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Research on Resource Allocation and Anti-jamming Technology for V2X Communication in a Vehicle-road Cooperation Scenario

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Abstract

Vehicle-road collaboration relies on V2X communication to realize real-time information interaction between vehicles and multiple agents. High dynamic topology, intensive deployment, and heterogeneous quality-of-service requirements make resource allocation and interference management face severe challenges. This paper systematically reviews the standardized resource allocation architecture of C-V2X and NR-V2X, analyzes the typical sources and classification system of interference in the vehicle-road cooperation scenario, and summarizes the resource allocation methods based on optimization theory, game theory, deep reinforcement learning, and graph neural networks, as well as the key anti-interference technologies such as power control, interference elimination, reconfigurable intelligent surfaces, etc. The research shows that the intelligent resource management framework integrating artificial intelligence and traditional optimization methods is becoming the mainstream direction, and the emerging paradigms such as communication control collaborative design, semantic communication, and synaesthesia integration provide new ideas for subsequent development.

Keywords

Vehicle-road coordination; V2X communication; resource allocation; anti-interference; deep reinforcement learning

1. Introduction

Through the real-time data exchange between vehicles and road infrastructure, vehicle-road collaboration breaks through the perception limitations of single-vehicle intelligence and provides core data support for collision warning, traffic efficiency optimization, and automatic driving. V2X communication covers vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-pedestrian (V2P), and other modes, and is the key enabling technology of information sharing and collaborative decision-making in vehicle-road collaboration [1, 2].

V2X communication carries two types of services with essential differences: security-related services (such as collision warning and cooperative sensing) have extremely stringent requirements for delay and reliability - the end-to-end delay needs to be less than 100ms, and the reliability reaches 99.999%; non-security services (such as infotainment and traffic efficiency optimization) focus on data rate and throughput. The coexistence of heterogeneous quality of service requirements in the same system makes resource allocation evolve from single-objective optimization to multi-objective trade-offs.

The inherent complexity of the vehicle-road collaboration scenario further exacerbates the challenge. The high mobility of vehicles causes the network topology to change rapidly and the channel state to fluctuate rapidly; In the urban environment, building occlusion, multipath fading, and co-channel interference caused by dense vehicles

make it difficult to ensure the quality of communication. In areas without base station coverage, vehicles rely on distributed autonomous resource selection mechanisms, and the uncertainty of resource conflict and interference increases significantly. The current standardized semi-continuous scheduling mechanism has limited efficiency in dealing with dynamic environments and sudden bursts, so a more intelligent adaptive resource management scheme is urgently needed.

2. V2X Communication Resource Allocation Architecture

2.1 Evolution of C-V2X Resource Allocation Mode

LTE-V2X defines two complementary resource allocation modes. Mode 3 (base station scheduling mode) relies on cellular coverage, and the base station centrally allocates time-frequency resources based on the global channel information. In theory, it can achieve global optimization and avoid conflicts. However, the signaling overhead increases sharply with the vehicle density, and it faces scalability bottlenecks in ultra-dense scenarios. Mode 4 (self-selection mode) for non-coverage scenarios, the vehicle can independently select idle resources by continuously sensing the channel and decoding the surrounding control information. Its distributed architecture has significant advantages in deployment flexibility, but is limited by inherent problems such as half-duplex constraints, hidden terminals, and resource selection conflicts [3, 4].

5G NR-V2X has systematically enhanced the autonomous mode on the basis of LTE. NR-V2X mode 2 extends a variety of resource selection options, including self-selection based on perception, selection based on cooperative user equipment, selection based on a preconfigured resource pool, and self-selection based on base station scheduling, and introduces a resource re-evaluation and preemption mechanism to allow vehicles to dynamically adjust reserved resources when high-priority services are involved. In addition, the repeated transmission strategy of the same packet improves reliability but increases the risk of channel congestion. It is necessary to carefully balance reliability and spectral efficiency. Generally speaking, the allocation mode is evolving from “centralized decision-making of base stations” to “vehicle autonomy+auxiliary cooperation”, but neither mode can fundamentally solve the problem of resource optimization in a highly dynamic environment.

3. Interference Analysis

3.1 Interference Sources and Classification

Classified by source: (1) co-channel interference—collision caused by multiple vehicles transmitting on the same time-frequency resources is the main source in autonomous mode; (2) adjacent channel interference—interference caused by signal leakage of adjacent frequency bands; (3) external system interference—signals from 802.11p, radar, Wi-Fi, and other systems; (4) hidden terminal interference—the sending vehicle cannot perceive other senders outside its communication range but within the communication range of the receiving vehicle.

Classified by transmission direction: V2V inter-link interference, V2I and V2V inter-link interference, cellular user and V2X user inter-link interference.

3.2 Spatio-Temporal Characteristics of Interference

In the time dimension, the high-speed movement of vehicles (up to 120km/h) causes the channel coherence time to be extremely short, and the interference power fluctuates violently in milliseconds. In the spatial dimension, complex environments, such as urban canyons, tunnels, and viaduct makes the signal transmission conditions significantly different, and the interference distribution is extremely uneven. The time-varying characteristics of traffic flow make the interference intensity change dramatically with time and place. The resource allocation algorithm needs not only rapid response to channel changes, but also certain prediction ability [5-7].

3.3 Impact of Interference on System Performance

Interference propagates layer by layer along the protocol stack, causing differentiated damage at different levels: the physical layer directly reduces the signal-to-interference-plus-noise ratio at the receiving end, increases the bit error rate, and significantly attenuates the link throughput; The MAC layer frequently triggers retransmission, which increases signaling overhead and access waiting delay, and reduces the effective utilization of spectrum; If the high-priority security messages in the application layer are lost or delayed due to interference, the surrounding vehicles will not be able to obtain early warning in time, which will directly threaten driving safety. Existing research and measurements show that a reasonable interference management strategy adapted to the Internet of vehicles scene

can achieve a gain of more than 100% in the effective transmission performance of the system in the high-density traffic scene, which has outstanding engineering application value [5-7].

4. Resource Allocation Method

4.1 Traditional Optimization and Game Theory Methods Based on Single-Point Decision-Making

In traditional resource allocation schemes, the problem is modeled as a constrained optimization model. The objectives include system throughput, transmission time delay, and energy efficiency. Constraints include power cap, delay boundary, and reliability requirements. In terms of specific implementation, the power control strategy has an adaptive centralized scheme based on a deep neural network and near-end strategy optimization (PPO), which aims to meet the link requirements with minimum power and suppress adjacent cell interference. There are also distributed models based on the Stackelberg game, which use fractional programming to transform the original problem into an equivalent parameter programming problem for solving. The advantage of this method is that the theoretical system is mature, and it can obtain the performance lower bound reference in static or quasi-static scenarios.

However, the traditional optimization path faces three inherent limitations: first, the algorithm is highly dependent on accurate channel state information (CSI) and global network topology knowledge, which is difficult to obtain and update in real time in the high-speed mobile Internet of vehicles environment; Second, most of the optimization problems constructed are non-convex, and the solution complexity increases exponentially with the number of vehicle nodes, which makes it difficult to meet the millisecond decision-making requirements. In contrast, the game theory method disperses the resource competition to each link through the non-cooperative or Stackelberg model, which effectively reduces the signaling overhead and supports distributed execution. However, the convergence and optimality of its equilibrium solution process in highly dynamic scenarios are difficult to guarantee, and the Nash equilibrium point may be far from the global optimum, which limits its reliable application in security-critical scenarios.

4.2 Deep Reinforcement Learning and Graph Neural Network Method Based on Temporal Interaction

In order to deal with the sequential decision-making problem in a dynamic environment, deep reinforcement learning (DRL) models resource allocation as a Markov decision process (MDP): Based on the channel quality, resource occupation, and other observation states, agents interact with the environment through actions (such as selecting resource blocks, adjusting power) and obtain rewards, and gradually learn the optimal strategy. In the single-agent architecture, existing research has introduced Double DQN enhanced by a multi-head attention mechanism to coordinate mixed V2I/V2V services under the framework of centralized training and decentralized execution; The multi-agent extension further integrates safety-related indicators such as location coding, information age (AOI), and collision time (TTC) to jointly optimize the communication and control performance. The core advantage of DRL is that it is free from accurate modeling of environment dynamics and can learn adaptively from experience, but its exploration efficiency and training stability still face challenges in sparse reward scenarios.

The introduction of a graphical neural network (GNN) makes up for the deficiency of DRL in the representation of spatial relationships from the perspective of structural modeling. In vehicle-road collaboration, the vehicle topology naturally forms a dynamic graph structure. The graph is constructed with the communication link as the node, and the time-varying adjacency relationship is captured using GraphSAGE and other architectures. Then the extracted topology features are fed into the DRL for sub-band allocation and power control decisions. The integration of GNN and DRL represents the current cutting-edge direction: the former is responsible for extracting structural spatial dependence from complex interactions, while the latter is responsible for policy optimization based on time-series cumulative return. The collaboration of the two shows better generalization ability and convergence speed than pure data-driven methods in ultra-dense networking scenarios.

5. Key Anti-Interference Technologies

5.1 Active Control at the Transmitter

Active control at the transmitter is the first line of defense for interference management. Power control directly restricts the interference coverage of each transmission link to surrounding nodes by adjusting the transmission power; reducing the power can effectively reduce the co-channel interference, but it needs to balance coverage reliability. Dynamic spectrum access allows vehicles to flexibly select idle frequency bands based on real-time spectrum sensing results to adapt to the time-varying characteristics of channel conditions and service loads. The combination of the two forms a “power frequency” two-dimensional control framework, which is effective in light load or quasi-static scenarios.

5.2 Passive Suppression at Receiver and Reconstruction of Propagation Environment

Interference cancellation at the receiving end improves the demodulation capability at the signal-processing level, which is an important supplement to the control at the transmitting end. NR-V2X allows multiple retransmissions of data packets to improve reliability, while the receiver equipped with serial interference cancellation (SIC) capability can further tap the potential of redundant transmission. Once a data packet is successfully decoded, the interference contribution of its duplicate copy can be removed from the received signal, creating better SNR conditions for decoding new data packets, and the performance gain can exceed 100% in high-interference scenarios. In the context of synaesthesia integration, the communication and sensing shared spectrum introduces a new mutual interference problem. Previous studies have proposed a peak vector cross product accumulation algorithm for filtering false targets generated by co-channel interference in target detection, and a partial rotation invariant MUSIC algorithm for near-field angle of arrival estimation, which realizes the robust operation of sensing function in interference environment.

RIS is composed of a large number of low-cost adjustable reflection units. By adjusting the phase and amplitude of electromagnetic waves, RIS can enhance the target direction signal, form a null in the interference direction, or provide additional reflection paths to overcome occlusion. Its passive reflection characteristics give it the advantage of very low power consumption, which is suitable for deployment in roadside infrastructure. Different from the signal processing at the receiving end, RIS takes the initiative to “shape” the wireless environment and improve the spatial isolation from the source. However, the technology still faces challenges in actual deployment, such as high channel estimation overhead, beam tracking lagging behind the rapid movement of vehicles, and so on. It needs to be combined with a lightweight feedback mechanism to play an effective role. In addition, technologies such as cooperative communication using spatial diversity to combat fading, cognitive radio to achieve spectrum hole sensing access, and blockchain to ensure the use of trusted records and fair distribution of resources can be used as a supplement to the above means, and together constitute a multi-level interference management ecosystem [8].

6. Conclusion

The research shows that V2X resource allocation is evolving from single communication index optimization to multi-objective, multi-agent, and communication control coordination comprehensive decision-making. The integration of deep reinforcement learning and graph neural networks provides a new way to deal with highly dynamic distributed scenes, while emerging paradigms such as semantic communication, synaesthesia integration, and large models bring paradigm change opportunities. In the future, we need to continue to make breakthroughs in algorithm generalization, practical deployment feasibility, communication control, collaborative optimization, and other aspects to provide support for large-scale commercial deployment of vehicle-road collaboration.

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