Image Matching Algorithm based on Feature-point and DAISY Descriptor

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Abstract—**Image matching technology is the research foundation of many computer vision problems, and the matching algorithm based on partial features of images is a research focus in this field. In order to overcome the unstable performance of classic SURF algorithm on rotation invariance, an image matching algorithm combined with SURF feature-point and DAISY descriptor is proposed. Based on the feature point detection of SURF algorithm, a principal direction distribution method for DAISY descriptor is put forward, and a novel DAISY descriptor is obtained according to the rotation of the principal direction. In this paper, our proposed algorithm, on the basis of slight increase in running time, improves the image matching capability of the classic SURF algorithm on image rotation. The experimental results show that our proposed algorithm has stronger robustness in a variety of complex cases, such as image blurring, illumination variation, JPEG compression ratio variation, field of view variation, etc. Our proposed algorithm can not only keep the merits of the original SURF algorithm on computation speed, but also improve the matching accuracy on rotation invariance.**

Index Terms—**Image Matching; DAISY Descriptor; SURF Feature-Point; Rotational Invariance**

I. INTRODUCTION

Image matching technology is the research foundation of computer vision problems, such as image registration, object recognition and tracking, 3D reconstruction, etc. It also is widely used in such fields as remote sensing, medicine, artificial intelligence, etc. [1-5]. The essence of image matching is to determine the geometrical transformation relationship between the reference image and the matched image. Image matching algorithms can be divided into two categories: gray-based matching and feature-based matching. The gray-based matching algorithm is intuitive and takes full advantage of the gray scale information, while the disadvantage of the algorithm is that it is sensitive to noise and illumination variation and its calculation stability is not high. The feature-based matching algorithm is currently still research focus, where the most important steps are the image feature extraction and matching. In addition, the key of exacting and matching is to obtain some feature-points with the higher correct matching rate.

Local feature descriptor in image is a core step of the image feature extraction and matching process. Over the past decade, lots of scholars have done tons of researches on the local feature descriptor, where local invariant feature descriptor is developed most quickly in computer application field [6 7]. It first calculates the local feature descriptors for each local feature point, and then determines whether these feature-points can be matched, according to the different descriptors. SIFT has proved to be the most robust local invariant feature descriptor in object recognition and matching. In the existing descriptor, SIFT algorithm proposed by Lowe, has average optimal performance [8], but the computational of SIFT descriptor is very complexity, its operation is also is very time-consuming. Therefore, on the basis of the SIFT algorithm, the SURF algorithm proposed by Bay et al. has been superior to the traditional SIFT algorithm [9]. It is worth noting that, although the SURF algorithm improves on speed for 3-4 times faster than SIFT algorithm, some scholars discover SURF algorithm is poor performance on a rotational invariance when they are compared with the performance of the local feature operator [10]. Therefore, if these local feature descriptors are introduced to overcome this deficiency, it will have a very significant influence on the accuracy of the extracted feature-points and related follow-up work.

DAISY descriptor [11] proposed by the Engin Tola et al. is a local invariant feature descriptor which is used in dense stereo matching. In addition, its matching performance and operation speed are relatively good. Although DAISY descriptor does not have rotational invariance, the calculation of descriptor is very convenient because it has a central-symmetrical structure, which makes it is very easy to obtain rotation invariance. Stefan Leutenegger et al., who combined the DAISY descriptors with BRIEF descriptor [12], have proposed novel BRISK descriptor [13], which has the advantage of rapid convergence and good numerical stability with minimum occupancy of computer storage. Based on the combination of features of the human retina with DAISY descriptor, Alexandre Alahi et al. have proposed a novel FREAK descriptor with density distribution of the human retina [14], where the descriptor is a binary descriptor and also has the advantage of rapid convergence. Yin Guo et al. have proposed an improved DAISY descriptor algorithm [15]. Firstly, the principal direction is assigned to DAISY descriptor, and then PCA is adopted to decline the dimensionality of the descriptor. Finally, combined with Harris corner detector, this will make the matching more quickly. The algorithm has a good result in image matching test, but the disadvantage is a large number of operations in data processing, where the computation

doi:10.4304/jmm.9.6.829-834

time is close to SIFT algorithm. LIU Tian-liang, et al. have proposed a dense stereo matching method based on DAISY descriptor and improved weight kernel [16]. On the basis of these features, such as simple and low complication, the method has a higher matching accuracy. In a word, DAISY descriptor has a greater advantage than the previous descriptors in the process of image matching, which is more suitable for the image matching.

In order to overcome the unstable performance of classic SURF algorithm on rotation invariance, a image matching algorithm combined with SURF feature-points and DAISY descriptor is proposed. Based on feature point detection of the SURF algorithm, a principal direction distribution method for DAISY descriptors is put forward, and a novel DAISY descriptor is obtained according to the rotation of the principal direction. In this paper, our proposed algorithm, on the basis of slight increase in operation cost, improves the image matching capability of the classic SURF algorithm on image rotation. Our proposed algorithm can not only keep the merits of the original SURF algorithm in computation speed, but also improve the matching accuracy on rotation invariance.

II. SURF IMAGE MATCHING ALGORITHM BASED ON DAISY DESCRIPTOR

SURF is a robust local feature detector, and can be used in computer vision tasks like object recognition or 3D reconstruction. It is partly inspired by the SIFT descriptor. Therefore, similarly to SIFT algorithm, the feature point detection of SURF algorithm still is based on scale space theory. In contrast, SIFT algorithm adopts Difference of Gaussians (DoG) to extract feature-points, while SURF uses an integer approximation as the determinant of Hessian blob detector, which can be computed extremely quickly with an integral image. As for a pixel point with scale σ in image, its Hessian matrix can be denoted as

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

where L is the convolution of the image with the second derivative of the Gaussian. In order to speed up the computation in SIFT algorithm, the Box filter is used to approximately replace the Gaussian filter. In addition, SIFT algorithm simplifies the calculation of determinant, which no longer computes the weight of each region separately, thus the determinant can be obtain by the following Equation:

$$\det(H)=\frac{\partial^2 f}{\partial^2 x^2}\frac{\partial^2 f}{\partial^2 y^2}-\left(\frac{\partial^2 f}{\partial^2 x\partial y}\right) \tag{2}$$

where $\partial f/\partial x$ is the convolution result of the image with the template.

Due to the use of integral image and the Box filter, the size of the filter is only changed in the scale-space constructed by the SURF algorithm, while the image size is constant. In contrast, the filtered image is continued to be filtered in SIFT filtering algorithm. SURF algorithm scale space is divided into several orders, and each order comprises a number of layers. Generally speaking, the number of orders is set to four, each order has four layer scale images, where the bottom image of each order is original image. The size of the filter in each layer is 2^{ij}, where i is the order of the image and j is the layer of the image. For instance, the filter sizes of the first-order image are 9,15,21,27, respectively. The different of the size is only 6 in the first order, while the different in other order is 12, 24, and 48. The corresponding scale of each image is 2^s, where s is the side length of the filter in the current image. After the approximation of the Hessian matrix determinant is obtained in each layer, the non-maximum suppression is performed in neighborhood. Therefore, the point can be selected as a feature point when only the value of the current point is bigger (smaller) than the value of 26 points around the pixel. Because the Box filter is used to approximately replace the Gaussian filter and integral image is used to accelerate the integration process, it is possible to improve the speed of operation in the case of high accuracy.

In order to make the SURF descriptor has rotation invariant, we first need to determine the principal direction of the feature points. Given the scale size of the feature point is s_{xy}, the Haar wavelet responses of the x and y directions in the integral image are computed in the region with a radius around the feature-point, where the size of Haar wavelet is *h*. In order to be more in line with the objective actual situation, these responses are given to Gaussian weighting coefficient, which the closer the location is to the feature-point, the stronger the weight, so the larger the corresponding contribution is. In other words, the farther the location is to the feature-point, the smaller the corresponding contribution is. Then, the quantization step size is set as 60 °to calculate the sum of the response values of the Haar wavelet for each region. Finally, the maximum distribution response is selected as principal direction of descriptor.

After the principal direction is selected, the axis is centered on the feature point, and then is rotated to the principal direction. Along with the principal direction, some rectangular areas around the feature points are selected to calculate the descriptor. The area is divided into sub-regions with different size, and then the Haar wavelet response in each sub-area is calculated. The Haar wavelet response values of the horizontal direction and the vertical direction relatives to principal direction, which are set to H_x, H_y, respectively. It is not necessary to accumulate the response values in each direction, but H_{xy} is calculated so as to enhance the robustness of the algorithm. The interest area is weighted with a Gaussian Kernel at the interest point to give some robustness for deformations and translations. As for each subarea of image, the descriptor of an interest point is the 16 vectors. Finally, the descriptor is normalized so as to achieve variations invariance, which can be represented as a linear scale of the descriptor.

DAISY descriptor is a local image descriptor, which is very efficient to compute densely. Its core idea is to convolve the different directional diagram of original image with Gaussian filtering function with different size. Due to the separability of Gaussian filtering function, the method has high efficiency, which is often used in the process of stereo vision dense matching.

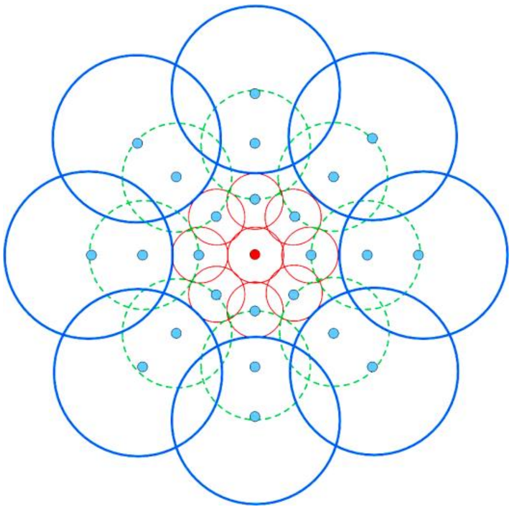

Figure 1. DAISY descriptor construction

DAISY descriptor is similar to daisy, which is constructed by some central-symmetrical circles, as shown in Figure 1. In general, around the red center point, a concentric structure of three layers with different radius is constructed, where there are 8 sampling points in each layer. These points are denoted with blue solid dots, and distribute on 45 degree intervals distribution. Since the sampling points per layer have the same Gauss value scale, the Gauss scale value gradually increases from the center to the outside. This structure makes the DAISY descriptor has the better robustness for image affine and illumination variation [7]. In addition, unlike the SIFT algorithm and SURF algorithm that use rectangular neighborhood, DAISY descriptor uses the circular neighborhood, which is because the circular neighborhood has the better positioning feature than rectangular neighborhood. And most of all, the DAISY descriptor can easily achieve the purpose of rotation, so the DAISY descriptor is adopted to describe feature points. The basic flow of DAISY descriptor is constructed as follows:

Firstly, the eight direction gradient of a pixel on the original image can be represented as $L_{xy} * \mathrm{D}_{xy}$, where D_{xy} denotes the gradient direction. Then, the sampling point Gauss convolution value of each layer in concentric circles can be obtained by multiple Gauss convolutions. The Gauss scale values can be represented by Equation (3), which is the convolution of the Gauss kernel with the gradient image. As for each pixel, a vector with a length of 8 can be obtained to represent local gradient direction histogram, which is written as H_{xy}. Therefore, we can get the DAISY descriptor Equation, which is denoted as follows:

$$\bar{x} = \frac{\partial^2 H^{-1}}{\partial^2 x} \frac{\partial H}{\partial x} \tag{3}$$

where, l denotes structural layers, ∂H denotes the direction of each layer, x denotes the coordinate of the sampling points on concentric circles centered around the pixel. Therefore, $\mathrm{H}is(x, y)$ is local gradient direction histogram of the sampling point. The structure in Figure 1 has the better average performance on power consumption, so this paper also uses a similar structure to verify the algorithm and the obtained feature vector also contains 8 dimensions. Euclidean distance of two vectors is used to measure the similarity between descriptors.

Although original DAISY descriptor does not have rotational invariance, the calculation of descriptor is very convenient because it has a central-symmetrical structure, which makes it very easy to obtain rotation invariance [18]. Since Gauss filter gradient direction of original image is indispensable when computing DAISY descriptor, the group of gradient direction histogram are similar to the direction histogram of the SIFT algorithm. So the principal direction distribution method proposed in the literature [18] is adopted to directly calculate the gradient histogram of the second layer of the center point and the maximum value direction is took as the principal direction of descriptor. The algorithm is equivalent to selecting direction with 45 degrees sampling, which has fast computation speed, but will reduce the matching accuracy. A novel principal direction distribution algorithm based on DAISY descriptor is proposed, which will improve the correct matching rate.

We select sample points on the outside circle, where the angle of rotation is denoted as the number of sampling points. According to the obtained gradient orientation histogram on the maximum scale direction, these points are accumulated so as to get the following Equations:

$$\mathrm{Dx}(\mathrm{X}_i) = \mathrm{I}(\mathrm{X}_i^1) - \mathrm{I}(\mathrm{X}_i^5) \tag{4}$$

$$\mathrm{Dy}(\mathrm{X}_i) = \mathrm{I}(\mathrm{X}_i^3) - \mathrm{I}(\mathrm{X}_i^7) \tag{5}$$

This is a decision-function to select the principal direction. After the feature point is calculated for a lap, 72 values will be obtained, and then the direction of the biggest value is selected as the principal direction of DAISY descriptor. The goal of choice is to use the gradient information of each direction as much as possible, which has higher precision than the principal orientation distribution algorithm of SURF algorithm and the algorithm of literature [18]. After obtaining the DAISY principal direction, the DAISY template will be rotated and aligned along the principal direction. In addition, sampling points of template on the 24 concentric circles will be recomputed according to the rotation angle, and the new gradient histogram is re-obtained by the direction map filtering with the different Gauss scale filter, so as to obtain new DAISY descriptor with rotation invariant.

The specific flowchart of image processing is described as follows:

1) Input the original image, compute its integral image, use Equation (1) to compute Hessian matrix of the integral image and non maximum suppression to detect feature point.

2) Eight direction gradient of the original image are computed, and then are filtered by Gauss filter.

3) The Equation (3) is adopted to distribute principal orientation for each feature point, and then the Equation (2) is used to get the feature descriptor after the DAISY descriptor is rotated to the principal direction.

4) Nearest neighbor ratio matching strategy is adopted to match feature descriptors. First, compute Euclidean distance of the descriptor feature vectors of feature point between the reference image and the matched image. If the distance of two feature points is the shortest, and the distance is 0.7 times more than sub-shortest distance, two feature points are considered as matching point pair; otherwise, we think the feature point has not matching point.

5) Verify the matching point-pair. There are two methods to obtain the mapping transformation matrix between the reference image and the matched image, which are RANSAC algorithm and classic matching database provided by Oxford University as a real transformation matrix. As for any a pair of matching points, these points are coincided in the ideal case after obtaining transformation matrix. Due to the influence of the noise, two points cannot be completely coincident. Therefore, this paper will use symmetric transfer error to judge, which the threshold is set as 0.002. When the symmetrical transfer error cost function value is less than the threshold, the matching point are the correct match point; otherwise it is the error matching point.

The specific flowchart of image processing is described as follow in Figure 2.

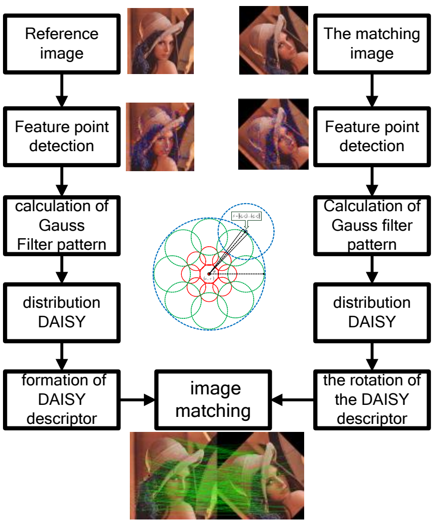

Figure 2. Algorithm flowchart

III. Experiment Result and Analysis

A. Rotation Invariance Detection

In order to verify the poor performance of SURF algorithm on rotation invariance, some classical images are adopted as experiment images, and every image is rotated from 0° to 180°. For comparison, our proposed algorithm is compared with SIFT algorithm, SURF algorithm, SURF principal orientation + DAISY descriptor, and the algorithm proposed by literature [18]. Precision and runtime of each matching algorithm are recorded, where Matching accuracy= Number of correct matching point / Total of matching point. The paper uses descriptor test method proposed by literature [19 20] to evaluate the performance of algorithms, where SIFT and SURF descriptor use the parameter settings of literature [7] and literature [8], respectively. All of the experiments are run under MATLAB v7.8 (R2012a) on PCs with an Inter Xeon CPU at 3.2GHz and 2 GB memory. All processes are simulated in MATLAB environment and do not include the MEX-file. Matching correct rate is shown in Figure 3.

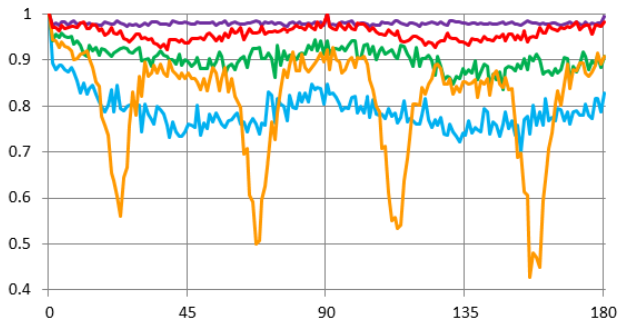

Figure 3. Matching correct rate of image Plane rotation test

TABLE I. PERFORMANCE COMPARISON OF ALGORITHMS IN ROTATION TESTS

Images	Algorithms	AMCR	MART	ARTF
 Plane	SIFT	97.95%	32.54s	11.86ms
	SURF	78.79%	3.82s	2.52ms
	SURF+DAISY	90.36%	5.54s	3.65ms
	Literature [17]	81.17%	3.88s	2.56ms
	Our algorithm	95.78%	5.17s	3.40ms
 Pepper	SIFT	94.68%	21.49s	12.99ms
	SURF	70.67%	3.47s	2.77ms
	SURF+DAISY	83.97%	5.19s	4.15ms
	Literature [17]	69.24%	3.45s	2.75ms
	Our algorithm	88.75%	3.91s	3.13ms
 Baboon	SIFT	99.17%	78.97s	10.6ms
	SURF	74.88%	5.76s	2.26ms
	SURF+DAISY	81.41%	8.24s	3.23ms
	Literature [18]	72.05%	5.34s	2.09ms
	Our algorithm	88.83%	7.64s	2.99ms
 Lena	SIFT	95.8%	28.91s	11.52ms
	SURF	65.8%	3.41s	2.38ms
	SURF+DAISY	76.7%	5.11s	3.58ms
	Literature [18]	65.13%	3.36s	2.35ms
	Our algorithm	85.5%	4.45s	3.11ms

Figure 3 is the correct-rate curve diagram of five matching algorithms on Plane original image and rotation image with the different rotation angle, where the x-coordinate and the y-coordinate indicate rotation angle and the matching rate, respectively. In addition, average performance of this algorithm is shown in Table 1. By comparing these matching rates from the Table 1, we can see that: SIFT descriptor has strong robustness on rotational invariance, and is also the most stable with the better result in all of algorithms. In addition, our

TABLE II. AVERAGE MATCHING CORRECT RATE OF ALGORITHMS ON EACH OXFORD CLASSIC MATCHING DATABASE (%)

Algorithms	Bikes	Graffiti	Wall	Leuven	UBC	Average
SIFT	58.01	34.76	71.74	81.87	84.41	66.16
SURF	70.70	29.89	67.59	69.81	85.77	64.75
SURF+DAISY	77.11	26.17	69.30	75.88	84.10	66.51
literature [18]	71.96	6.28	68.53	72.67	83.01	60.49
Our method	85.48	34.92	70.63	78.05	85.34	71.10

TABLE III. AVERAGE RUNNING TIME OF ALGORITHMS ON EACH OXFORD CLASSIC MATCHING DATABASE (UNIT: SECOND)

Algorithms	Bikes	Graffiti	Wall	Leuven	UBC	Average
SIFT	61.35	84.80	144.47	50.65	71.19	82.49
SURF	7.22	9.95	16.99	5.94	8.41	9.70
SURF+DAISY	10.42	12.91	19.79	8.52	11.74	12.68
literature [18]	6.99	8.02	12.14	5.70	7.35	8.04
Our method	10.05	12.09	18.44	8.02	10.98	11.92

proposed algorithm also has obtained the most matching points and average matching accuracy can reach more than 95%. The performance of SURF algorithm has verified its poor performance on image rotation, average matching accuracy can reach less than 70%, and the algorithm can obtain the less matching points. The third algorithm uses directly principal direction of the SURF algorithm to calculate the DAISY descriptor and has considerable improvement on average correct rate and the average number of correct matching points than the SURF algorithm, which shows DAISY descriptor matching capability is better than the original SURF descriptor in the case of the same feature point detection and principal direction. The fourth method is provided by the literature [18], it uses directly the center of the gradient histogram in the second layer to distribute the principal direction, which is a better algorithm when the angle change is small or the multiple of the angle. However, the rest of the angles will cause the larger error on the matching accuracy, which is because the principal direction is selected in units of angel. The last one is our proposed algorithm. The average number of matching points is very much close to the SIFT algorithm, the average accuracy rate is raised to near 90%, which is shown that the principal direction of our proposed algorithm is more suitable for DAISY descriptor than that of the SURF algorithm. In addition, our proposed algorithm is also more robust than the literature [17]. By comparing the average operation time of single matching(AOTSM) and average computation time of single feature points (ACTSFP), we can see that SIFT algorithm is very time-consuming, and the efficiency of the algorithm is almost five times as high as that of SURF algorithm. The literature [17] is faster than the SURF algorithm, which is because of its simple structure and easy method for distributing principal direction. The two algorithms, namely, SURF principal direction + DAISY descriptor, our algorithm), their average running times are slightly slower than the original SURF algorithm, but our algorithm is slightly faster than the principal direction of the SURF algorithm, which is shown our principal direction distribution method is faster than that of SURF algorithm. Considering comprehensively the matching results and computation times, our algorithm enhances the matching capability on the rotational invariance in the case of a slight increase of running time, and gets better results, which shows that our algorithm is more superior to the original SURF algorithm on the rotational invariance.

B. Matching Results and Analysis on Classic Database

The proposed descriptor is evaluated on the standard Oxford dataset, in which image pairs are under various image transformations, including viewpoint variation, scale and rotation variations, image blur, JPEG compression and illumination variations. Each group contains a total of six real images, the first image is denoted as a benchmark image, and the rest of the images are the matched images. In addition, Homography Matrix between the first image and other images is appended to data as the mapping transformation matrix, so it is convenient to validate the algorithm. It should be noted that the data with a large-scale variation is discussed in this paper, which is because the DAISY descriptor did not resolve the scale invariance.

According to the above results, we can see that our algorithm has the best performance in the fuzzy image (Bikes), which is because the image fuzzy has a big effect on gradient histogram of SIFT algorithm. DAISY descriptor itself uses the gradient histogram filtered by Gauss filter as a feature description, so image blurring has more prominent effect. Moreover, they are rotation invariant without relying on a reference orientation, further improving their robustness. Since SURF uses a similar local feature in SURF image matching, the significant performance improvement of our algorithm over SURF demonstrates the effectiveness and advantage of our proposed feature pooling scheme, i.e. pooling intensity order is more informative than rings. In most cases, our algorithm performance is better than DAISY. When images have blur or illumination changes, our algorithm is better, especially when encountering large illumination variation. Since the field of view alters, the matching accuracy of all methods is substantially reduced, but the average correct rate is still the highest in the algorithm. Our algorithm is slightly faster than the principal direction of the SURF algorithm, which shows principal direction distribution method is faster than that of SURF algorithm. In addition, our algorithm is significantly less than SIFT on running time. Considering comprehensively the matching results and computation time, our algorithm enhances the matching capability on the rotational invariance in the case of a slight increase of running time, and gets better results, which shows that our algorithm is more superior to the original SURF algorithm on the rotational invariance and is also the most advantage.

IV. Conclusion

Based on the disadvantage of original SURF algorithm on rotation invariance, this paper proposes a matching algorithm combined with SURF feature points and DAISY descriptor. The algorithm first adopts the SURF Hessian matrix calculation method to detect feature points so as to keep the quickness and accuracy of feature point during detection process, then calculates the gradient direction image of the original image and uses our proposed algorithm for DAISY descriptor to compute the principal direction of feature points. After the principal direction is selected, the axis is centered on the feature point, and then is rotated to the principal direction. Along with the principal direction, some rectangular areas around the feature points are selected to calculate the descriptor. Experimental results show that our algorithm improves the rotation invariance of original SURF algorithm while increasing the running time slightly, which can obtain more correct matching points. The proposed descriptor is evaluated on the standard Oxford dataset, in which image pairs are under various image transformations, including viewpoint variation, scale and rotation variations, image blur, JPEG compression and illumination variation. Our proposed image matching algorithm is combined with SURF feature points and DAISY descriptor, which has better running speed and stronger robustness than classical algorithms. However, our algorithm is not very ideal in the case of large image scale variation, which will be an improvement direction for the future work.

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