A FAST AND EFFECTIVE OUTLIER DETECTION METHOD FOR MATCHING UNCALIBRATED IMAGES

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ABSTRACT

Many image analysis tasks require an outlier detection procedure to identify the false matches. In this paper, a fast and effective outlier detection method is presented to match images in the uncalibrated case. This method employs a hypothesis test on the consistency of dominant orientations of the feature points to significantly increase the detection speed. Moreover, it can also effectively find the outliers that can not be identified by traditional RANSAC-based methods using epipolar constraint. Note that our method does not require the prior knowledge of camera parameters or the percentage of outliers. The experimental results show that our method outperforms the classical RANSAC-based methods both in speed and in accuracy of the results.

Index Terms **—** Outlier detection, image matching, orientation consistency test, RANSAC, epipolar constraint

1. INTRODUCTION

Outlier detection is an indispensable step in many computer vision and image analysis applications. The outliers are false matches of features that do not correspond to the same location in the real scene. The outlier detection methods usually utilize robust estimators and some constraints to find the outliers. In the uncalibrated case there are few constraints that can be used due to the unknown camera parameters and a variety of image content. The methods that combine the RANSAC-based estimators [1] and epipolar constraint [2] have been widely used and proved to be greatly effective in outlier detection [3].

The RANSAC (RANdom SAmple Consensus) algorithm [1] is a simple but powerful algorithm for computing model parameters when the given data set has a high percentage of outliers. As a robust estimator it has become a de facto standard in the computer vision and image analysis field. There also exists other estimators that could be used for rejecting outliers such as LMedS [4]. But they were found not as effective as RANSAC when the percentage of outlier is high or they can not give satisfied results in complicated applications.

There has been a raft of modifications to the basic RANSAC algorithm in the literature aiming at improving the performance of outlier detection. MLESAC [5] uses a different cost function to perform the maximum likelihood estimation instead of maximizing the number of inliers. It assumes that outliers have a uniform distribution and the parameters of the noise need to be provided as a prior knowledge. Some methods were proposed to overcome the drawbacks of the random sampling procedure in RANSAC, such as Guided-MLESAC [6] and PROSAC [7]. They draw the samples in a semi-random way from the match set. The drawing procedure tends to choose the matches that are more likely to be inliers according to the prior probabilities from the matching process or the scores indicating the system's belief whether the match is correct. The R-RANSAC [8] uses a statistically optimal strategy aiming to reduce the time for computing consensus scores. It performs a pre-evaluation test before checking all the matches. Recently, some methods like ARRSAC [9] have been proposed for the applications that require real-time performance. They try to obtain the best solutions with a limited time budget.

There exist some outlier detection methods that do not utilize robust estimators and epipolar constraints. ROR [10] takes into account the spatial information of the correspondences to reject the outliers even in cases where the percentage of false matches is very high. The limitation of ROR is that it assumes there is no significant camera rotation about the principal axis. And the camera's focal length is required to be known.

In this paper we propose a fast and effective outlier detection method for matching uncalibrated images. Our method employs a hypothesis test on the consistency of dominant orientations of the feature points. This prevents from checking the epipolar constraint with hypotheses that have low probabilities to be good. With this test, our method can also effectively identify the outliers that can not be identified by existing RANSAC-based methods using epipolar constraint. Experimental results show that the speed of our methods is about 5 times faster than the standard RANSAC method and the results contain less outliers.

The rest of this paper is organized as follows. Section 2 briefly describes RANSAC-based outlier detection methods and analyzes their limitations. Section 3 presents in detail the proposed method that utilizes hypothesis tests on the consistency of dominant orientations. Section 4 gives some experimental results on real images and the comparison with other methods. Conclusions and future works are discussed in Section 5.

2. THEORY OF OUTLIER DETECTION METHODS

The idea of the outlier detection methods is to check the matches against a constraint. The matches that are consistent with the constraint are identified as good matches while the matches that violate the constraint are rejected as outliers. Besides epipolar constraints, there exist some constraints could be used in image matching tasks such as topological constraint, ordering constraint, uniqueness constraint, etc. However, in the uncalibrated case the camera parameters and the motions between images are unknown. There could also be large rotation or significant scale changes between the images. The epipolar constraint has proved to be the most important and effective constraint for outlier detection in uncalibrated and complicated cases [2] [3].

The epipolar constraint is a geometry constraint between two views that are generated by two cameras observing a same object at different positions. If a match is correct then each feature point of the match should lie on its epipolar line. The epipolar line is determined by the coordinates of the points and the fundamental matrix. The fundamental matrix encodes all the geometric information between the two views and can be computed from the correct feature point correspondences.

The robust estimators like RANSAC are used to compute the fundamental matrix. They first randomly choose 8 correspondences from the match set. And then compute the matrix and check all matches against the epipolar constraint encapsulating by the fundamental matrix. Usually the distance between the feature point and its epipolar line is calculated to find the potential outliers. The procedure is repeated until reaching certain conditions and the result with the largest number of correct matches is output as final result.

There are two problems in the above standard RANSAC-based method. The first problem lies in the constraint checking stage. The 8 randomly drawn correspondences inevitably contain outliers, therefore the resulting fundamental matrix has the probability to be incorrect and the following checking stage will be meaningless. When the initial match set has a high percentage of outliers, it can be predicted that a number of fundamental matrix computations are not necessary. If we can identify the hypotheses that have high probabilities to be good and only perform the checking stage with these hypotheses, the efficiency of the method could be improved.

The second problem is that there exist some outliers, which lie in their epipolar lines. That means they can pass the epipolar constraint checking and will be recognized as correct matches. As shown in Fig. 1, the red crosses on both images indicate the feature points and the number near the cross is the index of matches. Feature points with the same index belong to a match. There are three outliers (false matches) with index 2, 42 and 61. They are marked with white circles for convenience. As far as we are concerned, such type of outlier can not be found by the existing outlier detection methods.

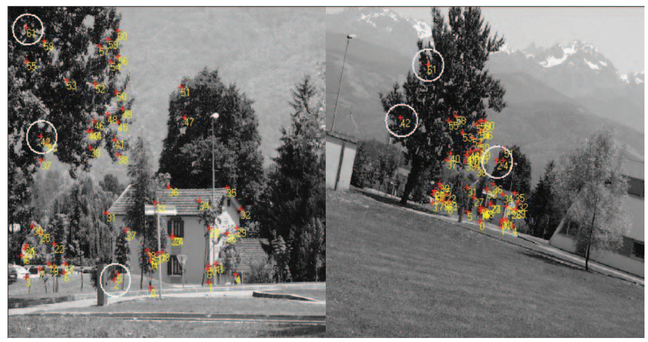

Fig. 1. Outliers lie in the epipolar lines

In the next section we will introduce a hypothesis test on the consistency of dominant orientations to deal with the above two problems.

3. PROPOSED METHOD USING ORIENTATION CONSISTENCY TEST

Dominant orientation is an angle value assigned to each feature point, which is calculated from the gray values in a small patch of images. It is used to achieve rotation invariant in matching procedure. Most state-of-the-art matching methods calculate the dominant orientations for feature points and store them for matching purpose, such as SIFT [11] and SURF [12].

From its computation procedure we can reach a conclusion that the difference of the dominant orientations between the two points in a correct match nearly equals the rotation angle between the two images. This can be easily understood as follows. Suppose the dominant orientation of one feature point is α. After rotating the image by β counter-clockwise, the dominant orientation of this feature point should be $\alpha+\beta$. Therefore, if the same location is detected as one feature point then its dominant orientation should be $\alpha+\beta$. Since the feature points are detected separately in two images, there always exist location errors and the assignment of dominant orientation can not be so accurate. Ideal in-plane rotation is also hardly found in practice. So even for correct matches the differences between the dominant orientations could not be the same value as the rotation angle of two images. The constraint of dominant orientation can then be defined as:

$$|\theta_d - \psi| < \sigma, \tag{1}$$

where θ_d is the difference between the dominant orientations of the two feature points in a correct match. ψ is the rotation angle between two images and σ is a threshold. We can then check all matches against this constraint to identify the outliers.

3.1 Proposed outlier detection method

The steps of the proposed outlier detection method using orientation consistency test are described as follows:

Step 1: Randomly draw 8 matches from the match set M.
Step 2: Let the differences of the dominant orientation between two features in each match be φ_i (i=1, 2, ..., 8). Accumulate φ_i to an array R with length of 36. Each element in R represents 10 degrees of rotation angle. If the value of φ_i falls into the orientation represented by R_j, then $R_j=R_j+1$ and $S_j=S_j+\varphi_i$. S is an array with the same length of R and S_j corresponds to the accumulated rotation angle in R_j.
Step 3: Calculate sums of every three neighboring elements in R. Select the max value as R_{sum_max}. If $R_{sum\_max} < N_t$, then go to Step 1. Here N_t is an empirical parameter. Otherwise let $\varphi_{aver}=S_{sum\_max} / R_{sum\_max}$. S_{sum_max} is defined as the sum of three neighboring elements in S corresponding to R_{sum_max}.
Step 4: Use 8-Point algorithm to compute fundamental matrix $\boldsymbol{F}_{tmp}$ from the 8 matches. For each match in M, compute the maximum distance r between the feature points and the epipolar lines. If $r \le d_t$, then $N_c=N_c+1$. d_t is a threshold of the distance and N_c stands for the number of matches that are consistent with $\boldsymbol{F}_{tmp}$.
Step 5: If N_c <20 then go to Step 6. Otherwise for each match that is consistent with $\boldsymbol{F}_{tmp}$, compute the difference of the dominant orientations θ_k. If $|\theta_k-\varphi_{aver}|\ge\sigma_t$, then $P_k=P_k+1$. σ_t is the threshold of difference of the dominant orientations and P_k keeps the penalty score for match k.
Step 6: If $N_c > N_{store}$, then $N_{store}=N_c$. N_{store} is the maximum number of N_c by far. Record the fundamental matrix $\boldsymbol{F}_{tmp}$, φ_{aver} and the matches being consistent with $\boldsymbol{F}_{tmp}$. The former values are discarded. If the terminated condition is reached then go to Step 7. Otherwise go to Step 1. The terminated condition could be that the predefined number of random drawings is reached or N_{store} is larger than a certain number.
Step 7: For each match that is recorded in Step 6 corresponding to the last N_{store}, compute the difference of the dominant orientation θ_k. Add one match to the final result if and only if $|\theta_k-\varphi_{aver}| < \sigma_t$ and $P_k<P_t$. P_t is the threshold of the penalty score.

Since in uncalibrated cases the rotation angle between two images is unknown, we could not directly use the dominant orientation constraint according to Eq (1). Here an alternative method is adopted to validate this constraint. It employs a test on the consistency of dominant orientations, which consists of step 2 and 3. The rotation angle between two images is estimated with φ_{aver}. R_{sum_max} is defined as the maximum number of matches that have consistent dominant orientation in the 8 chosen matches. Here having consistent dominant orientation means that the matches have similar differences of the dominant orientations. The variation of the differences should be no more than 20 degrees, which is defined in step 2. If R_{sum_max} is larger than N_t, the validation procedure continues. The 8 chosen matches are now considered to have high probability to generate the correct fundamental matrix. And they would maximize the number of inliers in this checking round. If R_{sum_max} is smaller than N_t, the validation procedure according to these 8 samples is terminated right away. This avoids the calculation of the fundamental matrix and the following epipolar constraint checking stage, which are the most time consuming parts in RANSAC-based methods.

Note that in step 5 we use a mechanism of penalizing the matches with big differences of the dominant orientation. The matches are scored if the differences of the dominant orientation are larger than the threshold σ_t. Here φ_{aver} is considered to be the estimation of the rotation angle of two images. These matches are likely to be the kind of outliers that lie in their epipolar lines. Although they happen to pass the epipolar constraint checking, they will be identified by the dominant orientation constraint. When we get the match set corresponding to the maximum number of inliers, the matches that are not able to pass the test on the dominant orientation constraint will be removed as well as the matches that have been penalized in the whole procedure. The remaining matches are output as the final result.

The value of N_t is set to 7, which achieves best performance in our tests. The values of thresholds d_t, σ_t, and P_t are 1.0, 25 and 1, respectively. We use these parameters throughout the following experiments.

4. EXPERIMENTAL RESULTS

In this section some experimental results on real images are demonstrated. Table 1 shows the comparison of experimental results with standard RANSAC algorithm and R-RANSAC algorithm. The experiments are carried out on the images shown in Fig. 1. The initial match set contains 236 matches and 74 of them are correct matches. The initial matching result is obtained with the matching method in [13], which uses a slightly modified version of SIFT's algorithm to compute the dominant orientations of the feature points.

For each method we perform the outlier detection for 100 times and calculate the averages. The terminated condition is that the maximum number of inliers is larger than 60 during the epipolar constraint checking stage.

Table 1. Comparison of experimental results with other methods

Method	Average Running Time (ms)	Average Number of Matches	Average Number of Correct Matches	Average Number of Outliers
RANSAC	1130	63.8	60.2	3.6
R-RANSAC	819	62.6	59.6	3.0
Our Method	205	62.0	61.8	0.2

The second column is the average running time of outlier detection procedure. The third column gives the average number of total matches in the final results. The fourth column is the average number of correct matches in the final results. And the last column is the average number of outliers in the final results. It is shown that our method runs about 4 and 5 times faster than other two methods. Moreover, our method generates the largest number of average correct matches and the lowest average number of outliers.

Figure 2 shows the comparison of false match ratios between our method and RANSAC method. In this experiment we use the **Boat** image sequence in INRIA public image database[1], which is a standard test set. The images in this sequence contain rotation and scale changes.

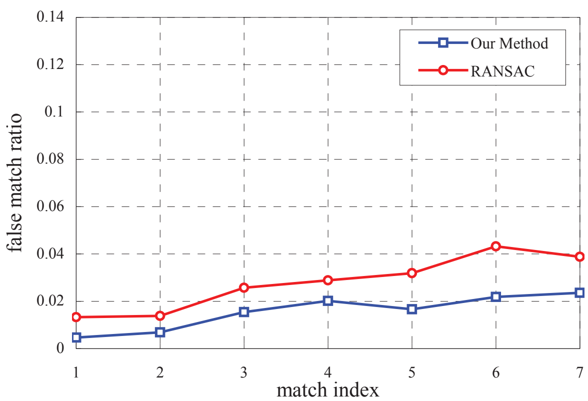

Fig. 2. Comparison of false match ratios

Images with index 1 to 7 are matched to the reference image with the index 0 in turn. Here we use the same matching method as mentioned above to obtain the initial matching results. For each initial matching result we perform the outlier detection using two methods to obtain the final matching result. The x axis is the index of 7 final matching results. The y axis indicates the false match ratio in the final matching results. Our method provides results with lower false match ratio than the standard RANSAC method in all matching tests.

5. CONCLUSIONS

We propose a fast and effective outlier detection method for matching uncalibrated images. The dominant orientation constraint is enforced through a hypothesis test to obtain significant computational savings, which is performed before the validation of epipolar constraint. It can also identify the outliers that can not be found by existing methods to provide results with better quality. Future work includes the study of incorporating non-uniform sampling into our method for further performance improvements.

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