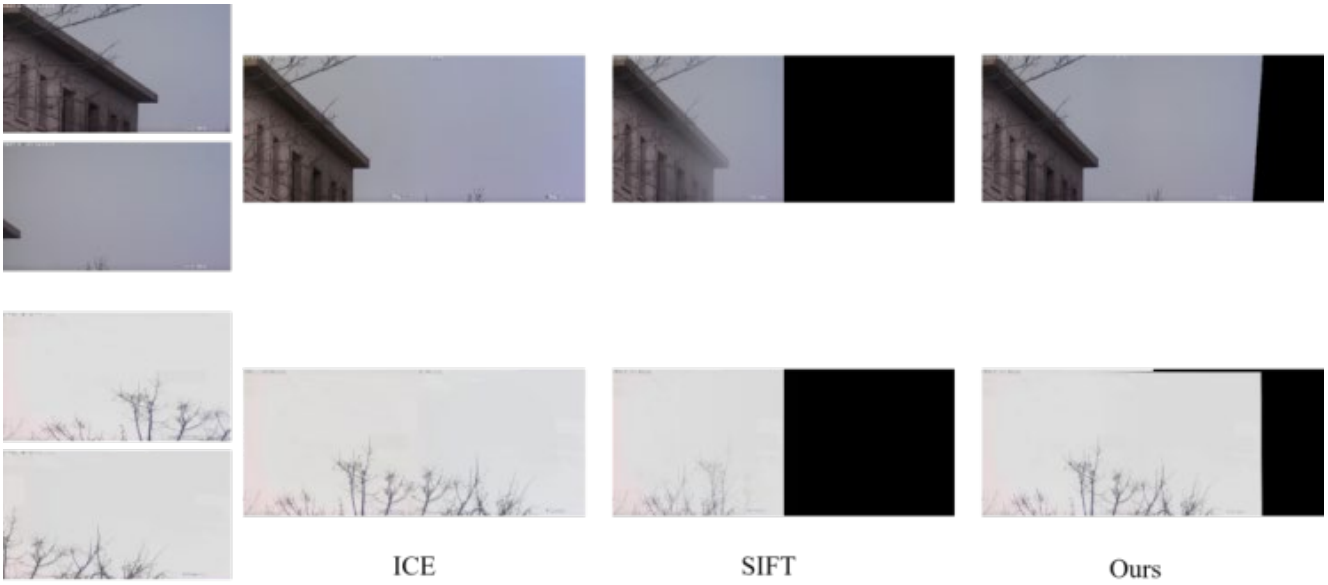


Figure 7. Image stitching for visible light images with weak texture and a resolution of 2448x2048

5.Conclusions

We came up with a new image stitching method that uses region-based feature extraction and geometric enhancement strategies to boost stitching performance in low-texture scenes. First, we use template matching to identify the effective areas for feature extraction in the reference image and the image to be stitched. Then, based on the initial matched point pairs, we process them and use morphological dilation to simulate the generation of pseudo feature point pairs, in order to tackle the problem of homography matrix estimation caused by insufficient data in such scenarios. Even with a very limited number of feature point matches, it's still possible to calculate the correct global transformation matrix, and it can handle slight feature point mismatches pretty well. Experimental comparisons show that the method proposed in this paper can still successfully stitch images in scenarios where traditional methods fail, providing a new approach for image stitching in low-texture scenes and having important significance for further research in this field. This method has been preliminarily tested in low light, strong backlight, and infrared scenarios, but it still needs further validation on larger and more diverse datasets. At the same time, this method shows good potential in manufacturing applications, especially suitable for stitching needs in weak-texture scenarios like industrial visual inspection or surface defect detection of large equipment. However, since the current experimental data wasn't collected from real manufacturing scenarios, it still needs further validation on industrial datasets before actual deployment. Compared to recent methods that rely on unsupervised deep network training to achieve robust stitching, our approach can be deployed in real-time without any training stage, making it more suitable for situations with limited computing resources or difficult data labeling.

References

[1] Pautrat R, Barath D, Larsson V, Oswald MR, Pollefeys M, Yu JY. GlueStick: Robust image matching by sticking points and lines together. In: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 2023. p. 9672-9682.

[2] Yang X, Yin Y, Xu H, Jing Q, Jiang Z, Liao T. Advancements of image and video stitching techniques: A review. IEEE Sens J. 2025;25(13):23526-23551. doi: 10.1109/JSEN.2025.3563082.

[3] Choi J, Lim H, Yun S, Shin M, Paik J. Image stitching method for surround view image without seamline. In: Proceedings of the International Conference on Electronics, Information, and Communication (ICEIC). Singapore; 2023 Feb. p. 1-4. doi: 10.1109/ICEIC57457.2023.10049955.

[4] Szeliski R. Video mosaics for virtual environments. IEEE Comput Graph Appl. 1996;16(2):22-30.

[5] Lyu W, Zhou Z, Chen L, Zhou Y. A survey on image and video stitching. Virtual Real Intell Hardw. 2019;1(1):55-83.

[6] Chen C, Lin K, Chen J, Li H, He Y. Seamless-through-breaking: Rethinking image stitching for optimal alignment. In: Proceedings of the Asian Conference on Computer Vision (ACCV). 2024. p. 455-469.

[7] Yu J, He Y, Zhang F, et al. An infrared image stitching method for wind turbine blade using UAV flight data and U-Net. IEEE Sens J. 2023;23(8):8727-8736.

[8] Huang Z, Wan X, Pan D, Ling X, Ling Z, Liang L, Li Y, Zhang Y. Robust feature matching with spatial smoothness constraints. Remote Sens. 2020;12(19):3158.

[9] Li Z, Wu D, Xu W, Wu Q, Yang G, Zhou D. Feature point matching method of weak texture environment in farmland based on improved GMS-PROSAC fusion algorithm. IEEE Access. 2025;13:4158-4169.

[10] Jiang SH, Lu Y, Li H, Hartley R. Learning optical flow from a few matches. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2021. p. 16587-16595.
[11] Subramanyam V, Kumar J, Singh SN. A hybrid descriptor for low-textural image stitching in real-time surface inspection systems. Multimed Tools Appl. 2024;83:20653-20675.
[12] Su K, Zhu M, Li C. Research and application of image stitching algorithm for industrial inspection based on RANSAC+SIFT. In: Proceedings of the 2026 IEEE 8th International Conference on Communications, Information System and Computer Engineering (CISCE); 2026 Mar 27-29; Guangzhou, China. IEEE; 2026. p. 523-527.
[13] Lowe DG. Distinctive image features from scale-invariant keypoints. Int J Comput Vis. 2004;60(2):91-110.
[14] Barnea I, Silverman HF. A class of algorithms for fast digital image registration. IEEE Trans Comput. 1972;C-21(2):179-186.
[15] Sun M, Xiao J, Lim EG, Zhang B, Zhao Y. Fast template matching and update for video object tracking and segmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2020. p. 10792-10799.
[16] Arya S, Mount DM, Netanyahu NS, Silverman R, Wu AY. An optimal algorithm for approximate nearest neighbor searching. J ACM. 1998;45(6):891-923.
[17] Fischler MA, Bolles RC. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Commun ACM. 1981;24(6):381-395.
[18] Ni K, Li Y, Ke C, Zhang Z, Cao W, Yang SX. A fast unsupervised image stitching model based on homography estimation. IEEE Sens J. 2024;24(18):29452-29467.
[19] Tang Z, Zhang Z, Feng J, Chen W, Zhu K, Yang W, Han W. A fast image stitching algorithm based on texture classification and improved SIFT. IEEE Access. 2024;12:124183-124191.
[20] Li A, Guo J, Guo Y. Image stitching based on semantic planar region consensus. IEEE Trans Image Process. 2021;30:5545-5558.
[21] Haralick RM, Sternberg SR, Zhuang X. Image analysis using mathematical morphology. IEEE Trans Pattern Anal Mach Intell. 1987;PAMI-9(4):532-550.