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Survey on heterogeneous aquatic robot systems: communication, perception, navigation, control, decision-making and energy management

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Highlights:

- This paper systematically outlines underwater heterogeneous robotic systems' composition and fundamental concepts, exploring their unique advantages in various application domains.
- It analyzes critical technologies in underwater heterogeneous robotic systems, including navigation and control, communication, perception, decision-making, and energy management. The paper also introduces the latest research progress and application cases.
- We summarize the primary challenges currently faced by research and outline future development directions, proposing potential research paths and solutions.

Abstract: Heterogeneous aquatic robot systems, consisting of ROVs, AUVs, ASVs, and UAVs, are vital for environmental exploration, monitoring, and task execution. This paper presents advancements in critical technologies within these systems, focusing on communication (underwater acoustic, radio, and optical), multi-sensor fusion, and collaborative navigation techniques. It reviews control strategies like deep reinforcement learning, end-to-end control, and large model-based methods, addressing autonomous decision-making and adaptability in complex environments. The paper also discusses energy management strategies for efficient storage, utilization, and recovery. Furthermore, it explores the ethical and environmental impacts of deploying such systems, emphasizing sustainability and minimizing ecological disruptions. Finally, case studies and applications in ocean exploration and environmental monitoring are highlighted, showcasing the real-world utility and future potential of heterogeneous aquatic robot systems. This work provides valuable insights into the technological, ethical, and practical considerations for developing these systems.

Keywords: heterogeneous aquatic robot system; aquatic robot communication technology; aquatic robot perception technology; aquatic robot control technology

1. Introduction

The Science article “125 Questions: Exploration and Discovery” mentions robots several times, illustrating that robots have become indispensable tools in today’s society, holding significant research value [1–5]. Heterogeneous aquatic robot systems, composed of various types of robots such as underwater remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), autonomous surface vehicles (ASVs), and uncrewed aerial vehicles (UAVs), play a crucial role in environmental exploration, monitoring, and task execution [6–8]. These systems extend their reach beyond traditional bodies of water like rivers, lakes, and oceans [9–11], expanding their role into near-water skies and adjacent land areas, creating a three-dimensional research and operational space [12,13]. Their ability to access underwater environments that are otherwise inaccessible to humans enables them to perform diverse tasks, including environmental monitoring [12,13], ecological research [14,15], resource exploration [16,17], and disaster response [18,19].

However, despite their immense potential, heterogeneous aquatic robot systems face several technical challenges that must be addressed to enable widespread and effective deployment. One major challenge is the communication systems, where signal attenuation and interference significantly hinder the effectiveness of underwater communication [20–22]. Robots must rely on multi-sensor fusion and intelligent algorithms for autonomous operation to adapt to dynamic underwater environments. This enables them to perceive obstacles, localize accurately, and map their surroundings. Furthermore, efficient navigation and control algorithms are essential for coordinating and executing tasks among multiple heterogeneous robots, mainly when these robots operate in challenging environments.

Diversifying aquatic robot technologies enables them to meet various exploration and operational needs. Traditional underwater Remotely operated vehicles (ROVs) are renowned for their high-precision operational capabilities but are limited in range by cable length or communication distance [23, 24]. Autonomous underwater vehicles (AUVs) surpass this limitation and can independently execute long-term missions, though they face challenges in adapting to complex environments and making real-time decisions [25–27]. Autonomous surface vehicles (ASVs) and unmanned aerial vehicles (UAVs) play crucial roles in wide-area coverage, communication [28, 29], and navigation support in vast water bodies [30–33]. However, they cannot directly engage in underwater operations. Given the variability and complexity of marine environments, a single aquatic robot often fails to meet all requirements. Therefore, there is an urgent need to develop a comprehensive system that integrates the strengths of multiple robot types. Such a system would harness the precise operations of ROVs, the autonomy of AUVs, the expansive operational capabilities of ASVs, and the aerial advantages of UAVs, facilitating more efficient and flexible task execution. Through this interdisciplinary collaboration, not only can mission success rates be enhanced, but it can also propel aquatic robot technology toward higher levels of intelligence and automation.

Despite demonstrating significant potential in theory and application, aquatic heterogeneous robot systems face various technical challenges during implementation. Firstly, complex navigation and control algorithms must be developed to achieve efficient collaboration and precise task allocation among robots. Secondly, innovative underwater communication technologies are urgently needed to overcome signal attenuation and interference issues due to restricted underwater communication conditions [20–22]. Additionally, the robots' autonomous perception capabilities are crucial for adapting to underwater environments, relying on advanced sensor technologies and intelligent algorithms. Moreover, the decision-making capability of heterogeneous robot systems in aquatic environments is paramount, necessitating intelligent algorithms to enhance their autonomy [34,35] and adaptability [36–38]. Finally, given the substantial energy consumption and limited endurance of underwater operations, there is an urgent need to develop efficient energy management systems and endurance technologies to extend operational time and enhance the reliability of mission execution. In summary, overcoming these challenges requires interdisciplinary collaboration [39,40] and the application of innovative technologies to propel aquatic heterogeneous robot systems to higher levels of development [41–44]. The timeline of the heterogeneous robotic system in the water domain is shown in the following Figure 1.

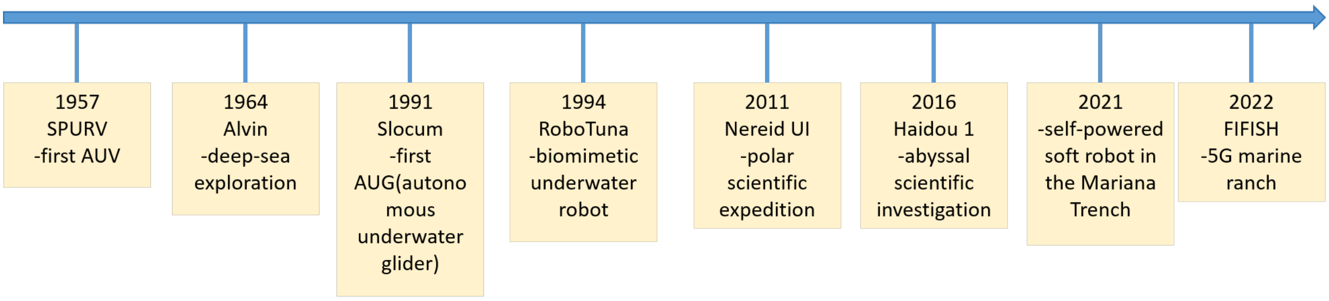

Figure 1. Heterogeneous robotic system timeline.

This paper reviews the latest research advancements in underwater heterogeneous robotic systems, systematically discussing key technologies and future directions in this field. The framework of this paper is shown in Figure 2, and the main contributions are as follows:

- This paper systematically outlines underwater heterogeneous robotic systems' composition and fundamental concepts, exploring their unique advantages in various application domains.
- It analyzes critical technologies in underwater heterogeneous robotic systems, including navigation and control, communication, perception, decision-making, and energy management. The paper also introduces the latest research progress and application cases.
- We summarize the primary challenges currently faced by research and outline future development directions, proposing potential research paths and solutions.

The remaining structure of this paper is as follows. The communications of the heterogeneous aquatic robot system, as discussed in Section 2. The perception of the heterogeneous aquatic robot system, as discussed in Section 3. The navigation of heterogeneous aquatic robot system, as discussed in Section 4. The Control of heterogeneous aquatic robot system, as discussed in Section 5. The Decision-making of heterogeneous aquatic robot system, as discussed in Section 6. The energy management of heterogeneous aquatic robot system, as discussed in Section 7. Ethical implications are elaborated in Section 8. Applications and cases in related areas are discussed in Section 9. Finally, we summarize the paper in Section 10. and provide an outlook on future research directions. The full structure of this paper is shown in Figure 3.

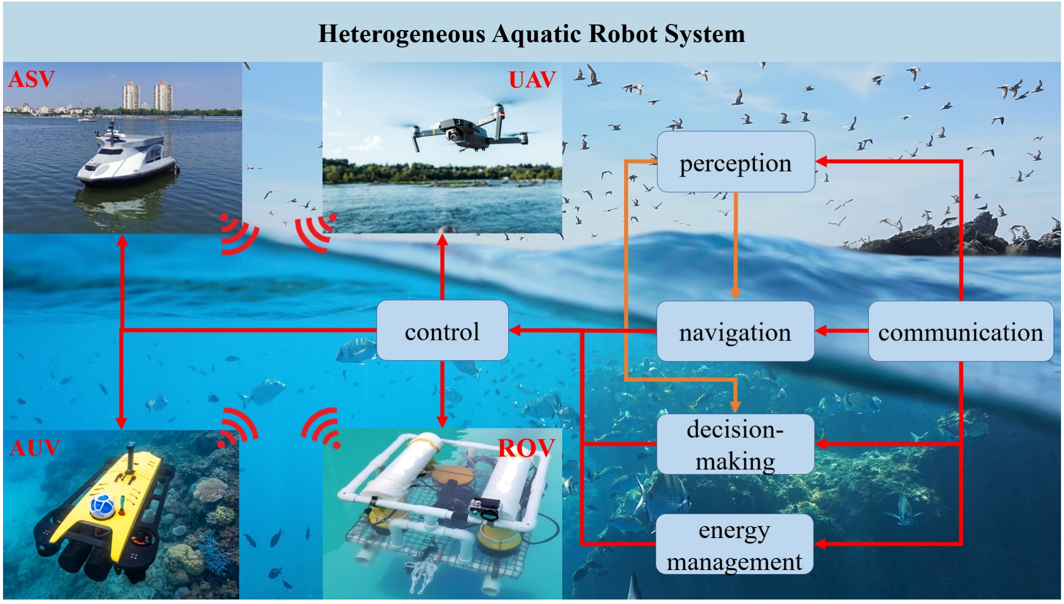

Figure 2. Framework diagram of heterogeneous aquatic robot system [45–48].

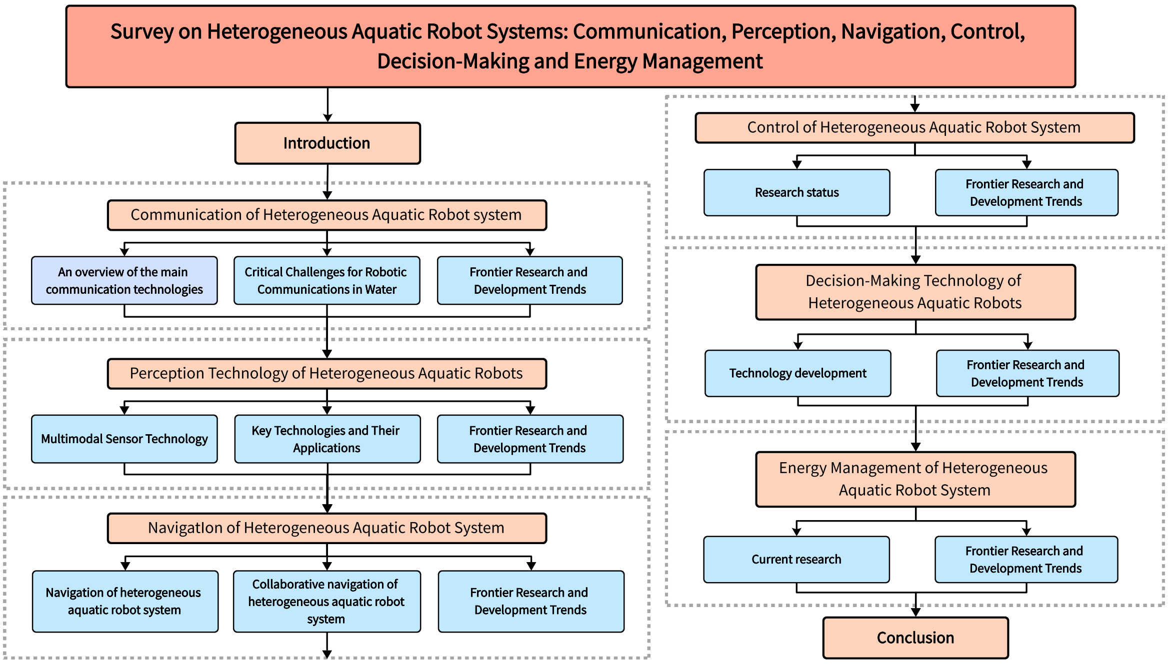

Figure 3. The overall structure of the paper.

2. Communication of heterogeneous aquatic robot system

Heterogeneous robot communication in water is critical for multi-robot systems, especially in applications such as ocean exploration, environmental monitoring, and underwater operations [49–51]. These robots, including AUVs and ASVs, require efficient and reliable communication to perform their tasks [52–54]. While hydroacoustic, radio, and optical communication are the primary communication technologies used in these systems, each has distinct advantages and limitations depending on the environmental conditions [55–57]. Challenges such as signal attenuation, interference, data transmission delays, and communication range still persist [58–60]. Recent research efforts are focused on developing hybrid communication systems, intelligent systems, and adaptive technologies to overcome these issues [61–63]. As technology continues to advance, heterogeneous robot communication systems are expected to become more integrated and effective in multi-robot operations.

2.1. An overview of the main communication technologies

Effective communication among heterogeneous robots in aquatic environments ensures that different types of robots can exchange data reliably across various environmental conditions. This section reviews the major communication technologies for heterogeneous aquatic robot systems: hydroacoustic communication, radio communication, and optical communication, highlighting their advantages, limitations, and suitable application scenarios, as summarized in Table 1.

Table 1. Comparison of major communication technologies for aquatic robots.

Methods	Specificities	Advantages	Disadvantages	Scenarios	Related work
Underwater acoustic communication	• Long distance of transmission • Slower speed ($\approx$ 1500 m/s) • Highly influenced by water temperature, salinity and depth	• Suitable for long distance communication • Suitable for deep-sea environments	• Limited bandwidth • Lower data transfer rate • Vulnerable to multipath effects and ambient noise interference	• Widely used for navigation, control and data transmission of AUVs in applications such as oceanographic exploration, environmental monitoring and military applications.	[55,64–75]
Radio communications	• Fast airborne propagation ($\approx 3 \times 10^8$ m/s) • Speed is severely attenuated in water	• High bandwidth • High speed transmission • Suitable for communication between surface robots and shore-based equipment	• Limited transmission distance under water • Highly affected by water absorption and attenuation	• Suitable for communication between ASVs and control centers, surface monitoring, search and rescue missions, *etc.*	[76–82]
Optical communications	• Light waves travel fast in water • Finite distance • Highly affected by water quality and suspended particulate matter	• High data transfer rate • Suitable for high bandwidth applications • Highly resistant to electromagnetic interference	• Limited transmission distance • Requires high alignment accuracy • Suitable for clear water environments	• Suitable for short-distance high-bandwidth data transmission, such as inter-robot communication in close proximity, data download and real-time video transmission.	[76,83–93]

The methods listed in Table 1 perform differently in different environments, as shown below:

Shallow Water: In shallow water environments, radio communication often performs well due to its ability to quickly transmit data at high speeds, although the effective range is limited. Optical communication can be used for short-range, high-bandwidth tasks such as real-time video transmission between nearby robots. However, signal interference from environmental factors such as surface waves or turbidity can degrade its performance.

Deep-Sea: Hydroacoustic communication remains the dominant choice for deep-sea exploration, where its long transmission range and reliability in complex environments outweigh its lower data transfer rate and vulnerability to interference from multipath effects. However, for real-time high-bandwidth tasks such as video streaming, optical communication is generally not feasible due to the limited range and reliance on clear water conditions.

Murky or High-Interference Environments: In environments with high turbidity, such as riverbeds or areas with significant suspended particulate matter, optical communication is often ineffective. In such conditions, hydroacoustic communication offers a better alternative, though it still faces challenges such as multipath interference and signal attenuation due to environmental noise.

Heterogeneous robotic communication technologies in the water domain cover various approaches, each with unique advantages and limitations. Hydroacoustic communication is suitable for long-range and deep-sea environments, radio communication has good application prospects in surface and shallow water areas, and optical communication excels in short-range, high-bandwidth transmission. The future trend will be to synthesize these technologies to develop hybrid communication systems adapted to different environments and application requirements to improve the overall performance of heterogeneous robotic systems in water.

2.2. Critical challenges for robotic communications in water

Despite the progress in communication technology, heterogeneous robotic communication in water still faces several significant challenges, including signal attenuation, interference, data transmission delay, and coverage limitations. These challenges vary depending on the specific aquatic environment, such as deep-sea or shallow coastal waters, and must be carefully considered when choosing the appropriate communication method.

2.2.1. Signal attenuation and interference

Signal attenuation is one of the main problems in underwater communication, and its severity depends on the type of environment. Hydroacoustic signals, for example, are highly sensitive to water temperature, salinity, and depth. In deep-sea environments, where these factors fluctuate significantly, hydroacoustic communication remains effective for long-range transmission but suffers from a slower data transfer rate and increased interference from ambient noise. In contrast, radio waves face significant attenuation even in shallow waters, limiting their effectiveness for underwater communication, especially as the distance increases. Optical signals, although offering high data rates, are highly sensitive to water clarity and suspended particulate matter, making them more suitable for short-range communication in clear water environments. In underwater environments, signal attenuation is an unavoidable problem. Hydroacoustic signals decay significantly with increasing propagation distance. The following Equation (1) can express signal attenuation:

$$A(d) = A_0 + 20\log_{10}(d) + \alpha d \tag{1}$$

where $A(d)$ is the attenuation at propagation distance d, P_0 is the initial intensity, and β is the medium-dependent attenuation coefficient. The attenuation is even more severe for radio waves, with high-frequency radio waves barely penetrating the water column. At the same time, low and medium-frequency radio waves are also subject to significant absorption and attenuation. The attenuation can be expressed as Equation (2):

$$P(d) = P_0 e^{-\beta d} \tag{2}$$

where $P(d)$ is the signal strength at propagation distance d, P_0 is the initial signal strength, and β is the absorption coefficient of the medium. Optical signals travel a limited distance in water and are strongly influenced by water quality, suspended particulate matter, and light refraction. The attenuation of the optical signal can be approximated as Equation (3):

$$I(d) = I_0 e^{-\kappa d} \tag{3}$$

where $I(d)$ is the light intensity at distance d, I_0 is the initial light intensity and κ is the absorption coefficient of the medium.

The complexity of the underwater environment makes communication signals susceptible to a variety of interferences. For example, the multipath effect is caused by the reflection and refraction of signals in water, which can cause delays and interference. The multipath effect can be represented as Equation (4):

$$r(t) = \sum_{i=1}^{N} a_i s(t - \tau_i) \tag{4}$$

where $r(t)$ is the received signal, a_i is the attenuation factor for each path, $s(t)$ is the transmitted signal, and τ_i is the delay for each path.

2.2.2. Data transmission delay

Data transmission latency is critical in heterogeneous robotic communication in waters, especially in applications requiring real-time control and data feedback. Hydroacoustic signals' relatively slow propagation speed (1500 m/s) leads to significant delays when communicating over long distances. The delay can be expressed as Equation (5):

$$T_d = \frac{d}{v} \tag{5}$$

where T_d is the delay time, d is the propagation distance and v is the propagation speed. When heterogeneous robots in water work together, communication delays may lead to synchronization problems of control commands and sensing data, affecting the system's overall performance. For example, in underwater detection and rescue missions, robots must respond quickly to commands and transmit real-time video and data, which requires very low latency in the communication system.

In order to reduce data transmission delays, various approaches can be taken. For example, developing efficient modulation and coding techniques to increase data transmission speed. Designing intelligent routing algorithms to optimize data transmission paths and reduce the number of relay nodes and the number of hops for data transmission. Use caching and preprocessing techniques to transmit important data in advance to reduce the burden of real-time data transmission. In addition, combining multiple communication technologies and utilizing their respective advantages to select the optimal communication method in different scenarios to minimize the transmission delay.

2.2.3. Communication distance and coverage

Heterogeneous robots in the water domain usually perform their tasks in vast marine environments, which poses a challenge to the coverage of communication systems. Although hydroacoustic communication is suitable for long-distance transmission, its limited bandwidth cannot meet the demand for high data rates. Radio communication has a wide coverage on the surface of the water, but has a limited effective transmission distance underwater. Optical communications are suitable for short-range, high-bandwidth transmission, but their coverage is limited by the propagation characteristics of optical signals.

In order to solve the problem of coverage, multi-hop network and relay node technology can be used to expand communication coverage through relay transmission between multiple robots. In addition, the application of a hybrid communication system can effectively combine the advantages of different communication technologies to optimize the system's coverage and transmission performance. Multi-hop networks are used to forward signals through multiple relay nodes, allowing the signals to cover a larger range. This method can significantly improve the communication distance, but it needs to solve the problems of routing, node coordination, and signal synchronization. The application of intelligent routing algorithms and self-organizing network protocols can improve the efficiency and reliability of multi-hop networks. The performance of a multi-hop network can be expressed as Equation (6):

$$D_{eff} = \sum_{i=1}^{N} d_i \tag{6}$$

where D_{eff} is the effective communication distance, and d_i is the distance per hop. Relay nodes can be fixed or mobile, and they are responsible for receiving, processing, and forwarding signals. Mobile relay nodes (e.g., unmanned ships or unmanned submarines) can dynamically adjust their position according to mission requirements to optimize communication paths and improve coverage. The design of relay nodes needs to take into account their energy consumption, processing power, and durability. The development of hybrid communication systems by combining different technologies such as hydroacoustic, radio, and optical communications allows for the selection of optimal communication methods in different environments and mission requirements. For example, hydroacoustic communication is used for long-distance communication, radio communication is used between surface and shore-based equipment, and optical communication is used for short-distance, high-bandwidth transmission. The design of hybrid communication systems needs to consider the compatibility and co-optimization of different communication technologies.

2.3. Frontier research and development trends

As watershed heterogeneous robotics evolves, so do communication technologies. Researchers are committed to overcoming existing technological challenges and exploring new communication methods and systems to improve the performance and application range of water heterogeneous robots. In this paper, we will discuss the current cutting-edge research directions and future trends, including three aspects of novel communication technologies, intelligent communication systems, and cross-domain cooperation.

2.3.1. New communication

Hydroacoustic communication is the main means of communication for underwater robots, and research in recent years has focused on improving its reliability and data transmission rate. For example, the hydroacoustic communication system based on orthogonal frequency division multiplexing (OFDM) improves spectral efficiency and anti-interference capability through multicarrier transmission [94–96]. However, a major limitation of hydroacoustic communication is the high attenuation of acoustic signals in water, which restricts the communication range. To mitigate this, possible solutions could involve the use of signal amplification techniques at regular intervals or the development of more energy-efficient acoustic transducers. Additionally, the complex underwater environment can cause multipath interference, which may be addressed through advanced equalization algorithms. Researchers have also explored adaptive modulation and coding techniques to optimize signal transmission and adapt to different underwater environments and communication conditions.

Optical communication has the advantages of high bandwidth and low latency and is suitable for short-range, high-data-rate transmission. In recent years, researchers have developed underwater optical communication systems based on blue and green lasers, which take advantage of the lower attenuation characteristics of these wavelengths to significantly increase transmission distances and data rates. Nonetheless, optical communication in water is highly sensitive to water turbidity and particle content. When the water is turbid, the laser beam can be scattered and absorbed, reducing the communication quality. Possible solutions might include using pre-processing algorithms to clean the received optical signals or developing optical communication systems that can adjust the wavelength according to the water quality. Also, the limited transmission range restricts its widespread application in large-scale underwater scenarios. To overcome this, a relay-based optical communication network could be established. In addition, underwater communication systems incorporating optical fiber technology are also being explored, with the aim of achieving long-distance, stable, and high-speed data transmission.

Magnetic induction communication utilizes a low-frequency magnetic field for signal transmission, which has good penetration capability and is suitable for communication in complex environments such as shallow water and mud. Researchers have developed novel magnetic induction antennas and modulation and demodulation techniques to improve communication efficiency and transmission distance. However, magnetic induction communication has relatively low data transfer rates compared to other methods. To enhance the data rate, new modulation schemes that can pack more information into the magnetic field could be investigated. Also, the need for a relatively large antenna size to achieve efficient transmission can be a hindrance in some applications. Miniaturization of magnetic induction antennas through advanced materials and manufacturing techniques could be a potential solution. Magnetic induction communication is expected to play an important role in specific application scenarios as a complement to hydroacoustic and optical communication.

2.3.2. Intelligent communication system

The Ad-hoc Network is capable of dynamically forming a network without pre-planning and is adaptive and suitable for heterogeneous robots working together in water. Researchers have developed self-organizing network protocols and routing algorithms based on machine learning and artificial intelligence to improve the adaptability and robustness of the network. For example, reinforcement learning algorithms can optimize routing and reduce communication delays and energy consumption [97–99]. However, a significant limitation of using machine-learning-based self-organizing network protocols in an underwater Ad-hoc Network is the high computational complexity. Underwater robots often have limited computing resources, which may lead to slow response times. To address this, possible solutions could be to develop lightweight machine-learning models specifically tailored for underwater robot computing capabilities or to offload some of the computational tasks to shore-based or cloud-based servers through long-range communication when available. Additionally, the dynamic nature of the underwater environment, such as water flow and temperature changes, can affect the stability of the Ad-hoc Network. To enhance stability, more advanced environmental sensing and prediction models could be integrated into the network protocols to proactively adapt to these changes.

Collaborative communication improves communication reliability and coverage by multipath transmission and relay enhancement of signals through cooperative work among multiple robots. Researchers have explored multi-hop relaying, cooperative coding, and multiple-input multiple-output (MIMO) techniques to improve the system's spectral efficiency and anti-jamming capability. In addition, collaborative communication strategies based on game theory can optimize resource allocation and communication scheduling among robots. Nonetheless, implementing collaborative communication in a real-world scenario with heterogeneous robots faces challenges. One major issue is the synchronization problem among different robots. As robots may have different hardware and software configurations, achieving precise synchronization for multi-hop relaying and cooperative coding can be difficult. Possible solutions might involve developing standardized synchronization protocols or using time-stamping techniques to ensure accurate signal alignment. Another limitation is the potential for increased energy consumption due to the additional communication and cooperation requirements. To mitigate this, energy-aware cooperative communication algorithms could be designed to balance performance and energy usage.

Cognitive radio technology enables communication systems to sense their surroundings and dynamically adjust communication parameters to adapt to changing spectrum resources and environmental conditions. Researchers have developed cognitive engines and intelligent spectrum management algorithms that enable watershed heterogeneous robots to achieve efficient and reliable communications in complex environments. Through spectrum sensing, dynamic spectrum access, and interference avoidance, cognitive radio technology improves the flexibility and performance of communication systems. However, cognitive radio technology in the context of underwater communication has its own set of limitations. The underwater electromagnetic environment is complex and often subject to interference from various sources, such as marine life and underwater electrical equipment. This can make accurate spectrum sensing challenging. Possible solutions could include developing more advanced interference-filtering techniques or using redundant sensing methods to improve the accuracy of spectrum sensing. Also, the dynamic nature of the underwater environment means that the spectrum availability can change rapidly. To better adapt to these rapid changes, more responsive and real-time spectrum management algorithms are needed.

2.3.3. Cross-cutting cooperation and applications

The development of heterogeneous robotic communication technologies in water requires multidisciplinary collaboration, including the fields of acoustics, optics, electrical engineering, computer science and artificial intelligence. Interdisciplinary research teams can synthesize their strengths to develop innovative communication systems and solutions. For example, high-performance underwater sensors and communication devices can be developed by combining advanced materials science, and computer vision and image processing technologies can be combined to enhance underwater image transmission and processing capabilities. However, achieving effective multidisciplinary collaboration faces significant challenges. Different disciplines often have their own terminologies, research methods, and work cultures. This can lead to miscommunication and inefficiencies in the development process. Possible solutions include organizing regular interdisciplinary workshops and training sessions to promote better understanding among team members. Also, establishing a common framework or ontology for communication-related concepts can help bridge the gap between different disciplines. Additionally, coordinating the research timelines and resource allocation among multiple disciplines can be difficult. To address this, a dedicated project management team with cross-disciplinary knowledge could be formed to ensure smooth progress [100–102].

The research of heterogeneous robot communication technology in water should be closely integrated with the needs of practical applications, such as ocean exploration, environmental monitoring, underwater archaeology, and disaster rescue. Researchers verify and optimize communication technology and promote its transformation to practical applications through cooperation with practical application fields. For example, in ocean exploration, a high-precision sensing data transmission system is developed to improve the efficiency and accuracy of ocean data collection; in disaster rescue, a rapid response communication system is developed to improve the coordination and efficiency of rescue operations. Nevertheless, the integration of research with practical applications is not without obstacles. One major issue is the translation of research findings into practical, deployable solutions. The gap between the ideal conditions in a research laboratory and the harsh, variable conditions in real-world applications can be substantial. To bridge this gap, more field-testing and prototyping in realistic scenarios are needed during the research and development process. Another limitation is the high cost associated with developing and deploying communication systems for some practical applications, especially in large-scale or remote areas. This can be mitigated by exploring cost-effective technologies and business models, such as shared-resource platforms or open-source hardware and software solutions.

With the diversity and complexity of heterogeneous robotic communication technologies in the watershed, the issues of standardization and interoperability have become increasingly important. Researchers and industry should work together to develop unified communication protocols and standards to ensure interoperability and compatibility between different systems and devices. Through standardization, the popularization and application of the technology will be promoted to facilitate the development of the industry and the expansion of the market. However, the process of developing and implementing unified communication protocols and standards is complex. There are often competing interests among different research groups, companies, and industries. Coordinating these interests to reach a consensus on standards can be time-consuming and difficult. Possible solutions involve establishing neutral, industry-wide standard-setting organizations with representation from all stakeholders. These organizations can use a transparent and inclusive decision-making process to develop standards. Also, ensuring compliance with the established standards can be a challenge. Incentives such as certification programs and regulatory support may be required to encourage adoption of the standards.

3. Perception technology of heterogeneous aquatic robots

Perception technology for heterogeneous aquatic robots is pivotal in advancing multi-robot systems, particularly in applications like ocean exploration and environmental monitoring. These robots encompass a variety of types, such as AUV and ASV, each requiring robust perception capabilities for effective operation in aquatic environments. Key components of this technology include sensor integration, data fusion techniques, and advanced algorithms to achieve comprehensive environmental awareness and precise localization. Current research focuses on enhancing sensor capabilities, optimizing data processing methods, and developing adaptive algorithms to overcome challenges such as varying water conditions, sensor limitations, and environmental complexities. Ultimately, advancements in perception technology for heterogeneous aquatic robots promise to significantly enhance their functionality and expand their applications in marine sciences, resource exploration, and underwater infrastructure inspection. Technologies and future trends of heterogeneous robotic systems in aquatic environments as shown in Figure 4.

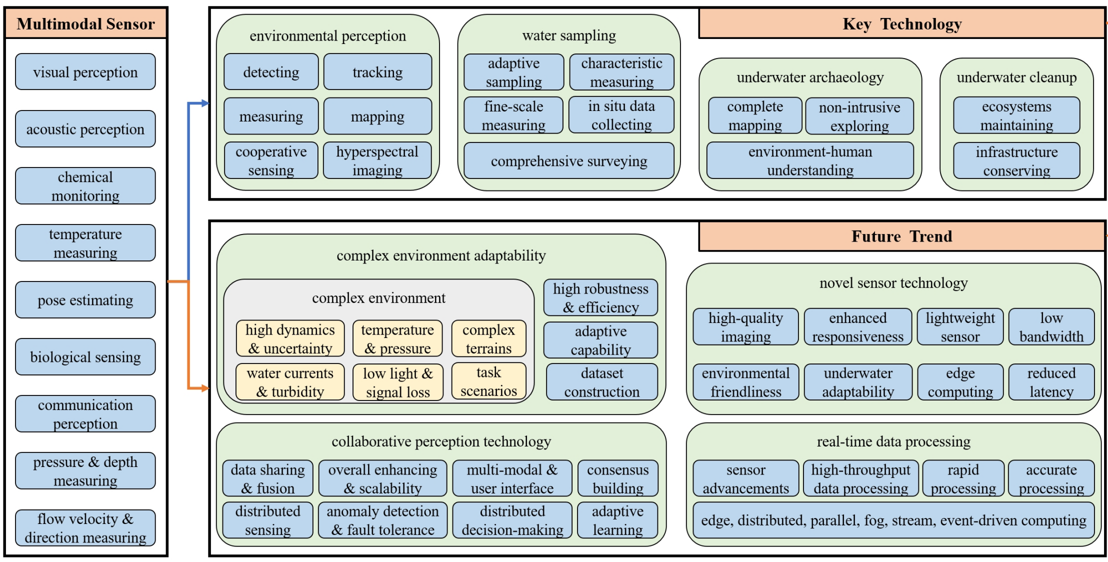

Figure 4. Perception technologies and future trends of heterogeneous robotic systems in aquatic environments.

3.1. *Multimodal sensor technology*

Heterogeneous aquatic robots are typically equipped with multiple types of sensors to meet the requirements of different environments and tasks. The main commonly used sensors and their operating principles are as follows:

3.1.1. Visual perception

Based on optical principles, a variety of advanced sensors are employed. Cameras capture high-resolution images that provide detailed visual information about the environment. Light Detection and Ranging (LiDAR) sensors, utilizing laser pulses, create precise 3D maps by measuring the time it takes for light to reflect back from objects, enabling accurate spatial perception. Laser rangefinders, or laser scalers, complement LiDAR by providing precise distance measurements for objects within the sensor's range. Hyperspectral irradiance sensors detect and analyze electromagnetic radiation across numerous wavelengths [103–105], offering insights into the spectral composition of light and its interaction with surfaces. Together, these sensors enable comprehensive scene recognition, precise object detection, and accurate localization across various aquatic environments [106–109].

3.1.2. Acoustic perception

Acoustic sensors can be categorized into two types: active and passive. Active sensors measure the position and characteristics of an object by emitting acoustic pulses, while passive sensors analyze background sounds in the natural environment. Sonar systems [106, 108] represent typical examples of active acoustics, including echolocation and multibeam sonar, used for obstacle detection, terrain mapping, and target tracking. Besides, within active acoustic sensors, an acoustic altimeter for measuring altitude from the seafloor [106] and an acoustic profiler [105] are capable of gathering data such as water depth and flow velocity. Acoustic sensors are widely utilized in marine science, marine engineering, and environmental monitoring, providing crucial underwater environmental information. They support applications in marine resource management, marine engineering design, hydrological research, and other related fields.

3.1.3. Chemical monitoring

Chemical monitoring in underwater environments utilizes sophisticated sensors to assess various parameters, including dissolved oxygen, pH, salinity, nutrients, chlorophyll levels, colored dissolved organic matter (cDOM), total suspended solids (TSS), and conductivity [110–112]. These parameters are critical for assessing water quality, detecting pollutants, and monitoring ecosystem health.

Unlike traditional sampling methods, heterogeneous underwater multi-robot systems enable real-time, in situ chemical sensing with higher spatiotemporal resolution. However, sensor drift, biofouling, and communication constraints affect measurement accuracy. Recent advancements incorporate adaptive calibration techniques and machine learning-based compensation models to enhance reliability. Multi-robot coordination allows for dynamic adaptation to environmental changes, optimizing sampling efficiency and coverage. Future advancements involve the development of bio-inspired chemical sensors to improve selectivity, along with the use of machine learning for predictive modeling to detect environmental anomalies at an early stage.

3.1.4. Pressure and depth measuring

Pressure and depth sensors are essential for estimating the diving depth and maintaining the stability of underwater robots. These sensors operate based on hydrostatic pressure variations, providing real-time depth measurements crucial for navigation, buoyancy control, and mission planning [106,108,111,112].

However, factors like sensor drift, nonlinearity in deep-water environments, and variations in temperature and salinity can impact measurement accuracy. To overcome these issues, recent developments combine real-time sensor fusion with inertial navigation systems (INS) and acoustic positioning, enhancing the reliability of depth estimation. Additionally, adaptive calibration techniques and machine learning-based corrections help mitigate long-term sensor degradation, ensuring robustness in heterogeneous underwater multi-robot systems.

3.1.5. Temperature measuring

Temperature sensors, such as thermistors and resistance temperature detectors (RTDs), are widely used in underwater robots to monitor water temperature variations, which are critical for understanding thermal stratification, detecting climate change effects, and assessing marine ecosystem health [111,112].

However, measurement accuracy can be affected by sensor drift, response time, and environmental factors such as biofouling and water flow dynamics. To enhance reliability, modern systems integrate temperature data with depth and salinity measurements for compensation, while machine learning-based corrections help mitigate long-term sensor degradation. In heterogeneous multi-robot systems, distributed temperature sensing enables large-scale environmental monitoring, improving spatial resolution and adaptability in dynamic aquatic environments.

3.1.6. Flow velocity and direction measuring

Accurate underwater flow velocity and direction measurement are crucial for navigation, station-keeping, and environmental monitoring in heterogeneous underwater multi-robot systems. Acoustic Doppler current profilers (ADCPs), electromagnetic flow meters, and mechanical propeller sensors are commonly used to capture real-time flow dynamics. These measurements assist in trajectory planning, energy-efficient path optimization, and detecting underwater currents influencing robotic operations.

However, sensor noise, turbulence-induced fluctuations, and calibration drift can impact measurement accuracy. Sens fusion techniques combining ADCP data with inertial measurement units (IMUs) and machine learning-based filtering methods are employed to enhance reliability. Additionally, distributed sensing among multiple robots enables more comprehensive flow mapping, improving adaptability in dynamic underwater environments.

3.1.7. Pose estimating

Accurate pose estimation is essential for underwater robots to maintain stability, execute precise maneuvers, and coordinate within multi-robot systems. This is usually accomplished by combining inertial measurement units (IMUs) with Global Navigation Satellite System (GNSS) data. IMUs supply real-time orientation updates, and GNSS provides absolute position references when accessible [112].

However, underwater environments pose challenges such as GNSS signal loss at depth and IMU drift over time. To overcome these limitations, contemporary systems utilize sensor fusion methods that integrate IMU data with Doppler velocity logs (DVLs), pressure sensors, and acoustic positioning systems. Moreover, filtering techniques like extended Kalman filters (EKF) and factor graph optimization are applied to improve accuracy and ensure long-term stability in pose estimation for multi-robot operations.

3.1.8. Biological sensing

Biological sensing in underwater environments involves using specialized sensors to detect and monitor aquatic organisms such as fish, corals, and plankton. These sensors leverage optical imaging, acoustic techniques, and environmental DNA (eDNA) analysis to assess biodiversity and ecosystem health. Passive acoustic monitoring (PAM) is handy for detecting marine life based on characteristic sound patterns, while fluorescence and hyperspectral imaging help identify specific biological markers.

However, challenges such as turbidity-induced signal attenuation, species differentiation accuracy, and data processing complexity affect measurement reliability. To overcome these issues, sensor fusion techniques combining optical, acoustic, and biochemical data are employed, along with machine learning algorithms for automated species classification. In heterogeneous multi-robot systems, distributed biological sensing enables large-scale, high-resolution ecological monitoring, improving conservation efforts and habitat assessment.

3.1.9. Communication perception

Underwater communication is crucial for coordinating multi-robot operations, enabling data exchange between robots and base stations. Unlike wireless communication on land, underwater environments mainly depend on acoustic modems and transducers because electromagnetic waves quickly lose strength in water [106]. Acoustic communication enables long-range transmission but is hindered by limited bandwidth, high latency, and vulnerability to multipath interference.

To mitigate these limitations, modern systems integrate adaptive modulation techniques, error correction algorithms, and network protocols optimized for dynamic underwater conditions. Additionally, hybrid communication frameworks combining acoustics with optical and radio-frequency (RF) methods are being explored to enhance reliability. In heterogeneous multi-robot systems, distributed communication strategies and delay-tolerant networking (DTN) approaches further improve data exchange efficiency in complex marine environments.

To optimize environmental perception, it is crucial to use multi-sensor data fusion methods, including Kalman filtering and particle filtering algorithms. These techniques can integrate data collected from different sensors to provide more accurate and reliable information. Additionally, ensuring spatiotemporal data synchronization is crucial for improving perception accuracy and consistency, as it allows data from various sensors to be synchronized in both time and space. Furthermore, the application of deep learning and artificial intelligence in processing and analyzing multimodal data significantly enhances the capabilities of target recognition and environmental understanding. The integration of these technologies can substantially improve the environmental perception performance of robots.

3.2. Key technologies and their applications

The perception technology of heterogeneous aquatic robots is of great significance in applications such as environmental perception, water sampling, underwater archaeology, and underwater cleanup. To successfully perform tasks in these typical scenarios and more general contexts, heterogeneous aquatic robots need to possess capabilities such as real-time environmental modeling, dynamic environmental monitoring, and target detection and recognition.

3.2.1. Environmental perception

Environmental perception involves the systematic investigation and interpretation of unknown or partially known environments. It supports heterogeneous aquatic robots in executing tasks by enabling object detection, tracking, and mapping. Lindsay *et al.* [113] proposed a multi-robot system equipped with above-water, surface, and underwater sensors to capture data for 3D reconstruction of floating targets. The sensor data are fused at the waterplane using a sliding correlation algorithm.

For swarm control, Yu *et al.* [114] developed a real-time visual tracking subsystem for multiple moving objects in biomimetic robotic fish. This system estimates both position and direction of all robots and a ball in real time. In unstructured 3D underwater environments, Shkurti *et al.* [107] introduced a robust convoying method using model-based object detection and temporal filtering to minimize tracking drift. Cooperative perception is essential for collaborative operations. Berlinger *et al.* [115–117] developed a fish-inspired robot swarm that uses visual impressions and blue-light LEDs for implicit, decentralized 3D neighborhood sensing, achieving complex group behaviors like synchrony and search-capture without centralized control, as shown in Figure 5.

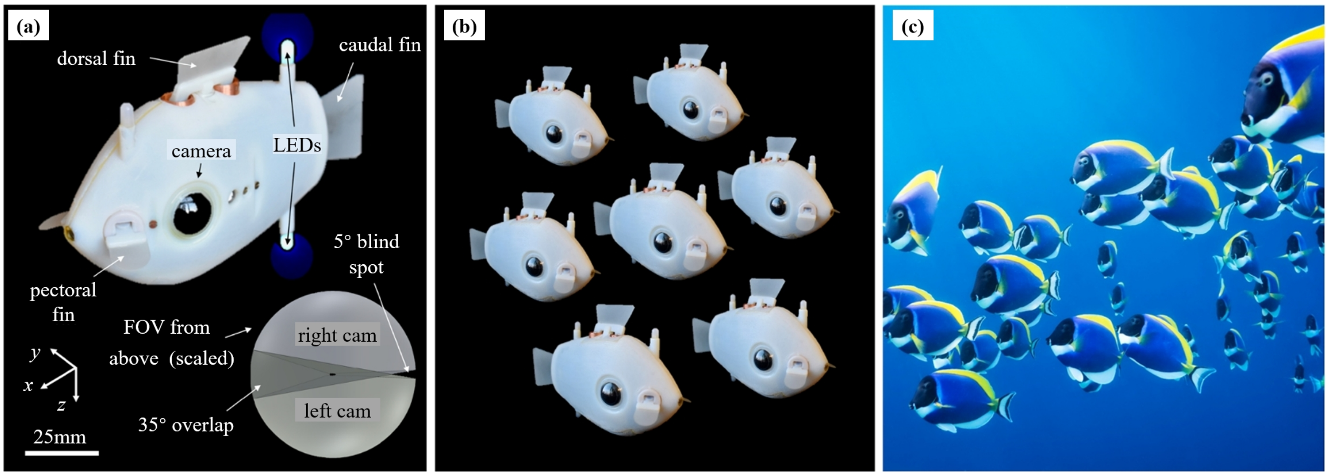

Figure 5. A swarm of fish-inspired miniature underwater robots [115].

To align sensor data from multiple robots, Sture and Ludvigsen [118] proposed a data-driven method for fusing AUV transect data using optimization and a Student-T process to eliminate outliers. This approach enhances multibeam echosounder data alignment across varying altitudes and directions.

Due to limited underwater visibility, working far from structures causes image degradation, while close proximity increases uncertainty. To address this, Xanthidis *et al.* [103] presented a dual-robot framework where proximal observers capture detailed images and distal observers provide localization and situational awareness. SLAM frameworks play a crucial role in autonomous underwater mapping. Leonardi *et al.* [119] introduced a scale-agnostic visual SLAM system optimized for station-keeping. Rahman *et al.* [108] proposed SVIn2, a tightly coupled SLAM system integrating sonar, vision, inertial, and pressure data, improving performance under challenging visibility and lighting conditions.

Underwater hyperspectral imaging (UHI) enhances optical characterization of seabed features. Løvås *et al.* [120] proposed a method for georegistering UHI data by building a photogrammetric 3D model using overlapping RGB images. Dumke *et al.* [121] demonstrated UHI as a taxonomic tool to identify megafauna based on spectral signatures, eliminating the need for physical sampling.

3.2.2. Water sampling

Water sampling evaluates the physical, chemical, and biological properties of aquatic environments, addressing the spatiotemporal variation within the water column. Adaptive and decentralized sampling strategies are employed to improve sampling efficiency.

Kemna *et al.* [122] introduced a decentralized coordination framework for multi-robot adaptive sampling using dynamic Voronoi partitions. Each robot performs informative sampling within its designated region. Ge *et al.* [110] proposed an AUV with an onboard Gaussian random field model for 3D salinity sampling in river plume systems. Fossum *et al.* [111] developed methods for fine-scale mapping of phytoplankton biomass in 3D using AUVs with chlorophyll and water quality sensors. These systems employ Gaussian Process models for spatial inference and GPU-based real-time data processing. Later work [123] leveraged remote sensing data to guide autonomous deployment and sampling strategies.

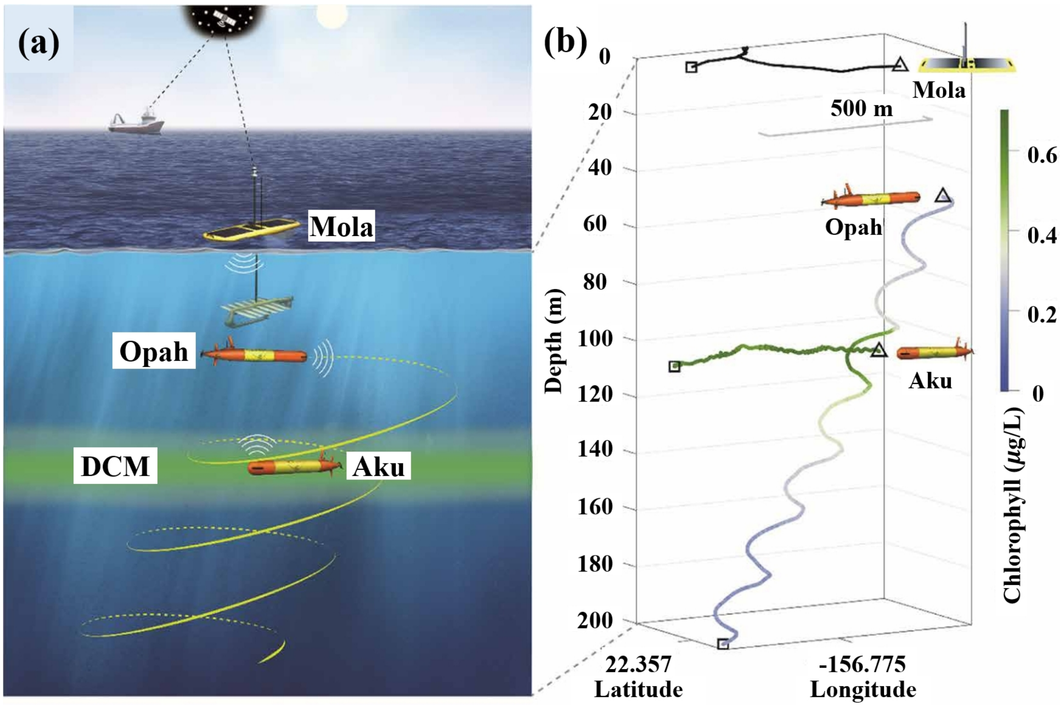

Figure 6. The system of coordinated autonomous robots [124]. **(a)** Illustration of the coordinated, fully autonomous operation of LRAUVs Aku and Opah, and Wave Glider Mola; **(b)** Tracks of Aku, Opah, and Mola from 31 March 10:03 to 10:40 UTC (from triangle to square). Aku was in the process of collecting one sample within the DCM, while Opah spiraled downward using Aku as the centroid navigational target. The color of the subsurface lines depicts the fluorescence-derived concentration of chlorophyll. Mola, on the sea surface (black line), tracked Aku and is seen dithering above for a short time as Aku's drift slowed and then accelerated.

Zhang *et al.* [124] addressed the challenge of in situ deep chlorophyll maximum (DCM) sampling using a coordinated system of AUVs and a surface vehicle, as shown in Figure 6. The system captures microbial community features by integrating environmental sensing, acoustic tracking, and satellite communications. For broader ocean monitoring, McCammon *et al.* [112] designed a heterogeneous ASV/AUV system to autonomously identify and track ocean salinity fronts using Gaussian Processes to model salinity and current vectors.

To investigate polar night zooplankton behavior, Ludvigsen *et al.* [105] deployed an ASV with hyperspectral and acoustic sensors. They revealed that artificial light from vessels alters zooplankton distribution, highlighting the importance of minimally invasive sampling platforms. For comprehensive freshwater monitoring, Kalaitzakis *et al.* [125] proposed a "marsupial" system combining UAV and ASV platforms. The UAV is carried by the ASV and deployed in remote areas, enabling extended-duration missions and high-resolution mapping.

3.2.3. Underwater archaeology

The significance of underwater archaeology lies in its preservation and study of valuable cultural heritage, as well as its exploration of past environments and human activities' impact on marine ecosystems. The use of robots for underwater exploration is essential because they can safely, efficiently, and accurately conduct tasks in extreme environments such as deep-sea and polar regions, providing crucial support for continuous observation and data collection.

Underwater Cultural Heritage (UCH), which spans several millennia, serves as a testament to our shared history. Oceans, seas, lakes, and rivers conceal and protect this invaluable heritage beneath their surfaces, yet it remains largely unknown and underestimated. Effective protection of UCH is impossible without raising awareness. Currently, these underwater relics face numerous threats, including looting, commercial exploitation, industrial trawling, coastal development, natural resource extraction, and seabed exploitation. Additionally, global warming, water acidification, and pollution further damage these historical remnants. To safeguard, understand, and promote this heritage, the United Nations Educational, Scientific and Cultural Organization (UNESCO) has been developing and implementing the 2001 Convention on the Protection of Underwater Cultural Heritage for over 20 years [126].

Wrecked ships are a significant part of Underwater Cultural Heritage. The Figaro, a floating whaling station, sank in 1908 after catching fire. It contained a variety of specialized equipment, including steam boilers and cooking vats for processing whale oil. Mogstad *et al.* [104] note that, to the best of their knowledge, the Figaro is the northernmost shipwreck in the world to be investigated by archaeologists. An interdisciplinary project was initiated to research the wreck along three main axes:

(1) Technology—to explore various non-intrusive technology-based methods using underwater robotics and sensors for mapping and investigating shipwrecks in high Arctic or other challenging environments.

(2) Archaeology—to gather data for a comprehensive mapping of the wreck using high-resolution sensors, aiding in the understanding of the Figaro's role in the history of whaling in Svalbard.

(3) Biology—to acquire and analyze sensor data that helps understand the wreck site as a human-made substrate for biofouling organisms.

Based on their research on the Figaro, Mogstad *et al.* [104] discovered that archaeological objects with strong protrusions support significantly higher levels of biofouling compared to their surrounding areas. As a result, high-density biological assemblages could serve as indicators for identifying human-made artifacts on the seafloor.

3.2.4. Underwater cleanup

Underwater environmental cleanup is crucial for maintaining the health of underwater ecosystems and ensuring the functionality of marine infrastructure. It involves the removal of pollutants, debris, and invasive species from underwater environments, thereby supporting biodiversity and ecosystem balance. Utilizing robots for underwater environmental cleanup is essential due to their ability to navigate challenging underwater terrain and execute precise cleaning operations efficiently and safely, minimizing human exposure to hazardous conditions and enhancing the effectiveness of environmental conservation efforts.

Pipeline inspection is a significant application of underwater environmental management. To minimize the reliance on divers for pipeline inspection, Patel *et al.* [106] developed two Shallow Water Inspection & Monitoring Robot (SWIM-R) vehicles and a companion ASV. The two SWIM-Rs are respectively for cleaning, which is responsible for removing marine growth from the pipe surface, and for inspection, which performs contact Ultrasonic Testing (UT) and Cathodic Protection (CP) measurements.

3.3. Frontier research and development trends

The perception technology of heterogeneous aquatic robots faces various challenges and opportunities for future development. Considerations include: (1) novel sensor technologies, encompassing high-quality imaging, high payload capacity, low environmental impact, and compatibility with edge computing platforms; (2) complex environment adaptability, where robustness challenges are prominent due to the dynamic and unpredictable nature of the surroundings; (3) real-time data processing, necessitating continuous advancements in algorithms and computational capabilities; and (4) collaborative perception technologies, leveraging multiple heterogeneous aquatic robots to achieve comprehensive, accurate, and efficient environmental sensing.

3.3.1. Novel sensor technologies

High-quality imaging sensors provide clearer and more detailed image data, aiding in precise identification and analysis of target objects and features in underwater environments. High payload capacity demands sensors that are lightweight and compact, enabling installation on various types and sizes of aquatic robots, while ensuring minimal impact on robot maneuverability and endurance. Low environmental impact emphasizes minimizing disturbance and damage to underwater ecological environments during sensor operation, thereby protecting marine life and ecosystems. Sensors adapted for edge computing platforms can perform real-time processing and analysis of collected data, reducing latency and bandwidth requirements for data transmission, and enhancing overall system responsiveness and decision-making capabilities. However, the development and implementation of such novel sensor technologies face several limitations. Developing high-quality imaging sensors with all the desired characteristics, like high resolution in low-light underwater conditions, is challenging and costly. The cost of research and production may limit their widespread adoption. Possible solutions could involve government subsidies or industry-university cooperation to share the cost of research and development. In terms of high payload-capacity sensors, achieving the right balance between weight, size, and functionality is difficult. New materials and manufacturing techniques need to be explored to develop sensors that are both lightweight and highly functional. For sensors with low environmental impact, ensuring that they truly cause minimal harm to the ecosystem requires extensive long-term environmental monitoring, which is time-consuming and resource-intensive. To address this, pre-deployment environmental impact assessment models could be developed. Regarding sensors for edge computing platforms, the integration of sensor hardware with edge computing software often requires significant engineering efforts due to differences in architecture and communication protocols. A standardized interface or middleware could be developed to simplify this integration process.

3.3.2. Complex environment adaptability

The aquatic environment is characterized by high dynamics and uncertainty, including variations in factors such as water currents, turbidity, temperature, and pressure, all of which impact the performance of perception systems. To enhance adaptability, perception systems require high robustness, capable of stable operation even under adverse conditions such as noise interference, low light, and signal attenuation. Furthermore, advanced algorithms and technologies need to be developed to enable robots to maintain efficient perception and navigation capabilities when encountering obstacles, complex terrains, and dynamic targets. Adaptive capability of perception systems is also crucial, allowing them to automatically adjust perception strategies and parameters in response to environmental changes, thereby enhancing adaptability and reliability across different task scenarios. Despite the importance of complex environment adaptability, current efforts face significant hurdles. Developing highly robust perception systems that can handle all the environmental factors simultaneously is extremely difficult. For example, while some algorithms may be effective against noise interference, they may not perform well under rapidly changing water currents. A possible solution is to develop modular perception systems, where different modules can be swapped or adjusted according to the dominant environmental factor. Another limitation is that the development of advanced algorithms for complex terrains and dynamic targets often requires a large amount of training data, which is challenging to collect in real-world underwater environments. Simulation-based training, combined with limited real-world data augmentation, could be a viable solution. Additionally, the real-time adjustment of perception strategies in response to environmental changes requires fast-acting and accurate environmental sensing. Improving the accuracy and speed of environmental sensors, such as developing more sensitive turbidity and temperature sensors, is necessary.

3.3.3. Real-time data processing

Real-time data processing is a crucial component of perception systems for heterogeneous aquatic robots, requiring systems to rapidly and accurately process large volumes of sensor data to support timely decision-making and actions. With advancements in sensor technology, the volume and complexity of data continue to increase, placing higher demands on the speed and efficiency of data processing. Therefore, there is a need to develop more efficient algorithms capable of fast data processing and analysis within limited computational resources. Additionally, leveraging parallel computing and distributed computing technologies can significantly enhance data processing capabilities and speed. The introduction of edge computing has greatly strengthened real-time processing capabilities, allowing some data processing tasks to be completed at the data collection site, thereby reducing latency in data transmission. Continual improvement of computing capabilities and optimization of algorithms ensure that perception systems can provide efficient and reliable real-time data processing support in complex and dynamic environments. Nonetheless, the pursuit of efficient real-time data processing has its own set of limitations. Developing algorithms that can process large volumes of data quickly while operating within the limited computational resources of aquatic robots is a major challenge. Existing algorithms may be computationally intensive and not suitable for the low-power processors typically used in these robots. One solution could be to develop specialized hardware-software co-design solutions, where the hardware architecture is optimized for the specific data processing algorithms. In terms of parallel and distributed computing, ensuring seamless communication and synchronization between different computing nodes in the underwater environment, which may have poor or intermittent communication channels, is difficult. Redundancy in communication links and more robust communication protocols need to be developed. For edge computing, the limited energy supply of aquatic robots may restrict the continuous operation of edge computing devices. Energy-harvesting technologies, such as using water-flow or solar energy (where applicable), could be integrated to power edge computing devices.

3.3.4. Collaborative perception technologies

The core of collaborative perception technology lies in enhancing overall system performance and reliability by enabling information sharing and complementarity among multiple robots. Each robot can be equipped with different types of sensors to collect environmental data from various dimensions, which are then integrated and analyzed through data fusion techniques to provide more comprehensive and accurate environmental information. Furthermore, collaborative work among robots extends coverage over larger areas, thereby enhancing task efficiency and effectiveness. In complex underwater environments, collaborative perception also improves system robustness and fault tolerance; for instance, if one robot encounters a malfunction, others can compensate to ensure task continuity. Developing effective collaborative control and communication algorithms enables robots to autonomously coordinate and divide tasks in dynamic and uncertain environments, which is crucial for achieving collaborative perception. Through the application of these technologies, heterogeneous aquatic robots can play a greater role in environmental monitoring, resource exploration, disaster response, and other domains. However, implementing collaborative perception technologies has its own set of difficulties. The development of effective data fusion techniques for different types of sensors is complex. Different sensors may have different sampling rates, data formats, and levels of accuracy, making it challenging to integrate the data seamlessly. Developing a unified data model and pre-processing steps for different sensor data could address this issue. Another limitation is the communication overhead in collaborative perception. Transmitting large amounts of sensor data between multiple robots in real-time requires significant bandwidth, which may not be available in the underwater communication environment. Compression algorithms specifically designed for underwater sensor data and more efficient communication protocols need to be developed. Additionally, ensuring the security of communication and data sharing among multiple robots is a concern, as underwater communication channels may be vulnerable to eavesdropping and interference. Encryption and authentication mechanisms need to be implemented to protect the data.

4. Navigation of heterogeneous aquatic robot system

Heterogeneous aquatic robot systems comprise various types of robots, each with distinct navigation requirements and challenges, yet unified by the goal of achieving precise and reliable positioning and navigation in aquatic environments. Collaborative navigation is a pivotal research area within these systems, focusing on information exchange and coordinated actions among multiple robots to enhance navigation efficiency and accuracy. This collaboration necessitates that each robot possesses a high degree of autonomous navigation capability and the ability to share environmental perception data, path planning information, and task execution status, thereby optimizing the overall system performance. Current research in the navigation of heterogeneous aquatic robots is progressing towards enhancing navigation accuracy, improving environmental adaptability, and achieving multi-robot collaborative navigation. The framework diagram of navigation and collaborative navigation for heterogeneous aquatic robotic systems is shown in Figure 7.

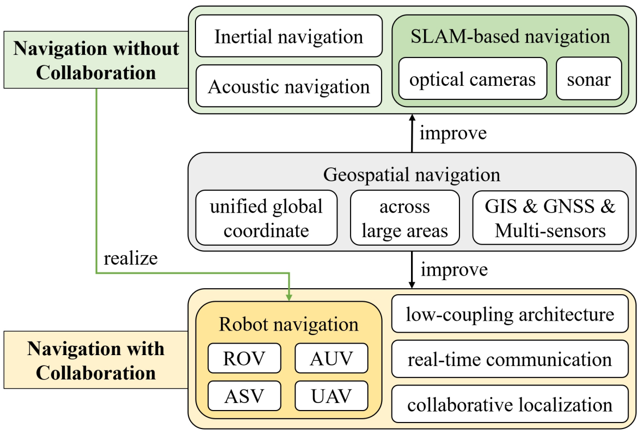

Figure 7. Navigation and collaborative navigation of heterogeneous aquatic robot system.

4.1. Navigation of heterogeneous aquatic robot system

4.1.1. Inertial navigation optimization

Inertial navigation holds a foundational role in autonomous unmanned systems. Using only inertial navigation results in unbounded errors, but there are still some methods that can optimize the performance of inertial navigation, making the final integrated navigation scheme more effective. For example, the inertial sensor offsets and other errors can be explicitly tracked, reducing the overall inertial navigation errors [127]. With some external sensor-based [128–130] schemes, water flow conditions can be detected and incorporated into the robot dynamics, reducing positioning and navigation errors. During navigation, using appropriate filtering methods, such as the variants of the Kalman Filter (KF) [131–133], the particle filter (PF) methods [134] or the cross-entropy based filter methods [135], can make better use of inertial sensor data and improve navigation accuracy. Overall, inertial navigation needs to be combined with various navigation and positioning methods mentioned next, serving as a fundamental method for high-precision navigation.

4.1.2. Acoustic navigation

In aquatic environments, due to the strong obstruction of electromagnetic signals by water, acoustic devices are more commonly used to achieve communication, positioning, sensing, and other functions for underwater robots. In acoustic navigation technology, positioning is achieved by measuring the Time of Flight (TOF) of acoustic signals to estimate distance. Specifically, acoustic positioning uses various forms of triangulation techniques to calculate the distance and orientation between sensors and beacons. Different acoustic positioning methods are distinguished by the deployment methods of the sensors and beacons. The Ultra-Short Baseline (USBL) method uses sensor distances on the order of 10 cm and determines the beacon's orientation based on the phase difference of sound signals [136–138]. This method is less dependent on sensor size but has a limited positioning range. The Long Baseline (LBL) method involves pre-setting multiple beacons on the seabed at the task site and uses the integrated sound signal TOF distance measurements to achieve AUV positioning [139]. In terms of technical details, the LBL method especially needs to consider the situation of abnormal TOF distance measurements [140] and handle the errors caused by TOF distance measurement delays using various methods [141]. The main drawback of the LBL method is the high cost and dependency on the working environment due to the need for pre-installed fixed beacons, but when conditions are suitable, the LBL method offers the highest accuracy, stability, and reliability. Due to the high cost associated with multiple beacons in LBL, some methods consider using only one fixed beacon to position the AUV, achieving good positioning results when the AUV's operating trajectory meets specific requirements [132,142,143].

4.1.3. SLAM-based navigation

With the development of Simultaneous localization and mapping (SLAM) algorithms, a large body of research has applied SLAM methods to underwater environments, achieving good results in AUV navigation and positioning [144–146]. SLAM-based navigation methods can be categorized into optical and sonar, based on the perception method.

A series of vision-based SLAM techniques using optical cameras have also been applied to AUV navigation and positioning, as shown in Figure 8. SLAM methods have bounded localization errors and can simultaneously generate maps of the mission area, making them suitable for certain types of tasks [147]. The limitations of visual methods include the performance deficiencies of underwater optical cameras, the obstruction, scattering, and insufficient illumination of visible light in underwater environments, which affect the perception range of visual methods. Moreover, most visual methods rely on rich, small-scale feature matching in the environment [148]. Therefore, visual methods are suitable for environments with abundant visual features and short working distances, such as coral reef exploration and shipwreck detection [149].

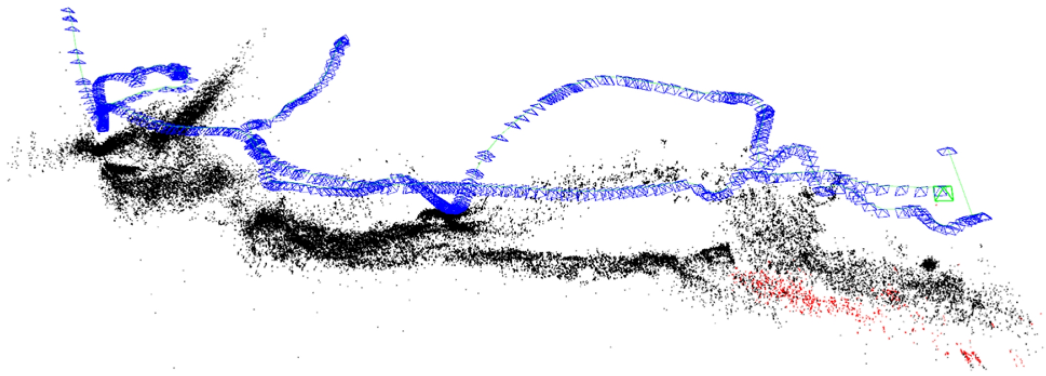

Figure 8. Vision-based SLAM example [119] on sequence 4 of the aqualoc dataset [150] (an underwater dataset for visual-inertial-pressure localization).

Compared to optical technology, sonar technology is a more mature underwater detection technology. Extensive research has developed corresponding SLAM algorithms for AUV navigation based on the technical characteristics of different types of sonar. Side-scan sonar achieves high-resolution imaging of seabed material by identifying varying echo intensities from the seabed, but it requires more complex post-processing. Forward-looking sonar is primarily used for mapping vertical features [151], making it suitable for environments with man-made underwater structures. Mechanical scanning imaging sonar has a slower update rate and is suitable for artificial environments with clear edges and boundaries. Synthetic aperture sonar (SAS) achieves high resolution through coherent processing of continuously displaced echoes, making it suitable for long-distance detection [152], but it requires complex image processing and precise micro-navigation. Multibeam sonar records depth data using multiple transducer arrays to create depth maps, enabling large-area seabed mapping [153]. Overall, imaging sonar is suitable for high-resolution imaging and feature detection, while ranging sonar is more advantageous for depth mapping and navigation.

4.1.4. Geospatial navigation

Geospatial navigation for heterogeneous aquatic robots involves integrating results from various navigation methods into a unified global coordinate system. By combining geographic information systems (GIS), global navigation satellite systems (GNSS), and multi-sensor data, this technology accurately determines the robot's position in complex aquatic environments. It enables high-precision perception of the surroundings and mapping. Geospatial navigation not only consolidates outputs from different navigation techniques but also facilitates precise navigation and localization over extensive geographic areas for aquatic robots, supporting applications in exploration, monitoring, and task execution.

4.2. Collaborative navigation of heterogeneous aquatic robot system

Based on the navigation technology of individual heterogeneous aquatic robots, multi-robot systems, particularly those with underwater, surface, and aerial collaborative operations, can achieve better navigation results through collaborative localization methods.

4.2.1. Collaborative navigation of robots

Theoretical research on collaborative navigation among robots [154] has long indicated that even without external positioning aids, multi-robot systems can achieve better localization results through mutual communication of their respective poses and relative distance measurements. Extensive studies have been conducted on the collaborative navigation of AUV clusters, focusing on error analysis [155], complexity analysis [156], and diverse application advancements [157,158]. The primary approaches in this technical route include convergence and stability analysis of multi-robot systems and iterative updates based on posterior probability using various filters and estimators [159]. For the application of heterogeneous aquatic robots, additional considerations must be given to the impact of communication bandwidth and latency on the system's performance.

4.2.2. Collaborative navigation of heterogeneous aquatic robots

Beyond theoretical analyses of collaborative navigation, some studies leverage the distinct functions, operating environments, and performance characteristics of different robots within heterogeneous groups to propose low-coupling and intuitive collaborative localization methods. For instance, some AUVs are equipped with superior navigation systems or periodically surface to obtain GNSS positioning. These accurately positioned AUVs within the heterogeneous robot system can achieve precise cluster localization through communication and relative distance measurements [160]. In acoustic navigation, some methods deploy beacons on GNSS-equipped buoys, vessels, or ASVs, avoiding the need for pre-positioned beacons in other acoustic localization methods. Beacons on ASVs can remain mobile during mission execution, providing multi-perspective range measurements for AUVs, thus avoiding the complexity of fixed beacon networks. ASVs, located at the water surface, can communicate acoustically with underwater robots and use radio signals to communicate with aerial or remote operators while continuously obtaining GNSS global positioning information. This makes ASVs effective as signal relays or tracking beacons for underwater robot groups, enhancing the operational capabilities of heterogeneous robot groups. Additionally, some works utilize the high mobility of UAVs, employing optical sensing to perform precise mapping and localization of task areas [161], thereby improving the navigation and localization accuracy of heterogeneous aquatic robot systems.

4.3. Frontier research and development trends

With continuous technological advancements, research and development in heterogeneous aquatic robot navigation systems are witnessing several frontier trends:

4.3.1. Collaborative navigation

Future research will focus on advancing collaborative navigation algorithms to enable real-time information exchange, decentralized decision-making, and coordinated movement among heterogeneous underwater robots. Effective collaboration improves navigation accuracy, expands operational coverage, and enhances robustness in dynamic environments.

However, challenges such as communication latency, bandwidth limitations, and inconsistent sensor data across different robot platforms must be addressed. To overcome these limitations, multi-robot systems will leverage predictive modeling, consensus-based control strategies, and adaptive task allocation mechanisms. Additionally, integrating reinforcement learning and swarm intelligence approaches will enable robots to dynamically adjust their behaviors based on environmental conditions and mission objectives. By enhancing cooperation and optimizing networked navigation strategies, future heterogeneous underwater robot systems will achieve greater efficiency in large-scale environmental monitoring, resource exploration, and autonomous surveillance.

4.3.2. Dynamic task assignment and replanning

Future navigation systems will increasingly incorporate dynamic task assignments and real-time path replanning to enhance adaptability in complex underwater environments. These systems will leverage real-time environmental data, robot status monitoring, and predictive modeling to autonomously adjust mission objectives, redistribute tasks, and optimize path selection.

However, uncertain ocean currents, limited communication bandwidth, and computational constraints make real-time decision-making difficult. To address these issues, multi-robot coordination strategies will integrate decentralized optimization algorithms, reinforcement learning-based planning, and bio-inspired swarm intelligence approaches. These methods will enable robots to adapt to changing conditions while maintaining efficiency and robustness collectively. By incorporating adaptive task allocation and intelligent replanning mechanisms, heterogeneous underwater multi-robot systems will achieve greater operational efficiency in applications such as environmental monitoring, underwater exploration, and search-and-rescue missions.

4.3.3. Autonomous learning and adaptation

Integrating machine learning and artificial intelligence enables underwater navigation systems to learn environmental features and adapt to dynamic conditions autonomously. Robots can refine their decision-making processes by analyzing historical and real-time sensor data, improving localization, obstacle avoidance, and mission planning in uncertain underwater environments.

However, challenges such as limited computational resources, noisy sensor data, and the scarcity of labeled underwater datasets hinder the effectiveness of learning-based approaches. To address these issues, future research will focus on energy-efficient deep learning models, self-supervised learning techniques, and domain adaptation strategies to enhance model generalization across diverse aquatic conditions. By continuously optimizing their navigation strategies, heterogeneous underwater multi-robot systems will improve operational robustness and efficiency in complex missions, such as deep-sea exploration, ecological monitoring, and underwater infrastructure inspection.

4.3.4. Standardization and modular design

Navigation systems' standardization and modular design play a crucial role in ensuring interoperability among heterogeneous underwater robots from different manufacturers. Establishing standard communication protocols, sensor interfaces, and software architectures enables seamless integration and cooperative operations in multi-robot deployments.

Achieving standardization faces challenges such as varying hardware specifications, proprietary software constraints, and the need for real-time adaptability in diverse underwater environments. To address these issues, future research will focus on developing open-source frameworks, flexible middleware architectures, and universal communication standards that enhance cross-platform compatibility.

4.3.5. Safety and ethical considerations

Safety and ethical concerns have gained significant attention with the increasing deployment of underwater robots. These systems must be designed to operate without disrupting marine ecosystems, harming aquatic life, or interfering with human activities. Additionally, ensuring reliable performance in unpredictable underwater environments remains a fundamental challenge.

One of the primary difficulties lies in real-time hazard detection and avoidance, particularly in dynamic conditions with limited communication and sensor accuracy. Addressing these issues requires the integration of fail-safe mechanisms, robust collision-avoidance strategies, and environmentally conscious design principles. Furthermore, the ethical implications of autonomous decision-making demand careful consideration, especially in scenarios involving resource exploration or military applications.

Moving forward, establishing standardized safety protocols and ethical frameworks will be crucial. Regulatory compliance, transparent AI decision-making, and sustainable deployment practices will play a key role in fostering the responsible adoption of heterogeneous underwater multi-robot systems across scientific, industrial, and environmental applications.

5. Control of heterogeneous aquatic robot system

The control technology for heterogeneous aquatic robot systems refers to the precise operation and coordination methods for various surface, underwater, and aerial robots, including ROVs, AUVs, ASVs, and UAVs. These robots require precise control to maintain stability, responsiveness, and coordination during task execution. The core goal of control technology is to ensure that robots can operate efficiently and safely according to predetermined trajectories and task requirements.

5.1. Research status

In recent years, significant progress has been made in the control technologies for heterogeneous aquatic robot systems. This progress spans multiple aspects, from theoretical advancements to practical implementations, addressing the unique challenges posed by the aquatic environment. The current research landscape can be categorized into several key areas:

5.1.1. Development and optimization of control theory

Currently, research on control theory focuses on nonlinear control, adaptive control, and robust control to address the uncertainties and dynamic changes in aquatic environments. Researchers are developing and optimizing various control algorithms, such as PID control, optimal control, and predictive control, to enhance the tracking accuracy and operational efficiency of robots. These advanced control theories aim to provide robust solutions to address the complexities and variability of aquatic environments, ensuring reliable performance under various conditions. The following is a brief overview:

- Proportional-integral-derivative (PID) control [162]: PID control is widely applied in various control systems due to its few parameters, simple structure, ease of implementation, and clear physical significance [163].
- Optimal control theory: Optimal control theory provides systematic procedures for the design of feedback control systems, laying the foundation for modern control theory and being a key concept in the field [164, 165].
- Adaptive control: Adaptive control ensures system stability in the presence of uncertain system model parameters [166–169]. Its characteristic lies in the design of appropriate estimation rates to effectively estimate and compensate for uncertainties or parameter variations in the system model.
- Backstepping control: Backstepping is a recursive design method based on the Lyapunov function. The basic idea is to decompose a complex nonlinear system into several subsystems, each with its Lyapunov function and intermediate virtual control variables, eventually integrating them into the overall system's control law [170].
- Neural network control: Neural network control is a branch of intelligent control that has excellent capabilities in estimating and identifying nonlinearity and uncertainty [171–173]. It opens new pathways for solving control problems in complex, nonlinear, uncertain, and unknown systems.
- Fuzzy control: Fuzzy control utilizes the basic ideas and theories of fuzzy mathematics to establish a linguistic analysis mathematical model for complex systems or processes [173, 174]. It translates natural language directly into algorithms that computers can understand, effectively controlling systems that are overly complex or difficult to describe precisely.
- Model Predictive Control (MPC): At each sampling instant, MPC determines the optimal control action by solving a finite-horizon open-loop optimal control problem, using the current system state as the starting point. Only the first control input from the computed optimal sequence is applied, and the process repeats at the next step. This approach allows MPC to anticipate and correct potential deviations proactively, demonstrating strong robustness to system parameter variations and environmental disturbances [175, 176].
- Sliding mode control: Sliding mode control is a type of nonlinear control characterized by control discontinuity. Its uniqueness lies in the dynamic change of the system's "structure" based on the current state (e.g., error and its derivatives), purposefully adjusting the system to follow a predetermined "sliding mode" trajectory [167].
- Deep Reinforcement Learning Control (DRL) : DRL combines the perception capabilities of deep learning with the decision-making abilities of reinforcement learning, enabling robots to autonomously learn and control in complex environments [177]. DRL uses neural networks to approximate value functions or policy functions in reinforcement learning problems, allowing for environmental perception, state evaluation, and action selection. For instance, Wu Hui *et al*. utilized reinforcement learning for AUV depth control [178], demonstrating the effectiveness of DRL in managing underwater robotic tasks. Similarly, I. Masmitja *et al*. implemented a reinforcement learning approach to enable AUVs to perform target tracking tasks in complex water flow environments [179].
- End-to-end control: End-to-end control leverages deep neural networks to directly learn the mapping

from sensor data (such as images, LIDAR signals, and tactile sensor data) to robot actuator control signals (such as motor torque and joint angles). This approach simplifies traditional control processes and reduces reliance on precise models.

- Large model-based control: This approach uses large-scale machine learning models, particularly deep learning models, to process and interpret the vast amount of sensor data received by robots and generate control commands. This method has rapidly developed in recent years, primarily due to advances in computational power and the availability of big data.

5.1.2. Innovation in control hardware

Innovations in control hardware are also a crucial part of the research, including the development of higher performance actuators and sensors. These hardware advancements can significantly improve the response speed and accuracy of control systems. High-precision sensors provide detailed environmental data, while advanced actuators enable precise movements, both of which are essential for the accurate execution of complex tasks. Additionally, integration of advanced materials and miniaturization of components contribute to the enhanced performance and reliability of the control hardware.

5.1.3. Development of control software

With the advancement of software technology, control software has become more user-friendly and powerful, capable of implementing more complex control logic and data processing. Modern control software integrates real-time data processing, advanced algorithms, and user interfaces that facilitate easier operation and monitoring. These software systems can adapt to changing conditions and optimize control parameters on-the-fly, enhancing the overall efficiency and effectiveness of robotic operations.

5.1.4. Real-time control and simulation

Research in real-time control technology ensures that robots can respond quickly to environmental changes, maintaining optimal performance even in dynamic scenarios [171]. Simulation technology is used to test and verify control strategies in a safe and controlled environment before deployment [180]. This approach helps in identifying potential issues and refining control algorithms, leading to more reliable and robust systems. Advanced simulation tools can model complex interactions between robots and their environments, providing valuable insights for improving control strategies.

5.1.5. Collaborative control mechanisms

Collaborative control among ROVs, AUVs, and ASVs is a current research hotspot, involving communication, coordination, and task allocation among multiple robots [181]. Effective collaborative control mechanisms enable robots to work together seamlessly, sharing information and resources to accomplish tasks more efficiently. This includes developing algorithms for cooperative path planning [182], distributed sensing, and coordinated decision-making [177], all of which are critical for multi-robot systems operating in challenging aquatic environments.

5.2. *Frontier research and development trends*

Looking ahead, the field of control technology for heterogeneous aquatic robots is poised for substantial advancements. Future research and development efforts are expected to focus on enhancing the intelligence, adaptability, and interoperability of control systems, as well as addressing broader societal and ethical considerations. Key areas of future development include:

5.2.1. Intelligent control strategies

Future control strategies will become more intelligent, utilizing artificial intelligence algorithms and collaborative control strategies to automatically adjust control parameters and adapt to different operating conditions. AI-driven control systems will be capable of learning from experience, improving their performance over time, and making autonomous decisions based on real-time data and predictive models. These intelligent systems will enhance the adaptability and resilience of robots in complex and changing environments. However, implementing intelligent control strategies in aquatic robots has several limitations. One major challenge is the high computational demand of AI algorithms. Aquatic robots typically have limited computing resources and power supply, which may not be sufficient to run complex AI algorithms in real-time. Developing lightweight AI models specifically tailored for the computational capabilities of aquatic robots, such as using neural network pruning or quantization techniques, could be a solution. Another limitation is the need for large amounts of high-quality training data. Collecting diverse and representative underwater data for training AI-driven control systems is extremely difficult due to the complex and dynamic nature of the underwater environment. Employing data augmentation techniques, using simulation-generated data in combination with real-world data, and leveraging transfer learning from related domains could help address this issue. Additionally, the instability of the underwater environment, such as water current fluctuations and temperature changes, can affect the performance of AI-based control systems. Developing algorithms that are more robust to environmental changes, for example, by incorporating environmental factors as additional input features, could enhance the adaptability of the intelligent control strategies.

5.2.2. Cross-domain collaborative operations

With the integrated use of different types of robots, cross-domain control technology will be developed to achieve seamless collaborative operations among underwater, surface, and aerial robots. This involves creating unified control frameworks that can manage diverse robotic platforms, enabling them to work together harmoniously. Cross-domain collaboration will enhance the overall capability and versatility of robotic systems, allowing them to perform a wider range of tasks more effectively. Despite its importance, achieving cross-domain collaborative operations in aquatic robot control has its difficulties. One key limitation is the communication gap between different types of robots operating in different domains. Underwater robots mainly use acoustic communication, which has low data transfer rates and high latency, while surface and aerial robots may use radio-frequency communication. Developing a unified communication protocol that can bridge these differences and ensure seamless data exchange among all types of robots is a significant challenge. Another challenge is the coordination of control commands for robots with different kinematic and dynamic characteristics. For example, underwater robots need to deal with buoyancy and water resistance, while aerial robots need to consider aerodynamics. Designing a control framework that can take into account these differences and allocate tasks appropriately to each robot type is necessary. Additionally, the differences in sensor capabilities and data formats among robots in different domains can pose problems for integrated perception and decision-making. Developing a common data representation and sensor fusion techniques that can handle data from various sources is crucial for effective cross-domain collaboration.

5.2.3. Distributed control architectures

Distributed control architectures will be further researched and applied to improve system scalability and fault tolerance. These architectures distribute control functions across multiple nodes, enhancing the robustness and flexibility of the system. Distributed control allows for decentralized decision-making, reducing the reliance on a central controller and improving the system's ability to handle failures and adapt to changing conditions. This approach is particularly beneficial for large-scale multi-robot systems operating in dynamic environments [183]. Nonetheless, the implementation of distributed control architectures in aquatic robot systems has its own set of limitations. One major issue is the communication latency and reliability in the underwater environment. In a distributed control system, nodes need to communicate with each other in a timely and reliable manner. However, the underwater communication channels, especially acoustic-based ones, are prone to interference, multipath propagation, and signal attenuation, which can lead to communication delays and data loss. Developing more reliable and high-speed underwater communication protocols, such as using optical or hybrid communication methods in combination with acoustic communication, could improve the situation. Another challenge is the coordination of decision-making among multiple nodes. Since each node makes its own decisions, conflicts may arise. Developing conflict-resolution algorithms and consensus-building mechanisms that can ensure consistent and efficient decision-making across all nodes is necessary. Additionally, the complexity of managing a distributed control system with multiple nodes, including node discovery, configuration, and maintenance, can be high. Developing automated management tools and self-organizing algorithms for the distributed control system could simplify the management process.

5.2.4. Safety protocols and ethical considerations

With increasing autonomy, research will place greater emphasis on developing safety protocols and addressing ethical issues to ensure that robot actions comply with safety and ethical standards. This includes establishing guidelines for safe operation, creating fail-safe mechanisms, and addressing the ethical implications of autonomous decision-making. Ensuring that robotic systems operate safely and ethically is crucial for gaining public trust and enabling widespread adoption of these technologies. Despite the importance of safety protocols and ethical considerations, implementing them in aquatic robot control has challenges. One key limitation is the lack of clear and comprehensive safety and ethical frameworks for aquatic robots. Defining what constitutes safe and ethical behavior in the underwater environment, especially in relation to potential impacts on marine life and human activities, is not straightforward. Conducting in-depth ethical and environmental impact studies and involving experts from various fields, such as ethics, law, marine biology, and environmental science, in the framework-building process could help. Another challenge is ensuring compliance with the established frameworks. Monitoring the actions of a large number of autonomous aquatic robots in real-time to ensure they adhere to safety and ethical standards is resource-intensive. Developing automated monitoring and auditing systems, such as using machine-learning-based anomaly detection techniques, could be a solution. Additionally, the cost of implementing safety and ethical measures, such as redundant safety systems and regular ethical reviews, may be a deterrent for some developers. Government incentives, such as grants or tax breaks for compliant projects, could encourage the adoption of safety and ethical practices.

5.2.5. Standardization of control technologies

To promote the exchange and application of technologies, the standardization of control technologies will be an important development direction. Standardization efforts aim to create common protocols, interfaces, and benchmarks that facilitate interoperability among different robotic systems and simplify integration and maintenance. Establishing standards will also support collaboration among researchers and manufacturers, accelerating the development and deployment of advanced control systems. However, the process of standardization of control technologies for aquatic robots has its own challenges. There are often strong vested interests among different research groups and manufacturers, which may resist the adoption of common standards. Encouraging industry-wide cooperation through incentives, such as preferential treatment in government-funded projects for compliant parties, could be a way to overcome this resistance. In terms of developing common protocols and interfaces, ensuring compatibility with existing and future robotic technologies is difficult. The rapid development of robotic technology means that standards need to be flexible enough to incorporate new advancements. Establishing a standard-setting organization with representatives from all stakeholders and a mechanism for regularly updating the standards could solve this problem. Additionally, the implementation of standards may require significant modifications to existing robotic systems, which can be costly and time-consuming. Developing migration plans and providing technical support for companies and researchers to transition to the new standards could ease the implementation process.

6. Decision-making technology of heterogeneous aquatic robots

The decision-making process in heterogeneous robotic systems operating in aquatic environments is fundamental to their collaborative capabilities. It encompasses effective coordination and task allocation in dynamic and uncertain underwater conditions. This process not only requires individual robots to make autonomous decisions but also necessitates the entire system to achieve information sharing, coordinated planning, and collective optimization.

6.1. Technology development

With the rapid advancement of artificial intelligence and autonomous systems, decision-making in heterogeneous robotic systems for aquatic environments has evolved from simple independent task execution to complex collaborative operations. This transformation requires the system to address not only the decision-making processes of individual robots but also the coordination, communication, and task allocation among multiple robots.

6.1.1. Perception fusion technology

Heterogeneous robotic systems in aquatic environments achieve precise perception of complex underwater settings by integrating various sensing modalities such as sonar and optical sensors [184]. The application of information fusion technology allows robots to obtain richer and more reliable environmental data, thereby supporting decision-making processes. For a detailed introduction, see Section 3. In the fish-inspired miniature underwater robots developed by F. Berlinger *et al.* [115–117], implicit communication through the observation and sensing of blue LED light enables local decision-making based on information extracted from images of neighboring robots, allowing for the realization of complex and dynamic 3D collective behaviors.

6.1.2. Collaborative decision-making

Collaborative decision-making algorithms encompass rule-based systems, distributed optimization algorithms, and consensus algorithms. Rule-based systems guide robot behavior using predefined rules, suitable for structured and predictable task environments. Distributed decision-making algorithms enable effective task coordination and decision-making in decentralized aquatic heterogeneous robot systems. These algorithms typically rely on local information and simple communication protocols, allowing robots to maintain individual autonomy while achieving coordinated actions at the group level. Consensus algorithms facilitate consensus decision-making among robot groups through the exchange of local information, enhancing system robustness and reliability without a central controller. Through distributed consensus algorithms, robot groups can swiftly respond to environmental changes or individual failures during task execution, ensuring continuity and robustness of operations [185,186]. Additionally, leveraging distributed optimization and consensus algorithms enables efficient task allocation, maximizing overall system performance and facilitating rapid adaptation to unforeseen circumstances. In summary, the application of collaborative decision-making algorithms significantly enhances collective intelligence and task execution capabilities of heterogeneous aquatic robot systems, equipping them with greater adaptability and resilience in complex environments.

6.1.3. Multi-objective optimization and reinforcement learning

Multi-objective optimization techniques in decision-making for heterogeneous aquatic robots handle multiple and potentially conflicting objectives such as efficiency, safety, and energy consumption [187–189]. These techniques define composite evaluation criteria and constraints to help robots find optimal trade-offs among different objectives. Simultaneously, the application of reinforcement learning enables robots to learn optimal behavioral strategies through interaction with the environment, particularly in dynamic and uncertain environments. Reinforcement learning provides an effective means for online learning and adaptation.

6.1.4. Risk perception and robustness

Risk perception and robustness are key elements in the decision-making processes of heterogeneous aquatic robotic systems. When operating under uncertainty and potential risks, robots must evaluate the outcomes of their actions and implement effective risk mitigation strategies. By integrating probabilistic models and robust optimization techniques, these systems can account for various uncertainties, thereby improving overall safety and reliability [190]. Furthermore, the use of robust control strategies enables robots to continue performing critical tasks even in the presence of sensor malfunctions or communication failures. To enable secure and confidential collaboration within robotic swarms, Ferrer *et al.* [191] propose a framework that encodes cooperative missions within an authenticated data structure, specifically a Merkle tree. Within this framework, robots are required to exchange cryptographic proofs to demonstrate their integrity to one another, ensuring trustworthy and secure cooperation throughout mission execution.

6.1.5. Human-machine interaction and collaborative decision-making

Human-machine interaction technology is crucial in heterogeneous aquatic robotic systems, enabling operators to understand and effectively control robot behavior through intuitive interfaces and real-time monitoring capabilities. Collaborative control strategies facilitate task planning and optimization through this human-machine interaction, enabling robot teams to autonomously coordinate actions and dynamically adjust task execution based on operator commands and environmental changes [192]. Additionally, integrated decision support systems leverage artificial intelligence to provide decision recommendations, enhancing operators' capability to handle complex tasks. Safety and ethical standards are rigorously integrated into the design, ensuring compliance of robot behavior. With the integration of personalized and adaptive functionalities, operators experience more customized interaction, while multimodal interaction methods make the interaction process more natural and intuitive. Ultimately, this human-machine collaboration enhances task efficiency and strengthens the adaptability and flexibility of robotic systems in diverse aquatic environments.

6.1.6. Behavioral decision-making

Behavioral decision-making for robots involves designing algorithms that enable robots to make choices based on a combination of programmed rules, learning from their environment, and adapting to new situations. These decisions are influenced by factors such as sensory inputs, internal states, and interactions with other robots or humans. The approach aims to mimic human-like decision processes, allowing robots to perform tasks efficiently, adapt to changes, and collaborate effectively in dynamic environments. For instance, Chen *et al.* [193] propose a path planning method based on behavioral decision-making to optimize energy use during the AUV's diving process. They employ a success-history based adaptive differential evolution algorithm with linear population size reduction to effectively plan an energy-saving path.

6.2. Frontier research and development trends

The development of decision-making technologies for heterogeneous underwater multi-robot systems is evolving toward greater intelligence, autonomy, and efficiency. Future advancements will emphasize real-time adaptability, robustness in uncertain environments, ethical considerations, and cross-domain applicability. These innovations will be driven by integrating artificial intelligence, multimodal sensing, and human-machine collaboration, enabling underwater robots to operate effectively in dynamic and unstructured environments with minimal human supervision.

6.2.1. Intelligent decision-making algorithms

Future decision-making systems will incorporate advanced artificial intelligence techniques, such as deep reinforcement learning, Bayesian decision models, and hybrid neuro-symbolic reasoning. These methods will enhance the ability of robots to process high-dimensional sensory data, predict environmental changes, and make optimal decisions under uncertainty. However, real-world deployment presents challenges such as data sparsity, computational efficiency, and the interpretability of AI-driven decisions. Addressing these issues will require the development of explainable AI models, lightweight inference frameworks, and domain adaptation techniques to improve generalizability across different aquatic environments.

6.2.2. Real-time capability and efficiency

Making rapid and efficient decisions is critical for heterogeneous underwater robots, particularly in dynamic and unpredictable marine environments. With advancements in onboard computing, edge AI, and parallel processing architectures, decision-making algorithms will increasingly focus on reducing latency while maintaining computational efficiency. Distributed decision-making frameworks, where multiple robots collaboratively process environmental data and share real-time insights, will further enhance operational responsiveness. However, challenges such as bandwidth limitations in underwater communication and power constraints necessitate the development of energy-efficient decision models that balance performance and resource consumption.

6.2.3. Autonomous learning capabilities

Heterogeneous underwater robots will progressively move toward self-learning systems capable of adapting to new conditions without human intervention. Reinforcement learning, transfer learning, and continual learning techniques will enable robots to refine their decision strategies based on accumulated experience. Future research will focus on overcoming limitations such as catastrophic forgetting, where robots lose previously learned knowledge, and the need for extensive training data. Implementing meta-learning frameworks and self-supervised learning approaches will allow robots to generalize across different tasks while minimizing the reliance on labeled data.

6.2.4. Multimodal data fusion

Integrating multimodal sensory data, including sonar, optical imaging, LiDAR, chemical sensors, and acoustic signals, enhances environmental perception and situational awareness. Effective data fusion techniques, such as Kalman filtering, deep sensor fusion networks, and graph-based inference models, will improve decision accuracy in complex underwater scenarios. However, challenges remain in synchronizing heterogeneous data streams, handling sensor failures, and filtering noise in low-visibility conditions. Future research will develop real-time, adaptive fusion mechanisms that dynamically adjust information processing strategies based on environmental conditions.

6.2.5. Robustness and fault tolerance

Ensuring the reliability of decision-making processes in underwater robots is crucial for mission success, especially in harsh and unpredictable environments. Robust decision systems must account for sensor degradation, communication disruptions, and unforeseen environmental changes. Adopting redundancy strategies, self-repairing algorithms, and uncertainty-aware decision models will improve resilience. Additionally, integrating probabilistic reasoning and anomaly detection mechanisms will allow robots to identify and compensate for faulty sensor readings, enhancing operational continuity even under adverse conditions.

6.2.6. Human-machine collaborative decision-making

Advancements in human-machine interaction technologies will enable more intuitive and effective collaboration between human operators and autonomous robots. Shared autonomy frameworks, where human expertise is seamlessly integrated with robotic intelligence, will improve decision-making in mission-critical applications such as deep-sea exploration and search-and-rescue operations. Future research will enhance communication interfaces, such as haptic feedback systems and augmented reality-based control platforms, to facilitate real-time situational awareness. Ethical considerations, including human override mechanisms and trust calibration in autonomous systems, will also be crucial to ensure safe and effective human-robot collaboration.

6.2.7. Cross-domain decision-making capability

As underwater robots are deployed in diverse operational domains—including marine research, resource exploration, disaster response, and military applications—decision-making technologies must evolve to handle cross-domain challenges. Developing universal decision models capable of adapting to different operational constraints will be essential. Future systems will incorporate hierarchical decision architectures that enable robots to transition seamlessly between structured (e.g., industrial pipeline inspection) and unstructured (e.g., deep-sea exploration) environments. Integrating multi-agent reinforcement learning and cloud-based knowledge sharing will enhance cross-domain adaptability, allowing robots to benefit from collective learning experiences.

6.2.8. Ethical and regulatory considerations

Ensuring ethical decision-making and compliance with regulatory standards is becoming a significant research priority with increasing autonomy in underwater robotic systems. Autonomous systems must be designed to operate without causing ecological harm, violating maritime laws, or posing risks to human safety. Future developments will involve formulating standardized ethical guidelines, AI transparency frameworks, and fail-safe mechanisms to ensure responsible robotic behavior. Collaboration with regulatory bodies and implementing compliance verification systems will facilitate the widespread adoption of autonomous underwater robots in real-world applications.

6.2.9. Ethics and compliance

As decision-making technologies for heterogeneous underwater robots become more autonomous, ensuring ethical behavior and regulatory compliance is becoming a fundamental requirement. Robots must operate within established legal frameworks, respect environmental protection guidelines, and avoid actions that could harm marine ecosystems or human activities.

A key challenge lies in defining and enforcing ethical constraints in autonomous systems, especially when decision-making involves trade-offs between mission objectives and environmental impact. To address these concerns, future research will focus on developing transparent AI models, explainable decision-making frameworks, and compliance verification mechanisms. Additionally, collaboration with policymakers and international regulatory bodies will be essential to establish standardized ethical guidelines, facilitating the responsible deployment of autonomous underwater robots.

6.2.10. Modularity and scalability

Modular design principles will play a crucial role in the evolution of decision-making technologies, allowing heterogeneous underwater robots to adapt flexibly to diverse operational scenarios. By implementing modular architectures, individual decision-making components—such as perception, planning, and control modules—can be independently upgraded or reconfigured without overhauling the entire system.

However, achieving seamless interoperability between different modules and ensuring compatibility across robot platforms remain significant challenges. Future advancements will focus on developing standardized software frameworks, plug-and-play hardware interfaces, and distributed decision-making architectures that enhance scalability. This approach will improve maintainability and enable efficient integration of emerging AI techniques, thereby extending the lifespan and adaptability of robotic systems.

6.2.11. Simulation and digital twin technology

Simulation and digital twin technologies are increasingly employed to refine and validate decision-making algorithms before real-world deployment. Digital twins create virtual replicas of physical robots and their operating environments, allowing researchers to test algorithms under various simulated conditions, identify potential failure points, and optimize performance without the risks and costs associated with field experiments.

Despite these advantages, challenges such as real-time synchronization between physical and virtual models, high computational demands, and accurate environmental modeling must be addressed. Future developments will focus on enhancing the fidelity of digital twin simulations through advanced physics-based modeling, real-time sensor feedback integration, and AI-driven predictive analytics. These improvements will accelerate decision algorithm optimization while reducing reliance on expensive real-world trials, ultimately improving the robustness and efficiency of heterogeneous underwater multi-robot systems.

7. Energy management of heterogeneous aquatic robot system

Heterogeneous aquatic robot systems are at the forefront of aquatic environment exploration and development technologies, widely applied in marine resource surveys, environmental monitoring, scientific research, and rescue missions. However, the unique characteristics of the aquatic environment, such as high pressure, low temperatures, darkness, ocean currents, and communication difficulties, pose severe energy supply challenges for these robots [194]. Effective energy management strategies are crucial for ensuring the continuous operation of these robots, improving operational efficiency, and guaranteeing mission success.

7.1. Current research

With the continuous advancement of ocean exploration, the energy management of heterogeneous aquatic robot systems has become a research hotspot. During task execution, the energy consumption patterns, efficiency, and sustainability directly affect the success rate of missions and the survivability of the robots. Therefore, advancements in energy management technologies are essential for driving technological progress in the field of aquatic robotics. Currently, researchers are addressing the challenges of energy management from multiple angles, including improving energy utilization efficiency, developing new energy harvesting technologies, enhancing battery and energy storage systems, applying intelligent control strategies, and achieving coordinated operations of multi-robot systems.

7.1.1. Energy efficiency optimization

Researchers are committed to developing highly efficient propulsion systems and energy use strategies to reduce energy losses and enhance the operational efficiency of robots. This includes using advanced hydrodynamic designs to reduce water resistance and optimizing task execution sequences and path planning through algorithms to minimize energy consumption. Research also involves improving the shape [195] and the movement patterns of robots, such as mimicking the swimming mechanisms of marine organisms to reduce energy expenditure. For instance, Yang *et al.* [196] propose an economic model predictive control (EMPC)-based controller to reduce the control energy of AUVs while performing waypoint tracking.

7.1.2. Energy harvesting technologies

To achieve self-sustained operation of heterogeneous aquatic robots, researchers are exploring the utilization of natural underwater energy sources, such as hydrodynamic energy, wave energy, solar energy, salinity gradient energy and thermal gradient energy [197–201]. The design of these energy harvesting systems and the enhancement of energy conversion efficiency are current research focuses, involving the development of new energy harvesting devices and the improvement of existing technologies. By deploying an energy-harvesting kite, Reed *et al.* [202] achieve efficient energy resupply and extended operational endurance for autonomous underwater vehicles during the execution of oceanographic observation missions.

7.1.3. Battery technologies and energy storage

Battery technology is at the core of energy supply for heterogeneous aquatic robots [203–205]. Current research focuses on increasing the energy density, cycling stability, and safety of batteries. New energy storage technologies, such as supercapacitors and fuel cells, are also being actively explored to provide more efficient energy storage solutions [206]. Research also emphasizes wireless energy transfer, Hydrogen energy storage and battery thermal management to ensure performance and longevity in extreme aquatic environments [207–210].

7.1.4. Intelligent control strategies

With the advancement of artificial intelligence technologies, intelligent control strategies are playing an increasingly significant role in the energy management of heterogeneous aquatic robots. Through machine learning and predictive algorithms, robots can adjust their energy consumption patterns in real-time based on task demands and environmental changes, achieving more precise and efficient energy management. Intelligent control strategies also include adaptive energy allocation algorithms that dynamically adjust energy usage based on the robot's real-time status and anticipated tasks. For instance, Lyu *et al.* [211] have developed a gliding hybrid aerial-aquatic vehicle, with experimental results indicating that underwater gliding consumes significantly less power than aerial propulsion. Tijjani *et al.* [212] have designed a ROV named Leonard, achieving passive stability through an optimized configuration of its center of buoyancy and center of gravity, thereby effectively reducing energy consumption.

7.1.5. Coordination

In heterogeneous aquatic robot systems, energy optimization can be significantly improved through coordinated control strategies. Researchers are exploring communication and coordination mechanisms to achieve energy sharing and task collaboration among robot swarms [213–217]. Further research into swarm intelligence will promote effective cooperation among robots, enhancing overall system energy utilization efficiency and task execution capability.

In the context of heterogeneous multirobot teams performing multiple tasks, Notomista *et al.* [213] propose an energy-aware framework that dynamically assigns tasks to robots in an online manner. Targeting long-duration autonomy, their approach emphasizes system survivability. Task prioritization and execution are formulated as constraints within an optimization problem that aims to minimize energy consumption at each time step, ensuring that robots operate efficiently while maintaining task effectiveness. Building on similar principles, Wang *et al.* [214] introduce a time- and energy-efficient minimum input optimization method that adjusts task priorities for individual or multiple AUVs, further enhancing the energy efficiency of task execution in underwater robotic operations.

Besides, the energy level of USVs is not directly reflected in the observed state, but energy consumption is primarily related to three parameters: speed, voyage, and displacement, which can be obtained in the observed state, allowing for the indirect calculation of energy consumption. Based on this, Zhao *et al.* [215] designed a formation control model that indirectly reflects the energy state. In the formation, once certain USVs deplete their energy, they autonomously withdraw from the formation, which is then dynamically restructured.

7.2. Unresolved issues and future research directions

In addressing the future challenges and opportunities in energy management for heterogeneous aquatic robot systems, researchers are focusing on a range of innovative technologies and interdisciplinary approaches to achieve breakthroughs in performance and expand the scope of applications [218]. Future developments will not only focus on enhancing the performance metrics of existing technologies but also on developing entirely new energy acquisition, storage, management, and utilization strategies. These research directions will collectively push the boundaries of aquatic robotics, providing stronger and more reliable technical support for sustainable marine resource development, in-depth marine environment monitoring, and frontier marine scientific exploration.

7.2.1. Limitations of existing energy storage technologies

Energy storage is key for aquatic robots. Current batteries like Li-ion, Li-Po, and fuel cells have flaws in energy density, efficiency, lifespan, and adaptability, which restricts robots in complex marine environments. Under extreme underwater conditions, Li-ion batteries face electrochemical instability due to electrolyte changes under high pressure, and their enclosures may be damaged. Low-temperature regions reduce ion transport, lessening capacity and speeding up degradation. High-energy-density batteries also have safety risks like a thermal runaway.

Alternative technologies such as supercapacitors and fuel cells have been studied. Supercapacitors have high power density but low energy density and need improvements for marine use. Hydrogen fuel cells are promising, yet hydrogen storage has leakage and catalytic degradation issues in saline environments. To address these, future research should develop high-pressure-resistant materials like solid-state electrolytes and use nanocoatings on battery casings. Graphene-based electrodes and self-heating can boost cold-weather performance. Hybrid systems, corrosion-resistant catalysts for fuel cells, and solid-state hydrogen storage materials can enhance energy storage for aquatic robots. Advancing energy storage technology is essential for better-performing aquatic robots. Integrating material science, electrochemical engineering, and energy management can lead to better-performing robotic systems in extreme marine environments, enabling more underwater exploration.

7.2.2. Adaptability of energy harvesting systems in complex marine environments

Aquatic robots struggle to get sustainable energy in unpredictable seas. Conventional batteries are insufficient, so harvesting from marine resources is explored. Hydrodynamic, wave, solar, salinity gradient, and thermal gradient energy harvesting face underwater efficiency, reliability, and adaptability issues. Hydrodynamic energy harvesting uses ocean currents but is sensitive to velocity and turbulence, with unstable output. Devices must resist high-pressure and biofouling. Research focuses on adaptive turbines and biomimetic harvesters. Wave energy harvesting has offshore potential but limited depth and structural risks in bad weather. Researchers develop flexible, submersible converters.

Solar energy benefits surface robots but is limited by clouds, turbidity, and cycles. Deep-sea use is unfeasible. High-efficiency solar cells are in development, and storage needs optimization. Salinity and thermal gradient energy harvesting are emerging but face membrane fouling and efficiency problems. Nanostructured materials are being explored. Energy harvesting in seas relies on intelligent management and integration. Autonomous regulation, hybrid systems, and machine-learning control are crucial. Future research should enhance durability, efficiency, and deployability. Bioinspired materials and field testing are important. Solving these can revolutionize aquatic robot autonomy.

7.2.3. Real-time adaptability of intelligent energy management systems

Efficient energy use is vital for long-term aquatic robot missions in dynamic marine settings. Traditional pre-programmed energy management cannot adapt to real-time changes. AI and ML integration offers a solution, but current intelligent strategies face issues in computational efficiency, prediction accuracy, and energy reallocation. Power distribution among robot subsystems like propulsion, sensing, and communication is a key problem. Though used for energy optimization, AI-driven methods such as RL and MPC are computationally complex and slow to respond. Lightweight neural networks and edge computing are being explored to speed up intelligent energy algorithms. Current intelligent energy systems rely on historical data for prediction, which fails during sudden environmental shifts. Adaptive learning with real-time sensor feedback, like hybrid AI models, is needed to boost responsiveness.

In multi-robot systems, coordinated energy allocation is crucial. Existing centralized multi-robot energy management has single-point-of-failure and communication problems. Decentralized control based on swarm intelligence, inspired by marine organism behavior, is being studied. Real-time energy management must also handle failures. Current fault-tolerant methods are not ideal for extended missions. Self-healing energy networks using AI-based anomaly detection could enhance resilience. Blockchain-based smart contracts for energy trading between robots are being explored to improve adaptability, especially in large-scale ocean missions. Future intelligent energy management should focus on better computational efficiency, real-time prediction, and decentralized decision-making. Combining AI control, sensor feedback, adaptive learning, and interdisciplinary efforts will lead to more autonomous and energy-efficient aquatic robot operations.

7.2.4. Energy coordination and optimization in multi-robot systems

Energy coordination in multi-robot systems is critical for optimizing mission efficiency and extending operational endurance. Unlike single-robot management, multi-robot energy optimization requires dynamic allocation strategies that consider task distribution, energy sharing, and motion planning under varying environmental conditions. However, existing approaches face challenges in balancing energy consumption, reducing communication overhead, and ensuring real-time adaptability.

One major challenge is the unequal energy consumption among heterogeneous robots, such as autonomous underwater vehicles (AUVs) and unmanned surface vehicles (USVs), due to differences in propulsion and sensing requirements. Traditional task allocation methods rely on static planning, which fails to adapt to real-time energy fluctuations. Recent research has introduced adaptive task scheduling using reinforcement learning and game theory, allowing robots to dynamically reassign tasks based on residual energy and mission priorities.

Inter-robot energy sharing offers a promising solution for extending operational time, but current wireless energy transfer (WET) technologies remain limited by transmission efficiency and alignment constraints. Advances in adaptive resonance circuits and beamforming techniques aim to improve power transfer effectiveness. Meanwhile, blockchain-based energy trading frameworks provide a decentralized mechanism for fair energy redistribution among robots without centralized control.

Efficient path planning also plays a key role in energy optimization, as unnecessary movements lead to excessive power consumption. Energy-aware trajectory planning integrates power constraints into navigation strategies, enabling robots to minimize propulsion costs. Swarm intelligence techniques, such as ant colony optimization (ACO), have been explored to enhance collective motion efficiency while reducing computational overhead.

Future research should focus on integrating real-time task allocation, energy-sharing mechanisms, and motion planning into a unified framework. Decentralized and event-driven coordination strategies will be crucial for reducing communication overhead while maintaining efficiency. By leveraging artificial intelligence and adaptive control, multi-robot systems can achieve improved energy efficiency, enhancing their potential for long-duration missions in ocean exploration, environmental monitoring, and autonomous marine operations.

7.2.5. Transition from laboratory research to real-world applications

Despite significant advancements in energy management for heterogeneous aquatic robots, many technologies remain confined to laboratory settings and controlled simulations. The transition to real-world deployment poses challenges related to environmental unpredictability, system integration, and long-term reliability. Energy management strategies that perform well in simulations often fail to account for dynamic oceanic conditions, including variable currents, biofouling, and extreme pressure, which can significantly impact energy efficiency and hardware durability.

One of the key barriers to real-world implementation is the lack of standardized energy management frameworks that allow for seamless integration of different power sources, storage systems, and energy-harvesting technologies. Current robotic platforms are often developed with proprietary energy architectures, limiting their adaptability to new energy optimization strategies. To address this, modular and interoperable energy management systems are needed to facilitate technology scalability and cross-platform deployment.

Another critical issue is the validation of energy optimization algorithms under real-world constraints. Laboratory experiments typically assume ideal energy consumption patterns and simplified mission scenarios, whereas field conditions introduce uncertainties such as fluctuating energy demand, communication disruptions, and unforeseen obstacles. Deploying robots in progressively complex environments—starting from controlled test sites to open-sea operations—will be essential for refining energy management algorithms.

Future efforts should focus on real-world testing through long-term autonomous deployments and collaborative research initiatives. Establishing standardized benchmarking protocols for evaluating energy efficiency in marine robotics will accelerate the transition from theoretical research to practical applications. By addressing these challenges, energy management technologies can move beyond laboratory demonstrations to enable robust, scalable, and sustainable solutions for real-world ocean exploration, environmental monitoring, and maritime operations.

8. Ethical and environmental impacts

As the deployment of heterogeneous aquatic robot systems becomes increasingly widespread, evaluating their ethical and environmental implications is crucial. While these systems offer significant advantages in marine exploration, environmental monitoring, and resource management, their integration into natural ecosystems introduces potential risks, including habitat disruption, pollution, and ecological imbalance. Addressing these concerns requires the development of responsible deployment strategies that minimize negative impacts while maximizing the benefits of robotic applications in marine environments.

8.1. Environmental risks and challenges

One of the primary concerns associated with aquatic robotic systems is their potential to disrupt fragile marine ecosystems. The presence of autonomous underwater vehicles (AUVs), uncrewed surface vehicles (USVs), and remotely operated vehicles (ROVs) in sensitive habitats such as coral reefs, deep-sea ecosystems, and coastal environments may interfere with marine life. Physical disturbances caused by robot propulsion systems, including turbulence, noise, and sediment resuspension, can disrupt the natural behaviors of aquatic organisms. For instance, high-frequency acoustic signals used for underwater communication and navigation may affect marine species' sensory perception and migration patterns, particularly cetaceans and fish that rely on echolocation.

Additionally, the increasing use of robotic systems raises concerns regarding energy consumption and potential pollution. Many robots rely on lithium-ion batteries or fuel cells, which pose environmental risks if leakage or improper disposal occurs. Disposing electronic waste from decommissioned robotic units can also contribute to marine pollution, mainly if non-biodegradable materials such as plastics and heavy metals are used in construction. Furthermore, introducing autonomous fleets at scale may alter predator-prey dynamics and disrupt existing food chains by influencing the distribution of marine species.

8.2. Strategies for mitigating environmental impact

To minimize the ecological footprint of aquatic robotic systems, researchers and engineers must prioritize environmentally sustainable design and deployment strategies. One key approach is the development of biodegradable and eco-friendly materials for robot construction. Using biodegradable polymers, corrosion-resistant coatings, and non-toxic battery chemistries can reduce the long-term environmental impact of robotic operations and mitigate pollution risks associated with hardware disposal.

Another essential consideration is the reduction of acoustic and hydrodynamic disturbances. Engineers are exploring quieter propulsion mechanisms, such as biomimetic designs inspired by fish and marine organisms, to minimize noise pollution and reduce turbulence. Optimizing navigation algorithms to avoid sensitive habitats, such as coral reefs and spawning grounds, can prevent unnecessary ecological disruptions.

Implementing energy-efficient and renewable power sources is also critical in reducing the environmental burden of robotic systems. Advances in solar energy harvesting, microbial fuel cells, and ocean thermal energy conversion (OTEC) can provide alternative power solutions that decrease reliance on conventional batteries and fossil fuel-based energy sources. These renewable energy solutions can extend mission durations while reducing the risk of chemical contamination from battery failures.

Furthermore, responsible deployment policies can ensure that robotic systems contribute positively to environmental protection. Regulatory frameworks should establish guidelines for monitoring the ecological impact of robotic operations, including requirements for environmental assessments before large-scale deployments. Integrating robotic systems into marine conservation efforts, such as habitat restoration projects and pollution cleanup initiatives, can also help offset their environmental footprint. Additionally, interdisciplinary collaboration between marine biologists, engineers, and policymakers can facilitate the development of ethical guidelines that align technological advancements with sustainability goals.

8.3. Ethical considerations and future perspectives

Beyond environmental concerns, deploying autonomous aquatic robots raises broader ethical questions regarding data privacy, accountability, and equitable access to marine resources. Robotic systems for ocean surveillance and resource exploration must be carefully regulated to prevent conflicts over territorial waters and ensure fair distribution of oceanic resources. Transparent data collection, sharing, and usage policies will be essential to addressing potential geopolitical and commercial disputes arising from autonomous marine operations.

Future research should focus on advancing eco-conscious robotic technologies that prioritize minimal ecological impact while enhancing marine conservation efforts. Integrating sustainability into the design, deployment, and operation of robotic systems makes it possible to harness the full potential of aquatic robotics without compromising the health of marine ecosystems. As robotics technology continues to evolve, a balanced approach that considers technological progress and environmental stewardship will be vital in shaping the future of autonomous marine exploration.

9. Applications and case studies

Heterogeneous aquatic robot systems have been successfully deployed in a wide range of real-world applications, demonstrating their ability to enhance marine exploration, environmental monitoring, and underwater infrastructure management. This section highlights several key case studies that showcase the practical implementation of these systems in various domains.

9.1. Environmental monitoring and oceanographic research

One of the most prominent applications of aquatic robot systems is large-scale marine environmental monitoring. For instance, the Monterey Bay Aquarium Research Institute (MBARI) has extensively deployed autonomous underwater vehicles (AUVs) and unmanned surface vehicles (USVs) for long-term oceanographic studies. These robotic systems are equipped with multi-sensor payloads to collect data on water temperature, salinity, dissolved oxygen levels, and marine biodiversity. In a recent MBARI-led study, a fleet of AUVs was used to map deep-sea ecosystems, providing valuable insights into the impact of climate change on marine habitats.

Similarly, the Seabed Autonomous Underwater Vehicle (Seabed AUV), developed by the Woods Hole Oceanographic Institution, has been deployed for coral reef monitoring. This system is designed for close-range seafloor imaging, producing high-resolution 3D maps of coral reefs to assess bleaching events and biodiversity loss. By integrating machine learning algorithms, researchers have automated the identification of coral species and ecosystem health indicators, improving the efficiency of conservation efforts.

9.2. Pollution cleanup and underwater waste management

Heterogeneous robotic systems have also been deployed to tackle marine pollution, including plastic waste removal and oil spill mitigation. The WasteShark, developed by RanMarine Technology, is a USV designed for autonomous water surface cleaning. Operating similarly to a robotic vacuum, it collects floating debris, algae, and plastic waste in ports and harbors. In multiple case studies across European cities, WasteShark has successfully removed thousands of kilograms of waste while minimizing human intervention.

For deep-sea waste retrieval, remotely operated vehicles (ROVs) such as Ocean Cleanup's Interceptor System have been deployed to remove submerged plastics from polluted ocean gyres. These systems utilize machine vision and AI-based detection to locate and retrieve underwater debris, contributing to large-scale ocean cleanup operations.

9.3. Deep-sea exploration and resource extraction

Heterogeneous aquatic robot teams have played a critical role in deep-sea exploration, particularly in mapping uncharted territories and searching for valuable mineral resources. The Nereus hybrid remotely operated vehicle (HROV), developed by Woods Hole Oceanographic Institution, was designed to operate at depths exceeding 10,000 meters in the Mariana Trench. Its successful deployment in the Challenger Deep provided high-resolution seafloor imagery, leading to groundbreaking discoveries about deep-sea hydrothermal vent ecosystems.

In commercial applications, companies such as Nautilus Minerals have used fleets of autonomous robots to explore seabed mineral deposits rich in rare earth metals. These robots operate under extreme pressure conditions, using sonar mapping and robotic arms to analyze deep-sea mining sites while minimizing human risk.

9.4. Search and rescue missions

Aquatic robots have been instrumental in disaster response and search-and-rescue operations, particularly after maritime accidents. During the 2011 Fukushima nuclear disaster, AUVs and ROVs were deployed to assess the condition of submerged reactor structures and detect radiation leaks. These robots, such as the Bluefin-21, played a crucial role in post-disaster evaluations without exposing human divers to hazardous environments.

Similarly, during the search for the missing Malaysia Airlines Flight MH370, underwater search teams used a combination of AUVs and sonar-equipped USVs to scan the vast ocean floor. The HUGIN 4500, an advanced AUV used in deep-sea search missions, successfully mapped over 120,000 square kilometers of the Indian Ocean, providing critical insights into oceanic topography.

9.5. Offshore infrastructure inspection and maintenance

In industrial settings, robotic systems are increasingly used for offshore oil rig inspection and underwater infrastructure maintenance. BP and Shell have incorporated robotic solutions such as the Eelume snake-like robot, which autonomously navigates underwater pipelines and inspects for potential leaks or structural weaknesses. By deploying such systems, companies can reduce the need for human divers, improving safety and reducing maintenance costs.

Similarly, the SAAB Seaeye Falcon, an ROV used for underwater pipeline inspections, has been deployed across multiple offshore energy sites. These robots perform non-destructive testing (NDT), using ultrasonic and laser scanning techniques to identify defects in underwater structures before they escalate into critical failures.

These case studies demonstrate the real-world impact of heterogeneous aquatic robot systems across various domains, from environmental conservation and disaster response to industrial applications and deep-sea exploration. By integrating AI-driven autonomy, energy-efficient propulsion, and multi-sensor capabilities, these systems have revolutionized marine research and operational efficiency. As robotic technologies continue to advance, their role in sustainable ocean management and intelligent marine exploration will become even more significant.

10. Conclusion

In conclusion, heterogeneous aquatic robot systems have great potential for applications in environmental monitoring, exploration, and task execution. This paper reviews the key technologies enabling these systems: communication, perception, navigation, control, decision-making, and energy management. Key advancements in communication technologies, such as underwater acoustic, radio, and optical systems, facilitate efficient collaboration among robots [219–221]. Multi-sensor fusion improves environmental awareness, while collaborative navigation and dynamic task allocation enhance system autonomy. Advanced control methods, including deep reinforcement learning and end-to-end control, show promise in improving task efficiency and adaptability. AI-based decision-making technologies increase the robots' ability to function in complex environments, and progress in energy management ensures more efficient operations [222–224]. Despite these advancements, challenges remain in system integration and real-time adaptability. This paper summarizes current research and identifies key areas for future development, providing a clear roadmap for further technological advancements in heterogeneous aquatic robot systems.

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Author's contribution

Ruonan Liu: conceptualization, formal analysis, writing—original draft; Xiuzhong Hu: data curation, visualization; Zihan Jiang: investigation, methodology; Junzhi Wang: resources, software; Weidong Zhang: supervision, project administration; writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interests

The authors declare no conflict of interest.

Nomenclature

Abbreviation	Description	Abbreviation	Description
ROV	Underwater Remotely Operated Vehicle	AUV	Autonomous Underwater Vehicle
ASV	Autonomous Surface Vehicle	UAV	Unmanned Aerial Vehicle
LiDAR	Light Detection and Ranging	IMU	Inertial Measurement Unit
GNSS	Global Navigation Satellite System	UHI	Underwater Hyperspectral Imaging
RGB	Red, Green, Blue	cDOM	Color Dissolved Organic Matter
TSM	Total Suspended Matter	SLAM	Simultaneous Localization and Mapping
GP	Gaussian Process	UT	Ultrasonic Testing
CP	Cathodic Protection	DCM	Deep Chlorophyll Maximum
OFDM	Orthogonal Frequency Division Multiplexing	MIMO	Multiple - Input Multiple - Output
USBL	Ultra - Short Baseline	LBL	Long Baseline
GIS	Geographic Information System	PID	Proportional - Integral - Derivative
MPC	Model Predictive Control	DRL	Deep Reinforcement Learning
UCH	Underwater Cultural Heritage	EMPC	Economic Model Predictive Control

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