A SAR Image Fast Stitching Algorithm Based on Machine Learning

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Abstract. Aiming at the splicing problem of Synthetic Aperture Radar (SAR) image, an improved algorithm for SURF is proposed to realize the fast splicing of SAR image. The SURF feature descriptor has scale invariance and rotation invariance, and has strong robustness to light intensity and affine transmission variation. The improved algorithm uses machine learning methods to build a binary classifier that identifies the key feature points in the SURF extracted feature points and eliminates the key feature points. In addition, the relief-F algorithm is used to reduce the dimensionality of the improved SURF descriptor to complete image registration. In the image fusion stage, a weighted fusion algorithm with a threshold is used to achieve seamless image mosaic. Experimental results show that the improved algorithm has strong real-time performance and robustness, and improves the efficiency of image registration. It can accurately mosaic multiple SAR images.

Keywords: SAR image · Fast image stitching · Machine learning
SURF · Image fusion

1 Introduction

The image splicing technology spatially aligns and aligns the image sequences with overlapping regions, and finally splices into a technique with a wide viewing angle panoramic image [1].

In recent years, it has been widely used in military, machine vision, virtual reality, medicine and other fields. Image mosaic technology as a hot issue of image processing has attracted many scholars at home and abroad to study it. Image splicing mainly includes image registration and image fusion. Among them, image registration is the core part of splicing.

Image fusion is another important step in image splicing. If the SAR images are directly and simply combined, there is a clear seam in the overlapped area of the stitched SAR images. In order to solve the above problems, this paper will study the fast splicing of SAR images based on machine learning, and propose a machine learning method to improve the SURF algorithm, identify key feature points, and

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eliminate the key feature points. In addition, the Relief-F algorithm [2] is used to simplify the improved SURF descriptor reduction and use it to train feature point classifiers. Finally, an improved weighted fusion algorithm [3] is used to fuse the images, which effectively solves the problems of blurring and ghosting and achieves seamless stitching of images.

2 The Basic Principle of SURF Algorithm

The SURF algorithm is an image splicing algorithm based on feature information proposed by Bay et al. [4]. It is proposed that the SIFT algorithm by Lowe [5] has large data volume high time complexity, and poor timeliness. SURF inherits the SIFT algorithm's advantages of strong anti-interference ability, high discrimination, and several times improvement in calculation speed [4].

The SURF algorithm is divided into two parts: feature point selection and feature point description.

(1) Feature point extraction: The SURF algorithm selects Hessian matrix-based detectors. For a point (x, y) on the input image I, the Hessian matrix on the scale space σ is expressed as shown in Eq. (1). Where, L_{xx} represents the second-order partial derivative of the Gaussian function to x and the convolution of the function image at the pixel point; likewise, L_{yy} represents the second-order partial derivative of the Gaussian function to y and the convolution of the function image at the pixel point.

$$\boldsymbol{H}(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{1}$$

Then calculate the discriminant of the Hessian matrix, and determine whether the point is an extremum point according to whether the discriminant value is positive or negative. Because the discriminant formula of Hessian matrix is relatively high in computational complexity, the Hessian value of the candidate feature point and its surrounding points is calculated by using box filter approximation instead of the second-order Gaussian filter, and the approximate discriminant value $\det(\boldsymbol{H}_{approx})$ is obtained, such as formula (2) as shown:

$$\det(\boldsymbol{H}_{approx}) = \boldsymbol{D}_{xx}\boldsymbol{D}_{yy} - (\omega \boldsymbol{D}_{xy})^2 \tag{2}$$

When the discriminant of the Hessian matrix has a local maximum, it is determined that the current point is a brighter or darker point than other points in the surrounding neighborhood, thereby locating the position of the key point. In a discrete digital image, the first derivative is the difference in gray levels of adjacent pixels. $\boldsymbol{D}_{xx}$,$\boldsymbol{D}_{yy}$ is the second derivative of the second derivative of its first derivative.

(2) Feature point description: The SURF algorithm feature point descriptor first constructs a window area centered on the feature point, divides this window into 4 × 4 sub-window areas, takes 5 × 5 sampling points in each sub-window, and calculates them separately. The Haar wavelet response of each sub-window region is horizontal and vertical, and the resulting wavelet coefficients are denoted as d_x and d_y. The wavelet coefficients of each subarea are weighted by a Gaussian function to obtain $\sum d_x$, $\sum d_y$, $\sum |d_x|$, $\sum |d_y|$, which constitute the four dimensions of the descriptor. Each 4 × 4 sub-window has a four-dimensional vector, so a total of 64-dimensional vectors are obtained, which is the descriptor of the SURF algorithm.

SURF algorithm provides a similar replacement for SIFT, which greatly reduces the processing time of feature point detection and matching. However, to further improve the SURF-based image registration efficiency, it is necessary to study the influence of different feature points on the matching speed.

3 Improvement of SURF Algorithm Based on Machine Learning

The main idea of extracting feature points based on machine learning [6] is to classify the feature points extracted by the SURF algorithm into two categories: (1) key feature points, which is key areas of image feature recognition, in the two images to be stitched, these the correspondence between feature points is more important; (2) Non-critical feature points have little influence on feature point matching and can be excluded from the matching process. Before machine learning, it is necessary to remove redundant information from SURF extracted feature points and establish a binary classifier that can distinguish these two types of feature points. A set of feature points K is extracted in the image I using the SURF algorithm. Each of the feature points $k_i \in \boldsymbol{K}$ can be described by a set of features F. The feature F is a feature image piece $\mathrm{Q}_{\omega}^{F}(k_i)$ having width ω centered on k_i extracted from. In addition, a classifier $\mathrm{Y}\left(Q_{\omega}^{F}\right) \in L$, $\mathrm{L} = \{-1, 1\}$ gives each feature point a label according to the feature patch, and when $\mathrm{Y}\left(Q_{\omega}^{F}\right) = 1$, k_i is considered as a key feature. Point; This feature point is discarded when $\mathrm{Y}\left(Q_{\omega}^{F}\right) = -1$. Then, feature point matching is performed using the improved and simplified SURF descriptors, and the feature point classifier is trained with it to complete the image registration.

3.1 Remove Redundant Information

When the training data set is established, if the feature points extracted from the image are close in spatial position, the feature image piece may contain redundant information, thereby reducing the matching efficiency. In order to avoid redundancy, it is necessary to add a distance constraint between the extracted feature points. A set of feature points extracted from image $\boldsymbol{I}$ is represented by K_I. For each pair of feature points $k_1 k_2 \in \boldsymbol{K}_I$ of the same mark (all marked as 1 or −1), ensure that the distance between them is larger than the critical value d, that is $dist(k_1, k_2) > d$, $dist$ is a distance function, Euclidean distance is used here, d is set to 5 pixels.

3.2 Balanced Processing of Training Data Sets

The feature points extracted by the above method may lead to imbalance of the training data set, that is, in the data set, the number of non-key feature points far exceeds the number of key feature points, and an accurate classification result cannot be obtained based on the classification of unbalanced data sets.

To solve this problem, a uniform training data set is created by sampling the original data set, and a classifier is trained using no substitute random sampling [7]. This method creates a data set smaller than the original data set. No replacement sampling ensures that training is a real-world example and will make the classifier more accurate.

3.3 Balanced Processing of Training Data Sets

Before entering the learning phase, the characteristics of the training examples need to be described. The quality of the feature has a direct impact on the performance of the classifier. The SURF descriptor has 64 dimensions and is generated by calculating the response of the Harr wavelet in the 4×4 sub-area centered on the feature point. In this paper, SURF descriptors are used to describe feature points, and the following four attributes are added: (1) Intensity of feature points, positive values represent black points, and negative values represent white points; (2) Gaussian models of extracted feature points; (3) Used to Find the traces of the Gaussian matrix of the feature points; (4) The direction of the feature points. Then 68-dimensional feature vectors are obtained.

In order to further simplify calculations and remove redundancy, the above-mentioned 68-dimensional SURF descriptor reduction is reduced to 48-dimension using Relief-F algorithm [2]. The simplified SURF descriptor is used to describe the key feature points in the classification. The basic idea of the Relief-F algorithm is to randomly select instances from the training data set, calculate their neighborhood, adjust the feature weight vector to distinguish the instance from its different categories of neighboring elements, and use it to train the feature point classifier.

4 SAR Image Fusion

In the process of image collection, due to different shooting fields and errors in image registration, if the images are directly stitched together, there will be obvious mis-spellings, so a reasonable fusion strategy should be adopted. Although the traditional weighted average method can achieve a smooth transition at the image mosaic, the image overlap region may appear blurred and distorted [8].

The algorithm uses a weighted smoothing process with a threshold [9]. A threshold value N is introduced in the algorithm. The difference between the pixel value before the smoothing and the weighted average value is calculated for the stitched image and compared with the threshold value $\boldsymbol{N}$. After taking the value. This method divides the image overlap area into three parts and fuses the three parts separately.

Let the overlapped parts of the two images to be stitched be I_1 and I_2, and the values of the corresponding pixel points are respectively im_1 and im_2, and the weighted average value is expressed as $Mean = d_1 \times im_1 + d_2 \times im_2 (0 \leq d_1 \leq 1, d_1 + d_2 = 1)$, im_3 represents the smoothed pixel value. The three sections divided from left to right in the overlapping area are denoted as L_1, L_2, L_3.

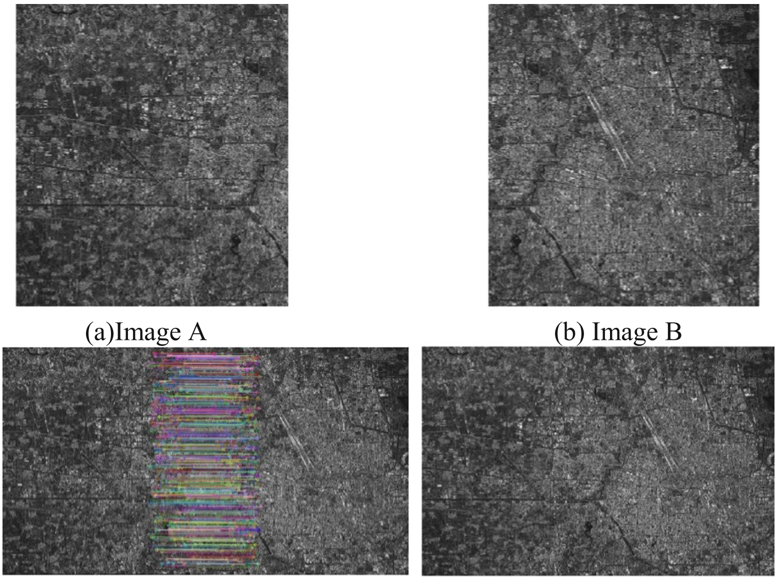
In L_1: when $|im_1 - Mean| < N, im_3 = Mean; otherwise, im_3 = im_1$.
In L_2: when $|max(im_1, im_2) - Mean| < N, im_3 = Mean; otherwise, im_3 = max(im_1, im_2)$.
In L_3: when $|im_2 - Mean| < N, im_3 = Mean; otherwise, im_3 = im_2$.

This smoothing method makes full use of the characteristics of SAR images in different regions. From the perspective of fusion effects, the resulting images are error-free stitching seams with good results and high speed.

5 Experimental Results and Analysis

The experimental platform personal computer was configured as an Intel Core i5-2450M 2.5GHZ with 4 GB of memory and the operating system was 32-bit Windows 7. The algorithm was based on OpenCV 2.4.8, programmed in C ++ and tested in Visual Studio 2010.

The experimental data is the SAR image captured by the first orbit of the satellite of No. 1 satellite of the environmental satellite. This experiment uses the Zhengzhou SAR image as the test image to show the mosaic effect of the proposed mosaic algorithm, and the algorithm is further analyzed by comparing the running time of the algorithm (Fig. 1 and Table 1).



(a)Image A (b) Image B

(c) Key feature point maps and fusion result graphs of two images

Fig. 1. Image mosaic experiment result chart

Table 1. The performance of the first set of images SURF and the improved algorithm.

Algorithm	Feature point detection time/s	Logarithm of feature points	Registration time/s
SURF	3.76	12472	3.58
The improved algorithm	4.83	6210	1.92

6 Conclusion

This paper presents a fast learning algorithm for SAR image mosaic based on machine learning. Using machine learning method, a binary classifier can be constructed to distinguish two types of feature points. Key feature points and non-critical feature points are identified to improve the original SURF. In addition, Relief-F algorithm is used to reduce the dimensionality of the improved SURF descriptors, and it is used to train feature point classifiers to complete SAR image feature point registration. In SAR image fusion, a threshold-based weighted fusion algorithm is used to achieve seamless image mosaic. The experimental results show that the proposed algorithm has good splicing effect, fast calculation speed, good robustness, and satisfies the practical application requirements of SAR image mosaic.

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