Journal of Marine Science and Technology

Volume 28 | Issue 6 Article 7

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Recommended Citation

Jeong, Sang-ki; Choi, Hyeung-Sik; Ji, Dea-Hyung; Vu, Mai The; Kim, Joon-Young; Hong, Sung Min; and Cho, Hyun Joon (2020) "A Study on an Accurate Underwater Location of Hybrid Underwater Gliders Using Machine Learning," *Journal of Marine Science and Technology*: Vol. 28: Iss. 6, Article 7.
DOI: DOI:10.6119/JMST.202012_28(6).0007
Available at: https://jmstt.ntou.edu.tw/journal/vol28/iss6/7

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Acknowledgements

This is the result of the research project titled “Data Collection System with Underwater Glider” (19-SN-MU-01) and “Research on key IoT technologies for real-time ocean data sensing” (PE99832). REF

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Journal of Marine Science and Technology, Vol. 28, No. 6, pp. 518-527 (2020)
DOI: 10.6119/JMST.202012_28(6).0007

A STUDY ON AN ACCURATE UNDERWATER LOCATION OF HYBRID UNDERWATER GLIDERS USING MACHINE LEARNING

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Key words: hybrid underwater gliders, neural network algorithm, machine learning, multi-layer structure.

ABSTRACT

A hybrid underwater glider (HUG) is marine observation equipment that consumes a small amount of energy and offers greater range and navigation times. To achieve reduced energy consumption, however, the HUG uses imprecise navigation sensors, such as mems-type GPS and AHRS, resulting in inaccurate coordination. This study makes a new attempt on the application of machine learning algorithms in a way that complements sensor data errors to improve navigation performance.

The proposed algorithm was used to a simulation of the HUG's navigation and control system, after which the updated heading angle was decided by using the previous position data and environmental data, such as ocean current and external forces. The learning algorithm was designed using three layers. Also, the Leaky ReLU activation function was used to solve the problems of gradient vanishing and dying ReLU of machine learning. And to improve the learning efficiency, active functions and the number of layers were changed. The simulation results show the excellent performance of the proposed learning algorithm.

Paper submitted 04/16/19; revised 05/06/20; accepted 07/03/20. Corresponding Author: Hyeung-Sik Choi (Email: hchoi@kmou.ac.kr)

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I. INTRODUCTION

There is a great deal of global interest in the ocean, which has abundant resources and energy. With this interest, there are active research and development of much marine-related equipment for exploring and developing the ocean (Ji et al., 2019).

One such equipment is an autonomous underwater vehicle (AUV). The AUV is suitable for autonomously undertaking a variety of underwater missions (Nhat et al., 2020). However, the AUV has a problem with small operations time due to battery energy limitations. To solve this problem, a long-range AUV to support chemical and biological sensing missions covering ranges of 1,000 kilometers or more was studied, where core electronics for the vehicle have been customized to minimize power consumption (Hobson et al., 2016).

As a long operation underwater vehicle, the underwater glider (UG) for marine surveying of the wide-area was developed, which can operate for two months with the same amount of battery of the AUV. The underwater glider, first designed and introduced in the United States in the early 2000s, comes in four commercial types, namely, Slocum, Spray, Sea glider, and Sea explorer as in Fig. 1.

However, although the UG can carry out a wide-area survey, it lacks precise navigation control. And, if the underwater glider has disturbance such as ocean currents, the disturbance makes the error of heading angle large, which increases by tracking error. As a result, the UG moves along an undesirable path and consumes more energy, as shown in the UG movement trajectory in Fig. 2

This study designed a navigation system using machine learning to improve the navigation accuracy of a hybrid underwater glider by adding a propeller to the existing underwater glider. This study did not consider the propulsion method in terms of the propellant used for the mission. The reason is that the main process the HUG moves is to control buoyancy. The HUG is also a marine observation device belonging to a class of underwater gliders, and its main method of movement is to control buoyancy. This method has many advantages in terms

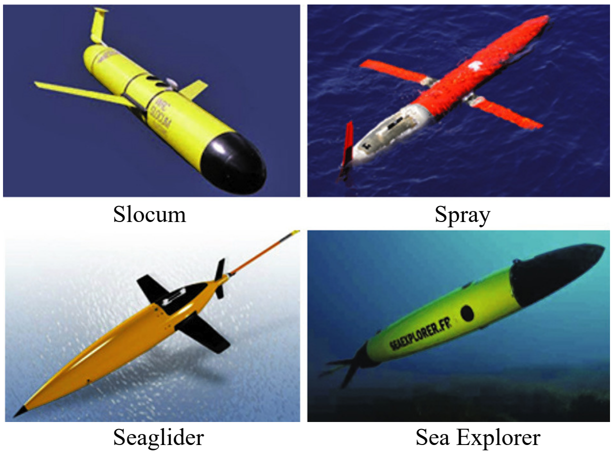
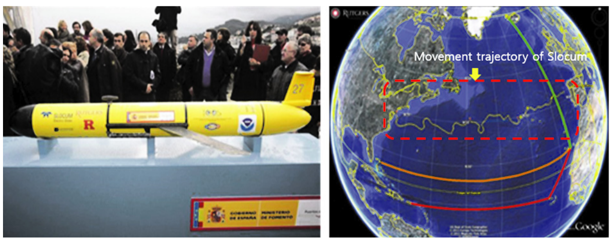


Fig. 1. Commercial underwater glider



(a) (b)

Fig. 2. (a) Slocum glider; (b) movement trajectory of Slocum glider

of energy consumption, but it is vulnerable to disturbances in the water.

In particular, the HUG does not obtain precise position data because it does not have a high-energy consumption navigation sensor, such as the Doppler velocity logger. Therefore, it is difficult to measure the position of the HUG accurately. Thus improve the position error of the HUG, a neural network PID control algorithm was used to control the behavior of the underwater HUG, including hydrodynamic coefficients, and based on this, a six-degree-of-freedom(DOF) motion simulator was designed.

Also, the neural network PID control algorithm, which is a control algorithm that changes the gain value of the PID controller in real-time by user error from the target value generated by the disturbance is applied to control the sliding angle of the HUG. And the navigation algorithm combining the HUG's model-based indirect position measurement method and machine learning method was studied to improve the accuracy of the HUG's navigation (Leonard and Graver,2001).

In studying the neural network application, some researches were performed for control of AUV. One of them is a study on a hybrid behavior-based scheme using reinforcement learning for high-level control of AUVs, where Q learning algorithm with a multi-layer neural network is used to learn behavior state/action mapping online (Carreras et al., 2005). Other

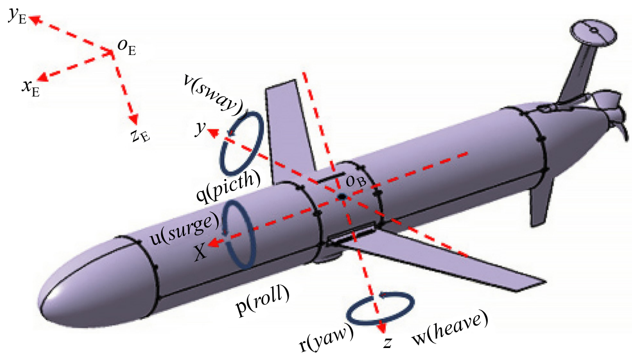


Fig. 3. Hybrid underwater glider's coordinate system

research the application of deep reinforcement learning controllers to 2-DOF horizontal motion in AUV trajectory tracking tasks, where for Partially Observable Markov Decision Process problem, AUVs learn from sequences of dynamic information (Huo et al., 2018). The indirect position measurement method uses the characteristics of the HUG that slides downward while maintaining a constant angle of attack (AOA) of the hull underwater by controlling buoyancy. This is measured using the HUG equation of motion with the depth measurement data, AOA of the hull, and coefficient of hydrodynamic force. Using the proposed neural network method, the model-based HUG navigation algorithm was designed by combining the estimated results from the estimate of the following location data using an indirect positioning method, which is the navigation algorithm of the existing HUG.

To implement these machine learning algorithms, a variety of supervisory learning machine learning models based on the datasets that study previous location and posture data was designed to be diverse and empirically designed to implement the optimal performance of the HUG.

In this study, a new trial of application of the machine learning algorithm composed of three layers to the navigation of the underwater glider was performed to improve the navigation performance. The proposed algorithm predicts the next data by learning the present navigation data of the HUG, including the previous disturbance, and they are used to next the navigation of the HUG. To verify the performance of the proposed neural network, a six-DOF HUG equation, including hydrodynamics and HUG navigation simulations, including underwater disturbances, was formulated (Carreras and Ridao, 2001).

1. HUG Motion Model and Control System Design

Fig. 3 shows the Earth−fixed coordinate system and body-fixed coordinate system used to express the HUG's motion underwater.

1.1 HUG dynamics and hydrodynamic force

The movement of the HUG can be expressed by gravity, buoyancy in the water, drag, and lift of the movement, and thrust of the thruster. The structure of the HUG consists of a hull, a buoyancy controller, an internal mass movement device,

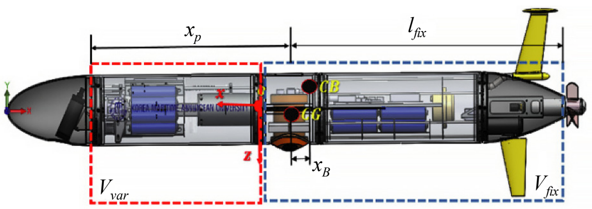


Fig. 4. Configuration of the center of mass and buoyancy center of HUG

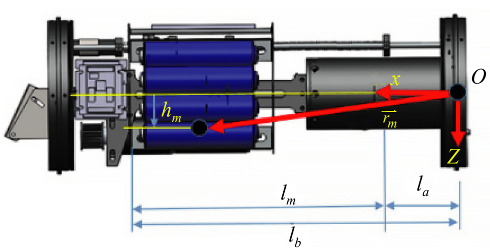


Fig. 5. Length information of the attitude control device

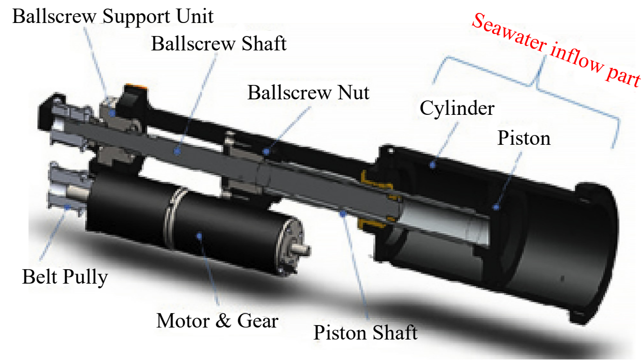


Fig. 6. Length information of the attitude control device

a propeller, a horizontal vane, and a rudder.

The buoyancy change, inertial force, added mass in water, and shape of these devices determine the motion characteristics of the HUG. Therefore, a dynamic analysis of the buoyancy engine generating the propulsion force of the HUG with the structure shown in Fig. 5 and the attitude control device dynamic analysis for controlling the posture when moving underwater is required (Fiorelli et al., 2006).

In Fig. 4, x_B is the distance from the center of gravity to the buoyancy center, and x_p is the distance from the end of the buoyancy engine piston to the center of gravity. V_{val} is the volume change part according to the buoyancy controller, and V_{fix} is a fixed volume. The buoyancy center that changes with the volume change is shown in Eq. 1.

$$\overrightarrow{\mathrm{r_{cb}}} = [\mathrm{x_B}, 0, 0]^{\mathrm{T}} = \left[\frac{\mathrm{V_{var}} * \frac{\mathrm{x_p}}{2} + V_{fix} * l_{fix}}{\mathrm{V_{var}} + V_{\mathrm{fix}}}, 0, 0 \right]^{\mathrm{T}} \quad (1)$$

In Fig. 5, the vector $\overrightarrow{r_m}$ change the center of gravity of the hull owing to the movement of the internal battery pack.

Changes the mass center $\overrightarrow{r_{CG}}$ and the moment I_o of inertia of the mass. Such a relationship can be represented by Equations 2~4 (Tran et al., 2015).

$$m_{total} = m_h + m_s + m_m \quad (2)$$

$$\overrightarrow{r_{cg}} = \begin{bmatrix} x_G \\ y_G \\ z_G \end{bmatrix} = \frac{m_h \overrightarrow{r_h} + m_s \overrightarrow{r_s} + m_m \overrightarrow{r_m}}{m_{total}} \quad (3)$$

Equation 3 expresses the value of $\overrightarrow{r_m}$, l_m, which changes by the change in x_m in real-time.

The change in the mass moment of inertia according to the change in the center of mass of the HUG was shown in Equation 4.

$$I_o = \left(I_h - m_h \widehat{r_h} \widehat{r_h}\right) + \left(I_s - m_s \widehat{r_s} \widehat{r_s}\right) + \left(I_m - m_m \widehat{r_m} \widehat{r_m}\right) \quad (4)$$

Here, $\widehat{r_h}$, $\widehat{r_s}$, $\widehat{r_m}$, and C are vector components to the center of mass.

Fig. 6 shows the buoyancy control device of the HUG. The buoyancy control device is a device that gains propulsion by changing the volume of the HUG (Kan et al., 2008).

The buoyancy control can be expressed as Equation 5.

$$\begin{aligned} & \mathrm{q} = \mathrm{D} * w_b - K_{leak} * P \\ & K_{leak} = \frac{K_{HP}}{\mu} \\ & P = \frac{\mu}{K_{HP}} q_{leak} \\ & q_{leak} = D * w_{bnom}(1 - \eta_v) \\ & \dot{x}_p = \frac{D * w_b - D * w_{bnom}(1 - \eta_v)}{A} \end{aligned} \quad (5)$$

In Equation 5, q is the discharge flow rate per unit time. A is the cross-sectional area of he buoyancy engine, D is the discharge flow rate per pump revolution, $w_b$is the rotational angular velocity of the motor connected to the pump, w_{bnom} is the nominal angular velocity, η_v is the volumetric efficiency of the pump, K_{leak} is the leak coefficient, K_{HP} is the Hagen-poise oil coefficient, μ is the viscosity coefficient, and $q_{leak}$is the emission.

Given that the HUG is a UG with propellers and a rudder applied to the existing underwater gliders, the following propulsion factor must be considered when the propeller is in operation. Further, each factor is represented by the external force applied to the axial and moment components of the hull owing to rotation and can be expressed in Equation 6 (Fossen, 1994).

$$
\begin{aligned}
&X_{prop} = -X_{u|u|}u|u| \\
&K_{prop} = (y_g W - y_b B)\cos\theta\cos\varphi + (z_g W - z_b B)\cos\theta\cos\varphi \\
&T_E * \dot{\delta r} + \delta r = \delta r_{respon} \\
&|\delta r| \le \delta r_{MAX}
\end{aligned} \tag{6}
$$

Equation 6 is the coefficient for forward propulsion of the HUG. T_E is a coefficient with time, δr is the angular velocity of the rudder, and δr_{max} is the maximum angular velocity of the rudder. The six-DOF equation, including the HUG's hydrodynamics force, is the same as Equations 7~12 (Prestero, 2001; Bhatta and Leonard, 2008; Fossen et al., 2008).

$$
\begin{aligned}
X = {} & X_{u|u|}u|u| + X_{\dot{u}}\dot{u} + X_{wq}wq + X_{qq}qq + X_{vr}vr \\
& + X_{rr}rr + X_{prop} + (W-B)\sin\theta
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
Y = {} & Y_{u|u|}u|u| + Y_{r|r|}r|r| + Y_{\dot{v}}\dot{v} + Y_{\dot{r}}\dot{r} + Y_{ur}ur \\
& + Y_{\omega p}\omega p + Y_{pq}pq + Y_{uv}uv + Y_{uu\delta_r}u^2\delta_r \\
& + (W-B)\cos\theta\sin\varphi
\end{aligned} \tag{8}
$$

$$
\begin{aligned}
Z = {} & Z_{\omega|\omega|}\omega|\omega| + Z_{q|q|}q|q| + Z_{\dot{\omega}}\dot{\omega} + Z_{\dot{q}}\dot{q} + Z_{uq}uq \\
& + Z_{vp}vp + Z_{rp}rp + Z_{uw}u\omega \\
& + (W-B)\cos\theta\cos\varphi
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
K = {} & K_{p|p|}p|p| + K_{\dot{p}}\dot{p} + K_{prop} + (y_G W - y_B B)\cos\theta\cos\varphi \\
& + (z_G W - z_B B)\cos\theta\sin\varphi
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
M = {} & M_{\omega|\omega|}\omega|\omega| + M_{q|q|}q|q| + M_{\dot{\omega}}\dot{\omega} + M_{\dot{q}}\dot{q} \\
& + M_{uq}uq + M_{vp}vp + M_{rp}rp + M_{u\omega}u\omega \\
& + (z_G W - z_B B)\sin\theta - (x_G W - x_B B)\cos\theta\cos\varphi
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
N = {} & N_{v|v|}v|v| + N_{r|r|}r|r| + N_{\dot{v}}\dot{v} + N_{\dot{r}}\dot{r} + N_{ur}ur \\
& + N_{wp} + N_{pq}pq + N_{uv}uv + N_{uu\delta_r}u^2\delta_r \\
& + (x_G W - x_B B)\cos\theta\sin\varphi \\
& + (y_G W - y_B B)\sin\theta
\end{aligned} \tag{12}
$$

The principal hydrodynamic coefficients used in Equations (7)~(12) are obtained from the experiment PMM, CFD analysis, and empirical equations (de Wit et al., 2000; Graver and Leonard, 2001; Seo et al., 2008).

1.2 HUG Control Algorithm

HUG uses propulsion methods that use buoyancy or propellant depending on the mission. Therefore, a variable control method is needed to adapt to different propulsion modes, and to this end, the neural network PID control algorithm is applied.

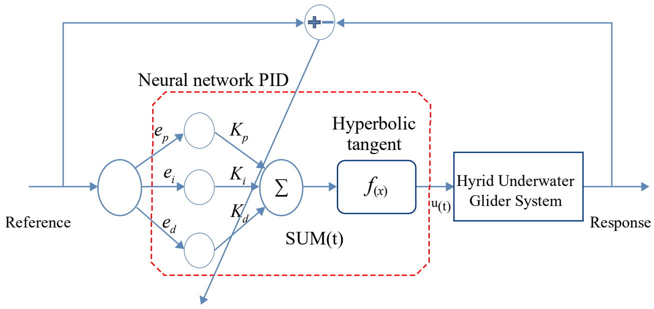


Fig. 7. Neural network PID control algorithm

This controller regulates the buoyancy control device and attitude control device to adjust the hull angle when the HUG moves (Jeong et al., 2019).

The three inputs in Fig. 7 are error values, error integral values, and differential values, which are used as the basis for the control algorithm of the PID, and the control inputs are each entered into the nonlinear active function, the hyperbolic tangent function. This controller is a single layer that ignores the gradient vanishing and uses a hyperbolic tangent function that is faster than the sigmoid function for the rapid response of the conventional controller. The hyperbolic tangent function and signal sum (t) input to the function are shown in Equation 13.

In this equation, *ref(t)* is the desired target, and $m(t)$ is the current measured value.

$$
\begin{aligned}
&f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \\
&sum(t) = K_p(t)e_p(t) + K_i(t)e_i(t) + K_d(t)e_d(t) \\
&e_p(t) = ref(t) - m(t) \\
&e_i(t) = \int e_p(t)\; e_d(t) = \frac{d}{dt}e_p(t)
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
&k_p(t+1) = k_p(t) - \eta_p e_p(t) e_p(t) * \frac{4e^{2sum}}{(1+e^{2sum})^2} * \frac{m(t)-m(t-1)}{u(t)-u(t-1)} \\
&k_i(t+1) = k_i(t) - \eta_i e_i(t) e_i(t) * \frac{4e^{2sum}}{(1+e^{2sum})^2} * \frac{m(t)-m(t-1)}{u(t)-u(t-1)} \\
&k_d(t+1) = k_d(t) - \eta_d e_d(t) e_d(t) * \frac{4e^{2sum}}{(1+e^{2sum})^2} * \frac{m(t)-m(t-1)}{u(t)-u(t-1)} \\
&\frac{\partial m}{\partial u} = \frac{\Delta m}{\frac{\Delta u}{\partial u}} = \frac{m(t)-m(t-1)}{u(t)-u(t-1)}
\end{aligned} \tag{14}
$$

Equation (14) is the final equation for calculating the gain of the neural network PID, and the controller calculates the gain until the final value is within the set target range.

At this time, if the error is appropriately reduced and a specific range of control performance is satisfied for the stability of the system, the operation is stopped.

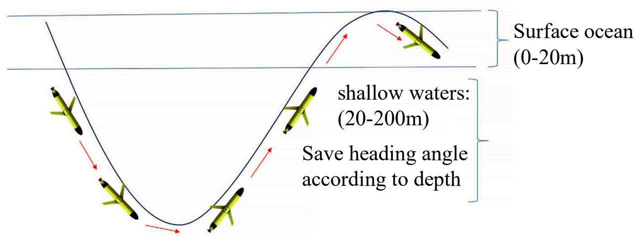


Fig. 8. Movement of the HUG in water

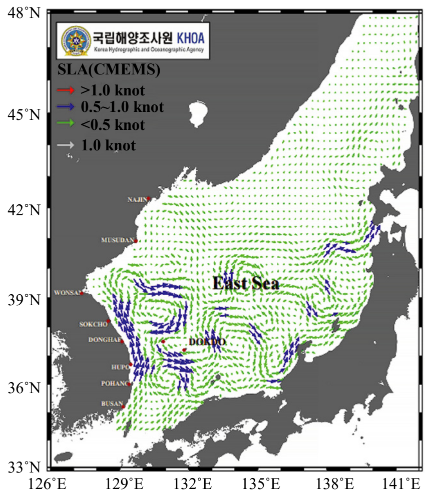


Fig. 9. Surface ocean current direction data (http://khoa.go.kr/koofs/eng/Observation / obs_real.do)

II. NAVIGATION ALGORITHM OF THE HUG BY EXTERNAL FORCE

Unlike conventional AUVs, hybrid underwater gliders do not use navigational sensors that consume much energy, such as DVL and USBL. The HUG calculates the heading angle to the next point of travel using AHRS and uses GPS to locate itself on the surface of the water and travels straight. Therefore, it is vulnerable to external forces, which is a significant cause of navigation error of all equipment of UGs. To reduce navigation errors, the HUG classifies the flow of tidal currents in the ocean surface (0~20 m) and shallow water (20~200 m) into individual disturbances that affect navigation errors.

1 Analysis of the Underwater Environment

The purpose of categorizing the effects of ocean currents in water is that the surface ocean currents are affected by wind, and the currents in shallow waters are affected by seawater circulation.

Surface ocean currents can be obtained using information from the Korea Hydrographic and Oceanographic Agency, as shown in Fig. 9.

However, shallow water current data from seawater circulation are inaccurate. Therefore, the angle error data for learning are collected using the heading angle

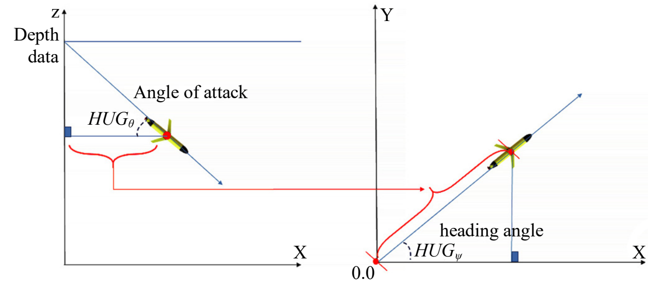


Fig. 10. Location indirect measuring method of the HUG

and AOA data of the HUG while moving because the previous movement data contain disturbances.

2 The position measurement method of the HUG

The HUG cannot measure its position directly owing to the simplicity of the navigation sensors. Therefore, the heading angles of the HUG, AOA, and depth information are used to calculate the position indirectly.

To measure the position of the HUG, first, the relationship between the body-fixed coordinates and earth-fixed coordinates is expressed using the angle of the hull and the acceleration. For this, heading and attitude sensors must be attached in the glider.

$$\begin{bmatrix}\dot{\varphi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix}=\begin{bmatrix}1 & \sin\phi\tan\theta & cos\phi\tan\theta\\ 0 & cos\phi & -sin\phi\\ 0 & sin\phi\sec\theta & cos\phi sec\phi\end{bmatrix}\begin{bmatrix}p\\ q\\ r\end{bmatrix}$$
$$=\begin{bmatrix}p+qsin\phi tan\theta+rcos\phi tan\theta\\ qcos\phi-rsin\phi\\ qsin\phi sec\theta+rcos\phi sec\theta\end{bmatrix} \tag{15}$$

By integrating the converted angular velocity, the position of the HUG is indirectly measured by using the HUG's fuselage angle, motion model, depth, and GPS data. Based on this, the existing HUG location measurement method is shown in Fig. 10.

$$\begin{aligned}&x=HUG_{\text{Depth Data}}/\tan\theta\\&\theta=HUG_{\text{angle of attack}}\\&y=x*\sin\psi\\&\psi=HUG_{\text{heading angle}}\\&z=HUG_{\text{Depth Data}}\end{aligned} \tag{16}$$

III. NAVIGATION ALGORITHM FOR THE HUG USING MACHINE LEARNING

For the navigation of the HUG, a line of sight (LOS) method line based on the calculated heading angle was used [3]. It does not make a separate turn during operation to minimize

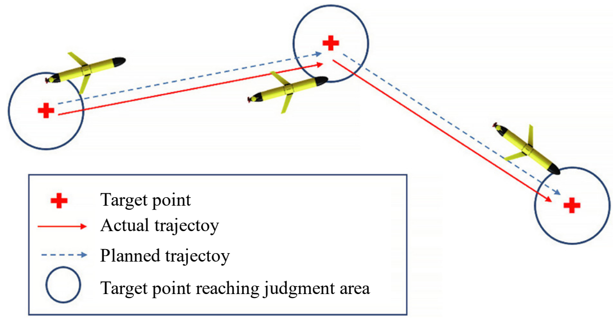


Fig. 11. Moving method of the HUG using LOS

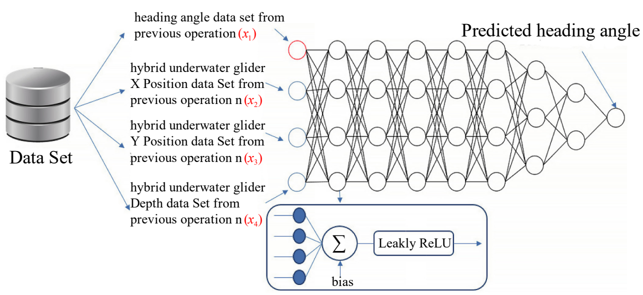


Fig. 12. Study model using machine learning

energy consumption. Therefore, the heading angle for the movement is calculated by learning the driving data (heading angle, depth, X, Y), including the previous disturbance, and adding the data derived from the learning result to the position of the rudder calculated by the LOS when moving to the next position.

1. LOS algorithm to determine the moving direction of HUG

In general, navigation algorithms used in underwater gliders are target point tracking and driving in a specific direction. This is called LOS. The HUG used in this study also uses this method as the basic navigation algorithm. The target point estimating technique is to let the UG drive toward the target point, as shown in Figure 11, and to move to the next target point when entering the target point determination area.

The algorithm of LOS can be represented by the following equation.

$$\psi_p = tan^{-1}\left[\frac{Y_k - Y(t)}{X_k - X(t)}\right]$$
$$\rho^2(t) = \left[X_k - X(t)\right]^2 + \left[Y_k - Y(t)\right]^2 < \rho_c^2 \tag{17}$$

In Equation 17, $[X(t), Y(T)]$ is the position of the unmanned UG and $[X_k, Y_k]$ is the position of the waypoint. Also, ρ_c represents the radius of the waypoint. Using this algorithm, the rudder angle is calculated and based on this, the direction of the HUG is determined.

2. HUG Navigation Algorithm using Machine Learning

To combine the estimates using a machine learning algorithm with the conventional LOS navigation algorithm, the estimates are computed by learning the movement data, including the previous disturbance. The data used for learning is the information from the saved dataset of the previous HUG. Here, the dataset is data that stores the previous heading angle (x^1), position X (x^2), position Y (x^3), and depth (x^4). It also reduces the cost function by using the difference between the heading angle of the previously measured HUG and the value calculated using the LOS algorithm.

In the total of the stored dataset, 80% was used as training data and 20% as test data, and standardization was used to remove the scale difference of the previous data.
Equation 18 of standardization is as follows.

$$x_{new} = \frac{x - \mu}{\sigma} \tag{18}$$

In the above equation, x_{new} is standardized data, x is the value of each element, μ is the mean, and σ is the standard deviation. Besides, regularization is used as a method to reduce the complexity of the model to solve the overfilling problem of machine learning. The equation of regularization is as follows:

$$\mathcal{L} = \frac{1}{n}\sum_i((Wx_i + b) - y_i)^2 + \lambda\sum W^2 \tag{19}$$

Equation 19 simplifies the cost function by adding the regularization strength (λ) and the square of the weight *(W)* to the cost function. Using this method, a machine learning algorithm is constructed, as shown in Fig. 12.

Leaky ReLU was used to prevent gradient vanishing and dying ReLU owing to the possibility of differential value loss during gradient backpropagation. In the algorithm of Fig. 12, the hypothesis and cost functions are as follows.

$$H(x) = (x_1\ x_2\ x_3\ x_4) * \begin{pmatrix} w_1 \ldots w_n \\ w_2 \ldots w_n \\ w_3 \ldots w_n \\ w_4 \ldots w_n \end{pmatrix} + \mathrm{b}$$

$$\mathrm{Cost}(W, b) = \frac{1}{m}\sum_{I=1}^{m} H(x_1^{(i)}, x_2^{(i)}, x_3^{(i)}, x_4^{(i)}) - y^{(i)})^2$$

The proposed HUG navigation algorithm improves the precision of the model-based HUG navigation by combining the estimated results using machine learning with the indirect position measurement method, which is the navigation algorithm of an underwater glider. This method is designed to achieve

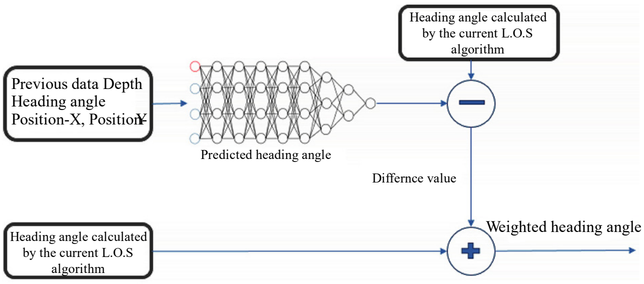


Fig. 13. Navigation algorithm of the HUG using machine learning

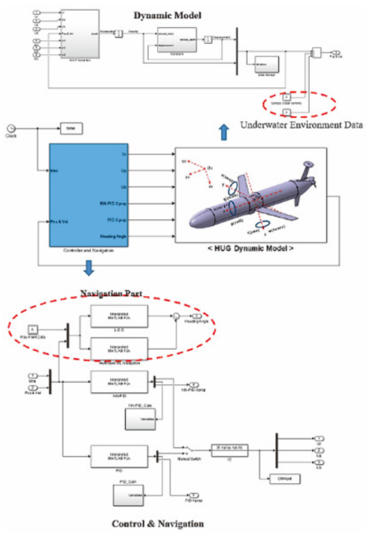


Fig. 14. Simulator of HUG

Table 1. Simulation conditions of motion performance

Index	Value
Moving depth	0~20 m
Parallel forward speed	2 knot
Sampling time	0.01 (sec)
Density of seawater	1.031 g/cm³

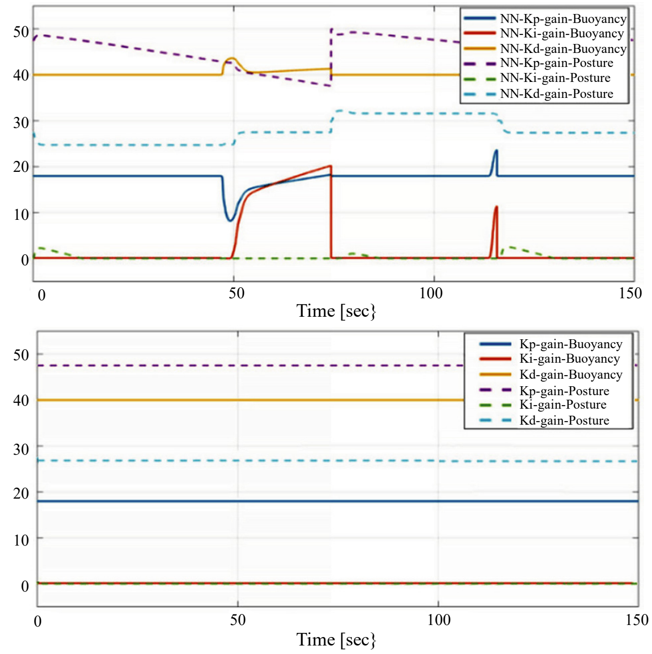


Fig. 15 Neural Network PID gain and simple PID

better performance by adapting to the variable ocean environment and can improve stability by applying two algorithms properly. The HUG navigation algorithm is shown in Fig. 13.

IV. SIMULATION AND PERFORMANCE RESULTS OF HUG

In order to verify the validity of the control and navigation algorithm, a dynamics simulator using MATLAB-Simulink was designed, as shown in Fig. 14. The simulator includes a six-DOF kinematics equation, hydrodynamic force, neural network PID controller, and navigation algorithm. The designed simulator was used to simulate the movement of the HUG.

The simulation uses buoyancy control on the HUG to move up and down underwater. At this time, it moves forward by using the generated thrust. The sliding angle is controlled by moving the battery during the movement. Based on this, a simulation of the navigation system and control system of the HUG was designed.

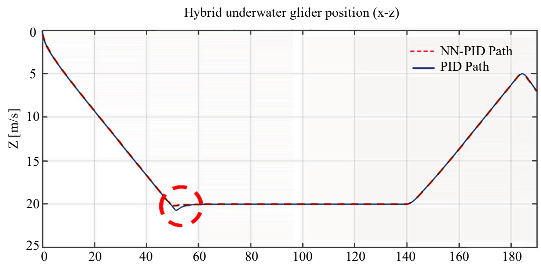
1. Performance of the HUG motion model and controller simulation results

First, the simulation of motion performance was conducted to verify the performance of the motion model and controller before verifying the navigation of the HUG. The simulation conditions for verifying motion performance are shown in Table 1.

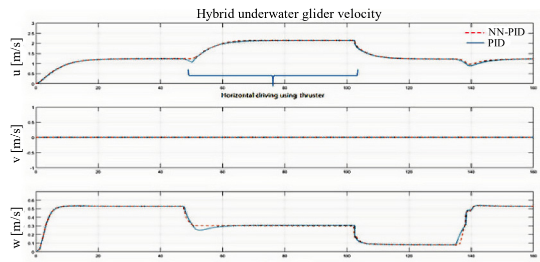
The main function of the HUG's attitude control algorithm is to adjust the gain appropriately to the surroundings to achieve better performance. It also makes a good movement with less energy consumption. Fig. 15 shows the gain of the neural network PID controller and a simple PID controller. The initial gain of the simple PID controller and the neural network PID controller is equal, but the gain is continually changing owing to changes and disturbances in the propulsion system.

Based on the attitude control algorithm of the HUG, the same result as that shown in Fig. 16 was obtained.

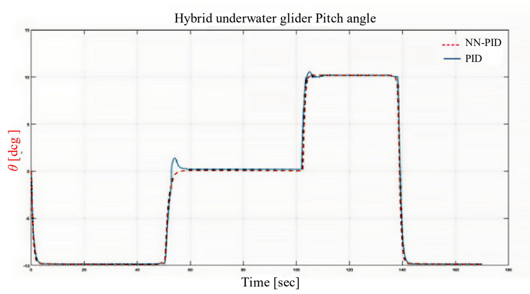
The graph shows the result of the posture control action under the condition of propulsion changes. In Fig. 16 (a), the trajectory graph of neural network PID clearly shows the performance improvement in the transient response control. Fig. 16 (b) shows the moving hull speed along the trajectory of Fig. 16 (a). Finally, Fig. 16 (c) shows the sliding angle of the hull at this time.



(a) Trajectory of the HUG (x-z)



(b) Speed of HUG



(C) Angle of the HUG

Fig. 16. (a) Trajectory of the HUG (X-Z), (b) Speed of HUG, (c) Angle of the HUG

The simulation results show that the neural network PID algorithm is more stable than the simple PID controller with a fixed gain when the propulsion method is changed. The comparison result is based on the largest error value. Unlike the simple PID controller, the overshoot error of the fuselage's AOA was reduced by approximately 23%, and the convergence speed to the control value was calculated to be 1.2 sec or less, which was faster than the simple PID algorithm with 2.6 sec. The motion simulation data were summarized in Table 2 for a simple comparison of the above results.

In Table 2, the smaller numbers of the piston movement of the buoyancy controller and mass movement of posture controller data indicate that neural network PID control reduces energy consumption.

2. Machine learning navigation algorithm simulation results

Based on the designed simulation, the navigation results of the HUG using the machine learning algorithm are shown in Fig. 17. The current data of the sea level used in the simulation were obtained from the Korea Hydrographic and Oceanographic Agency (KHOA) data and used in each step using the MATLAB-Simulink data storage block and applied to the HUG's equation of motion. The shallow sea current data were generated using the basic fluid flow model provided by the Delft-3D program.

Table 2. Motion simulation result

		neural network PID	simple PID
Maximum overshoot	Position of body	1.47 (%OS)	6.28 (%OS)
	Posture of body	1.96 (%OS)	7.41 (%OS)
settling time (2% of designed value)		1.2 (sec)	2.6 (sec)
Piston movement using buoyancy controller		0.8–1.4 (cm)	4.3–5.7 (cm)
Mass movement using posture controller		1.3–1.8 (cm)	2.8–4.3 (cm)

Table 3. Simulation conditions of navigation performance

Index	Value
Moving depth	0–20 m
Sampling time	0.01 (sec)
Sensor data update rate	100 Hz
Density of seawater	1.031 g/cm³
Surface ocean currents	From http://khoa.go.kr/koofs/eng/ Observation / obs_real.do.
Waypoint	Way point_1(40,30) Way point_2(100,80) Way point_3(200,50)

The simulation conditions for verifying navigation performance are shown in Table 3.

Fig. 17 shows the 3D trajectory of Fig. 18. The trajectory of data learning navigation using machine learning is represented by "ML Navigation," the conventional navigation algorithm is described by "LOS Navigation," and the planned trajectory is represented by the "desired trajectory." Fig. 18 shows a similar performance at the previous waypoint, but "ML Navigation," shows better performance after the second-way point tracking.

By learning the information including the disturbance of the previous two points, this data was applied to the heading angle calculation when moving to the next location, and simulations of the same environment resulted in a higher precision of 17% compared to the existing UG navigation.

V. CONCLUSIONS

In this study, a new trial of application of the machine learning algorithm composed of three layers to the navigation of the underwater glider was performed to improve the navigation performance. The proposed algorithm predicts the next data

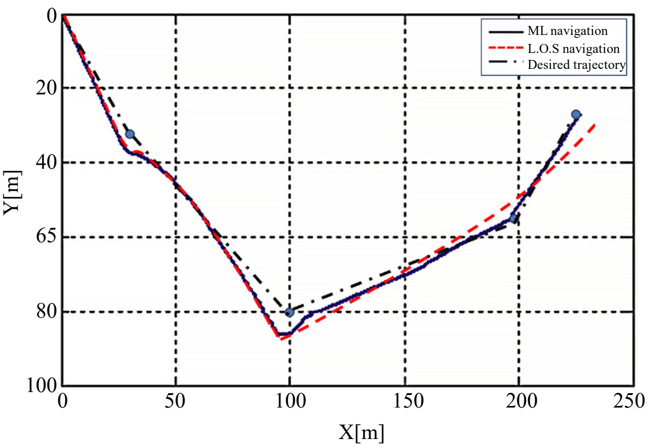


Fig. 17 Navigation simulation results of the HUG (X-Y)

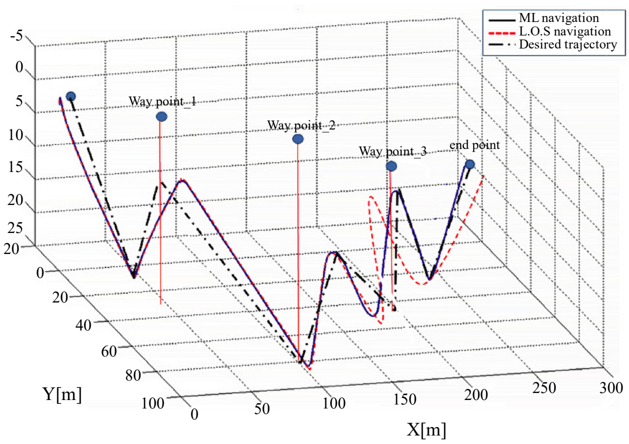


Fig. 18 Navigation simulation results of the HUG 3D (X-Y-Z)

by learning the present navigation data of the HUG, including the previous disturbance, and they are used to next the navigation of the HUG. Further, a method for improving the navigation precision of the UG using limited navigation sensors is proposed.

In order to show the performance of the machine learning algorithm, the dynamic model of the HUG was designed. The learning algorithm using multiple layers of the HUG navigation was applied to the simulation. In the machine learning algorithm, the Leaky ReLU activation function was used to solve the problems of gradient vanishing and dying ReLU. The learning model was designed by changing the number of floors empirically to improve learning efficiency. Also, the data were stably processed using standardization of the input data to obtain smooth learning results, and the regularization technique was used to address overfitting.

Finally, the proposed navigation simulation showed a 17% higher position accuracy than the conventional LOS navigation algorithm by using the proposed machine learning algorithm.

In the future, based on these results, further study will be conducted by applying the machine learning algorithm to the HUG navigation experiment.

ACKNOWLEDGMENT

This is the result of the research project titled “Data Collection System with Underwater Glider” (19-SN-MU-01) and “Research on key IoT technologies for real-time ocean data sensing” (PE99832).

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