Fast robust matching algorithm based on BRISK and GMS

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Abstract. In the image stitching technology, traditional feature extraction algorithms have uneven feature points distribution, many redundant features, time-consuming feature points precision matching and low image registration accuracy. In view of these problems, this paper proposes an improved image registration algorithm based on BRISK and GMS. In this method, the image is first divided into meshes and BRISK algorithm is used for extracting image features, then the Brute Force matching algorithm is used for rough image matching. Finally, the mesh motion estimation method is used for feature quantity statistics, and error matching is removed to obtain a set of fine matching feature points for image registration. This paper verified the robustness of the improved algorithm by comparing it with other methods in the Mikolajczyk data set. The experimental results show that this algorithm achieves higher matching accuracy on the basis of maintaining speed compared with the original algorithm, and the average accuracy is improved by 8.02%. It has better performance than the traditional algorithm, which can be used for occasions with higher requirements on registration accuracy and real-time performance.

1. Introduction

In video stitching technology, image registration has a very important role, which is directly related to the successful stitching of images and video[1]. At present, the feature-based method has better robustness for image changes such as illumination and rotation, which is the current mainstream registration technology.

The feature-based registration method is generally divided into three steps: key feature point detection, key feature point area description and feature point matching. In terms of feature detection, the common feature extraction methods include the Difference of Gaussian (DoG) spot-detector, Harris[2] and FAST[3] corner point detection algorithm. The former is scale-invariant but computationally intensive, while the latter is known for its speed. The common feature point descriptions include classic floating-point feature description operators, such as SIFT[4] and SURF[5], which are characterized by the use of gradient orientation histogram for description and have strong robustness. However, the large amount of computation cannot meet the real-time requirements. Binary feature descriptors include BRIEF[6], ORB[7], BRISK[8], FREAK[9], etc. As they are only involved in the gray scale comparison between pixel points, binary feature description has high computational efficiency and small storage space cost.

In the aspect of feature precise matching, random sampling consistency (RANSAC) algorithm[10] is usually adopted to eliminate false matching, and geometric information is used to realize robust matching of key points. However, the RANSAC algorithm randomly selects matching point pairs without considering the quality of rough matching, so the overall precision matching speed is slow. And the error matching rate and complexity are high[12]. The Grid-based Motion Statistics (GMS)[11]
algorithm takes the smoothness of Motion as a statistic to carry out the local region matching, which has a very good performance in realizing the robust matching of key points in terms of speed and matching effect.

Based on the above analysis, in view of video stitching for image registration algorithm speed, real-time and more accurate demand, this paper proposes a combined image matching algorithm of BRISK algorithm and GMS algorithm. The method retains the advantages of BRISK algorithm in rapid extraction of feature points, as well as good rotation invariance, scale invariance and robustness to noise. Combined with the advantages of GMS precision matching, it significantly improves the image registration accuracy under various imaging conditions.

2. Improved BRISK+GMS Algorithm Design
The quality of GMS matching increases with the improvement of feature invariance or significance, furthermore, the original feature number also affects the quality. In addition, BRISK algorithm in the process of feature extraction and matching mainly aims at the local information of the corner points of the image while ignoring the corner points distribution information. For the shortcomings of BRISK algorithm and the characteristics of GMS matching, this paper proposes an improvement. Based on the method of dividing mesh images, the paper conducts mesh division for input images[12], which is divided into 4x4 grids. Then, Using AGAST algorithm to detect feature points in each grid, so that the feature points are evenly distributed. In addition, the maximum feature points of each grid are set as 1000, and the number of feature points extracted from the detection grid is set as an adaptive threshold to make the feature points distributed evenly as far as possible, as shown in Fig.1.

![Fig.1 Grid division](image)

The improved feature matching algorithm realizes the complementary advantages of detection and description as well as the effective combination of rapidity and robustness. The algorithm first constructs scale pyramid for the input image and meshes the image. Then, AGAST algorithm is used to extract feature points, and non-maximum suppression of extracted feature points is used to obtain stable extremum points. The local gradient information of feature points is calculated to construct binary descriptors, and the Brute Force algorithm is used for violent rough matching. Finally, the GMS algorithm is used for accurate matching.

3. Experimental Results and Analysis
The experimental test equipment is ASUS notebook (Intel corei5-3230CPU, main frequency 2.60GHz, 4.00Gb memory), 64-bit Windows10 operating system. This paper uses Opencv3.3.1 and Visual Studio 2015 to write C++ code for experiment. This paper uses Opencv3.3.1 and Visual Studio 2015 to write C++ code for experiment.
3.1. Feature point distribution and time degree

In order to better reflect the feature distribution of the two algorithms, this paper adopts the self-study room image for detection, and the number of detection feature points is set to 1000. The distribution of extracted feature points is shown in Fig.2.

![Mesh detection](image1) ![Meshless detection](image2)

Fig.2 Gridding feature point detection

It can be seen from the above figure that the distribution of feature points is more uniform than before and the stacking situation of feature points is also improved. Before and after the improvement of BIRSK algorithm, the extraction time of feature points is compared, as shown in table 1 below.

| number of feature points | BRISK time/ms | Proposed method time/ms |
|--------------------------|---------------|-------------------------|
| 500                      | 9.475         | 10.234                  |
| 800                      | 11.346        | 11.875                  |
| 1000                     | 12.239        | 12.305                  |
| 2000                     | 13.504        | 13.978                  |

According to the table, the improved BRISK algorithm takes a little longer time to extract feature points due to the addition of mesh division in the calculation. In the case of little time difference, the distribution of feature points is more uniform.

3.2. Image feature matching

After feature extraction and rough registration, the experimental analysis was carried out from four different aspects: scale invariance, illumination invariance, rotation invariance and affine invariance. The Mikolajczyk data set (as illustrated in Fig.3) was used to verify its robustness. The algorithm execution process is listed as follows. Firstly, it carries out BRISK feature point detection, then BF rough registration and fine registration. Finally, the paper compares the experimental results of our algorithms, BRISK+GMS and BRISK+RANSAC.

![Mikolajczyk data set](image3)

Fig.3 Mikolajczyk data set
In the experiment, the number of feature points was 1000. The algorithm in this paper was compared with BRISK+GMS, BRISK+RANSAC, ORB+RANSAC and SURF+RANSAC. The accuracy of feature point matching is counted, which reflects the robustness of the algorithm. The higher the accuracy, the better. The equation (1) is:

\[
\text{ratioMatches} = \frac{\text{correctMatches}}{\text{Matches}} \times 100
\]  

(1)

Matches represents a matching pair filtered by the nearest neighbor to next neighbor distance ratio, co-rect matches means the correct matching pair after filtering out RANSAC. The results are shown in Table 2.

| Algorithm       | Images     | Fig(a) | Fig(b) | Fig(c) | Fig(d) |
|-----------------|------------|--------|--------|--------|--------|
| SURF+RANSAC     |            | 92.62  | 94.68  | 95.13  | 95.71  |
| BRISK+RANSAC    |            | 86.94  | 75.04  | 93.51  | 92.97  |
| ORB+RANSAC      |            | 91.78  | 93.47  | 90.18  | 94.87  |
| BRISK+GMS       |            | 89.73  | 95.01  | 89.12  | 91.66  |
| Proposed Method |            | 92.45  | 95.23  | 89.76  | 95.78  |

As can be seen from the table 2, the feature point matching accuracy of the proposed algorithm and SURF+RANSAC algorithm is the highest and close, and it has strong robustness to affine and illumination changes. The improved combinatorial algorithm has improved matching accuracy compared with the previous algorithm, and the maximum improvement is 21.2% in illumination performance. The accuracy decreased only in rotation, but the difference was small. The experimental matching is shown in Fig.4, which is a comparison diagram of BRISK+RANSAC matching for the algorithm in this paper.
The comprehensive properties of 4 kinds of invariance in the same environment with 1000 characteristic points. Fig.4(a) shows the registration effect under the condition of proportional scaling. The logarithm (498 pairs) of the correct registration feature points of the algorithm in this paper is 1.57 times that of the RANSAC algorithm (317 pairs). Fig.4(b) shows the registration effect under the condition of illumination change, and the correct registration logarithm (382 pairs) of the algorithm in this paper is 1.11 times that of the RANSAC algorithm (343 pairs). Fig.4(c) shows the registration effect under the condition of view Angle transformation, and the correct registration logarithm (94 pairs) of the algorithm in this paper is 0.96 times that of the RANSAC algorithm (97 pairs). Fig.4(d) shows the registration effect under the condition of affine transformation. The correct registration logarithm (837 pairs) of this algorithm is 1.01 times that of RANSAC algorithm (770 pairs). Compared with RANSAC algorithm, the matching accuracy of the invariant features of proportional scale, illumination and affine in this algorithm is improved and the method has better registration effect. The reason is that there is no upper limit for the number of iterations when RANSAC algorithm calculates parameters from a data set containing a large number of outliers, and the algorithm is highly dependent on environmental changes, leading to a reduction in registration rate. Motion smoothness leads to more matching point pairs in the neighborhood of matched feature points, but when there are no matching point pairs in the neighborhood of matched feature points, these feature points need to be filtered out. Based on the number of matching pairs in the neighborhood of feature points, this algorithm has higher matching accuracy.

4. Conclusion
Based on the results and discussions presented above, the conclusions are obtained as below:

In this paper, an improved feature registration algorithm is proposed, which combines BRISK and GMS algorithms and increases the distribution uniformity of characteristic points in a fast manner. Compared with the traditional RANSAC algorithm, the overall matching accuracy and robustness are improved. It has great significance and application prospect in video stitching, UAV aerial photography and other fields that require high real-time and accuracy.
References

[1] Li N, Xu Y, Wang C. Quasi-homography warps in image stitching[J]. IEEE Transactions on Multimedia, 2018, 20(6): 1365-1375.

[2] Harris C, Stephens M. A combined corner and edge detector[C]. Alvey vision conference. 1988, 15(50): 10-5244.

[3] Rosten E, Drummond T. Machine learning for high-speed corner detection[C]. European conference on computer vision. Springer, Berlin, Heidelberg, 2006: 430-443.

[4] Lowe D G. Object recognition from local scale-invariant features[C]. Computer vision, 1999. The proceedings of the seventh IEEE international conference on. Ieee, 1999, 2: 1150-1157.

[5] Bay H, Tuytelaars T, Van Gool L. Surf: Speeded up robust features[C]. European conference on computer vision. Springer, Berlin, Heidelberg, 2006: 404-417.

[6] Calonder M, Lepetit V, Strecha C, et al. Brief: Binary robust independent elementary features[C]. European conference on computer vision. Springer, Berlin, Heidelberg, 2010: 778-792.

[7] Rublee E, Rabaud V, Konolige K, et al. ORB: An efficient alternative to SIFT or SURF[C]. Computer Vision (ICCV), 2011 IEEE international conference on. IEEE, 2011: 2564-2571.

[8] Leutenegger S, Chli M, Siegwart R Y. BRISK: Binary robust invariant scalable keypoints[C]. Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011: 2548-2555.

[9] Alahi A, Ortiz R, Vanderheym P. Freak: Fast retina keypoint[C]. 2012 IEEE Conference on Computer Vision and Pattern Recognition. Ieee, 2012: 510-517.

[10] Tran Q H, Chin T J, Carneiro G, et al. In defence of RANSAC for outlier rejection in deformable registration[C]. European Conference on Computer Vision. Springer, Berlin, Heidelberg, 2012: 274-287.

[11] Bian J W, Lin W Y, Matsushita Y, et al. Gms: Grid-based motion statistics for fast, ultra-robust feature correspondence[C]. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2017: 2828-2837.

[12] Chang Liang. Research and implementation of robust real-time panoramic video mosaic technology based on ORB-GMS [D]. Zhengzhou University, 2018(in Chinese).