연합 학습기반 수중 사물 인터넷

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Federated Learning-Internet of Underwater Things

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요 약

Federated learning (FL) is a new paradigm in machine learning (ML) that enables multiple devices to collaboratively train a shared ML model without sharing their local data. FL is well-suited for applications where data is sensitive or difficult to transmit in large volumes, or where collaborative learning is required. The Internet of Underwater Things (IoUT) is a network of underwater devices that collect and exchange data. This data can be used for a variety of applications, such as monitoring water quality, detecting marine life, and tracking underwater vehicles. However, the harsh underwater environment makes it difficult to collect and transmit data in large volumes. FL can address these challenges by enabling devices to train a shared ML model without having to transmit their data to a central server. This can help to protect the privacy of the data and improve the efficiency of training. In this view, this paper provides a brief overview of Fed-IoUT, highlighting its various applications, challenges, and opportunities.

1. 서론

The Internet of Things (IoT) has been a breakthrough for the future of communications and computing and its development is growing dynamically [1]. IoT growth has been exponential in every field, including the Internet of Underwater Things (IoUT). The IoUT is a network of interconnected underwater devices that can sense, collect, and transmit data about the underwater environment. It is a promising technology for monitoring vast unexplored water areas [2]. Figure 1 is the general representation of underwater communication.

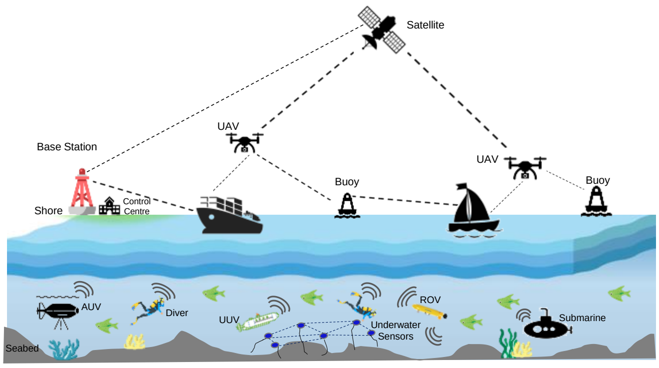

Figure 1: Underwater communication scenario.

However, a large volume of data produced by sensors, cameras and hydrophones has led to the concept of Big Marine Data (BMD). To ensure that BMD is managed properly, machine learning (ML) was brought into the light, so that the features could be learnt, and knowledge could be extracted for decision-making [3].

In traditional centralized ML, data is gathered from numerous sources and used to train a ML model in a single location. Nonetheless, ML has its limitations, so the concept of Federated Learning (FL) was introduced which demonstrated the feasibility of FL and its ability to deliver strong performance across a range of ML tasks [4]. The key advantages of FL are shown in Figure 2.

FL is a privacy-preserving ML approach where multiple parties can train a single model without sharing their raw training data. In FL, devices collaborate to train a global model on their local data and computational resources, while keeping their data private. This is done by exchanging only model updates, rather than the entire dataset, between the devices and the server [5]. Because of several advantages, there has been a growing interest in FL, and a few new FL algorithms have been proposed. FL is still a relatively new field, but it has the potential to revolutionize the way ML is used [6,7]. FL can be used to train ML models to analyze data such as water quality, temperature, and salinity and make predictions about the underwater environment while making it more secure and better [8,9].

Furthermore, recent studies have shown that federated transfer learning (FedTM) can be used to train ML models on a distributed network of devices without sharing local data. A combination of techniques, such as differential privacy and secure aggregation protects the privacy of local data and prevents defective nodes from influencing the training process [10].

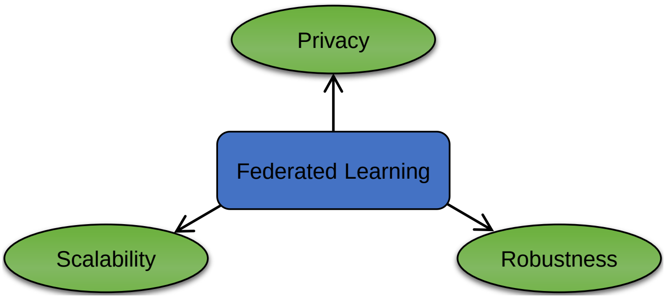

Figure 2: Key advantages of FL.

In addition, Federated Meta-Learning (FML) enhanced Acoustic Radio Cooperative (ARC) has been able to solve the problem of insufficient training data at a single buoy, by using the data distributed over multiple buoys [11].

This paper explores the utilization of FL within the context of IoUT and examines both the practical applications and the challenges that FL encounters in this domain. Additionally, it highlights various prospects and opportunities associated with FL in IoUT.

2. Applications

As the technology continues to develop, FL will likely be used in a wider range of applications to improve our understanding of the underwater environment and make it more sustainable. The trained ML models can be deployed on IoUT devices to monitor the environment in real -time. Some of the applications of FL in IoUT are described as follows:

A. Environmental monitoring: To monitor the underwater environment for pollutants, changes in water quality, and other threats FL framework can be applied. This can help to protect the environment and ensure the safety of humans and marine life [8]. For example, oil leakage can have a devastating impact on the environment and marine life. The trained FL models can then be used to monitor the environment in real-time and alert authorities to any oil spills.

B. Underwater navigation: To navigate underwater vehicles, which can be used for search and rescue operations, disaster relief, and other applications. For example, coral reefs are complex and fragile ecosystems, and it is important to navigate through them carefully to avoid damage. FL models can be trained from many underwater vehicles and sensor data that have navigated through or observed the coral reefs. This data can then be used to navigate through coral reefs safely and efficiently.

C. Underwater device fault detection: To detect faults in underwater equipment, such as sensors and actuators. For example, underwater sensors are critical for many applications, such as navigation, communication, and monitoring. Faults in underwater sensors can lead to accidents and other problems. Underwater sensors can collect the data regarding the faults and the FL models can be trained accordingly to detect the faults. The trained models can then be used to monitor the sensors in real-time and alert operators to any faults.

D. Fish migration: To predict fish migration patterns, which can be used to improve fishing practices and conserve fish populations [8]. These fish are important to the ecosystem, but their populations are declining. FL uses the data collected from sensors that are deployed in the ocean to track the migration patterns of these fish. The trained FL models can then be used to predict the migration patterns of these fish in real-time. This information can be used to conserve these fish populations.

3. Challenges and Opportunities

FL faces several significant challenges when applied to the IoUT, however, researchers are continuously working to make it better. Figure 3 shows the key challenges of FL in IoUT.

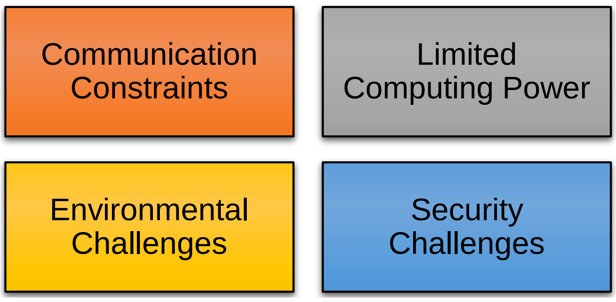

Figure 3: Key Challenges of FL in IoUT.

A. Communication constraints: The communication between devices in underwater IoT networks is often unreliable and has high latency. This can make it difficult to train FL models, as the devices may not be able to communicate with each other frequently enough. The underwater environment is a harsh environment, and it can be difficult to maintain reliable communication between devices. The water can absorb and scatter radio waves, making it difficult for devices to communicate with each other. The water can also be turbulent, which can cause the communication signal to be disrupted. To address this challenge, researchers are developing new communication protocols that are more reliable and have lower latency for IoUT networks.

B. Limited computing power: The devices in IoUT networks are often resource-constrained, with limited computing power and battery life. This can make it difficult to train FL models, as the devices may not be able to run the required computations. For example, consider an FL model that is being trained to predict fish migration patterns. The model needs to be able to process a large amount of data from many sensors. However, the devices that are collecting the data may not have enough computing power to process the data. This can make it difficult to train the model. To address this challenge, researchers are developing FL algorithms that are more efficient and can run on resource-constrained devices. They are also developing new ways to distribute the training of FL models across multiple devices.

C. Environmental challenges: The underwater environment is harsh and can damage devices. This can make it difficult to deploy and maintain FL models in IoUT networks. The underwater environment is harsh, and it can be difficult to deploy and maintain devices in this environment. The water can be corrosive, and it can also contain sediments and other debris that can damage devices. The water pressure can also be high, and this can also damage devices. Researchers are developing FL models that are more resilient to the harsh conditions of the underwater environment.

D. Security challenges: FL models are trained on data that is distributed across many devices. This makes them vulnerable to security attacks, such as data poisoning and model inversion attacks [8]. In a data poisoning attack, an adversary can inject malicious data into the training data of a FL model. This can cause the model to learn incorrect patterns, which can lead to the model making incorrect predictions. In a model inversion attack, an adversary can try to infer the private data of a device from the model parameters that are shared during the FL training process. This can be done by reverse engineering the model and using the model parameters to reconstruct the private data. To address these challenges the FL model should include data encryption and third-party security.

4. Conclusion

Federated learning (FL) is a promising technology for Internet of Underwater Things (IoUT) applications. It has the potential to improve the security, efficiency, and scalability of IoUT systems. However, several challenges need to be addressed before FL can be widely adopted for these applications. Researchers are actively working to overcome these challenges and make FL a more feasible solution for IoUT applications. This paper discussed the various key applications of FL for IoUT, as well as the key challenges and opportunities that need to be addressed. FL is expected to play an increasingly important role in the future of IoUT.

참고문헌

[1] Madakam, Somayya, Vihar Lake, Vihar Lake, and Vihar Lake. "Internet of Things (IoT): A literature review." Journal of Computer and Communications 3, no. 05 (2015): 164.

[2] Domingo, Mari Carmen. "An overview of the internet of underwater things." Journal of Network and Computer Applications 35, no. 6 (2012): 1879-1890.

[3] Jahanbakht, Mohammad, Wei Xiang, Lajos Hanzo, and Mostafa Rahimi Azghadi. "Internet of underwater things and big marine data analytics—a comprehensive survey." IEEE Communications Surveys & Tutorials 23, no. 2 (2021): 904-956.

[4] McMahan, Brendan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. "Communication-efficient learning of deep networks from decentralized data." In Artificial intelligence and statistics, pp. 1273-1282. PMLR, 2017.

[5] Sirohi, Deepika, Neeraj Kumar, Prashant Singh Rana, Sudeep Tanwar, Rahat Iqbal, and Mohammad Hijjii. "Federated learning for 6G-enabled secure communication systems: a comprehensive survey." Artificial Intelligence Review (2023): 1-93.

[6] Reddy, G. Pradeep, and YV Pavan Kumar. "A Beginner's Guide to Federated Learning." In 2023 Intelligent Methods, Systems, and Applications (IMSA), pp. 557-562. IEEE, 2023.

[7] Banabilah, Syreen, Moayad Aloqaily, Eitaa Alsayed, Nida Malik, and Yaser Jararweh. "Federated learning review: Fundamentals, enabling technologies, and future applications." Information processing & management 59, no. 6 (2022): 103061.

[8] Victor, Nancy, Mamoun Alazab, Sweta Bhattacharya, Sindri Magnusson, Praveen Kumar Reddy Maddikunta, Kadiyala Ramana, and Thippa Reddy Gadekallu. "Federated learning for IoUT: Concepts, applications, challenges and opportunities." arXiv preprint arXiv:2207.13976 (2022).

[9] Pei, Jiaming, Wenxuan Liu, Lukun Wang, Chao Liu, Ali Kashif Bashir, and Yue Wang. "Fed-IoUT: Opportunities and Challenges of Federated Learning in the Internet of Underwater Things." IEEE Internet of Things Magazine 6, no. 1 (2023): 108-112.

[10] He, Yu, Guangjie Han, Aohan Li, Tarik Taleb, Chenyang Wang, and Hao Yu. "A Federated Deep Reinforcement Learning-Based Trust Model in Underwater Acoustic Sensor Networks." IEEE Transactions on Mobile Computing (2023).

[11] Zhao, Hao, Fei Ji, Qiang Li, Quansheng Guan, Shuai Wang, and Miaowen Wen. "Federated meta-learning enhanced acoustic radio cooperative framework for ocean of things." IEEE Journal of Selected Topics in Signal Processing 16, no. 3 (2022): 474-486.

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