

Article

Research on Clustering-Based Fault Diagnosis during ROV Hovering Control

Jung-Hyeun Park ^{1,2} , Hyunjoon Cho ^{1,*}, Sang-Min Gil ^{1,2}, Ki-Beom Choo ³ , Myungjun Kim ⁴, Jiafeng Huang ^{1,2}, Dongwook Jung ^{1,2}, ChiUng Yun ^{1,2} and Hyeung-Sik Choi ^{1,*} 

- ¹ Department of Mechanical Engineering, Korea Maritime & Ocean University, Busan 49112, Republic of Korea; skrgus3020@g.kmou.ac.kr (J.-H.P.); ksm99429@g.kmou.ac.kr (S.-M.G.); hjf861203@163.com (J.H.); jdw0425@kmou.ac.kr (D.J.); yunchi99@g.kmou.ac.kr (C.Y.)
- ² Interdisciplinary Major of Ocean Renewable Energy Engineering, Korea Maritime & Ocean University, Busan 49112, Republic of Korea
- ³ Advanced-Intelligent Ship Research Division, Korea Research Institute of Ship & Ocean Engineering, Daejeon 34103, Republic of Korea; kbchoo@kriso.re.kr
- ⁴ Maritime R&D Center, LIG Nex1 Co., Ltd., Seongnam-si 13488, Republic of Korea; myungjun.kim@lignex1.com
- * Correspondence: jooninkmou@kmou.ac.kr (H.C.); hchoi@kmou.ac.kr (H.-S.C.); Tel.: +82-051-410-4297 (H.-S.C.)

Abstract: The objective of this study was to perform fault diagnosis (FD) specific to various faults that can occur in the thrusters of remotely operated vehicles (ROVs) during hovering control. Underwater thrusters are predominantly utilized as propulsion systems in the majority of ROVs and are essential components for implementing motions such as trajectory tracking and hovering. Faults in the underwater thrusters can limit the operational capabilities of ROVs, leading to permanent damage. Therefore, this study focused on the FD for faults frequently caused by external factors such as entanglement with floating debris and propeller breakage. For diagnosing faults, a data-based technique that identifies patterns according to data characteristics was utilized. In imitation of the fault situations, data for normal, breakage and entangled conditions were acquired, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was employed to differentiate between these fault conditions. The proposed methodology was validated by configuring an ROV and conducting experiments in an engineering water tank to verify the performance of the FD.

Keywords: ROV; underwater thruster; hovering control; fault diagnosis; DBSCAN



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1. Introduction

Among the various marine platforms for operations and exploration in the ocean, remotely operated vehicles (ROVs) refer to unmanned submarines remotely controlled via a tether line connected to a vessel/operator [1]. ROVs can perform a range of operations in deep-sea environments that are challenging for people to access because they can be powered continuously and steadily by a tether line or communicate in real-time at high volumes with a surface operator [2,3]. Owing to these characteristics, ROVs have been utilized for several decades in fields such as marine renewable energy, marine salvage, underwater resource development, marine science research, and inspection, maintenance, and repair of underwater facilities [4,5]. In particular, they are irreplaceable in the field of vessel and subsea equipment inspection via real-time imaging [6]. Also, work-class ROVs play a leading role in the oil and gas industry because of their stable power supply from ships, large payload capacity, and extensive operational range [6–8].

The unpredictable underwater environment in which ROVs operate exposes them to corrosion, temperature changes, high pressures, and floating debris, leading to various potential failures. Furthermore, the operation of ROV systems may require tether

management systems, launch and recovery systems, and professional operators, requiring more space and ships and increasing the expenses and preparation time [9]. Therefore, considering limited performance, cost, and efficiency, self-inspection for faults during ROV operations is necessary to decide whether to continue or suspend a mission [10]. Underwater thrusters are one of the most crucial components of ROV motion control. Most ROVs utilize them for propulsion whether a trajectory tracking or hovering [11]. Compared with other components, underwater thrusters are more prone to faults because of their direct interactions with the marine environment [12]. Damage to these thrusters can result in difficulties during mission execution [12]. Therefore, fault diagnosis (FD) of underwater thrusters has attracted considerable attention [13].

According to Isermann, FD typically involves three steps [14]: fault detection, which involves recognizing the occurrence of a problem within the target system for diagnosis; fault isolation, which involves determining the location and type of the fault; and fault identification, which involves determining the magnitude (size) of the fault. Liu et al. divided FD into model- and data-based analyses, which can be quantitative or qualitative [15]. Quantitative analysis involves mathematical formulas between the system's inputs and outputs, whereas qualitative analysis examines the relationships between different unit elements [16]. In most model-based FD applications for marine robotic systems, the models are simplified due to the difficulty of accurately obtaining hydrodynamic coefficients, which affects the FD accuracy [17]. Additionally, the small brushless direct current (BLDC)-type underwater thrusters utilized in this study tend to exhibit performance differences even among identical products. Furthermore, the performance degradation over long-term use has rendered model-based techniques unsuitable. Data-based techniques classify normal and fault states by identifying patterns based on data characteristics using measured parameters, state variables, and residuals as fault features [18]. The objective is to identify faults caused by external factors—particularly entanglement with floating debris and propeller breakage, which are among the most frequently occurring [19]. According to previous FD studies, the consumption current and rotation speed (in revolutions per minute, RPM) of underwater thrusters were selected as fault features for FD under normal conditions, propeller breakage, and entanglement [20]. A qualitative data-based approach was used to analyze the relationships between these different unit elements and faults. In this study, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) pattern recognition method was employed as the FD methodology. This method identifies clusters on the basis of the inclusion of the minimum number of points (MinPts) within an effective range ($\mathcal{E}$) centered around a point. DBSCAN has several advantages. (1) Because the distribution of data in space is clustered according to density, there is no need to specify the number of clusters separately [21]. (2) It increases the clustering accuracy by excluding noise, which can be caused by sensor measurement errors and environmental disturbances, such as waves and currents in marine environments. (3) Among clustering techniques, it has the advantages of short computation times and excellent performance in outlier detection [22]. Because of these advantages, DBSCAN is widely used for fault detection and FD [23–26]. Li et al. applied DBSCAN to diagnose the potential thermal runaway in batteries installed in electric vehicles [27]. Tian et al. used DBSCAN to increase the accuracy of FD in fuel cells by removing outliers from pressure-sensor data [28]. Considering these advantages and related research, the objective of this study was to diagnose faults for the propeller breakage and entanglement of underwater thrusters by applying DBSCAN.

This study focuses on the fault diagnosis of underwater thrusters during the hovering operation of ROVs. ROVs perform specialized tasks such as sample collection, submarine cable and pipeline installation, and real-time video inspections, all of which rely on hovering [29–31]. Hovering is essential for overcoming the effects of the marine environment, particularly currents, and achieving attitude stabilization and depth control in ROVs. It provides the fundamental functionality necessary for mission continuity and stability. However, while many studies have diagnosed faults in thrusters fixed to structures, research on fault diagnosis during actual hovering operations of ROVs was scarce, and experimental

verification was inadequate. Therefore, this study aims to diagnose faults occurring during the hovering operation of ROVs. Moreover, even for two thrusters of the same type, performance differences can occur, and long-term use can lead to performance degradation, causing variations in the rotation speed for the same control input. To address these issues, RPM control was performed to equalize the rotation speeds of underwater thrusters with different performances according to their control inputs. The RPM was measured using the back electromotive force (back-EMF) of a sensorless BLDC motor, and polynomial curve fitting was used to approximate the RPM curve for each control input. The most common external factors that can lead to underwater thruster faults, including propeller breakage and entanglement with floating debris, were imitated. During hovering operations of an ROV in an engineering water tank, current consumption and RPM data were collected for different fault imitation cases. DBSCAN—a pattern recognition technique—was applied to the acquired data. The proposed FD method's performance was verified through experiments in an engineering water tank.

The remainder of this paper is organized as follows. Section 2 presents the types of underwater thruster faults in this study and the fault diagnosis and hovering methodologies applied. Section 3 describes the ROV's hardware (HW) and software (SW) systems constructed to validate the proposed FD methods. Section 4 covers the experimental process in the engineering water tank, results, and application outcomes of the FD. Finally, Section 5 concludes the paper.

2. Faults and Methods

2.1. Thruster Faults

ROVs use propeller-type underwater thrusters as their primary propulsion system [32]. The underwater environment in which ROVs operate is unpredictable. Factors such as currents and pressure, as well as collisions with floating debris, can partially or totally damage underwater thrusters. This makes it more difficult to implement ROV motion, leading to mission failure or loss of the ROV [15,33]. This study focused on the most frequently occurring faults caused by external factors, such as entanglement with floating debris and propeller breakage [19].

Figure 1 illustrates the imitated fault situations. Entanglements were imitated using a net and rope (Ø7 mm), and for breakage situations, propeller blades were damaged to represent 33% and 66% of the total blade area. To apply data-based techniques, it is crucial to select appropriate fault features for underwater thrusters. According to prior research on underwater thruster FD, RPM and current data were used as fault features to diagnose propeller breakage and entanglement situations [20]. It is anticipated that changes in the area of contact with the fluid due to propeller breakage or entanglement result in torque variations [34]. A general equation representing the torque of the thruster is provided in Equation (1).

$$Q = \rho K_Q n^2 D^5 \quad (1)$$

where Q represents the torque of the thruster, ρ is the fluid density, K_Q is the torque coefficient, n represents the propeller rotation speed in revolutions per second (RPS), and D represents the diameter of the propeller. Equation (2) expresses the electrical torque of the DC motor.

$$Q = K_t I - J \frac{dn}{dt} \quad (2)$$

Here, K_t is the electrical torque constant, I represents the current, and J represents the moment of inertia. Assuming no change in the RPS, the current can be expressed in terms of the other variables:

$$I = \frac{\rho K_Q n^2 D^5}{K_t} \quad (3)$$

According to Equation (3), it is assessed that in the case of breakage with a reduced propeller diameter, the current will decrease while the rotational speed will increase. In the case of entanglement, the current will increase while the rotational speed will decrease. Therefore, the rotational speed (RPM) and the consumption current of the thruster were selected as fault features for FD.

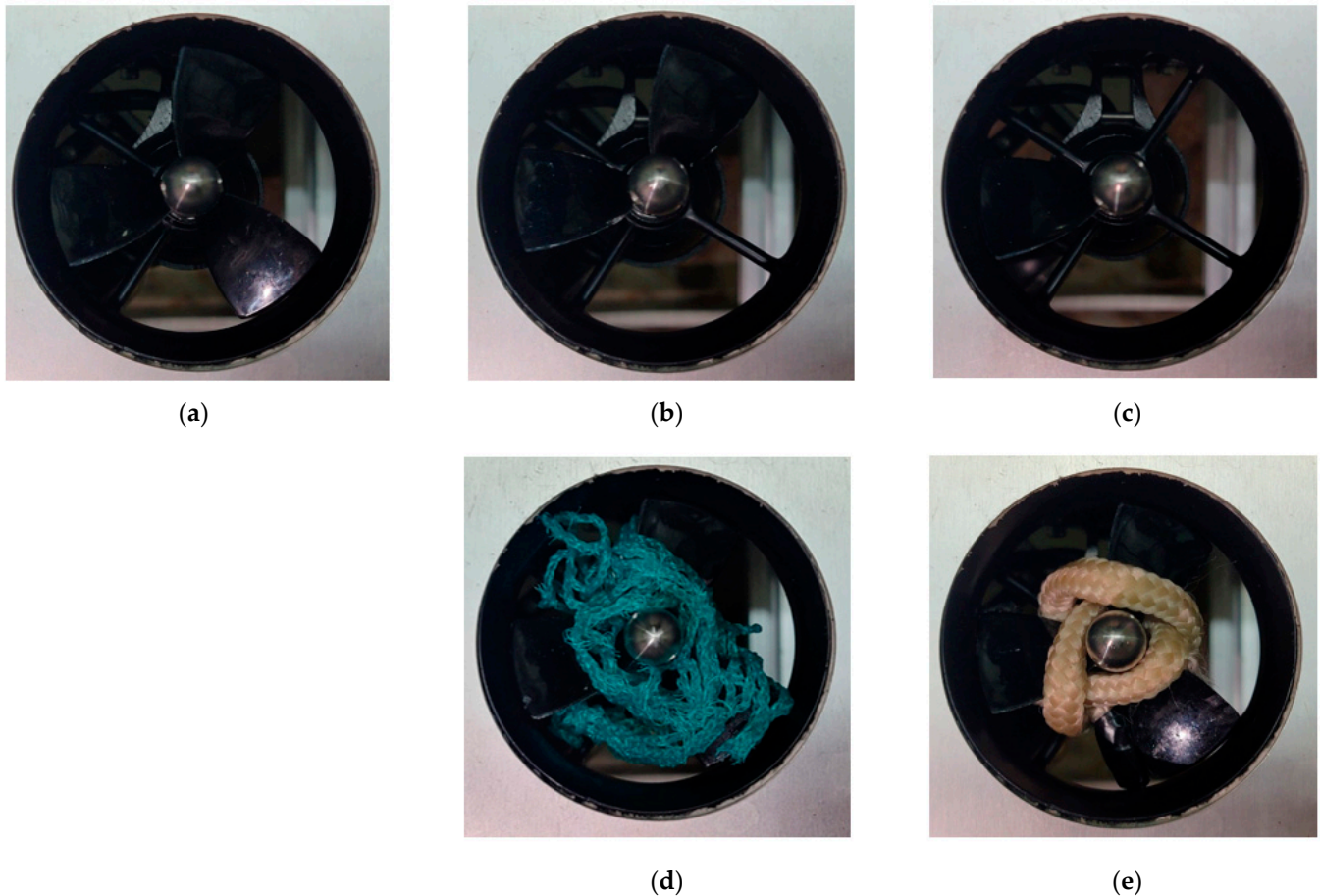


Figure 1. Imitated fault situations: (a) Normal (three propellers); (b) one-blade breakage; (c) two-blade breakage; (d) net; (e) rope.

2.2. Thruster Degradation

The underwater thrusters used in this study were small BLDC thrusters. BLDC motors are widely used in underwater thrusters because of their high dynamic response, excellent speed versus torque characteristics, and high efficiency [35]. However, performance differences can occur even among identical underwater thrusters. In addition, the physical characteristics of underwater thrusters change over time, and corrosion and aging progress more rapidly in marine environments than on land. Thus, aged thrusters may not produce the same thrust for identical control inputs, owing to changes in motor characteristics [36]. To verify the changes in motor characteristics due to aging, four BLDC motors from BlueRobotics (Torrance, CA, USA), T200 thrusters commonly used on marine platforms [37], and five T60-30 thrusters from CiLab (Seoul, Republic of Korea) currently used on an ROV were employed.

The experiment was conducted in an engineering tank with dimensions of $4.5 \times 2.5 \times 2.8 \text{ m}^3$ ($L \times W \times H$) and the system for data acquisition is shown in Figure 2. The T200s included a new thruster, one thruster from research conducted two years ago, and two thrusters from research conducted five years ago [38,39]. For the T60-30s, a new thruster and four thrusters currently mounted on the ROV were used. The electronic speed controllers (ESC) used were BlueRobotics' "Basic ESC", which employs chopper amplifiers for pulse-width modulation (PWM) as control inputs. With control inputs of 1100, 1500, and 1900 μs , this ESC operates in reverse at maximum speed, stops, and runs forward at maximum speed, respectively. The current sensor used was the WCS6800 manufactured by Winson (Hsinchu, Taiwan)—a Hall effect type sensor measuring up to 35 A with a 55 mV/A sensitivity. To measure the RPM of sensorless BLDC motors, a board was designed to read the period of the back-EMF and calculate the RPM, and its measurement principle and accuracy are discussed in Section 3.3. Control inputs ranging from -80% to 80% were continuously applied to the T200 and T60-30 thrusters, and consumption current and RPM data were acquired at a sampling rate of 10 Hz.

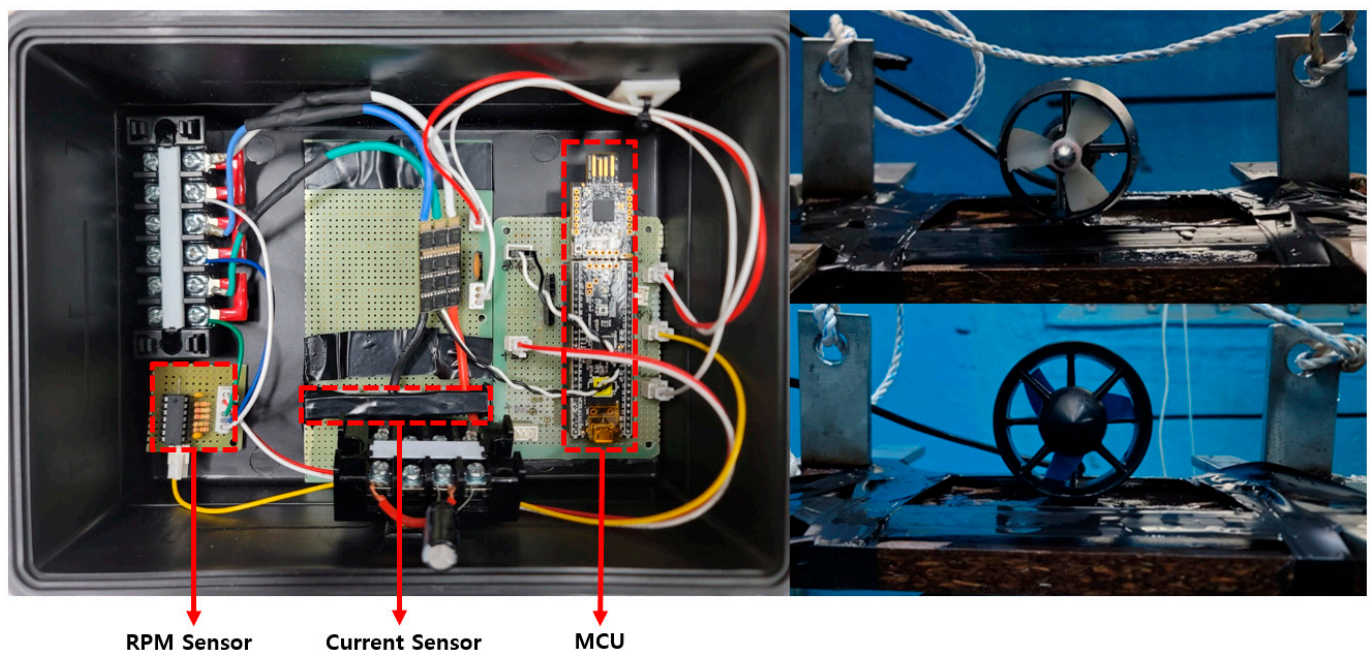


Figure 2. System for measuring the thruster RPM and consumption current.

The experimental results for the four T200 and five T60-30 thrusters are shown in Figure 3. Both types of thrusters have a $\pm 25 \mu\text{s}$ dead zone around the stop point (PWM: 1500). Figure 3a,b shows the trends in the RPM and current consumption of the T200 thrusters with various control inputs. Although the T200 thruster consumption currents are consistent across the segments, as they approach closer to their maximum rotation speeds, differences in the RPM become noticeable. Figure 3c,d shows the trends in the RPM and current consumption for the T60-30 thrusters with various control inputs. For the T60-30 thrusters, while the RPM was consistent across segments, there were differences in the current consumption. The measured data from the underwater thrusters confirmed that even identical thrusters exhibited significantly different characteristics.

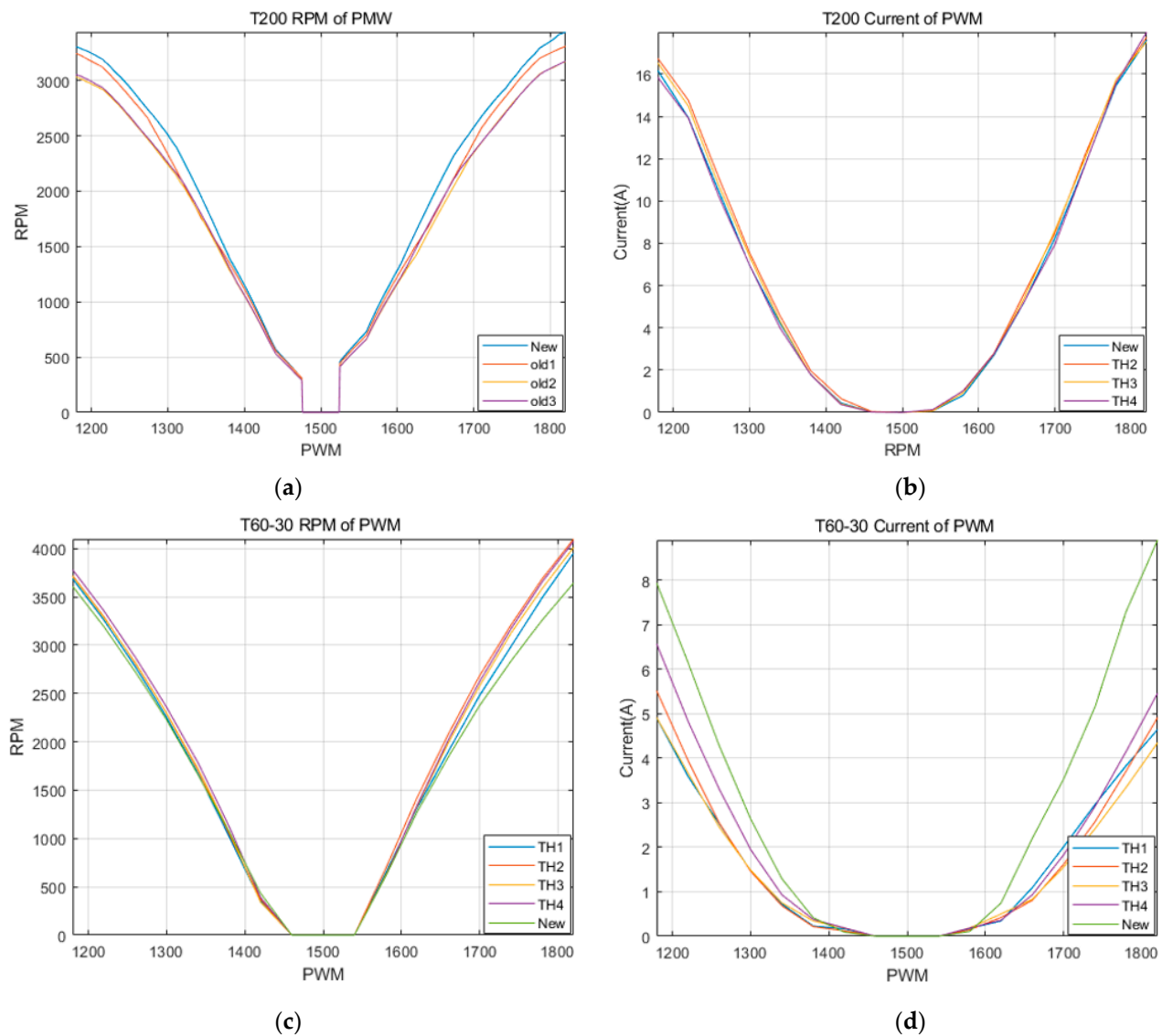


Figure 3. RPM and current by control input (PWM). (a) RPM of T200; (b) current of T200; (c) RPM of T60-30; (d) current of T60-30.

2.3. DBSCAN

Liu et al. divided FD into model and data-based analyses and incorporated both quantitative and qualitative analyses [15]. Quantitative analysis involves mathematical formulas between the system's inputs and outputs, whereas qualitative analysis examines the relationships between different unit elements [16].

- (1) Quantitative model-based analysis often utilizes mathematical modeling techniques, such as Kalman filters for state estimation and regression analysis for parameter estimation. For instance, Sun et al. employed a Gaussian particle filter to estimate the failure model and motion state of the thruster of an autonomous underwater vehicle (AUV) to diagnose faults [40], and Zhang applied an Adaptive Kalman filter for the parameter estimation of a thruster [41];
- (2) Qualitative model-based analysis typically employs causal models such as fault trees or uses abstraction layers for FD. Hereau et al. defined a fault tree based on predetermined fault types for diagnosing faults in underwater thrusters [42];
- (3) Quantitative data-based analyses generally employ statistical methods, such as principal component analysis (PCA) and neural networks (NNs). For example, Choo

et al. used PCA to diagnose faults, such as blade breakage and entanglement, in underwater thrusters [34], and Capocci et al. utilized a model-free pattern recognition neural network (PRNN) to detect and isolate external thruster faults in ROVs [12]. In the study by Zhao et al., an enhanced CNN was applied to detect defect patterns on the wafer surface by improving the traditional CNN and selectively restricting learning on important weights [43];

- (4) Qualitative data-based analyses use methods such as fuzzy logic, pattern recognition, and frequency analysis for FD. Tian et al. applied possibilistic fuzzy C-means (PFCM) to classify the types and degrees of faults that can occur in the underwater thrusters of an AUV [44].

In this study, considering the performance degradation due to the long-term use of underwater thrusters, data on normal and faulty states were collected to diagnose faults. The RPM and current consumption of underwater thrusters were selected as fault features, and a qualitative data-based approach was used to analyze the relationship between faults and normal conditions. To classify the thruster faults during hovering, DBSCAN—a pattern recognition technique—was employed in this study. DBSCAN recognizes clusters based on a core point, including the minimum number of points (MinPts) within a radial epsilon ($\mathcal{E}$).

$$N_{Eps}(p) = D \mid \text{dist}(p, q) \leq Eps \quad (4)$$

Here, D represents the dataset, and $\text{dist}(p, q)$ represents the distance between two points p and q . If the distance between p and q is within the radius $\mathcal{E}$, these points are considered neighbors. As illustrated in Figure 4, when drawing a circle of radius $\mathcal{E}$ from a point, if there are at least MinPts within the circle, that point is recognized as the core point. Points within $\mathcal{E}$ of a core point become border points, whereas those outside points are considered noise points. Through iterative processing, adjacent core points form clusters and points not belonging to a cluster are identified as noise.

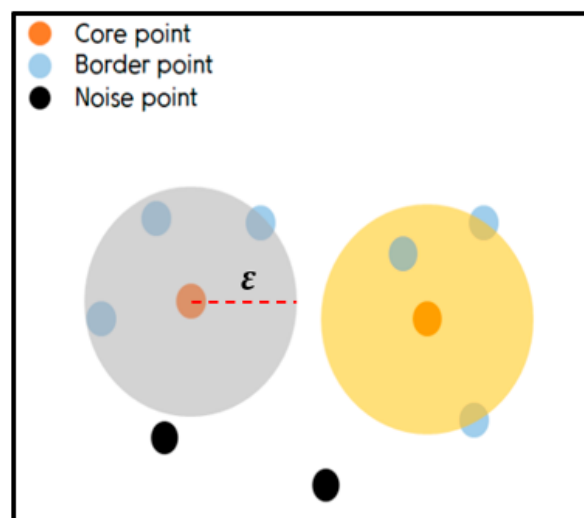


Figure 4. Diagram of DBSCAN.

The process of DBSCAN is as follows:

- (1) Set an arbitrary point p and count the number of points within the radius $\mathcal{E}$ of the given cluster that includes p ;
- (2) If the number of points within this radius is at least MinPts, consider point p as a core point and group the points within the radius into a cluster;
- (3) If the number of points within the radius is less than MinPts, pass it;

- (4) Repeat steps 1 to 3 for all points. If a new point “ p ” becomes a core point and belongs to the existing cluster (with p as the core point), the two clusters are considered connected and are merged into one cluster;
- (5) After completing the clustering process for all points, any point that does not belong to any cluster is considered a noise point. Additionally, points that belong to a cluster but are not core points are called border points. Through iterative processing, adjacent core points form clusters and points not belonging to a cluster are identified as noise.

In this study, the focus is on the fault diagnosis of underwater thrusters in ROVs; noise may occur owing to sensor measurement errors and environmental disturbances such as waves and wind in the marine environment, reducing the accuracy of FD. DBSCAN has the advantage of increasing the clustering accuracy because it clusters data while excluding noise. In this study, DBSCAN was applied for FD through the correlation of selected fault features, RPM, and consumption current based on the density in a two-dimensional (2D) Euclidean space.

MinPts represents the minimum number of points required within a radius $\mathcal{E}$ from a point to be considered a core point. With a small MinPts, noise may be included in the clustering process, and data may be misclassified. With large MinPts, parts of the data may be misidentified as noise, and data belonging to the same category may be separated into different clusters. According to Schubert et al., a common practice for DBSCAN is to set MinPts to twice the number of dimensions of the dataset [45].

$\mathcal{E}$ represents the effective radius from the core point. With an excessive $\mathcal{E}$, distinct datasets may be merged into the same cluster, whereas a small $\mathcal{E}$ may hinder cluster formation, necessitating the selection of an appropriate. To determine the $\mathcal{E}$, the elbow method with a sorted k-distance was applied. Arrange This method involves repeatedly calculating the distances between the data points, including the previously selected MinPts, and then sorting them in descending order.

Figure 5 is an illustration representing the elbow method with a sorted k-distance. The x-axis represents the sorted points, and the y-axis represents the k-distance. The optimal epsilon is determined as the y-value at the intersection near the elbow point where the dataset calculation ends.

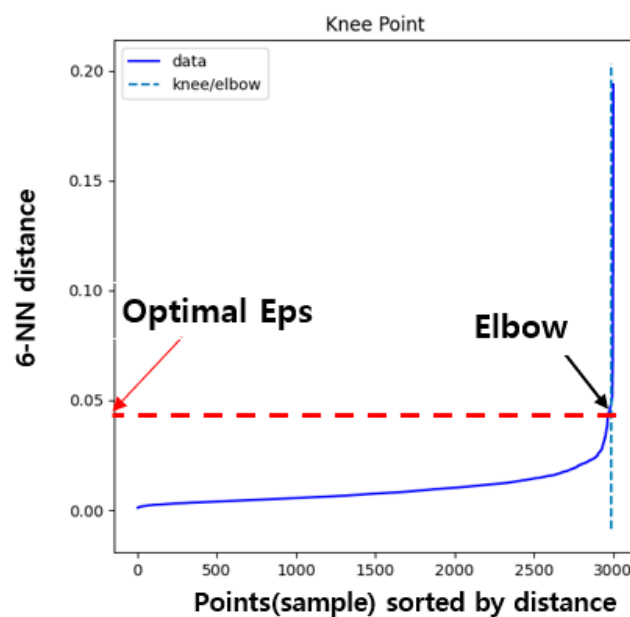


Figure 5. Illustration of elbow method with a sorted k-distance.

Figure 6 shows the anticipated data distribution in situations of breakage and entanglement, as inferred from Equation (3). As the situation approaches breakage, a decrease in the current and an increase in the RPM compared with normal conditions are expected. As the

situation approaches entanglement, an increase in the current and a decrease in the RPM are anticipated. As shown in Figure 6, the data distribution for each type of fault will spread diagonally from the normal state, and as the severity of the fault increases, the clusters will form further away from the normal state. Therefore, when applying DBSCAN, the larger the region dominated by the breakage series, the greater the extent of the breakage can be estimated. In the case of entanglement, the impact on the thruster can be inferred. In other words, it is possible to infer which fault has a more dominant influence on the current state of the thruster. It was determined that DBSCAN, which has advantages in nonlinear clustering, can classify faults according to the expected characteristics of the data, even in cases where there is no linear relationship.

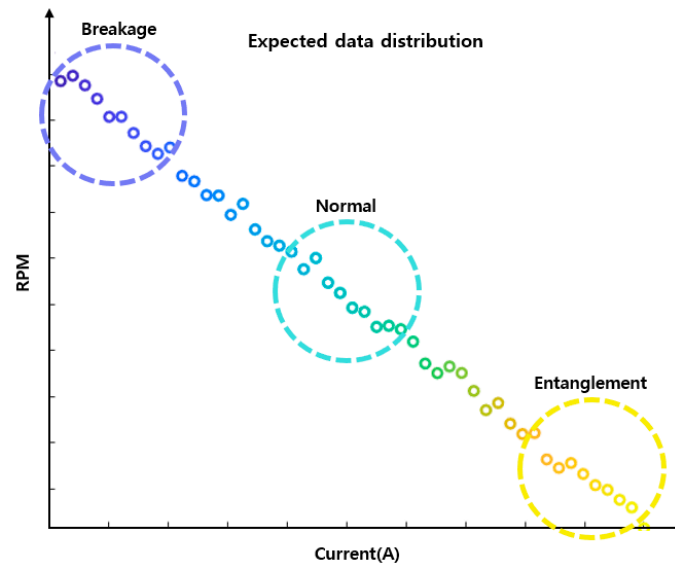


Figure 6. Expected data distribution when applied DBSCAN.

2.4. Hovering Control

To achieve consistent thrust among underwater thrusters with different thrusts, a hovering controller based on RPM control was designed. For the vertical thrusters to maintain the same RPM, a fourth-degree polynomial relationship between the control input (PWM) and RPM was calculated via polynomial curve fitting in “MATLAB R2024a”. This RPM-based control allows the ROV to maintain its roll, pitch, and depth at reference values through hovering control. The hovering control strategy is shown in Figure 7.

$$\begin{aligned} e_{\phi} &= \phi_R - \phi_Y \\ u_{\phi} &= K_{\phi P} e_{\phi} + K_{\phi I} \int e_{\phi} dt + K_{\phi D} \dot{e}_{\phi} \end{aligned} \quad (5)$$

Here, e_{ϕ} represents the error between the reference roll and output roll, ϕ_R represents the reference roll, ϕ_Y represents the output roll, and u_{ϕ} represents the roll PID calculation value.

$$\begin{aligned} e_{\theta} &= \theta_R - \theta_Y \\ u_{\theta} &= K_{\theta P} e_{\theta} + K_{\theta I} \int e_{\theta} dt + K_{\theta D} \dot{e}_{\theta} \end{aligned} \quad (6)$$

Here, e_{θ} represents the error between the reference pitch and output pitch, θ_R represents the reference pitch, θ_Y represents the output pitch, and u_{θ} represents the pitch PID calculation value.

$$\begin{aligned} e_D &= D_R - D_Y \\ u_D &= K_{DP} e_D + K_{DI} \int e_D dt + K_{DD} \dot{e}_D \end{aligned} \quad (7)$$

Here, e_D represents the error between the reference and output depths, D_R represents the reference depth, D_Y represents the output depth, and u_D represents the depth PID calculation value.

$$u_t = u_\phi + u_\theta + u_D \quad (8)$$

Here, u_t denotes the sum of the calculated values for roll, pitch, and depth PID control. The calculated u_t as an RPM value, performs RPM control according to the thrust direction of each thruster and implements hovering for the maintenance of attitude (roll and pitch) and depth.

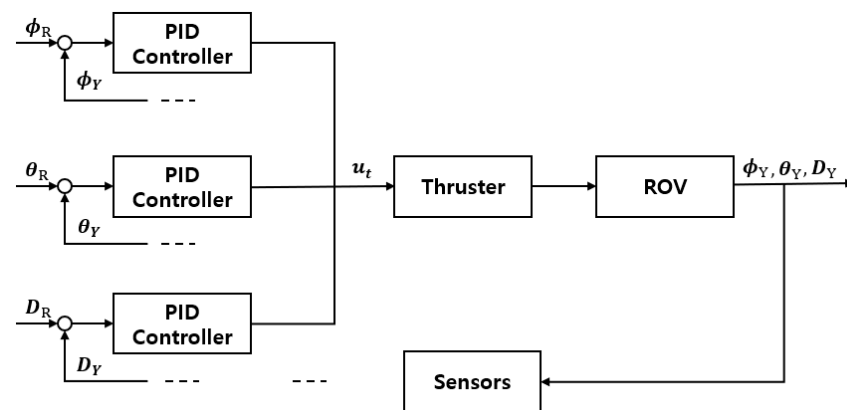


Figure 7. Hovering control: PID computation of roll, pitch, and depth errors based on RPM control.

Figure 8 shows the results of the hovering control for depth only, from the bottom of the engineering tank to the target depth (2.5 m), with the gain values related to the roll and pitch set to zero. In simple depth-hovering control, it can be observed that the four vertical thrusters are identical to those in RPM control.

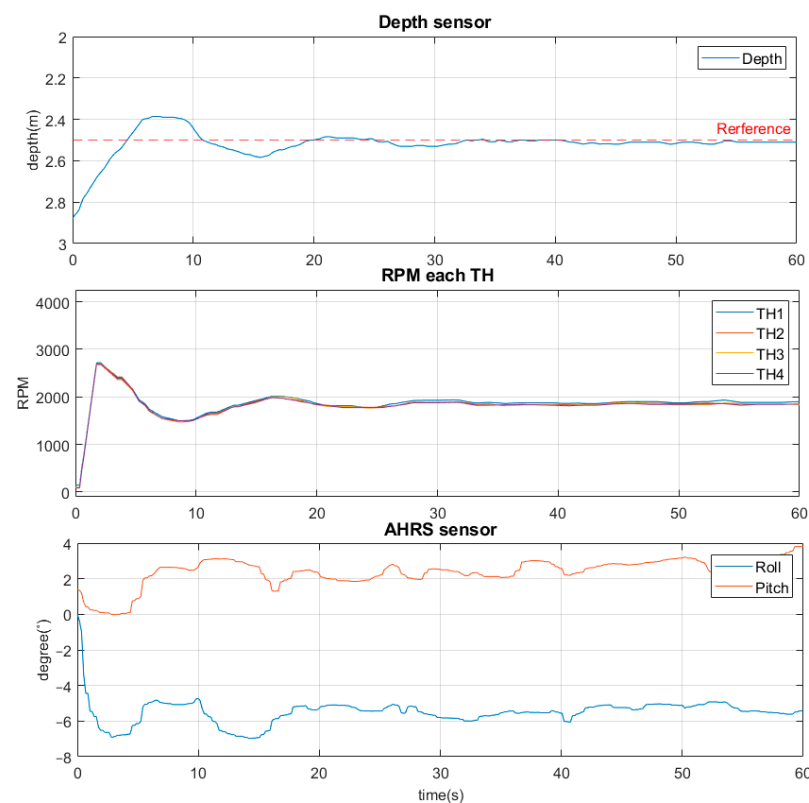


Figure 8. Results of reaching the target depth from the tank bottom and performing hovering: depth, RPM, and attitude data for only depth hovering control.

Figure 9 shows the overall strategy for the proposed ROV system. Before faults are diagnosed, the selected fault features (RPM and current consumption of the underwater thrusters) are acquired and subjected to a preprocessing step. According to the preprocessed data, faults are diagnosed using the DBSCAN method described in Section 2.3 to distinguish between normal, breakage, and entanglement.

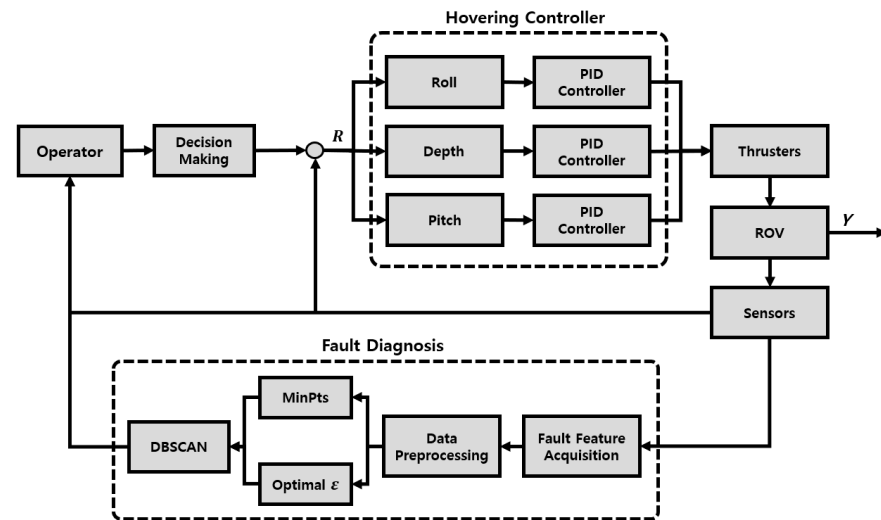


Figure 9. ROV system schematic. Two main processes are followed: hovering control and FD.

3. Configuration of ROV

3.1. Hardware System

For experimental verification of the proposed FD, an ROV was constructed with dimensions of $560 \times 435 \times 290 \text{ mm}^3$ ($L \times W \times H$), as shown in Figure 10. The design was developed using SolidWorks (2023) to ensure that the center of gravity and buoyancy coincided. To prevent this, the exterior shell was composed of aluminum, which is resistant to corrosion. The ROV comprised a main pressure cylinder for housing sensors and electronics, an auxiliary pressure vessel for power supply batteries, and eight thrusters. Four vertical thrusters controlled the roll, pitch, and heave motions, and four horizontal thrusters controlled the surge, sway, and yaw motions.

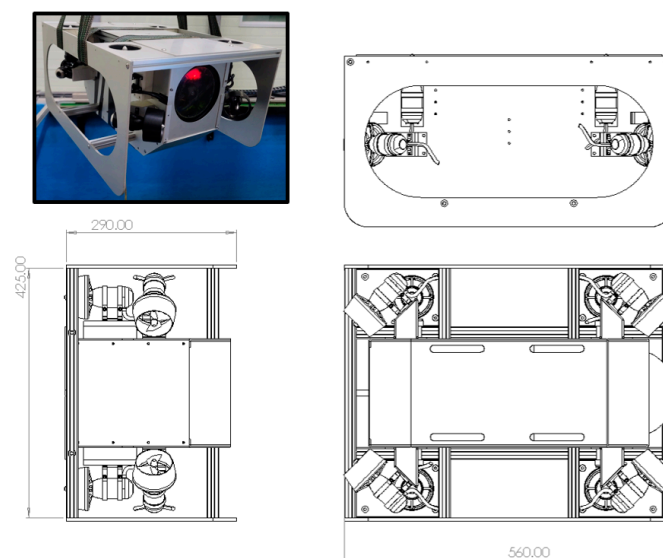


Figure 10. Manufactured ROV system and 2D schematics.

3.2. Control System

Figure 11 illustrates the control system of the ROV. Microcontroller Unit 1 (MCU1) is a control thruster, MCU2 is used for gathering sensor data, and MCU3 measures the back-EMF period to calculate the RPM. Additionally, a mini PC processes algorithms, collects data, and communicates with a PC on land. For measuring the attitude of ROV, E2BOX' "9DOFV5", an attitude and heading reference system (AHRS) sensor, was used. Its accuracy is ± 0.2 degrees, and it has a maximum output speed of 1kHz. For depth measurement, BlueRobotics' "MS5837", was used. This sensor operates on the principle of converting physical pressure into electrical signals and can measure up to 300 m with a resolution of 0.2 cm. For measuring the consumption current of the thruster, the current sensor used is the same product as the one described in Section 2.2.

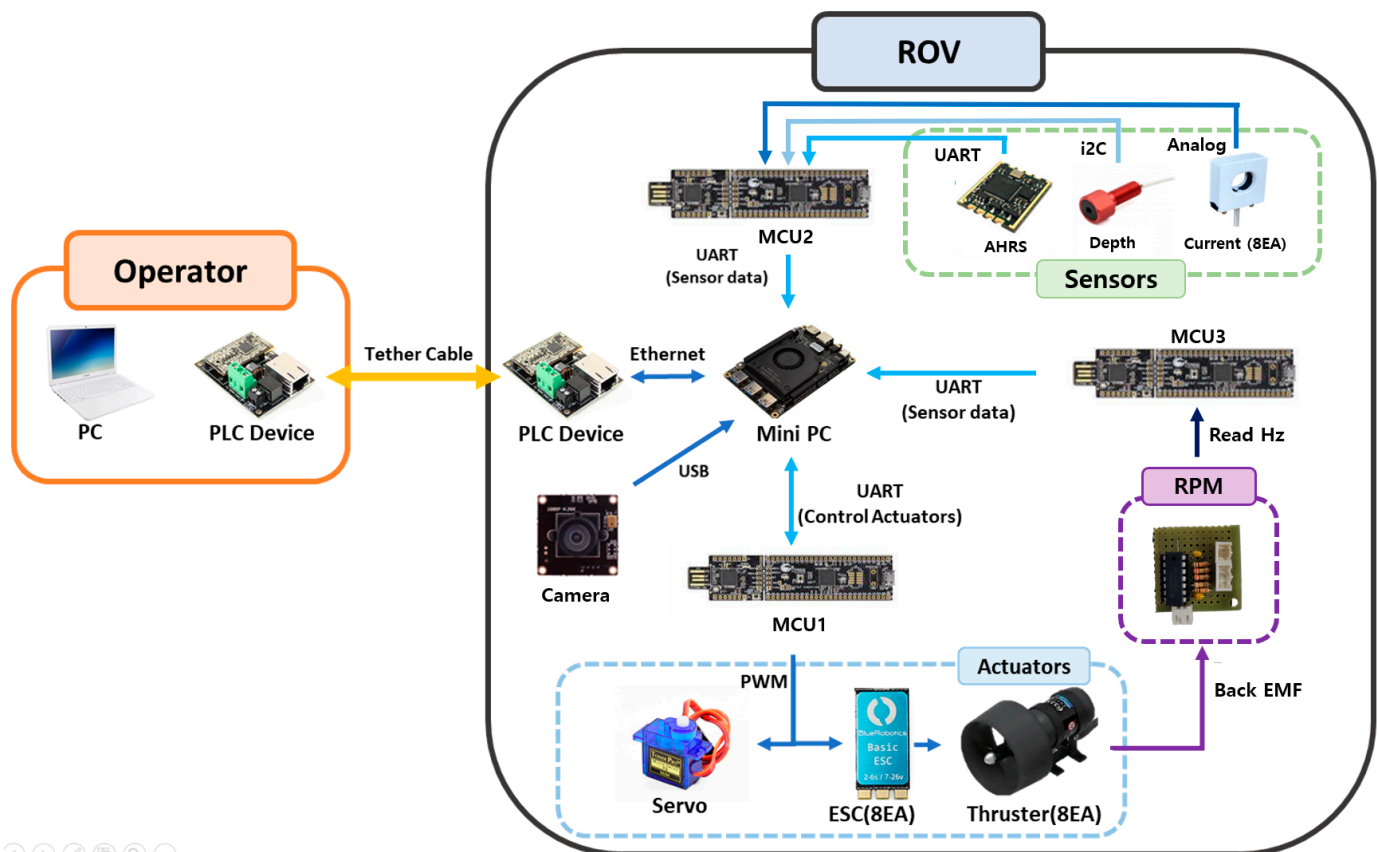


Figure 11. Diagram of the ROV control system.

As shown in Figure 12, a graphical user interface (GUI) was developed using C# to monitor and control the ROV. It allows real-time monitoring of the attitude data of the ROV, data feedback for thrust compensation, the transmission of motion-related commands to the ROV, and adjustment of the proportional–integral–derivative (PID) gain values for hovering control.

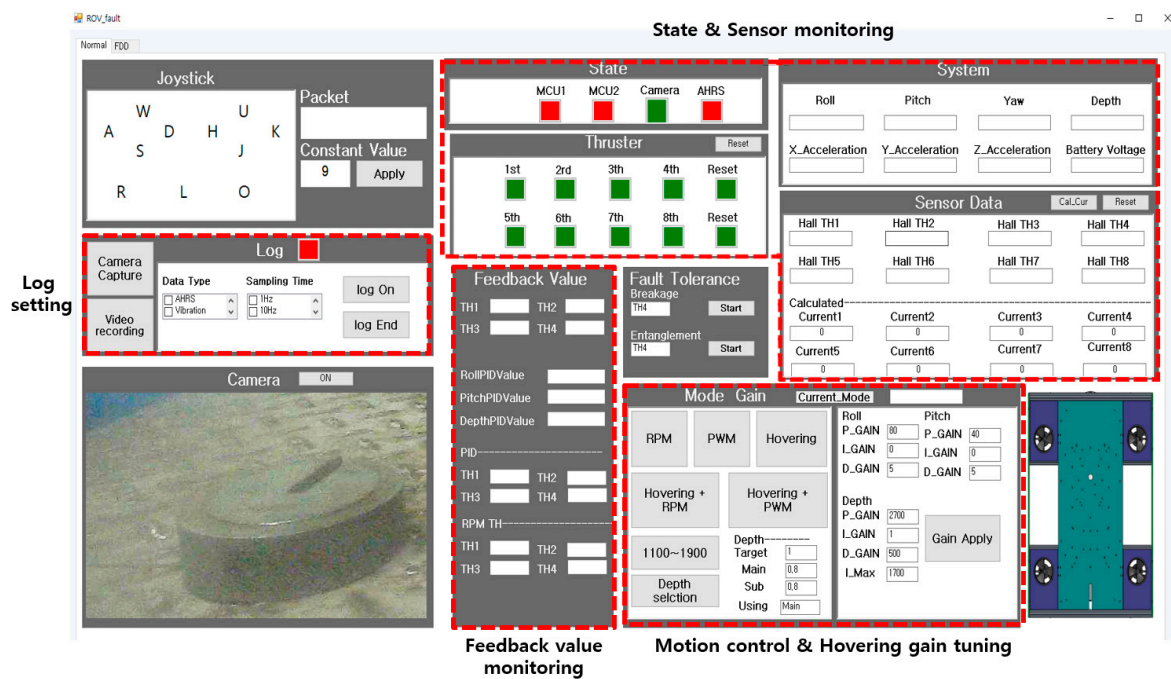


Figure 12. GUI program for the ROV system.

3.3. Back-EMF Measurement RPM Board

The objective of this study was to achieve consistent thrust through RPM control of underwater thrusters that are identical but have different performances. The utilized sensorless BLDC underwater thrusters lack built-in encoders for RPM feedback. Therefore, a board was developed to calculate the back-EMF period for the RPM computation and feedback to the MCU. Immediate feedback during variable control is crucial for real-time RPM control. Back-EMF allows fast feedback because it appears almost immediately in the opposite direction of the voltage applied to the winding, according to Lenz's law [46,47].

Figure 13 presents the back-EMF measurement circuit and board designed for RPM acquisition. An LM324 comparator detects the back-EMF and outputs it in pulse form, with the MCU reading the falling time of the pulse to calculate the RPM. Pins 4 and 11 of the LM324 are for power supply, connected to 5V and ground, respectively. Pins 2 and 3 are connected as shown in Figure 13a for detecting the back-EMF of the BLDC motor, and pin 1 outputs a pulse signal by comparing the two signals. The reliability of this method was confirmed through comparisons with a laser tachometer (manufactured by PeakTech, Germany) and an oscilloscope (manufactured by Tektronix, USA), as illustrated in Figure 14.

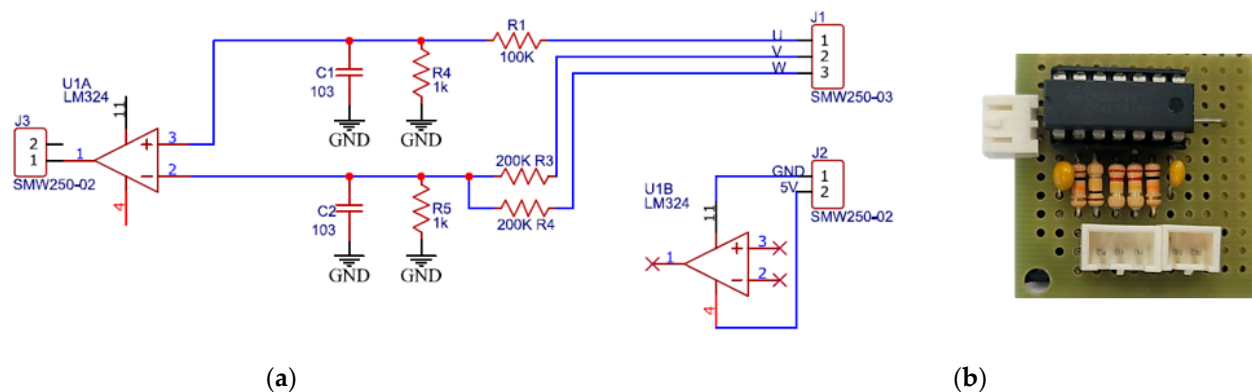


Figure 13. Back-EMF for RPM acquisition: (a) Measurement circuit; (b) measurement Board.

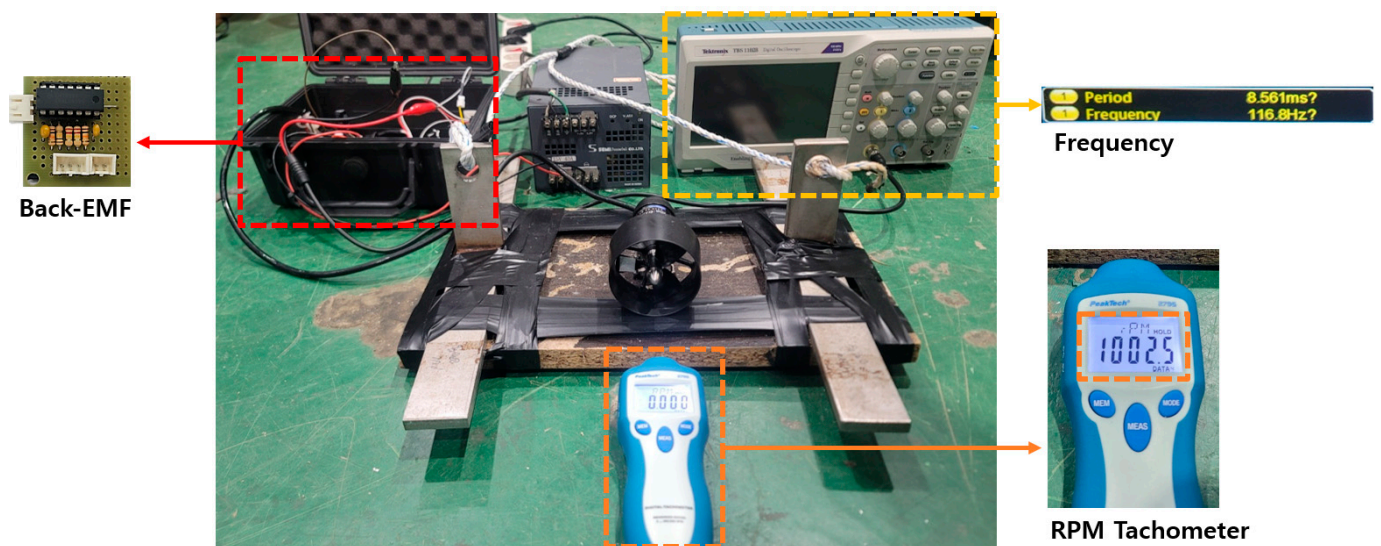


Figure 14. Back-EMF circuit verification experiment.

To validate the back-EMF circuit, experiments were configured as shown in Figure 14, for comparing (1) the RPM calculated by the MCU from the back-EMF period, (2) the RPM derived from frequency measurements on an oscilloscope, and (3) the RPM measured by a laser tachometer. The specifications of the RPM tachometer and oscilloscope used for the verification are presented in Table 1.

Table 1. Specifications of the RPM tachometer and oscilloscope.

	Tachometer	Oscilloscope
Measuring Range	2–199,999 rpm	~100 MHz
Sampling rate	0.5 s	2.0 GS/s
Accuracy	±0.05%	3% (vertical)

The ESC used in this study was the “Basic ESC” from BlueRobotics, which utilizes PWM as control inputs. This ESC was designed such that control inputs of 1100, 1500, and 1900 μ s result in the maximum reverse rotation speed, stop the motor, and result in the maximum forward rotation speed, respectively. The control inputs were varied discretely from –100% to 100% in increments of 100. The experiment was repeated five times, and the average values were calculated. The results are presented in Table 2.

Table 2. Average RPM results for each method.

Control Input	Back-EMF Board	Tachometer	Oscilloscope
1900	4253	4237	4230
1800	3245	3239	3241
1700	2131	2130	2132
1600	1002	1000	998
1400	801	803	799
1300	1941	1933	1932
1200	3058	3049	3049
1100	4201	4179	4174

The average RPM values for each method with respect to the control input are presented in Table 2. The error rate between the back-EMF board and the tachometer reached a maximum of 0.53%, and the error rate between the oscilloscope readings reached 0.64%. According to these validations, RPM control was executed to achieve consistent thrust among underwater thrusters with different thrusts.

4. Performance Evaluation of FD

4.1. Water-Tank Test Results

To validate the FD, experiments were conducted in an engineering water tank with dimensions of $4.5 \times 2.5 \times 2.8 \text{ m}^3$ ($L \times W \times H$). Data were collected at a 10 Hz sampling rate while changing the fault situations of vertical thruster TH4. Various fault situations were applied to the thruster, as shown in Figure 15. For both the normal and fault situations, the ROV was placed at the bottom of the tank (2.8 m), ascended to a target depth of 2 m, and maintained that target depth while keeping the roll and pitch angles at 0° through hovering control.

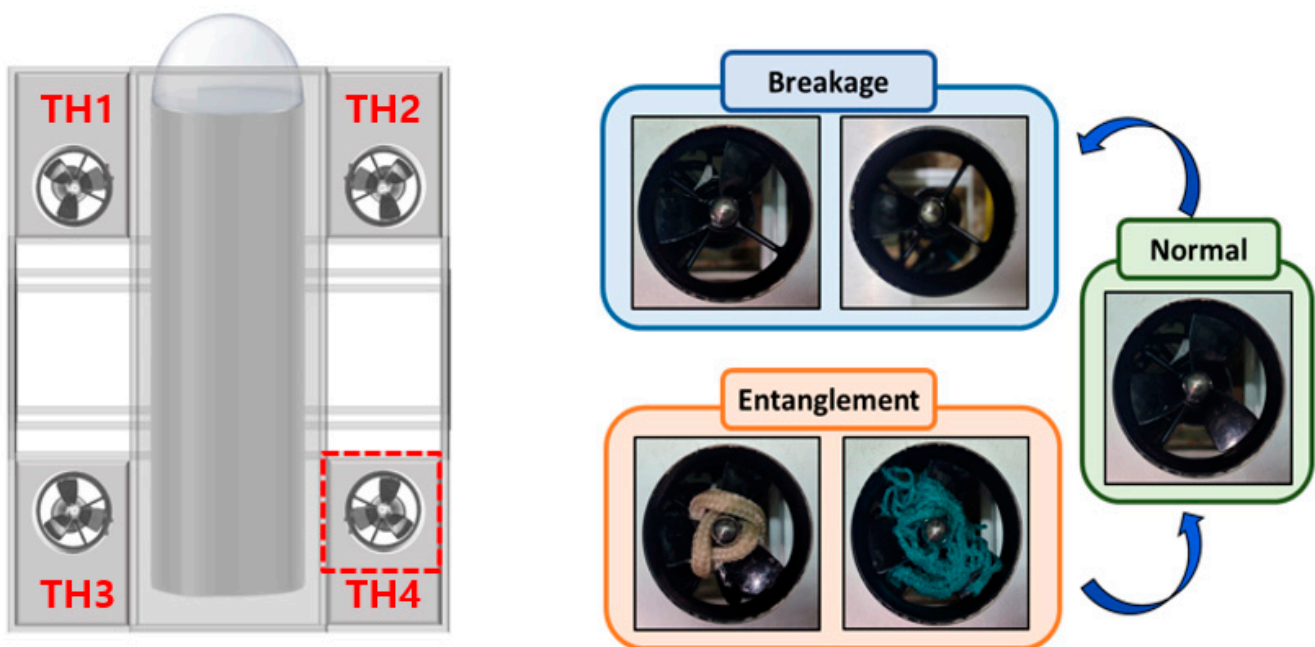


Figure 15. Tank experiment conditions: Alternating between normal and faulty situations of thruster TH4.

Figure 16 presents the results of hovering under normal conditions, including the depth and attitude outcomes. Figure 16a shows the depth and attitude data during hovering, and Figure 16b shows the normal distribution of the depth data during hovering control from the bottom of the tank to the target depth of 2 m. Typically, in control theory, the settling time is defined as the duration within which a system's response remains within $\pm 2\%$ or $\pm 5\%$ of the reference value once it reaches the steady state. However, in cases of entanglement, inconsistent thrust due to the entangled thruster can lead to an imbalance in attitude. To resolve this imbalance, thrusters generate thrust to stabilize the attitude, causing the ROV to hover in a tilted position without reaching the target depth. Therefore, in this study, the “hovering time” is defined as the time for which the depth data remain within one standard deviation ($\pm \sigma$) from the target depth during hovering. As illustrated in Figure 15, fault data were collected by changing the fault situations based on the hovering gain values of a normally operating propeller.

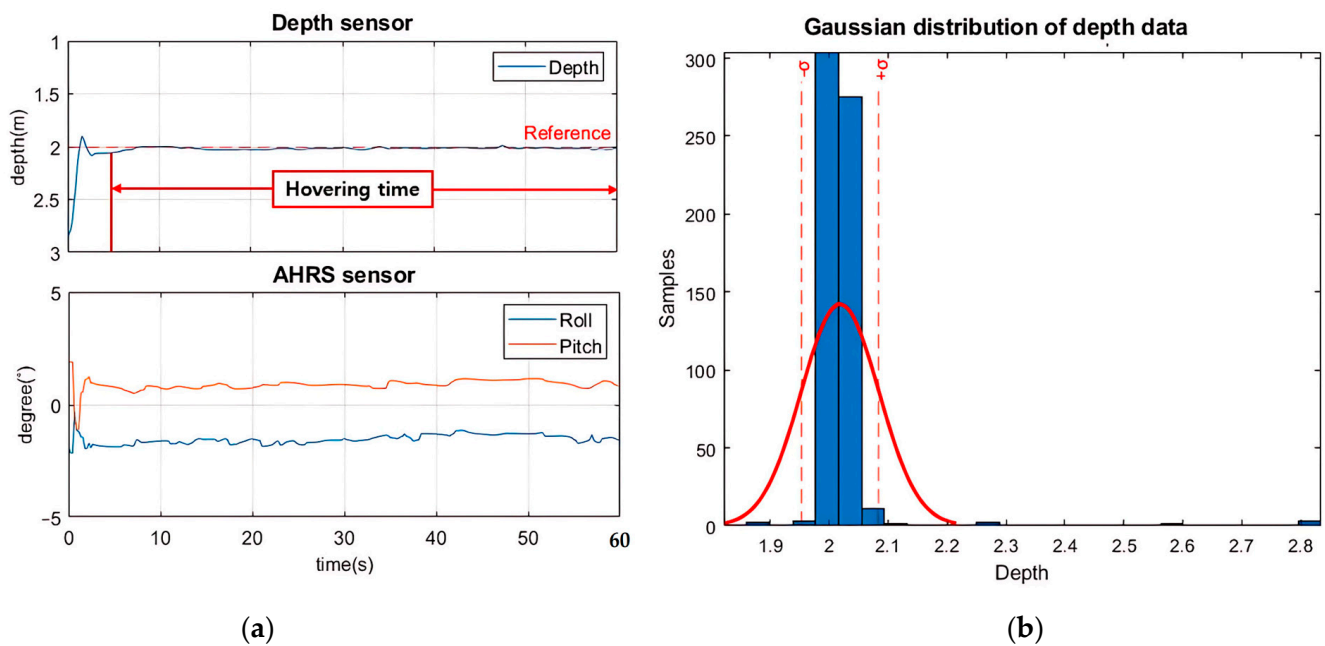


Figure 16. Depth and attitude results of hovering after reaching the target depth from the bottom of the engineering water tank under normal conditions: (a) Depth and attitude data acquired during hovering; (b) normal distribution of depth data during hovering; (a) hovering time: the time for which hovering around the target depth did not exceed $\pm\sigma$.

Figure 17 presents the depth and attitude data for each fault situation of TH4, including one-blade breakage (a), two-blade breakage (b), rope (c), and net (d). Breakage situations, such as (a) and (b), resulted in delayed hovering times owing to the weaker thrust relative to a normal thruster, with two-blade damage reaching hovering time later than one-blade damage. In contrast to entangled thrusters, breakage thrusters, which have weaker self-thrust, do not cause a significant change in the attitude rate. In entanglement situations, such as (c) and (d), the thrust exceeds that of breakage situations; thus, the hovering time is reached more quickly. However, inconsistent thrust due to debris entanglement causes an imbalance in attitude, and maintaining hovering control in a tilted position makes it difficult to reach a target depth of 2 m.

Table 3 presents the average current consumption and RPM data during the hovering period after the target depth was reached. As shown, the current decreases and the RPM increases in breakage situations compared with normal conditions, whereas in entanglement situations, the current increases and the RPM decreases or remains similar. These results validate the selected fault features (consumption current and RPM of the thruster) based on the torque equation of the thruster.

Table 3. Water-tank experiment results: data during hovering time of a faulty thruster (TH4).

Conditions	Battery Voltage (V)	Current (A)	RPM	Control Input
Normal	22.9	0.6648	1766	1630
One-blade breakage	22.58	0.5371	1809	1635
Two-blades breakage	22.70	0.4294	1954	1638
Rope	22.78	2.1645	1802	1658
Net	22.99	2.7734	1708	1666

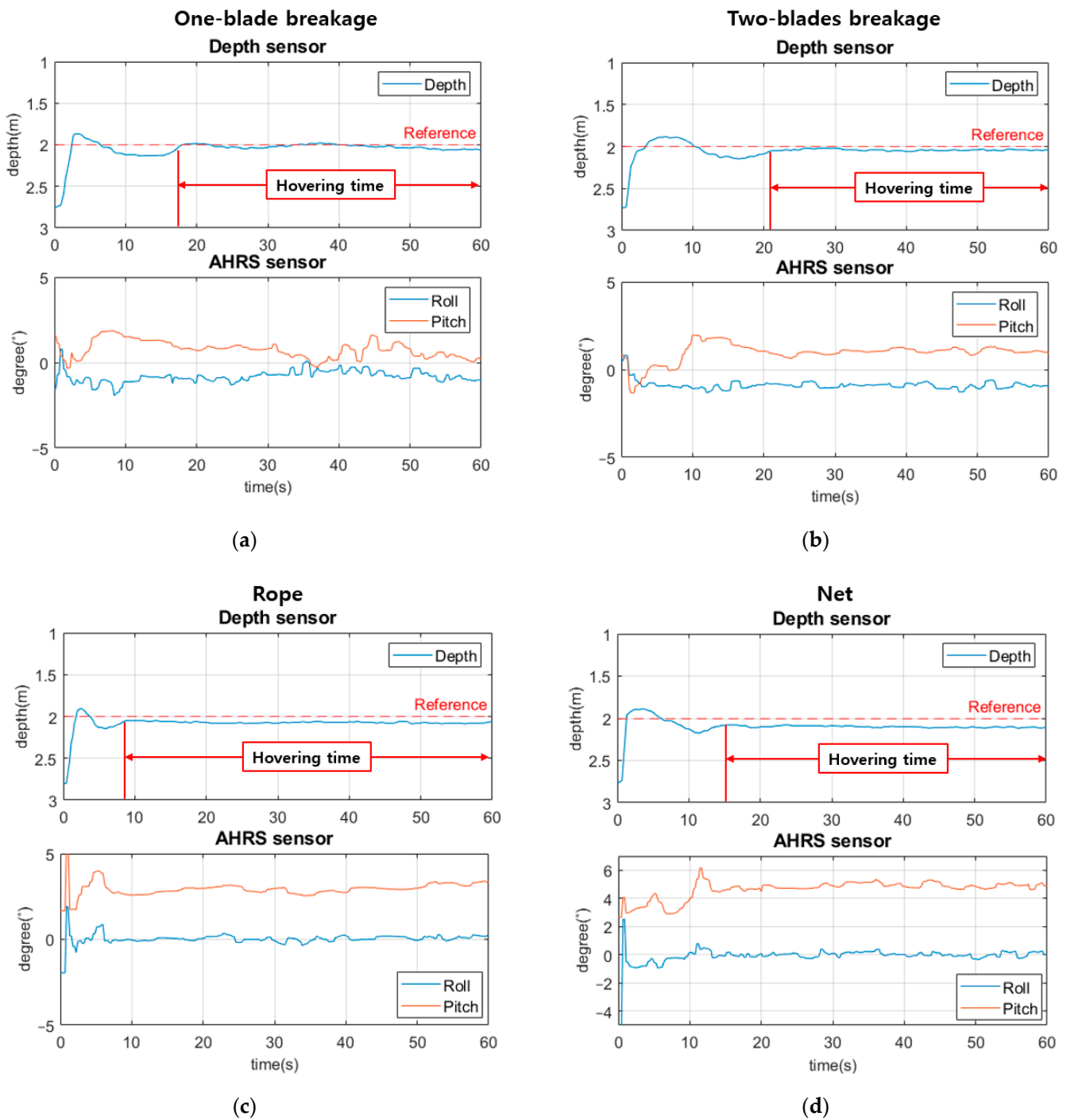


Figure 17. Results of reaching the target depth from the tank bottom and performing hovering in different fault situations: (a) One-blade breakage; (b) two-blade breakage; (c) rope; (d) net.

4.2. Results of FD

The FD algorithms applied in this study are shown in Figure 18. Before applying DBSCAN, a preprocessing step is performed after acquiring fault features such as RPM and current data. The data are scaled to expand the distribution of normal and fault data and then normalized to account for unit differences. Subsequently, samples of normal, breakage and entangled data are sorted, and DBSCAN is applied with $\mathcal{E} = 0.2$ and $\text{Minpts} = 4$, as mentioned in Section 2.3.

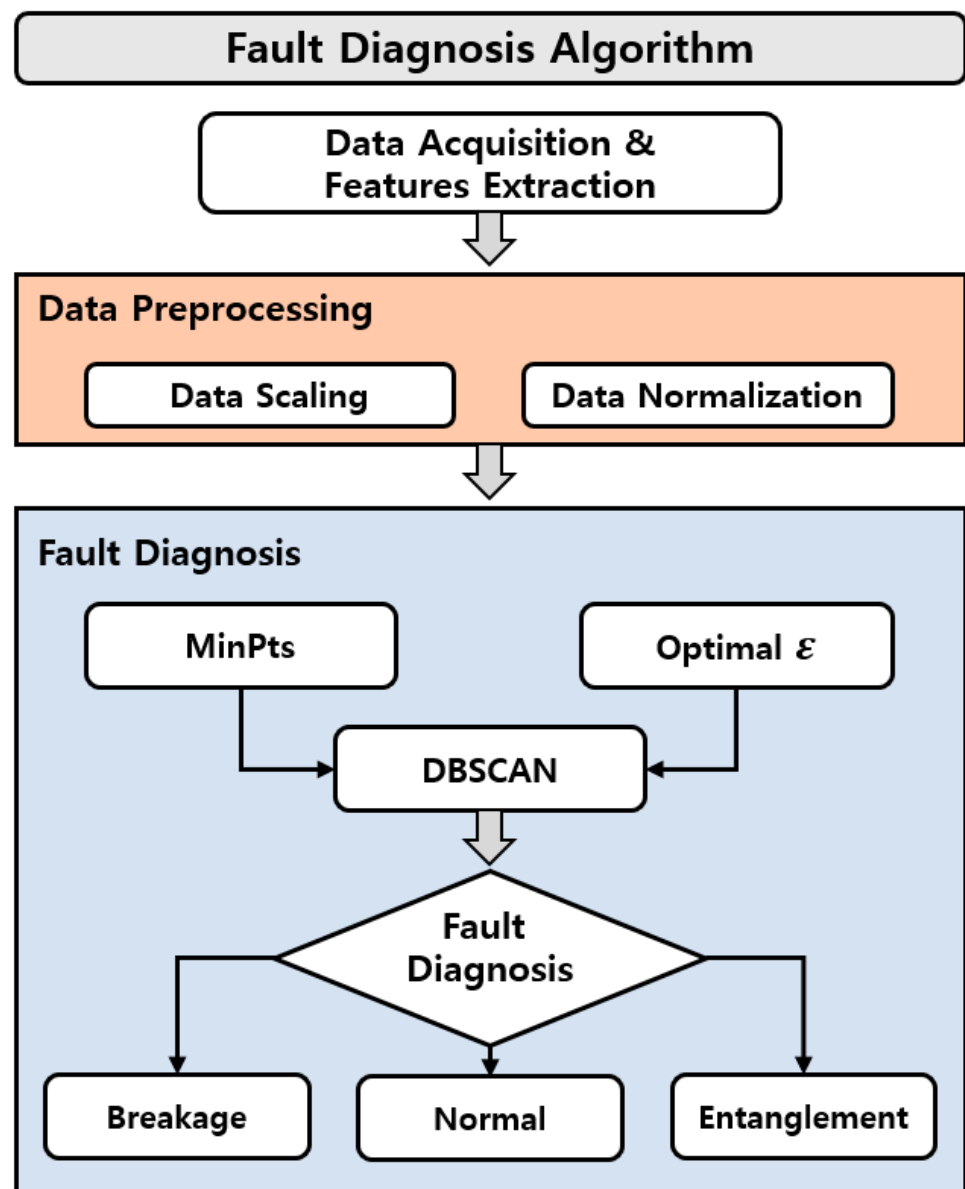


Figure 18. FD algorithms.

Figure 19 shows the clustering results obtained by applying DBSCAN to 200 samples of normal, two-blade damage, one-blade damage, rope, and net data, respectively. Breakage data are characterized by a lower current and higher RPM compared with normal data, whereas entanglement data are clustered separately owing to their relatively high current. Although the fault data and normal conditions did not have a linear relationship, as shown in Figure 6, the application of DBSCAN, which is effective for nonlinear clustering, resulted in fault classification.

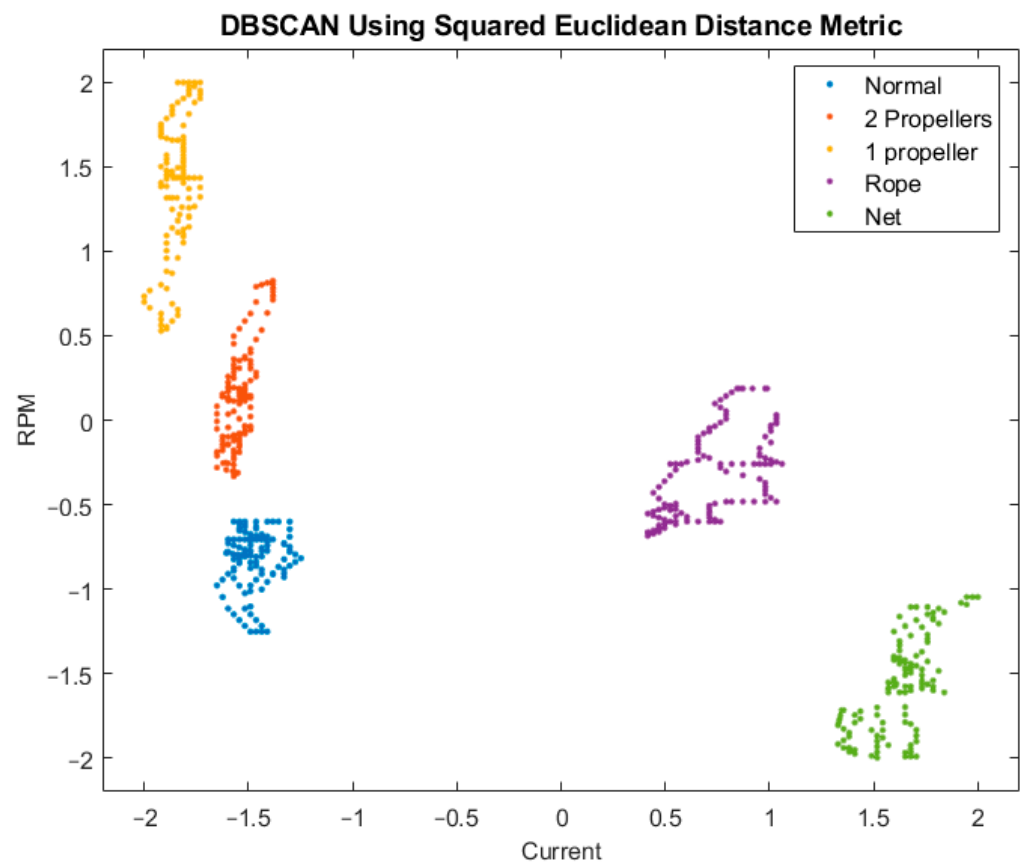


Figure 19. Results of applying DBSCAN.

5. Conclusions

This study addresses the FD methodology and the experimental verification for the most frequently occurring external factor-induced faults in ROV thrusters, such as propeller blade damage and entanglement with floating debris. For the diagnostic subject, the small BLDC thrusters, despite being the same model, exhibit performance differences. Therefore, experiments were conducted to verify the differences in rotational speed performance for each thruster per control input, as well as performance variations due to aging. To verify performance for each control input, the power consumption and RPMs of the underwater thrusters were acquired, and a board was designed to compute RPM by reading the period of the back-EMF for RPM acquisition. Based on the notable performance differences between thrusters, RPM control was implemented to achieve constant thrust across all units by utilizing polynomial curve fitting to define the relationship between rotational speed and control input for each thruster.

Fault diagnosis techniques are categorized into model-based and data-based methods, each further subdivided into quantitative and qualitative analyses. Given the characteristic performance differences among identical thrusters, the application of model-based fault diagnosis methodologies, which demand precise modeling, is challenging. The FD methodology used in this study was a qualitative data-based method that analyzed the relationship between faults and different unit features, such as RPM and current. A pattern recognition technique, DBSCAN, was applied to distinguish between normal, breakage, and entangled cases based on the selected features. Based on the results of the engineering water tank experiment, it was confirmed that clusters are formed similarly to the expected distribution of data. Future research aims to apply fault-tolerant control strategies for each fault situation to enhance hovering stability.

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