Image Stitching Quality Evaluation and Improvement Based on SIFT Features and RANSAC Algorithm

Jinsong Shen

School of International Education, GuangDong University of Technology, Guangzhou, 511495, China
3121010047@mail2.gdut.edu.cn

Abstract. Due to factors such as perspective and lighting, traditional stitching such as perspective and lighting algorithms find it difficult to achieve high-quality stitching results. Therefore, how to effectively improve the image stitching effect has become a hot research topic. The traditional image stitching technology mainly uses the SIFT (Scale Invariant Feature Transform) algorithm. By extracting key points from the image and describing their features, the local structural information of the image is obtained, laying the foundation for the next step of feature matching. This article uses the RANSAC (Random Sample Consensus) algorithm to identify and remove outliers, improving matching accuracy and robustness. This article takes the consistency of overlapping areas, color consistency, clarity, and geometric conversion accuracy as evaluation criteria. Based on this, the performance and effectiveness of the algorithm are comprehensively evaluated, providing a reliable solution for its practical application. The average gradient of Experiment Method 1 (Standard SIFT-RANSAC image mosaic) is 20.5, the edge sharpness is 0.78, and the detail retention is 75%. This article combines the SIFT characteristics with the RANSAC algorithm to achieve better and more natural stitching results.

Keywords: Image Stitching Quality Evaluation, SIFT Features, RANSAC Algorithm, Matching Accuracy

1 Introduction

Image stitching is a key technology in digital image processing, which is used to combine multiple overlapping or partially overlapping images into a complete image. It is widely used in aerospace, medical imaging, geographic information system (GIS) and other fields. However, due to the transformation between images, illumination, occlusion and other factors, the image stitching process often appears inaccurate stitching, unnatural joints, distortion and other quality problems. Especially when using automated algorithms for concatenation, it is a challenge to accurately identify matching points and apply appropriate transformations. Previous studies have found that the quality of image stitching is influenced by many factors, such as the accuracy of feature extraction and matching, and the removal of outliers. In response to the above issues, many scholars have proposed various methods such as local feature based

Y. Wang (ed.), *Proceedings of the 2024 2nd International Conference on Image, Algorithms and Artificial Intelligence (ICIAAI 2024)*, Advances in Computer Science Research 115,
https://doi.org/10.2991/978-94-6463-540-9_77

stitching and geometric transformation-based stitching. However, there are still some shortcomings in current research. The research results of this paper can effectively improve the quality and efficiency of image stitching and provide clearer and more accurate image information for different applications. The research results of this project will provide theoretical basis for the development of aerospace, medical imaging, virtual reality, geographic information system and other disciplines, and play a positive role in promoting the development and application of aerospace, medical imaging, virtual reality, geographic information system and other disciplines.

This article combines the SIFT characteristics with the Random Sample Consensus (RANSAC) algorithm to improve the current image stitching performance. Experimental results have shown that the research results of this article can not only effectively improve the quality of stitching, but also effectively solve the problem of image stitching, promoting its practical application process.

Firstly, this article intends to study key technologies such as SIFT feature extraction, matching, and RANSAC based on SIFT features and RANSAC algorithm. Secondly, this article adopts a new image stitching method based on SIFT features. Finally, we adjust the relevant parameters and improved the algorithm to achieve better stitching results and improve the quality of image stitching.

2 Related Work

Image stitching is an important research direction in the fields of computer vision and image processing. Tian C studied a new omnidirectional image quality evaluator based on view stitching [1]. Wang Z provided an overview of image stitching techniques [2]. Zhang J explored image stitching techniques based on the human visual system and SIFT algorithm [3]. Shi Z proposed a grid-based motion statistical matching method to eliminate image stitching distortion [4]. Cui Y provided an integrated learning blind stitching panoramic image quality evaluation based on local vision and global depth features [5]. Ma Fangda studied an image stitching quality evaluation algorithm based on convolutional neural networks [6]. Yang Yunyuan explored a fast-stitching method for high-resolution remote sensing images [7]. Zhong Minzhe explored a multi threshold SIFT image stitching algorithm based on texture classification [8]. Zhang Yang studied a research method for estimating the icing quality of power lines based on image stitching [9]. Huang Yuanbo explored the technique of underwater dam crack image stitching based on connected domain priors [10]. However, the graphic stitching effect in their research is not very good.

SIFT is a fast and robust feature extraction method that can better detect and describe feature points in images, improving the accuracy and robustness of stitching. On this basis, this article adopts a new image fusion method based on RANSAC, which can effectively remove erroneous feature points, reduce the interference of external points on the image, and make the image more accurate and stable. Image stitching has important applications in computer vision, medical image processing, aviation image processing, and other fields.

3 Method

3.1 Exploration Ideas Based on SIFT and RANSAC Methods

The SIFT and RANSAC methods used in this article can effectively solve problems such as perspective changes and lighting changes in real scenes, providing more reliable technical support for solving image stitching problems in complex backgrounds [11]. Image stitching is a key technology in image processing, which has a significant impact on the analysis and application of images. This article will conduct in-depth research on SIFT and RANSAC algorithms, promote the development of image processing theory and methods, improve overall technical level, and provide new ideas for solving more complex image processing problems.

The consistency $Overlap\_Ratior$ of overlapping areas is as follows:

$$Overlap\_Ratio = \frac{A \cap B}{min(A,B)} \tag{1}$$

Among them, A and B represent the number of pixels in the overlapping area of the two images, $A \cap B$ represents the number of identical pixels in the overlapping area, and $min(A, B)$ represents the minimum number of pixels in the overlapping area of the two images.

Color consistency $Color\_C$ is as follows:

$$Color\_C = \frac{1}{N} \sum_{i=1}^{N} \left(1 - \frac{d(i)}{max(d)}\right) \tag{2}$$

Among them, N represents the number of boxes in the color histogram, $d(i)$ represents the histogram distance between two images in the i-th box, and $max(d)$ represents the maximum value of histogram distance.

3.2 Improving Image Stitching Methods

SIFT feature extraction: Traditional image stitching techniques mainly use the SIFT algorithm. SIFT has the property of being invariant to rotation, scale, brightness, etc. and can robustly extract feature points in images. By extracting key points from the image and describing their features, the local structural information of the image is obtained, laying the foundation for the next step of feature matching.

Feature matching: In the process of image stitching, feature matching is a very important step. On this basis, a similarity calculation method based on feature descriptors was adopted. However, when encountering multiple overlapping areas or mutual occlusion, the accuracy of feature matching will decrease, thereby affecting the final stitching result.

Outlier removal: During feature matching, outliers are often generated due to factors such as noise, occlusion, or the complexity of the image itself. Due to the outliers in the image, effective segmentation of the image is necessary. On this basis, the RANSAC algorithm is used to identify and remove outliers, thereby improving matching accuracy and robustness.

Geometric transformation estimation: Based on feature matching, the geometric transformation relationship between two images is determined, thereby completing alignment and stitching. Traditional research often uses homography or matrices to characterize the transformation relationship between images. However, when encountering complex scenes or a large amount of occlusion, this algorithm often produces errors, which in turn affect the final stitching result.

Image fusion: After alignment, the two aligned images are merged to obtain the final stitching effect. The commonly used fusion techniques currently include weighted average method, multi resolution method, and Poisson's ratio method. This algorithm can achieve smooth transitions of images well without producing obvious stitching marks, thereby improving the quality of the stitched images.

Splicing quality evaluation: Finally, designing an evaluation index system to qualitatively and quantitatively evaluate the algorithms used. The common evaluation criteria include consistency of overlapping areas, consistency of colors, clarity, geometric conversion accuracy, etc. On this basis, the performance and effectiveness of the algorithm are comprehensively evaluated to provide reliable solutions for its practical application.

Image clarity assessment $Image\_Sharpness$ is as follows:

$$Image\_Sharpness = \sum_{x,y} G_x^2 + d(i) \tag{3}$$

G_x and G_y represent the horizontal and vertical gradients of the image, respectively, while x and y represent the coordinates of the image pixels.

The evaluation error p_Error of geometric transformation is as follows:

$$p\_Error = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{d_i}{max(d)}\right) \tag{4}$$

Among them, d_i represents the geometric transformation error of the i-th pair of matching points.

4 Results and Discussion

In this section, we comprehensively explore the evaluation and improvement strategies of image stitching technology using SIFT features and RANSAC algorithm. In the initial stage, the article elaborated on the basic principles and operational processes of image stitching, covering key steps from feature extraction and matching to geometric transformation and image fusion. Subsequently, research focused on the quality evaluation of image stitching, covering key indicators such as algorithm stability, visual effects, geometric transformations, and image clarity. By comparing the evaluation results with other technical solutions, this study established the effectiveness and superiority of the proposed improvement measures.

To ensure the accuracy and reliability of the experimental results, we used the following computer configuration as the experimental platform:

Processor: Intel Core i9-10900K, a high-performance CPU with powerful computing and multitasking capabilities, capable of meeting complex image stitching computing needs.

Memory: 64GB DDR4 RAM, sufficient memory capacity to ensure that there is no shortage of memory when processing large-scale image data, improving experimental efficiency and stability.

Storage device: 1TB NVMe SSD, high-speed solid-state drive can accelerate data read and write speed, reduce waiting time during the experiment.

4.1 Evaluation Indicators

Including algorithm stability and visual effects. The evaluation of algorithm stability is based on the consistency and reliability of the stitching effect of the algorithm under various environmental conditions. Effective stability can ensure that the algorithm maintains the accuracy and consistency of the stitching results when facing complex scenes. The evaluation of visual effects is carried out through manual visual inspection, mainly evaluating the naturalness, continuity, and seamless nature of the stitched images. These elements are important criteria for judging the effectiveness of image stitching technology and have a direct impact on the final user experience and practical application.

Regarding geometric transformations, we evaluate the accuracy of geometric parameters by analyzing parameters such as rotation angle and scaling ratio after image stitching. This step is the core of ensuring accurate alignment of image stitching. In the evaluation of image clarity, we measure whether the image quality has improved based on clarity indicators such as edge sharpness and contrast, because the improved image clarity meets higher application requirements and can better serve actual usage scenarios.

4.2 Color Consistency Assessment

The purpose is to conduct a comparative study on color matching between two images.

The experimental process involves selecting images with significant color differences as the stitching objects, stitching them together, and then measuring the color consistency of the stitched images, such as color histogram similarity. By evaluating the color consistency of various algorithms, it has been proven that the algorithm used in this paper can better preserve the consistency of image colors. Experimental method 1 is the benchmark method (Standard SIFT-RANSAC image mosaic), while experimental methods 2 (Color correction SIFT-RANSAC image mosaic) and 3 (Dynamic range optimization SIFT-RANSAC image mosaic) are improvement methods.

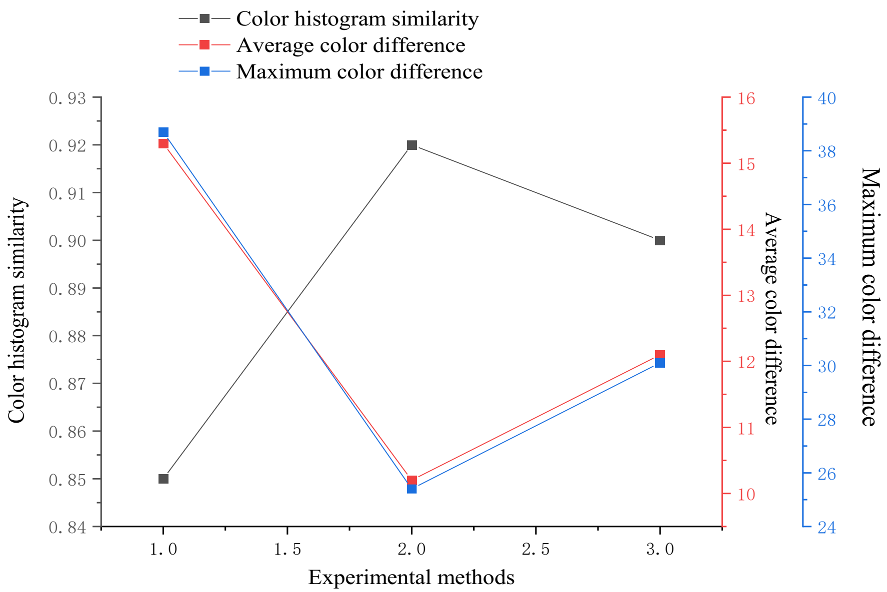

Fig. 1. Color consistency evaluation results

The color histogram similarity of Experiment Method 1 is 0.85, with an average color difference of 15.3 and a maximum color difference of 38.7; the color histogram similarity of Experiment Method 2 is 0.92, with an average color difference of 10.2 and a maximum color difference of 25.4. The color consistency evaluation results are shown in Figure 1.

4.3 Image Clarity Assessment

The research objective is to evaluate the sharpness and boundary clarity of the stitched images. During the experiment, images with high details and strong texture features were selected as stitching blocks, and their clarity indices such as grayscale were calculated. The clarity evaluation results of the two algorithms were compared to demonstrate that the algorithm used in this paper can effectively improve the clarity of images.

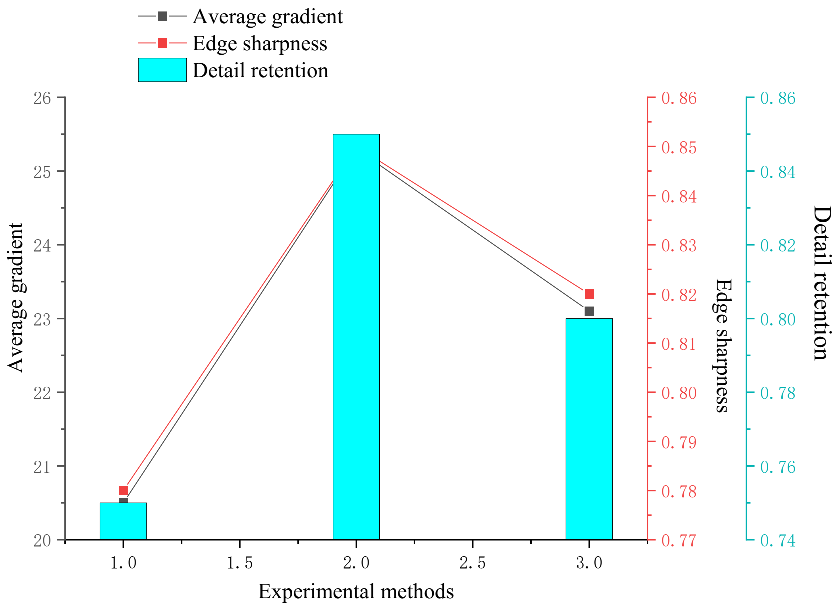

Fig. 2. Evaluation results of image clarity

Experimental method 1 has an average gradient of 20.5, edge sharpness of 0.78, and detail retention of 75%. Experimental method 2 has an average gradient of 25.3, edge sharpness of 0.85, and detail retention of 85%. The evaluation results of image clarity are shown in Figure 2.

4.4 Geometric Transformation Evaluation

The research objective is to perform geometric transformations on the concatenated images to achieve the desired results. On this basis, a multi-image stitching method based on wavelet transform was adopted, and the calculation results of different algorithms were compared to verify the accuracy of the algorithm.

The evaluation results of geometric transformations are shown in Figure 3. The rotation angle error of Experiment Method 1 is 0.5 degrees, the scaling error is 0.01, and the alignment accuracy is 85%; The rotation angle error of Experiment Method 2 is 0.3 degrees, the scaling error is 0.008, and the alignment accuracy is 92%.

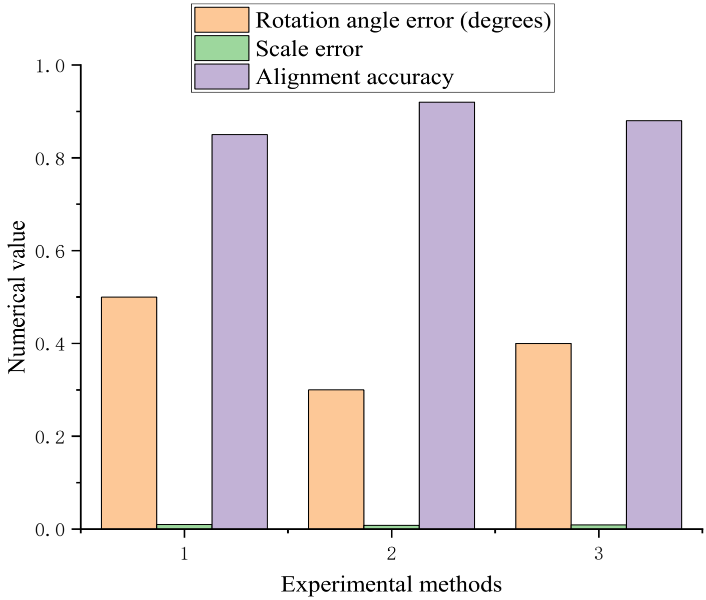

Fig. 3. Evaluation results of geometric transformations

4.5 Visual Effects Evaluation

The experimental objective is to perform manual visual inspection on the spliced images and conduct an overall visual evaluation.

Experimental process: Multiple observers are required to visually inspect the spliced images and subjectively evaluate their naturalness, continuity, and seamless performance. The total score for this is 5 points.

Experimental results: Through the evaluation of multiple individuals, it has been proven that the algorithm used in this article has better visual effects.

Table 1. Visual Effects Evaluation

Observer	Splicing naturalness	Continuity	Seamless	Overall satisfaction
Observer 1	4.5	4.2	4.0	4.3
Observer 2	4.3	4.5	4.2	4.4
Observer 3	4.8	4.4	4.3	4.5
Observer 4	4.2	4.1	3.9	4.1
Observer 5	4.6	4.3	4.1	4.3
Observer 1	4.5	4.2	4.0	4.3

The naturalness of task splicing for Observer 1 is 4.5 points, continuity is 4.2 points, seamless is 4.0 points, and overall satisfaction is 4.3 points; the naturalness of task splicing for Observer 2 is 4.3 points, continuity is 4.5 points, seamless is 4.2 points, and overall satisfaction is 4.4 points; the naturalness of task splicing for Observer 3 is 4.8 points, continuity is 4.4 points, seamless is 4.3 points, and overall satisfaction is 4.5 points. The visual effect evaluation is shown in Table 1.

The sample pictures in this article are shown in Figure 4.

Fig. 4. Sample images in this article

The splicing procedure is shown in Figure 5.

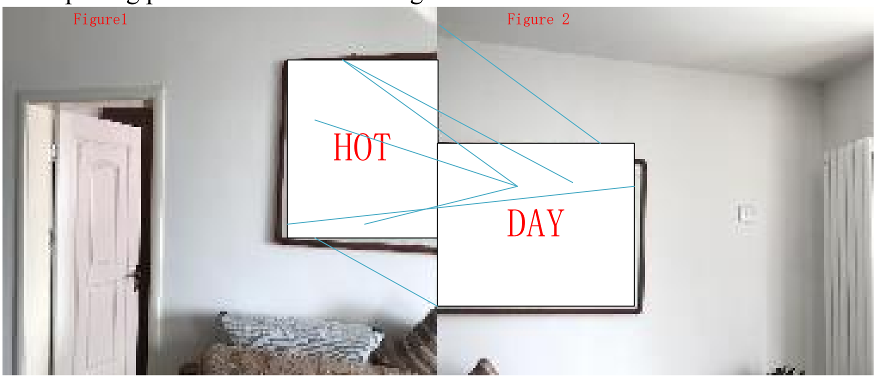

Fig. 5. Splicing process

4.6 Algorithm Stability Evaluation

The experimental objective is to verify the feasibility and stability of this method through image stitching experiments in multiple scenes.

Experimental process: Selecting images from different scenes, such as indoor and outdoor, lighting, etc., and evaluate the stitching results of the algorithm in different scenes. Finally, applying the adopted algorithm to multiple application scenarios and apply it to various application scenarios.

The stability evaluation results of the algorithm are shown in Table 2. When the indoor lighting is bright, the success rate of stitching is 95%, the average stitching time is 2.8 seconds, and the number of feature point matches is 180; when indoors in low light, the success rate of stitching is 90%, the average stitching time is 3.2 seconds, and the number of feature point matches is 150.

Table 2. Algorithm Stability Evaluation Results

Environment condition	Splicing success rate	Average splicing time (seconds)	Number of feature point matches	Splicing error (pixels)
Indoor brightness	95%	2.8	180	5.2
Indoor dimness	90%	3.2	150	6.8
Outdoor sunny days	98%	2.5	210	4.1
Outdoor cloudy weather	92%	2.9	170	5.5
Large changes in lighting	88%	3.5	140	7.3

The final image stitching effect is shown in Figure 6.

Fig. 6. Final image stitching effect

5 Conclusion

Traditional image stitching techniques have limitations due to factors such as perspective and lighting, resulting in unsatisfactory stitching results. On this basis, this article adopts a method that combines SIFT features with RANSAC algorithm to improve the traditional image stitching algorithm. Experimental results have shown that the algorithm used in this article can effectively improve the quality of image stitching and stability, through a series of image stitching experiments based on SIFT features and RANSAC algorithm, this study has accumulated a large amount of data and conducted in-depth analysis. In terms of algorithm stability, experimental results under different environments and lighting conditions have shown that the improved method has high accuracy and consistency, demonstrating its strong robustness and adaptability. The evaluation of visual effects also shows that most observers believe that the improved image has significantly improved naturalness, continuity, and seamless performance, greatly optimizing the visual experience. In addition, the evaluation results of geometric transformations show that the improved scheme significantly reduces errors in rotation angle and scaling ratio and improves the alignment accuracy of stitching. In terms of image clarity, the improvement of experimental indicators such as edge sharpness and contrast make the image clearer and more delicate, meeting higher application requirements. But there are still some shortcomings, such as sensitivity to lighting changes between different images. On this basis, this article will further improve the algorithm to enhance the robustness of the image and expand its application in a wider range of fields.

References

1. Tian C, Chai X, Chen G, et al. VSOIQE: A novel viewport-based stitched 360° omnidirectional image quality evaluator. IEEE Transactions on Circuits and Systems for Video Technology, 32(10): 6557-6572 (2022).
2. Wang Z, Yang Z. Review on image-stitching techniques. Multimedia Systems, 26(4): 413-430, (2020).
3. Zhang J, Xiu Y. Image stitching based on human visual system and SIFT algorithm. The Visual Computer,40(1): 427-439, (2024).
4. Shi Z, Wang P, Cao Q, et al. Misalignment-eliminated warping image stitching method with grid-based motion statistics matching. Multimedia Tools and Applications, 81(8): 10723-10742,(2022).
5. Cui Y, Jiang G, Yu M, et al. Local visual and global deep features based blind stitched panoramic image quality evaluation using ensemble learning. IEEE Transactions on Emerging Topics in Computational Intelligence, 6(5): 1222-1236,(2022).
6. Ma F., Liu Z., Chen S., et al. Image stitching quality evaluation algorithm based on VGG19 convolutional neural network. Journal of Qingdao University: Engineering Technology Edition,38 (2): 31-36,(2023).
7. Yang Y., Chen R.. High resolution remote sensing image fast stitching based on ED-SIFT algorithm. Surveying and Mapping Engineering, 32 (1): 8-13,(2023).
8. Zhong M., Tang Z., Wang Y., Yang C.. Multi threshold SIFT image stitching algorithm based on texture classification. Computer Simulation, 39 (10): 364-368,(2022).
9. Zhang Y., Shu Z., Chen L., et al. Research on the estimation of line icing quality based on image stitching. China Testing, 49 (5): 108-116,(2023).
10. [10] Huang Y., Zhang X., Xu Z., et al. Image stitching of underwater dam cracks based on connected domain priors. Chinese Journal of Stereology and Image Analysis, 25 (4): 408-418,(2020).
11. Ding H, Lihong L., Yuan G. Image registration algorithm combining GMS and VCS+GC-RANSAC.Journal of Computer Applications, 40(4):1138-1143,(2020).