

IOP Conference Series: Earth and Environmental Science

PAPER • **OPEN ACCESS**

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To cite this article: Keyong Jiang *et al* 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **440** 042004

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Monte Carlo Localization for an Autonomous Underwater Vehicle with a Low-Cost Sonar

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Abstract. This paper proposes a Monte Carlo based localization (MCL) algorithm for autonomous underwater vehicle (AUV) with a low-cost mechanical scanning imaging sonar (MSIS). As MSIS has a slow-sampling characteristic, its scan is distorted by the vehicle motion during the scan interval and the sonar readings are sparse. Our contribution is introducing this two-stage approach to overcome the shortages of MSIS to achieve accurate localization: 1) the scan formation module is devised to eliminate the motion induced distortion of sonar scan; 2) MCL is applied to estimate the AUV pose accurately by the Dead Reckoning (DR) result and the formed sonar scan. Results of simulation verify that the proposed algorithm performs well in terms of effectiveness and accuracy.

1. Introduction

The autonomous underwater vehicle (AUV) has been designed and deployed in underwater exploration during the last few decades. They are able to conduct various underwater missions, such as scientific sampling [1], air crash investigations [2], and reconnaissance. Localization is one of the most important abilities of AUVs to achieve those tasks autonomously.

Underwater localization is extremely challenging because GPS cannot be used for AUV localization in underwater environments and the vision-based localization of AUVs is difficult to be applied [3]. Therefore, traditional underwater acoustic position systems are used for underwater positioning, such as Long Baseline (LBL), Short Baseline (SBL), and Ultra-Short Baseline (USBL) [4]. These methods have a disadvantage that a lot of prerequisite operations should be conducted to maintain the localization accuracy, including prior baseline deployment, calibration, and recovery. To avoid these limitations and seek a low-cost solution, researchers have deployed different algorithms that depend on external environment information collected by sonars to accomplish localization.

MSIS is a kind of sonar sensor that has low cost, small size and low power consumption, which is selected as the perception sensor for localization in some literatures. Chen et al. [5] adopts GraphSLAM that incrementally constructs a pose graph and conducts graph optimization to correct AUV pose. Demim et al [6] introduced the Smooth Variable Structure Filter (SVSF) to solve the SLAM problem,



which is known to be very robust to modeling errors and uncertainties. The underwater sonar probabilistic iterative correspondence (uspIC) algorithm localized by the relative transformation calculated by scan matching, which was a variant of the Iterative Closest Point (ICP) [7]. Dong et al. [8] proposed a localization algorithm that obtains the estimation of AUV's pose by comparing the boundary of the reactor pool obtained from the sonar data by Hough Transform and least square fitting with the known map of the pool. Obviously, this approach was only suitable for structured manmade scene. Besides, the Monte Carlo Localization (MCL) is also used for AUV localization [9], although it is more widely applied to terrestrial mobile robot and vehicle in urban environment.

This paper proposes a Monte Carlo based localization algorithm for AUVs with slow-sampling MSIS, which is called MCL-MSIS. In order to improve the accuracy and real-time performance of the localization algorithm, the scan formation module is devised to eliminate the motion distortion and compensate for the shortcoming of sparse sonar data. Then the algorithm adopts the Kullback-Leibler distance (KLD) based MCL that takes advantage of processed sonar scans to continuously estimate the pose of AUV.

The rest of the paper is organized as follows. Section 2 illustrates the framework and algorithm of the proposed MCL-MSIS localization approach. Section 3 is about the simulation and results comparison between MSIS-MCL and uspIC. Finally, Section 4 concludes the paper.

2. The proposed algorithm

2.1. Characteristics and Problems of MSIS

MSIS is a type of digital ranging sonar, its transducer head emits a fan-shaped acoustic beam at a predetermined small angle increment along a direction, as shown in Fig.1. The MSIS raw data for each angle is an echo intensity profile which is discretized into a set of L data bins. According to the time of flight and the speed of sound in water, each intensity of echo has its corresponding position in the sonar coordinate system.

The characteristics of MSIS make it necessary to pre-process raw sonar data before localization. Firstly, the ranges and angles from the sensor to the relevant obstacle should be abstracted from echo intensity profiles. Therefore, the beam segmentation method proposed in [7] could be applied to obtain the sonar readings (range and angle). Secondly, these sonar readings should be corrected to eliminate the distortion caused by vehicle motion during the scan interval because the distortion will impose bad impact on localization accuracy. Furthermore, the slow-frequency of MSIS leads to another issue that the sonar readings are sparse because MSIS cannot obtain multiple scans in a second. In order to overcome the distortion and sparseness of sonar readings, a scan formation module is carefully designed and will be presented in the following subsection.

2.2. Dead Reckoning

Dead reckoning is a traditional navigation method that calculate the motion by velocities and angular velocities provided by Doppler Velocity Logs (DVL) and Inertial Motion Unit (IMU). However, it has unavoidable drift over time. To obtain the most desirable output, an Extended Kalman Filter (EKF) is adopted to substitute integration to estimate the motion of AUV.

Assuming that the process has a state vector $\mathbf{x}_k = [x_k \ y_k \ z_k \ \phi_k \ \theta_k \ \psi_k]^T$ at time k , $\mathbf{u}_k = [u_k \ v_k \ \omega_k \ p_k \ q_k \ r_k]^T$ is the control input. Based on the sampling time interval Δ_T , the process model is a non-linear discrete time system which can be described as:

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k) = \mathbf{x}_k + J(\mathbf{x}_k)\mathbf{u}_k\Delta_T \quad (1)$$

Where $J(\mathbf{x}_k)$ is the transformation matrix [10]. For simplicity, \sin, \cos, \tan are replaced by s, c, t respectively. However, u_k from DVL is disturbed by Gaussian noise $\omega_k \sim \mathcal{N}(0, Q_u)$ and thus other sensor information is required for error correction. u_k From DVL is disturbed by Gaussian noise $\omega_k \sim \mathcal{N}(0, Q_u)$. The state could be updated by:

$$\hat{\mathbf{x}}_{k+1|k} = f(\hat{\mathbf{x}}_{k|k}, \hat{\mathbf{u}}_k) \quad (2)$$

And the state error covariance matrix is calculated by:

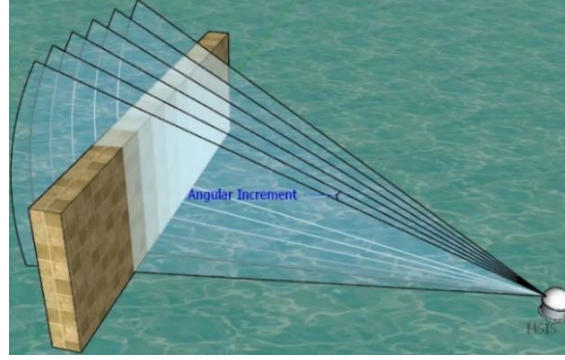


Figure 1. A working MSIS is emitting fan-shaped beam along a direction.

$$P_{k+1|k} = A_k P_{k|k} A_k^T + B_k Q_u B_k^T, \quad (3)$$

Where A_{k+1} and B_{k+1} are Jacobian matrices defined by:

$$A_k = \frac{\partial f}{\partial \mathbf{x}}(\hat{\mathbf{x}}_{k|k}, \mathbf{u}_k, 0), \quad (4)$$

$$B_k = \frac{\partial f}{\partial \mathbf{u}}(\hat{\mathbf{x}}_{k|k}, \mathbf{u}_k, 0) \quad (5)$$

The orientation measurement is provided by IMU:

$$h_{a,k} = H_{a,k} \mathbf{x}_k + \mu_{a,k} = [0_{3 \times 3} \ I_{3 \times 3}] \mathbf{x}_k + \mu_{a,k}, \quad (6)$$

Where I denotes the identity matrix and $\mu_{a,k}$ is also a zero-mean Gaussian noise but its covariance is R_a . Then the model prediction is updated by the standard EKF equations.

2.3. Scan Formation

The purpose of scan formation is to form a corrected scan while increasing the frequency of the formed scan. In this algorithm, a sonar reading p sampled in sonar reference $\{S\}$ is eventually transformed into \hat{p}^F , which is represented in current AUV coordinate system $\{F\}$. This functionality requires some steps, as follows. First, the process adopts two queue-type variables to store the history of sonar readings and transforms. Afterwards, sonar reading is transformed from polar coordinate to Cartesian coordinate. Then the dead reckoning corresponding to the specific sonar reading is find out by its timestamp, and the transform from $\{S\}$ to the world frame $\{W\}$ is obtained. The transform between the $\{S\}$ and the previous AUV body frame $\{R\}$ is a constant represented by \hat{T}_S^R . Later, according to these data, the sonar point can be converted into the current coordinate system $\{F\}$ by compounding and reversion operation when the latest sonar reading has been received. The transformation formula is obtained by the relationships between coordinate systems. Also, the variance of the point P_F is calculated by the variance of the current sonar relative to the $\{W\}$ and the covariance corresponding to the transform \hat{T}_F^W calculated in DR. At last, the currently formed scan is recorded as S_{cur} .

In order to increase the publish frequency of scan, a strategy is employed in this module that a newly arrived reading is combined with the last $N - 1$ readings to form a new scan. Therefore, the first element

of R_Q and T_Q are deleted after the scan has formed to ensure the storage of the latest N data. The reuse of readings shortens the period of scan to T/N , which achieves localization faster and improves the accuracy of localization because the scans do not vary dramatically.

2.4. Monte Carlo Localization

MCL algorithm is a combination of Monte Carlo method and Bayes Filter, which calculates the posterior distribution $p(\mathbf{x}_k | \mathbf{z}_{1:k}, \mathbf{u}_{1:k})$ to estimate the robot's pose [11]. In a 2D plane, \mathbf{x}_k is a three-dimensional vector $[x, y, \varphi]^T$ at discrete-time k , where x and y are the position of the robot in Cartesian coordinate and φ is the heading angle of the robot. \mathbf{z}_k is the sensor measurement, which refers to the sonar scan S_{cur} produced by scan formation at time k . \mathbf{u}_k is the robot motion and refers to the estimation of DR. In MCL, the posterior distribution approximation is realized by a set of N_k weighted particles:

$$p(\mathbf{x}_k | \mathbf{z}_{1:k}, \mathbf{u}_{1:k}) \approx \sum_{i=1}^{N_k} w_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i) \quad (7)$$

Where \mathbf{x}_k^i the random particles are sampled from $p(\mathbf{x}_k | \mathbf{z}_{1:k}, \mathbf{u}_{1:k})$, w_k^i are positive weights, and δ is Dirac delta function. The set of particles is denoted as $X_k = \{\mathbf{x}_k^i, w_k^i\}_{i=1}^{N_k}$.

Unfortunately, sampling directly from $p(\mathbf{x}_k | \mathbf{z}_{1:k}, \mathbf{u}_{1:k})$ is difficult because this distribution cannot be written as a general analytical expression. Therefore, the prior probability density function $p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{z}_k, \mathbf{u}_k)$ is used instead. Then the weight can be simplified as:

$$w_k^i = w_{k-1}^i p(\mathbf{z}_k | \mathbf{x}_k, map) \quad (8)$$

Where map is the known map, and $p(\mathbf{z}_k | \mathbf{x}_k, map)$ is the measurement probability [12].

Then, the resampling step is conducted to solve particle degradation problem by reserving particles with larger weights [13]. The KLD sampling is one of resampling approaches, which can adjust the number of particles dynamically during the filtering process [14]. To make sure that the KLD between sample-based approximation and true probability distribution is within the allowable range, the number of particles is determined based on the statistical bounds of the approximate quality of the samples. The dynamic bound M_χ [14] is depicted as:

$$M_\chi = \frac{c-1}{2\varepsilon} \left\{ 1 - \frac{2}{9(c-1)} + \sqrt{\frac{2}{9(c-1)} z_{1-\delta}} \right\}^3 \quad (9)$$

Where c the number of non-empty is bins in the state space histogram, and $z_{1-\delta}$ is the upper $1 - \delta$ quantile of the standard normal distribution [14]. ε And δ are predefined values. The degree of dispersion of the particles affects the size of M_χ [15].

3. Simulation

For the sake of illustrating the effectiveness of the proposed localization algorithm, simulation is carried out with widely-used middleware Robot Operating System (ROS) and 3D simulator *Gazebo*. Plugins for IMU, DVL, and MSIS sensors are embedded into *Gazebo* to publish corresponding sensor data. The outline of the simulated anomalous pool about 70 m \times 70 m (length \times width) is shown in Fig.2. Before simulation, the prior map of the environment has prepared. When *Gazebo* is launched, the AUV is controlled to move at an average speed of 0.1 m/s.

Figure 2 also presents the scans produced by raw sonar data and the scan formation corrected data. It is clear to see that the scan based on raw sonar data (blue dot) has a great deviation from the formed scan, which illustrates that the scan formation module can effectively eliminate the motion distortion and form scans that match the environment well as a laser scanner does.

Figure 3 shows the trajectories of the AUV, which are constructed from simulator data by MCL-MSIS, uspIC, dead reckoning and the ground truth, respectively. It can be noticed directly that the trajectory MCL-MSIS (red line) is closer to the ground truth (green line) than uspIC (blue line) in general. The location error comparison between MCL-MSIS, uspIC, and DR is given in Fig.4. The means of absolute error of the dead reckoning, uspIC, and MCL-MSIS gradually decreased to 1.09m, 0.95m, and 0.25m, respectively.

Although the uspIC usually can provide more accurate pose estimation than DR, it performed worse during the period of 800 to 1100 seconds due to its algorithm principle. It relies primarily on calculating the motion between two consecutive scans to estimate the trajectory of the AUV [7]. When the shape difference between these two scans is large, the error of the motion estimation is large too. Moreover, the estimation error is continuously accumulated. In simulator, the pool is unstructured and has large obstacles inside, which makes scans obtained at two close locations may vary greatly and causes that the error of scan matching is even larger than that of DR in some cases. On the contrary, the relationship between the two scans makes no difference to MCL-MSIS. Therefore, the localization accuracy of MCL-MSIS is better than uspIC, as shown in Fig.3 and Fig.4.

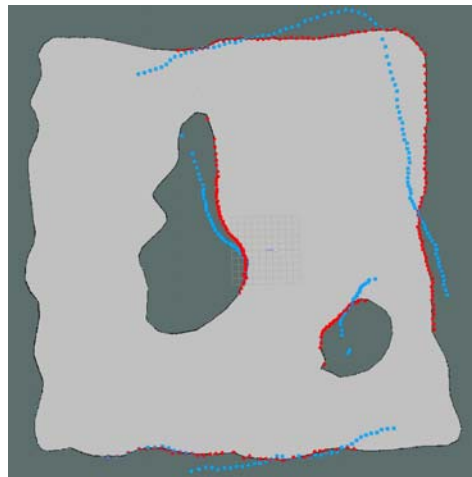


Figure 2. Scans produced by raw sonar data (blue dot) and the scan formation corrected data (red dot).

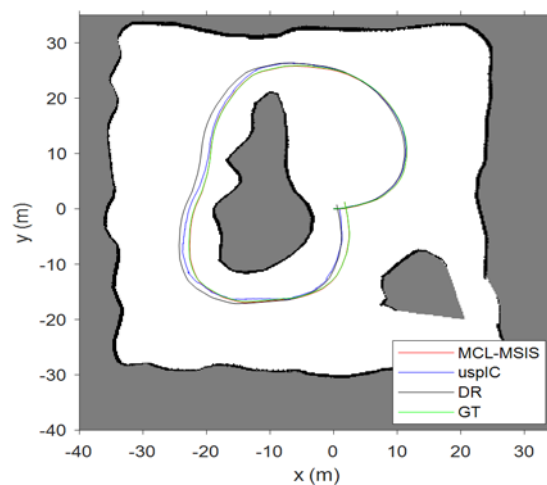


Figure 3. AUV trajectories constructed from simulator data by MCL-MSIS, uspIC, DR, and the ground truth (GT).

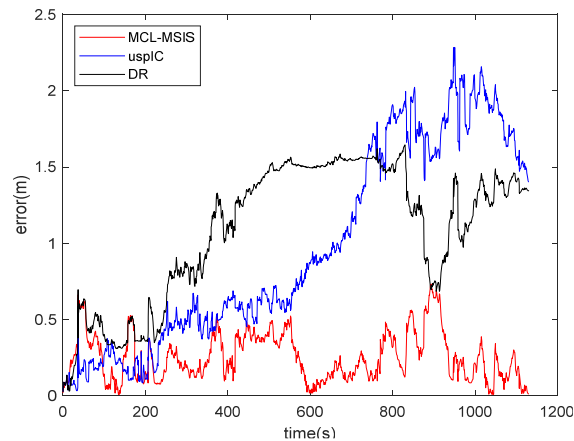


Figure 4. The pose error comparison (MCL-MSIS, uspIC, DR).

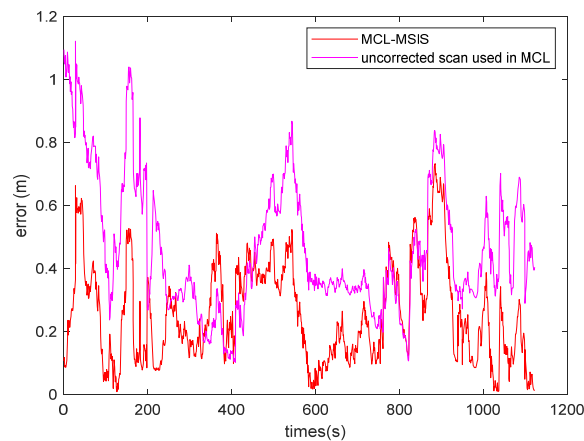


Figure 5. Errors of localization based on the corrected scan (MCL-MSIS) and uncorrected scan

In order to further reflect the effect of the scan formation module on MSIS-MCL, the uncorrected scans are brought into the algorithm to calculate the localization results. Figure 5 shows the errors of localization based on corrected scan and uncorrected scan. As the figure shows, the pose estimation error of MCL with uncorrected scan (magenta line) is always greater than that of MCL-MSIS (red line), which means that the scan formation module makes the localization result more accurate.

4. Conclusion

This paper proposes a novel localization algorithm framework for AUVs with slow-sampling MSIS, which is based on MCL and prior environment map in an unstructured environment. The main contribution of this paper is twofold: 1) a special strategy of scan formation based on data structure of queue is proposed; 2) a MCL algorithm combining the scan formation strategy and particle filter is developed to achieve a high accuracy of pose estimation. Simulation is conducted to verify the effectiveness of the proposed algorithm. The results demonstrate that the proposed MCL-MSIS outperforms the existing uspIC in term of localization accuracy.

Acknowledgments

This research was funded by National Natural Science Foundation of China (Grant No.61703262 and 61873158), the Natural Science Foundation of Shanghai (18ZR1415100), and 111 Project (Grant No. D18003).

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