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An Improved RANSAC Algorithm for Simultaneous Localization and Mapping

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Abstract. Image feature matching is an important part of SLAM (Simultaneous Localization and Mapping algorithm). In order to improve the implementation efficiency of standard RANSAC algorithm, this paper proposed a novel improved RANSAC algorithm to deal with the mismatch in the image matching procedure. Our method deals with raw sample data and predict the inliers in the sample data according to the Euclidean distance between feature descriptors. And then we estimated the homography matrix with the selected sample. The homography matrix is used to eliminate the characteristics of mismatch. Furthermore, a binary environment dictionary is created for loop detection and the experimental results demonstrate that this method improves the speed of loading time of the dictionary and the accuracy of SLAM.

1. Introduction

Image feature matching and scene recognition are two important parts of Simultaneous Localization and Mapping algorithm. Images can be matched by feature detection and feature match. How to effectively eliminate mismatch is one of the important research contents in computer vision and other related fields [1, 2]. The standard RANSAC (random sample consensus) algorithm is a robust method which proposed by Fischler and Bolles in 1981[3]. This algorithm can effectively realize the rejection of error information, and is a powerful model parameter estimation method. It is possibly the most widely used in image feature mismatch elimination and estimating a homography automatically [4, 5]. Moreover, the bag of words model [6] is widely used for scene recognition [7]. It used in the ORBSLAM [8] algorithm. However, because of the blindness in the processing of RANSAC algorithm, the efficiency of the algorithm is relatively low. In recent years, many advanced RANSAC algorithms have been proposed such as Pre-emptive RANSAC [9], R-RANSAC [10], Guided MLESAC [11] and PROSAC [12] (Progressive SAC). MLESAC [13] (Maximum Likelihood SAC) used the Gauss unbiased estimation algorithm, the maximum likelihood estimation process was converted to the minimum cost function. LO-RANSAC [14] (Local Optimized RANSAC) improved the accuracy of the algorithm by evaluating inliers two times. Recently, Chum and Matas developed a novel randomized RANSAC algorithm to save computational load and improved the algorithmic speed by typically evaluating a fraction of data points for models contaminated with outliers. In order to further improve the speed and accuracy of RANSAC and Simultaneous Localization and Mapping



algorithm, we present an improved RANSAC algorithm and build a binary environment dictionary for loop closure detection [15]. According to the experimental results, the time-consuming is shorter than traditional method and the accuracy is higher than ORBSLAM.

The rest of this paper is organized as follows: In Section 2, we summarize the main steps about how to build a binary environment dictionary. In Section 3, the main steps of the improved RANSAC algorithm are described. Our experiment results and analyses are described in Section 4. Finally, conclusions are drawn in Section 5.

2. The Creation of Binary Environment Dictionary

Scene recognition is an important part of SLAM system. The bag of words model is widely used for scene recognition. ORBSLAM algorithm has embedded a scene recognition module based on DBow2 for loop detection. However, there are some shortcomings in the public dictionary which used by the ORBSLAM algorithm. For instance, it costs too much time when loading dictionary in the text file. In order to increase the speed of loading and the accuracy, we create a binary environment dictionary.

The main steps are shown in figure 1. Firstly, a large set of environment images are obtained by camera. We use the camera to take an environment video and then every frame of environment video is saved. In order to enrich the environmental information, we rotated the frames. Secondly, the ORB feature points of all the images in the set and the ORB descriptors for each feature points are obtained. Thirdly, we use the K-Means algorithm to cluster the set of feature descriptors for the amount of bags we defined and train the bags with clustered feature descriptors. The visual dictionary is a hierarchical clustering tree, and each center of the leaf nodes is taken as a visual word. Fourthly, we obtain the visual vocabulary. Finally, the dictionary in the text file format is converted into binary type file by using boost libraries. In figure 2, we convert image features to feature histogram. Histogram is obtained from the binary environment dictionary which built above.

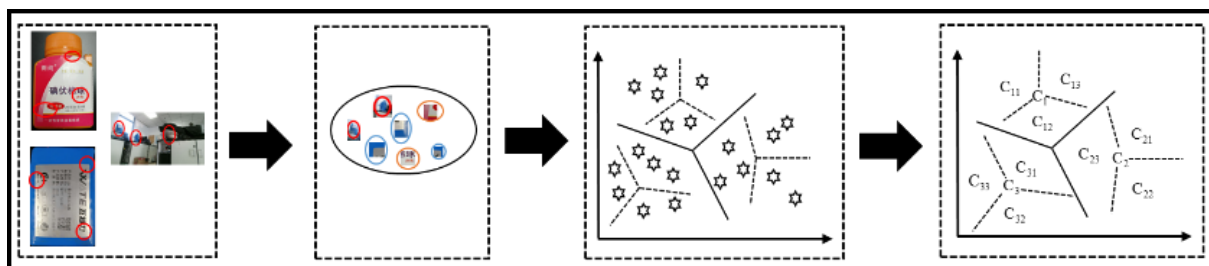


Figure 1. The steps of learning the visual word vocabulary.

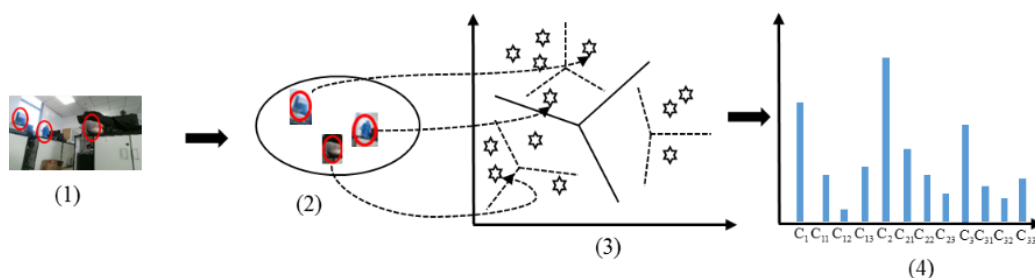


Figure 2. The steps of converting image features into feature histogram.

3. Improved Ransac Algorithm for Eliminating Feature Mismatch

The standard RANSAC algorithm is to estimate parameters of a mathematical model from a set of data which divides into inliers and outliers. However the standard RANSAC algorithm selects samples randomly. The random sampling has some disadvantages, for example, it increases the number of iteration when the number of outlier is higher than the inlier. If the set of data is contaminated with many outliers, it will cost too much time to compute the homography. It is necessary to choose the

appropriate data which is used to compute the homography. Therefore, this paper proposes an improved RANSAC algorithm.

This method can reduce the number of iterations and improve the accuracy of the algorithm. The main steps are as follows:

- (1) Get the feature points and the feature descriptors in the adjacent frames.
- (2) Calculate the nearest Euclidean distance and the next nearest Euclidean distance of the feature descriptors and the ratio of the former to later. The lower the value of ratio, the higher the probability of the correct matching point.
- (3) Select candidate samples, which ratio is lower than 0.7. And then, we sort candidate matching points, according to the Euclidean distance of the feature descriptors.
- (4) Estimate the parameters of the model from the candidate samples.
- (5) Calculate the number of inliers which support the parameters of the model.
- (6) If the number of inliers is better than that of the inliers in the current set, keep this set of inliers as the new current set of inliers.
- (7) Obtain the optimal homography matrix. When the set of inliers reaches the maximum and no longer changes, we terminate the loop. Using the maximum inliers set to calculate the homography. We use the homography to eliminate the mismatch of image features.

4. Experimental Results and Analysis

In order to prove the correctness and effectiveness of the algorithm, an experiment is carried out. We run our method on a laptop with CPU 2.4Gz, Intel Core i3 and 4G RAM. Our operating system is Ubuntu 14.04 LTS which executes C++ code and without using GPU. We obtain colour image and depth image through the Kinect sensor.

4.1. Experimental Results and Analysis of Improved RANSAC

The adjacent frames are obtained by Kinect camera. Image feature matching results as shown figure 3. We can see that the preliminary matching results of the image contain incorrect matches. We used the improved RANSAC method which proposed in this paper to eliminate mismatches, the results are shown in figure 4.

In order to verify the effectiveness of the proposed method, we have done some experiments comparing with the standard RANSAC algorithm. Standard RANSAC and improved RANSAC method are used to get the homography matrix. The feature points of the current frame are projected onto the previous frame by using the homography matrix. The result of the projection is shown in figure 5, the red points represents the real position of the feature points and the blue points represents the position of feature points after projection. As you can see from the result of projection, the improved RANSAC algorithm is better than the standard RANSAC method. In other words, the accuracy of our method is better than the original method. In addition, the standard RANSAC algorithm run in 0.80343 seconds, while the improved RANSAC algorithm run in 0.07835 seconds. We can see that the improved RANSAC algorithm is better than the standard RANSAC algorithm both in accuracy and the speed of execution.



Figure 3. Image preliminary matching results without using improved RANSAC algorithm.



Figure 4. The result of using improved RANSAC algorithm to eliminate mismatches.

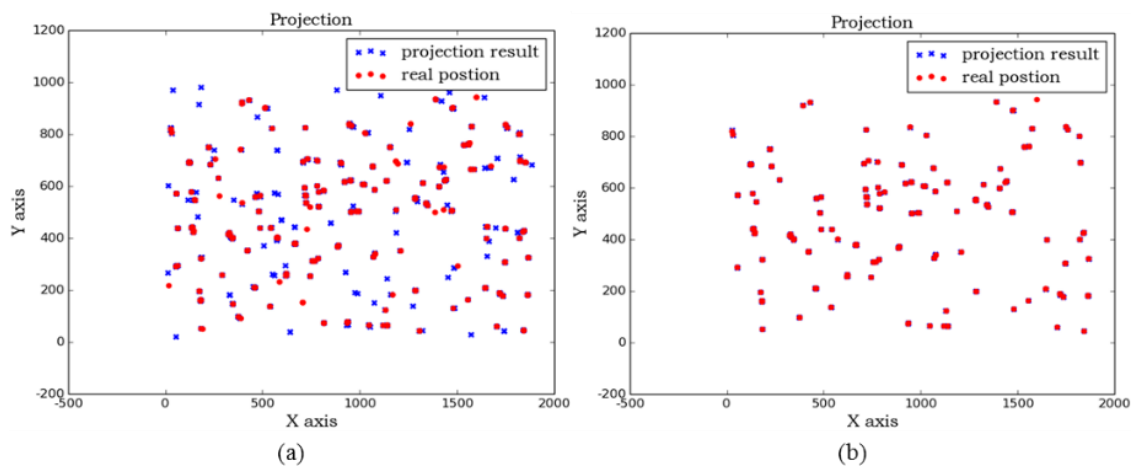


Figure 5. The result of feature point projection. The figure (a) is the result of standard RANSAC algorithm, the figure (b) is the result of the improved RANSAC algorithm.

4.2. Experimental Results and Analysis of Environmental Dictionary

To verify the effect of the environmental dictionary, `rgb_d_dataset_freiburg2_desk` dataset which provided by the Technical University of Munich in Germany is used to build environmental dictionary. After estimating the camera trajectory of the Kinect and saving the camera trajectory to a file, we need to evaluate the error in the estimated trajectory by comparing with the ground-truth. The absolute trajectory error directly measures the difference between points of the true and the estimated trajectory. We contrast with the public dictionary in ORBSLAM algorithm.

We calculate the size and loading time of two types of dictionaries. The public dictionary loading time is 14.945 seconds, while the binary environmental dictionary loading time is 0.420 seconds. And the size of public dictionary is 145 megabytes, the size of binary environmental dictionary is 44.5 megabytes. The result of camera trajectory estimation by using different dictionaries is shown in figure 6. In figure 6 (a), we can see that the root mean square error, mean square error and median error are obviously decreased. In figure 6 (b), the green line represents the estimated trajectory by using binary environmental dictionary, the blue line represents the estimated trajectory by using public dictionary and the red line represents the ground-truth. We can see that the green line is closer to the red line.

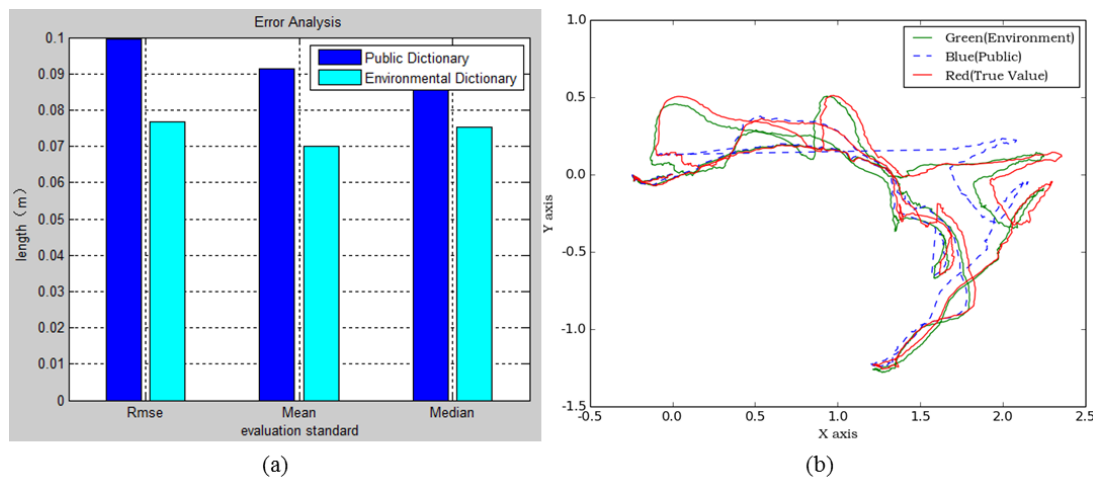


Figure 6. The result of camera trajectory estimation by using different dictionaries.

5. Conclusion

In this paper, we propose an improved RANSAC algorithm and create a binary environment dictionary. Firstly, the feature points and the feature descriptors in the adjacent frames are gained by extracting image features. Then, the nearest Euclidean distance and the next nearest Euclidean distance of the feature descriptors are calculated and the inliers in the sample data are predicted. Finally, the binary environment dictionary takes the place of the public dictionary in ORBSLAM algorithm. It can be seen from the results of two experiments, the improved RANSAC algorithm is better than the standard RANSAC algorithm both in accuracy and the speed of execution and the binary environment dictionary improved the accuracy of the ORBSLAM algorithm.

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