Machine-Learning-Aided Mission-Critical Internet of Underwater Things

Xiangwang Hou, Jingjing Wang, Zhengru Fang, Xin Zhang, Shenghui Song, Xudong Zhang, and Yong Ren

Abstract

With people paying more attention to marine resources, the Internet of Things (IoT) has been extended to underwater, promoting the development of the Internet of Underwater Things (IoUT). Various compelling IoUT applications bring a new age to maritime activities. However, some mission-critical maritime activities, including ocean earthquake forecasting, underwater navigation, and so on, pose a substantial challenge on existing IoUT architectures and relevant techniques. Therefore, in this article, to empower these implacable maritime activities, we conceive the concept of mission-critical IoUT and highlight its key features and challenges. Furthermore, to satisfy the stringent requirements of mission-critical IoUT, we propose a future maritime network architecture and machine-learning-aided key techniques in terms of information sensing, transmission, and processing. Moreover, we present our recent research on reliable and low-latency underwater information transmission. Finally, we provide the open issues and potential research trends for future mission-critical IoUT.

Introduction

The future network aims to integrate various communication networks to provide seamless information services anytime and anywhere. As an inalienable part of the future network, the maritime information network supports the traditional fishery industry, and plays a vital role in marine transport, international trade, and even military activities. With the aid of maritime satellites, we can fulfill wide-coverage and high-precision monitoring and reliable communications on the surface of the ocean. However, underwater information acquisition is a significantly difficult problem due to the complex underwater environments and limited technologies. Recently, the Internet of Underwater Things (IoUT) [1], relying on massive underwater sensors and equipment, provides a feasible approach for sensing, monitoring, and driving underwater environments as well as objects. Based on it, we can build a "smart ocean" characterized by transparency, controllability, and intelligence.

In the past few years, lots of efforts have been made to promote the emergence of some basic and practical IoUT applications, including environment monitoring, fishery resource detection, and so forth. These IoUT applications bring significant convenience and substantial economic value for human beings. Nevertheless, with the further development of marine exploration, more requirements are put forward for advanced IoUT applications, for instance, ocean earthquake forecasting, underwater navigation, underwater moving target detection, which can be referred to as mission-critical IoUT. Unlike the aforementioned IoUT applications, the so-called mission-critical IoUT applications have stringent requirements, including reliability, latency, timeliness, and so on. If the mission-critical IoUT applications' requirements are not met, it may lead to ineffective decision making and error control, and even systemic disasters. Although mission-critical IoUT has a promising prospect, the complex underwater environment poses several obstacles to its development, specifically the following.

Information Sensing: The primary facet for supporting mission-critical IoUT is to ensure data collection accuracy, determining whether the subsequent data analysis results are valid. However, due to the vast area and complex underwater environment, deployed IoUT devices are easily damaged or interfered with, demanding a set of approaches to realize accurate underwater information collection with fault tolerance and destruction resistance.

Information Transmission: Information transmission is one of the most challenging goals in complex underwater environments. The uneven temperature, salinity, static pressure, and other hydrological characteristics of seawater, and the time-varying ocean currents and irregular underwater topography lead to serious interference, which turns various mature communication methods (e.g., radio communication) powerless. Achieving reliable and timeliness-ensuring information transmission requires us to make a brand new design.

Information Processing: The data collected by IoUT devices is enormous, but with lots of useless information because of the sparse feature of the ocean, which leads to excessive delay of transmission, as well as a colossal waste of communication resources. Processing the collected data is exceptionally computation-intensive, and in the meantime, mission-critical IoUT has stringent timeliness requirements. Hence, it is essential to construct an efficient data processing framework and methodology to satisfy the requirements.

The bright future of mission-critical IoUT motivates us to conceive a novel maritime architecture that can meet the stringent demands, and collaborate well with terrestrial networks and

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space-air networks for unleashing the endless vitality of mission-critical IoUT. Moreover, the special underwater environments characterized by large scale, time variance and sparsity severely challenge the traditional network techniques relying on the deterministic method. There is an intensive demand for a series of revolutionized network techniques that can satisfy the stringent application requirements and adapt to the complex underwater environments.

However, as far as we know, there is no existing work specifically discussing the difficulties encountered by mission-critical IoUT and the corresponding solutions to empower it. Therefore, to bridge this gap, in this article, we are motivated to conceive a future maritime network architecture utilizing multiple heterogeneous platforms, including autonomous underwater vehicles (AUVs), floating platforms, satellites, unmanned aerial vehicles (UAVs), and so on, by integrating multiple communication methods. Furthermore, considering the advantages of machine learning (ML) algorithms in dealing with large-scale data, time-varying problems, as well as strong adaptive abilities [2], we are inspired to give our insights on ML-empowered key techniques for mission-critical IoUT in terms of effective and fault-tolerant information sensing, reliable and low-latency information transmission, and reliable and fast information processing, respectively.

This article commences with a discussion of current advances related to IoUT. Furthermore, we propose a future maritime network architecture and emphasize the ML-aided key techniques for mission-critical IoUT in terms of information sensing, information transmission, and information processing, respectively. After that, the latest research advances on information transmission for mission-critical IoUT are presented. Finally, the challenges and open issues are discussed, followed by the conclusions.

State-of-the-Art Literature on IoUT

Although the prosperous prospect of IoUT, compared to the terrestrial Internet of Things (IoT), the development of it remains at an early stage due to complex environments and technical difficulties.

In recognition of the strong application potential of the IoUT, Kao *et al*. [3] conducted a comprehensive survey of the early-stage literature of IoUT, and discussed its practical applications. Furthermore, the authors investigated the differences between IoUT and traditional IoT, and highlighted the challenges that IoUT may suffer. Qiu *et al.* [1] discussed the current advances, applications, and future system architecture of IoUT, and emphasized the crucial roles of cloud computing and fog computing in IoUT data processing. Focusing on the problem of underwater information transmission, Xu *et al.* [4] proposed a sender-receiver role-based scheduling protocol for energy-aware scheduling relying on spatial-temporal reuse. To transmit sensor data from IoUT devices to a remote onshore data processing center, Wang *et al.* [5] conceived a UAV-aided underwater information acquisition framework relying on sink nodes on the water surface and UAVs as intermediate relays. Zhou *et al*. [6] proposed an enhanced channel-aware routing protocol for IoUT, characterized by low energy consumption and adaptability to the marine environment. Moreover, Gupta *et al.* [7] illustrated existing information collection schemes for IoUT, and performed a comprehensive comparative analysis of them in terms of packet drop ratio, latency, energy consumption, and so on.

To sum up, several early-stage efforts have been made on the IoUT. However, there is still a lack of full knowledge on mission-critical IoUT, for which higher service requirements (e.g., latency, reliability, timeliness) make it intensely different. Hence, we are inspired to discuss its architecture, key techniques, and open issues systematically.

Future Maritime Network Architecture and Key Techniques for Mission-Critical IoUT

Future Maritime Network Architecture

The future maritime network can collaborate well with space-air networks and terrestrial networks to provide reliable and timely information services for mission-critical IoUT.

Maritime Network: As shown in Fig. 1, the maritime network can be divided into three layers.

Seabed Layer: On the seabed, massive IoUT devices (e.g., cameras, sensors, detection equipment) are deployed at the bottom of the ocean to collect a large amount of valuable ocean data to realize underwater environment perception. These IoUT devices can realize collaborative perception and information aggregation via optical cable communication, magneto-inductive communication, as well as underwater acoustic communication (UAC).

Underwater Layer: Furthermore, due to the enormous observation areas, AUVs, submersible buoys, and submarines are widely adopted to implement dynamic and flexible data transmission, fusion, and near-real-time underwater processing. Obviously, optical-cable-based communication is not suitable, and the radio frequency communication widely adopted in the terrestrial network cannot transmit the collected data across the water with high reliability and data rate due to the great propagation loss underwater. Therefore, UAC and wireless optical communication are better choices.

Surface Layer: By deploying floating platforms (e.g., surface base stations, ships, and buoys on the sea surface), several communication systems, such as 3G/4G/5G/WiMAX, can be adopted to realize data backhaul link with seashore terrestrial networks [8]. Moreover, in the far-reach sea area, utilizing satellites to support data backhaul is also a possible approach via L/S/C/Ka/Ku-band. In addition, the automatic identification system (AIS), as an open data transmission system, has been widely accepted in maritime traffic control and surveillance networks to collaborate with the aforementioned cellular communication systems and satellite systems to form the future maritime network.

Terrestrial Network: The terrestrial network mainly takes charge of three responsibilities. First, since several mission-critical IoUT services are employed on the seaside, such as smart seaport, orchestrating maritime and seashore communication infrastructures to support the mentioned sea-

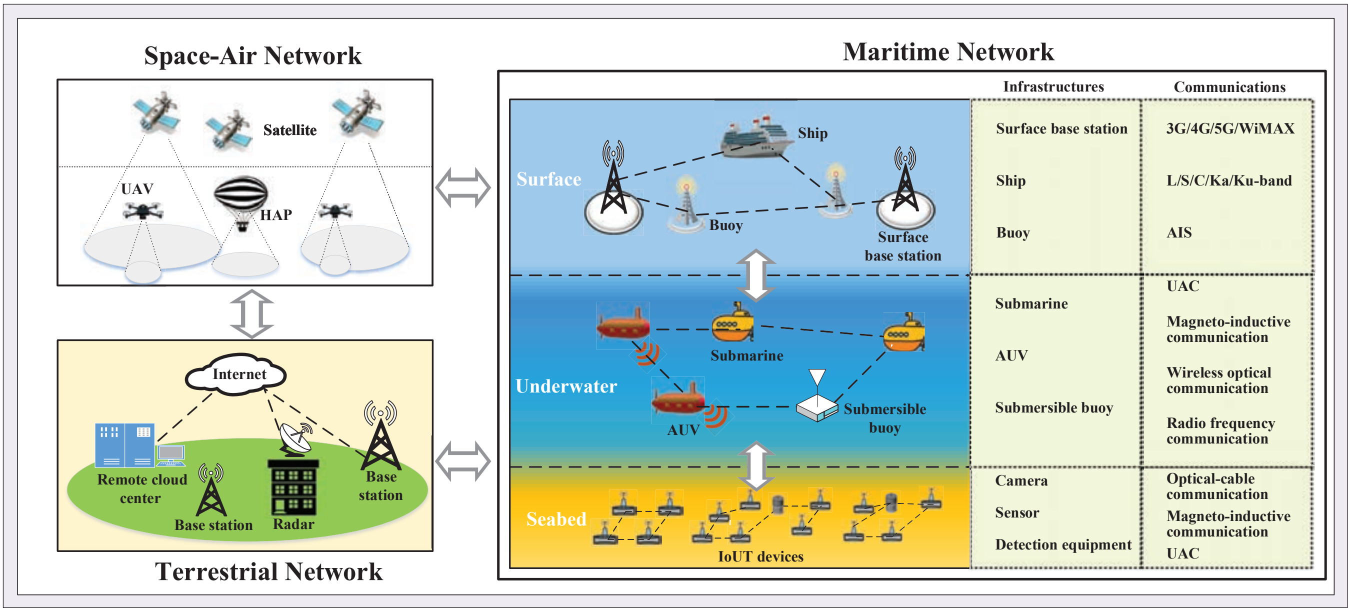

FIGURE 1. Future maritime network architecture for mission-critical IoUT.

shore services, is suitable and reliable. Second, a large amount of collected ocean data needs to be transmitted to the ground control center for further analysis, and the seashore network can relay massive data at a high data rate. Finally, although a proportion of the collected data is processed in the maritime network, terrestrial cloud computing is needed to realize data mining and long-term data storage for some data-intensive applications and applications without real-time processing requirements.

Space-Air Network: UAVs and high-altitude platforms (HAPs, e.g., balloons), characterized by high flexibility, can act as relay nodes or information sink nodes to provide information reinforcement services and emergency access services. Although the limited resources and weak throughput of satellite systems make them unsatisfactory in undertaking high-rate transmission services, their strong global coverage and high security inspire us to employ them to exchange secret keys, schedule network resources, and so on.

ML-Aided Key Techniques for Mission-Critical IoUT

Traditional network techniques relying on the deterministic method are no longer suitable for mission-critical IoUT, operating in complex underwater environments characterized by large scale, time variance, and sparsity. Therefore, we are motivated to employ ML to revolutionize network methodologies for satisfying the stringent requirements of mission-critical IoUT. Here, we give our insights on the ML-empowered key techniques from the aspects of effective and fault-tolerant information sensing, reliable and low-latency information transmission, and reliable and fast information processing, respectively.

Effective and Fault-Tolerant Information Sensing:

Fault-Tolerant IoUT Deployment Strategy: IoUT devices are often deployed in harsh underwater environments, and ensuring uninterrupted and accurate information sensing is a significant but difficult issue. On one hand, the energy consumption of the IoUT device is limited, and it is generally impossible to charge the device or replace its depleted battery. Once the battery runs out, the device cannot continue to work. On the other hand, obstacles, antenna angles, signal interference, and malicious attacks can also lead to failure of an IoUT device. Therefore, fault-tolerant IoUT device deployment strategy is extremely necessary to meet the high-reliability demands of mission-critical IoUT. However, in complex underwater environments, numerous factors may lead to device error or failure. The relationship between these factors and the probability of device failure are usually time-varying and nonlinear. It is difficult to derive a deterministic mathematical model. The deep neural network (DNN) [9], which has powerful inferring and data analysis capabilities using large amounts of historical data, is a suitable method to cope with it. We can employ DNN to capture the nonlinear and dynamic relationship between complex environments and system failure probability to obtain a near-optimal IoUT deployment strategy.

Multi-Resource Data Fusion: Solely relying on single-type IoUT devices cannot accurately obtain the information about the observation object due to the limitations of observation ability, which may lead to wrong decision or control, causing inestimable losses in mission-critical IoUT. Moreover, the complex underwater environments, involving ocean currents, biological activities, and so on, may bring random interference on IoUT devices. Thus, the accuracy and robustness of the collected data are significantly weakened. Therefore, it is essential to realize the collaborative perception and data fusion of diverse sensor data, which can dramatically cope with imperfect raw data for obtaining reliable and accurate information. However, traditional data fusion strategies, mainly including evidential belief reasoning fusion (e.g., Dempster-Shafer theory), probabilistic fusion (e.g., Bayesian theory), and rough set-based fusion, appear to be powerless [10] against the IoUT data fusion problems characterized by high-dimensionality and nonlinearity. ML is expected to bring new opportunities for data fusion. The

Machine learning methods	Mission-critical IoUT applications	Advantages	Disadvantages
Backpropagation neural networks	Large-scale sensing data fusion	High robustness	Need lots of data
		High scalability	High computational complexity
Elman neural networks	Navigation system	Strong adaptability to time-varying issue	High computational complexity
		High accuracy	
Support vector machine	Real-time sensing data fusion	Supporting small sample learning	Low convergence rate
		High robustness	Weak adaptability to large-scale data
Reinforcement learning	Distributed sensing data fusion	Strong global optimization ability	Weak scalability to data dimension
K-means clustering	Multi-target tracking	Low computational complexity	Stringent requirements on raw data
		High convergence rate	Low robustness
Fuzzy clustering	Intrusion detection	No need for prior information	Weak scalability to large-scale data
		No need for classification information	High computational complexity
Self-organizing clustering	Moving target indication	High robustness	Low convergence rate
		No need for prior information	High computational complexity

TABLE 1. Characteristics and application scenarios of the ML-enabled multi-source data fusion strategies in mission-critical IoUT.

Communication type	Communication range	Maximum rate	Advantages	Disadvantages
Acoustic communications	10^3 m	kb/s	Small attenuation	Low data rate
			Long transmission distance	Susceptible to interference
Radio communications	10^2 m	Mb/s	High data rate	Short transmission distance
			Low consumption	Severe multi-path interference
Visible light communications	10^2 m	100 Mb/s	High data rate	Severe scattering
			Low cost	Environmental damage
Magneto-inductive communications	10^1 m	Mb/s	High data rate	Short transmission distance

TABLE 2. Comparison of different underwater wireless communication methods.

characteristics and application scenarios of the ML-enabled multi-source data fusion strategies in mission-critical IoUT are summarized in Table 1.

Reliable and Low-Latency Transmission:

Multimodal Integrating Cooperative Communication: Due to severe multi-path interference, narrow available bandwidth, serious signal attenuation, and the Doppler effect of the underwater channel, underwater wireless communication has become one of the biggest problems restricting the development of mission-critical IoUT. At present, there are four recognized underwater wireless communication methods, including UAC, radio communication, wireless optical communication, mainly visible light communication (VLC) with the wavelength in 380~40 nm, and magnetic-inductive communication. Their advantages and disadvantages are shown in Table 2. We can see that none of them can solely meet the stringent transmission requirements of mission-critical IoUT. Hence, we are motivated to combine them to realize multimodal integrating cooperative communication. This means it can select different communication methods according to the different requirements for downlink and uplink channels, or use multiple communication methods simultaneously to realize highly reliable redundant transmission. At present, one of the most competitive research trends of multimodal integrated cooperative communications is underwater opto-acoustic communication. Opto-acoustic communication has the advantages of both optical communication and acoustic communication to achieve high data rate and long-distance transmission. Obviously, efficient channel perception and intelligent decisions in the complex environment are key enablers for realizing multimodal integrated cooperative communication. Reinforcement learning [11], one kind of ML, characterized by dynamic-adaptive learning ability, can play a crucial role in dealing with multi-dimensional complex channel perception and intelligent decision making.

Multi-AUV-Assisted Cooperative Information Collection and Transmission: To address the difficulty in building fixed observation stations and information access stations in the vast and complex marine environment, using flexible AUVs to realize information collection and transmission has been widely accepted. Unlike non-mission-critical IoUT services that just balance the multi-AUV system's cost and the average system performance, mission-critical IoUT makes stringent requirements on multi-AUV cooperation on a single task, even on a single time slot. Therefore, it motivates us to use fine-grained control of multi-AUV collaboration under the consideration of time-varying underwater environments, including path planning, and collaborative information collection and

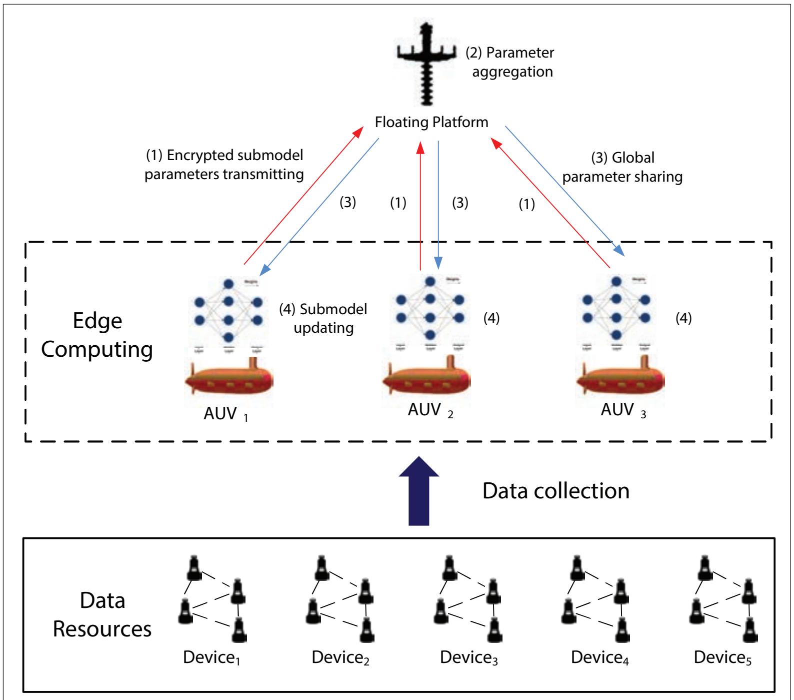

FIGURE 2. Edge computing enabled distributed federated learning.

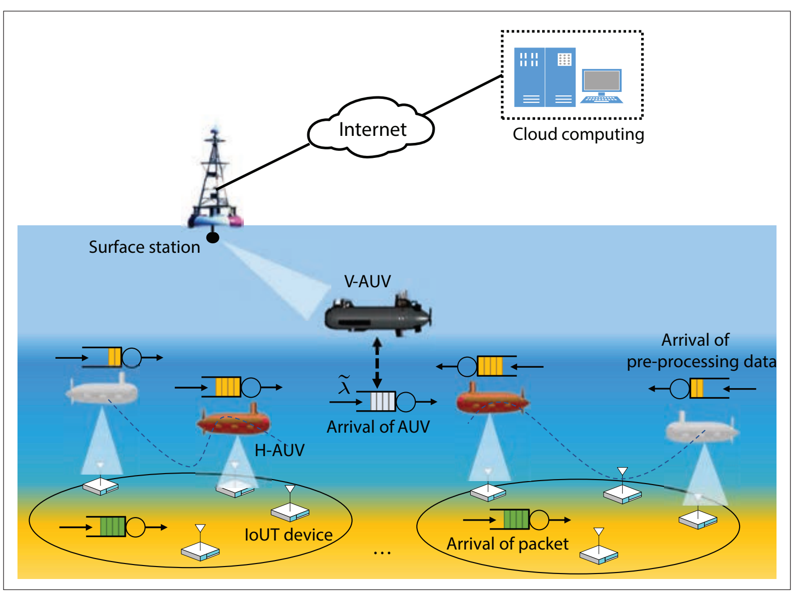

FIGURE 3. Multi-AUV-assisted information collection for mission-critical IoUT.

[1] Today's AUV has already equipped a large number of sensors and computing power to perform various tasks, including search and rescue, environment monitoring, underwater mapping, and so on. For instance, Proteus, developed by Huntington Ingalls Industries, weighing 3.7 tons with a payload of 1.6 tons, can operate continuously for 600 km at an average speed of 5–9 knots. The AUVs have enough payload space and power supply to run an ML model.

transmission. However, on one hand, the control of AUV is significantly related to complex and time-varying underwater environments, which makes it difficult to establish an accurate dynamic model. On the other hand, scheduling multiple AUVs to realize efficient cooperation within the stringent service requirements is also significantly hard. Hence, we can employ reinforcement learning to realize time-varying environment perception and motion optimal control without a definite model, and further utilize swarm intelligence algorithms to perform efficient multi-AUV cooperation.

Reliable and Fast Processing:

Reliability-Oriented Distributed Edge Computing: The cloud-computing-based data processing approach plays an essential role in non-mission-critical IoUT applications. By aggregating the amount of data to the cloud center and digging out the valuable information hidden behind the large-scale data by data mining technology, some marine activities, such as resource exploration and fish prediction, can be conducted well. However, it is not suitable for mission-critical IoUT due to the high transmission latency. The reason for the high transmission latency mainly includes two aspects. Specifically, on one hand, data from the IoUT devices to the cloud center is often over a long distance forwarded by many intermediate nodes. On the other hand, a significant portion of the collected raw data is useless, and transmitting them results in serious resource consumption and excessive latency. Therefore, we are motivated to introduce the concept of edge computing [12] to provide low-latency computing services for mission-critical IoUT. AUVs[1] and a floating platform, close to the data resources and with certain computing ability, can be seen as edge computing nodes to process the raw data at the edge of the network. In this way, on one hand, some mission-critical IoUT services are empowered. On the other hand, a large amount of useless data is preprocessed in the network edge, which can significantly reduce the amount of transmitted data and improve resource utilization. Furthermore, the excellent thermal conductivity of seawater can significantly release the power of the computing resources. Although edge computing can bring new opportunities to mission-critical IoUT, it should be noted that, different from cloud computing with high reliability, the edge computing nodes (e.g., AUVs) face varying interference underwater. Therefore, it is essential to conceive a reliability-oriented adaptive-learning distributed cooperation strategy driven by ML.

Secure Distributed Edge Learning Framework: Maximizing the potential value of collected data under the limited resources, as well as with high security, is intensely important in mission-critical IoUT, especially in some military scenarios. Therefore, an efficient and secure ML framework is urgently needed. Federated learning is a security-protected decentralized collaborative ML framework [13]. Under the federated learning framework, each node trains its sub-model independently and only needs to interwork the encrypted sub-model parameters with the fusion node to achieve a convergent global ML model. By this means, under the premise of ensuring security and minimizing communication overhead, an effective model for digging out the potential value of the collected data can be derived. The realization for distributed edge federated learning in mission-critical IoUT is shown in Fig. 2, which can be divided into four steps:

- Participants (referring to AUVs) train their own learning model, which can be considered as a sub-model of the global model, and send their encrypted sub-model parameters only to the fusion node (referring to floating platform).
- The fusion node performs parameter aggregation without any raw data from participants.
- The fusion node sends the updated global parameters to the participants.

- Participants update their respective sub-models with the updated global parameters they receive.

Multi-AUV-Assisted Information Collection for Mission-Critical IoUT

As aforementioned, multi-AUV-assisted cooperative information collection and transmission is crucial for mission-critical IoUT. Mission-critical IoUT needs to perceive the underwater physical environment in real time to provide timely and effective information for intelligent decision making and control. However, different from the terrestrial IoT relying on radio communication, the low underwater transmission rate and AUV movement speed seriously challenge the stringent timeliness requirements of mission-critical IoUT. Therefore, we introduce our recent work to solve this issue, that is, an age of information (AoI, an indicator of the freshness of information [14]) oriented multi-AUV-assisted information collection scheme [15].

As shown in Fig. 3, we have two kinds of AUVs, specifically, H-AUV and V-AUV. H-AUV moves horizontally to collect data from IoUT devices deployed in the seabed or floated in the seawater and relays the collected information to the V-AUV, while V-AUV moves vertically to transmit the information sent by H-AUV to the floating platform. This method can reduce the frequent floating and diving movement of H-AUV for providing uninterrupted time-efficient information collection and alleviating energy consumption. Moreover, the information collection process can be modeled as a limited-service vacation queueing system. Considering the timeliness requirements of mission-critical IoUT, peak AoI is adopted to measure the freshness of information, referring to the time elapsed since the generation time of the latest received packets update at the destination. Furthermore, by jointly considering AUVs' trajectories and the upper limit of the queueing length, the system's peak AoI is minimized under the energy constraints. Figure 4 shows the peak AoI vs. arrival rate $\tilde{\lambda}$ of H-AUVs. We can see that the proposed scheme with the adaptive algorithm is better than the multi-AUV schemes without an adaptive algorithm in terms of peak AoI. With the increase of the arrival rate $\tilde{\lambda}$, the systems are overloaded without an adaptive algorithm (i.e., M = 3, 4, 5), while the proposed scheme with the adaptive algorithm is stable all along and with minimal peak AoI.

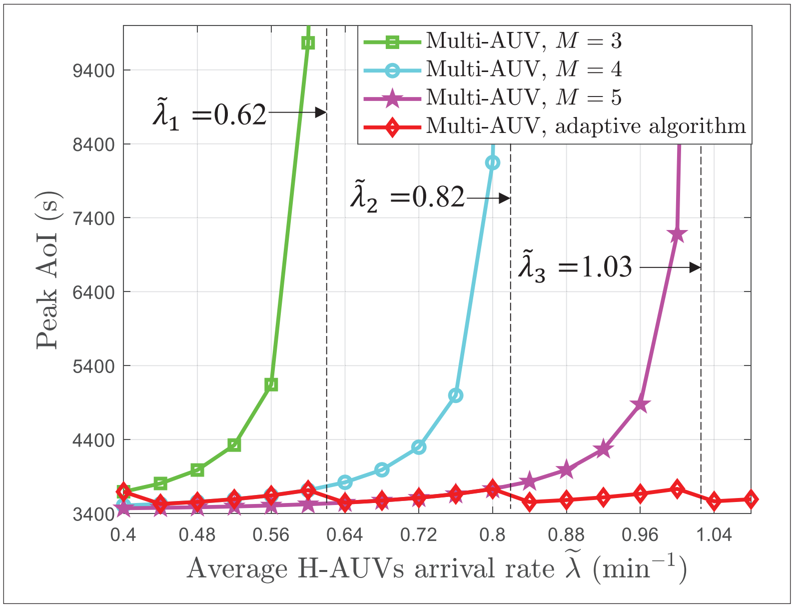

FIGURE4. Peak AoI with different arrival rates of H-AUVs [15].

Challenges and Open Issues

Reliable Multihop Transmission Control Protocol

Since most of the data must be transmitted in a multihop manner in mission-critical IoUT, the fading, noise, and interference in the marine environment will seriously threaten the reliability of communication, making it difficult to meet the requirements of mission-critical IoUT. Therefore, it is essential to comprehensively consider the factors of fairness, security, and data rate to conceive a highly reliable multihop transmission control protocol for large-scale heterogeneous networks. To deal with such a large-scale control decision optimization problem, reinforcement learning, which is good at learning in a complex environment, is a good choice.

Adaptively Adjusted Encryption and Coding Scheme

Constrained by the contradiction between limited resources and high security and reliability requirements of mission-critical IoUT, it is necessary to study an encryption and coding scheme with low resource occupancy. Supervised learning is satisfactory to realize an adaptively adjusted encryption and coding scheme according to the real-time channel characteristics, and recognize attack behaviors to ensure both the security and reliability requirements.

QoS-Aware Cognitive MAC Protocol Design

As aforementioned, UAC is the most commonly used information transmission approach underwater, but its long and time-varying propagation latency greatly challenges the medium access control (MAC) protocol design. Most of the literature on MAC protocol design is devoted to reducing the influence of long propagation latency. Nevertheless, for mission-critical IoUT, it is essential to take the quality of services (QoS) into consideration. However, the limitation of communication resources makes it difficult to satisfy the QoS requirements of mission-critical IoUT. Fortunately, it has been noted that long propagation latency and its spatiotemporal uncertainty can allow multiple transmissions to exist simultaneously in underwater acoustic media without collision and conflict, which opens up the possibility of spectrum sharing. Therefore, using ML to conceive a cognitive MAC protocol, which allows multiple nodes to access the same channel at the same frequency and the same time, can intensely improve the utilization of channel bandwidth.

Conclusions

To enable advanced marine activities, in this article, we present the concept of mission-critical IoUT and highlight its key features as well as challenges. Furthermore, we construct a future maritime network architecture for mission-critical IoUT, which can meet the stringent demands and collaborate well with terrestrial networks and space-air networks. Moreover, since the traditional model-driven network techniques rely on a deterministic method, they are unable to cope with the complex underwater environment featuring time-varying, nonlinear, large-scale, and sparse characteristics. Therefore, ML, which has strong capability in dealing with nonlinear and time-varying problems in complex environments, is employed to conceive the brand new design of network techniques for mission-critical IoUT, in terms of effective and fault-tolerant information sensing, reliable and low-latency transmission, as well as reliable and fast processing, respectively. Then we introduce our recent work on reliable and timely transmission, that is, AoI-oriented multi-AUV-assisted information collection. Finally, we envision the open issues and challenges that should be addressed in the future to exploit mission-critical IoUT. We hope that this article facilitates researchers to understand the challenges and potential research trends, and stimulate research interest in mission-critical IoUT.

In the future, we plan to conduct further in-depth research on maritime network architecture, including network protocol fusion with terrestrial networks, satellite networks, as well as air networks for improving the interoperability in the future network. Moreover, considering the widespread maritime radar systems and broadcasting systems, we are inspired to explore the coexistence paradigms with maritime radar systems and broadcasting systems for enhancing the utilization of both spectrum resources and infrastructures.

Acknowledgments

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