Analysis of Image Registration Algorithm RANSAC and Its Improved Algorithm

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Abstract. The RANSAC (random sampling consensus) algorithm is an estimation method that can obtain the optimal model in samples containing a lot of abnormal data. This algorithm uses a small number of points in the data to estimate the model, and then uses the remaining points to check the model. It is now widely used in computer vision image stitching. This algorithm has disadvantages such as slow operation speed and poor sample adaptability. In order to improve the efficiency of image registration, many researchers have made improvements on the basis of the RANSAC principle. This article introduces the principles and shortcomings of RANSAC, and introduces four ways to improve it in view of its shortcomings. The advantages and problems of the improved algorithm are analyzed to provide a basis for the field of image registration.

1. Introduction

Image stitching refers to the process of stitching multiple photos of the same scene with a certain overlapping area into a complete panorama. The most important thing in image stitching is the image registration algorithm. It can perfectly match and merge the pictures collected from different angles and different lighting factors into a panorama. The panoramic image can display the feature information of things within the range in a multi-directional and more comprehensive manner. In recent years, the focus of research on image stitching at home and abroad is basically on image registration.

In image registration, the feature points extracted by the feature extraction algorithm are prone to mismatches, so the matching effect is not good, and the RANSAC algorithm can effectively eliminate the mismatched point pairs, so that the image can achieve high-precision splicing effects. It is to estimate a high-precision parameter model through continuous iteration in a data set with errors. The flow of the RANSAC algorithm is as follows:

1. Select a random sample point pair with the least requirements for solving the model in the data set, and solve the model parameters according to the selected sample point pair;
2. Evaluate all points according to the model parameters, the ones smaller than the error threshold are the inner points, otherwise they are the outer points;
3. If the number of points in the current model exceeds the set threshold, it will be used as a candidate model and re-sample and repeat the above steps; if the number of points in the current model is less than the threshold, the model will be discarded and re-sampled;
4. When the number of iterations is greater than the maximum number of iterations N, stop the
iteration, otherwise repeat steps (1) to (3).

(5) After N iterations, if the number of interior points is less than the threshold, the algorithm ends in failure. Otherwise, the sample with the largest number of interior points is used to obtain the final model.

In order to ensure the feasibility of the algorithm, under the confidence p, at least one set of data in K samplings are all interior points, so the calculation formula for the minimum number of iterations K is as follows:

\[
K = \frac{\log(1 - p)}{\log(1 - \varepsilon^n)}
\] (1)

Among them is the proportion of inliers in the data set, n is the minimum sample to get the model parameters, and p is the confidence level (value 0.95 or 0.99).

It can be seen from the formula (1) that the RANSAC algorithm has great limitations: (1) The amount of calculation is huge and the time consuming is long. The efficiency of the method is related to the ratio of interior points and the size of the data set. (2) The extraction accuracy is not high. The method selects the smallest subset when calculating the parameters from the perspective of efficiency, and often the non-optimal parameters are obtained. In view of the shortcomings of the above algorithm, the main improvement ideas of the RANSAC algorithm: the selection method of iterative samples (the selected samples are all interior points) and the test of model parameters (the model does not need to be tested using all points).

2. Improved algorithm based on RANSAC

2.1. M-RANSAC

The M-RANSAC algorithm[1] first uses the HARRIS algorithm to extract the feature points, then uses the two-way normalization method to match the feature points, and then uses the distance pair value to sort the set of feature matching points according to the level of credibility, so that the set of point pairs with high credibility Ranked in the front, and then prioritize the model estimation of the set from the high-quality matching points, so as to make the correct model appear earlier; reduce the number of iterations and the amount of calculation, so the efficiency of the algorithm can be improved.

In the matching feature point pairs, if the i pair and the k pair are correct matching point pairs, they have a relationship with each other:

\[
x_i^i - x_r^i = x_j^k - x_r^k
\] (2)

\[
y_i^i - y_r^i = y_j^k - y_r^k
\] (3)

Formula (2) is that the line mark distance pair value of the i-th pair of feature points is equal to the line mark distance pair value of the k pair of feature points. Similarly, the formula (3) is the distance pair value of the column standard, and any two pairs of correct matching points should satisfy the above formula.

The M-RANSAC algorithm steps are as follows:

(1) Find the distance pair value of all feature point pairs, the row index value is stored in the x matrix, and the column index is stored in the y matrix.

(2) Count all the types of distance pairs, and record the number of each type.

(3) Arrange in descending order according to the number of types, and then divide the feature point pair set S into N sets (N is the number of types) $S_1 \sim S_N, S_1$ is the feature point pair set corresponding to
the most number of distance-value types, and \( S_2 \) is the second most numerous category corresponding set.

4) Re-divide all sets in (3) into \( J \) sets \( \{S_1\}, \{S_1, S_2\}, ..., \{S_1 \sim S_N\} \), set \( J \) incremental data error rates, and calculate the different error rates for each set. The maximum number of samples \( \text{Max} \).

5) Randomly select 4 pairs of matching points from the \( i \)-th set (\( i \) starts from 1), and solve the model parameters according to the selected point pairs. Once the collection is iterated, the number of samples is increased by 1. When the number of samples in the collection is greater than the maximum number of samples in the first collection, it will move to the next collection to start sampling. When the number of samples is less than \( \text{Max} \), go to step (6).

6) Count the interior point ratio and the Euclidean distance sum of the interior points in the current set model parameters. If the interior point ratio is greater than the set threshold \( B_1 \), and the Euclidean distance sum of the interior points is less than the set threshold \( T_1 \), then go to step (7), otherwise return to step (5).

7) Check the full data according to the model parameters. If the interior point ratio is greater than the threshold \( B_2 \) of the full data interior point ratio, and the Euclidean distance sum of the interior points is less than the full data threshold \( T_2 \), then go to step (8), otherwise go back to step (5).

8) Calculate all interior points according to the model parameters to obtain the optimal model.

The advantage of \( M \)-RANSAC is that it has good robustness when the model data volume is large and the error rate is high. The disadvantage is that more parameters need to be manually set.

2.2. Real-time adaptive RANSAC algorithm
This algorithm is divided into two parts: adaptive pre-check and iterative threshold pre-check. The affine transformation model is selected as the mapping model between images, and only 3 sets of matching points are needed to determine the unique solution\[^3\].

Adaptive pre-check steps:
1) Randomly select 3 groups from all matching point pairs, and perform collinear and regional similarity detection. If the three points are collinear or one of the points falls on the moving object, discard these point pairs and re-sampling; otherwise, build an affine transformation model based on these 3 sets of matching point pairs;

2) Set the error threshold \( \omega \) for interior point judgment, use the SURF algorithm for image matching, and then sort the Euclidean distance errors of the matching point pairs in ascending order, and select the first 100 groups of feature point pairs with the smallest Euclidean distance as the pre-test samples;

3) Set the pre-test threshold \( C \), use the samples in (2) to test the model one by one and count the number of internal points \( F_1 \). If \( F_1 > C \), test all matching point pairs and assign \( F_1 \) to \( C \), otherwise return first step.

Iterative threshold pre-inspection steps:
1) After the model passes the pre-test, count the remaining matching point pairs \( F_2 \) that pass the model;

2) At this time, the total number of interior points \( F = F_1 + F_2 \); if \( F \) is greater than the number of interior points \( F_{\text{best}} \) of the optimal sample previously sampled, assign \( F \) to \( F_{\text{best}} \), and update the interior point rate and the number of iterations at the same time; otherwise, return to adaptive and detection Step re-sampling.

3) When the number of samples \( D \) is greater than \( M \), the loop ends, and the optimal affine transformation model \( H \) is obtained. The whole process is shown in Figure 1.

The sampling times \( M \) and the interior point rate \( \varepsilon \) meet:

\[
(1 - \varepsilon^3)^M = 1 - P
\]

(4)

\( P \) is the degree of confidence, and generally takes a value of 0.99.
The algorithm can automatically update the pre-test threshold and iterative threshold for different samples, can adapt to different samples well, and increase the adaptability of the algorithm.

2.3. Improved RANSAC method with HSI model
In the iterative process of the RANSAC algorithm, most of the feature points are used to repeatedly verify the model, resulting in a large amount of calculation and low efficiency. Therefore, Yang Yu [3] et al. introduced the HSI model to constrain the feature points twice. HSI is hue, saturation, and brightness. The corresponding point pairs that meet these three constraints are regarded as feature
point pairs, otherwise they are directly eliminated. The process is as follows:

1. The matching feature point set \( S \) is extracted by the SURF algorithm, and the initial transformation matrix \( H \) and the Euclidean distance error threshold \( d \) are obtained by RANSAC;

2. Extract a group of feature points to be tested from \( S \), use \( H \) to calculate the Euclidean distance \( d_1 \) of this group of feature points, set the threshold to \( p \), if \( d - p \leq d_1 \leq d + p \), it is tentatively set as a feature point pair, otherwise it is directly removed.

3. Due to the influence of light and other factors, set a certain error threshold, and perform hue, saturation and brightness detection on the selected feature point pairs. If the error threshold is met, the corresponding point is a feature point pair, otherwise it is directly removed.

4. Perform the above two constraint conditions one by one on the feature point set \( S \) until the end of the test.

The advantage of this algorithm is that the accuracy of feature point matching is improved; the downside is that it takes less time than RANSAC, but when the amount of data is huge, because there is one more inspection process for each feature point, it takes time increase.

2.4. MAGSAC algorithm

The MAGSAC (Marginalizing Sample Consensus) algorithm was proposed by Daniel Barath, Jana Noskova and others in 2019\[4\]. The algorithm uses the \( \sigma \)-consen (threshold consistency) method to eliminate the need for artificially setting the interior point threshold \( \sigma \), and proposes a new to evaluate the quality of the model, a new termination standard for RANSAC was established based on the marginalization method. Specific steps are as follows:

1. Taking \( \sigma \) as a random variable, by solving the expectation of \( Q \), the average value \( Q^* \) of the model quality is obtained. The process of solving the expectation is the process of marginalizing and eliminating \( \sigma \). The mathematical form of the model quality function \( Q \):

\[
Q^*_{\text{MAGSAC}}(\theta, P) = \frac{1}{\sigma_{\text{max}}} \int_{0}^{\sigma_{\text{max}}} \ln L(\theta, P | \sigma) d\sigma
\]

\[
\approx -|P| \ln l + \frac{1}{\sigma_{\text{max}}} \sum_{i=1}^{K} [i(\ln 2C(p)l - \rho \ln \sigma_i) - \frac{R_i}{\sigma_i^2} + (\rho - 1)LR_i](\sigma_i - \sigma_{i-1}),
\]

Among them, \( \theta \) is the model parameter, \( P \) is the input point set, and \( \sigma \) is marginalized, so this function has nothing to do with \( \sigma \).

2. Calculate the probability that a point is an interior point according to the marginalization \( \sigma \), and use it as a weight to optimize the weighted least squares method to optimize the model. The solution form of interior point probability:

\[
L(p | \theta) \approx \frac{2C(p)}{\sigma_{\text{max}}} \sum_{i=1}^{K} (\sigma_i - \sigma_{i-1})
\]

\[
\sigma_i^{-\rho} D^{\rho-1}(\theta_{\sigma_i}, p) \exp \left( \frac{-D^2(\theta_{\sigma_i}, p)}{2\sigma_i^2} \right) .
\]

3. Solve the new number of iterations by the method of marginalization \( \sigma \).
The algorithm has a high degree of automation and can significantly improve the accuracy of model estimation. The disadvantage is that it will increase the amount of calculation.

2.5. Other improvement methods

Common improved algorithms include selection methods based on iterative samples: PROSAC[5], NAPSAC[6] and GROUPSAC[7]; methods based on sample pre-inspection: RANSAC-Tdd[8], RANSAC-SPRT[9] and Bail-Out Test[10]; methods based on model solving: LMedS[11], Mlesac[12] and Mapsac[13]. The classification of common improved algorithms is shown in Table 1.

In addition, Fan Yanguo and others improved RANSAC by randomly sampling in blocks to improve the accuracy of transformation parameters, thereby improving the degree of image matching[14]. Lei Siwen et al. used the principle of spatial consistency to detect the data set, thereby reducing the number of iterations[15]; combined with the PROSAC algorithm to sort the processed sample points to produce a better and accurate interior point set; finally, the L-M algorithm is used to obtain a high-precision image transformation matrix model.

Table 1. Common improved algorithms.

| Selection method based on iterative samples | Method based on sample pre-inspection | Methods based on model solving |
|------------------------------------------|-------------------------------------|--------------------------------|
| PROSAC                                    | RANSAC-Tdd                          | LMedS                          |
| NAPSAC                                    | RANSAC-SPRT                         | Mlesac                         |
| GROUPSAC                                  | Bail-Out Test                       | Mapsac                         |

3. Concluding remarks

The RANSAC algorithm plays a pivotal role in the field of image registration, and plays an important role in the field of target detection, remote sensing, and surveying and mapping[16]. At present, many scholars are studying its improved algorithm, which can improve the efficiency or accuracy of image registration. However, the research can also be strengthened from the following aspects: (1) In the feature point matching, all the outer points are excluded as much as possible, and the function of the inner points in the algorithm is improved. (2) Improve the automaticity of the algorithm and reduce the artificially set threshold. (3) Improve the adaptability of the algorithm; when the proportion of external points is large, the correct model can still be obtained.

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