

Research and Application of Visual Odometer Based on RGB-D Camera

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Abstract: Possessing accurate odometer is the basis of simultaneous localization and mapping accuracy of mobile robot. In view of the huge error and high cost of mobile robot odometer, the visual odometer based on depth camera (RGB-D) is studied. In this paper, the key points are extracted through ORB features which are matched by using fast nearest-neighbor algorithm. And the 3D-3D method is used to obtain the change of camera pose through nonlinear optimization in order to achieve a more accurate visual odometer, which will establish a stable foundation for precise positioning and mapping of mobile robots.

1 PREFACE

Mobile robot technology is currently one of the most active areas of research. Its wide range of applications can greatly facilitate people's production and life. Autonomous navigation technology (Liu, 2013) is the basis of being widely used for mobile robots. The traditional technology uses GPS to position and navigate, which has more accurate only when used outdoors. When the robot moves indoors, the GPS hardly obtain the positioning information and can not accurately position the robot. However, the autonomous navigation technology of the mobile robot requires the robot to accurately locate the robot, which requires the robot to carry the high-accuracy odometer. In the past, encoder, camera, laser radar, etc, are used to satisfy the needs of the odometer. Cameras are cheap and can get rich information. But because RGB cameras can only capture RGB images and can't capture deep images, which produce huge odometer errors sometimes. Encoder is cheaper, and the algorithm is relatively simple. But only using the encoder can produce greater error because of the wheel slippery and other factors. The greater error produces the greater uncertainty for positioning and mapping later. Although the lidar can accurately measure the mileage, but the price of lidar is too high to be applied widely.

In recent years, sensors that produce RGB images and deep images can solve these problems. In this paper, the RGB-D camera is Astra. The RGB-D

camera can generate RGB image and depth data at the same time. And 3D point cloud data can be obtained after the camera calibrated. RGB-D camera is cheap and can be used to get color images and depth data. Therefore, the RGB-D camera can achieve more accurate mileage and provide accurate mileage information for positioning and mapping of mobile robot.

2 EXTRACTION AND MATCHING OF FEATURES

The visual odometer is based on the information of adjacent images to estimate the motion of the camera, which provides a better basis for the precise positioning and mapping. The visual odometer that based on feature point method has been regarded as the mainstream method of visual odometer. It is a mature solution because of its stable operation and insensitive to light and dynamic objects.

In this paper, ORB feature (E. Rublee, 2011) is used to extract feature points and help solve FAST corner's omnidirectional problem. And the binary descriptor BRIEF make the feature extraction process be accelerated, which is very representative real-time image characteristics in current time. The ORB feature is composed of key points and descriptions. And the key point is an improved FAST corner. The descriptor is called BRIEF. Therefore, the extraction of ORB features has two steps:

2.1 Extraction of FAST corner points

Finding the "corner point" in the image and calculating the main direction of the feature points. FAST corner points mainly detect the obvious changes of partial pixel gray. If a pixel is significantly different from the pixel in the neighborhood, it is likely to be the corner point. FAST corner detection method is convenient compared with other corner detection methods. The process is as follows:

- First, selecting the pixel p in the image and assume the brightness I_p ;
- Setting a threshold T ;
- Taking the pixel p as the center, selecting a circle with radius 3 and taking 16 pixels on the circle;
- If the brightness of the continuous N pixels on the circle is greater than $I_p + T$ or less than $I_p - T$, then the pixel point can be considered as a feature point;
- Perform the above four steps for each pixel in the image to extract the feature points;

In general, taking N as 12 (that is FAST-12). In the FAST-12 algorithm, a predictive test can be added to quickly exclude pixels that are not angular points to further improve efficiency. Direct detection is used on each pixel's neighborhood round 1, 5, 9, and 13 pixel brightness. when there are three quarters of pixels greater than $I_p + T$ or less than $I_p - T$ at the same time, the pixel is likely to be a corner. As a result of the original FAST corner often appear the phenomenon of cluster, using the method of non-maximal value suppression keep only corner points of the maximum response value in a certain area. The Harris response value is calculated for each FAST corner point, and then the top N corner points with larger response values are extracted as the final congregation of corner points. Because FAST corner points are not directional and scale, the ORB adds a description of scale and rotation to it. Using the method of gray matter calculates the rotation of the characteristics by constructing the image pyramid and using the detection corner at every level of the pyramid to achieve the invariance of the scale. Hence, FAST corners of rotation and scale are produced.

2.2 Extraction of the BRIEF descriptor

It is used to describe the image area around the feature points. Because the ORB calculated the direction of key points at the extraction stage of FAST feature

points, the "Steer BRIEF" feature of the rotation was calculated by using the direction information to calculate the rotation invariance of the ORB.

The ORB can still perform well when it is in translation, rotation and scaling. The real-time performance of FAST and BRIEF combinations is also very good, which ensures the ORB features applied in the visual odometer. The fast approximation nearest neighbor algorithm in Opencv can rapidly deal with matching points. It can be used to accurately match the feature points in two pictures, because the algorithm is already very mature. The extraction of ORB feature points and the method of fast approximation nearest neighbor calculation can provide accurate data information for the camera position transform, and it can meet the real-time requirement of the odometer.

3 EXTRACT THE POSTURE CHANGE OF THE CAMERA

RGB-D camera (J. Sturm, 2013) can obtain RGB image and depth data, and ORB features can extract and match the features. A number of matching points can be captured to obtain a better set of matches after matching the two adjacent images:

$$P = \{p_1, K, p_n\}, P' = \{p'_1, L, p'_n\} \quad (1)$$

From the point obtained by the matching, assuming the Euclidean transformation R and t can be obtained:

$$p_i = Rp'_i + t \quad (2)$$

In this paper, there is no camera model in 3D pose estimation, so just consider the transformation between 3D points. In the estimation of the position (Kerl C, 2013), the method of the nearest point can solve the pose estimation. ICP is used to refer to the most recent point method. The problem of ICP can be solved by linear algebra or nonlinear optimization. Nonlinear optimization method can obtain the minimum error for camera position change, but the method of linear algebra can't guarantee the minimum error. This paper the method of nonlinear optimization solved ICP problem, through nonlinear optimization method to get precise camera position change.

The definition of error is:

$$e_i = p_i - (Rp'_i + t) \quad (3)$$

Therefore, the objective function required by nonlinear optimization method is obtained:

$$\min_{\xi} = \frac{1}{2} \sum_{i=1}^n \left\| p_i - \exp(\xi^{\wedge}) p_i' \right\|_2^2 \quad (4)$$

In this paper, Gauss Newton (Kummerle R, 2011) algorithm is used to solve nonlinear optimization. Gaussian Newton algorithm is one of the simple algorithms in optimization algorithm. The function can be first-order Taylor expansion:

$$e(x + \Delta x) \approx e(x) + J\Delta x \quad (5)$$

J is the derivative, and it's the Jacobian matrix. The incremental equation that will be introduced into Gauss Newton method:

$$H\Delta x = g \quad (6)$$

H is $J^T J$, g is $-J^T e$. The incremental equations can be found by iteratively finding the Jacobian matrix and the error.

In nonlinear optimization, the minimum value can be obtained by continuous iteration. In this paper, the position of camera is optimized by using g2o

optimized library, and the accurate position estimation can be obtained.

4 EXPERIMENTS

The experiment environment is ubuntu16.04 with opencv3 image processing library and g2o optimization library. The experiment uses Astra's depth camera to obtain RGB images and depth images. The resolution of the RGB image is 640 * 480 and the depth range is 0.6 to 8 meters. First, the two images captured by the camera are extracted and matched. The detect function in OpenCV can extract corner points, and the compute function calculates the BRIEF descriptor based on the corner points to extract features. Better matching points can be obtained, and the pose change of the camera can be estimated through the matching feature points in the two pictures.

The RGB image and depth image obtained through the RGB-D camera is shown in the figure below:

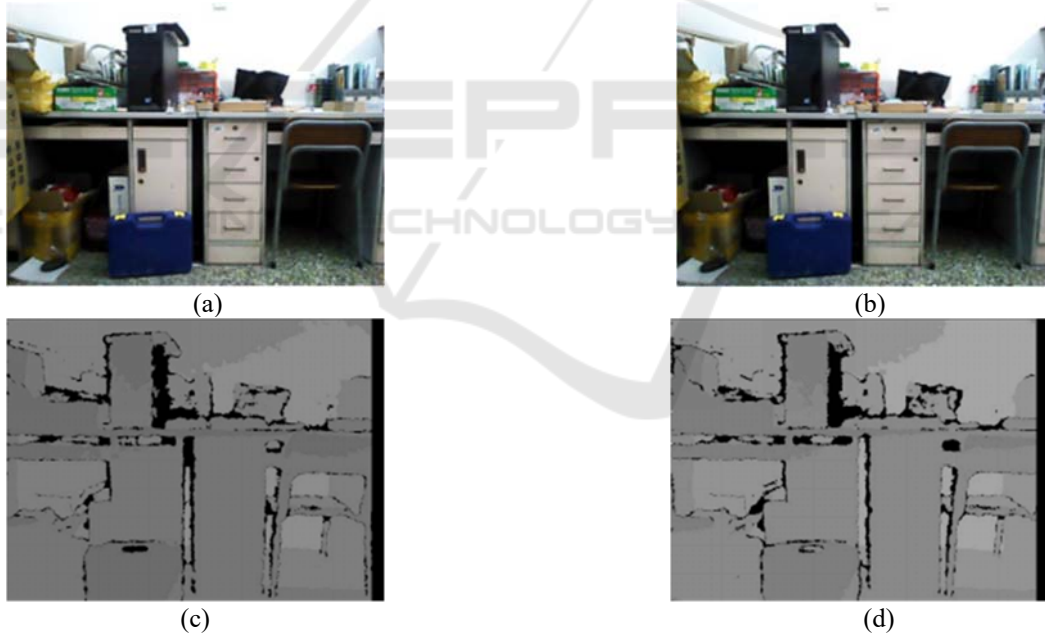


Figure 1

In figure 1, (a), (b) are RGB images, and (c)(d) are the depth images. The RGB image is extracted and matched by the ORB feature to obtain better matching points, and the obtained feature points are optimized

in the g2o optimization library to obtain the transformation matrix T of camera position change. It is shown in the following figure:

```

iteration= 0   chi2= 2238.005749   time= 0.000108687   cumTime= 0.0001
08687 edges= 217   schur= 0
iteration= 1   chi2= 2237.884770   time= 7.0516e-05   cumTime= 0.0001
79203 edges= 217   schur= 0
iteration= 2   chi2= 2237.884769   time= 5.4087e-05   cumTime= 0.0001
3329 edges= 217   schur= 0
iteration= 3   chi2= 2237.884769   time= 8.0675e-05   cumTime= 0.0001
13965 edges= 217   schur= 0
iteration= 4   chi2= 2237.884769   time= 6.8933e-05   cumTime= 0.0001
82898 edges= 217   schur= 0
iteration= 5   chi2= 2237.884769   time= 7.3348e-05   cumTime= 0.0001
56246 edges= 217   schur= 0
iteration= 6   chi2= 2237.884769   time= 5.0772e-05   cumTime= 0.0001
07018 edges= 217   schur= 0
iteration= 7   chi2= 2237.884769   time= 7.4325e-05   cumTime= 0.0001
81343 edges= 217   schur= 0
iteration= 8   chi2= 2237.884769   time= 5.0368e-05   cumTime= 0.0001
31711 edges= 217   schur= 0
iteration= 9   chi2= 2237.884769   time= 4.9984e-05   cumTime= 0.0001
81695 edges= 217   schur= 0
optimization costs time: 0.00121023 seconds.

after optimization:
T=
  0.999959  0.000356436  -0.009043  0.066168
 -0.00036392  0.999999  -0.0014312  -0.000738572
  0.00904248  0.0014344  0.999958  0.00273556
  0 0 0 1
    
```

Figure 2

In figure 2, the optimization of ICP has been stable until the fourth iteration. This shows that the algorithm has converged after the third iteration. The resulting transformation matrix is:

$$T = \begin{bmatrix} 0.999959 & 0.000356436 & -0.009043 & 0.066168 \\ -0.00036392 & 0.999999 & -0.0014312 & -0.000738572 \\ 0.00904248 & 0.0014344 & 0.999958 & 0.00273556 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

According to the transformation matrix, the camera shifted 0.066168 meters in the x direction, and shifted -0.000738572 meters in the y direction, and shifted 0.00273556 meters in the z direction. The camera shifted very small in y and z, and they

are negligible. Take the $T_{3 \times 3}$, which is the rotation matrix R. Convert R to quaternion:

$$q_0 = \frac{\sqrt{tr(R) + 1}}{2} \quad (7)$$

R into the equation (7) available $q_0 \approx 1$. The experimental result of this paper is that the camera translates 0.066168 meters in the x direction without rotation.

5 CONCLUSIONS

In this paper, RGB-D camera is used to obtain RGB images and depth images. The visual

odometer can obtain accurate camera's position by using algorithm of ORB feature extraction and nonlinear optimization. The data provide a foundation to accurately position and map for mobile robots.

REFERENCES

Liu T,Zhang X, Wei Z, et al. A robust fusion method for RGB-D SLAM[C]. Chinese Automation Congress. 2013:474-481.

E. Rublee, V. Rabaud, K. Konolige. Brdski, ORB: An efficient alternative to SIFT or SURF, in Proc. IEEE Int. Conf. Comput. Vis., 2011, vol. 13, pp. 2564–2571.

Robust Odometry Estimation for RGB-D Cameras (C. Kerl, J. Sturm, D. Cremers), In Proc. Of the IEEE Int. Conf. on Robotics and Automation (ICRA), 2013.

Kerl C, Sturm J, Cremers D. Robust odometry estimation for RGB-D cameras[J]. 2013:3748-3754.

Kummerle R, Grisetti G, Strasdat H, et al g2o: A general framework for graph optimization[C]: Robotics and Automation (ICRA), 2011 IEEE International Conference on, Shanghai, 2011.