Simultaneous Localization, Mapping and Detection of Moving Objects with Mobile Robot in DynamicEnvironments

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***Abstract*—This paper presents a novel approach for simultaneous localization, mapping (SLAM) and detection of moving objects based on matching 2D range scans. We use the uncertain region to judge the type of scan points, thereby improving the accuracy of distinction between the dynamic and static objects. The approach improves the accuracy of SLAM in dynamic environment, reduces the interference caused by moving objects, and enhances the practical utility of traditional methods of SLAM. Moreover, the approach expands fields of both research and application of SLAM in combination with target tracking method. Results in real robot experiments show the effectiveness of our method.**

Keywords-moving object detection, SLAM, mobile robot.

I. INTRODUCTION

If mobile robots want to operate in real world environments, The first challenge is reliable localization. Thus, most successful mobile robot systems have a localization module together with an priori known environment map in their system structure. Using this architecture, robots can make a reliable estimation of their position during operation. Unfortunately, in most cases, it is difficult to get a priori knowledge of environment, so in those situations, it needs robot run in an unknown position, in an unknown environment, and tries to incrementally build a map while using the same map to estimate its post in the environment. In the community of robotic, people refers this problem as simultaneous localization and map building (SLAM). Since the seminal research paper [1] about SLAM problem, scholar have developed several approaches to solve the issue, those solutions of SLAM can mainly be divided into two classes, the first is Bayesian filtering based method (e.g. [2],[3],[4]), this technique approximates the probability representation using samples of probability density distributions. The second is scan matching based method (e.g. [5],[6],[7]), this technique computes robot pose through estimating the displacement between two consecutive environment scans.

Most traditional SLAM systems assume that the environment is static during mapping, However, if a person walks through the sensor range of the robot during operating, those scan points caused by moving people may disturb the accuracy of SLAM[8]. Some scholar have been research this problem[8],[9],[10]. These approaches are based on traditional ICP(Iterative Closest Point) method, and they not use the uncertainty about odometry to improve accuracy of moving object detection. Aim at this problem, this paper present a new way to solve the problem of simultaneous localization , mapping and detection of moving object (SLAMMOT) which can estimated uncertain area of scan points, and using the uncertain area to improve the accuracy of moving object detection. The rest of the paper is organized as follows. In section II, the concept of coordinate transformation is given. Section III the ICP algorithms are explained. Section IV introduces how to generate occupied grid map. In section V, we present our approach to solve SLAMMOT problem. Section VI presents the experimental results from the application of our approach. Finally, section VII concludes the paper.

II. THE CONCEPT OF COORDINATE TRANSFORMATION

In order to make description more clearly, we first introduce the concept of coordinate transformation. In the process of our algorithm involves coordinate transformation between robot local coordinates and global coordinates, we call this transformation as "RG". Next, the symbol representation follows law as: superscript means reference coordinates and subscript means object. Let robot state in global coordinates as $r=[x_r^g\ y_r^g\ \theta_r^g]'$, Object state in robot local coordinates denote as C^r and when the object is robot $\tilde{r}$, let $C_{\tilde{r}}^r=[x_{\tilde{r}}^r\ y_{\tilde{r}}^r\ \theta_{\tilde{r}}^r]'$, it means the state of robot $\tilde{r}$ in robot r state represented coordinates. Similarly, when the object is scan point p, let $C_p^r=[x_p^r\ y_p^r]'$,it means the location of point in local robot r state represented coordinates. Meanwhile, object in global coordinate denote as C^g ,so the transformation ("RG") from robot local coordinate to global coordinate as follows.

1). when object is robot.

$$C_{\tilde{r}}^g=\begin{bmatrix}x_{\tilde{r}}^g\\ y_{\tilde{r}}^g\\ \theta_{\tilde{r}}^g\end{bmatrix}=RG(C_{\tilde{r}}^r,r)=\begin{bmatrix}\cos(\theta_r^g) & -\sin(\theta_r^g) & 0\\ \sin(\theta_r^g) & \cos(\theta_r^g) & 0\\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_{\tilde{r}}^r\\ y_{\tilde{r}}^r\\ \theta_{\tilde{r}}^r\end{bmatrix}+\begin{bmatrix}x_r^g\\ y_r^g\\ \theta_r^g\end{bmatrix} \quad (1)$$

2). when object is scan point.

$$C_p^g=\begin{bmatrix}x_p^g\\ y_p^g\end{bmatrix}=RG(C_p^r,r)=\begin{bmatrix}\cos(\theta_r^g) & -\sin(\theta_r^g)\\ \sin(\theta_r^g) & \cos(\theta_r^g)\end{bmatrix}\begin{bmatrix}x_p^r\\ y_p^r\end{bmatrix}+\begin{bmatrix}x_r^g\\ y_r^g\end{bmatrix} \quad (2)$$

above transform is correspond with inverse transformation in community of image processing, the function of the transform is compute object state representation in origin coordinate. The reason of "RG" is: the object alignment is

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conducted in robot local coordinate, and resulted displacement is also local coordinates representation, so we need to transform it to global coordinates and get object state in uniform metric.

III. THE PROCESS OF ICP ALGORITHM

In this paper we adopt Iterative Closest Point (ICP)[5] algorithm to solve the problem of robot pose estimation. ICP is a iteration process, we call it "alignment" and the target of it is to compute the relative transformational relation between "data point set" and "model point set". Let S_t and S_{t+1} is scan points set of robot getting from laser sensor at the time t and t+1, here S_t is model points set and S_{t+1} is data points set. The job of algorithm is compute relative transformational relation $v = [\Delta x_v \ \Delta y_v \ \Delta\theta_v]'$ let S_{t+1} matching with S_t Next, we denote the i^{th} point in S_t as p_i^{ref} , and i^{th} point in S_{t+1} as p_i^{dat} .

ICP can be divided into two parts: "the generation of corresponding points" and "the generation of registration between data and model points set". the process of ICP as follows.

1).*Initialization.* Let $S_0^{dat} = S^{dat}$, $v = [0\ 0\ 0]'$ and $k = 0$
Follow steps (2)-(5) are applied until convergence condition are satisfied.

2).*The generation of corresponding points.*

$$S_k^{ref} = Correspondent(S_k^{dat}, S^{ref}) \qquad (3)$$

for each point in S_k^{dat} find corresponding point in S^{ref} ,and get the corresponding model points sit S_k^{ref} which used to compute registration vector of this iteration k .

3).*The generation of registration between data and model points set.*

$$v_k = Displacement(S_k^{ref}, S^{dat}) \qquad (4)$$

According to S_k^{ref} and data points set S^{data} compute relative transformational relation v_k of this iteration k .

4).*Data points set S_k^{dat} update.*

$$S_{k+1}^{dat} = RG(S^{dat}, v^k) \qquad (5)$$

According relative transformational relation v_k and Equation(2) to get now transform data points set S_{k+1}^{dat} used in next k+1 round iteration.

5).*Judgment of termination condition.* Terminate the iteration when the change in mean square error falls below a preset threshold $\tau > 0$ specifying the desired precision of the registration: $d_k - d_{k+1} < \tau$ .Otherwise, run next cycle.

The article [5] has proved the convergence of ICP. In practical application, we can set a fixed iteration number, when the number of iteration is reaching, system end the iteration. Because the limitation of space here not give introduction, readers can refer [6] for more details.

IV. INTRODUCTION OF OCCUPIED GRID MAP

In practical applications such as: robots cooperative target hunting and object intrusion detection tasks, system needs a description of environment, grid map is a good representation to achieve this goal.

Grid map can use to represent 2D environment, the map is divided into several grids and each grid contain a value p^{occup} which represents the probability of this grid occupied by static object. Generally, we divide the probability span 0~1 into three intervals, and each interval represents occupancy, free and unknown states respectively. In begin of robot operation, all grids in map are in unknown state, when robot running, system uses Bayesian filter presented in [3] to update grid map, and the result map as shown in Fig.1 .

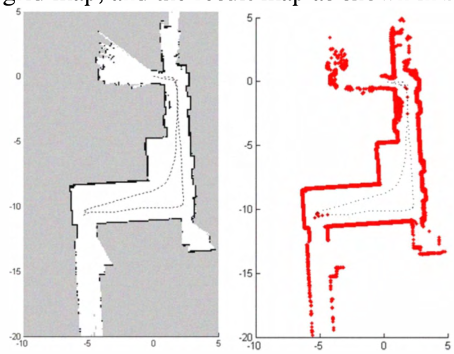


Figure 1. The grid map and the distribution of scan points in indoor environment.

The figure shows the occupied grid map of our laboratory (lift sub-plot) and corresponding distribution of scan points. the black grids ($p^{occup} > 0.8$)in grid map represent the area occupied by static objects, the gray grids ($0.2 < p^{occup} < 0.8$) in grid map represent the area where states are unknown, and the white grids ($p^{occup} < 0.2$) in grid map represent the area not occupied by static objects, solid black dots represent robot pose estimation at each time. The next section we will give the approach to detect those scan points caused by moving object. Our method is based on principle of the identical distribution of static objects in environment.

V. THE METHOD OF SIMULTANEOUS LOCALIZATION,MAPPING AND DETECTION OF MOVING OBJECT

A. *Moving objects caused scan points extraction*

Let $s_t = \{p_1, p_2, ..., p_{180}\}$ be scan points set obtained by robot laser scanner at time t, and the map of the static environment up to time t as M^t, $\hat{x}_t$ is robot pose in time t, scan points caused by moving object are denoted as $s_t^m = \{p_1, p_2, ... p_n\} \subseteq s_t$. So the task of moving object detection is solve follow equation.

$$s_t^m = f(s_t, \hat{x}_t, M^{t-1}) \qquad (6)$$

here we should note that the variable of $\hat{x}_t$ contained disturbance, normally, the disturbance caused by errors of robot odometry .

We used identity of static environment object to detect scan points caused by moving object. Particularly, M^t represents the environment static object, if the area where are not occupied by objects at previous time caused scan points currently, we deduce that this area now contain moving objects, and those scan points are caused by moving objects. However, if the area where it state is unknown at previous time caused scan points currently, we can not deduce that this area now contain moving objects, since those scan points may caused by new found objects. Above principle is shown in Fig.2.

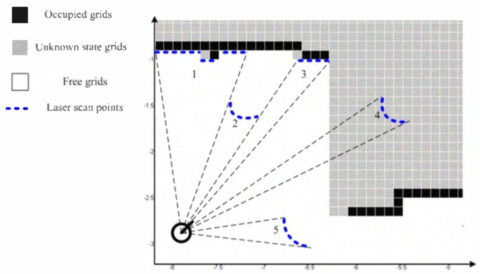


Figure 2. Judgment of the type of scan points.

In this figure, the blue dash lines represent five scan points sets caused by environment objects (marked 1-5).According to the principle, we can judge that scan points sets 1, 3 are caused by static objects, and scan points sets 2, 5 are caused by moving objects, however, so far, we can not judge the scan points set 4 caused by what kinds of objects, and those points can only used to update grid map.

As set forth, the existence of s_t^m influence the accuracy of ICP, so in the process of scan points type judgment, the pose of robot is only provided by odometry, and we not modify the robot pose by ICP. Since this robot pose contained error caused by environment noises, such as wheel skidded, here we need consider such errors in process of scan points type judgment. The approach we used as follows.

Let the robot state in global coordinates as $x_r = [x_r^g \; y_r^g \; \theta_r^g]'$, a single scan of laser, robot can get all beams as $sb_t = \{b_1, b_2, ..., b_{181}\}$, where $b_i = [r_i \;\; \theta_i]'$,and $r_i \in [0 \;\; \text{MAXRANGE}]$, $\theta \in [0 \;\; 180^\circ]$, it means deep and angle information of laser reflected ray i^{th} in robot local coordinates. The relationship between beam b_i and point p_i as follows.

$$p_i^r = [x_p^r \;\; y_p^r] = g(b_i) = \begin{bmatrix} r_i \cos(\theta_i) \\ r_i \sin(\theta_i) \end{bmatrix} \tag{7}$$

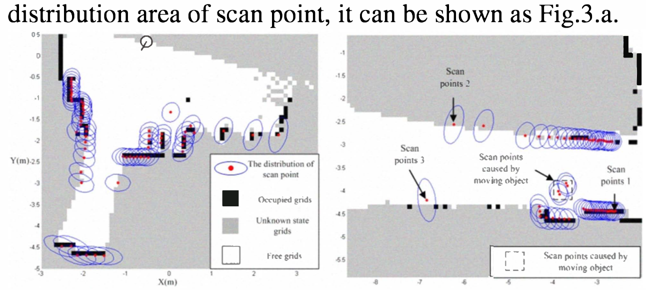
Where p_i^r is representation in robot local coordinates, so have superscript *r*. Let the location of point p_i in global coordinates is p_i^g ,we can get relationship as follow.

$$p_i^g = \begin{bmatrix} x_p^g \\ y_p^g \end{bmatrix} = LTG(x_r, g(b_i)) = \begin{bmatrix} \cos(\theta_r^g) & -\sin(\theta_r^g) \\ \sin(\theta_r^g) & \cos(\theta_r^g) \end{bmatrix} \begin{bmatrix} r_i \cos(\theta_i) \\ r_i \sin(\theta_i) \end{bmatrix} + \begin{bmatrix} x_r^g \\ y_r^g \end{bmatrix}$$
$$= \begin{bmatrix} \cos(\theta_r^g) & -\sin(\theta_r^g) \\ \sin(\theta_r^g) & \cos(\theta_r^g) \end{bmatrix} \begin{bmatrix} x_p^r \\ y_p^r \end{bmatrix} + \begin{bmatrix} x_r^g \\ y_r^g \end{bmatrix} \tag{8}$$

Eq.(8) transfers scan point p_i state p_i^r in robot local coordinates frame to scan point p_i state p_i^g in global coordinates frame. Let the error caused by odometry is a gauss white noises with covariance matrix R_r , and the error caused by laser observation is also a gauss white noises with covariance matrix R_l , According to error propagation formula, it can be obtained.

$$R_{p^g} = H_r R_r H_r' + H_l R_l H_l' \tag{9}$$

Where H_r , H_l are Jacobian of Eq.(8) with respect to x_r and b_i respectively. using E.q (9) we can obtain the error matrix (R_{p^g})of scan point (p_i^g) in global coordinates frame, and the R_{p^g} error matrix will help us to determine the distribution area of scan point, it can be shown as Fig.3.a.



(a)

Figure 3. The possibility of the distribution of scan points.(a) and Judgment of the type of scan points caused by static, moving objects(b).

Fig.3.a gives the possibility distribution of scan points, when $R_r = diog(0.1^2(m), 0.1^2(m), 0.05^2(rad))$, and $R_l =$ $diog(0.01^2(m), 0.005^2(m), 0.005^2(rad))$ In this figure the blue ellipse with red dot represent the possibility distribution of each scan point. the black , grey and white area represent states of grids in map.

When system determines the possibility distribution of each scan point, now we can use the principle of the identity of static environment objects to judge which scan points are caused by moving object, that is, if the possibility distribution of one scan point only contain free state grids, we believe that this scan point is caused by moving object, the result is shown in Fig.3.b. In Fig.3.b, scan points in area of dash line rectangle is caused by moving object. We can see in the figure, all grids in area of possibility distribution of those scan points are white (it represents those grids are in free states formerly), and it means those grids previously did not contained obstacles now exist obstacles. so we can judge those scan points caused by moving objects. However, in area of other scan point's possibility distribution are either contain black grids (marked scan points 1 in figure) or contain gray grids (marked scan points 2 in figure) or contain both of black and gray grids (marked scan points 3 in figure), it means those grids exist obstacles previously or states of those grids were unknown, so those scan points may be caused by static objects or new objects found by laser sensor.

After determining moving objects caused scan points s_t^m Next, we use follow process to further filter s_t^m .

1). Dividing. s_t^m into several subsets according to distance between each point in s_t^m ,Denoted as $s_{1,t}^m$, $s_{2,t}^m$,…, $s_{n,t}^m$,if the number of points in subset $s_{i,t}^m$ is less than a fixed threshold (*MINNUNBER*), we should discard $s_{i,t}^m$.

2). For each subset $s_{j,t}^m$ through step 1), system calculates the maximum *x*, *y* space between each points in the subset, and denoted they as max_x , max_y if max_x greater than a fixed threshold (*MAX X RANGE*) or max_y greater than a fixed threshold (*MAX Y RANGE*), we also discard subset $s_{j,t}^m$,because it is impossible for person to caused such a big reflection plane.

After above two steps, we assume the remains of subsets denoted as $s_t^m = \{s_{1,t}^m, s_{2,t}^m, ..., s_{n_2,t}^m\}$ is final scan points set s_t^m caused by moving objects. Now, this points set s_t^m is what we want to solve in Eq.6.

B. Dynamic objects caused points filter out ICP algorithm

Based on above approach of moving objects detection, in this section we present the improve ICP algorithm, and call it as Dynamic Objects Caused Points Filter Out ICP algorithm (DOCPFO ICP). The one circle of our algorithm as follows.

1). $\hat{r}_{t+1} = RG(r_t, u_t^{r_t})$:getting robot state through odometry information.

2). $s_{t+1}^{m,r_{t+1}} = f(s_{t+1}^{r_{t+1}}, \hat{r}_{t+1}, M_t)$: using function Eq.6. to extract scan points caused by moving objects at time $t+1$.

3) $s_{t+1}^{o,r_{t+1}} = s_{t+1}^{r_{t+1}} - s_{t+1}^{m,r_{t+1}}$: getting scan points caused by static objects.

4). $s_{t+1}^{o,r_t} = RG(s_{t+1}^{o,r_{t+1}}, u_t^{r_t})$:changing $s_{t+1}^{o,r_{t+1}}$ to r_t local coordinates frame.

5). $v^{r_t} = ICP(s_{t+1}^{o,r_t}, s_{t+1}^{o,r_{t+1}})$: using ICP to get the correcting value.

6). $r_{t+1} = RG(RG(u^{r_t}, v^{r_t}), r)$: using correcting value to update the pose of robot at time $t+1$.

7). $M_{t+1} = GRIDMAP\_UPDATE(M_t, r_{t+1}, s_{t+1}^{r_{t+1}})$: Based on the approach presented in [3] to update grid map.

In above algorithm, variable's subscript means time, input Values $s_{t+1}^{r_{t+1}}$ represents scan points obtained in robot local coordinates frame at time $t+1$, s_t^{o,r_t} represents scan points caused by static objects in previous iteration at time *t*, r_t is robot state in global coordinates frame, $u_t^{r_t}$ is odometry information about robot state transition , M_t is grid map. And output values $s_{t+1}^{m,r_{t+1}}$ is moving objects caused scan points distribution in robot local coordinates frame, $s_{t+1}^{o,r_{t+1}}$ is static objects caused scan points distribution in robot local coordinates frame, M_{t+1} and r_{t+1} are grid map and robot state after update. In step 1) using odometry information about robot state transition value $u_t^{r_t}$ to predict state of robot $\hat{r}_{t+1}$ at time $t+1$, $u_t^{r_t}$ is suffered noises. Step 2) based on Eq.6. computes scan points caused by moving objects $s_{t+1}^{m,r_{t+1}}$ (where superscript *m* means moving objects, r_{t+1} represents reference frame). Next, from step 3) to step 6), system uses static objects caused points to update robot state. Finally, In step 7), we use the approach designed in article [3] to update grid map.

VI. EXPERIMENTS

In this section, we will verify effectiveness of our algorithm through two groups of experiments. We implement our method on a Pioneer3DX mobile robot equipped with a Sick LMS-200 laser range scanner is shown in Fig. 4. In the first experiment, we test the ability of our algorithm to solve single moving object detection and the capacity to resist disturbance. The second experiment gives the results of our approach to deal with two moving objects situation.

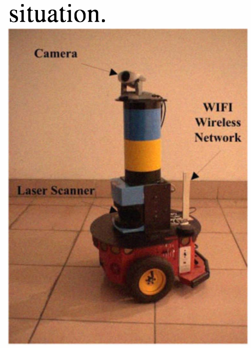


Figure. 4. The pioneer3DX moving objects.

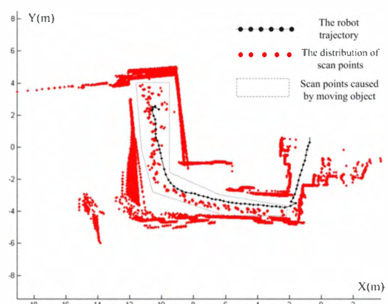


Figure. 5. SLAM errors caused by mobile robot.

Nextly, we present the results of first experiment. In the process of system running one people were walking through the environment leading to sensor corrupted readings. Fig. 5. gives results of scan points distribution only used ICP method. we can see from this figure , the disturbance caused by moving person has a great influence on accuracy of SLAM. The consistency of scan points distribution is poor. The results using our algorithm DOCPFO ICP is shown in Fig. 6. In this figure, Fig. 6(a),(b) and (c) are results of the distribution of static objects caused scan points, the distribution of moving objects caused scan points and the overall scan points distribution using DOCPFO ICP algorithm respectively. From those figures we can see the algorithm makes distinguish between static objects caused scan points (shown in Fig. 6(a)) and moving objects caused scan points (shown in Fig. 6(b)) accurately, and the consistency of the final overall scan points distribution is improved significantly in comparison with only ICP approach. Fig. 6(c) presents the grid map and robot trajectory of final experiment.

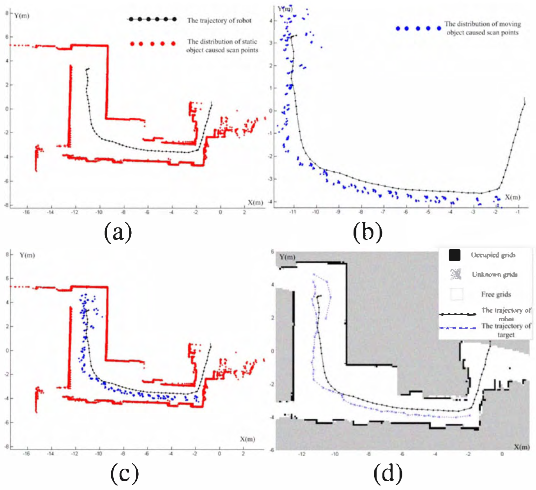


Figure 6. The result of DOCPFO ICP in environment contained one moving object

Finally, we present results of our algorithm in the situation that environment contains two moving objects. In the process of robot operation, object 1 and object 2 enter the view of robot one after another, and two moving objects stop motion before robot stopping. Fig. 7 shown results just using ICP. From this figure we can find that the disturbance is more serious than the disturbance caused by one moving object. Fig. 8(a), (b) and (c) depict the scan points distribution results from our system, solid dots in those figures represent robot location estimation at different time. The data points in Fig. 8(a) belonging to static objects are shown in red, the ellipse area contain scan points caused by inactive targets. The data points in Fig. 8(b) belonging to moving objects are shown in blue, Fig. 8(c) shows overall scan points distribution, and we can get from this figure that the consistency of scan points distribution is good. the final grid map and two moving targets overall position estimation as shown in Fig. 8(d).

VII. CONCLUSIONS

In this paper we have addressed the issue of simultaneous localization, mapping and detection of moving object. The investigation of SLAMOT problem can expand application areas of SLAM such as task of target tracking with robot in unknown environment. Our approach can effective overcomes the interference caused by moving objects and improves the practical ability of traditional SLAM method. Moreover, the method uses uncertain region of each scan points to judge points type, which includes moving objects caused points and static objects caused points, so improve the accuracy of distinction between the dynamic and static objects in environment. The experimental results confirm the validity of this approach.

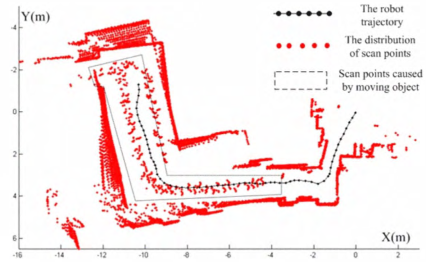


Figure 7. SLAM errors caused by two moving objects.

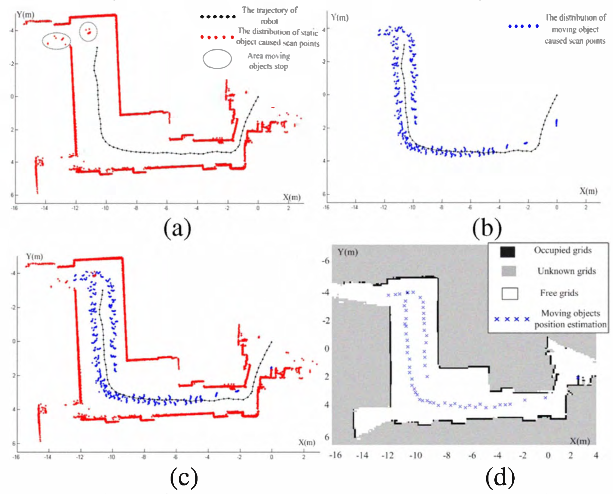


Figure 8. The result of DOCPFO ICP in environment contained two moving object

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