Synchronized 2D SLAM and 3D Mapping Based on Three Wheels Omni-directional Mobile Robot

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Abstract—**In this paper, we design a three wheels Omni-directional mobile robot (TOMR) and propose a method of simultaneous construction of 2D and 3D maps based on the mobile robot. To be more specific, we use information from a laser and a kinect to build 2D grid maps and 3D environment, respectively. The particle filter algorithm is used to achieve the pose of the robot, together with the OctoMap which is generated from a 3D point cloud map, to construct the 2D and 3D maps. An asymmetric environment is employed to test our proposed method and some state-of-the-art methods like RGB-D SLAM and ORB-SLAM. The experimental results show that the proposed method is efficient for synchronized 2D and 3D mapping and has better performance than other compared algorithms.**

I. Introduction

An omnidirectional mobile robot has some advantages, such as simple structures, strong mobility, simple controlling and precisely positioning. Thus, it is widely used in control tasks with limited space and high mobility requirements.

To realize autonomous navigation of the robot, localization and mapping based on an unfamiliar environment are major challenges for SLAM problems, which become hot issues in the field of robotics [1]. The building maps of visual-based and the laser-based are main types in the SLAM field. As we know, methods based on Extended Kalman Filter (EKF) and particle filter SLAM have become the most widely used algorithms in recent years. Rao-Blackwellized particle filter [2] and FastSLAM [3][4] are the popular particle filter SLAM algorithm. In visual-based SLAM methods, ORB-SLAM [5] and Direct Sparse Odometry [6] are two popular solutions. The main functions of the 2D and 3D maps can provide different environmental and structural information [7]. A laser range sensor is able to obtain the accurate distance according to the laser sensor reflection information, but has not the capacity to get 3D environmental information. Due to the lack of the 3D environmental information, which may affect the accuracy of the robot's trajectory when executing tasks.

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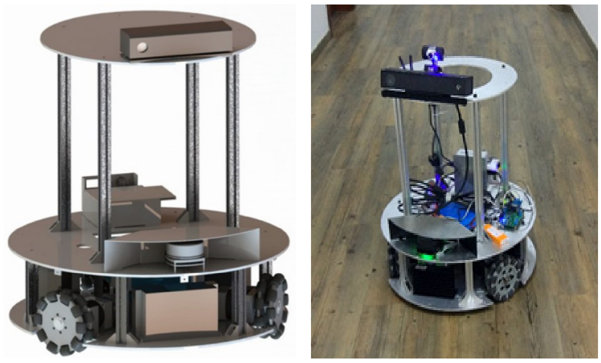

Fig.1. The prototype of the three wheels Omni-directional mobile robot.

Thus, building 3D maps is essential for the mobile robot platform. RGBD-SLAM[8][9] is probably the most prominent method of 3D Mapping, which can generate 3D sparse map. The main function of OctoMap is used to distinguish the grid space which is occupied or free [10].

Here, the Rao-Blackwellized Particle Filters (RBPF) [11] is used to build a 2D map and localize based on indoor environment. We implement a SLAM application based on the Omni-directional mobile robot designed by our lab as shown in Fig.1. The mobile platform equips with a lidar range sensor, a kinect sensor, and an inertial measurement unit. The computer operating system is ROS Indigo 14.04 operated on the Linux operating system. The experimental results are shown by using the RVIZ (ROS visualization tools). The open source Gmapping package is used to build 2D map, and obtaining 3D point cloud map based on the robot's pose transformation matrix, and also make a comparison with the previously studied methods [12][13] and the popular open source methods such as RGB-D and ORB-SLAM algorithm [14]. According to the experimental results, our method is efficient and better for synchronized 2D and 3D mapping.

The remainder of this paper is organized as follows. The system design of the Omni-directional mobile robot is presented in Section II. In Section III, we introduce the kinematic model of the Omni-directional mobile robot and present the method of synchronized 2D SLAM and 3D mapping. In Section IV, a set of experiments is carried out to demonstrate the superiority of our proposed method. Finally, conclusions are made in Section V.

II. System design of the mobile platform

The robot system includes two parts, including a robot platform and a server. The block diagram of the control system of mobile robot platform is shown in Fig.2. The robot platform includes driving module, positioning module, chip module and industrial computer module. The server includes human machine interface module, data processing module and path planning module.

Each module of the mobile robot can be regarded as a small subsystem, and the connection of each component of the mobile platform is shown in Fig.3.

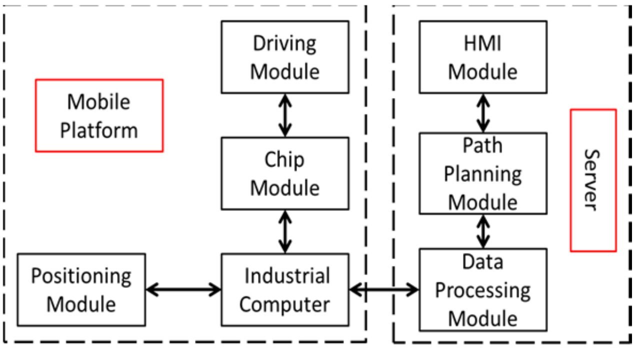

Fig.2. Block diagram of the mobile robot platform.

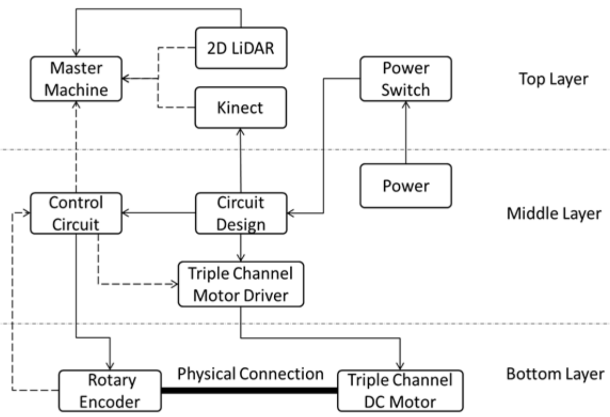

Fig.3. The connection of the subsystems.

The driving module is composed of three groups which drive the omnidirectional wheels and distribute equidistantly along the circumferential direction at the bottom of the robot platform. The driving module is composed of motor, omnidirectional wheel, support shaft and synchronous belt drive mechanism. The omnidirectional wheel is fixed and sleeved with the support shaft. The synchronous belt drive mechanism includes a driven wheel fixed at one end of the support shaft and a coaxial connection with the motor shaft. The driving wheel and the driven wheel are connected by synchronous belt. This structure can realize the Omni-directional motion of the robot platform and has flexible planar mobility.

The chip module receives control instructions from the industrial computer module, and feeds the speed of the chip module receives control instructions from the industrial computer module, and feeds the speed of omnidirectional wheel back to its data processing module to realize information communication.

The positioning module includes lidar, odometer and inertial navigation system. The color images and depth images of the surrounding environment is captured by kinect sensor, the effective distance of the depth image obtained by kinect is approximately 0.7m to 6m, and the measurement results have high accuracy at 0.7m to 4.0m. RGB images and depth images obtained by kinect are shown in Fig.4.

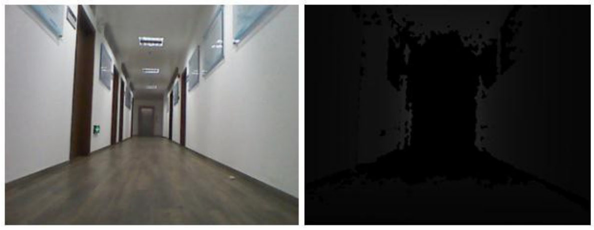

Fig.4. Color images and depth images obtained by kinect.

III. Method

In this section, we will introduce the kinematics model of the three-wheeled omnidirectional autonomous mobile robot platform and the method of synchronized construction of 2D SLAM and 3D maps. Kinematics model analysis mainly includes the establishment of kinematics model and state description of the robot. The synchronized construction method of 2D SLAM and 3D maps is realized by RBPF algorithm and 3D point cloud registration, finally generates 3D grid map construction based on octree.

A. Kinematics modeling

First we define a global coordinate system [x, y], showing in the moving environment, and the robot's pose can be defined as $P = [x, y, \theta]$. The global velocity of the robot can be written as $\dot{P} = [\dot{X}, \dot{Y}, \dot{\theta}]$. Where $\dot{P} = [\dot{X}, \dot{Y}, \dot{\theta}]$ is defined as the velocity of the robot in the global coordinate system. Meanwhile, robot coordinate system is shown by $[x_1, y_1]$. The center of robot coordinate system coincides with the center of gravity of the robot. The three Omni wheels are located at an angle α_i (i = 1, 2, 3) relative to the robot coordinate system. The three angles have a same degree that is 120°.

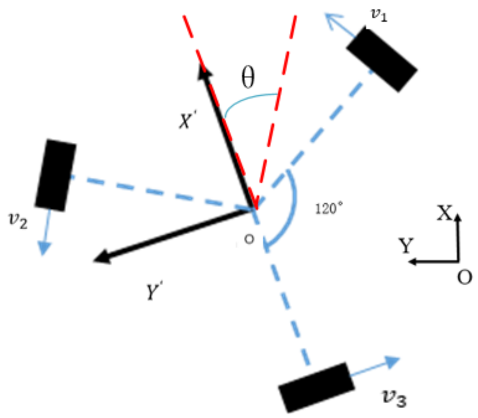

Fig.5. Kinematic diagram of the robot

Hence, we can obtained the relationship between the v_i (i=1, 2, 3) and u_i, which are defined as the angular velocities value of robot's wheel and the global velocity vector, respectively:

$$\begin{pmatrix} v_1 \\ v_2 \\ v_3 \end{pmatrix} = \begin{pmatrix} sin(\alpha/2) & cos(\alpha/2) & L \\ -sin(\alpha/2) & cos(\alpha/2) & L \\ 0 & -1 & L \end{pmatrix} \begin{pmatrix} v_X \\ v_Y \\ \omega \end{pmatrix} \quad (1)$$

The transformation relationship between global coordinate system and robot coordinate system can be shown with the following equation:

$$\begin{pmatrix}\dot{X}\\ \dot{Y}\\ \dot{\theta}\end{pmatrix}=\begin{pmatrix}\cos\theta & -\sin\theta & 0\\ \sin\theta & \cos\theta & 0\\ 0 & 0 & 1\end{pmatrix}\begin{pmatrix}v_X\\ v_Y\\ \omega\end{pmatrix} \tag{2}$$

According to (1) and (2) leads to:

$$\begin{pmatrix}v_1\\ v_2\\ v_3\end{pmatrix}=\begin{pmatrix}\sin(\frac{\alpha}{2}-\theta) & \cos(\frac{\alpha}{2}-\theta) & L\\ -\sin(\frac{\alpha}{2}+\theta) & \cos(\frac{\alpha}{2}+\theta) & L\\ \sin\theta & -\cos\theta & L\end{pmatrix}\begin{pmatrix}\dot{X}\\ \dot{Y}\\ \dot{\theta}\end{pmatrix} \tag{3}$$

Equation (3) implies that any velocity vector of the robot platform can be realized by using a set of unique omnidirectional wheel linear velocity output. Therefore, the overall motion control of the robot platform can be realized by controlling the speed of three omnidirectional wheels.

B. The method of Construction of 2D maps

In this work, the open source Gmapping package is used to to build our 2D indoor environmental map based on the Robot Operation System (ROS, 14.04 version) [11][15][16], which is a reliable and mature algorithm based on RBPF method and has stable effect.

From the view of probability, SLAM problem can be transformed into solving the joint posterior probability for the path of the mobile robot $x_{1:t} = x_1, x_2, \cdots, x_t$ and the map m_t based on the observation data $z_{1:t} = z_1, z_2, \cdots, z_t$ from lidar and the wheeled odometry measurements $u_{1:t} = u_1, u_2, \cdots, u_t$ while the initial position of the robot is specified.

Rao-Blackwellized particle filters (RBPF) is able to show the better performance to solve the SLAM problem for building 2D map [17]. Hence, the RBPF algorithm is used to to construct the 2D map based on the robot's odometry and Rplidar sensor information. The main function of the RBPF method is that we can obtain the joint posterior $p(x_{1:t}, m|z_{1:t}, u_{1:t-1})$ base on the observation data $z_{1:t}$ and wheeled odometry measurements u_t , this method decomposes the state space of Bayesian filter as follow:

$$p(x_{1:t}, m|z_{1:t}, u_{1:t-1}) = p(m|x_{1:t}, z_{1:t}) \cdot p(x_{1:t}|z_{1:t}, u_{1:t-1}) \tag{4}$$

Thus the path of the robot can be estimated by the probability $p(x_{1:t}|z_{1:t}, u_{1:t-1})$, then the map $p(m|x_{1:t}, z_{1:t})$ can be built with the observation model.

C. 3D map building based on 2D map

In this work, the robot maps the environment in both 2D and 3D while simultaneously localizing itself relative to the map. We use the RBPF algorithm with wheeled odometry and lidar range to obtain $u_{1:t}$ and z_t to locate the robot's pose in process of building the 2D map. Meanwhile, in the step of 3D map building, the kinect camera is used to obtain images information for the color and depth, and the pose of the kinect is replaced by the pose of the robot while constructing the 2D map to apply for building 3D mapping.

As the robot moves, x_t is defined as the robot's pose during the process of building 2D map at current time *t*. in order to build local 3D point cloud map, the pose transformation matrix is used to perform point cloud registration. According to the pose at adjacent moments, the pose transformation matrix can be obtained with following equation:

$$x_t = R \cdot x_{t-1} + t \tag{5}$$

The symbols of rotation matrix and translation vector are defined as *R* and *t*, respectively. After that, the following equations can be used for showing generating process of the 3D point cloud based on 2D images:

$$z = d/_{s} \tag{6}$$

$$x = (u - c_x) \cdot z/_{f_x} \tag{7}$$

$$y = (v - c_y) \cdot z/_{f_y} \tag{8}$$

where c_x , c_y , f_x , f_y are the internal parameters of kinect[18]. We use the symbol *d* to show depth information of images collected by kinect sensor and the scaling factor is shown with *s*. The coordinate system of the image pixels based on 2D image is defined as *u* and *v*. Meanwhile, according to the above equations, we can obtain the coordinate system of the 3D point cloud, which is defined as *x*, *y*, *z*. when we obtain the 3D point clouds at adjacent moments based on 2D images, we can perform point cloud registration based on pose transformation matrix, showing with the following equation:

$$T = \begin{pmatrix}R_{3\times3} & t_{3\times3}\\ 0_{1\times3} & 1\end{pmatrix} \in R_{4\times4} \tag{9}$$

It is inevitable that point clouds consume a large amount of storage and memory spaces, which can cause enormous waste of resources. To overcome this problem, researchers proposed a variety of methods for 3D map representation.

The octotree map (OctoMap)[10] is one of the most commonly used 3D maps among these models, which is not only to reduce storage and memory space for the point clouds, but also to set the map resolution according to the size of the environment, more space-saving compared to the points cloud representations, and able to expand the map efficiently for newly inserted data[19][20].

A typical hierarchical data structure that we used is defined as an octree, which is applied for spatial subdivision in 3D map. The voxel is defined as a node, which demonstrates the space contained. The cubic volume is shown in Fig. 6.

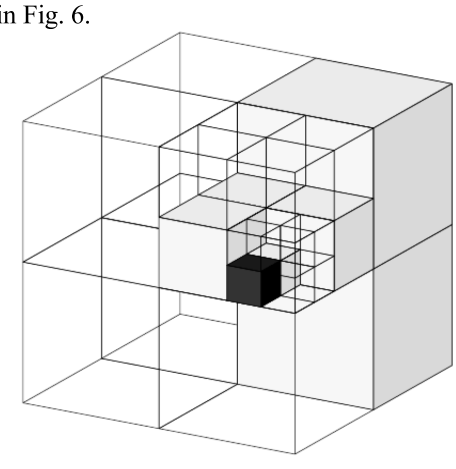

Fig.6. An example of an octree voxel structure and occupied (black) cells.

IV. RESULTS AND COMPARISON

A. Experiments and results

To test the effect of the approach, this work has conducted experiments on the robot (TOMR) developed by our lab. The experiment took place in the Science and technology building, 3th floor, Shantou University, where a corridor is approximately 30m in length and about 2m in width. The Fig.7 shows the experimental place information.

(a) (b)

Fig.7. Guangdong Key Laboratory of Digital Signal and Image Processing, Science and technology building, 3rd floor, Shantou University

The resulting 2D occupancy grid maps is generated by RBPF algorithm with the lidar range data and the wheeled odometry measurements, and realized in Gmapping. The constructed 2D map and experiment result is shown in Fig.8.

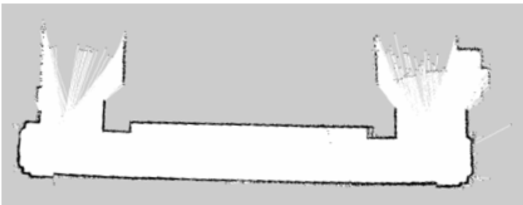

Fig.8. The 2D map generated by RBPF algorithm.

The mobile robot builds the 2D and 3D maps simultaneously, we obtained the robot's pose in real-time when the constructing 2D maps by subscribing the relative topic in ROS, and use robot's pose to replace the pose of the kinect to realize the localization function, then get the pose transformation matrix at the adjacent moment, together with the images at different moments from kinect to construct the 3D point cloud maps and converted into a 3D OctoMap.

Fig.9. The 3D map synchronized mapping with 2D map by three wheels Omni-directional mobile robot.

The 3D point cloud map synchronized mapping with 2D map is shown in Fig.9, and the 3D OctoMap is shown in Fig.10. As can be find in the result, the position and the height of the wall can be seen clearly according to the color of the 3D OctoMap.

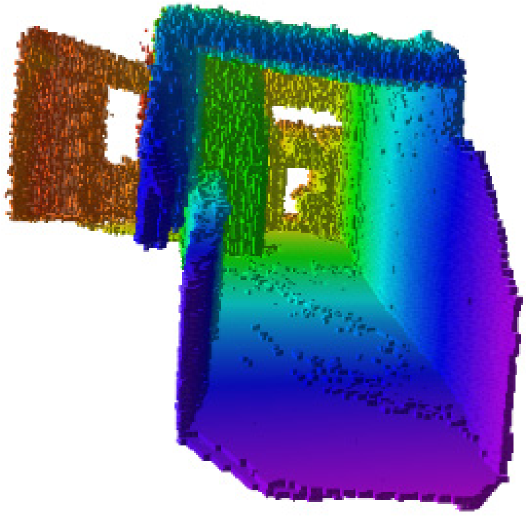

Fig. 10. The 3D OctoMap synchronized mapping with 2D map.

B. Comparisons

We also make comparisons with the popular algorithms such as RGB-D SLAM and ORB-SLAM and the previously studied methods of the hybrid mapping of 2D and 3D [12][13]. Figure 11 shows the experimental result of 3D point cloud maps based on RGB-D SLAM, the algorithm is prone to mismatch and cumulative errors in the similar scenes, which lead to a distorted image of the map. Figure 12 represents the experimental result of the ORB-SLAM, the method only get the sparse point cloud map, which is not available for observing the entire environment.

Fig.11. RGBD-SLAM: 3D map

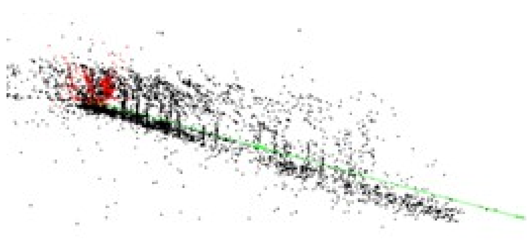

Fig.12. ORB-SLAM: 3D map

Figure 13 gives the result of 3D point cloud map builds with Monte Carlo Localization in 2D map [12], which needs to finish 2D SLAM before 3D mapping, yet the constructed 3D point cloud map require a large amount of storage and cannot be used for 3D navigation. Figure 14 is the result of simultaneous construction of 2D and 3D maps [13], but many 3D occupancy grids are scattered and cannot detect low obstacles above the ground precisely, which will affects the navigation of the robot.

According to the comparison of experimental results, our method builds the 2D and 3D maps simultaneously, while the 3D OctoMap is more accurate with less data storage, available for 3D navigation, and is obviously better for synchronized 2D and 3D mapping than the preceding methods.

Fig.13. 3D map based on Monte Carlo localization in 2D map

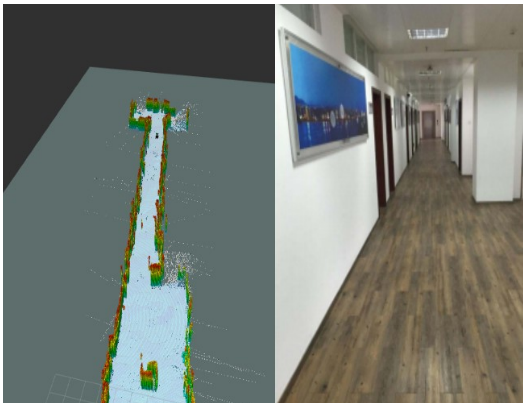

Fig.14. Simultaneous construction of 2D grid map and OctoMap

V. CONCLUSION

In this paper, we designed a mobile robot and implement the synchronized 2D SLAM and 3D mapping method on the mobile platform. The 2D map obtained by Rao-Blackwellized particle filter and the 3D map generated by octotree are merged for the synchronized construction of 2D and 3D maps. We use the pose obtained in 2D map to replace the pose of the kinect, and then build the 3D map based on the point cloud registration and converted into a 3D OctoMap. Some experiments show the proposed approach with the mobile robot in long corridor has a better performance than other compared algorithms.

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