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A Feature-Based Aerial Image Mapping Algorithm for UAV

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ABSTRACT

At present, the image stitching algorithm based on classical surf features is facing new challenges in the processing of UAV images. In order to improve the efficiency of aerial image stitching, a fast feature extraction and matching algorithm is proposed. At the feature extraction link, a local differential binary algorithm is proposed to describe the feature, which reduces the feature dimension compared with SURF descriptor while not reducing the feature differentiation. A local sensitive hash search algorithm is proposed to replace the kd tree search algorithm in feature matching, which improves the efficiency of nearest neighbor feature matching. The test results show that compared with the nearest neighbor matching algorithm based on SURF descriptor and kd tree search algorithm, the feature matching efficiency of this algorithm is obviously improved, and the matching accuracy is also improved. It is more suitable for feature-based UAV aerial image rapid mapping.

Keywords: *UAV, Image Stitching, Feature Extraction, Feature Matching.*

1. INTRODUCTION

In recent years, UAV low altitude remote sensing technology has been applied to many fields, such as disaster prevention and mitigation, military reconnaissance, land survey, environmental monitoring and so on [1]. Because of the limited field of vision of single image and the large overlap area between multiple images, UAV images generally need to complete the panoramic splicing of image sequences before they can be applied to practice. In order to obtain the whole information of the target area quickly, it is necessary to realize high efficiency image stitching [2]. Fast feature extraction and matching between images is the key to improve the efficiency of UAV image stitching.

In the field of computer vision, image matching technology has made new progress in the past ten years because of the local feature points with high robustness and high distinction. Among them, the fast robust feature extraction algorithm [3] (SURF) uses integral image, which greatly improves the efficiency of feature extraction, but SURF feature descriptor still uses floating-point numerical description, which has high memory cost and high complexity of feature matching. Then the local differential binary (LDB) descriptor [4] uses feature neighborhood gray and gradient information to generate binary feature description, which has the characteristics of strong distinction of floating-point descriptor and high matching efficiency of binary description. It is very suitable for UAV image stitching. This paper improves the traditional UAV image stitching algorithm by combining the advantages of fast feature location of SURF feature extraction algorithm and high matching efficiency LDB. Firstly, SURF feature extraction algorithm is used to locate features, then LDB is used to describe features, then local sensitive hash search algorithm [5] is used for approximate nearest neighbor rough matching, and finally random sample consensus (RANSAC) algorithm is used to obtain fine matching results.

2. IMAGE FEATURE EXTRACTION

SURF uses Hessian matrix to detect feature points. Hessian matrix of pixel I(x,y) is:

$$\mathrm{H}(\mathrm{I}(\mathrm{x},\mathrm{y})) = \begin{bmatrix} I_{xx} & I_{XY} \\ I_{XY} & I_{yy} \end{bmatrix}$$

Feature point location requires scale invariance. Therefore, before calculating the Hessian matrix, the Gaussian kernel is used to convolute the original image, and the scale s is added to form the detection formula under different scales:

$$\mathrm{H}(\mathrm{I}(\mathrm{x},\mathrm{y}),\sigma) = \begin{bmatrix} L_{xx}(x,y;\sigma) & L_{xy}(x,y;\sigma) \\ L_{xy}(x,y;\sigma) & L_{yy}(x,y;\sigma) \end{bmatrix}$$

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where,

$$L_{xx}(x,y;\sigma) = \frac{\partial\ (G(x,y,\sigma)\otimes x I(x,y))}{\partial x^2},$$

$$L_{xy}(x,y;\sigma) = \frac{\partial\ (G(x,y,\sigma)\otimes I(x,y))}{\partial x \partial y}$$

The Coarse localization of the extreme points of the sift feature extraction algorithm is done on the Difference of Gauss (DOG) pyramid. Different from SIFT features, SURF first calculates the determinant of Hessian matrix of each point, and then builds a pyramid through box filter to complete the rough location of feature points. The approximate formula of determinant of Hessian matrix is:

$$\det(\mathrm{H}) \approx D_{xx}D_{yy} - (0.9D_{xy})^2$$

3. LDB FEATURE DESCRIPTION ALGORITHM

The distinction and matching efficiency of feature descriptors are the key indexes to measure the quality of descriptors. LDB is highly distinguishable due to the combination of feature neighborhood strength information and gradient information. Furthermore, LDB has high matching efficiency due to the Hamming distance matching using binary description. LDB first divides the neighborhood of feature points into n*n grids of the same size, and calculates the average intensity information of each grid and the gradient information of x, y direction. The average intensity information can be quickly calculated by integral images, representing the overall statistical characteristics of the grid. Then the gradient information in the x and y directions is obtained by calculation, which represents the intensity change characteristics inside the grid. The calculation formula is:

$$I_{avg}(i) = \frac{1}{m}\sum_{x,y\in o(i)} I(x,y)$$

$$d_x(i) = G_x(i) \qquad d_y(i) = G_y(i)$$

Where, m is the number of pixels in each grid. By calculating the mean gray value and the gradient in the x and y directions, each grid is represented by the three characteristic information in formula (4), and then the binary description of each grid is determined by comparison and testing between grids. The test function is:

$$T(F(i),F(j)) = \begin{cases} 1, F(i) - F(j) > 0, i \neq j \\ 0, \quad \text{Other} \end{cases}$$

In order to improve the distinguishability and robustness of the descriptor, LDB adopts a multi-grid strategy. Each feature point neighborhood is divided into 2×2, 3×3, 4×4, 5×5 grids to generate a series of Binary descriptor. Small grids are highly discriminative, but they will be too sensitive to small changes and reduce robustness; large grids are strong, but are not sensitive to detail changes, which will reduce the discrimination. By combining the information of multiple large and small grids, the goal of both is achieved. At the same time, in order to realize the rotation invariance of features, LDB uses the gray-scale centroid method to determine the main direction. After determining the main direction, rotate the feature point neighborhood to the main direction, then divide the grid, and use the rotated integral image to calculate the gray average and gradient:

$$\begin{cases} \varepsilon_{acc}(t) = \varepsilon_{acc}(t-1) + \varepsilon_j, \\ b_t = \operatorname{argmin} \varepsilon_{acc}(t) \\ \varepsilon_{acc}(-1) = 0 \\ \varepsilon_j = \sum_{i=1}^{T} d_i[Y_i \neq h_j(X_i)] \end{cases}$$

4. IMAGE FEATURE MATCHING

4.1. Rough descriptor matching

The core of rough descriptor matching algorithm is to design data structure and matching strategy. The purpose of designing data structure is to establish index structure to reduce the time complexity of search. The binary descriptor search mainly includes linear search and local sensitive hash (LSH) algorithms. Linear search is the distance between the traversal calculation and all the descriptors to be matched. The local sensitive hash algorithm is to map all the descriptors to be matched through the hash function, and the feature points with high correlation are assigned to the same hash set, while the feature points with large differences are assigned to different sets. The sample descriptor is mapped to a hash set by a hash function, and then linear search matches with all the to-matching descriptors in the set. Matching strategy is a measure of matching credibility. In this paper, the approximate nearest neighbor matching algorithm is used to find the nearest and next neighboring matching points of the sample point. If the ratio of the nearest matching point distance to the second neighboring distance

is less than the set threshold, it indicates that the nearest neighbor matching point has a high matching confidence. This point is a matching point if accepted, otherwise the match is not accepted. In order to enhance the matching credibility, the matching can be further screened by reverse matching.

4.2 Feature point precision matching

The feature point matching pair is established preliminarily by rough matching, which needs to be further refined to eliminate the matching difference in order to establish the transformation model between images. For the fine matching process, RANSAC algorithm is used in this paper. Based on the affine transformation model of 8 parameters[7], 4 matching pairs are randomly drawn from the coarse matching pair to establish 8 equations to solve 8 parameters, and then the other matching points are projected by the solved transformation model. The residual is:

$$e = \|x_1(x, y; p) - x_2(x, y)\|$$

Among them, (x,y; p)is the coordinate of x(x,y) after the projection transformation, (x,y) is the coordinate of the point matching x(x,y). Compare the residual with the set residual threshold . If , it accepts the matching pair as an inner matching pair, otherwise it is an outer matching pair, so as to obtain the inner matching pair set under the model. Repeat the above steps S times (S>100), and select the interior point set with the largest number of interior point matching pairs as the final matching pair, and its corresponding 8-parameter affine transformation model is the initialization motion model.

5. TEST PROCESS AND EVALUATION CRITERIA

5.1. Test process

Test process is as shown in Figure 1.

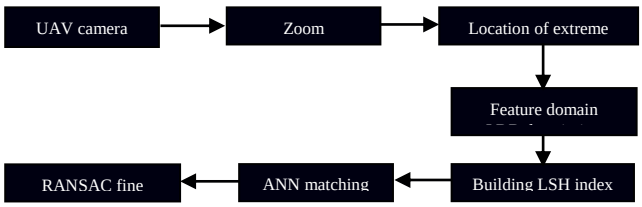

Figure 1 Algorithm Test Flow Chart

5.2. Evaluation criteria for testing algorithms

Index 1: Matching logarithm and distribution characteristics. For the same two images, the correct matching logarithm directly reflects the discrimination and stability of feature descriptors. Under the same nearest neighbor threshold condition, the more correct matching logarithm of descriptors, the better the discrimination and stability. At the same time, the more uniform the distribution of the correct matching pairs, the better the matching performance.

Index 2: Time consuming of algorithm. Feature extraction time represents the efficiency of feature extraction algorithm, and matching time represents the efficiency of matching algorithm.

Index 3: stitching RMS error. In the UAV image stitching, the stitching error is obtained by calculating the mean value of pixel position set error after all matching points are projected. The error formula of a single matching point is as follows:.

$$\mathrm{RMS}_{per} = \frac{1}{2}\left(\|H_1x_1 - x_2\| + \|H_2x_2 - x_1\|\right)$$

The root mean square error of all matching points is:

$$\mathrm{RMS}_{tot} = \sqrt{\frac{1}{2N}\sum_{i=1}^{N}\{\|H_1x_1 - x_2\| + \|H_2x_2 - x_1\|\}}$$

Where N is the matching logarithm, and, and are the projection matrices of two matching points and , respectively.

The traditional algorithm is the nearest neighbor matching based on SURF feature and kd tree search. The traditional method uses 64-dimensional floating-point SURF descriptor in feature description, and binary 32-bit LDB descriptor is used in this paper. In coarse matching, the same nearest neighbor matching threshold is set by using multi-thread parallel technology (nearest neighbor matching point distance / sub-nearest neighbor matching point distance). The traditional method uses improved kd search tree and KNN matching, this article uses LSH (Local Sensitive Hash) search algorithm and ANN matching. In the fine matching link, the RANSAC estimation algorithm is used to first match two adjacent images, then match multiple images, combine multiple image matching results, perform multiple image stitching, and analyze matching errors from the stitching results.

6. CONCLUSIONS

In order to improve the stitching efficiency of UAV aerial images, this paper proposes a new idea of UAV image feature extraction and matching. SURF feature extraction algorithm is used in feature location, local differential binary algorithm is used in feature description, and approximate nearest neighbor matching is carried out by local sensitive hash search algorithm. Finally, random sampling consistency algorithm is used to match accurately. Compared with the feature extraction and matching in the traditional UAV image stitching algorithm, the algorithm in this paper has greatly improved the feature extraction speed and matching speed, and the stability and discrimination of features have also been improved.

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