SLAM and a Novel Loop Closure Detection for Autonomous Underwater Vehicles

Shujing Zhang, Bo He*, Rui Nian, Yan Liang
Department of Electronics Engineering
Ocean University of China
Qingdao, China
sjzhang365@gmail.com; bhe@ouc.edu.cn (*correspondence author); nianrui_80@sina.com; liangyan@126.com

Tianhong Yan
Department of Mechanical & Electrical Engineering
China Jiliang University
Hangzhou, China
thyan@163.com

***Abstract*—SLAM has increasingly become a hot topic for vehicle applications in underwater environments, searching an accurate and effective method for loop closure detection is one of the key issues for SLAM. The benefit of closed loop is the repeated observation of features, which can update the overall vehicle trajectory and environmental map to get more precise localization and mapping. In this paper we explore a novel multi-restraint method of closed-loop detection based on the time limit, data association and the location deviation. The experimental results of simulation and sea trial verify the validity and feasibility of the proposed method for AUV SLAM in large-scale real world environments.**

Keywords—SLAM; Closed loop; AUV

I. INTRODUCTION

Simultaneous Localization and Mapping (SLAM) can be described as: an autonomous mobile vehicle leaves from an unknown location in an unknown environment, and gradually builds an environment map and calculates its location within this map [1-3]. When the vehicle navigates in a real area, it is inevitable for the vehicle to visit the same location repeatedly which is called closed loop. Closed-loop detection is a common problem in vehicle navigation: a vehicle determines whether its current location has been visited, and whether its trajectory and map needs to be updated.

Generally, most of the closed-loop detection methods depend on the probability solutions [4-6] which consider this detection problem as the Bayesian estimation. In order to calculate the probability of being outside the map built before for the vehicle, they usually assume that the landmarks of the environment agree with uniform distribution, that is, all observations from the sensors are assigned a fixed equal probability for the unexplored area. But that is not the case. These methods ignore the useful information in the environment, so, inevitably leads to poor robustness of SLAM, and the large computational cost. It is not suitable for real-time SLAM algorithm. Currently, research interests mainly focus on the closed-loop detection technology for outdoor 6D SLAM using 3D laser range scans [7-9] and the visual appearance-based SLAM using cameras [10-12]. In this paper we propose a novel multi-restraint method of closed-loop detection using a mechanical scanning forward-looking sonar.

II. SIMULTANEOUS LOCALIZATION AND MAPPING

The posterior for SLAM system can be described as [13]:

$$p(\mathbf{X}^t, \mathbf{M}, | \mathbf{Z}^t, \mathbf{U}^t, \mathbf{A}^t) \tag{1}$$

where $\mathbf{X}^t = \mathbf{x}_1, \cdots, \mathbf{x}_t$ is the vehicle path with state vector $\mathbf{x} = [x, y, \phi, v_x, v_y]^T$, $\mathbf{M} = \mathbf{m}_1, \cdots, \mathbf{m}_K$ denote the map containing K landmarks, $\mathbf{Z}^t, \mathbf{U}^t, \mathbf{A}^t$ present a sequence of observations, controls and data association respectively.

In order to obtain better estimates and reduce the computational cost, state vector $\mathbf{x}_t$ can be divided into the nonlinear portion $\mathbf{x}_t^N = [x, y]^T + \mathbf{w}^N$, and the linear portion $\mathbf{x}_t^L = [\phi, v_x, v_y]^T + \mathbf{w}^L$, where $\mathbf{w}^N = [N_x, N_y]^T$ and $\mathbf{w}^L = [N_\phi, N_{v_x}, N_{v_y}]^T$ is the additive zero mean uncorrelated Gaussian motion disturbances with covariance Q^N and Q^L. The superscript L and N stand for linear and nonlinear respectively.

The motion model for SLAM is shown as follows:

$$\begin{aligned}
&\mathbf{x}_t = [\,\mathbf{x}_t^N \, \mathbf{x}_t^L\,]^T \\
&\mathbf{x}_t^N \Rightarrow \begin{cases} x_t = x_{t-1} + (v_{x,t-1} \times \Delta t + 0.5 \times a_{x,t-1} \times \Delta t \times \Delta t) \times \cos(\phi_{t-1}) \\ \qquad - (v_{y,t-1} \times \Delta t + 0.5 \times a_{y,t-1} \times \Delta t \times \Delta t) \times \sin(\phi_{t-1}) + N_{x,t-1} \\ y_t = y_{t-1} + (v_{x,t-1} \times \Delta t + 0.5 \times a_{x,t-1} \times \Delta t \times \Delta t) \times \sin(\phi_{t-1}) \\ \qquad + (v_{y,t-1} \times \Delta t + 0.5 \times a_{y,t-1} \times \Delta t \times \Delta t) \times \cos(\phi_{t-1}) + N_{y,t-1} \end{cases} \\
&\mathbf{x}_t^L \Rightarrow \begin{cases} \phi_t = \phi_{t-1} + w_{t-1} \times \Delta t + N_{\phi,t-1} \\ v_{x,t} = v_{x,t-1} + a_{x,t-1} \times \Delta t + N_{v_x,t-1} \\ v_{y,t} = v_{y,t-1} + a_{y,t-1} \times \Delta t + N_{v_y,t-1} \end{cases}
\end{aligned} \tag{2}$$

Similar to the state vector, the observation vector is also divided into two portions $\mathbf{z}_t = [\mathbf{z}_t^N \, \mathbf{z}_t^L]^T$, where $\mathbf{z}_t^N$ is the observation vector from sonar and $\mathbf{z}_t^L$ is the observation vector from compass and DVL.

To map its surrounding environment, vehicle senses landmarks by imaging sonar which is able to measure range

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and bearing to landmarks as $\mathbf{z}_t^N = [r, \psi]^T$. The observed landmark position in global coordinate frame is denoted as $\mathbf{m}_t = [m_x, m_y]^T$, and the observation model of sonar is :

$$\mathbf{z}_t^N = \begin{bmatrix} r(\mathbf{x}_t, \mathbf{m}_t) \\ \psi(\mathbf{x}_t, \mathbf{m}_t) \end{bmatrix} = \begin{bmatrix} \sqrt{(m_x - x_t)^2 + (m_y - y_t)^2} \\ \tan^{-1}(\dfrac{m_y - y_t}{m_x - x_t}) - \phi_t \end{bmatrix} + N_t^N \quad (3)$$

where N_t^N is the nonlinear observation noise with zero mean and covariance R^N.

And the observation model of compass and DVL is:

$$\mathbf{z}_t^L = \begin{bmatrix} \phi_t \\ v_{x,t} \\ v_{y,t} \end{bmatrix} + N_t^L \quad (4)$$

where ϕ_t is the vehicle heading angle from the digital compass, $v_{x,t}$, $v_{y,t}$ are the vehicle velocities provided by DVL, and N_t^L is the linear observation noise with zero mean and covariance R^L.

III. A Novel Loop Closure Detection

In this paper we propose a novel multi-restraint method based on the time limit, data association and the location deviation using a mechanical scanning forward-looking sonar, it can be described by the following five rules:

(1) There is no closed loop in ΔT_1 time relative to the starting time T_0 of the vehicle path. The selection of ΔT_1 is based on the navigation environment and the acceptable size of the loop. If the vehicle sails in a vast area, and we just focus on the larger loop, ΔT_1 can be set to a relative large value. This selection method is also beneficial to remove the closed-loop illusion due to the retreat problem generated when the vehicle is started.

(2) There is no closed loop in the ΔT_2 time relative to the start time T_l of the loop. The appropriate selection of ΔT_2 can help reduce the number of the smaller loop generated in the navigation process. If the time interval ΔT_2 is set relatively large, the number of the detected closed-loops will be relatively small.

(3) The current observation landmarks can associate with the existed landmarks of the environment map. The necessary condition to generate a closed-loop is that there are some similarities between the current environment and the previous environment where the vehicle has passed. The data association can employ the popular methodologies, such as individual compatibility nearest neighbor (ICNN) and joint compatibility branch and bound (JCBB), both of them are based on the Mahalanobis distance [8]:

$$D^2 = V^T S^{-1} V \quad (5)$$

where V and S are the innovation and its covariance matrix respectively.

(4) The location deviation between the current vehicle position $[x_t, y_t]$ and the start position $[x_l, y_l]$ of the loop is less than the threshold *Dist*, that is：

$$D_{tl} = \sqrt{(x_t - x_l)^2 + (y_t - y_l)^2} \le Dist \quad (6)$$

The selection of the threshold *Dist* is extremely crucial, generally we can choose it according to the percentage of the navigation distance, such as 0.5%.

(5) There will be no closed loop again in the ΔT_3 time after the latest detected closed-loop. This limit is used to eliminate the situation that the vehicle generates multiple closed-loops continuously. As the vehicle may still meet the above four conditions during the successive voyage after the latest detected loop closure.

Next the above rules will be demonstrated by Fig. 1. The vehicle starts its navigation from point A. When it reaches point B nearby, landmark L1 is observed and added into the map. And it is the same with point C and landmark L2. After a while, the vehicle arrives at point D and observes landmark L2 again. If the time interval ΔT_{AD} when the vehicle reaches point A and point D satisfies the first rule (i.e. $\Delta T_{AD} \ge \Delta T_1$) and the time interval ΔT_{CD} satisfies the second rule (i.e. $\Delta T_{CD} \ge \Delta T_2$), then we can calculate the Euclid distance D_{CD} between point D and point C. Here we assume D_{CD} is greater than the threshold *Dist*, so the vehicle does not close a loop. Then it moves forward and arrives at point E and observes landmark L2 again. If the distance D_{CE} between point E and point C meets the forth rule, we consider the vehicle closes a loop. When the vehicle passes by point C, F and G, it meets all the rules but the fifth one. After time T ($T \ge \Delta T_3$), the vehicle arrives at point I, it observes landmark L1 and meets all the rules, so we detect the second closed loop.

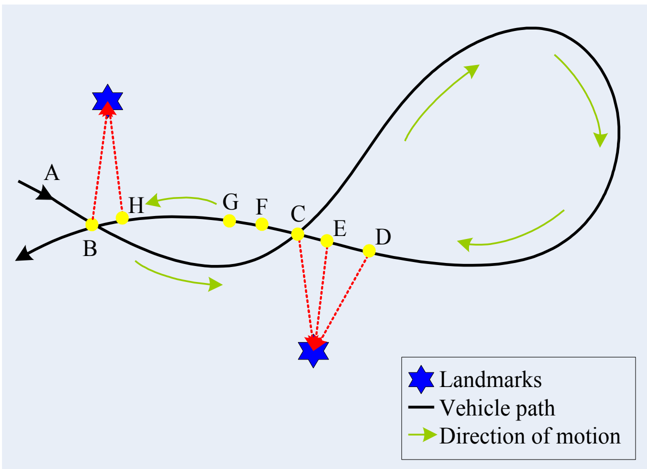


Fig. 1. Closed-loop detection.

IV. EXPERIMENTS AND ANALYSIS

In this section, our proposed algorithm will be tested in two environments, an artificial simulation environment and a real outdoor environment. In these two environments, SLAM is implemented by using the classical framework of extended Kalman filter (EKF) and the data association is performed by using the ICNN algorithm.

A. Simulation

Both Fig. 2 and Fig. 3 are obtained by using a couple of simulation data. There are no closed loops in Fig. 2 and a closed-loop in Fig. 3. The green line and the black line represent the true path and the estimated path from SLAM. The blue '*'s represent the true landmarks of the environment, while the red '+'s and their surrounding ellipses denote the estimated landmarks and their uncertainty.

It is obvious that the uncertainty of the landmark becomes smaller after a closed-loop. The green pentagram represents the first observed landmark when a closed loop is detected. It is easy to see that the closed loop can be detected correctly and the closed loop improves the vehicle trajectory and the map.

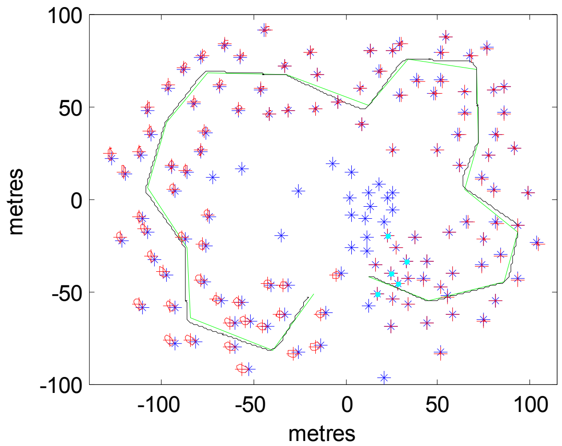


Fig. 2. No closed loops.

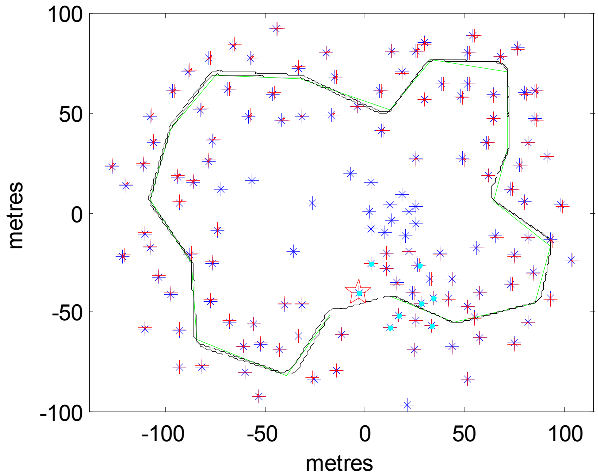
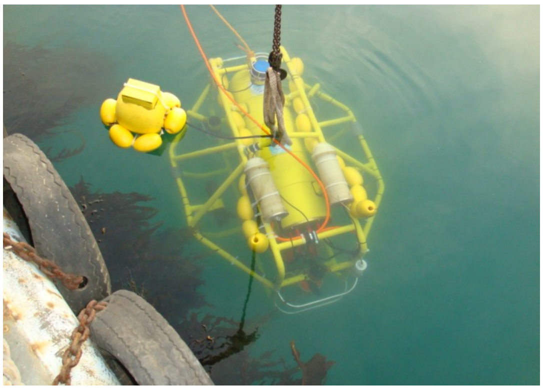


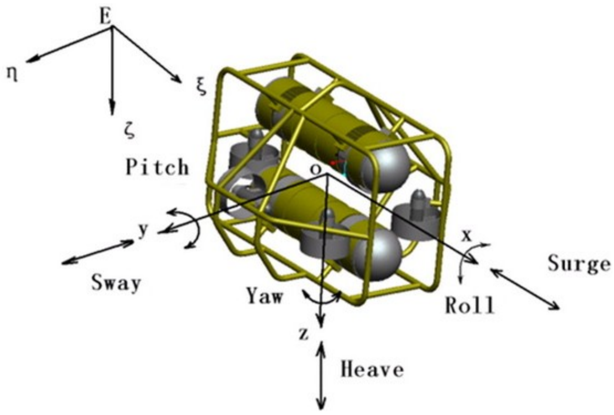
Fig. 3. A closed-loop.

B. Real World Exploration

The real world experiments were carried out at Tuandao Bay (Qingdao, China) and its dataset samples were obtained from the on-board sensors installed on our C-Ranger AUV platform [14-16] as shown in Fig. 4. Fig. 5 is the experimental result of trajectory and map for SLAM after the closed-loop detection. We can see that there are three loops, and all of them are detected correctly. Actually, each loop will improve the final estimated result effectually.



(a) C-Ranger is in deployment.



(b) The coordinate system of C-Ranger platform.

Fig. 4. C-Ranger AUV.

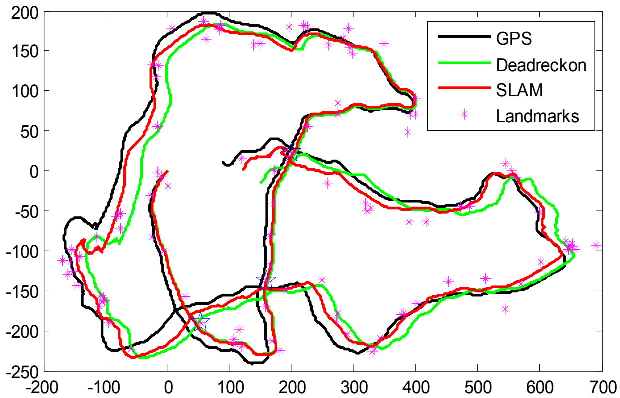


Fig. 5. Experimental result.

V. CONCLUSION

This paper presents a novel multi-restraint closed-loop detection approach based on the time limit, data association and the location deviation using a mechanical scanning forward-looking sonar. The experimental results of simulation and sea trial verify the validity and feasibility of the proposed method for AUV SLAM in real world environments.

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