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Fast RGBD-ICP with Bionic Vision Depth Perception Model

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***Abstract*— How to improve the real-time performance of 3D SLAM(Simultaneous Localization And Mapping) is a key issue of mobile robot. In this paper, a bionic vision depth perception model is researched aimed at real-time performance of RGBD SLAM, which takes the sensors's depth value as a parameter. As we all know, it is more clear as the distance closer and more obscure as the distance further of biological vision, scene over the depth of field can be negligible. According to that a gradient filter algorithm of point cloud based on sensors's depth value is researched, which can reduce the calculated cost of ICP(Iterative Closest Point) and improve RGBD SLAM efficiency to get high quality of 3D map. Three kinds of experiments based on bionic vision depth perception model are discussed.Compared it with fast random sampling algorithm, the experimental results show that the bionic vision depth perception model greatly improves the real-time performance of RGBD SLAM.**

Keywords— Kinect; ICP; bionic vision depth perception model; RGBD SLAM

I. INTRODUCTION

Precise location and rich map information can help more for mobile robot to realize the autonomous navigation under an uncertain environment, so SLAM has always been an important issue of mobile robot. SLAM refers that the robot build up the distribution of objects in the environment with the help of sensor data with noise and locate itself at the same time.

In order to realize the autonomous navigation of a robot independently, many researchers have proposed different SLAM methods. Those common SLAM algorithm can be divided into three categories, the first one is SLAM algorithm based on kalman filter, the second one is SLAM algorithm based on particle filter and the last one is SLAM algorithm based on EM(Expectation Maximization) model. SLAM algorithm based on kalman filter was first put forward by Smith[1], which expressed robot and the environment map through a state vectors, and estimated the mean and variance of state vector by using EKF(Extended Kalman Filter); SLAM algorithm based on particle filter used a number of discrete random sampling points (particles) to represent the posterior probability density function of the state variables, and it had a common applicability for the estimation problem of nonlinear non-gaussian system[2]. EM model based SLAM algorithm created maps into probability constraints of maximum likelihood estimation problem, had better performance on map creation and location, lowered the dependence on the accuracy of the data correlation, and improved the convergence of the algorithm of SLAM [3].

In the application of autonomous navigation, the choice of SLAM algorithm depends on the selected sensors. Both Jan Weingarten[4] and Friedman Chen[5] adopted laser scanners, the former built the 3D environment map and tracked the robot posture with extended kalman filter algorithm so as to realize 3D SLAM, while the later presented a SLAM method based on surrounding polar scanning technology widely used in robot navigation. Hertzberg C who regarded stereo camera as sensor, put forward an expanding visual SLAM system to create voxel map[6]. It is well known that laser scanner is too expensive while stereo camera has high computational complexity during scanning. In recent years with the emergence of RGB-D sensor who has high cost performance, Kinect gradually becomes research focus in the field of robotic SLAM. In 2010, RGB-D SLAM is put forward for the first time by Henry[7] from Massachusetts institute of technology, which obtains RGB figure and depth map by RGBD sensor data and then locates and draws a map with camera position and the aligned point clouds. In 2012, Henry[8] optimized this method, in the same year Fred Endres[9] from Technical University of Munich had a performance evaluation on RGB-D mapping and created a volumetric voxel representation that can be directly used for robot localization, path planning and navigation.

Since the RGB-D SLAM is a kind of low cost and high performance camera, which has strong innovation and great effect ,what's more, it can locate itself according to the camera position at the same time obtain a RGB-D map of the three dimensional environment, Kinect is widely used in mobile robotics SLAM and has always been a research hotspot in recent years. However, it differs from existing approaches in the way it performs frame-to-frame marching which needs high computational expense. For its relatively complex mapping principle, the algorithm also has its shortcomings, namely the poor real-time performance. In the process of sensor scanning scenario, a large amount of 3D point cloud data need to be matched continuously, which will take larger computational overhead. If the calculation of 3D point cloud matching cost can be reduced, it will speed up and improve real-time performance then.

This article focuses on how to enhance RGB-D SLAM real-time performance. We put forward a bionic vision model to improve the original 3D point cloud matching algorithm of ICP (Iterative Closest Point) algorithm. In fact, since ICP

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was put forward in 1992 for the first time by Besl[10], many research scholars had proposed different initialization methods of raw point gathers to improve the operation speed of the ICP algorithm. Turk and Levoy presented the uniform down sample on point cloud data sets[11]; Masuda adopted a category of random sampling and it took different sample points in each iteration[12]; Rusinkiewicz and Levoy[13] presented random sampling, which was relatively simple and easy to be implemented, in addition, for certain types of point set (e.g., "serrated" data sets), some small characteristics were very important to determine the correct alignment, so they introduced the vector space evenly aligned sampling to get good results. Jost and Hugli [14] used the scheme of coarse to fine resolution, increased the number of sampling points in later iterations, thus registration matching; Gelfand put forward covariance sampling points to keep both point clouds symmetric [15]. Daehwan Kim et al. proposed the FAST ICP algorithm that contains Hierarchical Model Point Selection (HMPS) and Logarithmic Data Point Search (LDPS) to improve the original point cloud sampling and searching method to rapid ICP matching[16]. Jia Chen[17] proposed HT-ICP, redefined the error equation of point cloud aimed at some overlapping point clouds so as to increase matching efficiency. Although the above methods improved the point cloud matching speed in a certain extent, the point cloud shape and scene conditions limit the real-time applications.

This paper abandoned the shape of point clouds, scene conditions and other similar limitations, mainly introduces a bionic vision model based on the principle of biological stadia combined with the characteristics of Kinect in the point cloud initialization section of the ICP algorithm, which regards depth of Kinect as a parameter, acts as a gradient filter in range of Kinect visibility. There are two advantages in such processing. Firstly, it makes full use of the depth information from Kinect sensor to apply the principle of bionic vision to the robot. Secondly, after the gradient filter of point clouds, the number of points were reduced, the cost of ICP is decreased , the quality of created map is acceptable, and the RGB-D SLAM acts over fluently in the real-time applications.

This paper is organized as follows: In section 2, ICP algorithm and bionic vision depth perception model is represented;In section 3, experiment platform is designed ,including the experiments and performance evaluation of bionic vision depth perception model on real-time platform. Finally, we summary some conclusions and plan the work to do in the future.

II. ICP AND BIONIC VISON DEPTH MODEL

A. RGBD-ICP

First, RGBD-ICP is a critical part in RGBD SLAM. This section describes the different components of RGB-D mapping. A flow chart of overall system is shown in Fig.1.

1) Feature extraction and alignment : Extracting features from RGB images, the optional algorithms are SIFT、SURF、ORB、SIFTGPU(the implementation of SIFTGPU requires high graphics card to the system configuration) and so on, then taking a feature matching with FLANN. (Fast Library for

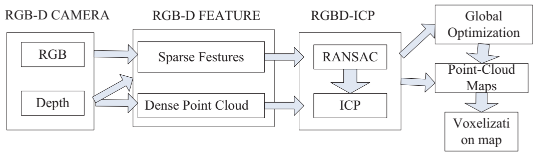


Fig.1. Overview of RGB-D SLAM

Approximate Nearest Neighbors) .

2)RANSAC: Random Sample Consensus, mainly eliminating the data which is far deviated from the normal range, or unable to adapt to the mathematical model, denoising the point cloud data which are got from feature extraction and matching , to have a point cloud initialization for ICP next stage.

3) RGB-D ICP: Aligning the current frame to the previous frame, then a new frame is added to the dense 3D model.

4) Global graph optimization: After feature extraction and the parallelly loop-closure testing of the sparse feature points, a global posture alignment process will be triggered.

5) Voxelization map: the voxel maps can be directly used for robot localization, path planning and navigation.

B. ICP

ICP (Iterative Closest Points) algorithm is a kind of key 3D matching algorithm, which called the corresponding point set registration algorithm. ICP algorithm is used for the alignment of two clouds of points, the model shape $M \triangleq \{m_i\}_{i=1}^{N_m}$ with N_m points and the data shape $M \triangleq \{p_i\}_{i=1}^{N_p}$ with N_P. The transformation of the data shape to the model shape is assumed to be linear with a rotation matrix R and translation vector t. The goal of the ICP algorithm is to find the translation parameters, for which the error(mostly least squares) between the transformed data shape points and the closest points of the model shape gets minimal. This characteristic is described as (1).

$$\min_{R,t,j\in\{1,2,\dots,N_m\}} \left(\sum_{i=1}^{N_P} \left\| Rp_i + t - m_j \right\|\right) \quad (1)$$

The procedure of ICP is almost the same in all alterations of the algorithm and is shown as following.

1) Initialization: The importance of the initialization lays in the fact that the ICP algorithm converges only to a local minimum. False matching can be reduced by good initialization methods.

2) Input Filters: 3D data sets are often composed by a large number of points. Since matching needs most of the calculation time with a complexity of O ($N_m \cdot N_p$)with the standard algorithm, the algorithm speeds up by reducing the number of points used. This step is done by an input filter.

3) Matching: The first step of the iteration is to find out the closest point to each transformed point of the data shape. This can be formulated as (2).

$$c(i) = \underset{j\in\{1,2\dots,N_m\}}{\arg\min} \left(\left\| m_j - (Rp_i + t) \right\|\right) \quad (2)$$

Matching needs the most of the calculation time. Therefore, this step is most frequently modified. The ICP proposed by Besl and McKay [1] calculates the distance to each point of the other set to find closest point. In 2001, the state of the art is using kd-tree search with a complexity of $O(N_m * \log N_P)$.

4) Outlier Filter: Data of two laser scans are normally not fully congruent. The points only appearing in one data set must not be considered in the error minimization. Therefore the outlier filter cuts off the not overlapping parts.

5) Error Minimization: The goal of error minimization is to find the new transformation parameters for the next iteration, effecting a smaller least squares error.

In 2001,Rusinkiewicz S had described the various factors influencing the ICP algorithm, improved and expanded the ICP algorithm. According to these factors the ICP algorithm is divided into six steps: sampling, matching, weights, remove, error metrics, minimized. Bionic vision depth perception model which is a method of sampling in the ICP algorithm is used to initialize the 3D point gathers.

C. Bionic Vision Depth Perception Mode

Within a certain range, the environmental awareness of creature is more clear as distance closer, more obscure as the distance further. When the distance is over far ,it is visible but low distinctiveness. What's more, environmental information in the field over the visibility does not affect the judgment within certain scope, which can be ignored then.

This paper futs forward a bionic vision depth perception model which endow robot vision sensors with biological vision perception effect. The description of the model is expressed with a set of piecewise function $h(d)$, which value is defined in [0, 1] and variable value is the scanning depth of the sensor, namely d , the filter coefficient of 3D point cloud. As shown in the（3）, with the increase of the depth distance d the function value h (d) decreases gradually.

$$h(d) = \begin{cases} -\left(\frac{d}{\beta}\right)^2 + 1, d \in (a, b) \\ 0, d \ \in ((0, a] \cup [b, +\infty)) \end{cases} \quad (3)$$

Where, the β is sensor visual range, a and b represent two poles in the best stadia range. In the interval (a, b), the quadratic function showed a trend of decreasing step by step. However, $(0, a]$ and $[b, +\infty)$ are indistinguishable interval, and $h(d)$ set to 0 means there is no need to deal with.

Each point in 3D point clouds corresponds to a sole d value. However, screening coefficient $h(d)$ is applied to a set of points, so the range from a and b will be divided into i intervals. In each interval the average depth is defined as $\overline{d_i}$. As the value of i changes, different $h(\overline{d_i})$ corresponds to it, and then to have a gradient filter between (a, b) based on the value of $h(\overline{d_i})$.

In image frames from Kinect's depth data flow, the distance z in specific (x, y, z) coordinates represents the depth of each pixel which is the closest distance to the camera plane in the range of depth sensor. The relationship between Kinect visual range and distance (unit: m) is as shown in Fig.2.Brown part is the unknown area, while white part and purple part correspond to the too close area or too far area in the distance respectively, the green area shows a normal viewing distance. Maximum depth is 4096 mm, value 0 usually indicates the depth value cannot be determined, which generally will be filtered out. Microsoft recommends to use within the scope of the value 1220 mm - 3810 mm in development. As a result, theβ is set as 4.096 m in bionic vision model, and then the pole value in a best stadia range is defined as 1.22 m, b is defined as 3.81 m. The visual model is shown as (4)

$$h(d) = \begin{cases} -\left(d/4.096\right)^2 + 1 & d \in (1.22\,, 3.81) \\ 0 & d \in (0\,, 1.22] \cup [3.81\,, +\infty) \end{cases} \quad (4)$$

Here, i is set to 3, sensor visual range (1.22, 3.81) is divided into three segments. The averaged depth of the 3D point clouds in the three segments were $\overline{d_1}$、$\overline{d_2}$ 、$\overline{d_3}$ as shown in (5), (6), (7). Taking the average depth values into the function h(d), three screening coefficients $h(\overline{d_1})$ 、$h(\overline{d_2})$、$h(\overline{d_3})$ can be obtained, which will do a great help to sample the point clouds .

$$\overline{d_1} \in (1.22\,, 2.08) \quad (5)$$

$$\overline{d_2} \in (2.08\,, 2.94) \quad (6)$$

$$\overline{d_3} \in (2.94\,, 3.81) \quad (7)$$

This section introduces the ICP algorithm and bionic vision depth percentage model. In order to assess the performance of the bionic vision model, the corresponding experiments will be taking in real-time platform following.

III. EXPERIMENTS

Three catagories of experiments are discussed. Firstly it's a static registration between two frames of point clouds. Secondly it's a crosswise dynamic scanning and a global scanning test was taken while the robot is moving at last.

A. Experiment Platform

The experiments are implemented by using a three omni-wheel mobile robot. The main module of experiment platform is designed as Fig.3. The laptop is the core unit of the whole system, which on the one hand connects with Kinect via USB to access to environment information, on the other hand it communicates with three omni-wheel robot by bluetooth to control its movement. The laptop is 2.4GHz CPU, 4 Gb of memory, and RGBD SLAM running environment is Ubuntu 12.4, ros - fuerte.

B. Static Registration

This section contains two kinds of small experiments: collecting point cloud information in ROS with Kinect and then sampling, showing and registrating them. Point cloud data collected in ROS are saved as PCD (Point Cloud Data)file format, which contains both coordinate and color of

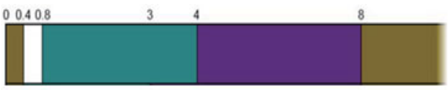


Fig.2. Stadia Range of Kinect

Fig. 3. Experiment platform

3D point cloud information. Since the registration of point clouds is based on the location, 3D coordinate data are just extracted for static registration . The resolution of the infrared data is 640 * 480 fps30, however, because of the time delay in ROS , each frame cannot reach 300000 pixels in the PCD but about 240000 pixels in the experiment.

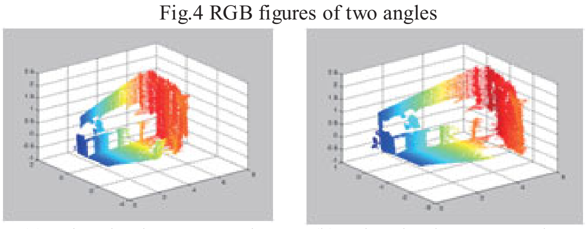
It's on a 90cm high desk in a 3.3 m * 6.1 m laboratory where Kinect is controlled to turn a small side trip(less than 10°) in a horizontal plane . The angle of rotation space is not so large to ensure the similarity of two scenarios which is good for registration . We collected two frames of RGB figures on the same scene as shown in Fig.4 (a) (b). Fig.5 (a) (b) display the 3D point clouds correspond to the above two frames and the coordinate unit is meter. The different colors represent the different depth values, also as we can see, the display of point cloud is a little different from two RGB figures , because the angles of view are different.

The point clouds under best stadia $d \in (1.22, 3.81)$ are shown in Fig.6. The point clouds after random sampling filter are shown in Fig.7. The point clouds after bionic vision depth perception model filter are shown in Fig.8. Comparing Fig.7 and Fig.8 we can see bionic vision depth perception model filter removed more points than random sampling filter, and as the distance grows the point cloud density become sparse gradually.

After three kinds of filter method was tested, the registration time, iterations and percentage error of the three kinds of point clouds are compared in Table Ⅰ. According to the Table Ⅰ, for a certain amount of point clouds, bionic visual depth perception model helps improve the registration efficiency of point clouds, and its efficiency is higher than fast random sampling algorithm.

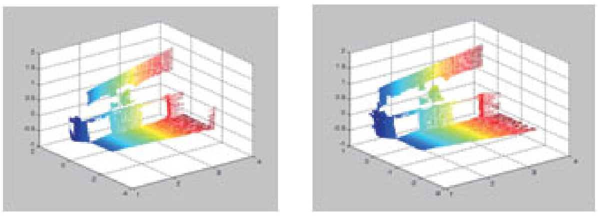
(a) the first frame RGB figure from Kinect　(b) the second frame RGB figure from Kinect

Fig.4 RGB figures of two angles



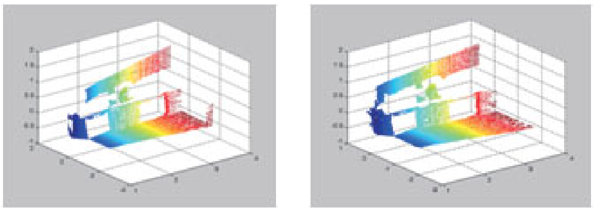
(a) point clouds corresponds to the first frame RGB figure　(b) point clouds corresponds to the second frame RGB figure

Fig. 5 Point clouds figures corresponding to two angles of RGB figure



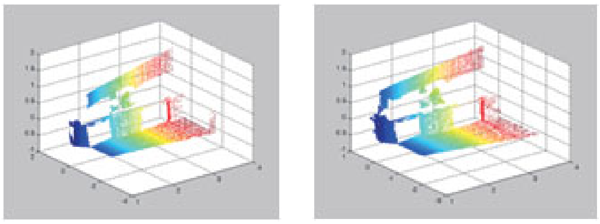
(a)The first frame point clouds figure in best stadia　(b) The second frame point clouds figure in best stadia

Fig.6 Point clouds in the best stadia



(a)The first frame point clouds figure after random filter　(b)The second frame point clouds figure after random filter

Fig 7. Point clouds figure after random sampling filter



(a)the first frame point clouds figure after Bionic Visual depth perception Model filter　(b)the second frame point clouds figure after Bionic Visual depth perception Model filter

Fig 8. Point clouds figure after Bionic Visual depth perception Model filter

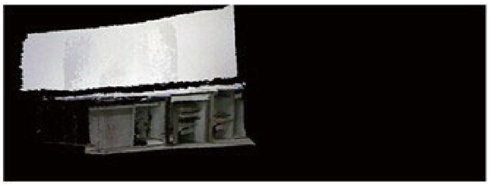
C. Crosswise Dynamic Scanning

In crosswise dynamic scanning experiment three groups of scanning rate is designed to search environmental information . The Kinect is fixed on the 360 ° rotating servo motor , let it rotate 90 ° in the process of RGBDSLAM to collect environmental information. RGB figure from 0 ° to 90 ° is regard as reference shown in Fig.9.In the middle of the figure, a pot of flower is just on the corner.

Fig 9. RGB figure scanning from 0 ° to 90 °

TABLE I. RESUKTS OF ICP PROCESS OF THREE KINDS OF POINT CLOUD

Experiment Ⅰ	Registration time（s）	Iterations	Percentage Error（%）
The original point cloud	72.14	29	1.4085
Point cloud after Random filter	66.39	26	1.3002
Point cloud after Bionic Visual depth perception Model filter	53.04	21	1.1079



(a) matching scene with original RGBD SLAM at ω= π/2 rad/s

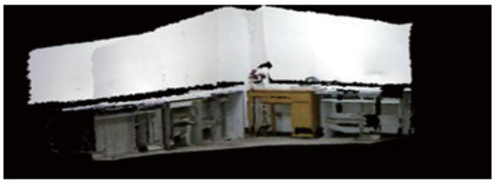
(b) matching scene with random sampling filter at ω= π/2 rad/s

(c) matching scene with bionic visual depth perception Model filter at ω= π/2 rad/s

Fig 10. θ=90° ω=π/2 rad/s

(a) matching scene with original RGBD SLAM at ω=π/6rad/s

(b) matching scene with random sampling filter at ω= π/6 rad/s



（c）matching scene with Bionic Visual depth perception Model filter at ω=π/6rad/s

Fig 11. θ=90° ω=π/6rad/s

(a) matching scene with original RGBD SLAM at ω=π/12rad/s

(b) matching scene with random sampling filter at ω= π/12 rad/s

(c) matching scene with bionic visual depth perception Model filter at ω= π/12 rad/s

Fig 12. θ=90° ω=π/12 rad/s

As shown in Fig.10.,Fig.11. ,and Fig.12., Fig.(a) is the original running conditions of RGBD SLAM, Fig.(b) is scanning figure with random sampling filter, Fig.(c) is scanning figure with bionic vision depth perception model filter, θ is called rotating angle, ω is rotating angular velocity. As scanning figures shown there has some noise and its distribution is accidental, so it is lack of clarity.

Table Ⅱ summarizes the three conditions of crosswise dynamic scanning:

When Kinect is at the speed of 45°/s or 30°/s, because of the high rotate speed, it has no enough time to registrate during RGBD SLAM, and map reconstruction interrupts . Especially when the rate is 45°/s, only parts of scenes can be captured and the scene matching integrity is about 50% in Table Ⅱ.

When the rotating speed is 30°/s, integrity of bionic vision depth perception model is greater than the other two cases;

When the rotating speed is 15°/s, almost the scope of the global figure can be gotten from 0 ° to 90 °, in Table Ⅱ the integrity is more than 95%, however the clarity of bionic visual depth perception model is the best.

As the rotating angular velocity decreases, the reserved time for registration becomes rich, scanning information of the environment increase, too. In each set of images, when the scanning angle and angular velocity is certain, bionic visual

TABLE II. CONTRAST OF SCAN RESUKTS IN THREE CONDITIONS

Scanning Speed of Kinect	45°/s		30°/s		15°/s	
Scanning graphics properties	integrity	articulation	integrity	articulation	integrity	articulation
The original RGBD SLAM	< 50%	average	70%	average	> 95%	average
After random sampling filter	> 50%	good	80%	good	> 95%	good
After bionic visual depth perception model filter	> 50%	distinction	90%	distinction	> 95%	distinction

depth perception model filter brings more environment information compared to the original conditions and fast random sampling filter and its efficiency is relatively high. In brief, the bionic vision depth perception model does improve the speed of RGBD SLAM, and the best scanning speed of Kinect is under 15°/s .

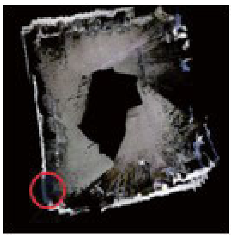
D. Globle scanning test

In a 10.5 m * 6 m laboratory , Kinect is setting on a three omni-wheel mobile robot. During the time of the original RGBD SLAM scanning test and RGBD SLAM using random sampling test, the RGBDSLAM often jumps out and interruptes mapping when scanning the whole environment ,but the experiment test of bionic visual depth perception model in RGBD SLAM runs smoothly.

Our omni-wheel mobile robot circled the laboratory and scaned the indoor environmental information, while the linear velocity of the robot is kept at about 0.2 m/s, at which speed the fluency of RGBD SLAM is the best through lots of tests. Fig.13 (a) is a global vertical view figure, and Fig.13 (b) is a global side vertical view. As Kinect is setting on the omni-directional mobile robot and its position is about 33cm high above the ground, the limited scope of Kinect can not reach scene above this level all round and the central area of the desktop. The local details of two red circles is expressed in Fig.13 (c), which shows the clarity of scanning image in the process of marching.

IV. Summary and Future Work

This paper proposed a bionic vision depth perception model with Kinect's depth value as a parameter and carried it on with RGBD SLAM system. This model is to have a gradient filter of point cloud on sensors's horizon according to the depth combined with principle of biological stadia ,thus reduces the ICP calculated cost, improves RGBD SLAM efficiency on the condition of meeting high quality of 3D map.



（a）Global vertical view

（b）Global side vertical view

（c）The local detail obtained from RGBD SLAM in laboratory

Fig.13. Robot in the process of marching

The bionic vision depth perception model not only can be applied to RGBD SLAM ,it is also of great significance for other types of 3D SLAM on real-time study.

During the experiments, we can see RGBD SLAM also exist some problems in accuracy of locating and mapping, especially when the characteristic points of environment are few, the alignment between frames brings some errors leading to camera pose estimation drift, which results in inaccurate mapping. Considering the above problem, we will use IMU to enhance RGBD SLAM algorithm to improve the RGBD SLAM locating accuracy in future work.

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