An Improved UAV Aerial Image Mosaic Algorithm Based on GMS-RANSAC

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***Abstract*—The aerial image mosaic algorithm needs to ensure the real-time performance of the algorithm and the natural transition of image fusion. In order to improve the matching performance of the algorithm, an improved UAV aerial image registration algorithm based on GMS-RANSAC is proposed. The improved algorithm introduces the idea of partitioning, divides the image into meshes and then performs feature extraction on each mesh, uses the bidirectional BF algorithm and the GMS algorithm to perform accurate feature value matching, and finally uses the improved RANSAC algorithm for further feature purification to obtain a high-quality correct interior point set. This paper combines the characteristics of GMS algorithm to improve the RANSAC algorithm, reduce the number of iterations of the algorithm, and reduce the time complexity of the algorithm. The improved image registration algorithm has higher accuracy and shorter running time. After the registration is completed, the image is merged to obtain a mosaic image.**

Keywords-image mosaic; grid-based motion statistics; feature matching; RANSAC

I. Introduction

Aerial panoramic image stitching technology refers to the use of a specific technology to register the images, and then merge them into a wide field of view high-resolution image, so that the stitched image contains more useful information. The key to aerial image stitching is to improve the stitching speed and matching accuracy. Algorithms for extracting image features mainly include SIFT [1] algorithm, SURF [2] algorithm, ORB [3] algorithm and BRISK [4] algorithm. In the feature extraction phase, The ORB algorithm proposed by Rubble in 2011 is selected, which is a real-time feature extraction algorithm. This algorithm improves the FAST algorithm and introduces a scale pyramid. The sum of the feature points after extracting the feature values of the n original mosaic images of different scales is stored as the oFAST feature points of the original image. In addition, ORB also introduces the BRIEF algorithm for eigenvalue description. In this paper, the stitching algorithm first divides the image into a grid image, then uses Brute-Force [5] matching to extract the feature points, and then uses the two-way matching strategy [6] to filter the wrong matching feature pairs. Finally, the GMS [7] algorithm is used to verify whether all feature pairs match exactly. The GMS algorithm proposed by Bian in 2017 is a real-time, robust and stable algorithm for filtering error matching based on motion smoothing term constraint. It separates true feature matches from false feature match through neighborhood statistical function relationships. In 2018, Chen Fangjie and others optimized the GMS, optimized the nine-grid grid statistics to the five-grid grid statistics, and improved the calculation of the 7-times rotation matrix to the calculation of the 3-times rotation matrix [8], but the rotation invariance of the algorithm is reduced. In 2019, Zhu Chengde and others improved GMS-RANSAC, introduced the principle of distance consistency, and used the similarity between distances to eliminate outliers in the fitting set [9], but the algorithm's running time is increased. This paper proposes an improved GMS-RANSAC algorithm based on RANSAC [10], which greatly reduces the number of iterative, speeds up the function's convergence speed, and improves the accuracy of matching.

II. Improved GMS-RANSAC Algorithm

A. GMS Algorithm

The GMS algorithm is called grid-based motion statistics algorithm. It considers that the true matching's motion is smooth, while the incorrect matching's motion is not smooth. By judging the right and wrong of multiple small neighborhoods in the 3D neighborhood corresponding to the feature, the right and wrong analysis of the feature can be realized. The number of matching pairs near the correct matching features is sufficient, and there are almost no matching pairs near the false matching features. Based on these assumptions, the GMS algorithm divides the area where the features are into 9 small areas, and statistics the matching pairs of the 8 neighborhoods around the small area. The threshold τ is obtained based on statistical knowledge, and the threshold τ can be used to distinguish estimates quantities thereby removing false matching pairs. Fig. 1 shows the probability distribution of neighborhood scores for correct and false matches.

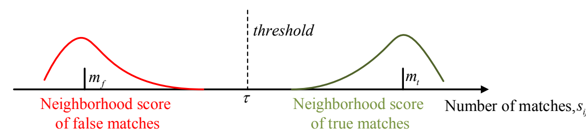


Figure 1. Probability distribution of neighborhood scores for correct and false matches.

B. RANSAC Algorithm

The RANSAC algorithm is called Random Sampling Consistency Algorithm. The specific steps of the algorithm are as follows:

1) Randomly select 4 pairs of points from the set of input sampling points as a hypothetical interior points, and solve the transformation model according to the transformation relationship between them.
2) Calculate the projection error threshold of all matching points in the model, and consider the points with errors within the threshold range as the "internal points" applicable to the model, calculate the number of matching feature pairs in the internal points set.
3) When the current number of interior points is greater than the number of interior points in the optimal set, the optimal set is updated and the number of iterations is increased by one.
4) If the number of iterations is equal to the preset number, the final internal point set is recorded as the current optimal set. Otherwise, set the interior point set as the new set of input samples and go to step 1.
5) Recalculate the mathematical model with the current optimal set to obtain the final mathematical model.

C. Improved GMS-RANSAC Algorithm Principle

The stability of RANSAC algorithm comes from the continuous iteration of the algorithm. Aiming at the traditional RANSAC problem and combining the characteristics of GMS, the RANSAC-GMS algorithm has been improved from the following three aspects:

1) The traditional RANSAC model treats all matching pairs indiscriminately, ignores the differences between feature points, and randomly selects the initial set, which will cause too many iterations. From Fig. 1 we can know the relationship between the number of neighborhood scores and the probability of correctly matching events. When the number of neighborhood scores is small, the probability of matching is small. Therefore, consider dividing the initial matching pair set according to the neighborhood support amount. The initial matching set is divided into two parts according to the value of the neighborhood support amount s_{ij} . The specific process is to record the threshold τ and the maximum value of the current neighborhood support amount $s_{\max}$, use $s_{middle} = (\tau + s_{\max})/2$ as the cutoff value for the initial estimated set, and use the feature pairs that meet $s_{ij} > s_{middle}$ as the data subset to improve the original sampling point selection. This increases the percentage of interior points in the set and records the matching pairs in the resulting set as $cell - pair\{i, j\}$.
2) In order to make the RANSAC input matching pair $cell - pair\{i, j\}$ more evenly dispersed, the subsets are further sorted and grouped according to the value of s_{ij} . The value of s_{ij} represents the number of matching pairs near the feature point. The number of matching pairs in the same neighborhood is the same, and there is a high probability that feature points with large s_{ij} values are close to each other. The method of dividing s_{ij} into 4 groups will make the input parameters no longer limited to a part of the image feature set, and each group will be denoted as $J_i (i = 1, 2, 3, 4)$.
3) In order to avoid unnecessary calculations before discarding the wrong model, a pair of feature values are randomly sampled from each group of $J_i (i = 1, 2, 3, 4)$ during sampling, and the four pairs of feature points are used to estimate the homography matrix model. Then, a random pair is selected from each group of $J_i (i = 1, 2, 3, 4)$, and 4 pairs of feature points are verified in advance. If any of the pair of feature points does not meet the requirements, the model is discarded without verifying the remaining points.

The flowchart of the improved GMS-RANSAC algorithm is shown in Fig. 2.

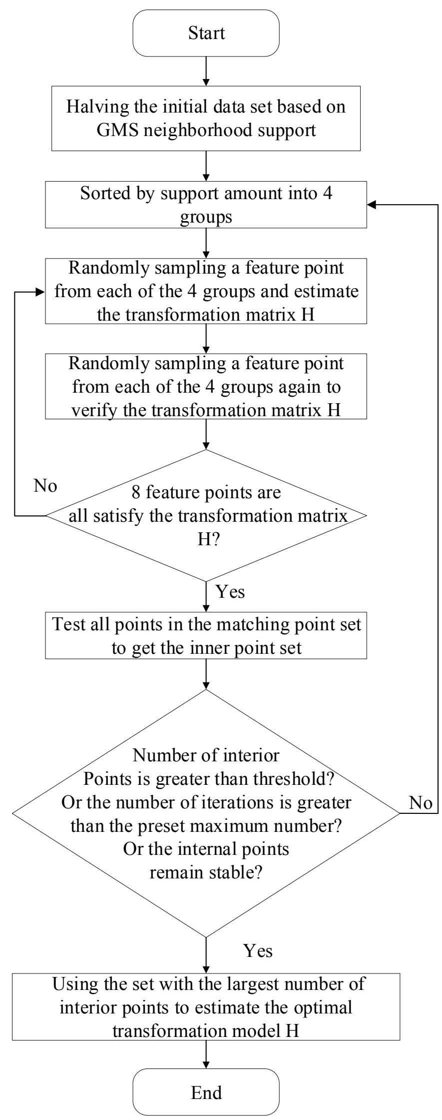


Figure 2. Improved GMS-RANSAC algorithm flowchart

III. IMPROVED IMAGE REGISTRATION PROCESS

Based on the improved RANSAC algorithm, a partitioning strategy is introduced and an improved image registration algorithm is proposed. The image matching algorithm flow based on the improved GMS-RANSAC proposed in this paper is as follows:

1) Dividing the original image into a grid image.
2) Using the ORB algorithm to extract the features and keeping the maximum point of the response value.
3) Using BF matching algorithm with two-way matching strategy.
4) Remove mismatched pairs using GMS algorithm.
5) Based on the improved RANSAC algorithm proposed in this paper, the mismatch points are eliminated and the transformation matrix H is calculated.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This experiment was completed on a PC equipped with Intel Core i7, 2.20GHz, memory 8.00GHz and operating system Windows10. The algorithm is implemented on Visual Studio 2015 software based on the OpenCV vision library. The program is written in C ++.

A. Image Matching Experiment Verification

As shown in Fig. 3, Fig. 4 and Fig. 5, the original experimental images includes three groups, the size of group A, group B and group Care 1000×800 , 1280×720 and 1000×750 respectively.

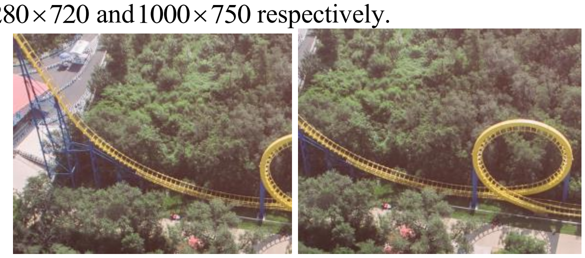


Figure 3. Original image of group A experiment.

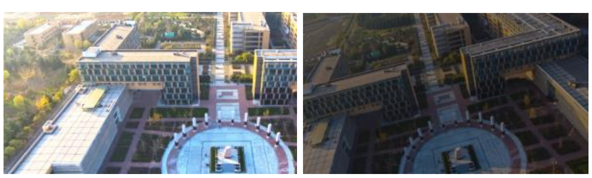
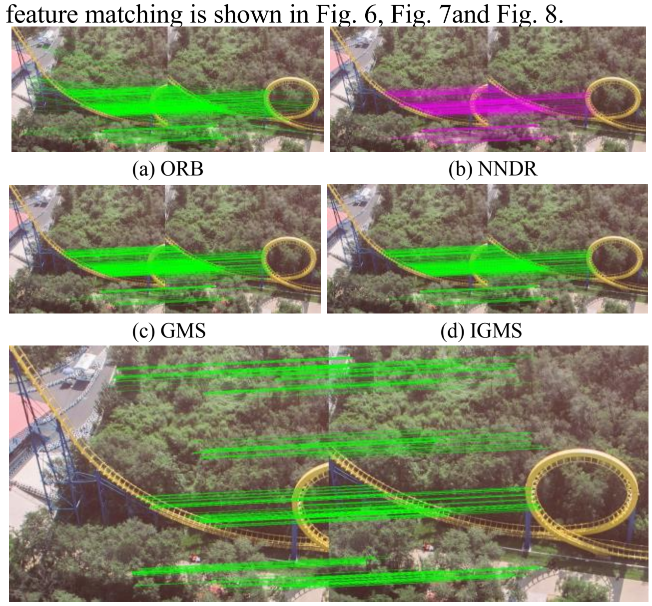


Figure 4. Original image of group B experiment

Figure 5. Original image of group C experiment

In order to verify the practicability of the registration algorithm, the aerial pictures of Group A, Group B and Group C were verified. Group B images have a large angular rotation transformation and lighting changes. Group C images have a large perspective difference. Compare the algorithm in this article with the ORB algorithm, NNDR algorithm, GMS algorithm, and IGMS, and perform quantitative calculations on the three matching evaluation indicators of running time, matching accuracy (CMR), and matching accuracy (RMSE) to evaluate the performance of the algorithm. Among them, the ORB algorithm uses a two-way matching strategy for feature filtering and the RANSAC for conversion model fitting. The NNDR algorithm uses the ORB + KNN + LSH algorithm for feature registration. The ratio threshold is 0.45. IGMS [6] combines GMS with bilateral matching, and combines coarse and fine matching, which increases the accuracy of matching. The effect of feature matching is shown in Fig. 6, Fig. 7and Fig. 8.

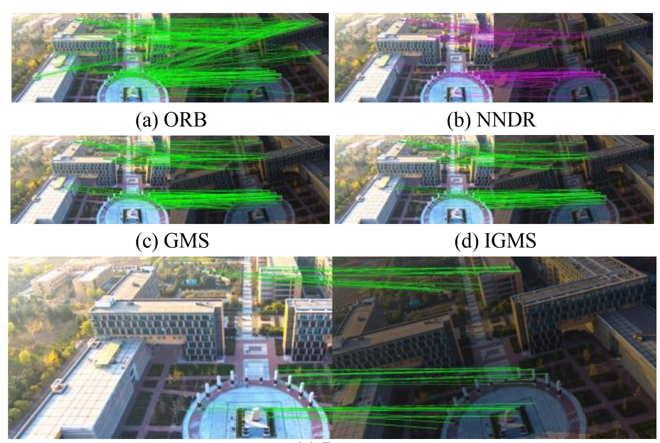


(a) ORB (b) NNDR

(c) GMS (d) IGMS

(e) Paper

Figure 6. Comparison chart of feature matching effect of group A.



(a) ORB (b) NNDR

(c) GMS (d) IGMS

(e) Paper

Figure 7. Comparison chart of feature matching effect of group B

(a) ORB (b) NNDR

(c) GMS

(d) IGMS

(e) Paper

Figure 8. Comparison chart of feature matching effect of group C

A. Evaluation index

Matching algorithm evaluation indicators include three indicators: execution time, CMR and $RMSE$.

1) Matching time: The shorter the running time of the algorithm, the more efficiency it's execution will be.
2) Matching Correction Rate: N_c is the number of interior points, and N' is the number of feature points for accurate registration. The higher the CMR, the higher the accuracy of the algorithm.

$$C_{MR} = \frac{N_C}{N'} \tag{1}$$

3) RMSE: RMSE refers to the root mean square error of the algorithm. $f(x_i', y_i')$ is the coordinate of the registered image, (x_i, y_i) is the coordinate of the reference image. The smaller the RMSE, the higher the registration accuracy.

$$E_{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N'} \left\| (x_i, y_i) - f(x_i', y_i') \right\|^2} \tag{2}$$

The evaluation results of the image matching effect are shown in Table I, Table II and Table III.

TABLE I. GROUP A IMAGE MATCHING EFFECT EVALUATION

ALGORITHM	Evaluation Index				
	N'	N_c	CMR	$RMSE$	$Time/ms$
ORB	631	492	77.97%	1.00773	13.3618
NNDR	276	255	92.39%	0.80886	24.9612
GMS	536	485	90.49%	1.08428	13.1631
IGMS	480	445	92.71%	1.01836	13.4156
Paper	295	287	97.29%	0.88644	10.5906

TABLE II. GROUP B IMAGE MATCHING EFFECT EVALUATION

ALGORITHM	Evaluation Index				
	N'	N_c	CMR	$RMSE$	$Time/ms$
ORB	601	295	49.08%	1.32596	13.8959
NNDR	134	121	90.30%	0.96969	22.3993
GMS	473	348	73.57%	1.32125	12.6458
IGMS	330	278	84.24%	1.31203	13.3645
Paper	82	79	96.34%	0.93218	9.8434

TABLE III. GROUP C IMAGE MATCHING EFFECT EVALUATION

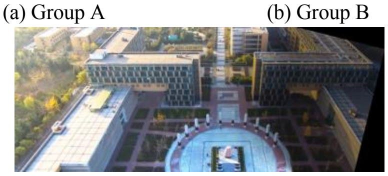
ALGORITHM	Evaluation Index				
	N'	N_c	CMR	$RMSE$	$Time/ms$
ORB	367	581	63.17%	1.07624	13.8624
NNDR	55	53	96.36%	0.88873	24.1471
GMS	374	342	91.44%	1.1829	12.7937
IGMS	295	277	93.90%	1.06862	13.381
Paper	99	97	97.97%	0.86656	9.9785

From the above experimental results, it can be seen that the ORB algorithm has the lowest matching accuracy rate, and the matched feature image contains more obvious mismatched point pairs. The algorithm in this paper has the highest matching rate, which can effectively remove the wrong matching pairs. When the group B graph contains large rotation and brightness differences, the performance improvement is more significant than other algorithms. Up to 96.34% registration rate of the algorithm in this paper. As far as RMSE is concerned, both NNDR and the algorithm in this paper can achieve the best registration accuracy, but the algorithm in this paper takes less than 1/2 of the time in NNDR. As an improved registration algorithm based on GMS algorithm, the algorithm in this paper has achieved a significant performance improvement compared to the Improved GMS algorithm. It can ensure that the accuracy rate is improved by at least 4 percentage points. The registration experiments for images with changes in rotation, lighting, and perspective show that the improved RANSAC algorithm makes the registration effective value error smaller, the iteration speed is faster, and the matching time can be saved by more than 20%, which is suitable for aerial image stitching processing.

The aerial image mosaic based on the improved algorithm is shown in Fig. 9:

(a) Group A

(b) Group B



(c) Group C

Figure 9. The result of image mosaic

V. CONCLUSION

In this paper, experiments are performed on three sets of aerial images to verify the performance improvement of the improved registration algorithm based on GMS-RANSAC. Experimental results show that the running time of the algorithm is shorter than that of ORB, BRISK, NNDR, GMS and IGMS and the matching accuracy of the algorithm is significantly improved. Therefore, this algorithm can meet the requirements of aerial stitching algorithm and has practical value.

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