Research on Planar Mosaic Method for Colored Textures of Regularly Symmetric Jar-type Cultural Relics

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Abstract

The use of stitching methods to obtain side view unfolded images of jar-shaped cultural relics with regular symmetrical shapes is of great significance for the digital presentation of cultural heritage. However, traditional image stitching methods face issues such as inaccurate feature point matching, visible seams, and color inconsistencies when processing jar-shaped cultural relics with curved surfaces from different perspectives. To address these issues, this paper proposes an improved SURF algorithm and a multi-band gradient fusion framework. The method dynamically adjusts the extraction threshold of the traditional SURF algorithm based on the image's contrast and edge density, and then extracts feature points. The RANSAC algorithm is used to filter matching points and eliminate mismatches. Subsequently, the images are fused using the multi-band gradient fusion framework, which separates low-frequency illumination information from high-frequency texture information. The low-frequency part ensures illumination consistency, while the high-frequency part repairs seam issues in the stitched areas. Experimental results show that the improved algorithm significantly increases the number of correctly matched points when processing texture images, and effectively solves the seam and color inconsistency problems in stitched images. The fused images exhibit visual effects that are significantly superior to those of traditional stitching methods. This method effectively overcomes the limitations of traditional methods in practical applications and provides strong technical support for the digital presentation of cultural relics.

1. Introduction

As an important carrier of ancient culture, canned cultural relics often contain rich historical, artistic, and cultural information in their side textures (Chen, 2010). However, due to the three-dimensional shape of the ar, its side texture is often limited by the viewing angle and shape in actual observation, as shown in Figure 1, making it difficult to fully present its full picture. Therefore, unfolding the side texture of canned cultural relics into a panoramic unfolding image (Liu and Wang, 2023) is of great significance.

In recent years, researchers in the fields of computer vision and cultural heritage digitization (Zong and Ren, 2017) have been committed to improving texture stitching and display methods to better present the details and overall features of cultural relics. Among them, high-precision collection, stitching, and fusion of the side textures of cultural relics to generate unfolded images of cultural relics textures is a highly valuable and efficient method (Zhao et al, 2007).

The side texture images of ar shaped cultural relics with regular symmetry provide an ideal testing platform for verifying the application of image fusion algorithms and side texture unfolding due to their small geometric deformation, enabling more accurate evaluation of the algorithm's ability to handle texture details and lighting changes. The complexity and diversity of the texture on the side of cultural relics require image stitching algorithms to have higher accuracy and robustness; On the other hand, the actual demand for digital protection of cultural heritage, especially in on-site archaeology, cultural relic restoration, and museum exhibitions (Xu et al, 2022), has put forward higher requirements for the actual quality of image stitching (Zhang and Li, 2011). Therefore, researching more efficient and high-quality image stitching and fusion algorithms has significant value.

SURF algorithm is a feature-based image matching algorithm proposed by Bay et al. (Bay et al, 2008), which solves the disadvantages of high computational complexity and long time consumption of SIFT algorithm while maintaining its excellent performance characteristics. The SURF algorithm significantly improves computational speed through improvements in interest point extraction and feature vector description. The SURF algorithm has a certain robustness to scale changes and rotations in images (Li et al, 2023), but when processing the texture of cultural relics on the side, existing feature point detection methods may not fully adapt to these subtle feature differences due to the complex texture structure and small geometric changes on the surface of cultural relics (Lu et al, 2025). There are still challenges in image fusion in multi perspective texture stitching (Liu et al, 2019). So, while maintaining high fidelity, the demand for solving feature matching and image fusion problems has not yet been met.

Therefore, this article uses an improved adaptive threshold SURF algorithm and a multi band gradient fusion framework for color texture plane stitching of regular symmetrical jar shaped cultural relics. The improved SURF algorithm dynamically adjusts the threshold for detecting keypoints by dividing the image into blocks and using adaptive contrast and adaptive edges (Zhao and Yue, 2016), improving the feature detection ability for complex texture areas of cultural relics. Subsequently, the feature descriptors are optimized to improve the speed and accuracy of feature matching. In addition, by introducing the RANSAC algorithm (Liu et al, 2017), the probability model and residual compensation mechanism are used to effectively suppress incorrect matches.

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Due to the deformation of the surface texture of the jar shaped cultural relics after two-dimensional unfolding, solving the fusion problem at the image stitching point during the stitching process is another important focus of this study. In the image fusion stage, a gradient domain and multi band fusion framework are used to separate the low-frequency illumination layer and high-frequency texture layer of the input image through multi-scale Laplace pyramid decomposition (Dong et al, 2007), ensuring smooth transition of low-frequency components and repairing the misalignment and stitching edge artifacts of high-frequency textures. This method not only eliminates visible stitching artifacts, but also effectively solves the color discontinuity problem that occurs during image fusion, providing a high-precision texture stitching solution for the digitization and protection of cultural heritage.

The contribution of this study lies in proposing a high-precision texture stitching technology that combines mathematical rigor and engineering practicality, providing technical support for the protection, restoration, reverse engineering, and digital display of cultural relics.

Figure 1. Side view of Yuan blue and white porcelain jar

2. Theory and Method

2.1 Overview of the Existing SURF Algorithm

The SURF algorithm detects keypoints by calculating the determinant of the Hessian matrix in different scale spaces. Specifically, for any point (x, y) and scale σ in the image, the definition of the Hessian matrix H (X, σ) is:

$$H(X,\sigma)=\begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (1)$$

In the equation, $L_{xx}(X, \sigma)$is the convolution of second-order Gaussian filtering $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image at point X. Similarly, $L_{xy}(X, \sigma)$ $L_{yy}(X, \sigma)$ can be calculated.

To accelerate computation, SURF adopts the integral graph approximation of Gaussian second-order derivative kernel and efficiently approximates Gaussian second-order derivative using square filters, thereby greatly improving the speed of feature point detection. In terms of feature description, SURF first determines the main direction within each interest point neighborhood, and then divides it into several sub regions (such as 4 × 4) based on this direction. Calculate the response of Haar wavelets in the x and y directions (i.e. local brightness changes) within each subregion, and calculate their sum and absolute value sum. Finally, concatenate the statistics of all subregions into a feature descriptor. The descriptor constructed in this way not only has robustness against rotation and scale changes, but also effectively distinguishes different local structures.

Although the SURF algorithm has good feature point matching performance, there are still some issues with the efficiency of feature point distribution discrimination and accurate matching when processing images with complex textures and different resolutions.

The SURF algorithm uses a fixed global threshold to detect feature points. This method may detect a large number of redundant feature points in simple texture areas, while important feature points may be missed in complex texture areas. This' one size fits all 'strategy cannot adapt to the differences in texture complexity in different regions of the image. When facing image regions with different texture complexities, it is difficult to flexibly adapt and achieve a good balance between the accuracy and efficiency of feature point detection.

A common method to improve the accuracy of feature point extraction in complex regions is to lower the global threshold. However, although this method can increase the number of feature points in complex regions to a certain extent, it may also lead to a significant decrease in the efficiency of feature point detection.

These issues limit its application in some image processing tasks that require high precision and efficiency, especially when dealing with images with different texture complexities and resolutions. This problem is particularly evident.

2.2 Block-Based Detection and Threshold Adaptation

To address these issues, this paper proposes an improved SURF algorithm that utilizes block detection and adaptive threshold adjustment, optimizes feature descriptors, and employs FLANN and improved RANSAC algorithms for feature matching and geometric validation. This algorithm improves the accuracy and matching precision of feature point detection without reducing efficiency.

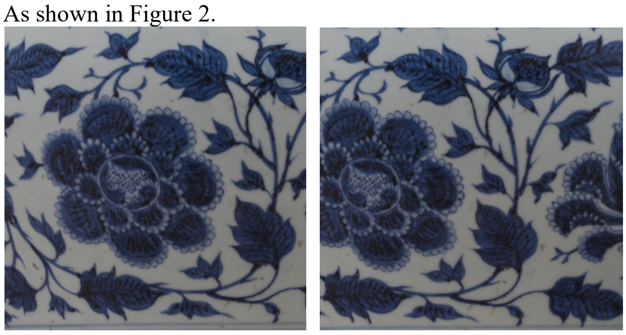
When performing block detection, the input image is first evenly divided into 4 × 4 sub blocks. This partitioning ensures that each sub block has sufficient pixels for statistics while also adapting well to most common resolution images. It can reflect the local characteristics of each part of the image in detail without causing too few pixels or unstable statistics like finer partitioning. The number of blocks can be flexibly adjusted according to the size and complexity of the image. For example, for high-resolution or structurally complex images, more sub blocks can be used to achieve more detailed adaptive adjustment.

On this basis, the concept of adaptive threshold is introduced: the adaptive threshold of each sub block is obtained by fusing normalized contrast and edge density. Contrast is used to measure the degree of difference between light and dark areas in an image, while edge density is typically used to measure the number and distribution of edges in an image.

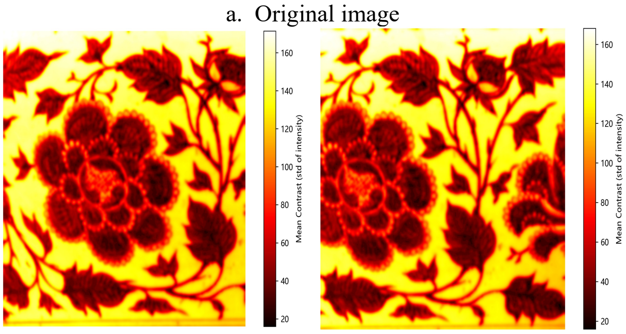
$$\text{Edge} = \begin{cases} 1 & \text{if} \sqrt{G_x^2 + G_y^2} > T \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Where G_x = gradient in the x direction
G_y = gradient in the y direction
T= predefined threshold
Edge = binary edge map

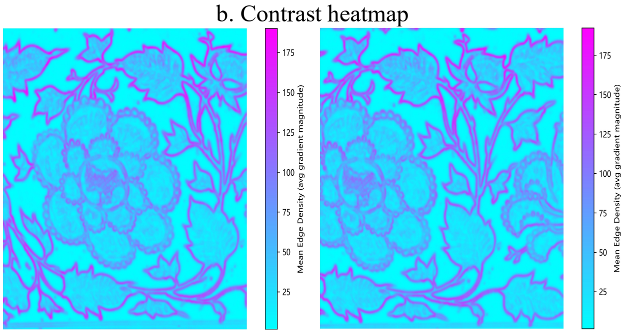
These two indicators can help identify the boundaries and details of different texture regions in the image to be stitched. As shown in Figure 2.



a. Original image



b. Contrast heatmap

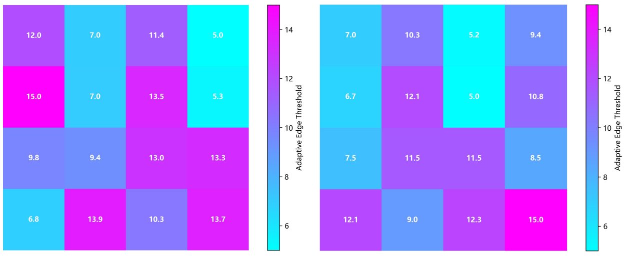


c. Edge density heatmap

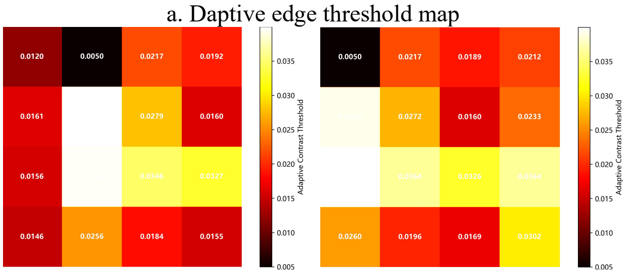
Figure 2. Preprocessed image to be stitched

When extracting feature points from different sub blocks, unlike traditional weighting strategies, this algorithm adopts a two-level adaptive threshold filtering mechanism. Dynamically adjust the contrast threshold based on the local statistical characteristics of each sub block, retaining only candidate feature points with contrast above the threshold. Next, further calculate the edge strength of these candidate points and perform secondary screening based on the adaptive edge threshold.

Due to the higher contrast, the larger the normalization value. Therefore, by reducing the default threshold of 0.04 commonly used in traditional SURF algorithms, more feature points can be detected in complex regions. The threshold map after partitioning is shown in Figure 3.



a. Daptive edge threshold map



b. Adaptive contrast threshold diagram

Figure 3. Threshold data graph for splicing images

2.3 Feature Matching with Geometric Validation

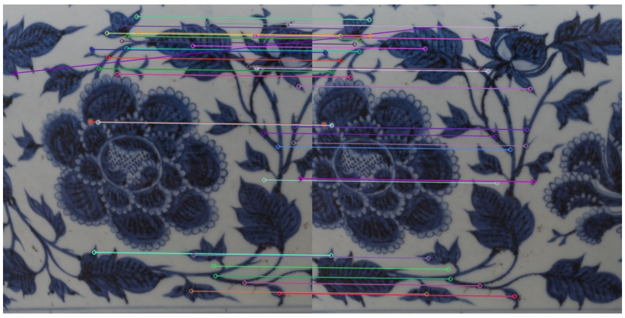
This article uses the Fast library for approximate nearest neighbors (FLANN) algorithm for feature matching, which can effectively eliminate feature mismatches in most complex images. The FLANN algorithm is an efficient nearest neighbor search method suitable for large-scale feature point matching tasks. The basic execution process is as follows:

1. Feature point distance calculation: Consider the feature point set of the first image as the reference set, and the feature point set of the second image as the query set. Calculate the Euclidean distance between each feature point in the reference set and all feature points in the query set.

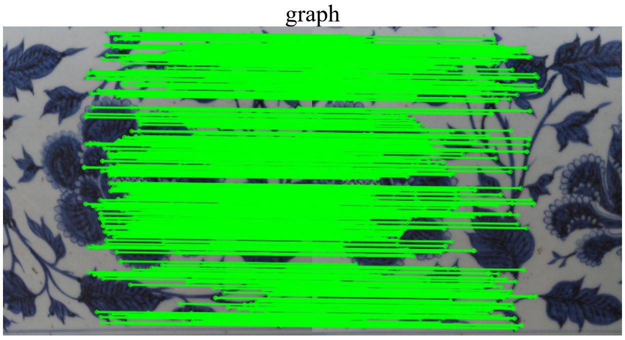
2. Nearest Neighbor Selection: For each feature point in the reference set, identify the two closest feature points in the query set, namely the nearest neighbor and the second nearest neighbor.

3. Distance ratio screening: Use distance ratio testing to screen matching pairs. Specifically, if the Euclidean distance ratio between the nearest neighbor and the second nearest neighbor is less than the threshold, it is considered that these two feature points are matched. Here, threshold is a preset threshold used to control the strictness of the matching. The selection of threshold has a significant impact on the quality and quantity of matching results. In this study, we chose 0.6 as the threshold, which is a commonly used value that strikes a balance between accuracy and recall.

While using the FLANN matching algorithm, a matching filtering strategy based on distance ratio is introduced to further improve the reliability of matching. This strategy works by comparing the distance ratio between two feature points in each matching pair, ensuring that only when the distance between two feature points is significantly smaller than other candidate matches, they are considered a true match. In addition, to ensure the geometric consistency of the matching results, we employed an improved RANSAC algorithm for geometric validation. The RANSAC algorithm can identify inliers from matching pairs, further verifying the accuracy of the matching. Figure 4 shows the matching effect of the improved SURF algorithm.



a. Improve the top 50 matching points in the SURF matching graph



b. Improves the SURF by matching all matching points in the graph

Figure 4. Adaptive Dynamic Threshold Improved SURF Matching Diagram

2.4 Multi-Band Gradient Fusion Framework

Image fusion is a crucial step that involves seamlessly merging images captured from multiple perspectives or different regions into a continuous panoramic image. To achieve visual consistency, detail preservation, and lighting smoothness in image fusion, a gradient domain and multi band fusion framework were adopted. Firstly, homography algorithm is used for image distortion and movement during image alignment, so that the images to be stitched are basically aligned. Univariate transformation is the process of mapping points on one image to corresponding points on another image using a 3x3 transformation rectangle H, expressed as

$$\boldsymbol{H} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \tag{3}$$

After applying the above mapping formula for image transformation, we enter the crucial step of image fusion. The purpose of this step is to minimize the seams caused by alignment and stitching, as well as inconsistencies in image information such as brightness and color tone, in order to make the transition of the image stitching area smoother and more aesthetically pleasing.

We adopted a gradient domain and multi band fusion framework, which performed well in eliminating seams, preserving details, and optimizing lighting consistency. Gradient domain image fusion is an advanced technique that achieves seamless fusion by operating in the gradient domain rather than the pixel domain. The basic idea of this method is to decompose the image into a base layer and a detail layer. The basic layer mainly contains lighting and shadow information, usually obtained through average or median filters; The detail layer contains edge and texture information, which is the difference between the original image and the base layer. During the stitching process, we calculate gradient maps for each pair of images to be stitched, then fuse the gradient maps, and finally reconstruct the final fused image through gradient information. The advantage of this method is that it can effectively preserve the details and edge information of the image, while reducing the problems of seam and lighting inconsistency.

The multi band fusion framework is a technique that decomposes an image into multiple frequency bands and fuses them separately. This method allows us to finely control the different frequency components of the image, achieving better results in preserving details and eliminating seams. By using multi-scale transformations such as wavelet transform to decompose each image into multiple frequency bands, each band captures different levels of detail in the image, ranging from low-frequency global lighting changes to high-frequency local texture details. We fuse each frequency band independently: low-frequency components are usually fused using averaging or weighted averaging methods to maintain consistency between lighting and shadows; The intermediate and high-frequency components are fused using gradient domain fusion method to preserve edge and texture details. Finally, the fused frequency bands are recombined through inverse transformation (such as inverse wavelet transform) to reconstruct the final fused image.

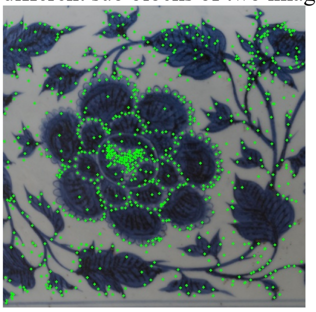
3. Experimental Results and Analysis

3.1 Experimental Subjects

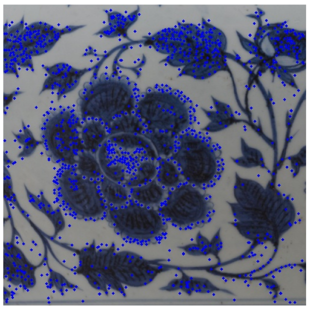
The dataset of this experiment consists of side texture photos of regular symmetrical jar shaped cultural relics, which are specifically used to evaluate the accuracy of the proposed image fusion algorithm in processing cultural relic images with complex textures. The reason for choosing regular symmetrical jar shaped cultural relics as experimental objects is that the texture of these cultural relics causes less distortion during image stitching when captured from different perspectives, which helps simplify the alignment and transformation calculations in the image stitching process and fully tests the algorithm's ability in detail preservation and lighting consistency. At the same time, many cultural heritages and artworks have similar symmetrical characteristics. Therefore, selecting such cultural relics as experimental subjects not only helps with algorithm development, but also facilitates the application of research results to practical cultural heritage protection and display.

3.2 Comparison of Feature Point Matching Accuracy

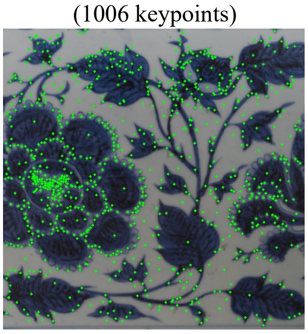
The improved SURF algorithm first divides the image into 4 × 4 sub blocks. For each sub block, the algorithm calculates the average contrast and edge density to select sub blocks with higher complexity, and dynamically adjusts the contrast threshold and edge threshold accordingly. The adjusted threshold is used for the detection of feature points in each sub block. The adaptive threshold adjustment strategy enables the algorithm to detect more feature points in areas with rich texture or high contrast, thereby improving the accuracy and visual effect of stitching. The experimental results show that the improved algorithm has achieved significant improvements in feature point detection, especially in complex areas of the image. The specific results are as follows: Compared with the traditional SURF algorithm, the improved algorithm significantly increases the number of feature points detected. For the first image, the number of feature points increased from 1006 to 1679, with a growth rate of 66.90%; For the second image, the number of feature points increased from 1045 to 1487, with a growth rate of 42.30%. Figure 5 shows a comparison of the feature point extraction performance between the original algorithm and the improved algorithm, while Figure 6 shows the adjustment of the number of feature points in different sub blocks of two images.



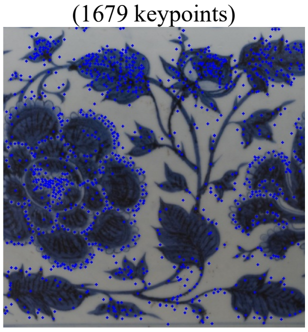
a. Image1 Original SURF (1006 keypoints)



b. Imagel Improved SURF (1679 keypoints)

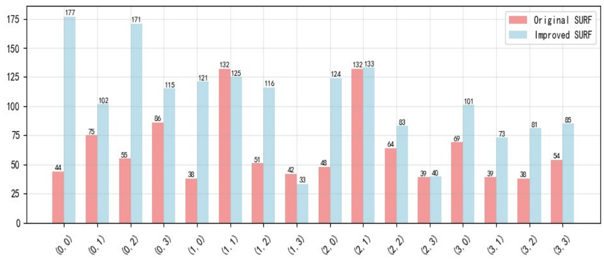


c. Image2 Original SURF (1045 keypoints)

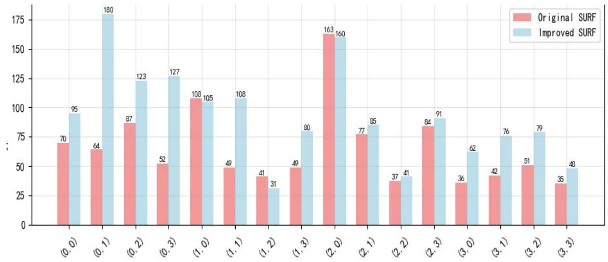


d. Image2 Improved SURF (1487 keypoints)

Figure 5. Feature point extraction diagram of the original SURF algorithm and the improved SURF algorithm



a. Change in the number of feature points in image 1



b. Change in the number of feature points in image 2

Figure 6. Change in the number of feature points in sub blocks

To quantify the differences between the algorithm proposed in this article and traditional algorithms, and to verify the accuracy of feature point extraction, an equal number of feature points were randomly selected. By controlling the number of feature points involved in matching between the two algorithms and eliminating the influence of quantity differences, the focus was on the feature matching quality and verification ability of the algorithm itself. As shown in Table 1

Index	The original SURF algorithm	Adaptive Threshold SURF Algorithm
Number of feature points selected for matching	1000	1000
Number of matching point pairs	603	588
Number of interior points	523	548
Proportion of interior points (%)	86.73	93.20

Table 1. Comparison of algorithm performance

Interior points refer to feature points that conform to consistency models (such as affine transformations, homography matrices, etc.) during the image matching process. These points have high matching reliability in the two images and can reliably support the geometric relationship between the images.

The adaptive threshold SURF algorithm has significantly improved the number and proportion of inliers, indicating that the improved algorithm has significantly improved the accuracy of geometric transformation models, thereby enhancing the reliability of feature point matching and the quality of image stitching.

3.3 Comparison of Image Fusion Results

In the experiment, we used multiple pairs of images with complex textures and different resolutions to evaluate the performance of different algorithms in practical applications. Figures 7 and 8 show the comparison of the processing results between the improved algorithm and the traditional SURF algorithm.

Figure 7 shows the image fused using the traditional exposure fusion algorithm. It can be observed that there are obvious seams and color discontinuities in the stitching area of the image. Figure 8 shows the fusion results obtained by the gradient domain and multi band fusion framework algorithm proposed by the application. The images generated by the improved algorithm use distance transformation to create more natural transitions, and ensure smooth fusion through a 5-layer pyramid structure. The algorithm effectively avoids color discontinuity caused by hard boundaries, achieving seamless stitching visually. The color transition is smoother, and the stitching area shows almost no seams, demonstrating better visual consistency.

Figure 7. Traditional exposure fusion splicing results

Figure 8. Improved fusion algorithm splicing results

In the image fusion stage, gradient domain processing and multi band decomposition strategies further optimize the consistency of color and texture. Before fusion, automatic color correction is performed on overlapping areas to make the tone and brightness of the two images more consistent. Then, multi band fusion is performed to greatly alleviate color discontinuity and reduce stitching artifacts.

4. Conclusion

The improved SURF algorithm enhances the feature detection capability for complex texture regions by dynamically adjusting contrast and edge thresholds, thereby improving the speed and accuracy of feature matching. In addition, the introduced RANSAC algorithm effectively suppresses mismatches and optimizes the image fusion process through probability models and residual compensation mechanisms. In the image fusion stage, the application of gradient domain and multi band fusion framework ensures smooth transition of low-frequency components, and repairs the misalignment of high-frequency textures and edge artifacts of stitching, significantly improving the visual consistency and detail preservation of the image stitching area.

The experimental results show that the algorithm proposed in this study can effectively reduce seams, preserve details, and optimize lighting consistency when processing images with complex textures and different lighting conditions. Especially in the stitching of side texture images of regular symmetrical jar shaped cultural relics, this algorithm demonstrates its advantages in evaluating texture details and handling lighting changes.

Future work will focus on further optimizing algorithm performance, exploring its potential in more diverse application scenarios, and planning to apply the algorithm to more types of cultural heritage digitization projects to verify its universality and effectiveness. The improved SURF algorithm and multi band gradient fusion framework proposed in this study provide an efficient and robust new method for image stitching, particularly suitable for applications such as digital protection of cultural heritage.

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