Experimental Results of Real-time Sonar-based Underwater Localization Using Landmarks

Yeongjun Lee, Jinwoo Choi and Hyun-Taek Choi
Ocean System Engineering Research Division
Korea Research Institute of Ships and Ocean engineering (KRISO)
Daejeon, Sounth Korea
Email: {*leeyeongjun,jwchoi,htchoi*}@ *kriso.re.kr*

***Abstract*—This paper presents experimental results of a real-time sonar-based localization technique using the probability-based landmark-recognition method. Sonar based localization is used for the navigation of unmanned underwater vehicle (UUVs). Inertial sensors such as inertial measurement unitss (IMUs), doppler velocisy logs (DVLs), and external information obtained from sonar are combined using the extended kalman filter (EKF) technique to obtain the navigation information. We estimate the vehicle location using inertial sensor data, and it is corrected using sonar data, which provides the relative position between the vehicle and a landmark placed on the bottom. To verify the suitability of the proposed method, we perform experiments in a basin environment using the UUV, "yShark".**

Keywords: ***Sonar based SLAM; Underwater recognition; Imaging sonar; Localization, UUV;***

I. INTRODUCTION

Over the past few years, the localization *(or navigation)* methods using vision sensors have been actively researched in the field of underwater robotics [1]–[4]. Generally, vision sensors are used to correct the predicted locations of vehicles that are estimated by inertial sensors such as inertial measurement unitss (IMUs), doppler velocisy logs (DVLs). Accordingly, the localization performance depends on the image quality and image-processing technique that is employed. However, the perception range of optical systems is limited by a number of problems such as turbidity, light, and the presence of floaters in underwater environments. Hence, sonar systems such as multi-beam, side-scan sonar, and imaging sonar are employed to overcome these difficulties [5]–[8].

Imaging sonar, specifically dual-frequency identification sonar (DIDSON) [9], measures the geometrical location of objects, namely the distance and direction. Imaging sonar can detect objects at distance of up to several tens of meters away, and is not affected by turbidity or poor illumination. However, the obtained sonar image has a weakness in that it is very unstable because of the characteristics of ultrasonic waves. This makes it difficult for objects to be recognized using imaging sonar.

To overcome this weakness, we have preliminary studied about a landmarks for the detection of objects using imaging sonar in noisy conditions [10], [11]. In this paper, we propose sonar-based localization method using the probability-based landmark-recognition for the navigation of UUVs. The probability-based landmark-recognition method is based on Bayes theorem [12] to improve the detectability. It recursively evaluated the probabilities of detecting landmarks that math a fixed ID. From this process, we can get not only the ID but also the distance and the direction of landmarks, because it is possible to get a geometric information from sonar image. Consequently, the recognized landmark is used as external sensor information to correct the navigation of underwater robots by extended Kalman filter-(EKF-)based localization. The proposed sonar based localization is implemented such that it can be carried out in real time. We verified the proposed sonar-based localization method by performing basin experiments using an unmanned underwater vihicle (UUV) *(yShark)*, and we present the results below.

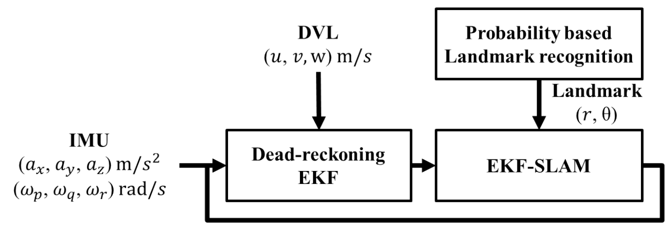

Fig. 1. Overview of sonar-based localization : A sonar based localization is seperated two parts, 1) probability based landmark recognition and 2) sonar based SLAM using extended kalman filter (EKF).

II. SONAR-BASED LOCALIZATION

A. Overall Process

The proposed sonar-based localization technique consists of two processes (Fig.1). First, the probability-based landmark-recognition state perceives an artificial landmark based on Bayes theorem. Second, the EKF-based localization state obtains the navigation information such as $\{X, Y, Z, \phi, \theta, \psi\}$ of the underwater robot using IMU, DVL, and landmarks. Although second state is specifically separated in the dead-reckoning state and the simultaneous localization and mapping (SLAM) state, they simultaneously work as a single process.

B. Probability-based Landmark Recognition

To recognize artificial landmarks, we designed a probability-based landmark-recognition framework that consists of 1) candidate selection 2) elimination of noisy data, and 3) Bayesian feature estimation. Step 1 and 2 followed our previous study

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[11]. In the Bayesian feature estimation step, we estimated the probabilities of obtaining each landmark's ID (*or feature*) using the method based on Bayes theorem, and we repeatedly evaluated the probabilities in a series of images. As a result, the high probability of the feature is to be used as its ID. The probabilities are calculated sequentially using (1)-(3).

$$\bar{p}(x_t(m)) = \sum_{j=1}^{M_{t-1}} p(x_{t-1}(j)) \cdot p(m,j) \tag{1}$$

We estimate the probability $\bar{p}(x_t(m))$ using the pre-probability $p(x_{t-1}(j))$ at landmark j, and the process model $p(m,j) = p(l_t(m) = l_{t-1}(j))$, which is the probability that the landmark j at *t-1* corresponds to the landmark m at time t.

$$\hat{p}(x_t(m)) \mid z_t(m)) = \frac{p(z_t(m) \mid x_t(m)) \cdot \bar{p}(x_t(m))}{p(z_t(m))} \tag{2}$$

Equation (2) is based on Bayes theorem. This function carries out the normalization of the conditional probability. The measurement model $p(z_t(m) \mid x_t(m))$ describes the probability that the real ID k is recognized as the feature j by the measurement system. It is determined by the performance and properties of the measurement system and is given a priori. The normalized probability is divided by the normalizer $p(z_t(m))$ to make the total probability theorem works for the conditional probability.

$$p(x_t(m)) = \sum_{j=1}^{F_f} \hat{p}(x_t(m) \mid z_t(m)) \cdot p(z_t(m)) \tag{3}$$

Finally, the measurement $p(z_t(m))$ updates the normalized probability, and we obtain the probabilities of detecting each landmark. The ID that has the highest probability, is determined to be a landmark's ID.

C. EKF Localization Algorithm

If the landmarks ID is recognized, we are able to obtain its location as the distance and azimuth from the UUV. Further, it is possible to estimate the three-dimensional (3-D) relative location of the UUV. To do this, the EKF-SLAM algorithm was implemented [13] [14]. EKF-SLAM is composed of prediction and update stages that can estimate the SLAM state (4) and its covariance matrix (5) in a recursive way, and it is given by :

$$\mathbf{x}(k) = \begin{bmatrix} \mathbf{x}_v^T & \mathbf{p}_1^T & \cdots & \mathbf{p}_N^T \end{bmatrix}^T \tag{4}$$

$$\mathbf{P}(k) = \begin{bmatrix} \mathbf{P}_{vv} & \mathbf{P}_{vm} \\ \mathbf{P}_{vm}^T & \mathbf{P}_{mm} \end{bmatrix} \tag{5}$$

where $\mathbf{x}_v$ is the robot pose, $\mathbf{p}_i$ is the i^{th} landmark position, $\mathbf{P}_{vv}$ is the robot covariance submatrix, $\mathbf{P}_{vm}$ is the covariance between the robot and landmarks and $\mathbf{P}_{mm}$ is the landmark covariance.

In the prediction stage, DVL and IMU are used to predict the location of the vehicle using dead reckoning. The predicted robot location is then corrected using external sensor information. Subsequently, the update stage is accomplished using the innovation (7), as well as the difference between the predicted observation (6) and the real observation, $\mathbf{z}(k)$,

$$\hat{\mathbf{z}}(k) = \mathbf{h}(\hat{\mathbf{x}}_v^-(k), \hat{\mathbf{p}}^-(k)) \tag{6}$$

$$\mathbf{e}(k) = \mathbf{z}(k) - \hat{\mathbf{z}}(k) \tag{7}$$

where $\mathbf{h}(\cdot)$ is the observation model between the robot and the associated landmark, and the observation $\mathbf{z}(k)$ is to be the final range and azimuth of artificial landmarks. $\hat{\mathbf{x}}_v^-(k)$, $\hat{\mathbf{p}}^-(k)$ are the predicted SLAM states that are found via odometry.

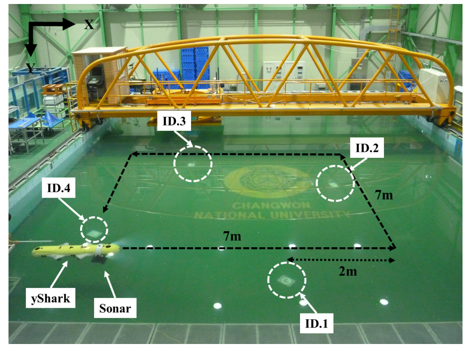


Fig. 2. Experimental setup (Changwon National University, South Korea)

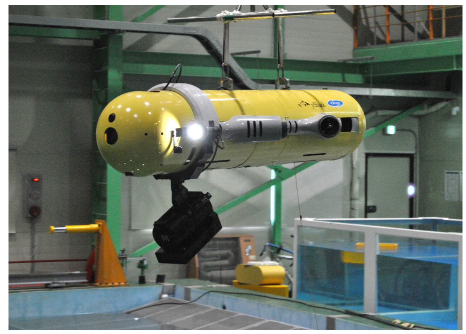


Fig. 3. yShark (KRISO)

III. Experimental Result

We performed experiments to verify the performance of the proposed sonar-based localization in a basin at Changwon National University in South Korea.

As shown in Fig. 2, the basin has $20m \times 14m \times 1.7m$ (length × width × depth). We used a UUV "*yShark*" equipped with imaging sonar *DIDSON*, as shown in Fig. 3. Artificial landmarks placed on the bottom had distances that ranged from at least $1.7m$ to $2.3m$ from a DIDSON. The sonar focused on these objects by assuming a pose with 30° tilted, and indicated the area from 1.25 m to 2.5 m. The yShark followed the rectangle path manually, and the average speed was about *0.15 m/s*.

The sonar-based localization results are shown in Fig.4. The robot followed a path three times, and we can show the estimated robot location as well as the estimated landmark position, which changed at every turn. Although we

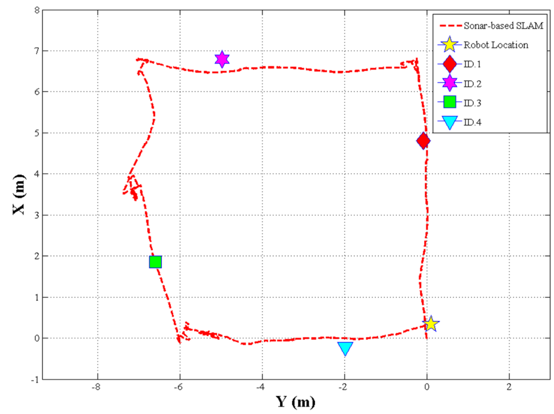
TABLE I
ESTIMATED LOCATION OF LANDMARKS

Location (unit: meter)	ID *1*	ID *2*	ID *3*	ID *4*
X_{true}	5.00	7.00	2.00	0.00
Y_{true}	0.00	-5.00	-7.00	-2.00
$\hat{X}$	4.81 (-0.19)	6.74 (-0.26)	1.85 (-0.15)	-0.14 (-0.14)
$\hat{Y}$	-0.07 (-0.07)	-5.01 (-0.01)	-6.85 (0.15)	-1.82 (0.18)

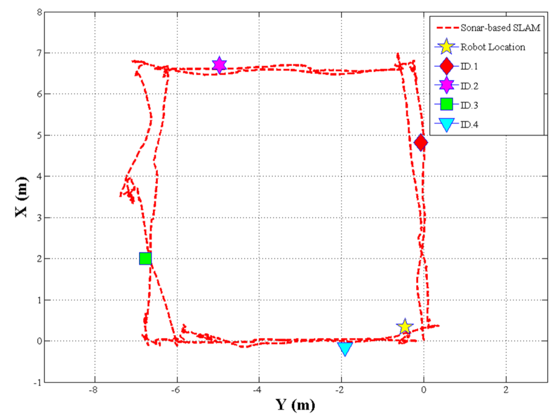
have not compared the results using true data, such as that obtainged from differential global positioning system (DGPS), the robot was able to successfully localize a rectangular path. In addition, the robot's location error was bounded during the experiment. The estimated robot path saw it return to its initial location well, and the final error between the initial and final locations was $x_{err} = -0.3013m$, $y_{err} = -0.1758m$. This result includes an estimation error and an experimental error.

Fig.5 shows the yaw data of the underwater robot. We can see that this data shifted by about 90°, because the yShark turned at the corner of the path. This means that the robot pose was correctly estimated throughtout the whole experiment. The markers in Fig.4 show the estimated locations of the landmarks which are properly arranged in a line. The estimated landmark locations are given in Table. I.

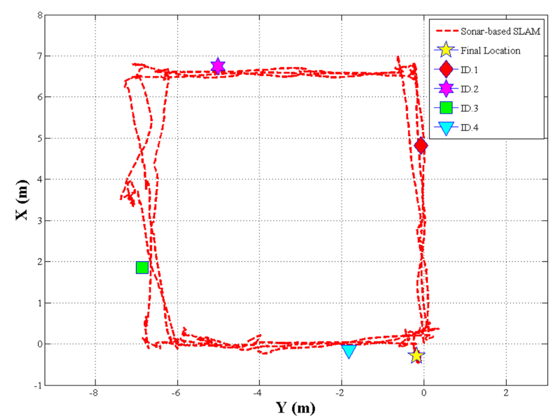
The results of the landmark-recognition process are shown in Fig.6. In the sonar images, the artificial landmarks were correctly recognized by their ID.



(a) T=833.1 (s)



(b) T=1369.4 (s)



(c) T=2039.0 (s) : final location

Fig. 4. Result of sonar based localization : The underwater robot path has bent because it was controlled by joystick manually. However, the landmark position was correctly estimated by the algorithm.

IV. CONCLUSION

In this paper, we presented a realtime sonar-based localization method that use landmarks for underwater robot navigation. The acoustic image is very unstable because it uses an ultrasonic wave. Therefore, it is difficult to recognize any objects. To solve this problem, we designed a probability-based landmark-recognition method to improve the detectability using imaging sonar. After the landmarks are recognized, we can obtain the proper range and direction relative to the artificial landmarks. Landmark-related information is very useful, and is considered as external data for correcting dead-reckoning navigation. It is also used as the bounds of SLAM estimation with high frequency updates. Further, we used landmarks to reduce the uncertainty of SLAM estimation. We verified a suitable estimated robot path and the location of landmarks by performing experiments in a basin.

In this paper, we did not compare the true position in the basin experiment because it is difficult to know the precise true position under the water. Therefore, for this, we will try to measure the true location using long-base line (LBL) system and verify the proposed localization algorithm.

ACKNOWLEDGMENT

This work has been done by "Development of basic SLAM technologies for autonomous underwater robot and software environment for MOOS-IvP." funded by KRISO, and "Development of an autonomous swimming technology with less than

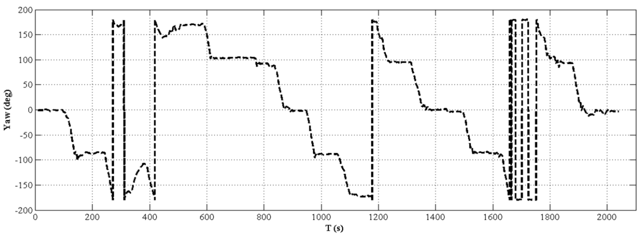


Fig. 5. Yaw data of yShark : The yaw data chattered three times. The reason is that the range of yaw is between $-180°$ to $180°$.

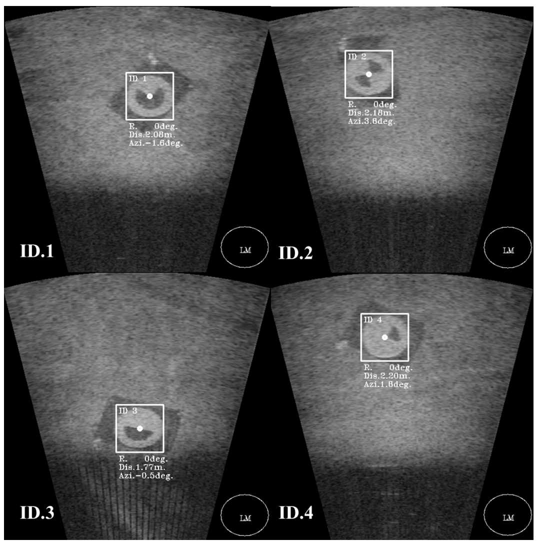


Fig. 6. Recognized landmarks

1.0m position error for underwater robot operating in man-made structural environment" funded by Ministry of Trade, Industry & Energy (MOTIE).

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