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A Method Using Auxiliary Direction to Improve SURF Recall

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Abstract

Classic SURF algorithm may lead to matching failure, low recall because of incorrect main direction when constructing feature points describing operator. To solve it, A Method using auxiliary direction to improve SURF recall is put forward. The improved algorithm first select out auxiliary direction which is similar to main direction in characteristics, then generate new operator for describing the auxiliary direction characteristic. When matching, the improved algorithm adopts stricter nearest neighbor proportion inhibition. Experimental results show that feature point recall increase about 6% compared with the classical SURF while maintaining the precision.

Keywords: *SURF, Auxiliary direction, Recall, Precision, Nearest neighbor*

1. Introduction

Matching point pairs of one identity object in two pictures that are not completely the same is the basic task in the application of computer vision. There are some common algorithms for detecting feature points, such as Harris [1], Hessian-Laplace [2, 3], Sift, SURF, *etc.*, of which Harris algorithm detects feature points by finding points which change greatly in gray level of both X direction and Y direction [4], but it doesn't have scale invariability. Sift algorithm was formulated in 1999, which attempts to find critical points in spaces of different scales [5], and obtains corresponding scale, position, rotation angle and so on, which have scale invariability and be used widely [6]. The main flaw of Sift is slow. SURF algorithm is the improvement of Sift algorithm [7]. It chiefly accelerates the calculating process by integral image. Its speed is approximately three times of Sift algorithm and the performance of intensity roughness and fuzzy is also better than Sift [8, 9].

SURF algorithm needs to calculate the principal direction of every feature points to ensure the rotation angle of local feature for the calculation of the descriptor [10, 11]. This procedure mainly is to find the strongest direction, *i.e.*, the principal direction, depending on the change of gray level and gradient in local area [12]. But there may be some deviation in the principal direction we have found, and it may influence the rotation of descriptor and the matching of feature point pairs. In this paper, a SURF algorithm improved by auxiliary direction is introduced. It uses auxiliary direction to improve the performance of the algorithm for those feature points that the principal directions are not determined enough.

2. Detecting and Matching Feature Points in SURF

The procedure of classical SURF algorithm consists of constructing scale space, determining feature points, distributing principal direction and generating descriptor.

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Feature point pairs can be matched after we get the set of descriptors of feature points of two images [13- 15].

2.1 Constructing Scale Space

To reach the goal of scale invariability, we need to find feature points in different scale spaces. Specifically, we would convolute the image I(x,y) with the Gaussian kernel, which is shown in equation(1).

$$L(x, y, \sigma) = I(x, y) * G(x, y, \sigma) \tag{1}$$

G(x,y,σ) is Gaussian function in different scales. To smooth the image in multi-level, we need to use different Gaussian kernels to convolute with the image. Every level can also be decomposed to multi-scale. Then, constructing DoG scale space by subtracting the continuous image of Gaussian scale space successively.

In this process, we use box filter with integral image to approximately calculate the value of Hessian determinant. The speed of calculating is improved in a great degree because we only need addition and subtraction.

2.2 Determining Feature Points

One point can be determined as a feature point if it satisfies one of the following:

(1)The value of Hessian determinant is greater than a threshold;

(2)In this scale and adjacent two scales, selecting 3*3 area centered by current point in each scale, there would be 27 pixels. The gray value of current point is the maximum or minimum of these 27 pixels.

Because the marked feature points are in different scale spaces, we need to apply 3-D linear interpolation to map them into the original image, thus the feature points we obtained are in sub-pixel level.

2.3 Distributing Principal Direction

In order to make the algorithm be directional invariable, we need to distribute a principal direction for every feature point, and then rotate the descriptor according to the principal direction.

In the scale of the feature point, calculating the vertical and horizontal feature of the Harr wavelet of all points in the area of the sector that has the radian of 1/3 and the radius of 6 times of current scale, rotating this sector in some interval, using its horizontal wavelet feature and vertical wavelet feature, we would generate the local direction vector. Rotated it 360 degree, we would find the longest one of those wavelet feature vectors, which the direction is exactly the principal direction of this feature point.

2.4 Generating Descriptor

Selecting a rectangular area centered by the feature point that the length of side is 20 times of current scale, rotate the rectangle and its content according to the principal direction, and divide this area into 16 blocks. In each sub-block, calculate the sum of the feature of Harr wavelet and the sum of absolute value of the feature of Harr wavelet in horizontal and vertical direction for those 25 pixels. There are 4 description data in each sub-block. Hence, the descriptor of every feature points includes 64 description data in all.

2.5 Matching Feature Points

In SURF algorithm, there are many ways to match feature points. One simple and common way is following:

(1)Detect all feature points in two images A and B that are waiting for matching, and save their feature descriptors.

(2)Traversal all feature points in image A. For each descriptor, calculate the Euclidean distance of all feature descriptors of image B. Mark the minimal distance as Dis1, the second smallest distance as Dis2. If (Dis1/Dis2) < proportional threshold, then preliminary matching succeeds. This step is called nearest neighbor proportion inhibition. Generally, the value of this threshold would be 0.7. It should be mentioned that the smaller threshold, the larger proportion of correct matching, i.e., the higher precision, but the correct matching point pairs would be smaller, i.e., the smaller recall.

(3) Bidirectional matching. Transpose the image A and B in step 2 with the same matching standard. If the matching pairs of image B and A is the same as the result of image A and B, keep it as a matching result, else ignore it.

2.6 The Performance Index of Algorithm

Precision and recall are two performance indexes in the measurement of the algorithm of detecting and matching feature points.

Precision=the number of detected correct matching pairs/ the number of all detected matching pairs.

Recall=the number of detected correct matching pairs/ (the number of detected correct matching pairs + the number of undetected correct matching pairs).

In general, the standard of the correctness of detecting is that the difference of the position of matched feature point and its corresponding real position is less than 1.5 pixels. Under the same condition, the higher indexes, the better performance of the algorithm.

3. Using Auxiliary Direction to Improve SURF Algorithm

3.1 The Reason of Introducing Auxiliary Direction

Using the method introduced in section 2, detecting and matching feature points to the image called A in Figure 1, which the width is 437 pixels and the height is 417 pixels, and to the image called B, which is added Gaussian noise (mean = 0, variance = 0.015). 733 feature points have been detected in A, and SURF algorithm totally matches 324 pairs, of which the numbers of correct matching point pairs are 266 and the number of wrong matching point pair is 58.

Figure 1. Image for Testing

The further statistics for the result is following. There are 352 feature points in the 733 feature points detected in A that don’t have corresponding feature points in B, since B is interfered by noise, and it didn’t generate the feature points corresponding to this part in

A. In 381 pairs remained, SURF obtains 266 of them. 115 of them are matched incorrectly or abandoned. In these 381 pairs, there are 144 pairs which the absolute value of radian difference of the principal direction of corresponding feature point is greater than 0.05, 76 pairs which the value is greater than 0.1, and 46 pairs which the value is greater than 0.2. We can find that some matching pairs, which would be correct, cannot be matched correctly because of the interference of noise. There might be a large deviation in the calculation of principal direction, which causes the incorrectness of matching.

In 266 correct matching pairs found by SURF, there are 195 pairs which the absolute value of radian difference of the principal direction of corresponding feature points is between [0, 0.05], 53 pairs which the value is between (0.05, 0.1], 18 pairs which the value is greater than 0.1, and the maximum of the value is 0.26. We can see that the probability of matching correctly would be reduced greatly, if the difference of radian is greater than 0.1. In 58 incorrect matching pairs, there are 53 feature points of A has no corresponding feature points to be draw in corresponding area of 1.5 pixels of B, and the absolute value of radian difference of the principal direction of the 5 pairs remained which has the corresponding feature point is 0.11, 0.04, 2.93, 2.21, 0.24. We can see that there are 4 pairs, which should be matched correctly, matched to other feature point because of incorrect principal direction. For the situation of salt and pepper noise, fuzzy and shear transformation, our studying team has also done related experiments, which is similar to the situation above.

In view of the analysis above, this paper introduced auxiliary direction in the calculation in the basis of the SURF algorithm, expecting to achieve a better effect of matching in the following two aspects.

(1) Introduce auxiliary direction to increase the number of correct matching pairs.

(2) Reduce the incorrect matching result because of the incorrectness of the principal direction in some extent.

3.2 The Method of Introducing Auxiliary Direction

There is also some introduce of the usage of auxiliary direction in Sift algorithm. Using orientation histogram to find the principal direction, if the peak of one direction is greater than 80% of the peak of the principal direction, let it be the auxiliary direction of this feature point, and generate feature information, which is at the same position of the feature point. It would improve the robustness of the algorithm. Appropriate auxiliary feature information would affect the algorithm, improve the performance, and not affect the original correct matching result as well.

Combined with SURF, the method of introducing auxiliary direction in this paper is following:

(1) After rotate 1/3 radian sector continuously to ensure the principal direction of current feature, denote the length of Harr wavelet feature vector of principal direction as lenMain, denote the length of Harr wavelet feature vector of other sectors as lenAux. If the equation (2) is satisfied, sort lenAux of these sectors from big to small, and calculate the direction of vectors corresponding to these sectors.

$$lenAux > (lenMain * Threshold1) \tag{2}$$

(2) Deal these vectors successively. Denote the direction of one vector as directionAux, and denote the determined principal direction of this feature point and other auxiliary feature direction as direction(i), where i corresponds to every existing direction. If for every existing direction, equation (3) is satisfied, then add directionAux as auxiliary direction to this feature point.

$$Abs(directionAux - direction(i)) > Threshold2 \tag{3}$$

(3) Using this auxiliary direction, combining with the scale information of feature point, one can calculate a descriptor, generating a new feature descriptor which is at the same position of the descriptor of principal direction but has different content.

(4) In the course of proposition inhibition, because the descriptors generated by principal direction and auxiliary direction at the same position might be close, the different descriptors at the same position would not involve in inhibition, *i.e.,* the second smallest Euclidean distance would not select the descriptor that is at the same position of the smallest Euclidean distance, preventing from abandoning correct matching pairs.

(5) After the matching completed, there might be a situation that at one position the feature point of the principal direction and of the auxiliary direction matched with the feature point of the principal direction and of the auxiliary direction simultaneously at the same position in other image. For repeated matching like that, only keep one matching point pairs. Because the matching results at the same position have been eliminated, the number of correct feature point pairs in the set of awaiting feature points won't change, the denominator of precision won't change.

There are some problems that should be illustrated.

(1) We should only consider that there is some probability that the principal direction is wrong if one feature point has an auxiliary direction, since the principal direction corresponds to longest Harr wavelet feature vector, thus the probability that the principal direction is correct is greater than that of the auxiliary direction.

(2) Consider the value of Threshold1; if it were too large, the auxiliary feature information we obtained would be less. As a consequence, the algorithm won't be improved substantial. On the other hand, if the value of Threshold1 were too small, there would be too much auxiliary feature information, which would causes larger computational complexity, and moreover, it might causes more wrong matching. The value of this threshold in Sift is 0.8, but each column corresponds 10 degrees in the gradient histogram when selecting the principal direction, which are 36 columns in total. As Figure 2(a) shows, there are only 8 columns for simplification. Since the range of the angle occupied by each column is small, the difference of the peaks of the histogram is large. In SURF, the sector is 60 degrees, As Figure 2(b) shows. Since the difference of wavelet feature magnitude of adjacent sectors is not large, the value of Threshold1 in this paper is 0.92. Hence, the number of auxiliary feature descriptor would be moderate, which would help the job of matching feature points be accomplished well.

(a) Sift (b) Surf

Figure 2. The Calculation of the Principal Direction in Sift and Surf

(3) The value of Threshold2 in this paper is 0.1 rad. The method of calculating principal direction in SURF is different from Sift. Its principal direction is not the middle direction of the sector. Instead, it is determined by the local directional vector generated by horizontal wavelet feature and vertical wavelet feature. Hence, in some adjacent sectors, the lengths of their Harr wavelet feature vectors are very close, and the direction of each vectors are very close too. In this situation, we cannot generate an auxiliary direction; otherwise it would generate two feature descriptors that are very close, which goes against the calculation of matching later. The reason why we choose 0.1 rad is that

the differences of principal directions of a large amount of correct matching pairs are less than 0.1. At the same time, the 0.1 rad here would select appropriate auxiliary direction well, with Threshold1 (0.92).

3.3 The Preliminary Effect of Introducing Auxiliary Direction

According to the method introduced in 3.2, combined the new descriptor to with the set of descriptors generated by principal direction, then match image 1 and the image processed by Gaussian noise (mean = 0, variance = 0.02) and salt and pepper noise (density = 0.02) according to the procedure introduced in 2.5. The result of comparison is shown in Table 1. For convenience, we use ISURF to denote the algorithm in this paper. The latter value denotes the proportion threshold of auxiliary direction descriptor if it's in matching.

Table 1. Comparative Results

Index	Algorithm	Noise parameter	Recall (%)	Precision (%)	Time (s)
1	SURF	Gauss 0.02	80.4	82.0	4.29
2	ISURF 0.7	Gauss 0.02	86.1	81.5	6.26
3	ISURF 0.6	Gauss 0.02	83.9	82.4	6.17
4	ISURF 0.5	Gauss 0.02	82.9	82.7	6.12
5	SURF	Salt-pepper 0.02	85.0	84.1	3.80
6	ISURF 0.7	Salt-pepper 0.02	89.3	84.3	5.33
7	ISURF 0.6	Salt-pepper 0.02	88.2	84.9	5.33
8	ISURF 0.5	Salt-pepper 0.02	87.5	85.2	5.31

From the 2nd row and the 6th row of Table 1, we could see that the recall is increased after the auxiliary direction descriptor is added, but sometimes the precision would be reduced. Analyzing the data, we would find that, because the probability of the correctness of auxiliary direction is lower than the probability of the correctness of principal direction, the recall would be increased, but the precision won't if we use the same method of inhibition of principal direction descriptor. Sometimes, the precision would even be reduced. Hence, we are considering using different strategy of inhibition to the descriptor of auxiliary direction and principal direction.

3.4 The Changes of Matching Inhibition Policy

Told in Section 2.5, the normal strategy is, if the ratio of the minimum of Euclidean distance and the second smallest Euclidean distance corresponding to matching pairs is more than 0.7, the matching would fail. If lower its threshold, the precision would increase, but it would reduce the number of matching pairs and then reduce the recall. In order to strictly inhibit the auxiliary direction descriptor this has higher probability to be incorrect. In this paper, if those two matching descriptor are both generated by principal direction, set the value of threshold to 0.7. If any of those descriptors are generated by auxiliary direction, set the value of threshold to 0.6 [10]. Corresponding effect are shown in the 3rd row and the 7th row of Table 1, and the data shows that the recall is increased, at the same time the precision is almost equal to or higher than the SURF algorithm. The data from the 4th row and the 8th row in the table use a stricter threshold 0.5, and the precision has been increased but the recall has been reduced.

The precision and the recall are the major indexes of the performance of the algorithm; the improvement of the algorithm should be balanced between two indexes instead of focus on only one index. In this paper we finally chose 0.6 as the threshold of the auxiliary direction descriptor which would be most appropriate.

The result of experiments from Table1 shows that the strict inhibition to the matching which the auxiliary descriptor involves would work well. Here is some detailed analysis.

(1)Some mismatched descriptors are found and saved in results, causing the recall increasing.

(2)A fraction of incorrect point pairs of principal direction descriptors can be correct.

(3)The precision dose not increasing apparently, for some new auxiliary direction descriptors could add some new incorrect matching. Using the strict inhibit threshold could apparently control the number of increased incorrect matching, in order to ensure the precision is not affected.

3.5 The Flow Diagram of the Improvement

The algorithm has been improved in two aspects: adding auxiliary direction descriptors and using it to do feature matching. The process is shown in Figure 3.

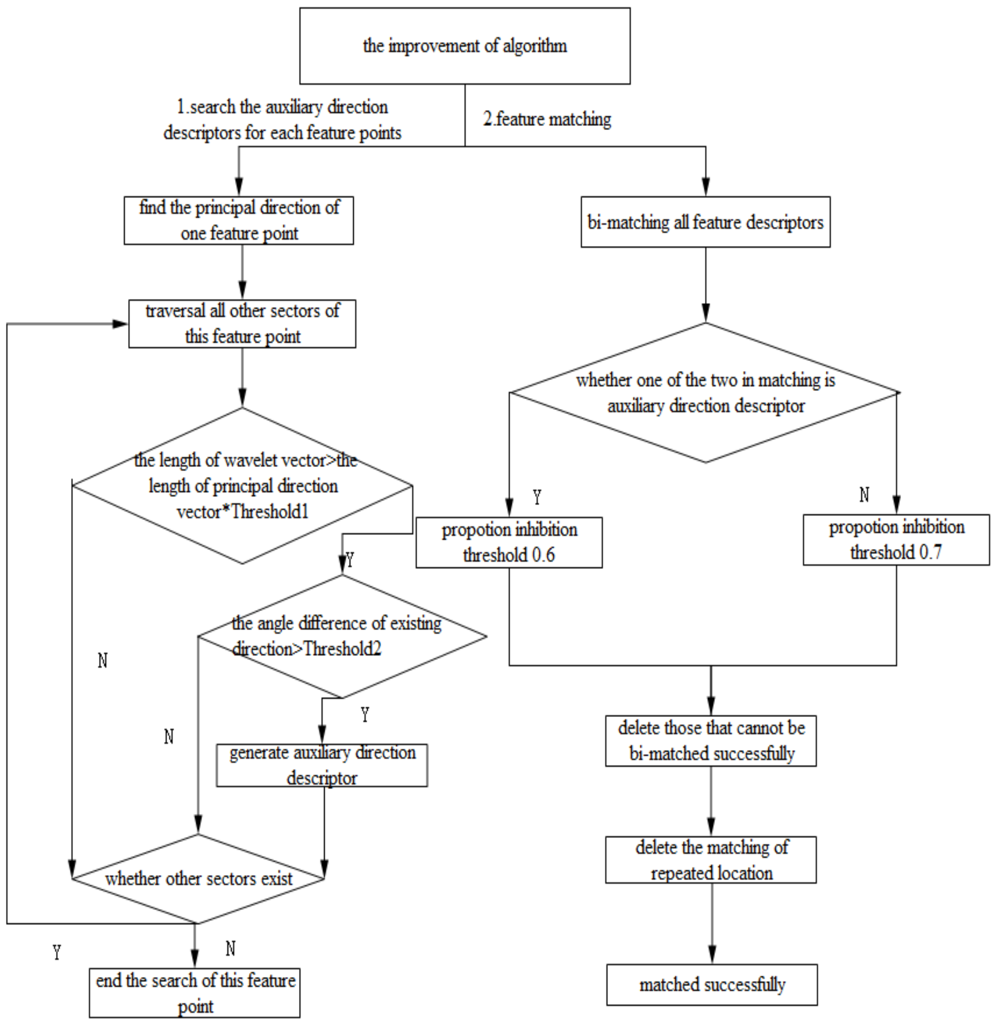


Figure 3. The Flow Diagram of the Improvement

4. The Result and the Analysis of the Experiment

4.1. Experimental Parameters Setting

The algorithm involves mainly two parameters.

(1) When selecting auxiliary direction, the ratio of the length of Harr wavelet feature vector to the length of principal direction vector should be greater than Threshold1. Select 0.92 in the experiment.

(2) The absolute value of radian difference of new auxiliary direction and of existing direction should be greater than Threshold2. Select 0.1 in the experiment.

Comparing Figure1 with images processed with Gaussian noise (mean = 0 variance = 0.01) or salt-pepper noise (density = 0.05), then change the value of two parameters above. When changing one parameter, the other remains constant suggested in this paper. Comparative results are shown in Table 2, T1 stands for Threshold1 and T2 stands for Threshold2.

Table 2. Comparative Results

Index	T1	T2	Noise parameter	Recall (%)	Precision (%)	Time(S)
1	0.92	0.1	Gauss 0.01	84.9	85.6	6.11
2	0.89	0.1	Gauss 0.01	85.7	85.5	6.60
3	0.95	0.1	Gauss 0.01	84.1	85.7	5.38
4	0.92	0.05	Gauss 0.01	84.9	85.8	7.15
5	0.92	0.15	Gauss 0.01	84.7	85.3	5.68
6	0.92	0.1	Salt-pepper 0.05	81.2	82.9	5.98
7	0.89	0.1	Salt-pepper 0.05	81.5	82.2	6.43
8	0.95	0.1	Salt-pepper 0.05	79.3	82.7	5.27
9	0.92	0.05	Salt-pepper 0.05	80.4	83.2	7.04
10	0.92	0.15	Salt-pepper 0.05	80.7	82.8	5.33

In Table 2, the results shown in the 1st row and the 6th row correspond to the suggested parameter in this paper.

When the threshold increases, the number of auxiliary direction feature descriptors reduces, precision improves, recall and time consuming decrease, and vice versa. Also note that the threshold is reduced to a certain extent, then down lower on the effect of improving the precision is sometimes limited.

The 2nd row compared with the 1st and the 7th row compared with the 6th, the comparative result shows that recall is improved, precision is flat or decreased and time-consuming is increased.

The 5th row compared with the 1th and the 10th row compared with the 6th, the comparative result shows that time-consuming is decreased, but recall and precision are decreased slightly.

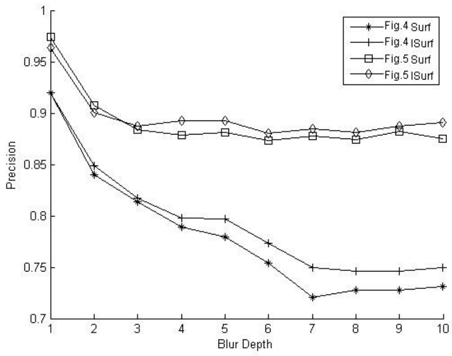
Taking the factors of recall, precision and time-consuming, especially recall into account, in this paper, Threshold1 selects 0.92, Threshold2 selects 0.1.

4.2. Contrast Experiment

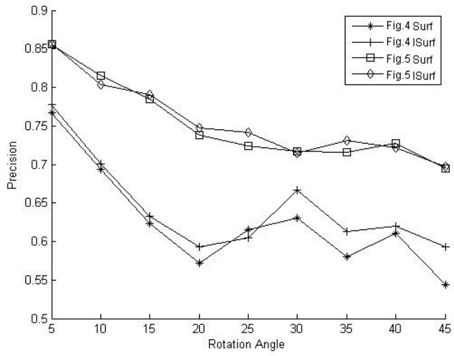
In order to verify the effect of the improved algorithm proposed in this paper, algorithm is compared with classical SURF algorithm in the Matlab2010 platform. To facilitate the distinction, in this paper, ISURF stands for improved algorithm, legend using "+" and diamond, SURF algorithm represents uses "*" and "□". Experimental pictures show in Figure 4 and Figure 5, Figure 4 with 300*337 pixels, Figure5 with 720*480 pixels. Because experiments discussed above using Gaussian noise and salt and pepper noise, this section perform the precision and recall rate comparison test from Gaussian blur, rotation transformation, shearing transformation and scaling four areas, the results show in Figure 6, Figure 7. Where the Gaussian blur window size is 7 * 7, using standard deviation to control blur depth; rotating counter-clockwise with various angles around the center of the image; scaling the image size that a certain percentage of narrow; vertical shearing transformation is vertical shearing, other parameters did not mention here use default parameter values of Matlab.

Figure 4. Flower

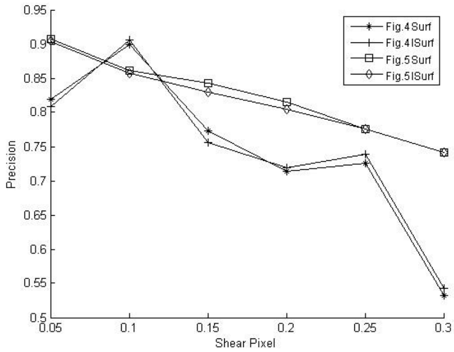
Figure 5. Landscape



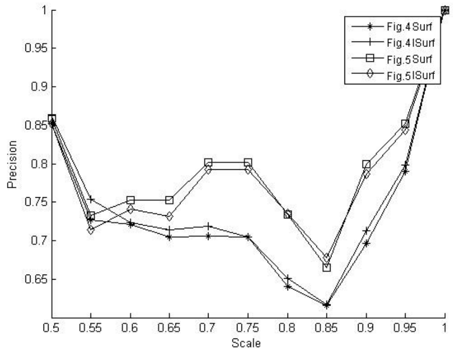
(a)Gauss Blur



(b)Rotation Change

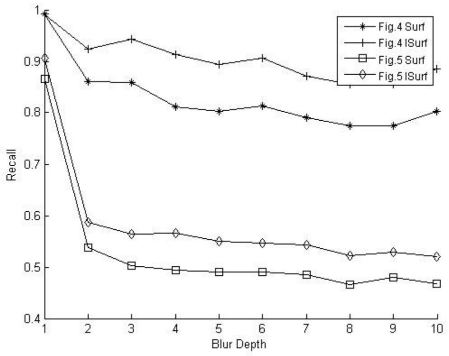


(c)Shear Change

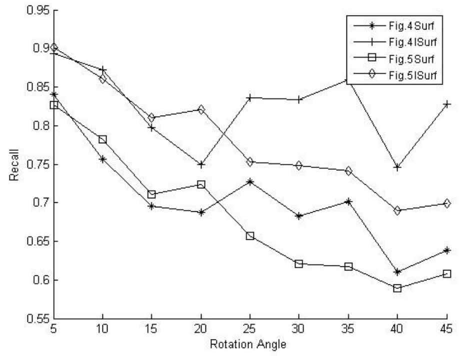


(d)Scale Change

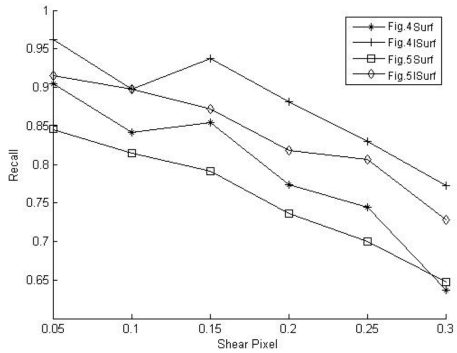
Figure 6. Precision Comparison



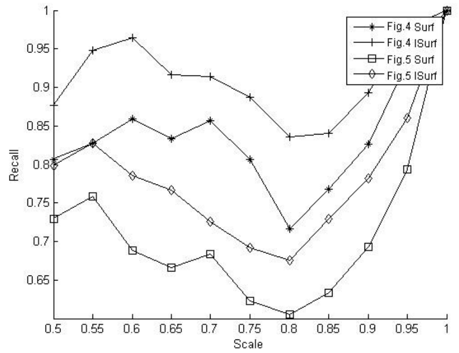
(a)Gauss Blur



(b)Rotation Change



(c)Shear Change



(d)Scale Change

Figure 7. Recall Comparison

4.3 Analysis of Experimental Results

Experimental results of precision show in Figure 6, which show that using improved algorithm precision is better than SURF or remains flat on the condition of angle rotation and blur.

The experimental results of matching feature points recall show in Figure 7, the data shows that the improved algorithm compared with the SURF algorithm can improve the recall of feature points facing scaling, rotation angle, shearing transformation and fuzzy, and in most cases increased by 4-10%, an average of 6%. In particular, when a large change exists in the image, the algorithm performs well. Indicated in Figure 7 (b), after the 45 degrees rotation, for Figure 4 SURF recall rate is about 65%, while the improved algorithm recall rate is about 85%, increased significantly, reflecting the strong robustness.

It should be noted, of course, improved algorithm joins a series of operations associated with the auxiliary direction, so time-consuming is increased compared with SURF. On the other hand, looking at Figure 6 and Figure 7, the algorithm can be seen little change in the face of two test images with a little difference, such as which the Gaussian blur and depth of a scaling ratio are closed to 1, because the choose of the principal direction of the feature points of the two images is essentially unaffected, the performance has been enhanced only a little.

5 Conclusions

In this paper, through introducing the auxiliary direction generated feature point descriptor involved in feature matching, setting appropriate parameters for the conditions of introducing auxiliary direction, and using stricter nearest neighbor inhibition strategy for matching involving auxiliary direction descriptor. Experimental results show that the improved algorithm discussed in this paper can guarantee precision in basically the same premise, or better, to improve the algorithm's recall rate of about 6 percent with respect to the classical SURF, increasing the number of correct matching pairs, providing more effective information of location for image post-processing, while improving the robustness of the algorithm. From another perspective, though there is no detailed experimental data, it can be inferred that, if properly decrease the proportion inhibition threshold of principal direction feature descriptor, then the recall will be flat with the original algorithm, the precision rate will be improved.

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