Research on Scalable Real-Time Image Mosaic Technology Based on Improved SURF

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Abstract. Due to the presence of light and angle distortion, the image mosaic results is not ideal, which makes it difficult to identify subsequent ground object. To tackle this problem, this paper proposes an image mosaic technology based on the improved SURF (Speed-Up Robust Features) algorithm. After extracting image feature points, using Hessian matrix trace algorithm for image matching, and then the RANSAC algorithm purified the image feature point pairs. Finally, the image was stitched using a weighted smoothing algorithm. Experiments verify the effectiveness of this algorithm for image stitching with deviated scale and angle of view. At the same time, the algorithm is applied to the field of scalable real-time images stitching, and has achieved good results.

1. Introduction
With the advent of the era of big data, traditional surveying and mapping cannot satisfy people's requirements. The surveying and mapping industry is also increasingly oriented toward information and intelligence. The mobile mapping system has been widely used due to its fast measurement speed and can save a lot of manpower and material resources, gradually replacing the traditional measurement. After the acquisition of a measurable real scene image, we can get the of the required data plaque or traffic sign according to the needs, (Han, Mei, and B. G. Yang. 2013) but the single picture may not complete the information of the ground objects, and the information will be more complete after the mosaic of the scalable real scene image, which can improve the extraction precision of the ground information.

Lowe D (2004) proposed the SIFT algorithm, which makes the image maintain good robustness in translation, rotation and other image transformation, but the complexity is relatively high. Herbert Bay T Tuytelaars and LV Gool (2006) proposed the SURF algorithm on the basis of SIFT algorithm. On the basis of ensuring the rotation invariance and scale invariance of the image, the speed of image processing was speeded up, and the blurred character of the image was greatly improved. It was a stable and fast feature extraction algorithm.

2. SURF Feature Extraction and Matching
This paper uses SURF algorithm to extract image feature points. In order to ensure the invariance of the feature points, the general feature point extraction process usually adopts the image pyramid method, but in this case, the image will be blurred. In the SURF algorithm, instead of using an image...
pyramid, box filtering is used instead of Gaussian filtering (Wang et al. 2015) to avoid downsampling of the image, thereby greatly reducing the complexity of the algorithm and improving the speed of the algorithm. At the same time, the Haar wavelet transform is used. The stability of the splicing has also been improved. The algorithm is mainly divided into five parts:

2.1. Integrate the Image
The use of the integral image is one of the keys to the speed improvement of the SURF algorithm.

\[ S(x, y) = \sum_{i=0}^{i<x} \sum_{j=0}^{j<y} I(x, y) \]  

In the formula, \( I(x, y) \) is the gray value of the image at \( (x, y) \), and \( S(x, y) \) is the area of the integral image.

2.2. Find the Local Extreme Points
The SURF algorithm uses box filtering instead of Gaussian filtering to calculate Gaussian values for all points in the image. The point with the largest value is the feature point. The Gaussian function is as follows:

\[ H(X, \sigma) = \begin{bmatrix} D_{xx}(X, \sigma) & D_{xy}(X, \sigma) \\ D_{yx}(X, \sigma) & D_{yy}(X, \sigma) \end{bmatrix} \]  

In the formula, \( X \) is the coordinates of the image space point, and \( D_{xx}(x, \sigma) \), \( D_{yy}(x, \sigma) \), \( D_{xy}(x, \sigma) \), \( D_{yx}(x, \sigma) \) is the second-order difference operation of the Gaussian function in the corresponding direction, respectively.

2.3. Determination of Main Direction of Feature Points
A main direction is set up in the feature point area so that it can be rotated without deformation. The SURF algorithm first determines a 60 degree sector area with a feature point as the center, calculates the Haar-wavelet response value on the transverse ordinate, and carries out Gauss weighting, sums the wavelet response values of all the feature points, and obtains the general direction of the region. The general direction of the area is the direction of the arrow line in the figure below. At the same time, the total direction of all areas is calculated in steps of 30 degrees. The position with the largest total direction is the main direction of the feature points. The specific process is shown in the figure below.

![Figure 1. Determining the main direction of feature points](image-url)
2.4. Establishment of Feature Point Descriptors

First, a rectangular area is built at the center of the feature point and rotated to the main direction to get the rotation without deformation. Then the region is divided into $4 \times 4$ sub regions of 5 pixels $\times$ 5 pixels, and the sum of the Haar wavelet response values and the sum of the absolute values of each sampling point in the direction of X and y are calculated respectively. The four vectors are used as the eigenvectors of the subregion, and the whole region can obtain the 64 dimensional eigenvectors. It may be expressed as:

$$v = (\sum dx + \sum dy + \sum|dx| + \sum|dy|)$$  \hspace{1cm} (3)

2.5. Feature Point Match

2.5.1. Distance Matching Method. The matching of feature points is usually a feature point in an image as the standard point. The feature point in the other image is the target, and the distance D between the two feature vectors is calculated respectively. When the distance is less than a given threshold, the two points are identified as the same point.

2.5.2. Improved Matching Algorithm Based on Hessian Matrix Trace. The positive and negative of the Hessian matrix trace can divide the image feature points into two categories: the first is that the image is brighter than the background image, and the second is that the image is darker than the background image. In image matching, the feature points are matched according to the two types, the search range is reduced, the efficiency of the algorithm is improved, and only the feature points of the same type are compared, and the matching accuracy is also improved. Through experimental verification, taking a set of data as an example, as shown in the following table, it can be clearly seen that the algorithm speed has been greatly improved.

| Algorithm                     | The Number of Matching Points | The Matching Time |
|-------------------------------|------------------------------|------------------|
| Distance Matching Method      | 184                          | 0.178s           |
| Hessian Matrix Trace Algorithm| 318                          | 0.228s           |

3. Image Registration and Mosaic

Image mosaic is a mosaic of two overlapped images into one image, and the overlap is the key to stitching. Image registration is the transformation relation model of another image based on one image. The common models include affine transformation, polynomial transformation, perspective transformation and so on. The measurable real image generally has the characteristics of translation, rotation and scaling, so the transformation model with 8 parameters is chosen.

$$\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} h_0 & h_1 & h_2 \\ h_3 & h_4 & h_5 \\ h_6 & h_7 & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \\ 1 \end{bmatrix}$$  \hspace{1cm} (4)

In the formula, ($x_0$, $y_0,1$) ($x_1$, $y_1,1$) are the feature points coordinates of the standard image and the image to be registered respectively, ($h_1, h_2, h_3, h_4, h_5, h_6, h_7,1$) are projection transformation parameters. The process of finding the transformation model is to find the parameters of the projection transformation. There are 8 parameters in the formula, so at least 4 sets of feature points are needed to solve the characteristic transformation equations. In order to get more accurate transformation parameters, the RANSAC algorithm is used to purify the feature points and eliminate the larger error data.
3.1. **RANSAC Algorithm**

The RANSAC algorithm, the random sampling consensus algorithm, is a typical feature point-based algorithm used in image registration (Olofsson, Kenneth, Holmgren, and Olsson, 2014: 4323-4344). It has high robustness and good effect on noise and feature points. Eliminate the error match in the experiment. The experimental data are measured by MMS, and the two images are matched without the RANSAC algorithm and with the RANSAC algorithm. The results are shown as the following table.

| Algorithm                | Number of Matching Points before Fault Tolerance | Number of Matching Points after Fault Tolerance | Matching Correctness |
|--------------------------|--------------------------------------------------|------------------------------------------------|----------------------|
| No RANSAC algorithm      | 108                                              | 80                                              | 74.1%                |
| Adding RANSAC algorithm  | 158                                              | 134                                             | 84.8%                |

From the data in the table, the correct rate of matching is greatly improved, and the number of correct matching points obtained from the same image is increased from 80 to 134, and the number is obviously improved, and it can be clearly seen from the contrast picture in the following group.

**Figure 2.** The image before eliminating the error point

**Figure 3.** The image after eliminating the error point
3.2. Image Fusion

After determining the transformation matrix of the image, the overlapped region and its corresponding relationship can be obtained, and image splicing and fusion can be carried out. It usually needs to smooth the stitching problem caused by illumination and other reasons (Milad, Malekzadeh and Seyedarabi, 2016:23-31) in this paper, the weighted average method is used to process the information of the overlapping region. This algorithm does not simply average the gray value of the image, but performs the weighted operation to obtain the pixel value of the final overlapping region.

\[ f'(x, y) = \begin{cases} 
  f_1(x, y) & (x, y) \in f_1(x, y) \\
  k_1 f_1(x, y) + k_2 f_2(x, y) & (x, y) \in f_1(x, y) \cap f_2(x, y) \\
  f_2(x, y) & (x, y) \in f_2(x, y) 
\end{cases} \]  

(5)

In the formula, \( k_1, k_2 \) are values of luminance information corresponding to the overlapping area in the two images, where \( k_1, k_2 \) sum to 1, and \( k_1, k_2 \) are determined by gradual transition from the first map to second images.

3.3. Image Mosaicking Results

The experimental data in this paper is the measurable real scene image collected by MMS, and the Root Mean Square Error (RMES) between the transformed feature point coordinates and the reference coordinates is used as the accuracy evaluation criterion. The experimental data is 20 groups, including various lighting conditions, parallax changes of the image, of which there are 3 groups of data due to poor exposure conditions, and it is difficult to extract image feature information, so that the final mosaic results are not ideal. The rest of the results are all better. Taking a set of data as an example, the experimental results were statistically calculated from aspects such as accuracy, and compared with the SIFT algorithm, as shown in the following table:

| Algorithm                | Mosaicking Correctness | RMSE | Registration |
|--------------------------|------------------------|------|--------------|
| SIFT                     | 74%                    | 0.54 | 4.28s        |
| **The Presented Algorithm** | **85%**               | **0.61** | **2.13s**    |

It can be seen from the table that the accuracy of the algorithm is improved, and the registration time is increased by 49.7%, and the registration speed is obviously improved. The following is the panorama of four images. These four images are the images collected by the mobile mapping vehicle in the corner part, and there is a certain angle deformation. However, from the result, the stitching results are better, and the stitching of the measurable real scene can be completed automatically.
4. Summary
In this paper, a modified SURF algorithm based on feature points is proposed on the basis of SURF and SIFT algorithm to extract feature points, and it is applied to the field of measurable real image mosaic. The algorithm adopts the improved matching algorithm based on Hessian matrix trace after extracting the feature points of the image, which improves the speed and accuracy of the algorithm. Then, the error matching point information can be eliminated by the RANSAC method, and the accuracy of image mosaic is improved. Experiments show that the algorithm proposed in this paper has better effect on image size and binocular parallax, and has great application value.

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