Proceedings of the 4th International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2026.33960

Federated Learning in Wireless Networks: Developments, Challenges and Future Directions

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Abstract. In recent years, federated learning has played an important role in people's life, and this paper focuses on how to use federated learning in communication. In this paper, intelligent signal processing, resource allocation and other aspects are analyzed. First, this paper reviewed the relevant papers in recent years and analyzed how to apply federated learning to the research of various majors. It is learned that the communication problems encountered in recent years have been solved by the help of federated learning. Some scholars have focused on the spectrum problem, especially the cooperative spectrum sensing in heterogeneous environment and the dynamic spectrum access in satellite network. Others focus on resource allocation, especially network slicing and 6G system. Federated learning can achieve the balance between performance and energy efficiency. There are also scholars who analyze how federated learning can be used in signal processing, such as massive MIMO systems. Although each study focuses on a particular aspect, they all have a common point: they use federated learning to achieve distributed intelligence, and various devices can learn from each other without sharing raw data. This method can not only protect user privacy, but also improve system performance. In this study, federated learning can make full use of the spectrum, improve the efficiency of resource allocation, and make signal processing more efficient, but also protect user privacy. Generally speaking, federated learning can provide a good way for the development of next generation communication system.

Keywords: Communication networks, federated learning, privacy preservation

1. Introduction

In the current world, technology is an important force that promotes the development of science and technology. The changes brought about by technology have affected people's lives in many aspects, and the integration degree between the two is getting higher and higher, which has led to the rapid increase of data and the rapid increase of the number of connected devices, and also brought challenges in the process of processing data and protecting user privacy. In order to solve this problem, many scholars have put forward reasonable suggestions, among which federated learning has attracted the attention of the industry.

Federated learning is a method of training models with the help of data from multiple servers or devices, without sharing data. In this way, the model can work independently in each device, and

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each device can train the model with the help of local data, and only pass the model update to the server. The server integrates the model updates and optimizes the model in this way. The biggest advantage of this method is that it can protect user privacy and does not need to move data.

Federated learning has contributed to the development of many fields without sharing raw data. In the field of health care, the patient's personal information will not be leaked in the process of training AI model [1], which is enough to reflect the respect for the patient. In the financial field, FL can help a series of banks to build a strong fraud detection system, which can detect credit card fraud without exposing the customer's sensitive data [2]. In the case of self-driving cars, this technology can be used to learn from the driving experience of other cars and improve the navigation performance without uploading video footage [3]. In the process of building smart cities, FL can be used to train models by a series of departments, including environmental monitoring, traffic management and so on, to track air quality and manage power consumption [4]. In the case of wireless communication, FL can also play an important role [5].

In this study, the research results of the predecessors are systematically sorted out, and the development of FL technology is analyzed, which can provide reference for the development of wireless network in the next stage. In this study, FL technology is applied to wireless network, and the application of FL technology in signal processing, spectrum management and so on is analyzed, and the research results are sorted out, and the problems existing in the current research are analyzed, and the next stage of research direction is pointed out.

2. Applications for federated learning in wireless networks

In this section, the article deeply analyzes that the application of wireless network can be divided into three aspects, that is, intelligent signal processing, resource allocation and spectrum management, and the conclusion was drawed that the application of spectrum management can not only improve the access rate of spectrum, but also improve the performance of spectrum sensing, which requires the cooperation of all parties to achieve the goal of making full use of the spectrum. Resource allocation is to analyze how to allocate computing resources and communication resources to achieve the purpose of joint optimization, and to analyze how to allocate resources reasonably in the case of network slicing. Intelligent signal processing can be used in signal detection, channel estimation and so on. In the above three aspects, the introduction of federated learning can make the data transmission more efficient, and the privacy of users can be guaranteed.

2.1. Spectrum management

2.1.1. Dynamic spectrum access

Shen et al. [6] put forward a feasible scheme for solving the problem of LEO satellite Internet of Things, which can be described as FDSA. The purpose of the study is to solve the problem of interference, and the change of spectrum availability is too fast. The method is implemented in two steps. The first is to divide users into different groups according to their historical location information, and the second is to use PPO to learn which channel to access. The local training is completed by each user, and the value network is sent to the server, where the global model is generated. The scheme can not only solve the interference problem, but also protect the privacy of users. Simulation results show that the access rate of the scheme can reach 90% when the number of users reaches 60, which is significantly better than the traditional solution [6].

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2.1.2. Spectrum sensing

Xu et al. pointed out that in the process of cooperative spectrum sensing, there are two problems that need to be solved urgently, one is the problem of data leakage, the other is the problem of high communication overhead [7]. In order to solve these two problems, federated learning technology is introduced into the research, and the raw data of users will not be shared in this way, but only the model parameters will be shared. In the study, the Swin-Transformer is used to extract features from the time-frequency spectrum map, and the continuous wavelet transform is used to deal with the local data. The fusion center collects the model of each user, aggregates it, and sends the updated model to each user. In order to make a decision, the K-order fusion method is used in the fusion center to obtain the results of local sensing. The key results show that the detection probability can be improved by 45% and the false alarm probability can be reduced by 13% by using the method in this study, which is significantly better than the existing methods [7]. It can be seen that the research results can support the conclusion that federated learning has a higher application value in the field of spectrum sensing.

2.2. Resource allocation

2.2.1. Joint optimization of computational and communication resources

Alqahtani et al. [8] constructed FLARE framework, which can play an important role in the process of managing energy, computing and communication resources in 6G IoT network, and can also play an important role in the process of federated learning. This method is divided into three parts: first, the gradient is quantized, the accuracy is reduced, and the communication cost is reduced; second, the routing algorithm is designed, the path is adjusted, the power consumption is reduced, and the delay is reduced; third, the server is virtualized, the idle server is turned off, and the pricing mechanism is used to achieve the purpose of cost control. The study found that this method can save 5% of resources and improve power efficiency by 4%. It can be seen that even if the workload increases significantly, the performance of the network can be guaranteed to be at least 90% [8].

2.2.2. Dynamic resource allocation in network slicing

Krishnamoorthy et al. put forward FL-DRAM framework, which uses federated learning and reinforcement learning to allocate network resources in the 6G network environment [9]. Through analysis, it is found that the method can solve the problems of bandwidth allocation and delay, which are the key problems to be solved at present. The method has multiple components. First of all, it can deal with the missing data in the data set, and can also eliminate the noise in the data set with the help of deep learning and statistics. In this study, FL-DRAM is used to analyze the three-layer structure, and the results are relatively ideal. There is convincing evidence that edge devices can train locally, fog nodes can integrate updates, and central servers can complete the aggregation. According to the above analysis, the accuracy of PerFedRL can reach 97.23%, which is significantly higher than that of FedAvg and FedProx. According to the research data, the training time of AFUM is reduced by 35%. Key results show that energy consumption can be reduced by 47.84% and bandwidth utilization can reach 95.32%. From the research data, the robustness of security measures can reach 99.12%, the delay can be reduced by 56.61%, and the bandwidth efficiency can be increased by 86.09% [9].

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2.3. Intelligent signal processing

Nugroho et al. [10] analyzed the signal processing of wireless communication in the context of federated learning, and pointed out that in the process of studying millimeter wave massive MIMO systems, three signal processing tasks need to be completed: signal detection, beamforming and channel estimation. In the process of channel estimation, users can use pilot signals to train models and share parameters with the base station. In the process of beamforming, users can use LiDAR and radar to obtain channel data and train models, and only update the model to achieve the purpose of collaborative learning. In the process of signal detection, the detection model of multiple users can be trained without the need to centralize the received signals. The survey points out that in most cases, the implementation of this method is to use horizontal federated learning, which requires synchronization aggregation and IID data [10].

3. Discussion

In this chapter, the application of wireless communication technology in the process of federated learning is analyzed from the aspects of security, cost and so on. In the process of writing the paper, it is obvious that the three problems are repeatedly mentioned, which are the security of data transmission, the cost of communication and the heterogeneity of data. In this case, the problems that have not yet been solved are analyzed, and it is necessary to carry out in-depth research on this basis. In the process of writing this paper, it is found that there are two major prospects: one is to improve the communication technology, the other is to improve the efficiency of communication.

3.1. Current challenges

3.1.1. Communication cost

The biggest problem in the promotion of federated learning is how to save communication costs. Sabah et al. [11] pointed out that the more edge servers are involved in training, the greater the communication overhead will be. Deep learning models can reach hundreds of megabytes, and the number of communication rounds required for FL can reach hundreds or even thousands of times. The long-distance transmission of model updates will bring a heavy burden. Sha et al. [12] pointed out that the communication cost is too high, which will lead to bottlenecks, especially in wireless networks with limited bandwidth. With the expansion of the system scale, the time spent on parameter transmission is even higher than the time saved in distributed computing.

3.1.2. Data heterogeneity

Data heterogeneity is also a major challenge. Xiao et al. [13] pointed out that in the process of over-the-air federated learning, the data sets of various clients are different, which will lead to significant differences in aggregation weights, and the signals received by the base station will also change, especially when the weight of a certain client is relatively small, the noise will be relatively large. Sabah et al. [11] pointed out that the data distribution of each client is different, which is not conducive to the improvement of communication efficiency and the improvement of privacy protection. Traditional FL method can not deal with this problem.

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3.1.3. Security and privacy threats

Security and privacy issues should also be paid attention to. Xiao et al. pointed out that the server can not see the user's update in the process of federated learning, which is different from the traditional defense method [13]. In this case, it is difficult to find bad participants. Sha et al. pointed out that attackers can damage the model by putting bad data into the set [12]. This attack will have a negative impact on the performance of the model, and the fairness can not be guaranteed, which will lead to the contradiction between training efficiency and privacy.

3.2. Future prospects

3.2.1. Communication technologies enabling federated learning

The birth of 6G and 5G networks has ushered in new possibilities for the development of wireless communication, and the application of federated learning can be promoted by using the advantages of 5G and 6G networks, and the transmission speed is relatively fast, which can optimize the communication parameters of FL training, including spectrum, bandwidth and so on. With the development of 5G and 6G networks, a variety of scenarios will be created, and a large amount of data will be generated, which will play an important role in the process of protecting privacy. Sha et al. [12] also put forward the same view. The operation of mmWave massive MIMO system in the 100GHz-1THz band can create a good environment for the development of wireless data centers. Xiao et al. [13] have the same idea as this paper.

3.2.2. Adaptive communication optimization and client scheduling

The most critical content of federated learning is to construct a perfect system, which can not only meet the needs of edge clients, but also adapt to the network environment. In fact, the wireless environment is not ideal, the bandwidth is relatively low, and all clients can not be trained at the same time. Therefore, when selecting participants, it is necessary to analyze the model and find ways to make the model converge quickly, which is a problem that all researchers should pay attention to in system design.

In addition to the selection of clients, many scholars also agree that power control is an important content. Some clients have weak channel connections, which require higher transmission power to ensure that the model update can be carried out smoothly without being disturbed by noise. Optimize the selection of users and control the power, which is an effective strategy, but also has a series of technical problems.

In the next stage of development, the framework should be more efficient, so that it can adjust the communication status in real time in the process of selecting clients, and should not be bound by the rules of random selection or fixed selection. In addition, it is also necessary to compress the model adaptively.

The above views have been supported by a large number of scholars: Sha et al. [12] pointed out that in the process of user selection, the impact of bandwidth should be considered. Xiao et al. [13] pointed out that power control is a key issue in the wireless FL scenario. Sabah et al. [11] pointed out that the importance of real-time metrics and adaptive compression should be fully recognized.

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4. Conclusion

In this study, the application of federated learning in the field of communication is analyzed, focusing on three aspects: signal processing, resource allocation and spectrum management. In the process of research, the literature is reviewed, and it is found that the application of federated learning can solve a series of problems in the above areas. This paper points out that the introduction of federated learning into the communication system can play a role in protecting private information, which is conducive to the promotion of large-scale models, and can also improve the efficiency of the system, which should be fully considered in the construction of modern communication network. This paper also points out the problems faced by federated learning and puts forward reasonable suggestions for its development.

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