Advancements and Challenges in Underwater Soft Robotics: Materials, Control and Integration

[1]Lekha T R, [2]Saravanakumar K, [3]Akshaya V S and [4]Aravindhan K
[1]Department of Information Technology, SNS College of Engineering, Coimbatore, Tamil Nadu, India.
[2,3]Department of Computer Science and Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India.
[4]School of Computing and Information Technology, REVA University, Bangalore, India.
[1]lekhaa86@gmail.com, [2]saravanakumar.k_cse@sece.ac.in, [3]vsakshaya@gmail.com, [4]aravindhan03@gmail.com

Correspondence should be addressed to Lekha T R : lekhaa86@gmail.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202404049
Received 10 October 2023; Revised from 10 December 2023; Accepted 20 March 2024.
Available online 05 April 2024.

Abstract – This article focuses on the progress of underwater robots and the importance of software architectures in building robust and autonomous systems. The researchers underscore the challenges linked to implementation and stress the need for comprehensive validation of both reliability and efficacy. Their argument is on the extensive implementation of a globally applicable architectural framework that complies with established standards and guarantees interoperability within the field of robotics. The research also covers advancements in underwater soft robotics, which include the development of models, materials, sensors, control systems, power storage, and actuation techniques. This article explores the challenges and potential applications of underwater soft robotics, highlighting the need of collaboration across many fields and advancements in mechanical design and control methods. In the last section of the paper, the control approach and algorithms used to underwater exploration robots are reviewed. Particular attention is given to the application of Proportional Integral Derivative (PID) control and the incorporation of Backpropagation Neural Network (BPNN) for PID parameter determination.

Keywords – Backpropagation Neural Network, Proportional Integral Derivative, Microcontroller Unit, Gradient Descent, Real-Time Operating System

I. INTRODUCTION

Recently, the robotics technology has made great strides, from rugged robots to intelligent service robots. Currently, underwater robots are being developed using robotic intelligence, sensors, and advanced material technologies. These robots are designed for a wide range of applications and their missions are becoming increasingly complex compared to traditional tasks like hydrographic surveys, which involve simple and one-way data collection. With the growing need to handle complexity in challenging and ever-changing situations, it is essential to combine many software components, ranging from hardware drivers to advanced learning algorithms, inside a software framework. Researchers have shown significant interest in software architectures as a crucial aspect of building robot systems. This is because software architectures go beyond being a mere collection of components, such as software libraries. They provide a robust development environment that facilitates abstraction and modularity.

Several researchers in the field of underwater robotics have presented their own software frameworks, demonstrating how to develop autonomous capabilities [1,2,3]. However, these findings have not addressed the challenges of implementation and providing rigorous evidence of stability and performance. Given that the majority of recently created architectural designs have been categorized as hybrid, the classification of architectural groupings may no longer be a significant concern. We have shifted our focus to a universal architecture that is linked to established standards and compatibility. Choosing the appropriate software architecture is crucial for simplifying the process of specifying, implementing, and validating the performance of robot systems. While there is no definitive meaning of architecture of software for a robot, it is challenging to directly evaluate software architectures. However, we can assess their quality based on various criteria such as standardization, predictability, generality, reactivity, modularity, robustness, and extendibility.

Nevertheless, constructing an architecture that adheres to the standards is very difficult to do without any pre-existing framework or foundation. Instead of this, a middleware, which serves as the shared foundation of a software architecture, has gained popularity in the field of robotics. The system has several software components, as shown in **Fig 1.** It is necessary to choose a suitable Real-Time Operating System (RTOS) independently. As ocean research and advancement progress, intelligent underwater robots have become crucial tools for exploration and operations. Their worth is increasingly evident and they are extensively used in offshore oil production, applications of military, natural resources extraction, and fishing. With the growing quantity of bridge and highway building, geological investigation is necessary to guarantee the project's safety. Conventional mechanical detecting technology has challenges when it comes to handling the unfamiliar and intricate underwater environment.

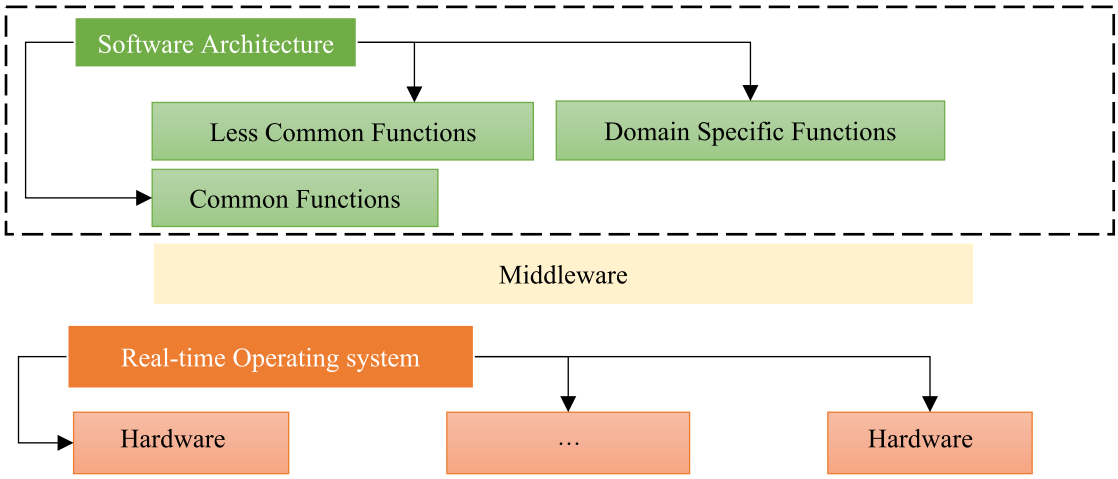

Fig 1. Software Architecture for a Robot

Based on the current research and advancement of hardware innovation in the laboratory's sonar detection system, a new underwater detecting robot has been designed. This robot can execute fixed-point hovering placement, carry an underwater sonar detector to clear propeller silt, and regulate its movement in both the vertical and horizontal planes, including floating, diving, and horizontal motion.

The purpose of this study is to discuss the growing intricacy of underwater robots and the need for resilient software frameworks to manage this intricacy. The objective of the study is to provide a thorough summary of the present research and progress in underwater robotics, including improvements in hardware innovation, materials science, actuation methods, sensing and control, and modeling. The research also emphasizes the difficulties and restrictions in the sector and suggests using machine learning methods, including reinforcement learning, to improve control precision. The objective of research is to enhance the progress of underwater soft robots and provide valuable insights for future advancements in the area. The remaining sections of the paper are organized as follows: **Section II** presents a review of previous literature works related to the concept of underground soft robotics. **Section III** focusses on the structural design of underwater exploration robot. In **Section IV,** the control approaches of underground robots are provided: traditional PID control approach, and the control approach based on BPNN-PID. Lastly, a summary of the research findings is provided in **Section V**.

II. RELATED WORKS

Calisti et al. [4] reviewed the advancements in underwater soft robotics, focusing on several aspects such as modeling, manufacturing materials, sensing and control, actuation techniques, power storage, and locomotion patterns. In summary, various materials, including hydrogels, silicone rubber, LCE, SMA, DE, IPMC, PZT, and SMP, are reasonably advanced in their development. The production techniques include compressible needle casting, 3D/4D printing, SDM, thread-reinforced pneumatic chambers, and soft photolithography. The systems of actuation may be classified into three primary categories: fluid-driven systems, variable-length tendons, and EAP (electroactive polymer) systems. Swimming is a prevalent and efficient mode of movement for aquatic species. Hu and Yu [5] specifically examine four swimming patterns: wave undulation, rowing, hydrodynamically powered, and jet propulsion, as explained in detail before.

According to Nawaz et al. [6], the power storage of underwater robots is advancing to become more autonomous, portable, smaller in size, capable of lasting longer, and able to use a variety of energy sources. The high degree of freedom (DOF) shown by soft robots poses a challenge in achieving inverse kinematic modeling, therefore making the precise control of soft robots an ongoing area of study interest. In the present day, the progress of machine learning has paved the way for soft robotics that use sensor-detected data to enhance closed-loop control, hence increasing control accuracy. Among several machine learning techniques, reinforcement learning clearly stands out as the most promising one. Furthermore, the use of modeling is crucial in the fabrication of the robot, as it enables researchers to enhance the design. Model of nonlinear ontology model for soft robotics is derived from the modeling using mathematical theory. The objective is to reduce the discrepancy between simulation results and actual experimental data. In recent times, several academics have developed models for continuum robots using various methods such as CC/PCC, FEM, VC, Cosserat theory, and others.

According to Subad, Cross, and Park [7], underwater soft robots are predominantly constructed using pliable materials. In contrast to their rigid counterparts, these robots possess a surplus of degrees of freedom, enabling them to exhibit highly flexible movements and actively or passively alter their shape in response to the surrounding habitat. Consequently, underwater soft robots demonstrate superior adaptability, and flexibility. They offer significant advantages in tasks such as human-machine interaction, delicate product handling, and underwater operations in confined spaces, effectively compensating for the limitations of the robots that are rigid. It compensates for the limitations of inflexible robots and advances the development, perception, control, and use of robots to a more advanced level. Soft robot ontology materials have a resemblance to soft biological tissues, enabling them to navigate unfamiliar terrain, accurately imitate the movement patterns of mollusks, endure substantial hits without sustaining harm, and maneuver through intricate and confined places. These qualities surpass the constraints of inflexible robots and significantly streamline the design physical construction of robot`s offering new concepts for the investigation of mobile robots that are bionic.

According to MajidiCarmel [8], underwater soft robots need a wide range of expertise because of their unique operating conditions and the materials used to construct their bodies. Hence, in order to achieve a significant advancement in this domain, it is essential to enhance all the disciplines associated with its progress. Currently, the development of robots is in its early stages and there are many technological limitations. Consequently, creating robots that can match the level of sophistication shown in present land robots is a very tough task.

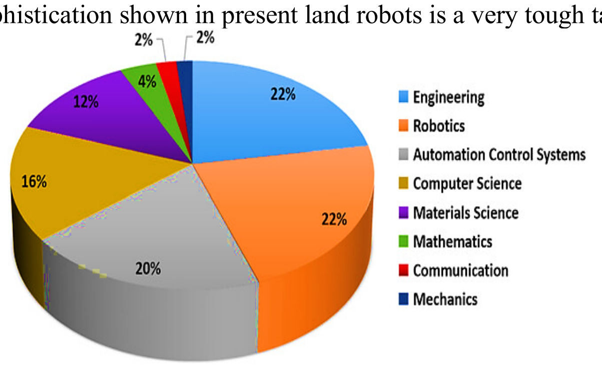

Fig 2. The last years have seen a disciplinary spread of underwater soft robots.

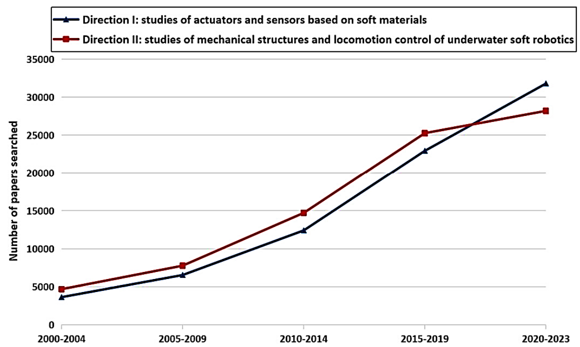

Fig 3: Google Scholar inquiry on underwater soft robotics, January 2023

Fig 2 illustrates the distribution of several disciplines within the sector of soft robotics underwater in past years. The proportions in the figure indicate the relative relevance of each discipline, with a larger percentage indicating a greater level of importance. By analyzing the research subjects distribution in this subject during the last decade, it has been shown that the field of materials science has the biggest share compared to other disciplines, including engineering and robotics. Conversely, the mechanical direction comprises the smallest proportion (see Figure 2). Furthermore, via the consolidation of research findings from experts in the domain of underwater soft robotics, we have identified two primary avenues of exploration. Direction I encompass the investigation of sensors and actuators utilizing soft materials, while direction II centers on the examination of locomotion control and mechanical structures. This involves advancing control strategies and employing sensors, actuators, and materials within mechanical structures. Both orientations are mutually complimentary.

Fig 3 displays the publications number in the past years for each of them. Since the 2000s, there has been a consistent and ongoing increase in the number of papers on underwater soft robotics in both directions, following a similar pattern [9]. The growth of Direction I has been accelerating, with a significant increase in the number of researchers and the advancement of their accomplishments. Through collaborative efforts, researchers have successfully produced advanced actuators and sensors by harnessing the potential of intelligent soft materials. Hence, there is a pressing need for enhancements in direction II, in order to devise superior control techniques and integrate mechanical designs that result in underwater soft robots exhibiting enhanced performance.

According to Scaradozzi, Palmieri, Costa, and Pinelli [10], underwater robots has had significant advancements in several aspects like as structure, driving technology, modeling approaches, and control algorithms in recent years. Nevertheless, the exploration of soft robotics is still in its nascent stages, since it represents a novel kind of robotic technology. Research on underwater soft robots encompasses several areas such as materials science, chemistry, machinery, control systems, and other related fields. Significant challenges have been seen in the field of sensing: material selection, control, and structural design technologies (see to **Table 1**).

In general, underwater robots are assuming a more expansive role in underwater manipulation, movement, identification, military applications, and several other domains. Underwater soft robots possess superior safety features and can dynamically adjust to the shape of objects, whether actively or passively. They offer distinct advantages in gripping objects of various shapes, particularly those that are soft and delicate. The successful implementation of a sensory-driven approach to gripping delicate objects underwater would greatly advance the improvement of integration technology of human-robot. Furthermore, the underwater soft robots will evolve with the objective of increased maneuverability, reduced weight, and a highly advanced system. Highly agile subaquatic soft robots are more suited for achieving swift underwater navigation objectives. Enhanced flexibility and compactness would greatly facilitate the identification of restricted underwater spaces by soft robots. A high level of system integration refers to the extensive integration of structure, hardware, software, and control algorithms. This integration is beneficial for achieving underwater soft robots' intelligent operation and has promising applications in underwater cluster operations, air, ground cooperative operations, and space.

Table 1. Challenges Faced in the Field of Underwater Soft Robots Sensing

Challenge	**Description**
Materials	More research must be done in this field to produce novel active soft materials and underwater soft robots with intelligence of biomechanic akin to mollusks. Furthermore, it is critical to produce materials with unique mechanical characteristics at varied underwater pressures and in different directions.
Structure	Although underwater soft robots are very flexible, they have limitations in several applications, including limited strength, insufficient stiffness, and low loads. While it is feasible to enhance the rigidity of flexible robots by incorporating materials like fibres that are elastic into silicone or using the principle of jamming, this approach does not result in a significant transformation.
Control	The soft robot underwater has an unlimited number of DOF; however, the actual number of drivers is restricted. Consequently, accomplishing precise real-time control presents a very demanding task. Hence, it is quite significant to investigate the intelligent control algorithms of bionic for soft robots.
Integration of control, sense, and actuation	Robots that are flexible primarily use goods that are intelligent and innovative constructions to accomplish integration of the drive and body, enabling them to perform specific activities via preprogramming. The advancement of 3D printing technology, flexible electronics technology, and integrated flexible sensors, has made it feasible to integrate drive sensing control into soft robots.

This article presents research on the design and creation of an underwater robot equipped with a sonar sensing system. The robot exhibits multifunctionality, including fixed-point hovering placement, propeller silt cleaning, and motion control in both horizontal and vertical planes. The research moreover examines progress in underwater soft robotics, encompassing breakthroughs in modeling, manufacturing materials, sensing and control, actuation strategies, power storage, and locomotion patterns. The authors emphasize the difficulties in attaining accurate control of soft robots because of their extensive range of motion. They suggest using machine learning methods, including reinforcement learning, to improve control precision. The research highlights the significance of modeling in the construction of underwater robots and explores the benefits of using soft robotics for jobs involving human-machine interaction and underwater operations in restricted areas. The authors emphasize the need of multidisciplinary cooperation and developments in mechanical design and control approaches to further optimize the performance of underwater soft robots.

III. STRUCTURAL DESIGN OF UNDERWATER EXPLORATION ROBOT

Robotics is an engineering discipline that encompasses the ideation, design, production, and functioning of programmed robots capable of independently carrying out designated tasks. Submarine robotics may be categorized into many groups, as seen in **Fig 4.** One of these groups is specifically focused on underwater robotics, which includes unmanned water vehicles. Underwater robots have been under research for many decades, primarily focusing on the advancement of manned aquatic vehicles. However, in recent decades, the high expenses associated with constructing and operating these vehicles have prompted researchers to focus on developing robots or unmanned underwater vehicles (UUVs). Over time, these robots have been improved and utilized in various applications to promote the well-being and sustainable development of the planet. Given the massive size of the seas and the challenges humans have in exploring them, a significant portion of the oceans, almost two-thirds of the globe, remains unexplored.

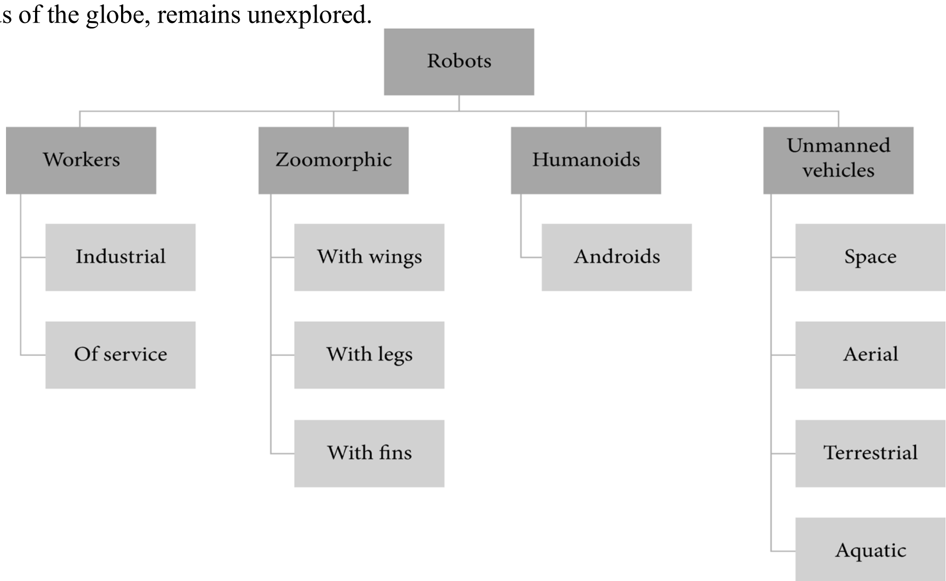

Fig 4. Position of Autonomous Watercraft Inside a Fundamental Robotics Classification

According to Amy et al. [11], over 37% of the world's population lives within 100 kilometers of the ocean. Consequently, understanding the marine environment has and will persistently influence the future viability of the human race. Hence, researchers have endeavored to create autonomous vehicles that exhibit escalating efficiency and are capable of offering underwater repair and maintenance services, as well as conducting explorations in progressively deeper marine habitats. The subject of this research is a diminutive detecting robot designed for underwater exploration. The control computer program and framework's equipment are specifically designed to accommodate the robot's motion characteristics. To ensure the robot remains lightweight and small, it requires the use of buoyancy materials.

Additionally, the robot must be tightly sealed to prevent any water leakage or other related issues in its underwater working environment. The platform of ground control establishes communication with the robot and transmits precise instructions for motion control. Underwater geological inquiry is achieved as the robot of exploring underwater simultaneously transmits data detection in the opposite direction to the console. To improve the establishment of the movement model for an underwater exploration robot, the motion in the vertical and horizontal planes is separated due to the presence of cross coupling phenomena in its three-dimensional motion.

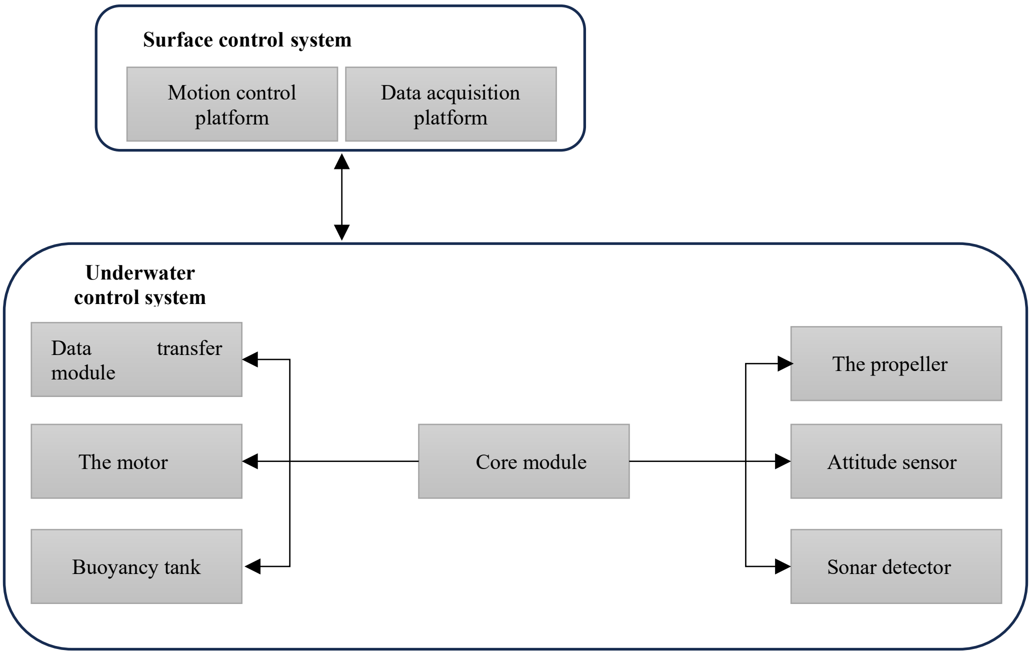

Fig 5. The Robot Framework System for Exploration of Underwater

Fig 5 shows a detailed diagram of the underwater exploration robot's framework construction. As technology advances, the capabilities of microcontrollers have become more robust, making them extensively used in many applications such as electrical appliances, vehicles, and robotics. The fundamental architectural configuration of an underwater exploration robot mostly comprises the following five components: The components of the cabin are the buoyancy tank, core cabin, main structure, propeller, and motor. The primary control board utilizes the STM32F427 microcontroller unit (MCU), which incorporates a wireless connection module and facilitates data transfer via a serial port. Submerged robot control revolves around the central aspect of postural control.

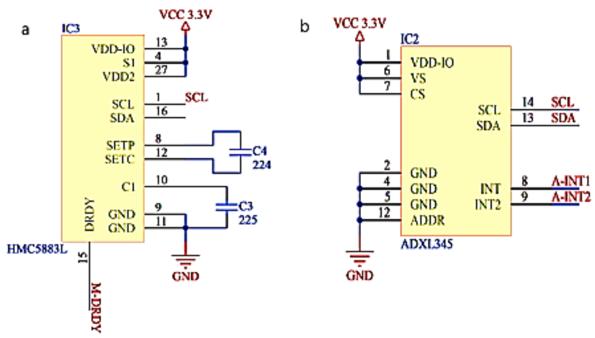

Fig 6. A schematic design illustrating a modern compass with three axes; (b) A triaxial accelerometer schematic diagram.

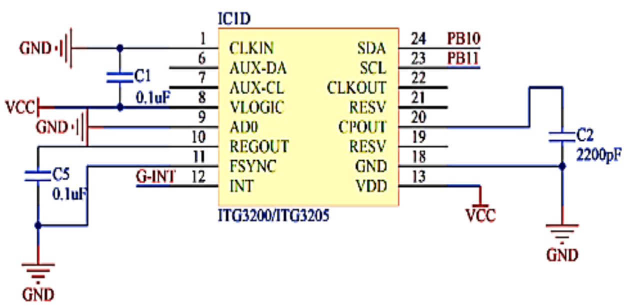

Fig 7. Circuit schematic for a three-axis gyroscope.

To enhance the precision of the underwater robot's control, we have included our own IMU sensor module into the underwater exploration robot. This module combines HMC5883L three-axis digital compass (see Figure 6), ITG-3205 three-axis gyroscope (see **Fig 7**), and the ADXL345 three-axis accelerometer. Below is a schematic illustration of the circuit. The underwater exploration robot's stability is assessed while it is suspended using the IMU sensor module. The sonar detector makes use of the project's in-house constructed sonar detector, with STM32F103 serving as the main chip of control. Once the underwater exploration robot reaches the designated location via the transmission of control instructions, the sonar detector collects underwater geological data, which is then communicated to the platform of surface control. Subsequently, the data line is analyzed using the program to achieve the discovery of undersea addresses. The STM32 single-chip microprocessor is primarily employed by the primary microcontroller in the central cabin's control and drive circuit, as described in this article. With KEIL MDK, the supporting software is created. The exploration robots of underwater control of motion flow chart are shown in **Fig 8.**

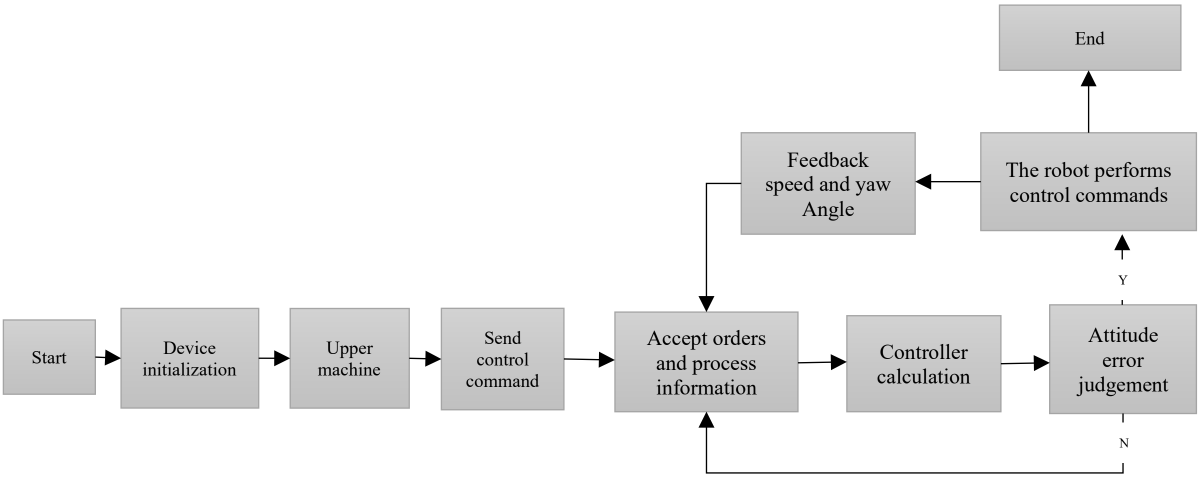

Fig 8. The Undersea Exploration Robot's Motion Control Flow Chart

IV. CONTROL APPROACH OF UNDERWATER ROBOT

Traditional PID control approach

Several control algorithms exist for underwater robots [12]. The Proportional Integral Derivative (PID) [13] is now the most extensively used control algorithm due to its maturity, effectiveness, and excellent resilience. It offers the benefits of a simple algorithm. PID control, or proportional integral differential control, is a method that combines the error values of a system and provides feedback to the controlled object in a linear manner. The algorithm formula is shown below.

$$u(t) = K_p e(t) + \frac{K_p}{T_i}\int_0^1 e(t)dt + K_p T_i \frac{de(t)}{dt} \tag{1}$$

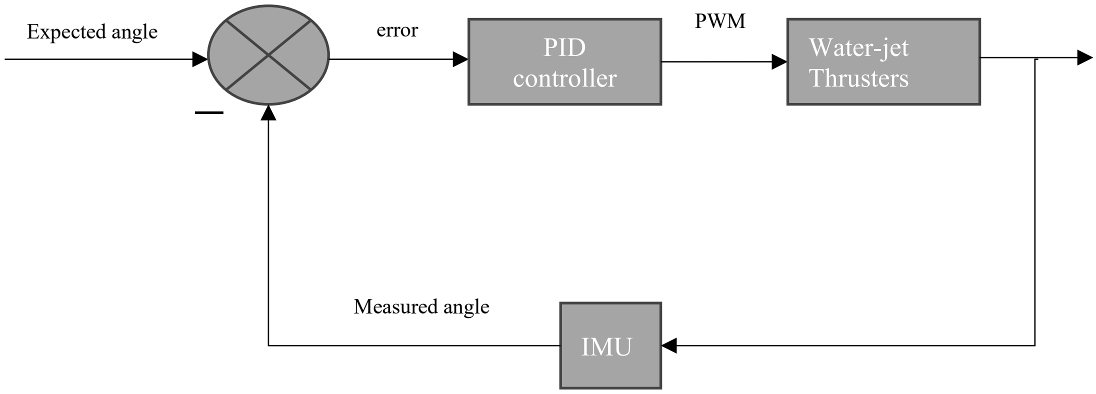

Fig 9. Diagram Illustrating the Structure of A Conventional PID System of Control.

The traditional PID controller [14] has been extensively used across numerous domains since its inception, yielding significant accomplishments, particularly in its pivotal impact on industrial production lines. It has several benefits, including a straightforward composition and excellent durability. According to Nishikawa, Sannomiya, Ohta, and Tanaka [15], the input quantity of PID control is determined by the discrepancy between the feedback amount and the intended value. This input quantity is derived by considering the proportional, integral, and differential components, and their total yields the control quantity. Typically, conventional PID is appropriate for systems that exhibit linearity. **Fig 9** displays the block diagram of a conventional PID control system.

The PID controller control law is:

$$u(t) = K_p[e(t) + \frac{1}{Ti}\int_0^t e(t)\,dt + T_d\frac{de(t)}{dt}] = K_p e(t) + K_t\int_o^t e(t)dt + K_d\frac{de(t)}{dt} \tag{2}$$

The variables in the equation are as follows: the error is indicated by $e(t)$, the proportional gain coefficient is indicated by K_p, the differential coefficient is indicated by K_d, and the integral coefficient indicated by K_i.

The conventional approach for calculating digital PID involves two types: location PID and incremental PID. Unlike PID, which computes the absolute magnitude of the control variable, incremental PID calculates the variable control change. Hence, the incremental PID method is simpler and more comfortable. Equation (1) allows for obtaining PID expressions incrementally by recursive means:

$$u(k) = K_p[e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)] \tag{3}$$

Control approach based on BPNN-PID

While the incremental PID control method does have significant benefits compared to other operating algorithms, it also exhibits several issues and weaknesses in actual use. Establishing a model for controlled objects is challenging due to factors such as nonlinearity and temporal variation, resulting in the inability to achieve the desired outcome. Simultaneously, the PID parameters have challenges in adapting to intricate variations for immediate configuration, owing to the impact of external factors. To address the issue of inadequate flexibility of the aforementioned parameters and enhance the motion control in underwater exploration robot stability. The algorithm of BP is employed to calculate the PID. The BPNN primarily performs calculations and learns from the training data via two processes: forward propagation of data and reverse correction of errors.

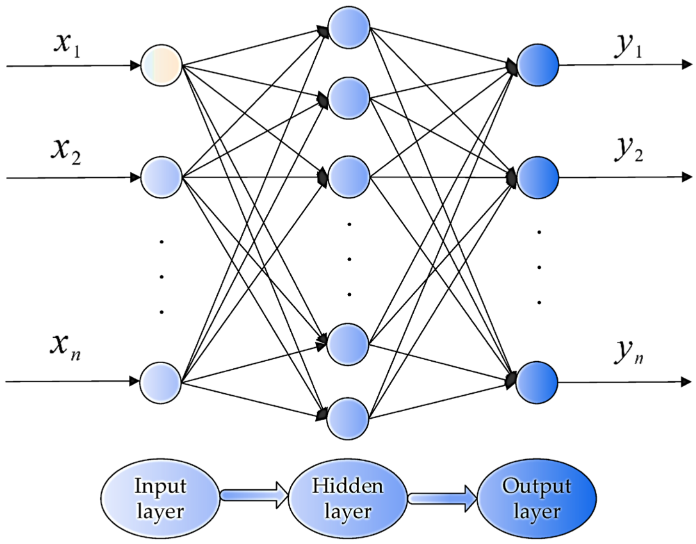

Fig 10. The Fundamental Architecture of A Conventional Backpropagation Neural Network (BPNN)

A multilayer feedforward neural network may be referred to as a BPNN when the error back propagation method is used. Its inherent characteristics make it excel in nonlinear mapping tasks, such as function approximation and pattern recognition. The backpropagation model of neural network is of three layers: output, hidden, and input. The basic architecture of the BPNN model is shown in **Fig 10.** The layer of input is used for processing the kind and magnitude of the input. The presence of many control layers and activation functions in the hidden layer allows for the potential of nonlinear mapping. The output layer is responsible for generating specific information.

The output of the neuron model structure is often represented as a non-linear combination of the input and weight, as seen in equation (4).

$$\hat{y}_i = f(\sum_{t=1}^{n} w_{ij}\, x_i - b_{ij}) \tag{4}$$

The output of the neuron is denoted as $\hat{y}_j$, whereas the output of another neuron is represented as x_i. The bias and weight of the neuron are indicated by b_{ij} and w_{ij} respectively. Additionally, $f(x)$ refers to the activation function.

The loss function often used for optimization is shown in equation (5).

$$E = \sum_{t=1}^{n} (\hat{y}_i - y_t)^2 \tag{5}$$

where $\hat{y}_i$ represents the predicted value and E denotes the loss function.

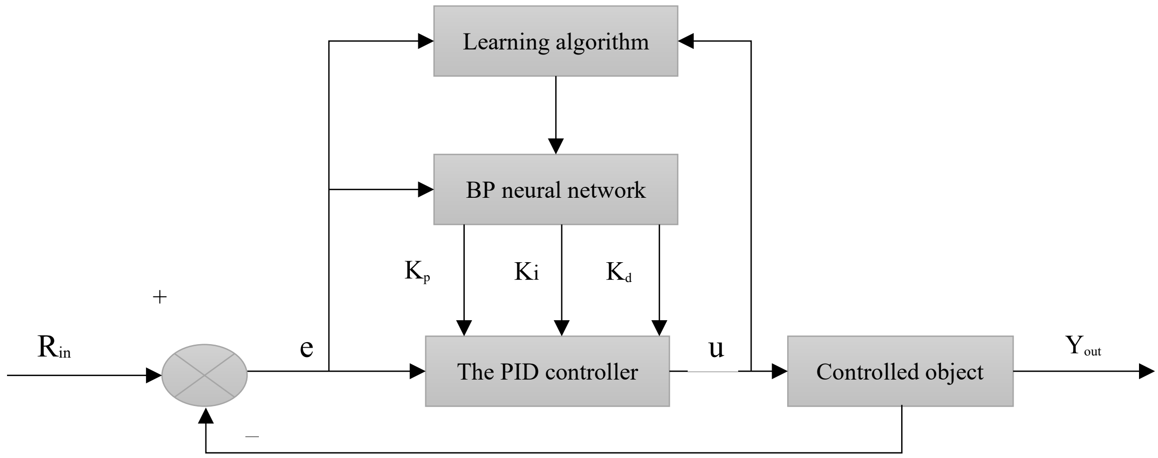

Fig 11. Schematic illustration of a PID control unit constructed using a Backpropagation Neural Network (BPNN)

Gradient Descent (GD) is often used for the purpose of minimizing weights.

$$w_\eta = w_\eta - \eta \frac{\partial E(w_\eta)}{\partial w_\eta} \tag{6}$$

where η represents the learning rate.

Figure 10 illustrates the sequential phases involved in the Backpropagation Neural Network (BPNN) method. The BPNN architecture diagram reveals the presence of an import layer.

$$o_j^{(1)} = x(j) \qquad j = ,2,3,4 \tag{7}$$

Where: $x(j)$ represents the import of the Node of input, and $o_j^{(1)}$ represents the import of the input node. Node of implicit export and import refer to the automatic importing and exporting of nodes without the need for explicit instructions.

$$o_i^{(2)}(k) = g\left[\sum\nolimits_{j=0}^{m} w_y^{(2)} o_j^1\right], \qquad i = 1,2,3,4,5 \tag{8}$$

The variables in the equation are defined as follows: $w_{ij}^{(2)}$ is the node of export coefficient of weighting, and $g(x)$ is the function of the Sigmoid defined as $g(x) = tanh(x)$. The output node output and input values

$$0_l^{(3)}(k) = f[\sum\nolimits_{i-o}^{q} w_{ij}^{(3)} o_i^{(2)}], \qquad l = 1,2,3 \tag{9}$$

The variables in question are $w_{ij}^{(3)}$, which represents the coefficient of weighting of the output node, and $f(x)$, which represents the function of activation. The goal function of BPNN is considered as:

$$E(k) = \frac{1}{2}[r(k) - y(k)] \tag{10}$$

Therefore, we are able to get:

$$\frac{\partial E(k)}{\partial w_{li}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial o_i^{(3)}(k)} \cdot \frac{\partial o_i^{(3)}(k)}{\partial net_l^{(3)}(k)} \cdot \frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}} \tag{11}$$

Thus, based on the aforementioned approach, the formula for determining the export node weight in BPNN can be derived:

$$\Delta w_{li}^{(3)}(k) = ne(k)sgn\frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial o_l^{(3)}(k)} \cdot f^l[net_l^{(3)}(k)]o_i^{(3)}(k) + \alpha \Delta w_{li}^{(3)}(k-1) \tag{12}$$

Similarly, the computation algorithm for the weight of a hidden node in a BPNN may be expressed as follows:

$$\Delta w_y^{(2)}(k) = n[g^l\left(net_l^{(2)}(k)\right)\sum\nolimits_{l=1}^{3} \delta_l^{(3)} w_{li}^{(3)}(k)]o_j^{(1)}(k) + \alpha \Delta w_{li}^{(2)}(k-1) \tag{13}$$

The calculation of PID and BPNN control can be summarized as follows: the weights of the output and hidden layers are adjusted based on feedback data of error and input values, using a learning rate and inertia coefficient. This process leads to the acquisition of the initial fitting parameters. The traditional PID controller is combined with a Backpropagation Neural Network (BPNN), which utilizes the neural network's inherent ability to learn autonomously in order to decide the parameters. The technique outlined above involves the integration of PID and BPNN control unit. The resulting structure, which incorporates both the PID and BPNN, is seen in **Fig 11**. The structure of the control unit consists of a PID CU. The second approach used for computation is the BPNN. The network's output is sent to the PID controller parameters through network training.

V. CONCLUSION

Current research on underwater robotics has shown notable progress. The importance of software architectures in constructing resilient robot systems has been recognized, however, further study is required to address implementation difficulties and substantiate the stability and performance of these designs. The increasing popularity of a universal architecture that is connected to well-established standards and ensures compatibility is being seen in the field. Significant developments have been made in the sector of soft robotics, particularly in the areas of modeling, manufacturing goods, sensing and control, power storage, and actuation methods. These robots provide benefits in activities such as human-machine interaction, precise product manipulation, and subaquatic work in limited areas. Nevertheless, there are obstacles in attaining meticulous command and augmenting mechanical designs. The study fields in underwater soft robotics mostly prioritize materials science, although there is a pressing need for progress in mechanical structures and locomotion control.

The field of soft robotics is now in its nascent phase, and there exist some technical constraints that need attention. In order to create underwater soft robots that possess biomechanical intelligence, it is imperative to advance the development of innovative active soft materials and manufacturing procedures. These robots possess the capacity for utilization in several domains, such as undersea exploration, military operations, and human-robot integration. The control framework for underwater exploration robots encompasses motion control, posture control, and the use of sensors for accurate control. The PID control technique is extensively used; nonetheless, there is a need for enhanced adaptability in parameter adjustment. The combination of Backpropagation Neural Network (BPNN) with PID control has potential in improving stability and motion control. In general, the study of underwater robots and soft robotics has achieved substantial advancements, however there are obstacles to be surmounted. Additional progress in materials, control algorithms, and mechanical designs is necessary to attain enhanced efficiency and capability in underwater robots.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests.

References

[1]. L. L. Whitcomb, "Underwater robotics: out of the research laboratory and into the field," Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065), Nov. 2002, doi: 10.1109/robot.2000.844135.

[2]. D. Lee, G. Kim, D.-H. Kim, H. Myung, and H. Choi, "Vision-based object detection and tracking for autonomous navigation of underwater robots," Ocean Engineering, vol. 48, pp. 59–68, Jul. 2012, doi: 10.1016/j.oceaneng.2012.04.006.

[3]. S. B. Williams, O. Pizarro, D. Steinberg, A. Friedman, and M. Bryson, "Reflections on a decade of autonomous underwater vehicles operations for marine survey at the Australian Centre for Field Robotics," Annual Reviews in Control, vol. 42, pp. 158–165, Jan. 2016, doi: 10.1016/j.arcontrol.2016.09.010.

[4]. M. Calisti, M. Cianchetti, M. Manti, F. Corucci, and C. Laschi, "Contest-Driven Soft-Robotics Boost: The RoboSoft Grand Challenge," Frontiers in Robotics and AI, vol. 3, Sep. 2016, doi: 10.3389/frobt.2016.00055.

[5]. Q.-Q. Hu and Y. Yu, "The hydrodynamic effects of undulating patterns on propulsion and braking performances of long-based fin," AIP Advances, vol. 12, no. 3, Mar. 2022, doi: 10.1063/5.0083912.

[6]. S. J. Nawaz, M. Hussain, S. Watson, N. Trigoni, and P. N. Green, "An underwater robotic network for monitoring nuclear waste storage pools," in Springer eBooks, 2010, pp. 236–255. doi: 10.1007/978-3-642-11528-8_17.

[7]. R. A. S. I. Subad, L. B. Cross, and K. Park, "Soft robotic hands and tactile sensors for underwater robotics," Applied Mechanics, vol. 2, no. 2, pp. 356–383, Jun. 2021, doi: 10.3390/applmech2020021.

[8]. MajidiCarmel, "Soft Robotics: A Perspective—Current Trends and Prospects for the Future," Soft Robotics, vol. 1, no. 1, pp. 5–11, Mar. 2014, doi: 10.1089/soro.2013.0001.

[9]. Y. Sun et al., "Soft Mobile Robots: a Review of Soft Robotic Locomotion Modes," Current Robotics Reports, vol. 2, no. 4, pp. 371–397, Dec. 2021, doi: 10.1007/s43154-021-00070-5.

[10]. D. Scaradozzi, G. Palmieri, D. Costa, and A. Pinelli, "BCF swimming locomotion for autonomous underwater robots: a review and a novel solution to improve control and efficiency," Ocean Engineering, vol. 130, pp. 437–453, Jan. 2017, doi: 10.1016/j.oceaneng.2016.11.055.

[11]. G. L. Amy et al., "Membrane-based seawater desalination: Present and future prospects," Desalination, vol. 401, pp. 16–21, Jan. 2017, doi: 10.1016/j.desal.2016.10.002.

[12]. G. S, D. T, and A. Haldorai, "A Supervised Machine Learning Model for Tool Condition Monitoring in Smart Manufacturing," Defence Science Journal, vol. 72, no. 5, pp. 712–720, Nov. 2022, doi: 10.14429/dsj.72.17533.

[13]. R. Subha, A. Haldorai, and A. Ramu, "An Optimal Approach to Enhance Context Aware Description Administration Service for Cloud Robots in a Deep Learning Environment," Wireless Personal Communications, vol. 117, no. 4, pp. 3343–3358, Feb. 2021, doi: 10.1007/s11277-021-08073-3.

[14]. W. Li, "Design of a hybrid fuzzy logic proportional plus conventional integral-derivative controller," IEEE Transactions on Fuzzy Systems, vol. 6, no. 4, pp. 449–463, Jan. 1998, doi: 10.1109/91.728430.

[15]. Y. Nishikawa, N. Sannomiya, T. Ohta, and H. Tanaka, "A method for auto-tuning of PID control parameters," Automatica, vol. 20, no. 3, pp. 321–332, May 1984, doi: 10.1016/0005-1098(84)90047-5.