Research on Purifying Paired Feature Point Based on RANSAC Algorithm

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Abstract. Aiming at the problem that the matching precision of feature points in ORB algorithm is not high enough, an improved feature point matching purification algorithm was proposed. After detecting the feature points of the images, the BF algorithm was used to calculate the Hamming distance between the feature points. Then filtering some wrong matching points through two-way matching, the preliminary matching point pairs were obtained, and then the appropriate distance threshold was set to further filter the matching point pairs, finally using the random sample consensus (RANSAC) algorithm to purify. The experimental results show that the improved feature point matching purification algorithm can improve the matching accuracy under the condition of ensuring the real-time performance of the algorithm.

1. Introduction

Visual Odometry (VO) can estimate the camera’s own motion trajectory based on the image taken by the camera, mainly used for positioning and navigation of mobile robots [1]. Compared with GPS positioning, VO does not require any prior information of the scene, and can work normally when the GPS fails. Compared with laser radar positioning, VO has low cost and has broad market application prospects. The feature detection and matching of images in VO affects the real-time and accuracy of the entire VO system. Common image feature extraction methods include: HOG features, Harris features, SIFT features, SURF features [2-4], etc. In 1999, David Lowe firstly proposed the SIFT algorithm at the International Conference on Computer Vision (ICCV) [5]. SIFT features remain invariant to rotation, scale scaling, and brightness variation, and maintain a certain degree of stability for viewing angle changes, affine transformation, and noise, widely used in feature extraction and matching of images. With the wide application of computer vision technology, the real-time requirements of the algorithm are getting higher and higher in practical applications. In 2011, Ruble proposed the ORB algorithm [6]. The ORB algorithm is two orders of magnitude faster than the SIFT algorithm, which has a good practical application effect in V-SLAM, but the matching accuracy is slightly insufficient compared with the SIFT algorithm.

The RANSAC algorithm [7] uses an iterative method to estimate the parameters of a mathematical model from a set of observation data containing a large number of outliers, which can greatly improve the accuracy of feature point matching. The accuracy of the parameters estimated by the RANSAC algorithm is proportional to the number of iterations. However, there is no upper limit to the number of iterations of the RANSAC algorithm. If the upper limit of the number of iterations is set, the result...
may not be the optimal result, and may even get the wrong result, but if the number of iterations is too many, it will reduce the real-time performance of the algorithm \[8\]. Therefore, when the generated matching point pairs are purified by the RANSAC algorithm, the RANSAC algorithm needs to be further optimized.

2. ORB Algorithm

2.1. oFAST Key Points

The FAST feature is a kind of corner feature \[9\], which is defined: if the intensity of a pixel is greatly different from the intensity of a sufficient number of pixels in its neighborhood, then the pixel can be used as a corner point. As shown in Figure 1, 16 pixels \( P_i (i = 1, 2...16) \) are distributed on a circle having a radius of 3 centered on the pixel point \( P \), and the intensity threshold is set to \( g \), if there are more than 9 points that make \(| I(P) - I(P_i) | > g \), in which \( I(P) \) represents the intensity of pixel \( P \), thus the pixel \( P \) is selected as a corner point. Then, through the non-maximum suppression method \[10\], the FAST score value of the extracted feature points is calculated, and the points with lower score values are filtered out.

![Figure 1. Photograph of detecting FAST feature points](image)

The calculation speed is best advantage of the FAST algorithm, but the FAST algorithm has two shortcomings: one is that the feature point cannot satisfy the scale change, and the other is that the feature point cannot maintain a good rotation invariance. By constructing the image pyramid \[11\] and scaling the image according to the scale factor, the sensitivity of the feature points to the scale change can be eliminated. In order to make the feature points have rotation invariance, the direction of the feature points needs to be defined, and the centroid in radius can be calculated by the moment, just calculating the ratio of the product of the coordinates of all the pixel points corresponding to \( x \) in this region to the coordinates of the coordinates of all pixels corresponding to \( y \), then the direction of the feature point is defined as the line connecting the feature point and the centroid \[12\]. The moment is defined as follows:

\[
m_{pq} = \sum_{x,y} x^p y^q I(x, y)
\]

\(I(x, y)\) represents the intensity of the image, then the centroid of this area is:

\[
C = \left( \frac{m_{01}}{m_{00}}, \frac{m_{10}}{m_{00}} \right)
\]

Taking the feature point coordinates as the origin, the direction angle can be defined by the atan2 function:

\[
\theta = \text{atan2}(m_{y1}, m_{y0})
\]

2.2. rBRIEF Descriptor

The ORB algorithm uses the BRIEF algorithm to calculate the descriptor, and the feature point descriptor extracted by the BRIEF algorithm is a binary string. In the block \( E \) of \( S \times S \) around the
feature point \( P \), \( n \) pairs of pixel points are randomly selected, Gaussian smoothing is performed on \( 2 \times n \) points, and the intensity of the point pair is replaced by the average intensity in the \( 5 \times 5 \) neighborhood. Then compare the magnitude of the intensity of each pair of points and record the comparison result as 0 and 1. Define the \( \tau \) test:

\[
\tau(E; a, b) = \begin{cases} 
1 & \rightarrow I(E_a) < I(E_b) \\
0 & \rightarrow I(E_a) \geq I(E_b) 
\end{cases}
\]

\( I(E_a) \) and \( I(E_b) \) respectively represent the intensity of block \( E \) at point \( a \) and point \( b \), and the resulting binary string is:

\[
f_n(p) = \sum_{i=1}^{15 \times 15} 2^{i-1} \tau(p; x_i, y_i)
\]

The descriptor generated by the BRIEF algorithm has a good matching effect when the rotation change is not large, but a large number of mismatches occur when the matched image undergoes a large rotation. Therefore, the improved rBRIEF algorithm is used in the ORB algorithm to calculate descriptors. In the rBRIEF algorithm, the point pairs of the descriptor are not randomly generated, but statistical methods are used to select the point pair. The method of selecting a point pair set is as follows:

1. Firstly, 300k feature point test sets are established. Point pairs are obtained by \( M \) methods in the neighbourhood of each feature point, and a binary matrix \( Q \) of \( 300k \times M \) is synthesized.
2. For the matrix \( Q \), the average value of each column is obtained, and the column vectors of the \( Q \) matrix are reordered in order from the average value to the distance of 0.5, forming a matrix \( T \).
3. Greedy search: put the column vector to \( R \) which is closest to 0.5 in \( T \), compare the next column in \( T \) with all the elements in \( R \), and calculate whether their correlation reaches the threshold. If yes, the current position is discarded, and if it is not reached, it is added to \( R \) until 256 pairs of descriptors are selected.

3. Feature Point Matching Purification

3.1. Preliminary Screening

Since the number of iterations of the RANSAC algorithm directly affects the accuracy of the \( M \) matrix estimation, the excessive number of iterations reduces the real-time performance of the ORB algorithm. Therefore, in order to reduce the number of iterations as much as possible, before the improved RANSAC algorithm is used to purify the feature matching point pairs, the feature matching point pairs need to be initially screened to filter out the more obvious mismatched pairs.

3.2. RANSAC Algorithm

When the RANSAC algorithm is used to purify the matched feature point pairs, it is necessary to estimate the parameters of the transformation matrix \( M \) as accurately as possible from the data samples containing incorrect matching points, and find the estimation result satisfying the error condition by iteratively. And constantly update the optimal solution. The specific algorithm flow is as follows:

1. Randomly select a minimum RANSAC sample from the matched feature point pairs, that is 4 pairs of feature matching points, and set the upper limit of the number of iterations.
2. Solve \( M \) based on RANSAC samples.
3. Determine whether the other feature point pairs in the sample set satisfy the transformation matrix \( M \) according to the error threshold.
4. If there are enough sample feature point pairs to satisfy \( M \), then \( M \) is reserved, otherwise the estimation is considered wrong and the RANSAC sample is reselected.
5. Repeat steps (1)-(4), and when the number of iterations reaches the upper limit, the algorithm ends.
3.3. Improved Preliminary Screening

In the traditional RANSAC algorithm, the selection of data samples is based on random sampling. The selection of the next set of sample data is not related to the previous group, and the effect of stepwise optimization cannot be achieved. But the improved RANSAC algorithm obtains the transformation matrix $M$ which satisfies the matching rate threshold, the selection of the next set of sample data is constrained by certain conditions, and the more suitable transformation matrix $M$ is directionally searched. The specific algorithm steps are as follows:

1. Select 4 pairs of feature matching points $A_1B_1, A_2B_2, A_3B_3$, and $A_4B_4$ as the minimum RANSAC samples, the upper limit of the number of iterations is set to $K$, the error threshold is set to $W$, the correct matching rate threshold is set to $P$, and the optimal match rate is set to $L$.

2. Solve $M$ based on RANSAC samples.

3. Verify the remaining matching point pairs with $M$ and calculate the error. If the error is less than the threshold $W$, it is considered to be the correct matching point pair. Calculate the correct matching rate $P_k$. If $P_k < P$, return to step (1). If $P < P_k < L$, perform step (4). If $P_k > L$, output $M$.

4. Compare the Hamming distances of $A_1B_1, A_2B_2, A_3B_3$, and $A_4B_4$, and make the matching point pairs with the smallest Hamming distance as the fixed sample points of $(k+1)$ iterations. Then randomly select 3 pairs of feature matching points to form the minimum RANSAC samples.

5. Calculate the correct matching ratio $P_{k+1}$ of the $(k+1)$ iteration. If $P_{k+1} < P_k$, re-randomly extract 3 pairs of feature matching points. If $P_k < P_{k+1} < L$, return to step (4). If $P_{k+1} > L$, output $M$.

6. When the number of iterations reaches the upper limit $K$ or the optimal matching rate $L$ is satisfied, the algorithm ends.

4. Analysis of Experimental

The experimental platform is Linux Ubuntu 16.04 operating system, i5-8250U CPU, 1.6GHz, 8G memory, using open source computer vision library OpenCV3.1.0. In the experiment, two mobile phones were used to capture two pictures with a resolution of 640×480 from different angles and different distances.

The Figure 2 shows the feature point picture of a desktop photo extracted using the ORB algorithm. From the photo, it can be found that the feature points extracted by the ORB algorithm are concentrated. The Figure 3 is a feature point matching diagram without using any purification algorithm, the Figure 4 shows a feature point matching diagram purified by the RANSAC algorithm, and the Figure 5 shows a feature point matching diagram purified by the improved RANSAC algorithm.

![Figure 2. Photograph of ORB feature points](image-url)
From the feature point matching graph, the feature point matching graph using RANSAC algorithm has obvious purification effect, but there are still obvious mismatching point pairs. However, in the feature point matching graph purified by the improved RANSAC algorithm, no obvious mismatched pair is seen, which proves that the improved RANSAC algorithm has better matching accuracy than the traditional RANSAC algorithm. Moreover, the calculation speed is not degraded compared with the traditional RANSAC algorithm. Since the expected matching rate threshold is set, when the optimal matching rate is reached within the upper limit of the number of iterations, the matching speed can be greatly improved. The specific data is shown in Table 1.

| Algorithm          | Matching Logarithm | Error Logarithm | Correct Rate | Total Time(s) |
|--------------------|--------------------|-----------------|--------------|---------------|
| RANSAC             | 154                | 23              | 85.06%       | 0.348         |
| Improved RANSAC    | 121                | 9               | 92.56%       | 0.322         |
5. Summary

Feature matching is a key part of VO. The accuracy of feature matching directly affects the accuracy of camera pose estimation. Aiming at the problem that the matching accuracy of ORB algorithm is not high enough, firstly, the two-way matching and Hamming distance threshold are used to match the matching feature point pairs, and some obvious mismatched pairs are filtered out, then purifying by improved RANSAC algorithm. The experimental results show that the improved RANSAC algorithm effectively improves the accuracy of feature point matching, and does not affect the real-time performance of the ORB algorithm. It lays a good foundation for the next step of studying the monocular visual odometer and V-SLAM system.

6. References
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