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# Fast Bi-directional SIFT Algorithm and Application

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***Abstract***

*SIFT (Scale invariant feature transform) descriptor is one of the most effective local features that is used for scale, rotation and illumination invariant of automatic image registration. In this paper a fast bi-directional matching algorithm based on SIFT was proposed for improving match accuracy and reducing match time. Firstly the single-feature points and multi-feature points in two images were extracted, and then matched all these feature points respectively by using the BBF (Best Bin First)-based bi-directional matching algorithm. The integrated matching correspondences were the final matches. The experimental results showed that the proposed algorithm can reduce mismatch probability and decrease the matching time.*

***Keywords**: Invariant Features, SIFT, fast bi-directional match, BBF*

## 1. Introduction

Feature extraction is one of the most important research areas in image matching. The quality of feature extraction affects the final match result directly. Feature descriptor is local features detected from image, such as angle points [1], edges [2], contours [3], *etc.*, then according to the needs of matching target, the features to be combined and transformed, and then get steady feature vector, it can make matching easy. The image matching problem is transformed into feature matching. In recent years, in the area of computer vision, target recognition and matching based on local invariant descriptors [4-6] has made significant progress.

SIFT (Scale invariant feature transform) [7] is a local feature descriptor proposed by David Lowe in 1999, and has more in-depth development and perfection in 2004 [8]. It has the following advantages: describe pattern feature well, keep the structure information and feature points stable, even if there are translation ,rotation, scaling ,noise, affine transformation between the two images, SIFT feature matching algorithm still has a strong ability to match [9, 10]. Meanwhile, it also has the very high scalability and can easily combine with other forms of eigenvectors.

However it is difficult to meet require due to its high algorithm complexity, long computation time, slowly speed of image matching. In addition it will often appear incorrect matching point pairs, so many scholars have carried on the improvement to it. Ke Y. [11] proposed a dimension reduction on the SIFT feature by PCA in 2004 and it has got a good result. It's effective when it can be calculated in advance, but it will increase the amount of

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calculation when it's for real-time situation. Luke [12] uses simplified SIFT algorithm for indoor image retrieval and positioning, is only applicable to specific scenarios, and the optimization of computational complexity is small. Qian [13] adopted to calculate neighborhood gradient by step size of adaptive sampling window and bidirectional matching method to improve the algorithm. This makes the algorithm overall time reduced by 20% on average.

In order to reduce the mismatch rate, a fast bi-directional matching algorithm is proposed. It can not only remove the mismatched feature points, but also reduce the running time of matching algorithms.

## 2. SIFT-based of Bi-Directional Image Matching Algorithm

### 2.1. Image Matching based on SIFT

SIFT consists of four major stages[6]: 1) uses difference-of-Gaussian function for Scale-space extreme detection; 2) key point localization; 3) 1 or more orientation assignment for each key point; 4) key point descriptor is created from local image gradients. The main step of algorithm [13] is:

1) Detect the scale-space extreme points: Under a variety of reasonable assumptions the only possible scale-space kernel is the Gaussian function. Therefore, the scale space of an image is defined as a function:

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

Where * is the convolution operation, that is a variable-scale Gaussian,

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)} / 2\sigma^2 \tag{2}$$

To efficiently detect stable key point locations in scale space, using scale-space extreme in the difference-of-Gaussian function convolved with the image. DOG operator is:

$$D(x, y, s) = (G(x, y, ks) - G(x, y, s)) * I(x, y) = L(x, y, ks) - L(x, y, s) \tag{3}$$

In order to find extreme points in scale space, and each sample point compare to all of its neighbors to know whether the image scale larger or smaller than its domain and adjacent domains point scale. The middle of checkpoint and with the same scales of 8 neighboring points. Compare with the upper and lower 9×2 total of 26 points which corresponding to the adjacent scales. Ensuring the two-dimensional image in space and space scales are detected extreme point.

2) Precise positioning extreme point: Three-dimensional quadratic function through the preparation and precise determination of location and scale of key points, while removing the low contrast and unstable critical points in order to enhance the stability of match and improve noise immunity.

3) Orientations are assigned to each key point location: The key point neighborhood pixel gradient direction distribution to describe the direction of parameters specified for each key point, so that the operator with rotation invariance. For each image sample, $L(x,y)$, at this scale, the gradient magnitude, $m(x,y)$, and orientation, $\theta(x,y)$, is precompiled using pixel differences:

$$m(x, y) = \sqrt{(L(x+1, y) - L(X-1, Y))^2 + (L(X, Y+1) - l(X, Y-1))^2} \tag{4}$$

$$\theta(x, y) = \alpha \tan 2((L(x, y+1) - L(x, y-1) / (L(x+1, y) - L(x-1, y))) \tag{5}$$

Multiple orientations assigned to key points from an orientation histogram, which significantly improve stability of matching.

4) Generation of key point descriptors: After the orientations of the key points have been assigned, the gradient magnitude and orientation are computed at each sample point in their nearby region. A Gaussian function is used to weight the magnitude of each sample point. The feature descriptor is computed by accumulating the orientation histograms on the 4×4 sub regions. Each histogram has 8 bins, so the SIFT feature descriptor has 4×4×8=128 elements. Finally, the feature vector is normalized o reduce the effects of illumination change. Figure 1 is the result of SIFT feature points extraction of an ordinary image and an ear image from USTB ear image library respectively.

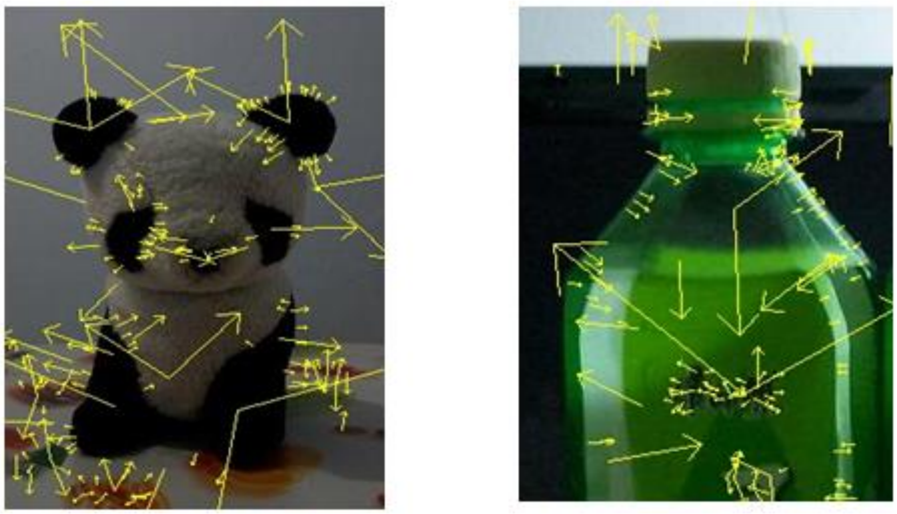


**Figure 1. SIFT Feature Points Extraction of Images**

When using image matching features base on SIFT, after feature vector generated from the two images, take a critical point of Image 1, and to find out two key points from Image 2 where their euclidean distance is the shortest. Lowe found a method that can distinguish the nearest neighbor and second nearest neighbor. If distance percentage is less than a threshold of T, that is the right match.

Lowe and others proposed use of BBF algorithm to find the nearest neighbor and second nearest neighbor. It is a modified *k-d* tree search algorithm. In fact, *k-d* tree algorithm spent most of the time in searching node, and only parts of the nearest neighbor nodes to meet the conditions. Therefore, they could limit k-d tree's leaf nodes to reduce the search time. When backdate search, the nodes and the queried nodes are the order of increasing distance to search nodes. Searching along with a branch direction of the current node, a member will be joined the priority queue. This member records the information of a branch of the node in another direction, the location of the node in the tree and the distance between the node and the queried node. Finish searching a leaf node, the first term which is deleted from the priority queue as the current node. Continue to search for other branches that include the most nearest node.

### 2.2. Fast Bi-Directional Image Matching Algorithm

Mismatching rate is the number of the mismatching point pair on the ratio of the number of matching point pair. It is an important measurement in image registration which measure algorithm performance. Although SIFT features operator has good stability and uniqueness, the phenomenon of feature point's mismatching still exists in actual matching. The paper summarized some reason that mismatching point pairs during the matching image using the SIFT-based operator:

1) Two different images, the different coordinates position of the Image 1 that may exist similar area in shapes, similar to Image 2 within the corresponding region. Once extracted SIFT operator, the feature vector is very similar and may have mistakenly assigned;

2) As the SIFT operator's own characteristics, the image of the same coordinate point may have multi-feature vectors. Multi-point feature vector matching theory can improve the robustness of the matching algorithm, but the actual match, the same image on multiple is similar to different points within the region, may have similar multi-feature vector. In this case, the image matching with the images to be matched will increase the possibility of mismatching;

3) Select the matching threshold value $T$. When $T$ is small ($T$=0.4), the matching accuracy rate is higher and the mismatch rate reduce naturally; when $T$ is large ($T$>=0.8), Mismatch rate increase; in the field of the actual registration and recognition, we can adjust threshold value to meet the change of application requirement. When $T$=0.6, for the general demand, all the experimental threshold values are obtained $T$= 0.6 in this paper.

Factors 1) and 2) can produce obvious mismatching and many to one mismatching, or even lead to duplicate match point. In this paper we propose BBF-based bi-directional matching algorithm. The first matching reserve the matching point pairs 1 and 2 in the original image. Second matching, the known has been matched feature point $P(x, y)$ of Image 2, a new matching point will be find out from all feature points of Image 1, Euclidean distance of new matching point $P(x, y)$ seek respectively the with Image 1, the Euclidean distance of original point that $P(x, y)$ in the first match with Image 1. Choose a smaller Euclidean distance of matching point pair that is the correct matching point pair. If the Euclidean distance is equaled, we view the original and the new match point that Image 1 corresponds to $P(x, y)$ having the same coordinates of points. This bi-directional matching algorithm aims at the factors 1) and 2) to mismatch point pair's existence. It not only can effectively reduce the apparent mismatching, but also reduce the many to one mismatching. Based on the above ideas, this paper has realized the corresponding algorithm that based on exhaustive bi-directional matching.

Because of SIFT operator itself has the characteristics, this paper view multi-feature vectors which have the same position in the image as many feature points. The position coordinates of the points with a single feature vector as a single feature point. Quick match: before two images match, at first, images were respectively extracted from a single feature point and multi-feature points, match a single feature point and then match the multi-feature points. The integrated matching point pairs as the final matches. This method that compared to the direct matching two images of all the feature points can reduce the run time.

Set, $n$: image 1, the total number of feature points; n1: image 1, the number of single feature point; $n2$: image 1, the number of multi-feature points; m: Image 2, the total number of feature points; $m1$: image 2 the number of single feature point; m2: image 2, the number of multi-feature points; then: $n = n1 + n2$, $m = m1 + m2$ direct matching time complexity: $O(nm)$; fast matching time complexity: $O(n1m1 + n2m2)$.

For ease of calculation, in image 1,the number of cycles used to approximate the core code which replace the execution time of algorithm, another set, $a(0 < a < n)$: $a$=$n1$;$k1$: in image 1, the proportion of single feature point held by the multi-feature points, That $n2 = k1 \times a$; $n = (1 + k1) \times a$;$b(0<b<m)$;$b$=$m1$; $k2$:in image 2, the proportion of single feature

point held by the multi-feature points, that $m2=k2\times b$; $m=(1+k2)\times b$. Time difference of two algorithms is: $\Delta=(mn)-(n1m1+n2m2)=(k1\_k2)ab>0$ , this equation shows the direct matching comparing with the fast matching can reduce the running time of algorithms. The thought of fast matching combined with bi-directional matching in section 2.1, this paper presents BBF-based fast bi-directional matching. At first, separating the single feature point and multi-feature points from two images, then using BBF-based bi-directional matching match the single feature point, and then using BBF-based bi-directional matching match the multi-feature points. The matching point pairs of synthesis as the final matching result. Based on the above ideas, this realization of the corresponding of fast bi-directional matching algorithm based on the exhaustion.

## 3. Experiments Results and Analysis

Experimental images derived from Avi Kelman [6] testing image libraries and some photographs of real life. We chose 8 images from the Avi Kelman image library to create a test image database, after processing the image data is created three groups:

1) The first group: the original image and rotate 45º;

2) The second group: the original 0.6 times with 45º of rotation and scaling of the images;

3) The third group: the original image and rotate 45º, scaling of 0.6 times, 0.01 gaussian noise variance of the image,

At first, comparing the difference between BBF-based bi-directional matching and other algorithms in time and mismatch probability, further comparing the difference between BBF-based fast bi-directional matching and BBF-based bi-directional match on the running time. Finally, making an integrated test to compared with the BBF-based algorithm matching, BBF-based bi-directional matching, BBF-based fast bi-directional matching about the time and mismatch probability differences mismatch probability. Mismatch rate *errorratio* is: $misMatches/totalMatches$, the *totalMatches* obtained by matching the total number of matching point pairs, *misMatches* obtained by artificial selection that the wrong number of matching point pair.

Do some changes based on the original image to obtain three group of test data, such as rotation, scaling, add Gaussian noise processing, with the increasing of the complexity of the image changes, the number of feature points which are waiting for match are also gradually reduced. Figure 2, Figure 3 and Figure 4 list the comparison of the rate of mismatch in different matching methods.

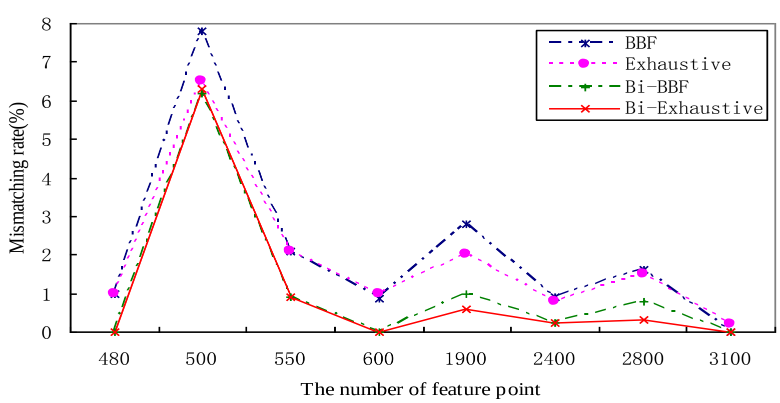



**Figure 2. First Group of Mismatch Rate Test Results**

We can find that no matter the number of matching feature points did any change, both the BBF bidirectional matching method and double match both exhaustive method can reduce the rate of mismatch from the comparison of Figure 2, Figure 3 and Figure 4. Even if the image complex changes, the rate of mismatch can be reduced relatively.

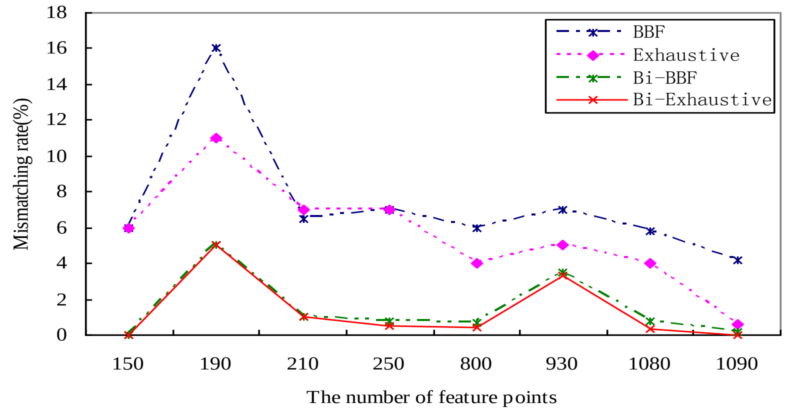



**Figure 3. Second Group of Mismatch Rate Test Results**

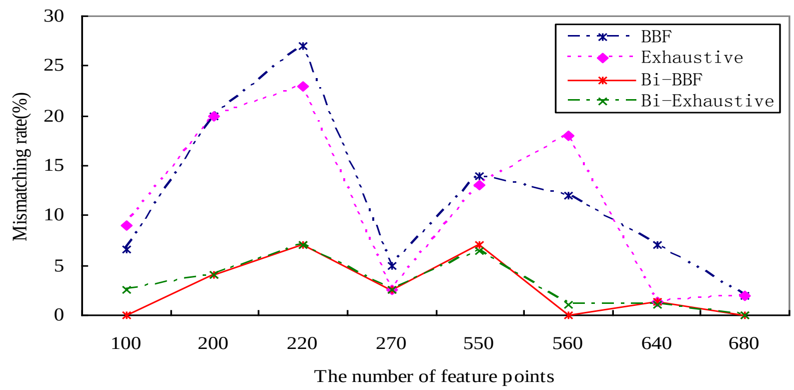



**Figure 4. Third Group of Mismatch Rate Test Results**

From the data of Table 1 and Table 2 we can see the comparison of the running time of the three groups of text data in different matching methods.

**Table 1. Exhaustion Method Bilateral Matching and Exhaustion Method Fast Bilateral Matching in Match Time Comparison**

| Images on | Exhausts the bilateral matching | Exhausts the fast bilateral matching | Reduced percentage |
|---|---|---|---|
| (The 1st pair,517,661) | 375ms | 266 ms | 29.06% |
| (The 2nd pair,370,399) | 156 ms | 125 ms | 19.87% |
| (The 3rd pair,497,470) | 266 ms | 219 ms | 17.66% |
| (The 4th pair,446,721) | 359 ms | 234 ms | 34.81% |
| (The 5th pair,3169,2504) | 8282 ms | 5735 ms | 30.75% |
| (The 6th pair,2534,3364) | 9704 ms | 6469 ms | 33.33% |
| (The 7th pair,1704,2168) | 3969 ms | 2782 ms | 29.90% |
| (The 8th pair,2001,2859) | 6359 ms | 4578 ms | 28.00% |
| Total | 29470 ms | 20408 ms | 30.74% |

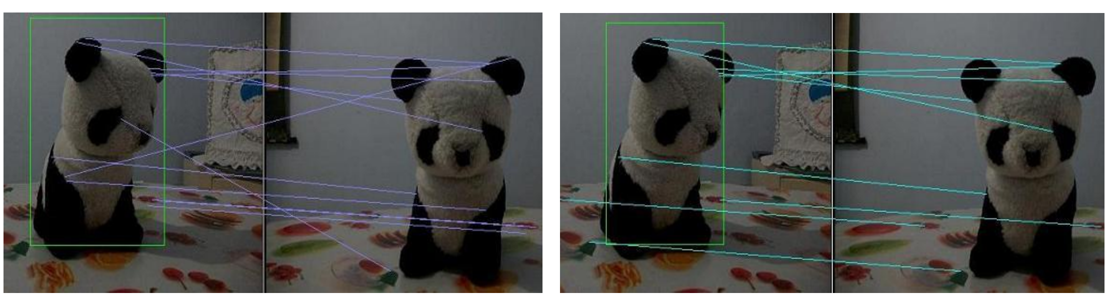
Table 1 and Table 2 lists the test results of this experiment. Comprehensive analysis of Table 1 and Table 2, confirmed the fast matching algorithm can reduce the running time of image registration. The data of Table 2 indicate that regardless of the number of feature points, relative to the BBF bidirectional matching, fast algorithm based on BBF bidirectional matching can reduce 40% of the running time of image matching at least. The fast algorithm based on BBF bidirectional matching methods can solve the problem of original bidirectional matching methods which running time is too long.

**Table 2. BBF Bilateral Matching and BBF Fast Bilateral Matching in Match Time Comparison**

| Images on | BBF bilateral matching | BBF bidirectional fast match | Reduced percentage |
|---|---|---|---|
| (The 1st pair,517,661) | 501ms | 250ms | 50.09% |
| (The 2nd pair,370,399) | 328ms | 141ms | 57.01% |
| (The 3rd pair,497,470) | 422ms | 203ms | 51.89% |
| (The 4th pair,446,721) | 453ms | 235ms | 48.12% |
| (The 5th pair,3169,2504) | 2672ms | 1437ms | 46.22% |
| (The 6th pair,2534,3364) | 2469ms | 1359ms | 44.95% |
| (The 7th pair,1704,2168) | 1625ms | 875ms | 46.15% |
| (The 8th pair,2001,2859) | 2001ms | 1093ms | 45.37% |
| Total | 10471ms | 5593ms | 46.58% |

Experiment 3: To verify Fast Bi-BBF time complexity. We select 8 set of images of the human ear experiment comparison of BBF-based bi-directional matching, the difference of BBF-based bi-directional matching based on fast matching's idea (that is, BBF-based is fast than bi-directional matching) in running time. From the data of Table 1 we can see that, regardless of the matching number of feature points, BBF-based is fast than bi-directional matching and it can reduce the running time at least 40%.

Figure 5 is the test results of panda image. Considering the change of space angle when taking pictures. Figure 5(a) is the test result which is matching with the BBF matching method. Relative to the total number is 12; the number of mismatch is five. Figure 5(b) is the test result which is matching with fast algorithm based on BBF bidirectional matching method. Relative to the total number is 10; the number of mismatch is 2.



(a) (b)

**Figure 5. Panda Image Test Results**

Above all, the test result showed that compared with the BBF matching methods this BBF bilateral matching methods can reduce the rate of mismatch. And there is 42% reduction in the running time of match between the BBF bilateral matching methods and the BBF matching methods. In the case of the number of feature points is less than 7000, the average running time is 637 ms.

## 4. Conclusions

In this paper, a fast bidirectional matching based on the BBF method is proposed. Using this method can get enough number of matching points, improve matching speed, and reduce the number of mismatch point; the matching success rate is high. In the end, the algorithm was applied to ear image recognition. Through a large number of experiments in USTB database, the acquisition angle and lighting conditions change of the human ear image, the wrong matching rate can be maintained at low levels, so can get a high recognition rate.

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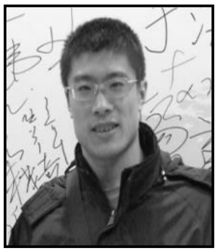
## Authors



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