Federated Learning for Vehicular Networks Based on DDMC Modulation

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***Abstract*—With the development of intelligent vehicles and wireless network communications, deploying machine learning on vehicles and using federated learning (FL) for large-scale learning is a widely discussed research topic. However, when vehicles are moving at high speeds, the impact of Doppler and rapid link dynamics cannot be ignored. Compared with the conventional time-frequency domain multi-carrier (TFMC) modulation schemes, the delay-Doppler domain multi-carrier (DDMC) modulation schemes can better overcome the problems caused by high-speed movement and DDMC shows higher robustness in high-speed vehicle network systems. In this work, we combined a deep reinforcement learning (DRL) network selection strategy with different modulation schemes and evaluated the performance of federated learning at various speeds. The results show that using DDMC improves federated learning performance compared to TFMC in high-speed mobile environments, and maintains performance even at increased speeds.**

***Index Terms*—delay-Doppler domain, ODDM, OTFS, OFDM, federated learning, wireless communication.**

I. Introduction

The development of chip technology and wireless communication technology has made it possible for vehicles with powerful computing power and stable Internet access to become widely available in the market. With high-performance processor chips, vehicles have efficient information processing capabilities, enabling them to quickly acquire and analyze environmental data. Current network communication technology enables vehicles to connect to the Internet and maintain stable data transmission.

To achieve the goal of safe assisted driving or fully autonomous driving, large-scale learning using artificial intelligence is necessary. However, the use of driving data from a single device for learning is limited. Collecting more data from other vehicles for large-scale learning can improve the efficiency and reliability of learning. The communication capabilities provided by stable wireless networks enable vehicles to communicate with neighboring vehicles and cloud servers, making large-scale learning in the Internet of Vehicles (IoV) possible. However, in large-scale learning scenarios that involving data from many devices, privacy cannot be ignored. From the perspective of privacy issues, it is not wise to directly upload data collected by sensors on each device to the cloud for large-scale learning. In addition, poor network quality may also lead to degraded learning performance. Federated learning was proposed by Google in [1], which shows excellent privacy protection capabilities in large-scale learning by transmitting local training models instead of privacy-sensitive data.

Advances in wireless network technology have enabled a large number of devices to simultaneously provide data to machine learning models. However, in high-speed mobile scenarios, conventional TFMC modulation scheme shows its shortcomings in maintaining stable communication [2]. Delay-Doppler domain multi-carrier modulation, which was newly proposed in recent years, is considered to be a reliable solution to the communication problems of high-speed wireless devices. Delay-Doppler domain based modulation schemes can effectively solve the shortcomings of OFDM in the face of time-varying channels [3]. It is a technology that brings great breakthroughs to communications on vehicular networks.

In this work, we considered a scenario of high-speed vehicles deployed with FL which is also considered in our former work [4]. Compared with former work, we introduced different modulation schemes for simulation experiments and comparisons. Through simulation experiments, we tested the performance differences of FL under various factors, such as speeds and modulation schemes. We concluded that different modulation schemes are effective in implementing FL in high-speed vehicle networks.

The main contributions of this paper can be summarized as follows:

- Under different modulation schemes, the same DRL-based network switching algorithm is used to ensure the continuity of federated learning.
- The performance of federated learning in an IoV environment based on different modulation schemes was verified through simulation.
- The performance of federated learning in IoV environment of three modulation schemes, OFDM, OTFS and ODDM, is compared and analyzed.

In the remainder of this paper, we first briefly introduce various modulation schemes for TFMC and DDMC, as well as FL for connected vehicles in Section II. We then present the simulation environment used in this research and the necessary DRL-based adaptive network switching scheme in Section III. Based on the proposed system model and simulation scheme, we test the performance of FL under various conditions in Section IV. Finally, we provide conclusions in Section IV.

II. Modulation Schemes and Federated Learning for IoV

In this section, we will introduce the modulation schemes and federated learning that are the main focus of this research.

We will explain the basic characteristics of different modulation schemes, the framework of FL, and the reasoning behind using FL for IoV applications in this research.

A. TFMC and DDMC

For vehicles in high-speed motion, the wireless channel environment may change at any time as the vehicle's position changes. Channel delay and Doppler shift have a significant impact on communication performance. Orthogonal Frequency Division Multiplexing (OFDM), as one of the traditional TFMC modulation schemes, has the advantages of low sensitivity to inter-symbol interference (ISI) and easy bandwidth division [5], [6].

However, OFDM is considered to have weaknesses in high-mobility and high-frequency scenarios. In recent years, with the introduction of Orthogonal Time-Frequency Space (OTFS) in [7], [8], research and discussion on new modulation schemes based on the delay-Doppler (DD) domain has gradually increased. Until recently, the mainstream DDMC modulation scheme was OTFS. Extensive research has been conducted on the performance analysis and improvement of OTFS [3]. Subsequently, a new DDMC modulation waveform, called Delay Doppler Plane Orthogonal Pulse (DDOP) [9], was discovered and discussed in 2022. DDOP exhibits ideal local orthogonality and a new DDMC modulation scheme introduced by DDOP, called Orthogonal Delay Doppler Division Multiplexing (ODDM), was proposed in [10]. It addresses the drawback of [8], which lacks ideal dual-orthogonal pulses.

DDMC modulation scheme is closely related to the IoV. High-frequency carriers are increasingly being used for wireless communications. This trend poses a challenge for stable communication among IoV devices with high mobility and high carrier frequencies. ODDM, a groundbreaking new DDMC modulation scheme, addresses potential issues with OTFS and demonstrates significant potential and research value. While ODDM is still in its early stages of research and many unexplored areas remain, it is worthy of application in practical IoV scenarios.

B. OTFS

OTFS is a widely discussed modulation scheme based on DD domain. The TF and DD domain in OTFS modulation can be expressed as following:

$$TF\ domain : \left\{n^{'}T, m^{'}\Delta f\right\} \tag{1}$$

$$DD\ domain : \left\{\frac{m}{M\Delta f}, \frac{n}{NT}\right\} \tag{2}$$

where $n^{'} = (0, 1, ..., N-1)$ means $n^{'th}$ OTFS frame and N means the number for OTFS frames, T means the duration of each time slot, $\Delta f = \frac{1}{T}$ means the each subcarrier, $m^{'} = (0, 1, ..., M-1)$ means $m^{'th}$ sub-carrier and M means number of sub-carrier in each time slot.

For the equation of DD domain, $\frac{1}{M\Delta f}$ means the delay resolution of the signal and m means m^{th} delay [11]. Similarly, $\frac{1}{NT}$ means the Doppler resolution of the signal and n means n^{th} Doppler.

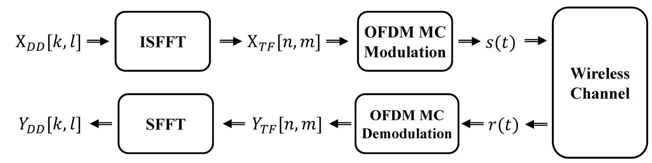

Fig. 1. Transmitter and receiver architecture of ISFFT-based OTFS.

The modulation and demodulation process of OTFS using inverse symplectic finite Fourier transform (ISFFT) is shown in the Figure 1 and can be expressed as

$$\begin{aligned} s(t) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{M-1} ISFFT\left(X_{DD}\left[k, l\right]\right) \\ g_{tx}\left(t - n^{'}\right) e^{j2\pi m^{'}\Delta f\left(t - n^{'}T\right)} \end{aligned} \tag{3}$$

C. ODDM

Then, we discuss ODDM, which also performs signal processing in the DD domain. The TF and DD planes of ODDM can be expressed as [9], [12]

$$TF\ domain : \left\{n^{'}T, m^{'}\frac{1}{T}\right\} \tag{4}$$

$$DD\ domain : \left\{\frac{mT}{M}, \frac{n}{NT}\right\} \tag{5}$$

Time-domain discrete samples of m^{th} ODDM symbol can be obtained using IDFT (inverse discrete Fourier transform) like conventional OFDM as

$$x[m, \dot{n}] = \sum_{n=0}^{N-1} X[m, n] e^{j2\pi\frac{\dot{n}n}{N}}, \dot{n} = 0, \ldots N-1 \tag{6}$$

where $\dot{n}$ refers the index of the time-domain discrete samples spaced by T. The signal in time domain of m^{th} ODDM symbol can be expressed as

$$x_m(t) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X[m, n] e^{j2\pi\frac{\dot{n}n}{N}} a(t - \dot{n}T) \tag{7}$$

where $a(t)$ is a square-root Nyquist pulse. The most important content in ODDM is DDOP, an orthogonal pulse in DD domain, which can be expressed as following.

$$u(t) = \sum_{\dot{n}=0}^{N-1} a\left(t - \dot{n}T_0\right) \tag{8}$$

Figure 2 shows simplified TF signal positioning for five multi-carrier modulation schemes: time division multiplexing (TDM), frequency division multiplexing (FDM), and the aforementioned OFDM, OTFS, and ODDM. TDM and FDM pulses overlap only in the time and frequency domains. OFDM pulses

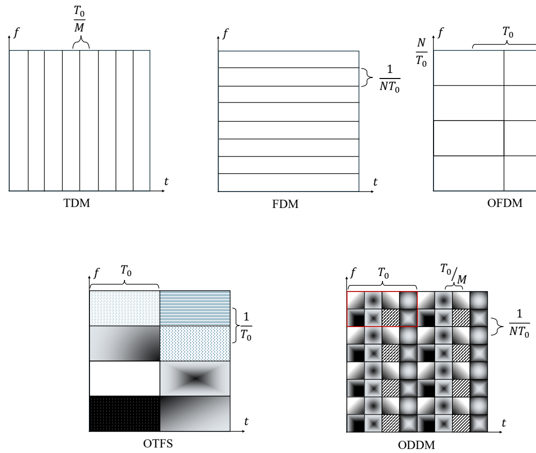

Fig. 2. Comparison of different modulation schemes.

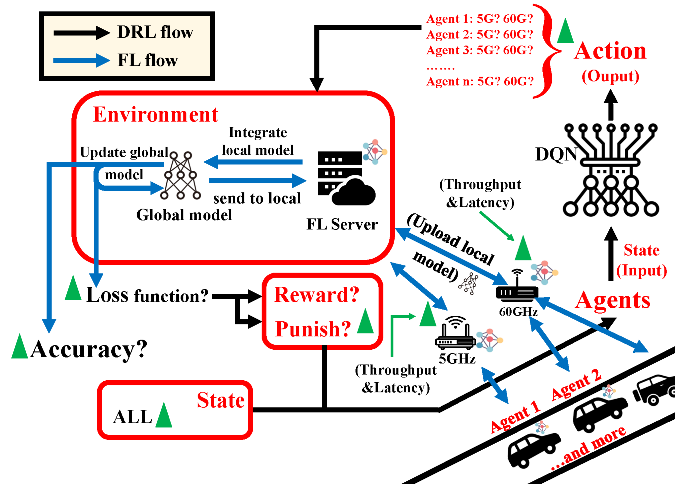

Fig. 3. Workflow of DRL and FL components for the vehicles network.

overlap only in the frequency domain, while OFDM symbols are independent in the time domain.

It can be known that although OTFS is based on the DD domain, its design requires mapping the signal from the DD domain to the TF domain before transmission using OFDM. As a result, the signal localization of OTFS in the TF domain is similar to that of OFDM.

D. Federated learning for IoV

When leveraging IoT device data on a large scale, the collection and use of such data, often containing sensitive and private information, poses ethical and legal challenges. Furthermore, the volume of data generated by IoT devices places a heavy burden on network infrastructure. For example, with limited network bandwidth, transmitting raw video data from cameras for centralized processing is impractical. These limitations require innovative approaches to data processing and model training [13].

Federated learning has emerged as an effective solution to these challenges and has garnered significant attention in recent years. FL leverages the computing power of participating devices to perform local training on data collected by their sensors. Instead of sharing raw data, these devices transmit locally trained models to a central server, which aggregates these models into a global model. This global model is then shared with all devices. This approach not only minimizes the amount of data transmitted but also enhances privacy by avoiding the direct transmission of sensitive information.

In the Internet of Things (IoT), IoV is a prominent application that demonstrates the potential of FL. These vehicles are equipped with a variety of sensors, enabling them to collect rich datasets for machine learning tasks such as obstacle detection and route planning. The FL paradigm allows for local model training in vehicles, preserving privacy while reducing bandwidth consumption. Furthermore, FL facilitates collaborative learning between vehicles operating in diverse environments, such as urban and rural roads, thereby enhancing the robustness and adaptability of machine learning models [14]. The application of IoV often follows the connection limitations of the network. There are many previous research focused on IoV related research on the network [15]. In this work, we will focus on the impact of modulation schemes on FL performance in high-speed IoV environments.

III. System Model and Network Selection

In this work, two Wi-Fi access points (APs) are considered to serve multiple vehicles, with one operating in the 5 GHz band and the other in the 60 GHz band. Among the users served by the APs, there are both FL vehicles participating in FL and common devices that do not participate in FL. FL vehicles transmit FL models through the wireless network they access, and at the same time, common devices also transmit their own data through their respective connected networks. There is mutual interference when a large number of devices transmitting in the same wireless spectrum, and this interference has nothing to do with whether the vehicles participate in FL. The vehicles participating in FL move at a constant speed on a straight road. As the vehicles move, the wireless channel environment also changes.

Many previous works have mentioned that due to the physical characteristics of wireless channels [16], the performance of FL based on wireless networks for model transmission will be affected by the wireless communication environment. In this work, the transmission of the FL model of the FL vehicle is affected by the quality of the wireless channel. There is mutual interference between devices using the same spectrum for transmission, which affects the performance of FL. This interference also varies depending on factors such as the number of devices transmitting simultaneously. Due to the large differences in the physical characteristics of the 5 GHz and 60 GHz spectrums, the selection of different Wi-Fi networks will affect the performance of FL. In the simulation of this work, the devices participating in FL choose between two Wi-Fi networks in order to obtain better FL performance.

The network selection algorithm used in the simulation of this paper is based on DRL and was previously published in [4]. The figure 3 shows the system model and machine learning flows. The following is a brief summary of this DRL-based algorithm.

- *Agent*: All vehicles which participate in FL act as agents in the DRL process. The set of agents can be represented as follows:

$$\mathcal{N} = [1, 2, 3, ..., N_{FL}] \tag{9}$$

$\mathcal{N}$ is a set of N_{FL} vehicles which perform federated learning.

- *Action*: As the beginning of each step, each FL agent decides on the action for current step. Network which will be used for the next step needs to be selected for all N_{FL} vehicles within the set $\mathcal{N}$. The network selected by algorithm for N^{th} vehicles is expressed as D_N, the value of D_N is 0 or 1 for switching to other network or keep stay in current network. Hence, the action a_t chosen in step t can be expressed as following

$$a_t = \begin{bmatrix} D_1 & D_2 & D_3 & ... & D_{N_{FL}} \end{bmatrix} \tag{10}$$

- *Reward*: The primary objective of DRL-based algorithms is to enhance the performance of federated learning. To achieve this, the algorithm is penalized when federated learning performance shows a relative decline and rewarded when it exhibits an upward trend. In the proposed algorithm, the loss function of the vehicles participating in federated learning is used as an indicator to evaluate the current performance trend of the system. Supposing that action a_t is chosen for step t, the loss function for N^{th} vehicles is expressed as $f_{Loss}(N)$, the reward for the action a_t can be expressed as following

$$\mathcal{R}_{a_t} = \begin{cases} \sigma Reward, \sum_{i=1}^{N_{FL}} f_{Loss}(N)\, decreases. \\ Punish, \sum_{i=1}^{N_{FL}} f_{Loss}(N)\, increases. \end{cases} \tag{11}$$

Where σ is the coefficient used to adjust the appropriate reward.

IV. Simulation Results

The DRL-based network selection algorithm from Section III is used. The available networks are still the two Wi-Fi networks based on the 5 GHz and 60 GHz frequency bands. In the simulation group of various modulation schemes, both networks use the same modulation scheme, and there is no such situation where one uses TFMC and the other uses DDMC.

Simulation parameters for this work are provided in TABLE I. This section presents simulation results and provides an analysis. By simulating different modulation schemes and vehicle speeds, a performance comparison between TFMC and DDMC for the specific application of federated learning is conducted.

Figure 4 illustrates the accuracy of federated learning with different vehicle speeds (80 km/h and 120 km/h) and different modulation schemes (TFMC and DDMC). The conventional OFDM is used for the TFMC baseline, while ODDM and OTFS is used for the DDMC baselines.

TABLE I
PARAMETER SETTINGS

Carrier frequency	5 GHz and 60 GHz
Modulation alphabet	16QAM
Data frame	7995 B
Beacon Interval	150 ms
Contention-Based Access Periods	0.4
σ (DRL) for TFMC	2.30
σ (DRL) for DDMC	2.05
M (OTFS, ODDM)	512
N (OTFS, ODDM)	64
RTS	20 Octets
CTS	26 Octets
ACK	14 Octets
SIFS	$2.5\mu s$
RIFS	$8.5\mu s$
DIFS	$12\mu s$
vehicle speed (km/h)	80, 120
Data set	IID MNIST
Batch size	32

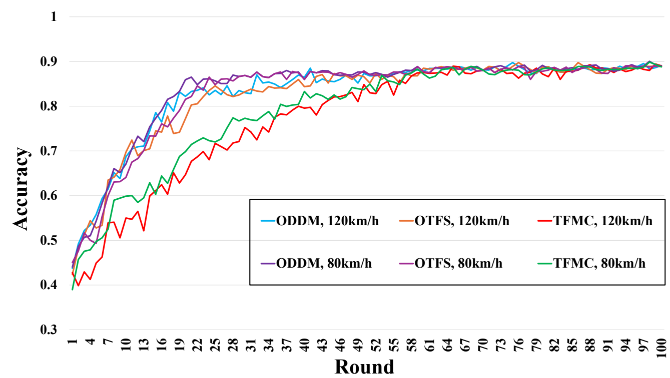

Fig. 4. Federated learning accuracy under different speeds and different modulation scheme.

The simulation results in Figure 4 demonstrate that the performance of federated learning varies significantly under different conditions. By comparing the performance of different modulation schemes, the results clearly indicate that DDMC provides a substantial performance advantage over TFMC in high-speed vehicular network scenarios. The DDMC scheme achieves 80% accuracy with far fewer rounds than the TFMC scheme. Since federated learning model transmission relies on network quality, owing to its superior resilience to Doppler effects, DDMC enables federated learning to achieve superior learning outcomes in high-speed mobile scenarios.

Additionally, the performance gap between the two baselines using DDMC is minimal, clearly indicating that DDMC has little performance impact as speed increases.

The performance gap under these four conditions can also be observed more intuitively from Figure 5 and 6. In this

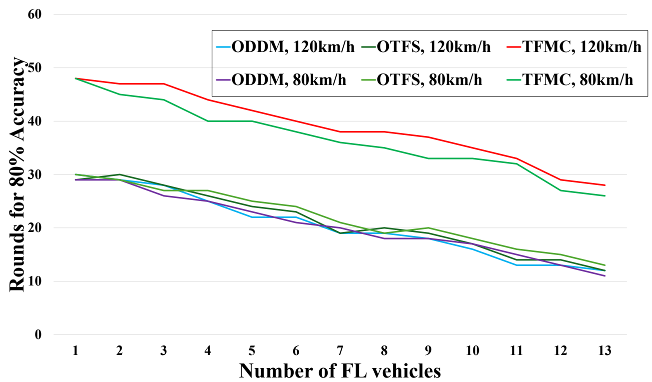

Fig. 5. Federated learning accuracy under different speeds and different modulation scheme.

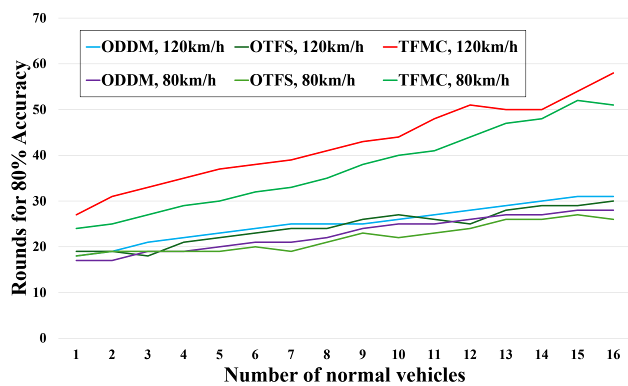

Fig. 6. Federated learning accuracy under different speeds and different modulation scheme.

simulation, the number of rounds required for federated learning to achieve 80% accuracy is recorded, and it is maintained for 5 rounds to ensure the results are not affected by unstable fluctuations in learning accuracy. Similar conclusions to those drawn from Figure 4 can be made from these two figures. The number of vehicles participating in federated learning or the number of normal vehicles is adjusted, and the number of rounds required for federated learning to reach a certain accuracy is observed. Compared to Figure 4, these two figures more clearly illustrate that there is a significant performance gap between DDMC and TFMC. Federated learning with the TFMC modulation scheme typically requires 10-20 additional rounds than the DDMC modulation scheme to achieve the target accuracy.

CONCLUSION

In this paper, we investigate the impact of modulation schemes on the learning performance of high-speed vehicles participating in federated learning. By combining network selection strategies with different modulation schemes, we analyze how modulation methods affect the transmission efficiency and accuracy of federated learning under high-mobility conditions. Specifically, this chapter compares the performance of traditional TFMC and DDMC modulation in a high-speed vehicle scenario. Simulation results demonstrate that DDMC exhibits greater robustness against Doppler effects than traditional TFMC modulation.

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