Multi-Granularity Collaborative Decision With Cognitive Networking in Intelligent Transportation Systems

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***Abstract*— Cognitive networking is a valuable enabler to improve the capability of intelligent transportation system (ITS) by analyzing and utilizing the heterogeneous traffic information. However, the significant increase in the amount of decision-making tasks makes it difficult to guarantee real-time performance of decision response. This paper focuses on the problem of the quality and real-time assurance of collaborative decision-making response in large-scale ITS during multi-task parallelism execution. First, a collaborative decision architecture with cognitive networking is developed, which introduces the advanced 6G communication technology to enhance information interaction capability of vehicle-road-cloud collaboration, and lays the foundation for multi-task real-time decision-making with inevitable fuzzy information in the perception process. Then, a multi-task parallel multi-granularity collaborative decision model (MPMCD) is designed to improve knowledge discovery ability for decision-making process by building multi-granularity information structures. An AI-driven cognitive networking collaborative decision-making (ACNCD) algorithm is further proposed based on MPMCD model to support multi-task parallel vehicle-road-cloud collaborative real-time decision. Extensive simulation experiments are carried out to evaluate ACNCD algorithm in terms of several performance criteria including decision response time, accuracy, and accident rate. The obtained results show that the comprehensive decision-making performance of ACNCD outperforms other relevant existing algorithms.**

***Index Terms*— Cognitive networking, granular computing, real-time decision, deep learning, intelligent transportation system.**

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I. Introduction

With the rapid development of intelligent transportation system (ITS), real-time cooperative decision-making of vehicles is realized by using cognitive networking. Cognitive networking technology timely allocates resources for collaborative decision-making tasks in dynamic environment aiming to meet the tasks' requirement goals through both perception and prediction capabilities. Although the performance of collaborative decision-making in ITS is further ensured by incorporating new communication technologies such as 6G, the coexistence of multiple decision tasks brings challenges to the response time and accuracy of decision-making. Especially in the dynamic and complex environment of ITS, vehicles can only obtain information for decision-making through partial observation. The fuzziness of the data seriously affects the accuracy and response time of collaborative decision-making. Considering the granular decomposition has obvious advantages in feature extraction and description of uncertain information, therefore the introduction of granular computing to cognitive networking-driven ITS can strengthen the ability of knowledge discovery for uncertain data in decision-making process.

Cognitive networking originated from the cognitive radio concept and cognitive ring structure proposed by Mitola [1] in 1999, and was defined by Thomas [2] as a network that performs cognitive processes. Many decision-making methods based on cognitive networking for ITS have been developed. Zhao *et al.* [3] designed the information-center networking in combination with cognitive networking and applied it to the route planning decision problem in ITS, which uses the analytical capabilities of the network to achieve active cognitive access to traffic data, but it cannot support the execution of multi-task parallel decision-making. On the other hand, multi-granularity decision-making theory is used in ITS to deal with the execution of decision-making tasks in complex environments. Lyu *et al.* [4] proposed a long-term multi-granularity deep framework for driver status detection to provide safe driving guarantee functions for ITS.

This paper combines cognitive networking and multi-granularity decision-making to ensure the accuracy and response time of ITS decision-making in a dynamic and complex environment. An collaborative decision architecture with cognitive networking is designed to support multi-task

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collaborative decision-making in ITS. In order to strengthen the understanding of fuzzy data for ITS decision-making tasks and achieve precise decision-making, a multi-granularity parallel multi-task real-time decision-making model and an AI-driven cognitive networking cooperative decision-making algorithm are proposed. The contributions are summarized as follows:

1) A collaborative decision architecture with cognitive networking is constructed to support multi-task parallel decision-making in ITS. It reveals the impact of multi-task parallel on decision-making performance and uses the advantage of cognitive network to perceive environmental changes, and then solve the real-time problem of multi-task parallel decision-making in ITS.
2) A MPMCD model is proposed. It granulates the data sources of ITS decision tasks and constructs a level-compatible granular space to describe the possible relevance between tasks, and then further integrates CapsNet and LSTM to construct a multi-task learning network.
3) An ACNCD algorithm is developed to achieve multi-task collaborative real-time decision-making in ITS. It uses the mathematical framework of deep Q-learning and realizes sequential decision-making ideas through the integration of local training within the layer and iteration between layers.
4) The average fluctuation degree and accident rate of ACNCD algorithm were extensively simulated under path planning tasks and emergency avoidance tasks, the average decision response time and decision accuracy of four algorithms including ACNCD are compared, and the performance of ACNCD algorithm is analyzed.

The rest of this paper is organized as follows. Section II introduces some related work. The collaborative decision architecture of cognitive networking and impacts of multi-task parallelism on decision-making performance are presented in Section III. In Section IV, the MPMCD model is described in detail. Section V gives the proposed algorithm ACNCD, and the simulation results and analysis are presented in Section VI. Section VII concludes the paper.

II. Related Work

In this section, the work related to the research content of this paper is described from three perspectives: *A)* cognitive networking, *B)* granular computing, and *C)* real-time decision.

A. Cognitive Networking

As an advanced technology that can cope with complex dynamic environments, cognitive networking technology brings the possibility of efficient parallel decision-making to ITS. Chen *et al.* [5] proposed Cognitive Internet of Vehicles to ensure suitable cost and stable connectivity. Sharma *et al.* [6] integrate cloud computing into the cognitive radio adhoc vehicular networking, allowing vehicles to share network resources and provide more extensive network information for decision-making. Zhang *et al.* [7] introduced a full-duplex cognitive network adaptive mode selection scheme based on neural network prediction. Qian *et al.* [8] designed a secure and delay-sensitive content caching scheme of cognitive vehicular networks to satisfy delay-sensitive contents requirements of vehicles. Rathee *et al.* [9] proposed a cognitive radio technique for blockchain-enabled Internet of Vehicles to prevent data alteration from these malicious devices and allow vehicles to track legal and illegal activities in the network. Robert *et al.* [10] introduced cognitive networking with genetic algorithm optimized fuzzy decision system to reduce the channel switching rate, hidden node interferences and efficient spectrum allocation. The above methods are all aimed at a single decision-making task. Different from them, this paper uses cognitive networking technology to support multi-task parallel decision-making in ITS.

B. Granular Computing

Granular computing combines rough set theory to granulate information sources from different perspectives, and form multi-perspective and multi-level expressions of decision data according to the granularity and their interrelationships, which helps to obtain more accurate decision-making results. Pedrycz *et al.* [11] proposed a way of organizing knowledge about the available data and relationships existing base on granular computing to support flexible adjustment of abstraction levels in data analysis and system modeling. Aniello *et al.* [12] designed a granular computing framework for approximate reasoning in situation awareness to guarantees a high degree of flexibility in the process of creating granular structures to satisfy the wide variety of requirements for perception and comprehension of situations. Dai *et al.* [13] presented a fuzzy rule extraction approach using Gaussian kernel-based granular computing to achieve better classification performance of deducing reduction subset with fewer attributes. Li *et al.* [14] proposed a robust fastest path optimization model base on big data granular computing decision making to generate the optimal routing strategy by detecting, collecting and analyzing important traffic incident information, and transforming it into probabilistic information granular that can be used for urban routing navigation. Javier *et al.* [15] proposed a granular procedure for estimating missing information in fuzzy preference relations to improve the ability of group decision-making under the condition of lack of information. This paper further explores the application of granular computing to realize the multi-task parallel decision-making in ITS with fuzzy perception information.

C. Real-Time Decision

Real-time decision-making is the basis for ensuring the overall stable and safe operation of intelligent transportation system. Zhu *et al.* [16] introduced a role-based collaborative computing method based on E-CARGO model, which uses roles as basic components to promote the idea of collaborative activities and provide solutions for multitasking parallel decision-making conflicts. Zhang *et al.* [17] developed an attention model for perceiving environmental changes to solve dynamic version of the traveling salesman problem under the

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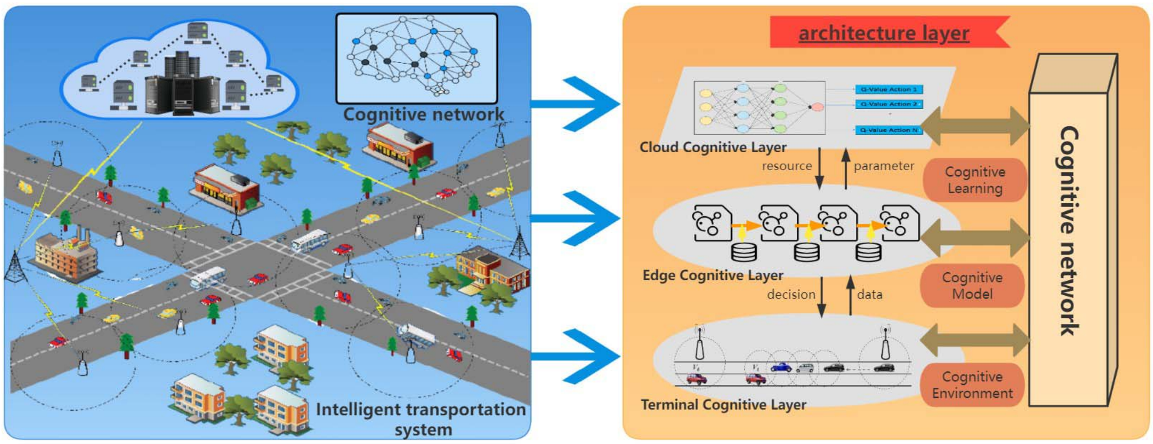

Fig. 1. ITS collaborative decision-making architecture.

dynamic version. Lin *et al.* [18] proposed a dynamic en-route decision route guidance scheme to effectively alleviate road congestion caused by the sudden increase of vehicles and reduce travel time. Wang *et al.* [19] established a hybrid-VANET-enhanced transportation system, which utilizes vehicular ad hoc networks and cellular systems to achieve real-time communications between vehicles, roadside units, and vehicle-traffic servers in an efficient manner. Cao *et al.* [20] presented a strategy search framework based on distributed fusion to accelerate the learning process of decision models through variance reduction and asynchronous exploration. Jiang *et al.* [21] introduced a deep Q-learning method based on empirical replay and heuristic knowledge, which can provide more effective data for training process and make decisions for path planning more quickly. The above methods lack sufficient mining of environmental fuzzy information and knowledge sharing among tasks in real-time decision making. In this paper, a multi-task real-time decision-making method is designed from the perspective of information granularity and shared continuous iteration to improve the real-time performance of decision response in multi-task parallel ITS.

III. System Architecture and Problem Formulation

In this section, an ITS collaborative decision architecture with cognitive networking is designed. In contrast to existing computing paradigms in the vehicle environment [22], this architecture uses 6G technology and granular computing to support efficient transmission and dynamic interaction of perceptual information among intelligent vehicles, the problem of parallel task decision making in ITS under fuzzy data conditions is further analyzed.

A. ITS Collaborative Decision Architecture With Cognitive Networking

Cognitive networking improves the adaptive capabilities of ITS and supports dynamic perception decision-making in large-scale and complex network environments. Compared with traditional networking technologies that lack self-learning capabilities, cognitive networking is sensitive to environmental changes and has the following obvious advantages for multi-task collaborative decision-making in large-scale ITS [23]:

1) It is easy to combine 6G technology to provide more efficient end-to-end data transmission, and can meet the timeliness and reliability requirements of collaborative decision-making for information acquisition and distribution in complex environments 24].
2) It supports the coordination of decision-making tasks between heterogeneous devices, such as data identification, collection, and training. The communication restrictions between devices participating in collaboration are further weakened to accommodate more frequent interactions.
3) The self-learning function of the cognitive network can update the strategy selection criteria by analyzing the execution results according to the perceived environmental information and strategy selection, and further optimize the parameter configuration of the strategy.

As shown in Fig. 1, the ITS collaborative decision with cognitive network architecture is divided into three sub-layers: terminal cognitive layer, edge cognitive layer, and cloud cognitive layer. Among them, the terminal cognitive layer consists mainly of intelligent vehicles and roadside units (RSUs), which collect and share perceptual data, execute the decision results of the edge layer. The edge cognitive layer combines the environmental perception results of the terminal cognitive layer to form appropriate decisions to achieve task goals. The cloud cognitive layer assists the decision analysis of the edge cognitive layer to adjust various parameter configurations in the decision-making process to make it as efficient as possible. It also centrally dispatches and manages vehicles and RSUs through the powerful global control capabilities of the cloud, and adjusts system attributes such as participating devices and interaction methods in real-time according to the actual status of the other two layers.

B. Problem Formulation of Multi-Task Parallel Decision in ITS

Although the collaborative decision-making architecture with cognitive network provides the ability to efficiently

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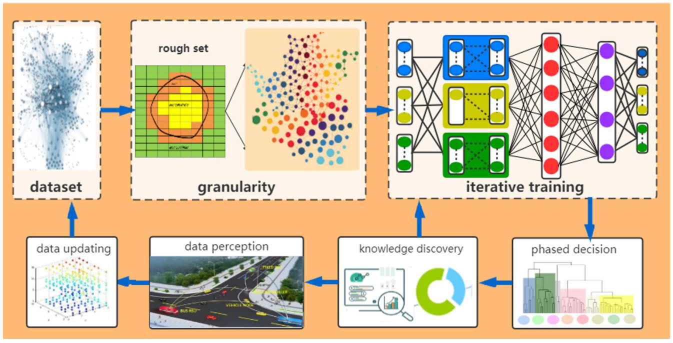

Fig. 2. The execution process of decision-making tasks.

execute parallel tasks, The inherently ambiguous perception of decision data in the complex and changing traffic environment makes it more difficult to achieve collaborative decision-making goals in large-scale ITS. For the multi-task parallel collaborative decision-making in ITS, the problem that needs to be solved is how to overcome the influence of ambiguity in the perception data to obtain the decision result that meets the quality requirements, and how to exploit the collaboration between tasks in the decision-making process to improve decision-making effectiveness.

As shown in Fig. 2, the execution process of decision-making tasks is accompanied by frequent updates of perception data, and the generation of decision-making results depends on sequential iterative data training. This means that the decision model requires real-time data identification and knowledge discovery to cope with the dynamic changes of the ITS complex environment. In other words, both the quality of decision-making results and response time depend on the knowledge discovery ability in the decision-making process. The fuzziness of data and the complexity of multi-task parallelism greatly increase the difficulty of knowledge discovery, which in turn affects real-time performance of multi-task collaborative decision-making. In order to improve the knowledge discovery and transfer ability in the decision-making process, the granular computing is introduced for knowledge discovery with fuzzy data. The process of granular is an abstraction of the inherent influence between fuzzy data and decision-making goals, and the most likely decision result is reflected numerically through known data. Considering that rough set theory can effectively express incomplete data and uncertain knowledge, the rough sets are established for each ITS task before the granularity is constructed.

Rough set construction is the process of finding an expandable approximate range of the target. For obtaining objective and accurate results in the multi-task parallel mode, it is necessary to comprehensively consider the mutual influence of multiple tasks and construct multi-granularity rough sets. For any task m_i in parallel task set $M = \{m_1, m_2, \ldots, m_n\}$ in ITS, a 2-tuple $K_i =< U_i, R_i >$ is used to represent the approximate space corresponding to its rough set. $U_i = \{u_1, u_2, \ldots, u_l\}$ refers to the domain of task m_i, which is a non-empty finite set that describes task m_i from different angles and set $u_a \in U_i$ is a concept or category. For example, the distribution of vehicles and people around the road belongs to different attributes of decision information, and different attention is assigned according to tasks, $R_i = \{r_1, r_2, \ldots, r_c\}$ represents the set of equivalence relations between each u_a. Defining $\underline{R_i^o}(u_a)$, $\overline{R_i^o}(u_a)$ is a rough set of set $u_a \in U_i$ with respect to binary relationship R_i^o, then $BN(u_a) = \overline{R_i^o}(u_a) - \underline{R_i^o}(u_a)$ is called the boundary domain of u_a, where $\underline{R_i^o}(u_a)$ and $\overline{R_i^o}(u_a)$ represent the lower approximation set and the upper approximation set, respectively, which are represented as follows:

$$\underline{R_i^o}(u_a) = \{[x]_{r1} \subseteq u_a \vee [x]_{r2} \subseteq u_a \vee \ldots \vee [x]_{rc} \subseteq u_a | x \in U_i\} \quad (1)$$

$$\overline{R_i^o}(u_a) = C(\underline{R_i^o}(C(u_a))) \quad (2)$$

where $[x]_{rc}$ represents the equivalence class of x respect to relationship r_c, and $C(u_a)$ refers to the complementary set of u_a. The multi-granularity space in the current domain is formed by calculating each granularity in U_i. At present, only the granularity generated in the single task of intelligent vehicles is considered, and the cross and overlap of concepts and information between domains cannot be ignored when multiple tasks are executed in parallel. For the set of parallel tasks M, the 3-tuple $P_M =< U, R, \delta >$ is defined as the approximate space under task parallelism, where $\delta = \{\delta_1, \delta_2, \ldots, \delta_q\}$ is the set representing equivalence relationship of granularities between different domains [25]. For any granularities u_a in U, defining its lower approximation and upper approximation as $\sum_{e=1}^{q} \underline{R_i^o}(u_a)$ and $\sum_{e=1}^{q} \overline{R_i^o}(u_a)$, which are represented as follows:

$$\sum_{e=1}^{q} \underline{R_i^o}(u_a) = \{[y]_{\delta 1} \subseteq u_a \vee [y]_{\delta 2} \subseteq u_a \vee \ldots \vee [y]_{\delta q} \subseteq u_a | y \in U\} \quad (3)$$

$$\sum_{e=1}^{q} \overline{R_i^o}(u_a) = C(\sum_{e=1}^{q} \underline{R_i^o}(C(u_a))) \quad (4)$$

Defining a reasonable rough set range helps to mine the potential information of data and the data association between tasks, thereby improving the knowledge discovery ability of multi-task parallel collaborative decision-making with fuzzy data.

IV. Multi-Task Parallel Multi-Granularity Collaborative Decision Model

In this section, in order to deal with multi-task parallel decision-making in a perceptually fuzzy environment, a task-based hierarchical compatible granularity space is established to provide a basis for enhancing data sharing among tasks in ITS, and a neural network model is further designed to process multi-tasks in real time.

A. Compatible Granularity Space

Knowledge transfer between different tasks can effectively reduce learning costs and improve real-time decision-making performance, the compatible granular space model needs to be designed as an important form of knowledge transfer. First of all, the degree of similarity between domains in different traffic tasks needs to be measured. The lager value refers to the higher

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similarity. For any two elements u_a and u_b in domains U_i, U_j generated by any two tasks m_i, m_j in set M, the parameter z_{ab} is defined to describe the relevance, which is expressed as:

$$z_{ab} = \frac{|\sum_{e=1}^{q} \underline{R_i^o}(u_a) \cap \sum_{e=1}^{q} \underline{R_j^o}(u_b)|}{|U|} \tag{5}$$

Comprehensive considering the relevance of each element can measure the similarity between domains:

$$Z_{ij} = \frac{|\sum_{u_a \in U_i} \sum_{u_b \in U_j} z_{ab}|}{2|U|} \tag{6}$$

where Z_{ij} represents the similarity between domains U_i and U_j and the range of values is [0, 1], the larger value means the higher coincident degree, that is more compatible. If domains U_i and U_j are completely independent, the Z_{ij} will equal to 0.

Due to the highly dynamics of decision-making tasks in ITS, the structure of compatible granularity space should be able to change with the change of traffic task set. The compatible parameter ρ is a threshold defined by Z_{ij}, whose value varies with attributes and status of actual tasks and $\rho \in [0, 1]$. Considering ρ can adjusted in real time with task changes, the ρ-sensitive induced compatibility function τ^ρ meet the adaptive adjustment function of compatible granularity space. The definition of τ^ρ is as follows:

$$\tau^\rho(U_i, U_j) = \forall u_a \in U_i, u_b \in U_j | Z_{ij} \geqslant \rho \tag{7}$$

The compatible granularity space model that corresponds to the task set M^T in time period T is defined as follows:

$$CSp = < M^T, U, \tau^\rho > \tag{8}$$

where U represents the domain set of M^T, τ^ρ represents the induced compatibility function of M^T, the specific form of τ^ρ need to consider the respective execution characteristics of tasks and the coordination requirements between tasks. Compatible granularity space can be changed with the attributes and status of the actual task, which can not only ensure the accuracy of decision results, but also ensure real-time performance to the maximum extent.

B. Granular Computing Driven Parallel Task Decision-Making

Granularity-based decision-making in ITS needs to rely on the granular space formed by a large amount of traffic information. The same granulation information has different effects on the decision outcome in different tasks. For example, vehicle braking distance information is finer in the emergency collision avoidance task than in the path planning task. The hierarchical spatial structure from coarse to fine helps to enhance the understanding of the granularity in the domain. Therefore, a hierarchical compatible granularity space is established for multi-task parallel decision-making.

Assuming that any task m_i in ITS has an independent decision table and a set of decision rules. The decision table represents all the effective information and knowledge that can be obtained in granular space corresponding to the task m_i. That is, any target task m_i is considered to can be obtained and measured by limited attributes. The decision table of m_i is defined as $S_i = \{U_i, C_i, D_i, V_i, f_i, L_i\}$, where U_i represents the entire domain corresponding to m_i, C_i is the set of conditional attributes, D_i refers to the set of decision-making attributes. V_i represents the corresponding value range under each decision attribute, that is, the value range after decision-making of attribute $\eta \in D_i$ is V_i^η. f_i is the set of decision functions and each attribute has its corresponding decision function, namely $f_i : U_i \times D_i$. L_i refers to the set of similar granularities of other tasks, and the fuzzy information can be supplemented by selecting similar granularity from other tasks in L_i.

The decision rule is the rule knowledge generated in the decision table, which is determined by the specific task. The thickness of granularity is specified by the strictness of decision rules. That is, if a certain granularity has little influence on the decision result under the decision rule corresponding to the current task, the granularity is coarse granularity. In order to quantify the strictness of decision rules to granularities in the decision table, the decision rule is expressed in the form of vector and its strictness is determined by the modulus of the vector. For S_i and any conditional attribute subset $B \subseteq C_i$, the decision rule can be defined as follows:

$$\wedge\{(\alpha, v_i^\eta) : \alpha \in B \quad and \quad v_i^\eta \in (V_i^\alpha \cup \{*\})\} \rightarrow d = v_i^d \tag{9}$$

where $v_i^d \in V_i$, d represents the corresponding decision attribute, and $\{*\}$ represents the corresponding property value that is independent of the current rule. The modulus of the vector is positively related to the number of non-$*$ attribute values, which is defined as $\|\chi\|$, and the larger $\|\chi\|$ refers to the finer granularity.

In particular, granularities located in multiple domains exist simultaneously under two or more decision rules, which means that they have different roughness for different tasks. In order to maximize the efficiency of task parallel execution, the roughness of such granularities is defined as follows:

$$\|\hat{\chi}\| = \left\lceil \sum_{a=1}^{\Omega} \frac{\|\chi\|^a}{\|\chi\|_{max}^a} \right\rceil \tag{10}$$

where Ω represents the number of tasks (domains) related to the current granularities, and $\|\chi\|_{max}^a$ represents the highest level of the granularity in a certain domain.

In order to realize the multi-task parallel decision-making of ITS, it is necessary to solve the problem of task parallel conflict and real-time response. For the former, the capsule neural network (CapsNet) encapsulate granularities in the form of vectors instead of scalars by combining the hierarchical compatible granularity space and effectively express the interactive relationship of granularities between different tasks, adjust granularities weights by task status to form optimal decision results. In view of the latter, Considering that long short-term memory network (LSTM) can effectively capture the long-term dependencies of information [26], the best decision results can be obtained by describing and training

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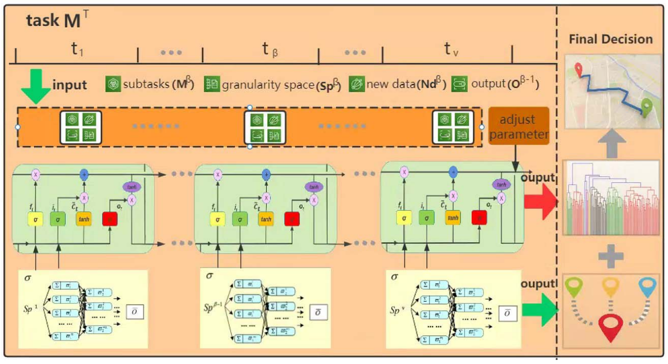

Fig. 3. Multi-task parallel multi-granularity collaborative decision model training.

complex interactive environments [27]. Therefore, a multi-task parallel multi-granularity collaborative decision model is designed by combining CapsNet and LSTM.

As shown in Fig. 3, the model is a sequential decision, assuming that the training of M^T requires ν iteration stages, the specific time of each stage is determined by the attributes of task and the decision state of current stage. The set of subtasks at any time period $t_\beta \in T$ is defined as $M^\beta = \{m_1^\beta, m_2^\beta, \ldots, m_n^\beta\}, \beta \in [1, \nu]$, and its corresponding hierarchical compatible granularity space is $Sp^\beta = \{s_1^\beta, s_2^\beta, \ldots, s_n^\beta\}$. Each stage of the learning process is completed together with CapsNet and LSTM. During the training of the capsule network, the input of layer β is represented by $I_\beta = [M^\beta, Sp^\beta, O^{\beta-1}, Nd^\beta]$, where $O^{\beta-1}$ and Nd^β represent the output and the new data at stage $\beta - 1$, respectively. Each granularity is formed into a corresponding capsule, and the high-level capsule with more sufficient information is obtained by reasonably assigning weights. The initial weight of each stage is determined by the level of granularity(formula 10, 11). The initial weight of stage β is defined as w^β, and the transformation way between capsule layers is:

$$\varpi_{h+1} = Sq(\sum_{\hat{\omega}_k \in \omega_h} \sum_{\hat{\varpi}_k \in \varpi_h} \hat{\omega}_k \hat{\varpi}_k) + \lambda_h, w_0 = w^\beta \qquad (11)$$

where $Sq(\cdot)$ represents a squeeze function, that is, $Suq(\cdot) = \frac{\|\cdot\|^2}{1+\|\cdot\|^2}\frac{\cdot}{\|\cdot\|}$. ϖ_h represents the capsule set of layer h, and the high-level weight is determined by the real-time status of the task. In order to prevent over-fitting, only several iterations are required to make information characteristics clear and then output the intermediate result $\bar{O}^\beta$.

During the training of the LSTM, first, filtering out invalid conclusions in $O^{\beta-1}$ by inputting $Sp^{\beta-1}$ and $O^{\beta-1}$ into the forget gate for generating $\tilde{O}^{\beta-1}$, while adding the intermediate result $\bar{O}^\beta$, $\tilde{O}^{\beta-1}$ and Nd^β into the input gate at the same time, then updating the granular space state and getting the comprehensive input $\tilde{I}^\beta$, finally obtaining the output O^β by the σ output gate and the $tanh$ activation function. The whole process of MPMCD is described in Algorithm I.

Algorithm 1 Multi-Task Parallel Multi-Granularity Collaborative Decision

```
while β stage do
    take Sp^{β-1} and O^{β-1} into forget gate: Õ^{β-1} ← {Sp^{β-1}, O^{β-1}};
    take I_β into CapsNet;
    Initialization the weight set w^β and w_0 ← w^β;
    while h layer do
        ϖ_{h+1} = Suq(Σ_{ŵ_k∈ω_h} Σ_{ϖ̂_k∈ϖ_h} ŵ_k ϖ̂_k) + λ_h
    end while
    output Ō^β;
    take Ō^β, Õ^{β-1} and Nd^β into input gate: Ĩ^β ← {Ō^β, Õ^{β-1}, Nd^β}
    O^β ←[tanh(·), σ(·)]— Ĩ^β
end while
```

V. AI-Driven Cognitive Networking Collaborative Decision-Making Algorithm

A. Deep Q-Learning Under MPMCD

Faced with a complex and dynamic traffic environment, vehicles and other distractors will bring a huge state space, especially when the system is facing multi-task parallelism, the increase in the amount of calculation will be particularly prominent, in order to adapt the huge state space and real-time dynamic data generated in the decision-making process, reinforcement learning based on the MPMCD model is used for multi-task parallel decision-making in ITS. Deep Q-learning (DQN) is an improvement of Q-learning, which calculates Q-value iteratively to achieve the final decision goal and adds an experience replay mechanism to train the learning process of reinforcement learning compared to Q-learning. This means that deep Q-learning combines the data and state that have been generated, and trains in small batches, which randomly avoids the influence of time series correlation, and makes the historical data and state effectively used. So DQN is more suitable for MPMCD model than Q-learning. Three main components of the DQN algorithm include state, action, and award, the state is a joint state space, which consists of the decision tasks of diverse vehicle in ITS, and the available capacity of each RSU, the action is a state of continuous decision making, defined as the real-time decision of the vehicle for handling various traffic tasks in ITS. As a reward function needs to be related to the objective of tasks, we set the reward as the length of time to achieve the objective. The learning aims to minimize this reward.

DQN calculates the corresponding Q-value by inputting the current decision state ζ, namely $Q(\zeta, a)$, where a represents the performed action, and adopts ε-greedy strategy to decide the action. The best action is selected according to the reward, and the process is looped until the increase in the reward is no longer obvious. Combined with the structure of MPMCD, the DQN process is divided into two parts, which respectively serve the CapsNet of each single stage and the whole sequential decision-making stage.

In a single stage, the CapsNet obtains the optimal decision-making result by adjusting the weight of the capsule

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corresponding to granularities. Therefore, the initial state of the single stage $\bar{\varepsilon}_0$ is the state of the capsule corresponding to each granularity in the compatible granular space, and the action a corresponds to how to get the high-level capsules with clearest characteristics, that is, to obtain the maximum Q-value. Each layer makes the next decision based on the output $O(\varepsilon, a, \theta)$ of current layer, where θ represents the network learning parameter. Taking any two tasks m_i, m_j as an example, the loss function $l(\theta)$ in the single stage is as follows:

$$
\begin{aligned}
l(\theta) = \frac{1}{p+q}[p(r_{h+1} + \gamma^i \max_{a'} Q(\varpi^i_{h+1}, a', \theta) \\
- Q(\varpi^i_h, a^i_h, \theta)^2) + q(r_{h+1} + \gamma^j \max_{a'} Q(\varpi^j_{h+1}, a', \theta) \\
- Q(\varpi^j_h, a^j_h, \theta)^2)] \qquad (12)
\end{aligned}
$$

where p and q are constants, and the update method of parameter θ is:

$$\theta = \theta - \alpha \frac{\partial l(\theta)}{\partial \theta} \qquad (13)$$

For the parallel decision-making process, the number of iterations between different tasks may diverge. The DQN in MPMCD focuses on the comprehensive status of multi-tasks. Even if some tasks have been completed, as long as there are other tasks in progress, the comprehensive status will be updated continuously. On the other hand, the continued participation of completed tasks in the subsequent calculations of the overall decision-making process leads to unnecessary time and resource consumption. In order to solve the above problems, the task m_i is marked with a variable ψ_i. When the Q-value becomes stable, that is, when the task ends, taking $\psi_i = 0$, otherwise $\psi_i = 1$. For any two parallel tasks m_i and m_j, the loss function $L(\tilde{\theta})$ of the overall parallel decision-making process is expressed as follows:

$$
\begin{aligned}
L(\tilde{\theta}) = (\frac{\psi_i}{\tilde{p}} + \frac{\psi_j}{\tilde{q}})[\frac{\psi_i}{\tilde{p}}(\tilde{r}_{\beta+1} + \tilde{\gamma}^i \max_{\tilde{a}'} Q(\vartheta^i_{\beta+1}, \tilde{a}', \tilde{\theta}) \\
- Q(\vartheta^i_\beta, \tilde{a}^i_h, \tilde{\theta})^2) + \frac{\psi_j}{\tilde{q}}(r_{h+1} + \tilde{\gamma}^j \max_{\tilde{a}'} Q(\vartheta^j_{\beta+1}, \tilde{a}', \tilde{\theta}) \\
- Q(\vartheta^j_\beta, \tilde{a}^j_h, \tilde{\theta})^2)] \qquad (14)
\end{aligned}
$$

The update method of parameter $\tilde{\theta}$ is similar to single stage. It can bee seen that the Q-value corresponding to the early ended task is not affect the loss function and the status of other subsequent tasks. In addition, tasks with stable Q-value can be separated and ended in time by mark ψ, which reduces decision-making costs and ensures the real-time performance of the tasks.

B. AI-Driven Cognitive Networking Collaborative Decision-Making

Multi-task parallel decision-making in ITS requires efficient perception and recognition of massive data and task status. Utilizing the powerful dynamic perception ability provided by the cognitive networking, the ACNCD algorithm is designed to ensure the real-time performance of multi-task decision-making. In ACNCD, the core problem is to calculate the corresponding results in time based on the status changes in the task set and the new data added in real time.

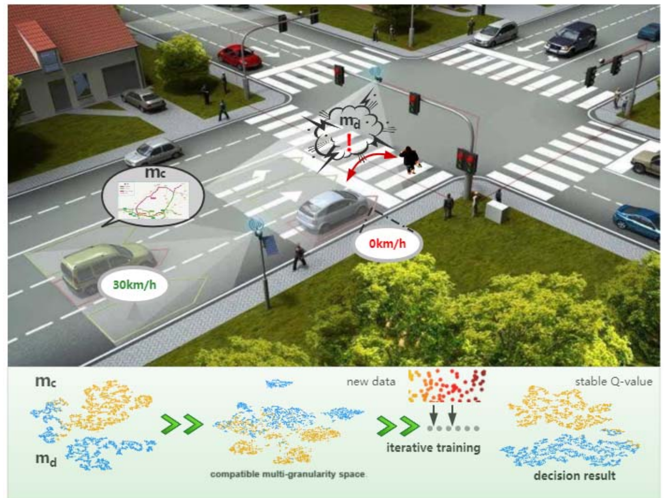

Fig. 4. Path planning task and emergency avoidance task in intelligent transportation scenario.

Through reinforcement learning based on the MPMCD model, the cognitive network system in ITS completes the real-time decision-making of parallel tasks, and the decision-making results of each task are encapsulated in capsules. According to the status and data update of the task set, the sequential decision-making forms the real-time intermediate conclusion with the greatest profit in real time in a dynamic and orderly manner, and iterates repeatedly to achieve the final goal. As shown in Fig. 4, taking the path planning task m_c and the dangerous emergency avoidance task m_d as examples, a compatible multi-granularity space is first established according to the road states related to the two tasks and used as the input of the first stage. The granularity types between different tasks may overlap but their status are different. For example, although both m_c and m_d are related to the movement state of roadside pedestrians, the latter pays more attention to this point and m_d is given a higher granularity weight. At the end of the current stage, the new task status is output and new data needs to be input according to the real-time position and the surrounding environment of vehicles to continue the next stage of training. When the Q-value is stable, the corresponding task is separated and decision result is output. In addition, considering that the Q-value update strategy of each task is relatively independent, the ACNCD algorithm also supports the addition of new tasks to the intermediate parallel task set. The detailed process of ACNCD is shown in Algorithm II.

VI. Performance Analysis

In this section, the proposed ACNCD algorithm is evaluated by using the VISSIM simulator. Due to the wide variety of decision-making tasks in ITS and their different characteristics, it is unrealistic to test all aspects of various tasks. Therefore, path planning tasks and emergency avoidance tasks are selected as typical examples to test the real-time and correctness of the decision response of the ACNCD algorithm.

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Algorithm 2 AI-Driven Cognitive Networking Collaborative Decision-Making Algorithm

Input: the task set $\hat{M}$ that consists of any number of tasks;
Initialization: Initializing compatible multi-granularity space Sp^1;
$\beta = 1$;
while the $\tilde{\theta}$ of all task in $\hat{M}$ are not stable **do**
  while β state **do**
    if new task join into $\hat{M}$ **then**
      change $\hat{M}$ and update Sp^β;
    end if
    input $I_\beta = [\hat{M}^\beta, Sp^\beta, O^{\beta-1}, Nd^\beta]$;
    calculate and output when θ is stable;
    $\beta += 1$;
  end while
  for $c = 1; c >= sizeof(\hat{M}); c++$ **do**
    if the $\tilde{\theta}$ of m_c is stable **then**
      separate m_c and output result;
    end if
  end for
end while

TABLE I
PARAMETERS CONSIDERED FOR SIMULATION

Simulation parameters	Values
Number of intersections	15
The test duration (hours)	2
The total number of test vehicles	1000
Number of fixed route vehicles	800
Number of non-fixed route vehicles	140
Number of randomly added vehicles	60

The parameters in the simulation are shown in Table I. Number of fixed route vehicles represents the vehicles that have determined their driving route to cause road congestion. Number of non-fixed route vehicles refers to the number of vehicles requiring real-time path planning. Number of randomly added vehicles refers to the number of randomly distributed vehicles added to the road section to create accidents.

During the entire test time, all vehicles staggered into the test scene. For the test vehicle, the path planning task continues until it reaches the destination and its driving route can be changed in real time with traffic congestion. If any vehicle detects that there are vehicles randomly distributed for emergency encounters at the intersection that is going to pass, the emergency avoidance task is triggered, that is, the simulation scenario is in the parallel execution state of the two decision-making tasks. In addition, in order to simulate the existence of data ambiguity, 10% of non-task participating vehicles are randomly selected to stop sharing data intermittently to cause uncertainty in decision data.

For the stability evaluation of the ACNCD algorithm, the convergence of ACNCD algorithm based on DQN is verified by comparing with Q-learning and Sarsa algorithm. Fig. 5 shows the Q values of the three reinforcement learning algorithms in 1000 iterations. Obviously, as the number of iterations increases, the real-time decision performance of

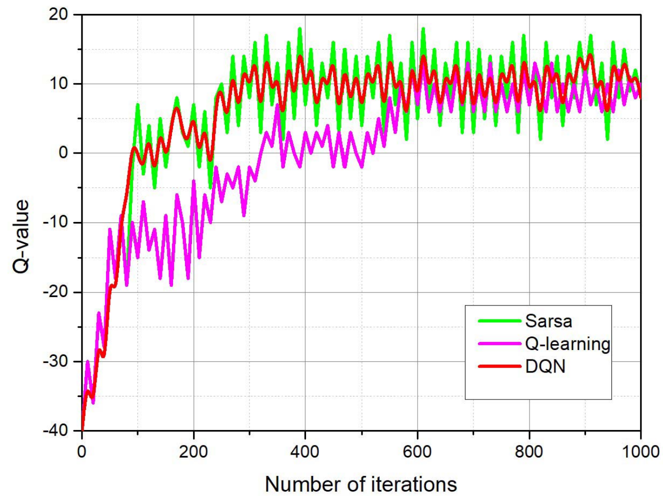

Fig. 5. Convergence of the three algorithms.

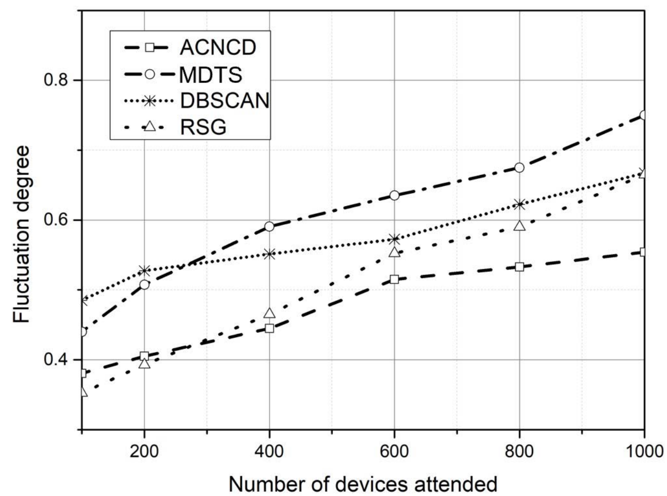

Fig. 6. Fluctuation of the number of congested intersections.

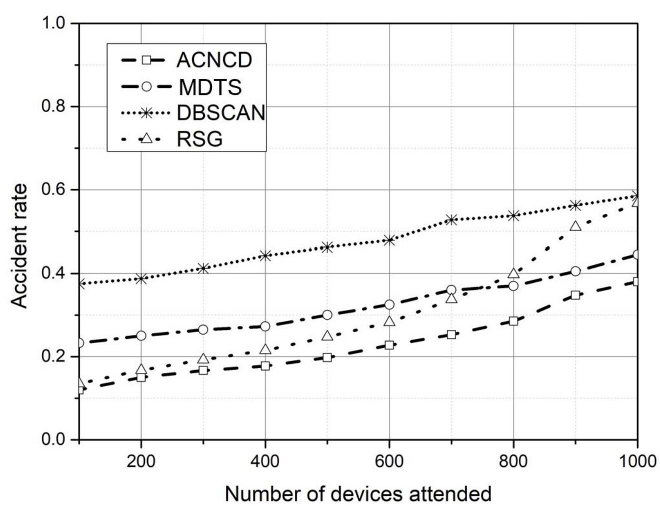

Fig. 7. Accident rate of the number of congested intersections.

ACNCD is better and more stable, while the other two scheduling algorithms show strong oscillation. In order to verify the scalability of multi-task decision making method

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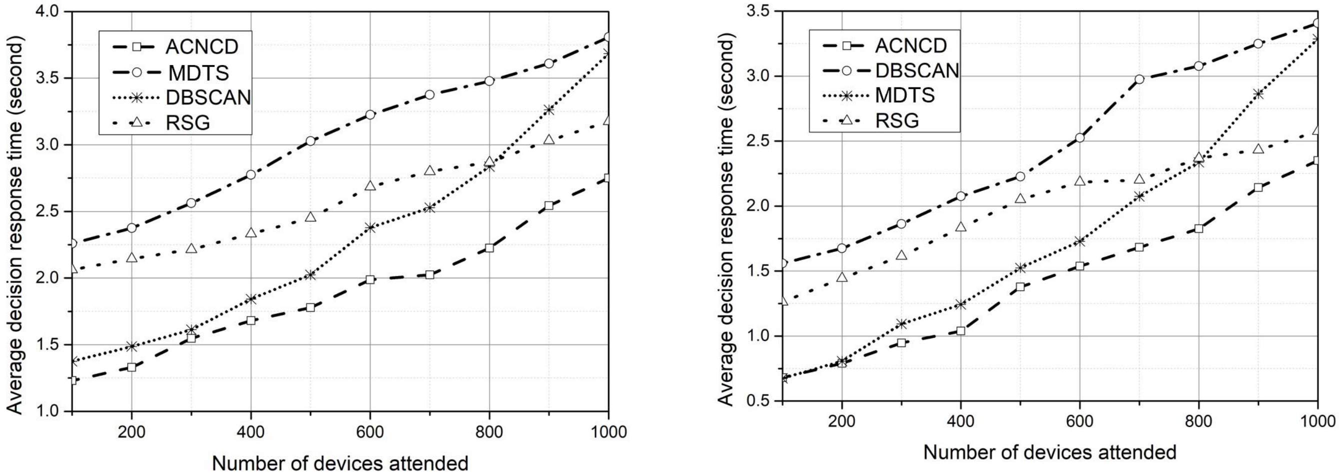

(a) The path planning task

(b) The emergency avoidance task

Fig. 8. Average decision response time of the four algorithms.

TABLE II

NUMBER OF ITERATIONS N FOR THE CONVERGENCE OF ALGORITHMS AND THE EXECUTION TIME T PER ITERATION

Algorithm	Tasks=30		Tasks=50		Tasks=100	
	T	N	T	N	T	N
DQN	0.027	320	0.034	483	0.048	705
Q-learning	0.041	416	0.095	548	0.18	692
Sarsa	0.025	332	0.089	504	0.162	826

based on DQN, the number of iterations for the convergence of algorithms and the execution time per iteration are further tested under different task numbers. It can be seen from Table II, the multi-task decision making method based on DQN has much lower complexity and less execution time for each iteration than the other two algorithms. Although the multi-task decision making method based on DQN need more iterations to converge in large-scale task scenarios, but the total execution time of their convergence is still much lower than the other two algorithms. In fact, the ACNCD has shown its superiority in algorithm design through fine-grained modeling of perception information and knowledge sharing at the neural network layer. The above experiments further prove that ACNCD algorithm can achieve better performance in solving multi-task parallel real-time decision problems.

The decision-making performance of path planning task and emergency avoidance task are measured separately from two aspects of road congestion and accident rate.Specifically, defining parameter $\mu = N_h/S_h$ indicates whether the road is congested. The road between two adjacent intersections is divided as a road segment. N_h represents the current number of vehicles on the road segment h, and S_h represents the maximum number of vehicles that can be accommodated on the h. When $\mu > 0.6$, the road is congested. In the simulation, taking 10 minutes as the time period, the average fluctuation degree of the number of congested road sections after vehicles entered the test scene is recorded and compared with the expected. If the degree of fluctuation is lower than expected, it indicates that the ACNCD algorithm is effective for path planning tasks. The accident rate is represented by the parameter $P = A/|V|$, also recorded in units of 10 minutes, where A and $|V|$ are the number of accidents and the number of vehicles that randomly. It is worth noting that the accident in the simulation is defined as the two vehicles being close by less than 0.5 meters, rather than a real collision. In the simulation, the multi-task deep reinforcement learning approach for scalable parallel task scheduling (MDTS), the density-based clustering algorithm (DBSCAN), and the reverse stackelberg games algorithms (RSG) are compared with ACNCD under the condition of data ambiguity. MDTS achieves scheduling of parallel traffic tasks by addressing the curse of dimensionality when dealing with complex parallel computing environments and tasks with different properties [29]. In RSG, the reverse Stackelberg game is utilized to model vehicle routing, and the systematic optimal vehicle routing is achieved according to the predicted traffic conditions [30]. The density-based clustering algorithm identify the traffic patterns under both normal and abnormal conditions, it performs prediction by the discovery of the particular traffic pattern that is formed [31]. Fig. 6 and Fig. 7 shows the results as follows.

We further test ACNCD in terms of decision response time, decision accuracy. Fig. 8(a) and Fig. 8(b) shows the comparative experimental results of the average decision response time in the presence of fuzzy data. It can be seen that although the response time of the four algorithms increases with the increase of the number of vehicles in the road scene, the ACNCD is obviously more advantageous than the other three algorithms in terms of decision speed based on fuzzy data. This is because the adaptive and compatible granular space constructed by the ACDN algorithm accelerates the knowledge discovery in the decision-making process. The average response time performance of MDTS and RSG is poor, the average response time of DBSCAN is excellent when there are fewer vehicles on the road, but the time performance of DBSCAN is affected by the increase in the number of vehicles.

Then, the middle 1 hour of the simulation is selected and 5 minutes is used as the time interval to measure the decision accuracy of these algorithms. As shown in Fig. 9(a)

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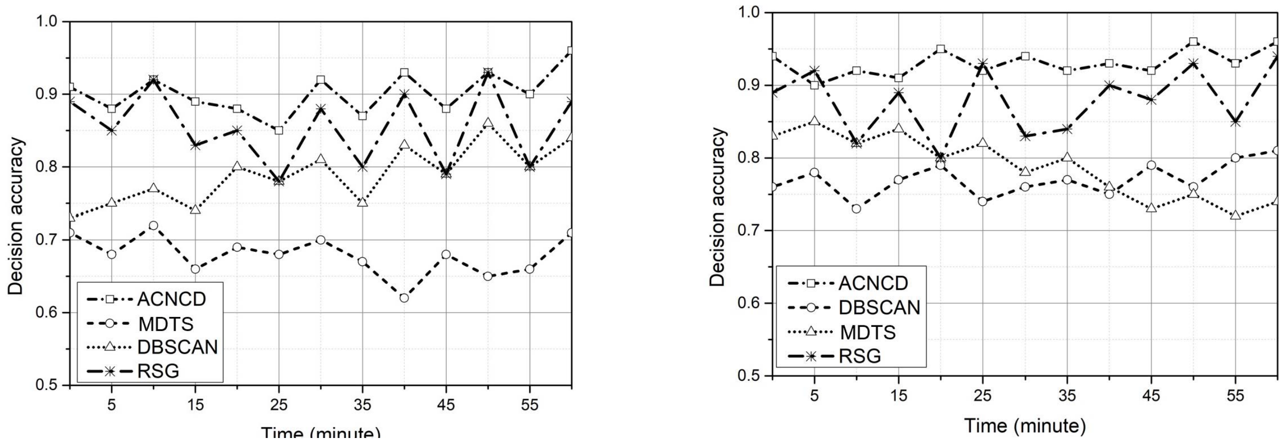

(a) The path planning task

(b) The emergency avoidance task

Fig. 9. The decision accuracy of the four algorithms.

TABLE III

AVERAGE DECISION RESPONSE TIME UNDER DIFFERENT NUMBER OF TASKS

Number of vehicles	Two tasks(P/E)	Three tasks(P/E/M)	Four tasks(P/E/M/S)
200	1.33/0.79	1.35/0.82/1.08	1.40/0.89/1.12/1.83
400	1.68/1.03	1.71/1.07/1.23	1.78/1.11/1.28/2.12
600	1.99/1.53	2.05/1.60/1.87	2.13/1.69/1.98/2.53
800	2.22/1.82	2.30/1.91/2.12	2.41/2.03/2.21/3.01
1000	2.75/2.35	2.86/2.44/2.68	2.99/0.79/2.54/3.66

and Fig. 9(b), it can be seen the decision accuracy of two tasks of MDTS is the worse, the decision accuracy of DBSCAN increases with time. The curve of the RSG algorithm fluctuates violently and can not keep high decision accuracy, the ACNCD algorithm is the highest, and the stability of decision accuracy is the best over time, which indicating that the ACNCD algorithm is more suitable for the multi-task parallel decision-making. The ACNCD algorithm supports the dynamic adjustment of tasks and the timely update of information in the iterative process of sequential decision-making, so that the decision-making results are more in line with the actual needs of task execution in ITS.

In addition, in order to better analyze the time performance of the algorithm in scenarios with a large number of tasks, the multi-row switching tasks (M) and parking spot selection tasks (S) were added to test the average decision response time on the basis of the completed path planning(P) and emergency avoidance tasks(E). Table III shows the influence of different numbers of parallel tasks and different sizes of vehicles on the average decision response time. With the increase of parallel tasks, the average response time does not change significantly. As the ACNCD algorithm establishes hierarchical compatible granularity space to increase the ability of information sharing and knowledge migration, it optimizes the reinforcement learning process and ensures real-time decision-making in multi-task scenarios.

VII. CONCLUSION

This paper has studied the multi-granularity collaborative decision that supports the cognitive networking in ITS to meet multi-task parallel decision in complex dynamic environments. First, an ITS collaborative decision architecture with cognitive networking is designed, according to which the issues of multi-task parallel decision-making and potential solutions have been analyzed. Then, the MPMCD model has been designed by combining the ideas of granular computing and sequential decision-making, which makes full use of the respective advantages of CapsNet and LSTM to execute multi-task parallel decision-making with fuzzy data. Finally, combined with deep Q-learning, an AI-driven cognitive networking collaborative decision-making (ACNCD) is proposed to realize multi-task parallel decision-making in ITS supported by cognitive networking. The simulation results have shown that ACNCD optimally performs the parallel decision-making with cognitive networking for ITS, effectively reduces the decision-making time and is more suitable for fuzzy data. As future work, we will solve resource optimization problems in the online decision-making process and support more types of intelligent decision-making tasks in ITS.

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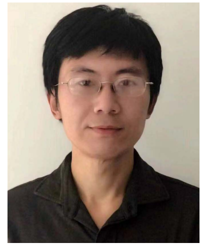

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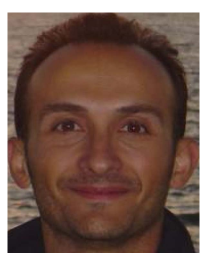

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