ISSN 2616-5775 Vol. 7, Issue 11: 72-77, DOI: 10.25236/AJCIS.2024.071110

Image Mosaic algorithm based on feature matching and its optimization

Haoyu Ma

School of Computer Science, University of Nottingham, Nottingham, UK

Abstract: *With the evolution of the field of computational vision, image stitching technology has been widely penetrated into a variety of application scenarios, such as panorama image production and telemedicine image integration, and its influence can not be underestimated. The core intention of this paper is to explore and optimize the image alignment algorithm based on vertex features, so as to achieve excellent image fusion results. Firstly, we review the development of image stitching technology and the existing corner detection algorithms, and select several classical corner detection methods for comparison and analysis. On this basis, this paper proposes an improved feature matching algorithm, which uses corner features for image registration, so as to achieve seamless image stitching. Experiments show that the proposed algorithm not only improves the accuracy of image registration, but also improves the quality of Mosaic images. The experimental results show that the optimized algorithm has better robustness and speed when processing image Mosaic tasks in complex scenes. The research results of this paper are of great significance to promote the practical application of image stitching technology, and provide a new idea for future research.*

Keywords: *Image Mosaic, corner detection, feature matching, ORB algorithm, feature descriptor*

1. Introduction

With the continuous evolution of computer vision technology, image integration technology has gradually become an indispensable practical tool. This technology involves the integration of several overlapping local images into a seamless panoramic image, which plays a key role in many fields such as panoramic photography production, medical imaging synthesis, geographic remote sensing observation and virtual reality [1]. Panoramic photography, for example, is a technique often used by photographers to create an extended field of view by combining multiple frames. In medical applications, image Mosaic enables physicians to obtain a comprehensive view of the lesion by combining multi-angle images, further supporting more accurate diagnosis and treatment decisions. The core mechanism of this technique mainly covers two key aspects of image alignment and fusion. Image alignment. This allows multiple images to be aligned under a unified frame of reference, while the fusion process involves performing composite processing on the calibrated images. In these two steps, feature matching plays a crucial role. Feature matching is to realize the registration between images by detecting and matching the significant feature points in the images. Among them, corner points become one of the commonly used feature detection objects because of their unique local properties and stability.

In this study, we can explore and improve the image alignment strategy oriented by corner characteristics, so as to achieve the perfect image fusion effect. By improving the feature matching algorithm, the accuracy of image registration is improved to ensure that the image is geometrically more consistent. The image fusion process is finely optimized to improve the coherence and harmony of visual presentation. The embedded multi-scale characteristic detection mechanism and weighted matching technology not only strengthen the stability of the algorithm in the face of diversified environments, but also improve the operational efficiency, taking into account the dual optimization of efficiency and accuracy.

2. Literature review

With the development of computer vision technology, the image stitching process has been perfected and has become popular in many kinds of operations such as panoramic photography, medical image combination, remote sensing and so on. The core of this process is the image alignment and integration process, and feature recognition matching plays an important role in this process, which is an effective

ISSN 2616-5775 Vol. 7, Issue 11: 72-77, DOI: 10.25236/AJCIS.2024.071110

method to ensure image alignment. Corner points are widely used in feature detection because of their uniqueness and stability in images.

In recent years, the evolution of image processing technology has given birth to the extensive exploration of image calibration methods based on corner characteristics analysis, and the practice and research of such methods have shown a booming trend. Its core operations can generally be summarized into several key stages. First, they involve accurate corner recognition, then building unique feature representations, then clever matching of features, and finally implementing geometric transformations to ensure accurate alignment of image elements. This section will review the development of image Mosaic technology, and focus on several classic corner detection algorithms and their characteristics.

2.1. The development of corner detection algorithm

Corner detection algorithm is an important part of image Mosaic technology, its purpose is to find points with significant characteristics in the image. These points usually have good repeatability and stability, and are the basis of feature matching [2]. The following are some classic corner detection algorithms and their characteristics:

1) Harris corner detection algorithm is one of the earliest widely used corner detection methods. The basic principle is to move within a window and calculate the score of the change in pixel intensity within that window. If there is a large change in all directions, the point is considered a corner point.

2) ORB (Oriented FAST and Rotated BRIEF). The ORB algorithm combines the advantages of FAST corner detection and BRIEF descriptor, and has higher detection speed and better rotation invariance. The FAST algorithm detects corners quickly, while BRIEF is used to generate concise binary feature descriptors. ORB algorithm improves the efficiency of feature matching by using Hamming distance to compare feature vectors. With the help of contrast evaluation mechanism, FAST corner detection algorithm verifies the gray level of the core pixel and the gray value of a series of successive peripheral pixels to determine whether the point is represented as a corner feature. Image alignment technology This allows coordinate synchronization of multiple frames of images, which plays an indispensable role in image fusion. The traditional alignment strategy usually covers several stages such as feature detection, feature representation, feature correspondence and geometric transformation.

In recent years, with the boom of deep learning, many strategies have begun to apply deep neural network architecture, such as convolutional neural network (CNN), cleverly to image alignment practice, in order to obtain more stable feature representation, so as to enhance the robustness of the algorithm [3-4].However, for the application scenarios with high real-time requirements, the traditional method still has irreplaceable advantages. Through continuous optimization of traditional methods, researchers have developed a variety of efficient image registration algorithms. These algorithms usually combine multiple feature detection methods and use global optimization strategies to find the best registration parameters.

2.2. Feature matching

Feature matching refers to finding the corresponding feature points in two images. Common feature matching methods include: nearest neighbor matching (finding the matching point pair with the nearest Hamming distance). And nearest neighbor ratio (NNDR) (calculate the distance ratio of the nearest neighbor to the next nearest neighbor, and remove the matching point pairs with large distance ratios.) In order to obtain accurate image registration results, it is necessary to estimate the geometric transformation relationship between two images according to the result of feature matching. Commonly used geometric transformation models include affine transformation and parallel projection transformation [5]. In this study, we used Homography to model the relationship between the two images, taking into account the simple displacement and displacement between the images.

Through the review of existing corner detection algorithms, it can be seen that Harris corner detection algorithm has some limitations in computational complexity and rotation invariance, while ORB algorithm has greater advantages in practical applications because of its higher detection speed and better rotation invariance. Next, we will introduce the methodology adopted in this paper in detail, and verify the effectiveness of the proposed improved algorithm through experiments.

ISSN 2616-5775 Vol. 7, Issue 11: 72-77, DOI: 10.25236/AJCIS.2024.071110

3. Methodology

3.1. Harris corner detection algorithm

Harris corner detection algorithm is a classic corner detection method. Its basic principle is to move in a window and calculate the score of the pixel intensity change in the window. If there is a large change in all directions, the point is considered a corner point. Harris Corner detector identifies corner points by calculating the response function R:

$$\mathrm{R} = \det(m) - k\big(trace(m)\big)^2 \tag{1}$$

Where m is a matrix of image gradients and k is an empirical constant. The Harris corner detector is simple and effective, but it has limitations in terms of computation and rotation invarian.

3.2. ORB algorithm

The ORB algorithm combines the advantages of FAST corner detection and BRIEF descriptor, and has higher detection speed and better rotation invariance. FAST algorithm quickly detects corner points. The algorithm determines whether the center point is a corner point by comparing the gray value of the center point with a certain number of continuous pixels around it. If most of these consecutive pixel points (such as 9 consecutive points) have gray values above or below the gray value of the center point plus or minus a threshold, the center point is considered a corner point. BRIEF is used to generate concise binary feature descriptors, which construct a binary vector by comparing the gray values of a series of pixel pairs in a selected area of the image. The main idea is that each corner of image I_1 is found in image $I_2$by using the matching method based on normalized correlation, and the unidirectional matching set of image I_1 to I_2D is obtained. Then for each corner of image I_2, the matching corner is found in imageI_1, and the unidirectional matching set from image I_2 to imageI_1 is obtained. The ORB binary is the intersection of these two matching sets,

For images I_1 and I_2, $\mathrm{C1}(m, m^x)$ is used to represent the corner pointm of image I_1 to the corner point m^x of image I_2

The ORB binary formula is as follows:

$$\mathrm{C1}(m, m^x) = \frac{\sum_{xy\epsilon w}[I_1(x.y)-N_1]-[I_2(x,y^1)-N_2]}{\sqrt{\sum_{xy\epsilon w}[I_1(x,y)-N_1]^2}\sqrt{\sum_{xy\epsilon w}[I_2(x^1,y^1)-N_2]}^2} \tag{2}$$

$$\mathrm{C2}(m^x, m) = \frac{\sum_{xy\epsilon w}[I_2(x,y)-N_2][I_1(x,y)-I_1]}{\sqrt{\sum_{xy\epsilon w}[I_2(x,y)-N_2]^2}\sqrt{\sum_{xy\epsilon w}[I_1(x,y)-N_1]^2}} \tag{3}$$

In order to reduce the space complexity, three one-dimensional data are used to replace the two-dimensional array C. The concrete implementation steps are: m is the number of corner points in image I_1, Nis the number of corner points in imageI_2.

Initialize N to store the binary relation value $\mathrm{C1}(m, m^x)$ for each corner of the first corner I_2 in image I_1. Starting from the second corner of image I_1, the binary phase relation values $\mathrm{C1}(m, m^x)$) and $\mathrm{C2}(m^x, m)$ of the I-th corner of image I_1 and each corner of image I_2 are calculated. If C1>C2, then the corner of image I_1 and the corner of image I_2 are a pair of matching points, and the binary matching is successful

3.3. Application of feature descriptors

The function of feature descriptors is to extract local information around corner points after detecting corner points, so as to match features between different images. A BRIEF descriptor is a feature descriptor based on local pixel contrast, which compares a series of pixel pairs in a selected area to obtain a binary vector. This descriptor is simple and computationally fast, but it is sensitive to illumination changes and rotation. The ORB descriptor is an improvement over the BRIEF descriptor with added rotation invariance. The ORB enhances the robustness of the feature descriptor by calculating the orientation of the corner point and aligning the orientation of the BRIEF descriptor with it.

Each pair of data set of matching points is sorted from smallest to largest according to the distance from the new point to the corresponding matching point after binary transformation. According to the number of repeated sampling, the size n of the generated set conforming to the correct model points is determined, and Y matching points and the NTH matching point are selected from the first N of the sorted matching points to form a new sample set. The model parameters are calculated according to the sample set, and the distance between the new point and the corresponding matching point obtained by the remaining matching points after model transformation is calculated. Meanwhile, the logarithm X of matching points within the allowable error range is calculated. Repeat the above steps, when the proportion of internal points reaches the maximum and is greater than the preset threshold or the number of points no longer increases, the corresponding matching point pair set is the maximum internal point set. The final binary transformation matrix is calculated from the inner point set again.

4. Literature References

4.1. Experimental environment construction

A series of experiments were carried out on standard computing equipment to confirm the efficiency of the image alignment algorithm based on corner characteristics. The experimental Settings are as follows. A PC with a central processor equipped with the Intel Core i7 architecture, supplemented by 16GB of running memory, and a high-end hardware platform with an NVIDIA GeForce RTX 2080 Ti graphics processor. The operating system is Windows 10. The development work relies on Python programming language and PyCharm as integrated development environment. Meanwhile, OpenCV image computing library is used to fully mine and process visual data during the experiment. A variety of publicly available datasets were used to evaluate algorithm performance, including but not limited to: BSDS500, which contains various types of nature images, covering multiple categories such as cityscapes, natural landscapes, indoor scenes, etc. The Middlebury Stereo Benchmark provides a series of stereo image pairs with depth information to evaluate the performance of algorithms in 3D reconstruction. Aachen Day-night, which contains images of the same locations taken during the Day and Night, is used to test the algorithm's performance under varying lighting conditions.

4.2. Experimental result

In this paper, the improved ORB binary matching method is tested by using the corner detection method.

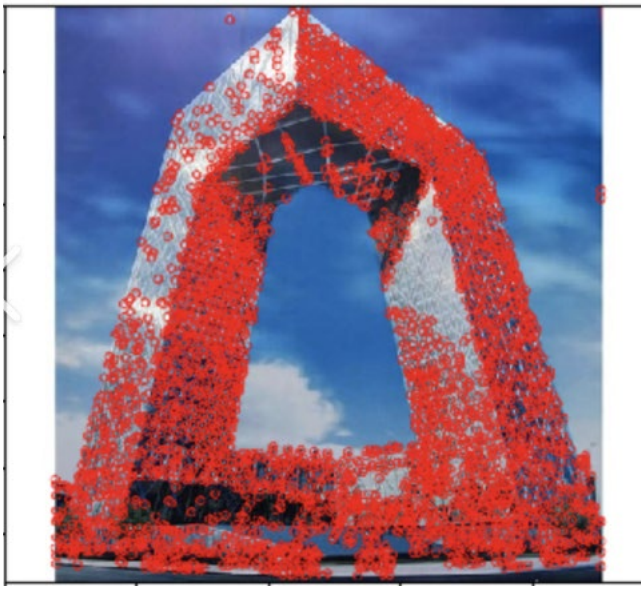

Figure 1: Harris Building image

ISSN 2616-5775 Vol. 7, Issue 11: 72-77, DOI: 10.25236/AJCIS.2024.071110

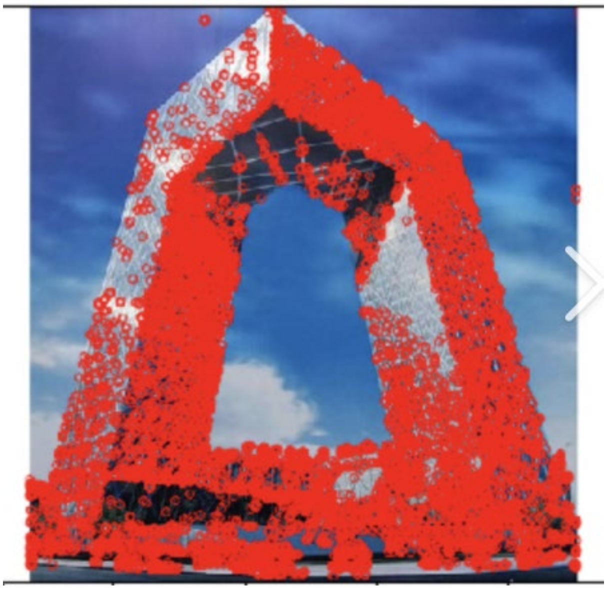

Figure 2: ORB's image of the building

Figure 1 shows the image of Harris' building before the improvement of corner detection method. There are 308 corner points in total. The uneven distribution of these points makes the image blurred. Figure 2 shows the ORB building image after the improved corner detection method, with a total of 462 corner points, which are evenly distributed in the obvious outline of the image. Through comparison, it can be seen that the improved ORB corner detection method is superior to the previous Harris corner detection method in feature matching image stitching.

Table 1: Table 1 Comparison of algorithm results

Method	Harris	ORB
Matching point pair	236	271
Time(msec)	465	406

Table 1 is a statistical table for ORB and Harris, which shows that ORB matches more points than Harrs, but takes less time.

Table 2: Precision comparison table

Method	Data	Accuracy rate	Error rate
ORB	581	88%	0.8
Harris	581	70%	1.2

It can be seen from Table 2 that the accuracy of ORB is higher than Harris, and the error rate of ORB is lower than Harris when detecting the same number of corners

5. Conclusion and prospect of future work

The aim of this study is to improve the quality and efficiency of image Mosaic by improving the image registration algorithm based on corner features. By comparing and analyzing the existing corner detection algorithms and using ORB algorithm, a complete image registration process is designed, including feature detection, feature matching and feature descriptor application. The experimental results show that the quality and efficiency of image Mosaic can be improved by improving the image registration algorithm based on corner features. Future research will further explore the combination of deep learning techniques and traditional feature matching techniques, with a view to achieving more accurate and robust image registration and stitching in a wider range of scenes. Exploring optimized feature identification and pairing strategies is critical, especially for real-time processing requirements. In addition, although visible light images are widely used in a variety of contexts, it is worth noting that other types of image data, such as infrared or ultrasonic images, also show irreplaceable advantages in specific applications. Studying the registration method between multimodal images can help to solve more practical problems. Cross-modal feature matching methods can be explored to achieve accurate registration between different types of images. As the amount of image data continues to increase, the ability to process large-scale image sets becomes particularly important. How to improve the scalability

ISSN 2616-5775 Vol. 7, Issue 11: 72-77, DOI: 10.25236/AJCIS.2024.071110

and efficiency of the algorithm without affecting the registration accuracy is a problem worth discussing. Distributed computing and parallel processing techniques can be studied to accelerate the processing of large-scale image sets. Although current algorithms perform well in most cases, there is still room for improvement under extreme conditions (such as greatly varying lighting, very different viewing angles, etc.). Research on how to enhance the robustness of the algorithm under these special conditions is also a direction of future research. More advanced feature descriptors and matching algorithms can be explored to cope with complex environmental changes. Through the above summary and prospect, this study provides a comprehensive optimization scheme for image registration algorithm based on corner features, and points out the key direction of future research. It is hoped that these results can promote the development of image stitching technology and expand its application potential in more fields.

References

[1] Adel E, Elmogy M, Elbakry H. Image stitching based on feature extraction techniques: a survey[J]. International Journal of Computer Applications, 2014, 99(6): 1-8.

[2] Ravi C, Gowda R M. Development of image stitching using feature detection and feature matching techniques[C]//2020 IEEE international conference for innovation in technology (INOCON). IEEE, 2020: 1-7.

[3] Brown M, Lowe D G. Automatic panoramic image stitching using invariant features[J]. International journal of computer vision, 2007, 74: 59-73.

[4] Adel E, Elmogy M, Elbakry H. Image stitching system based on ORB feature based technique and compensation blending[J]. International Journal of Advanced Computer Science and Applications, 2015, 6(9).

[5] Juan L, Oubong G. SURF applied in panorama image stitching[C]//2010 2nd international conference on image processing theory, tools and applications. IEEE, 2010: 495-499.