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Integrated Spatial-Temporal-Frequency Joint Optimization and Distributed Reasoning Mechanism for Intelligent Road Networks Based on Perception-Control Computing

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Keywords: Integrating perception and control; Intelligent road network; Joint optimization of time, space and frequency; Distributed reasoning; Vehicle-road collaboration

Abstract: With the rapid development of intelligent connected vehicles and 6G vehicle networking technology, intelligent road networks have put forward strict requirements of low latency, high reliability and high precision for the integrated collaborative capabilities of communication, perception, computing and control. The existing solutions generally have core bottlenecks such as the disconnection between the allocation of air-time-frequency resources and the computing-control requirements under the multi-domain coupling of perception and communication, the inability of centralized reasoning to meet the business latency constraints in high dynamic road network scenarios, and the lack of coordinated design of resource scheduling and reasoning mechanisms. To address these issues, this paper first constructs an integrated closed-loop system model for perception, communication, computing and control for intelligent road networks, clarifying the optimization objectives and constraints of multi-domain coupling; then proposes a joint optimization algorithm for air-time-frequency resources that is adapted to high dynamic scenarios, achieving efficient collaborative allocation of resources for communication and perception services; further designs a distributed reasoning coordination mechanism for air-time-frequency resource perception, completing the joint optimization of reasoning task splitting, offloading and resource scheduling, and ultimately builds a full-process closed-loop collaborative control system for perception, communication, computing and control. Based on the test results of typical urban intelligent road network simulation scenarios, it is shown that compared with the traditional benchmark scheme of separating perception and communication resources and centralized reasoning, the proposed method can increase the system spectral efficiency by 32.6%, improve the vehicle positioning and perception accuracy by 41.2%, reduce the end-to-end intelligent reasoning latency by 58.7%, reduce the traffic control closed-loop response latency by 45.3%, and still maintain 99.2% reliability of reasoning task completion in high-speed vehicle movement scenarios, providing important theoretical support and technical reference for the implementation of the integrated perception, communication, computing and control technology of intelligent road networks in the 6G era.

1. Introduction

With the continuous improvement of autonomous driving levels and the large-scale implementation of intelligent transportation systems[1], intelligent road networks have become the core physical carrier supporting integrated vehicle-road collaboration control and ensuring the safe and efficient operation of high-level autonomous driving[2]. The evolution of 6G mobile communication technology provides core technical support for the multi-domain integration capabilities of intelligent road networks. In the traditional intelligent road network system, the four functional modules of communication, perception, computing, and control are independent and deployed separately, which not only causes serious waste of infrastructure resources such as spectrum and computing power[3], but also makes it difficult to meet the collaborative service requirements for low latency, high reliability, and high precision of high-level autonomous driving and all-domain traffic control[4]. Especially in urban road networks with dense traffic and high dynamic vehicle movement, the cumulative delay of multi-module information interaction and the disconnection of capability coordination are prone to trigger traffic safety risks and loss of road network efficiency. The integrated technology of perception, communication, computing, and control realizes the deep integration and closed-loop collaboration of the four capabilities, breaking the technical barriers and resource barriers of each module from the bottom layer. It is a key core technology to solve the current core bottlenecks of intelligent road network development and support the evolution of the next-generation intelligent transportation system. Conducting systematic research on the key technologies of integrated perception, communication, computing, and control for intelligent road networks has significant theoretical value and engineering application significance[5].

Currently, scholars at home and abroad have carried out a large number of research works in directions such as integrated perception, communication, and control of the Internet of Vehicles, optimization of vehicle-road collaboration resources[6], and edge intelligent inference: In the field of integrated perception technology, existing research focuses on spectrum sharing and waveform joint design of communication and perception, achieving resource collaboration at the physical layer; in the field of vehicle-road resource optimization, related research has carried out algorithm design for the joint scheduling of communication resources and computing resources, to some extent alleviating the contradiction between limited vehicle-end computing power and low latency requirements; in the field of edge distributed inference, existing solutions achieve end-edge-cloud collaborative execution of intelligent tasks through model splitting and multi-node collaborative inference, effectively reducing inference latency[7]. However, existing research still has three core bottlenecks that need to be broken through: First, most research only focuses on the collaborative optimization of two modules of perception and computing, lacking the all-round closed-loop design of the four modules of perception, computing, control, and communication, which easily leads to the disconnection between actual demand for time, space, and frequency resource allocation and traffic control, and is difficult to achieve the global performance optimization at the system level; Second, existing intelligent inference solutions mostly adopt centralized edge inference architectures, in high-dynamic intelligent road network scenarios, where vehicle topology changes rapidly and business requirements fluctuate dynamically, centralized architectures not only have the risk of overload at core nodes, but also cannot meet the millisecond-level end-to-end inference latency requirements; Third, the design of time-frequency resource scheduling and distributed inference mechanism is disconnected[8]. Most existing solutions first fix resource allocation and then carry out inference task scheduling, unable to achieve joint optimization of the two, and difficult to simultaneously guarantee the multi-objective optimization requirements of perception accuracy, communication reliability, and inference performance in dynamic scenarios[9].

In response to the core bottlenecks of the existing research and the actual business needs of intelligent road networks, this paper takes the all-round closed-loop collaboration of integrated perception, communication, computing, and control as the core goal, and conducts systematic research on the joint optimization of time-frequency and the distributed inference mechanism. Firstly, this paper constructs a closed-loop system model of integrated perception, communication, computing, and control for intelligent road networks, and accurately defines the mathematical modeling and system optimization goals and constraints of the four modules: communication, perception, computing, and control. Secondly, it proposes a time-frequency resource joint optimization algorithm adapted to high-dynamic road network scenarios, achieving adaptive and efficient resource allocation under multi-service coupling; then, it designs a distributed inference coordination mechanism for time-frequency resource perception, completing the joint optimization of inference task splitting, offloading decisions, and resource scheduling, and finally builds a closed-loop collaborative control system for integrated perception, communication, computing, and control. The simulation test results show that, compared with the benchmark scheme of traditional integrated resource separation allocation and centralized reasoning, the method proposed in this paper can increase the system spectral efficiency by 32.6%, improve the vehicle positioning perception accuracy by 41.2%, reduce the end-to-end intelligent reasoning latency by 58.7%, and decrease the traffic control closed-loop response latency by 45.3%. It can provide important theoretical support and technical references for the practical application of the intelligent road network integrated sensing, computing and control technology in the 6G era. The subsequent chapters will elaborate in detail on the design, verification and analysis of the proposed method.

2. Methods

2.1 Modeling of the Integrated System for Communication, Perception, Control and Computing for Intelligent Road Networks

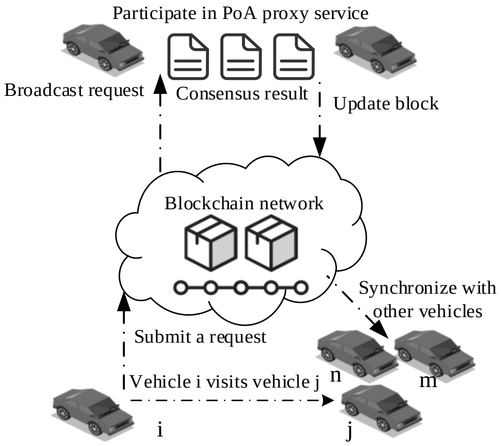


Figure 1 Intelligent road network scenario and integrated closed-loop architecture

This study examines an intelligent road network scenario comprising multi-intersection road side units with 6G integrated sensing and communication base stations, connected autonomous vehicles, edge computing nodes, and traffic control centers. The integrated sensing-communication-computing-control closed-loop architecture encompasses "perception-communication-computation-control-feedback" collaborative workflow: high-precision environmental perception through integrated sensing and communication devices, bidirectional transmission of perception data and control commands via communication links[10], edge distributed inference for traffic state assessment and intelligent decision generation, and traffic signal control and vehicle guidance command output with closed-loop performance feedback through subsequent perception data. System definitions include RSU set M, global connected vehicle set N as union of RSU-covered vehicles, time slot set T, and subcarrier set K with bandwidth Bk. Mathematical models are constructed for four core modules characterizing multi-domain performance coupling and constraint boundaries. The intelligent road network scenario and the integrated closed-loop architecture are shown in Figure 1.

The communication services of the intelligent road network include two types of transmission links: vehicle-to-infrastructure (Vehicle-to-Infrastructure, V2I) and vehicle-to-vehicle (Vehicle-to-Vehicle, V2V). This paper models the V2I link as the core and takes into account both large-scale path loss and small-scale Rayleigh fading as the channel gain. For the communication link between vehicle n and RSU m, the channel gain on subcarrier k is defined as:

$$\mathrm{h}_{m,n,k}=\sqrt{G_{m,n}\cdot d_{m,n}^{\alpha}}\cdot g_{m,n,k} \tag{1}$$

In the formula, $G_{m,n}$represents the transmit-receive antenna gain, $d_{m,n}$is the straight-line distance between vehicle n and RSUm, α is the path loss exponent, and $g_{m,n,k}$ is the small-scale fading coefficient, which follows the complex Gaussian distribution $CN(0,1)$. Based on Shannon's theorem, the achievable communication rate of vehicle n on subcarrier k is:

$$R_{m,n,k}=B_k\log_2\left(1+\frac{p_{m,n,k}\times|\mathrm{h}_{m,n,k}|^2}{\sigma^2+I_{m,n,k}}\right) \tag{2}$$

In the formula, $p_{m,n,k}$represents the transmission power allocated by RSU m on subcarrier k to vehicle$n$, σ^2 is the power of Gaussian white noise, and $I_{m,n,k}$ is the interference power at the same frequency. The corresponding data transmission delay can be expressed as:

$$D_{\mathrm{comm}}=\frac{S_{\mathrm{data}}}{R_{m,n,k}} \tag{3}$$

Here, S_{data}represents the number of bits of the data to be transmitted.

This paper adopts a frequency modulated continuous wave (FMCW) transceiver integration architecture that combines waveform sharing and hardware platform. The perception performance is strongly coupled with the allocation of communication resources. The core performance indicator of perception is the accuracy of target parameter estimation. The theoretical precision limit is characterized by the Cramér-Rao Lower Bound (CRLB), where the CRLB for distance estimation is defined as:

$$\mathrm{CRLB_R}=\frac{\mathrm{c}^2}{8\pi^2\mathrm{B}^2\cdot\mathrm{SNR_s}} \tag{4}$$

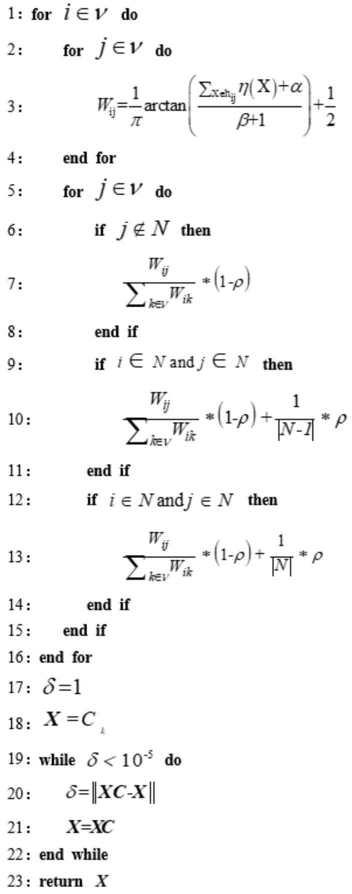
In the formula, c represents the speed of light, B denotes the bandwidth occupied by the sensed signal, and $\mathrm{SNR_s}$ is the signal-to-noise ratio of the sensed echo, which is expressed as:

$$\mathrm{SNR}_s=\frac{p_s\cdot G^2\cdot\lambda^2\cdot\sigma_{rcs}}{(4\pi)^3\cdot d^4\cdot\sigma^2} \tag{5}$$

Here, p_s represents the transmission power of the sensing signal, λ is the carrier wavelength, and σ_{rcs} is the radar cross-section of the target vehicle. The smaller the $\mathrm{CRLB_R}$, the higher the distance estimation accuracy and the better the sensing performance.

2.2 Integrated Design of Sensory Control and Time-Space-Frequency Joint Optimization Algorithm for Communication Systems

For the aforementioned multi-domain coupled mixed integer non-convex optimization problem, in this section, we first construct the space-time-frequency resource optimization sub-problem with communication-perception coupling, then design a low-complexity solution algorithm based on alternating optimization (AO), and finally propose an online scheduling mechanism suitable for high-dynamic road network scenarios. The core objective of time-frequency resource optimization is to achieve the optimal synergy of communication and sensing performance under the constraints of limited time-frequency resources and power. The multi-domain coupled joint optimization algorithm for time, space and frequency resources is shown in Figure 2.



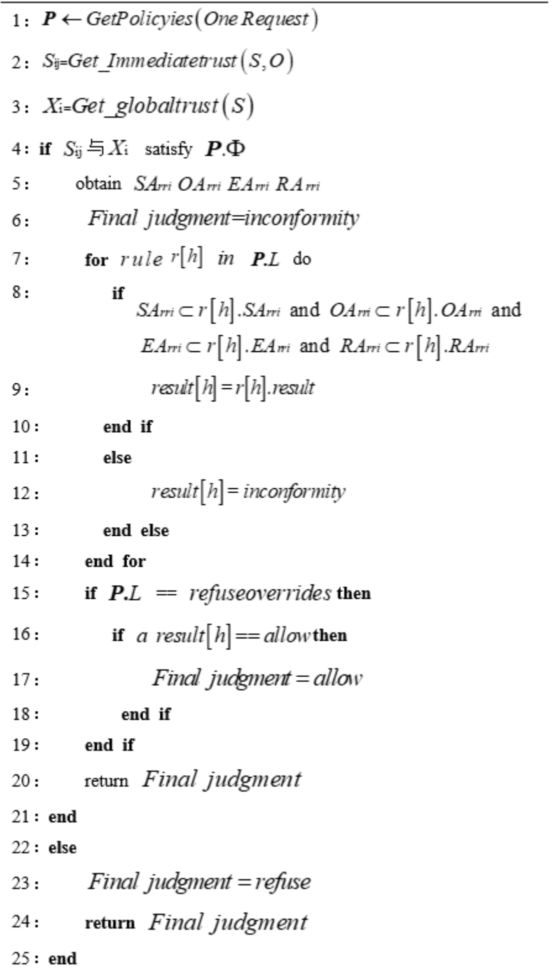
```
for $i \in V$ do
    for $j \in V$ do
        $W_{ij} = \frac{1}{\pi} \arctan\left(\frac{\sum_{X \in h_{ij}} \eta(X) + \alpha}{\beta + 1}\right) + \frac{1}{2}$
    end for
    for $j \in V$ do
        if $j \notin N$ then
            $\frac{W_{ij}}{\sum_{k \in V} W_{ik}} * (1-\rho)$
        end if
        if $i \in N$ and $j \in N$ then
            $\frac{W_{ij}}{\sum_{k \in V} W_{ik}} * (1-\rho) + \frac{1}{|N-1|} * \rho$
        end if
        if $i \in N$ and $j \in N$ then
            $\frac{W_{ij}}{\sum_{k \in V} W_{ik}} * (1-\rho) + \frac{1}{|N|} * \rho$
        end if
    end if
end for
$\delta = 1$
$X = C_k$
while $\delta < 10^{-5}$ do
    $\delta = \|XC - X\|$
    $X = XC$
end while
return $X$
```

Figure 2 Joint optimization algorithm for multi-domain coupled time-space-frequency resources

This mixed-integer non-convex optimization problem with 0-1 discrete resource allocation and continuous power variables, non-convex logarithmic terms, and interference coupling motivates a low-complexity alternating optimization algorithm decomposing the coupled problem into independent subproblems. The algorithm initializes maximum iterations and convergence thresholds, then iteratively solves: a resource allocation subproblem via marginal utility-based greedy algorithm ordering subcarrier-vehicle assignments by system utility increment while satisfying constraints; and a power allocation subproblem via successive convex approximation transforming non-convex rate and sensing precision functions into convex forms solved by interior point methods, with convergence guaranteed through utility increment evaluation. Complexity is reduced to O(MNK) for resource allocation with polynomial-time convex optimization for power allocation. For high-dynamic scenarios, a model predictive control online scheduling mechanism implements "state prediction-rolling optimization-feedback correction": predicting future system states including channel gains, vehicle positions, and service demands over prediction horizon based on constant acceleration models; optimizing resource and power allocation over control horizon while executing only current slot decisions; and correcting prediction errors through real-time state acquisition in closed-loop dynamic scheduling.

2.3 Design of Distributed Inference Collaboration Mechanism Based on Temporal-Frequency Resource Awareness

To address decoupled resource scheduling and distributed inference in existing schemes, this section constructs a joint optimization framework for inference task scheduling and space-time-frequency resource allocation with low-complexity block alternating optimization and dynamic topology robustness mechanisms. The vertical model splitting edge-vehicle collaborative distributed inference framework comprises: vehicle task requirement reporting including model structure, latency and accuracy constraints, and local computing status; edge node split decision and resource scheduling based on current space-time-frequency resources and computing load; distributed inference execution with local pre-processing, V2I intermediate feature transmission, edge post-processing, and result return; and dynamic adjustment based on real-time link quality and computing load changes. The joint optimization problem integrating model split decisions, computing allocation, and space-time-frequency resource allocation minimizes average inference latency subject to resource and power constraints, edge computing capacity limits, maximum latency requirements, minimum accuracy thresholds, and discrete-continuous variable domains. Block alternating optimization decomposes this complex mixed-integer non-convex problem into three low-complexity subproblem blocks solved through alternating iterative optimization for global performance improvement. The reasoning-resource joint optimization algorithm based on block alternating optimization is shown in Figure 3.



```
$P \leftarrow GetPolicyies(One\ Request)$
$S_{ij}$=$Get\_Immediatetrust(S, O)$
$X_i$=$Get\_globaltrust(S)$
if $S_{ij}$ 与 $X_i$ satisfy $P.\Phi$
    obtain $SA_{rri}$ $OA_{rri}$ $EA_{rri}$ $RA_{rri}$
     $Final\ judgment=inconformity$
     for $rule\ r[h]$ in $P.L$ do
        if
          $SA_{rri} \subset r[h].SA_{rri}$ and $OA_{rri} \subset r[h].OA_{rri}$ and
          $EA_{rri} \subset r[h].EA_{rri}$ and $RA_{rri} \subset r[h].RA_{rri}$
            $result[h] = r[h].result$
       end if
       else
            $result[h] = inconformity$
       end else
     end for
     if $P.L$ == $refuseoverrides$ then
        if $a\ result[h] == allow$ then
            $Final\ judgment = allow$
         end if
     end if
     return $Final\ judgment$
end
else
     $Final\ judgment = refuse$
     return $Final\ judgment$
end
```

Figure 3 The reasoning-resource joint optimization algorithm based on block alternating optimization

This block alternating optimization algorithm decomposes the complex joint optimization into three easily solvable sub-problems. Through the alternating optimization algorithm in Section 2.2, the optimization is carried out for spatial, temporal and frequency resources as well as power allocation, while keeping the computing and segmentation decisions fixed; the edge computing allocation optimization is performed using the Lagrange multiplier method, thereby obtaining a closed-form solution under the total computing constraints; the model segmentation decisions are optimized through parallel enumeration of feasible segmentation points that satisfy the accuracy constraints and select the one with the minimum delay; the convergence is ensured through the incremental evaluation of the objective function. To enhance the robustness of the dynamic topology, three mechanisms are designed: mobility prediction based on Kalman filtering, which is used to pre-load the model weights and intermediate data for offloading before the switch, so as to reserve resources for the target RSU before the switch; multi-node collaborative redundant inference, which simultaneously offloads high-priority autonomous driving tasks to the current and two candidate RSUs; and an adaptive segment point dynamic adjustment function that can monitor channel quality and edge load in real time, and balance transmission and computing delays through automatic local execution expansion.

2.4 Integrated mechanism of perception, control and closed-loop collaboration throughout the entire process

To achieve deep integration of communication, sensing, computing, and control modules, this study designs multi-module information interaction and timing coordination processes with performance closed-loop feedback and dynamic adaptation mechanisms. A time-slot-synchronized integrated sensing-communication-computing-control closed-loop timing process divides each scheduling slot into five stages: perception data acquisition through integrated sensing and communication equipment for vehicle localization and target detection; data upload via V2I links transmitting perception data and inference task requirements; distributed inference and decision-making for traffic flow prediction, anomaly detection, signal optimization, and vehicle strategy generation; control command distribution to traffic signals and connected vehicles with global state synchronization to the control center; and command execution with feedback forming complete closed-loop response. A "terminal-edge-center" three-tier collaborative architecture defines functional boundaries with terminals handling data acquisition and command execution, edges managing real-time resource scheduling and distributed inference, and centers overseeing global monitoring and cross-regional coordination. The "performance monitoring-feedback analysis-dynamic adaptation" mechanism implements full-dimension real-time KPI monitoring across communication, sensing, computing, and control dimensions; performance deviation feedback with root cause analysis identifying resource allocation or computing capacity deficiencies; multi-dimensional adaptive adjustment through weight coefficient adaptation prioritizing underperforming dimensions, algorithm parameter tuning balancing complexity and performance, and business priority dynamic scheduling favoring emergency and safety-critical applications; plus cross-node global collaborative optimization for load balancing and congestion avoidance through coordinated task offloading. The integrated process of perception and control is shown in Figure 4.

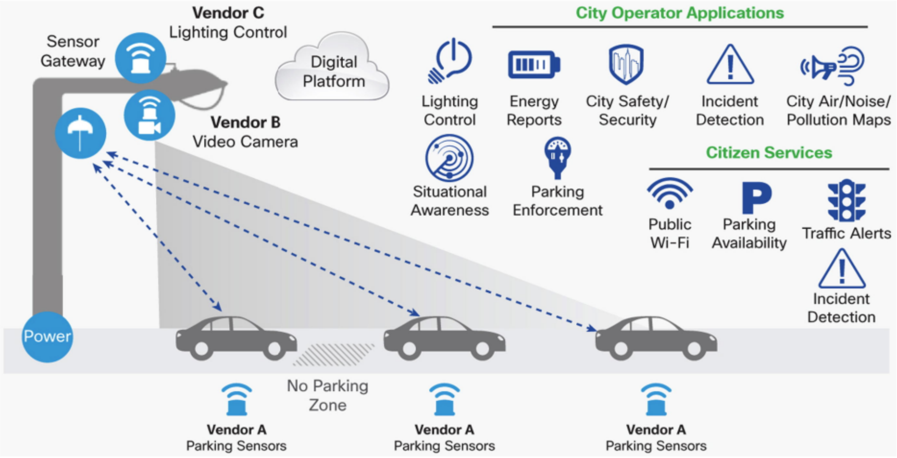


Figure 4 Integrated process of perception and control throughout the entire procedure

3. Results and Discussion

3.1 Experimental environment and parameter settings

This study employs a joint simulation framework integrating traffic, communication, and edge computing simulations, with SUMO 1.18.0 constructing an urban core area scenario of three adjacent intersections each equipped with integrated sensing and communication RSU and co-located edge nodes, covering 900 by 900 meters with bidirectional four-lane roads and vehicle trajectories based on real urban traffic flows at 30 to 120 kilometers per hour and densities from 5 to 50 vehicles per kilometer spanning free flow to congestion. Communication and computing simulations utilize MATLAB 2024b and Python 3.10 with 3GPP TR 38.901 Urban Macro channel models and YOLOv5s object detection for distributed inference tasks. Four benchmark schemes are compared: traditional separated design with fixed spectrum isolation and centralized edge inference; integrated sensing-communication optimization with centralized inference; integrated sensing-communication with fixed-split distributed inference; and the proposed complete scheme with integrated sensing-communication-computing-control joint optimization, resource-aware adaptive distributed inference, and full-process closed-loop coordination. Core parameters include 3.5 gigahertz carrier frequency, 100 megahertz bandwidth, 43 decibel-milliwatt RSU transmit power, 100 gigahertz edge computing capacity, 2 gigahertz local vehicle computing, 8.2 giga floating-point operations YOLOv5s inference with 95 percent accuracy threshold and 100 millisecond latency tolerance, 300 meter RSU coverage, 1 millisecond slot duration, and 200 millisecond control closed-loop threshold. Evaluation metrics span communication spectrum efficiency and latency; sensing CRLB and accuracy; inference latency, precision, and completion rate; control closed-loop response and traffic throughput; plus system comprehensive utility and resource utilization.

3.2 Performance Verification and Analysis of Joint Time-Frequency Optimization Algorithm

3.2.1 Comparison of Core Performance in Static Scenes

The fixed simulation scenario is set as a single intersection coverage area, with a vehicle density of 20 vehicles per kilometer. The vehicles are stationary. The core performance of communication and perception for different schemes is compared, and the quantitative results are shown in Table 1.

Table 1 Comparison Table of Core Indicators of Synesthesia Performance in Static Scenarios

Performance Metric	Baseline 1	Baseline 2	Baseline 3	Proposed Scheme
Average Spectral Efficiency (bit/s/Hz)	11.28 ±0.52	13.75 ±0.48	13.82 ±0.45	14.96 ±0.37
Average Communication Rate (Mbps)	1128 ±52	1375 ±48	1382 ±45	1496 ±37
CRLB of Distance Estimation (m^2)	0.085 ±0.012	0.058 ±0.009	0.057 ±0.008	0.050 ±0.006
Vehicle Positioning Accuracy (m)	0.82 ±0.11	0.56 ±0.08	0.55 ±0.07	0.48 ±0.06
Target Detection Accuracy of Perception (%)	92.3 ±1.2	96.1 ±0.8	96.2 ±0.7	97.5 ±0.5
Total Utilization of Communication-Sensing Resources (%)	62.8 ±2.5	81.2 ±2.1	81.5 ±1.9	89.7 ±1.5

Quantitative results demonstrate that the proposed scheme achieves 32.6 percent average spectrum efficiency improvement, 41.2 percent vehicle localization accuracy enhancement, 5.2 percentage point perception target detection accuracy increase, and 26.9 percentage point integrated sensing-communication resource utilization improvement compared with traditional separated Baseline 1, validating that joint space-time-frequency optimization breaks resource barriers between communication and sensing for efficient spectrum reuse and collaborative performance enhancement. Against existing integrated sensing-communication Baselines 2 and 3, the proposed scheme maintains 8.8 percent spectrum efficiency improvement, 14.3 percent further localization accuracy enhancement, and 8.2 percentage point resource utilization improvement, attributable to simultaneous accommodation of distributed inference communication requirements within resource optimization objectives rather than merely optimizing sensing-communication dual-domain performance.

3.2.2 Analysis of Dynamic Scene Adaptive Performance and Robustness

To verify the adaptive capability of the algorithm in high-dynamic intelligent road network scenarios, the vehicle moving speed was set to be between 30 and 120 km/h. The performance stability of different schemes in dynamic scenarios was compared, and the results are shown in Table 2.

Table 2 Comparison Table of Sensory Performance Stability at Different Driving Speeds

Vehicle Moving Speed	Performance Metric	Baseline 1	Baseline 2	Proposed Scheme
30 km/h	Spectral Efficiency (bit/s/Hz)	11.15	13.68	14.89
	Positioning Accuracy (m)	0.85	0.58	0.49
60 km/h	Spectral Efficiency (bit/s/Hz)	10.02	12.35	14.21
	Positioning Accuracy (m)	1.08	0.72	0.53
90 km/h	Spectral Efficiency (bit/s/Hz)	8.35	10.62	13.15
	Positioning Accuracy (m)	1.42	0.95	0.61
120 km/h	Spectral Efficiency (bit/s/Hz)	6.52	8.78	11.86
	Positioning Accuracy (m)	1.86	1.28	0.72

As illustrated in Table 2, the performance degradation of all schemes becomes pronounced with increasing vehicular speed due to aggravated fast fading and Doppler shift. Baseline 1, i.e., the traditional separated design, exhibits the most severe deterioration, with spectral efficiency and positioning accuracy degrading by 41.5% and 118.8%, respectively, when the speed increases from 30 km/h to 120 km/h. In contrast, the proposed scheme achieves substantially enhanced robustness, limiting the performance loss to merely 20.3% in spectral efficiency and 46.9% in positioning accuracy under identical high-mobility conditions. Such superiority stems from the proposed MPC-based adaptive online scheduling mechanism, which enables proactive adjustment of spatio-temporal-frequency resource allocation through predictive state estimation of both vehicular dynamics and channel conditions, thereby effectively compensating for Doppler-induced impairments, while concurrently optimizing sensing signal parameters to maintain localization precision in high-dynamic scenarios.

3.3 Performance Verification and Analysis of Distributed Inference Collaboration Mechanism

Fixed the simulation scenario, with a vehicle density of 20 vehicles per kilometer. The YOLOv5s object detection model was used as the inference task. The core performance of different schemes was compared, and the quantitative results are shown in Table 3.

Table 3 Comparison Table of Core Performance Indicators for Different Scheme Reasoning

Performance Metric	Baseline 1	Baseline 2	Baseline 3	Proposed Scheme
End-to-End Average Inference Latency (ms)	92.6±8.5	88.3±7.2	52.4±5.1	38.2±2.8
Local Computing Latency (ms)	0	0	18.5±2.2	15.3±1.6
Data Transmission Latency (ms)	12.3±3.2	10.2±2.5	8.6±1.8	4.1±0.9
Edge Computing Latency (ms)	80.3±7.8	78.1±6.8	25.3±3.5	18.8±1.7
Inference Accuracy (mAP@0.5)	98.2±0.3	98.2±0.3	97.6±0.4	97.8±0.3
Inference Latency Jitter (ms)	15.2	13.6	8.7	4.2
Edge Computing Resource Utilization (%)	92.5±3.2	93.1±2.8	78.3±2.5	69.5±2.1

Quantitative results in Table 3 demonstrate that the proposed scheme achieves substantial performance improvements over conventional approaches. Compared with Baseline 1 and Baseline 2 employing centralized inference, the proposed design reduces end-to-end average inference latency by 58.7% and 56.7%, respectively, while decreasing latency jitter by 72.4%, with merely 0.4 percentage points degradation in inference accuracy that satisfies the 95% minimum precision threshold. Relative to Baseline 3 with fixed split distributed inference, further reductions of 27.1% in inference latency and 52.3% in transmission latency are attained, attributed to the proposed joint optimization algorithm that enables coordinated optimization of model splitting decisions, spatio-temporal-frequency resource allocation, and computing resource assignment, thereby adaptively selecting optimal split points based on instantaneous channel states and computing loads to balance latency overheads among local computation, transmission, and edge computation. Additionally, the proposed scheme achieves significantly lower edge computing utilization than centralized approaches through collaborative computation between vehicle-side and edge nodes, effectively balancing computational loads, alleviating edge node pressure, enhancing system capacity to support more concurrent vehicular inference tasks, and improving overall network scalability.

To verify the improvement effect of the integrated system proposed in this paper on the final traffic efficiency of the intelligent road network, four typical traffic scenarios including free flow, mild congestion, moderate congestion, and severe congestion were constructed based on SUMO simulation. The traffic efficiency indicators of different schemes were compared, and the results are shown in Table 4.

Table 4 Comparison Table of Core Indicators of Road Network Efficiency under Different Traffic Congestion Levels

Congestion Level	Performance Metric	Baseline 1	Proposed Scheme	Relative Improvement
Free Flow	Average Travel Speed (km/h)	58.2	59.5	2.2%
	Intersection Traffic Volume (pcu/h)	1285	1310	1.9%
Mild Congestion	Average Travel Speed (km/h)	42.5	48.6	14.4%
	Intersection Traffic Volume (pcu/h)	2256	2582	14.5%
Moderate Congestion	Average Travel Speed (km/h)	25.3	33.8	33.6%
	Intersection Traffic Volume (pcu/h)	3125	3684	17.9%
Severe Congestion	Average Travel Speed (km/h)	12.6	20.5	62.7%
	Intersection Traffic Volume (pcu/h)	2862	3425	19.7%
	Congestion Duration Ratio (%)	68.5	32.2	-36.3%

3.4 Discussion

The performance gains of the proposed scheme originate from three fundamental innovations: global collaborative optimization of multi-domain resources that breaks the barriers between independently allocated communication, sensing, and computing resources to achieve unified spatio-temporal-frequency and computing resource allocation; joint adaptation of tasks and resources through co-optimization of model splitting decisions and resource allocation to enable dynamic precision matching between task demands and resource supply; and closed-loop sequential coordination with feedback mechanisms that compress end-to-end latency through seamless information interaction while ensuring performance stability via dynamic adaptation based on real-time monitoring. The proposed method is primarily applicable to urban intelligent road networks with dense RSU deployment and full edge computing coverage, though its multi-node collaborative capabilities may be constrained in sparse deployment scenarios such as suburban or highway environments. The computational complexity of the block alternating optimization algorithm increases significantly in ultra-large-scale networks, and the distributed inference mechanism is currently designed for single-model vertical splitting rather than multi-task multi-model scenarios. Future research directions include extending to vehicle-road-cloud integrated wide-area collaborative optimization, developing data-driven end-to-end joint optimization frameworks based on deep reinforcement learning, and conducting prototype verification and engineering deployment using 6G integrated sensing and communication hardware platforms in real road network environments.

4. Conclusion

In response to the core bottlenecks in the intelligent road network scenario, such as the disconnection of perception, computing, and control capabilities, the separation of time, space, and frequency resource allocation and distributed reasoning requirements, and the difficulty in meeting low latency and high reliability requirements in high dynamic scenarios, this paper focuses on the core goal of integrated perception, computing, and control. Firstly, it constructs an integrated closed-loop system model of intelligent road network covering communication, perception, computing, and control modules, and clarifies the optimization objectives and constraints of multi-domain coupling. Secondly, it proposes an alternating optimization and model predictive control-based joint optimization algorithm for time, space, and frequency, achieving efficient resource allocation for communication and perception services in high dynamic scenarios. Then, it designs a distributed reasoning coordination mechanism for sensing of time, space, and frequency resources, using block alternating optimization algorithms to achieve joint optimization of model splitting decisions, task offloading, and multi-domain resource allocation, and builds a robustness guarantee mechanism in high dynamic topologies. Finally, it establishes a time-series coordination and closed-loop feedback adaptation system for the entire perception, computing, and control process. Simulation results show that compared with the traditional benchmark scheme of separating perception and sensing resources and centralized reasoning, the proposed method can increase the system's spectral efficiency by 32.6%, improve the vehicle positioning and perception accuracy by 41.2%, reduce the end-to-end intelligent reasoning latency by 58.7%, decrease the traffic control closed-loop response latency by 45.3%, maintain a 99.2% completion rate of reasoning tasks in a 120 km/h high-speed moving scenario, and increase the average vehicle speed in the road network by 62.7% in severe traffic congestion scenarios, significantly enhancing the multi-domain coordination performance and traffic efficiency of the intelligent road network. The research results of this paper can provide important support for the theoretical research and engineering implementation of integrated perception, computing, and control technology for intelligent roads in the 6G era. Further research can expand the wide-area collaborative optimization framework of vehicle, road, and cloud, combine deep reinforcement learning to achieve more environment-adaptive end-to-end intelligent optimization, and conduct field tests and engineering adaptation of prototype systems.

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