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An Improved FAST+SURF Fast Matching Algorithm

Aomei Li^a, Wanli Jiang^{a,*}, Weihua Yuan^a, Dehui Dai^a, Siyu Zhang^a, Zhe Wei^a

^a Army Officer Academy of PLA, Hefei, Anhui, China

* Corresponding authors: 454227653@qq.com

Abstract

Target matching is an important part of image registration and mosaic. Based on a lot of real-time application requirements, the requirement of fast matching is also put forward. The classical matching algorithm has the problems of large computation and slow speed. Aiming at the problems existing in the classical algorithm, a fast matching algorithm based on the combination of FAST feature points and SURF descriptor is proposed. Experiments show that compared to the classic SIFT matching algorithm, the method is very good to achieve the goal of fast matching, in addition to the algorithm also improves the accuracy of the matching.

Keywords: Fast matching, SIFT, FAST feature points, SURF descriptor

1. Introduction

Image matching is a key technology in the field of image processing. Many scholars have done a lot of work in this area, the focus of research focused on matching accuracy and real-time, etc.

Image matching is often divided into matching based on gray correlation and image feature¹. The matching method based on gray correlation is a method which is used to search the matching image. The computation of this method is large, and it is very sensitive to image scaling and rotation². Based on the characteristics of the image matching method using feature information of images. For example, Harris algorithm, respectively, in the template image and the image to be matched to extract Harris corner point information. Then, the correlation coefficient is used to search the most relevant position in the image to be matched, but this method still has no scale and rotation-invariant³. In 2004, the SIFT algorithm proposed by Lowe⁴, by introducing Laplace of Gaussian operators realize the scale and rotation invariant feature points, to achieve automatic image matching, but also correspondingly increase the computing workload, can not meet the requirements of real-time. In 2006, Bay⁵ proposed the SURF algorithm based on SIFT algorithm, the main direction of the calculation method using Haar wavelet feature points, can greatly

improve the speed of image matching, while feature extraction and descriptor structure and other aspects of the improvement, but still can not meet the requirements of real-time. For the texture information rich images, Rosten proposed a more real-time FAST feature points⁶, FAST feature points extracted only with the image of the gray value, and therefore does not have the scale rotation invariant. A representative feature algorithm is analyzed⁷ and the SURF algorithm is proved to be the best performance algorithm.

Aiming at the problem of real-time speed of image matching, feature points are extracted by feature point detection algorithm in real-time detection and texture information of FAST algorithm, and the FAST feature points are improved by using the Laplace operator weighted^{8,9}, and describe the characteristics of the SURF descriptor, use the BBF¹⁰ to match, so that it remains the rotation invariant of the SURF algorithm, and has a certain affine invariant, to achieve real-time matching requirements.

2. Fast matching algorithm design of improved FAST+SURF

In order to realize the fast matching of target extraction, using the Laplace operator on weighted FAST feature points to further optimize the feature point extraction will be strengthened, to give strong robustness SURF descriptors, in order to achieve the goal of fast matching.

2.1. Enhanced FAST feature point selection

FAST is a corner detection method, the most obvious advantage of this method is its computational efficiency. In order to improve the selection of FAST feature points, the original Gauss Laplace, and then calculate the FAST feature points, feature selection and object edge has such close relation.

$$\Delta[G_{\sigma}(x, y) * f(x, y)] = [\Delta G_{\sigma}(x, y)] * f(x, y) = LoG * f(x, y) \quad (1)$$

$$I_1 = I_0 + \alpha * LoG * f(x, y) \quad (2)$$

Formula (2) is the weighted coefficient of the Laplace operator, by controlling this factor to enhance the detection of the feature points. In addition, the method of FAST feature point detection is to determine a feature point by comparing a pixel difference or a sum of pixel sums on a circle centered on the pixel, and if there are consecutive N pixels larger than the threshold value of the pixel value or more. If the center pixel value is smaller than the threshold, the pixel is regarded as the feature point.

$$\begin{cases} lx > lp + th \\ lx < lp - th \end{cases} \quad (3)$$

Another approach to fast extraction of FAST feature points is to detect non-feature points, which can greatly improve the detection efficiency. For example, the detection of 16 points (radius is 3 pixels circle), N take 8, then if the center point is non-feature point, then 1,5,9,13 four points do not meet the above formula, the center point is non-feature point.

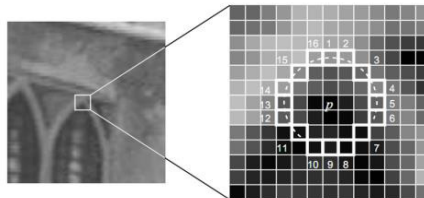


Fig. 1. FAST feature point detection

2.2. SURF descriptor construct

SURF algorithm is divided into two steps: feature point extraction and descriptor construction. The SURF descriptor construction comprises the construction of the main direction of the feature point and the surrounding image information. The core of SURF feature point detection is Hessian matrix^{11,12}. Firstly, the Gaussian filtering is applied to the image, and then the Hessian matrix is obtained by Gaussian difference method. The characteristic points are obtained by comparing the characteristics of the matrix. In addition, the direction of the feature points to extract the key points as the center 8X8 window, in the 4X4 box on the calculation of eight directions of the gradient histogram can get direction information.

- Feature point direction

First, each direction of interest is given a directional characteristic, so that it has rotation invariance. Then Haar wavelet template is used to process the image with the center of interest as the center and S as the radius. The wavelet response of X and Y directions is obtained by Haar wavelet template. Haar wavelet template as shown below:

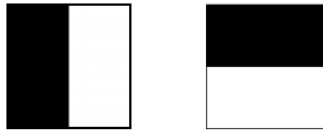


Fig. 2. Haar wavelet template.

In Figure 2, the left side is the response to calculate the X direction, the right side is to calculate the Y direction response. After the Haar wavelet template processing, we can get the corresponding X , Y direction response of the point of interest in this circular field. And then use the circle angle of 60 degrees fan-shaped rotation around the point of interest to calculate the fan at the current angle, it includes the Haar wavelet response and, because each point we calculate the Haar wavelet response is the X , Y direction response, Therefore, the sum of the Haar wavelet responses included in this sector is a vector, and the vector obtained by rotating the sector for one week is recorded. The angle corresponding to the vector length is denoted as the direction of the point of interest. The process diagram is as follows:

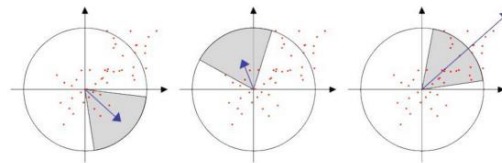


Fig. 3. The process diagram for determining the main direction.

- Constructor descriptor

A square neighborhood centered on the point of interest is determined, and the direction of the identified point of interest is taken as the Y direction of the square neighborhood. In practice, rotating the image will reduce the computational efficiency, so we directly use Haar wavelet to process the image, and then interpolate to get the dx and dy direction of the wavelet point of interest (The process is to divide the square region into 4×4 sub-regions, and then use Haar wavelet filter for processing). Then for each sub-region dx , dy , $|dx|$, $|dy|$ are summed, you can get it the corresponding 4-dimensional vector, thus obtaining a 64-dimensional vector of a point of interest, the vector is the point of interest. The schematic diagram is as follows:

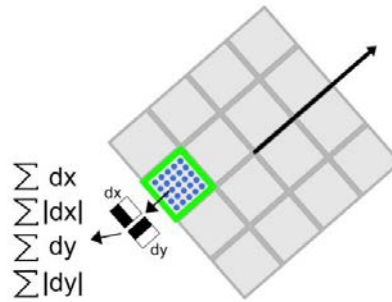


Fig. 4. A schematic diagram of the construction descriptor process.

2.3. Improved FAST + SURF Algorithm Flow

SURF algorithm in the selection of feature points to be constructed Hessian matrix, and the adjacent scale Gaussian image subtraction to obtain differential DOG(difference of Gaussian)¹³ image steps. These steps have a large amount of computation, consumption of memory and other issues. FAST feature points instead of SURF feature point detection, can be formed with FAST feature points SURF descriptor image matching algorithm.

Specific steps are as follows:

- (1) Processing the reference image and the image to be matched respectively using the Gauss pyramid;
- (2) The reference image and the image to be matched are respectively processed by the Laplace operator;
- (3) Using FAST algorithm to extract feature points;
- (4) Determining the main direction of the FAST feature points on the two images;
- (5) Constructing the SURF descriptor of the FAST feature point;
- (6) Using BBF to match ;
- (7) Select the minimum matching distance of 3 times the best selection of matching point threshold for screening;
- (8) According to the shape of the template to further filter to improve the matching accuracy.

3. Experiment and analysis

In order to verify the effectiveness of the matching algorithm in this paper, experiments were carried out from three aspects: matching correctness, extracting feature points and matching efficiency. The experimental results are compared with SIFT algorithm, SURF algorithm, FAST + SURF algorithm. By comparing the two sets of experimental data, it can be seen that the algorithm has the advantage of high matching efficiency under the condition of guaranteeing the correct rate. The selected image to be matched is a book photo, and a real-time image acquired by a Lenovo T420S notebook camera is tested. The experimental hardware environment is Intel Core i5 2.50 GHz CPU, 4GB RAM; the software environment is Microsoft Visual Studio 2010.0 and OpenCV 2.4.8.

Table 1. Experiment 1.

Number of pyramids	SIFT		SURF		FAST		Improved FAST	
	Number of feature points	Time (ms)	Number of feature points	Time (ms)	Number of feature points	Time (ms)	Number of feature points	Time (ms)
0	621	855	211	185	554	58	1728	180
1	214	295	55	67	171	37	254	48
2	67	96	6	29	56	25	92	36
3	14	52	×	×	13	19	26	28

Experiments were performed in the laboratory, in the background, in the presence of experimental devices, and so on. The table 1 lists the number of feature points extracted by the four algorithms and the time required to extract

the feature points(0,1,2 in the table indicates the number of layers under the pyramid).FAST and improved FAST is the fastest.Followed by the SURF algorithm, and finally the SIFT algorithm.In addition, the number of feature points extracted by FAST is twice that of FAST in the same situation.In this paper, the improved FAST feature points are used to optimize the feature point extraction, and it is more real-time than SIFT and SURF.

Table 2.Experiment 2.

Algorithm	Number of matching points	Mismatched points are removed	Matching time/ms	No match time-consuming/ms
Traditional SIFT	621	149	1871.6	1708.9
Traditional SURF	211	55	444.6	568.2
Traditional FAST+SURF	554	118	433.7	416.7
SIFT	14	7	102.8	70
SURF	6	5	70.5	50.4
FAST+SURF	56	37	90.9	258.5
This paper algorithm	26	13	68.2	39.4

Table 2 shows the experimental results. The time in the table is the mean value of the time taken for 10 consecutive treatments.The FAST algorithm is a combination of the FAST feature and the SURF descriptor. Because of the combination of the FAST and SURF descriptors, the feature points are less and the feature points are unstable.So this article FAST + SURF used two pyramid down sampling.In addition, the robustness of SIFT algorithm is very strong, and after three pyramid sampling, still have a good matching effect, but the matching speed of the algorithm is still the slowest;SURF algorithm in Table 1 can be seen in the pyramid when the three layers can not extract the corresponding feature points, it is still using the 2 pyramid.In addition SURF algorithm running time faster than FAST, because SURF extracted feature points less(And there are more errors).The FAST method extracts more feature points, but the SURF algorithm is more robust than the FAST, so it still has a good matching effect;The speed of this paper algorithm is the fastest, and has a good matching effect.In Table 2, "traditional" means that it is not under-pyramid-down-sampled, and the non-target indicates that the improved algorithm is as real as possible.In addition, from the time-consuming non-matching time point of view this algorithm also has good real-time.SURF algorithm followed,because the feature points extracted by the SURF algorithm are less, it takes less time.FAST + SURF algorithm consumes more, because the features of the image extraction more, resulting in time-consuming, and finally the traditional algorithm.

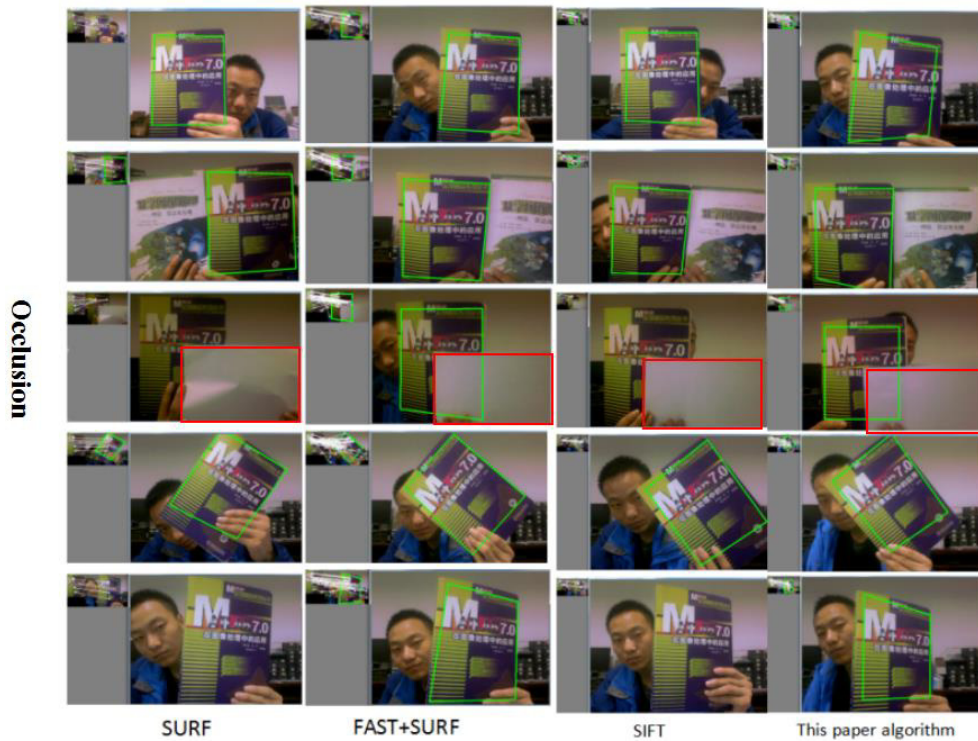


Fig 5

Figure 5 is the image in the rotation, occlusion and confusion for the purpose of the experiment carried out. SURF algorithm and SIFT algorithm in the experiment can not be achieved when the occlusion of the match. This is because after a number of down sampling, these two methods to extract the feature points less. In addition, SURF algorithm in the presence of affine transformation can not achieve matching, this is related to the less feature points extracted by the SURF algorithm. FAST + SURF algorithm and this paper algorithm in these types of cases can be achieved match. This paper algorithm has the correct matching in the case, and has a very fast real-time. Figure 6. The matching results of the proposed algorithm under rotation, affine and occlusion conditions.



Fig 6

4. Conclusions

In this paper, an improved FAST feature point combined with SURF descriptor matching algorithm is proposed, which realizes the real-time matching of target. The experimental results are compared with those of SIFT algorithm, SURF algorithm and FAST + SURF algorithm. The improved FAST feature point is 50% higher than the FAST feature point in the same situation, and the extracted feature point is more excellent. The proposed algorithm has two orders of magnitude higher matching speed than traditional SIFT algorithm, and compared with the traditional SURF algorithm increased by an order of magnitude. Because this algorithm is improved by the Laplace operator to extract the feature points, this method has good matching effect and real-time property for objects with rich feature points.

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