Proceedings of CONF-SEML 2025 Symposium: Machine Learning Theory and Applications
DOI: 10.54254/2755-2721/160/2025.TJ23498

Theoretical Approaches, Practical Applications and Development Trends of Intelligent Control

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Abstract: The advent of Industry 4.0 and the Internet of Things (IoT) has led to a surge in system complexity, propelling the development of intelligent control systems that exhibit autonomy and adaptivity. These systems have found widespread application in diverse domains, including industry, transportation, and healthcare. The present study focuses on three mainstream methods of intelligent control: fuzzy logic control, neural network control, and reinforcement control. In addition to a review of the latest research in this field from the past five years, the study also examines the latest application areas of current expansion. In light of the prevailing trends in the domain of intelligent control, a rational analysis has been conducted to assess the technical, ethical, and practical limitations and challenges pertinent to this field. This analysis has led to the conclusion that intelligent control systems are poised to evolve towards higher degrees of autonomy, safety, and sustainability in the future.

Keywords: intelligent control, fuzzy logic control, neural network control, reinforcement learning

1. Introduction

Intelligent control emerged as a breakthrough in the limitations of traditional control methods. Traditional control (e.g., PID control) relies on precise mathematical models and struggles to meet the challenges of complex, nonlinear, and highly uncertain systems. With the popularity of Industry 4.0 and the Internet of Things (IoT), system complexity has increased significantly, and the need for implementation decisions and multi-objective optimization in dynamic environments has driven the evolution of intelligent control towards autonomy and adaptivity. Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), etc. are driving the transformation of intelligent control from "rule-based" to "data-driven" by enhancing the system's perception, learning and decision-making capabilities.

The core of intelligent control is to enable the system to adjust its strategy autonomously in dynamic environments and to realize flexible control strategies by imitating human decision-making, learning ability or biological mechanisms. Currently, intelligent control has evolved from a single algorithm to a complex system that integrates multiple technologies. By integrating artificial intelligence (AI), Internet of Things (IoT), cloud computing, big data and other technologies, intelligent control systems achieve the optimization of the entire process of perception, decision-making and execution. Intelligent control adopts key technologies such as fuzzy control, neural

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network, reinforcement learning and multi-technology fusion, which enables the application scope to be expanded from traditional industry to life services, city management, healthcare and other fields.

This paper presents a comprehensive review of the development of the field of intelligent control. Chapter 1 covers the current status of the field of intelligent control, Chapter 2 covers the latest research on key technologies of intelligent control methods and related applications in the past five years, and Chapter 3 analyses the challenges and development trends of intelligent control.

2. Basic concepts of intelligent control

2.1. Basic principle

The basic principle of intelligent control is to solve the autonomous decision-making and optimization problems of complex systems by integrating traditional control theory and artificial intelligence methods. Such systems usually have nonlinear, time-varying or highly uncertain characteristics that are difficult to describe by accurate mathematical models. It focuses on system modeling and control strategies, emphasizing data-driven and adaptive learning capabilities so that the system can adjust its behavior autonomously in dynamic environments.

In system modeling, traditional control uses math to build accurate models, but these models can have errors that affect control. Intelligent control uses data-driven approaches to overcome this. Neural networks learn system dynamics from sensor data without equations. Fuzzy systems transform inputs into outputs using linguistic rules based on expert experience. Reinforcement learning interacts with the environment to build models that predict future states to optimize control. Hybrid modeling combines physical laws and data-driven approaches.

The design of control strategies is another key part of intelligent control. While traditional methods rely on fixed parameters, intelligent methods enhance adaptivity by introducing AI techniques. Fuzzy control transforms human experience into a rule base to handle nonlinear and linguistic knowledge. Neural network control utilizes its nonlinear fitting ability to learn a system model directly as a controller or adjust the network weights to adapt to changes. Reinforcement learning, on the other hand, optimizes long-term goals through trial-and-error mechanisms, such as minimizing energy consumption when training a robot to walk [1]. Key techniques for reinforcement learning include Q-learning and policy gradient methods. Hybrid strategies combine the advantages of traditional and intelligent approaches, such as adjusting PID parameters with fuzzy logic to adapt to changes or using neural networks to predict states and optimize control.

The realization of intelligent control relies on data and models working together. Neural networks and reinforcement learning need a lot of training data, which can be obtained in simulation environments and real interactions. Control theory provides stability guarantees for AI methods. It's challenging to balance model flexibility with theoretical reliability, as neural networks are a black box and reinforcement learning is computationally demanding. Future directions include using lightweight models, collaborating with computers, and designing physically guided AI to encourage its use in more fields like autonomous driving and smart manufacturing.

2.2. Mainstream methods

Fuzzy control is an intelligent control method based on fuzzy logic, which is good at dealing with complex systems with uncertainty, non-linearity or difficulty in establishing an accurate mathematical model. It imitates the empirical decision making of human beings in actual operation, reasoning about the input information through linguistic "fuzzy rules", and finally outputting reasonable control signals, which is suitable for controlling home appliances and optimizing traffic signals.

Neural network control is a type of intelligent control based on artificial neural networks (ANNs). It mimics the learning and adaptive abilities of biological neural systems. Neural network control is

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effective in complex systems. In conventional uses, neural networks usually do two things related to control: first, they model the system and generate control instructions; and second, they adjust parameters in a classical control structure to adapt to changes. This approach has advantages like being able to operate without a precise math model and adapting through data-driven methods. But it needs enough data to train, and is highly complex.

Genetic systems use optimization and learning methods based on the principles of biological evolution. They simulate natural selection, genetic recombination, and mutation to search for optimal solutions. The system's processes include: randomly generating candidate solutions, screening individuals based on an objective function, retaining high-fitness individuals using roulette wheel techniques, exchanging gene segments to generate new solutions, and randomly modifying some genes to maintain diversity. This method is adept at global search for complex nonlinear problems, and it is commonly used in parameter optimization, combinatorial design, and other scenarios, despite requiring high computational cost.

3. Intelligent control key technology

3.1. Fuzzy logic control

The core principle of fuzzy logic control uses fuzzy sets and affiliation functions. Unlike traditional sets, which use either/or, these sets allow degrees of affiliation between 0 and 1, closer to human intuition of fuzzy language such as "high" and "low." The control rules are usually constructed in the form of "if-then" rules, covering various possible combinations of inputs. When performing control, precise inputs are first converted into affiliation degrees. Corresponding rules are activated, and integrated reasoning is performed. Finally, the fuzzy conclusions are transformed into specific control instructions through defuzzification. When executing control, precise inputs are first converted into affiliation, and then rules are activated according to the rule base. Finally, the fuzzy conclusions are converted into specific control instructions through defuzzification, as shown in Fig. 1 [2].

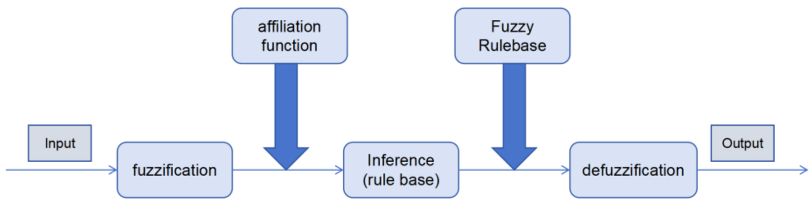

Figure 1: The process of fuzzy logic control

Fuzzy logic control systems are frequently utilized to approximate unknown dynamical systems and are extensively employed for the control of nonlinear systems. In order to ensure that the constraints are not violated and all outputs are bounded, many adaptive fuzzy control schemes have been proposed to design controllers that can fulfill the requirements [3]. Fuzzy logic control finds application in a variety of scenarios that demand flexible control. Such scenarios include household appliances (as evidenced by certain Dyson vacuum cleaner models), industrial automation (as exemplified by the Mitsubishi elevator system), and transportation (as demonstrated by Toyota's ECT-i system).

In [4], an adaptive fuzzy control scheme for multi-input multi-output systems with time-varying full-state constraints and unknown control directions is proposed, wherein fuzzy logic is utilized to

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regulate approximate unknown dynamic functions. The sensor is responsible for the measurement of the output of the subsystem, and it is also responsible for the generation of the tracking error z_i.The adaptive law is designed to update the parameter estimation error based on the tracking error z_i, thereby compensating for system uncertainty in real time. The estimation error is then employed to adjust the control direction through the Nussbaum function N_i, thereby generating an intermediate signal ∂_i. The actual controller integrates the virtual controller and parameter estimates to generate a final control quantity, which is used to drive the actuator, thereby adjusting the subsystem state. Subsequent to the actuator's action, the subsystem's state undergoes an update, and the sensors are subjected to re-measurement, thereby establishing a closed-loop feedback system. In this control scheme, the system uncertainty is addressed through online estimation error compensation. The Nussbaum function and virtual controller are designed to ensure the global stabilization of the closed-loop system. This scheme is applicable to multi-stage systems in series or parallel scenarios, and the state of each level is gradually calmed by backstepping. The designed virtual controller (1), the actual controller (2), and the adaptive laws (3) and (4) are designed in such a way that all outputs and error signals of the system are bounded, concurrently, the tracking error $z_{i,j}$ satisfies $lim_{t\to\infty} z_{i,j}(t) = 0$.[5] also developed a fuzzy adaptive time-varying control method to approximate the uncertain dynamics function and unknown parameters. This ensures that the tracking error can be converged to a small neighborhood close to zero. The difference is that [5] incorporated a fault-tolerant module to design the controller according to the fault-tolerant time-varying. Inspired by the discussions in [4] [5, 6] and others, the adaptive fuzzy control scheme proposed in [3] allows the system state to converge asymptotically to the origin rather than to a neighborhood of the origin. In this study, adaptive fuzzy control is integrated with state constraints to guarantee that the state consistently satisfies the constraints. This is achieved by employing a fuzzy logic system to approximate an unknown nonlinear function, thereby introducing a barrier component to the control law.

$$\alpha_{i,l} = \mathrm{N}_{i,l}(\nu_{i,l})\bar{\alpha}_{i,l} \tag{1}$$

$$u_{i,n} = \mathrm{N}_{i,n}(\upsilon_{i,n})\bar{\alpha}_{i,n} \tag{2}$$

$$\dot{\widehat{\Theta}}_{i,n} = \frac{\varpi_{i,n}\kappa_{i,n}^{T}(\mathrm{X}_{i,n})\kappa_{i,n}(\mathrm{X}_{i,n})\eta_{i.n}^{2}}{2\varsigma_{i,n}^{2}} - \beta_{i,n}\widehat{\Theta}_{i,n} \tag{3}$$

$$\dot{\hat{\varrho}}_{i,n} = \gamma_{i,n}\eta_{i,n} - \zeta_{i,n}\hat{\varrho}_{i,n} \tag{4}$$

3.2. Neural network control

Neural networks model nonlinear, time-varying, or high-dimensional dynamic systems, or generate control signals through network structure, especially for scenarios that are difficult to model by traditional methods. They can adjust their weights through online/offline learning to achieve optimal control. In practice, they are combined with other methods to improve robustness. Neural networks are widely used in intelligent systems (e.g., DJI's 2024 model uses multi-intelligence collaborative flight control technology), the energy field (Tesla's drive system uses permanent magnet synchronous motor speed control technology), and other fields.

Dynamic systems are always affected by unknown factors and external disturbances. Standard methods can't always achieve systemwide robustness, so [7] introduced a radial basis function neural network for differential processing of sliding film surfaces. The global sliding model controller is hard to implement because of its need for a detailed understanding of the model. This approach is rarely used compared to that of feedforward neural networks. The RNN, which combines a feedforward neural network with a feedback loop, has shown an effective solution to the poor performance of feedforward neural networks. The process of adjusting parameters is simple, and the

DOI: 10.54254/2755-2721/160/2025.TJ23498

basic RNN network structure is shown in Figure 2. The improved capabilities of RNNs have led to the creation of many advanced RNN models to deal with specific challenges.

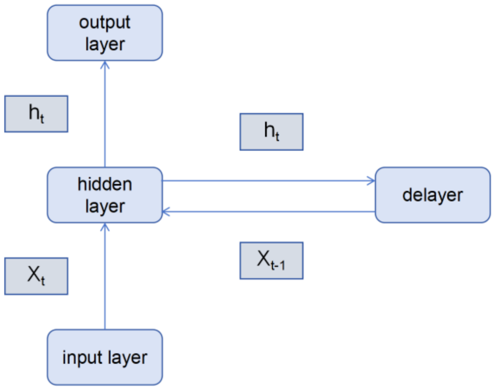

Figure 2: RNN basic network structure

Inspired by multilayer perceptron and RNN mechanisms, [8] introduced a controller based on a double hidden layer recurrent neural network (DHLRNN), ensuring stability and robustness. This DHLRNN contains two hidden layers and dynamic recurrent connections, representing memory elements. The adaptive parameter and structure learning process of the HLRNN is faster and more precise than RNNs.[8] proposed a new controller (6) based on the equivalent controller (5). The ideal global sliding mode controller can be obtained from (6) under the condition that all system parameters are known. The global sliding mode controller facilitates the attainment of optimal trajectory characteristics and ensures the global asymptotic stability of the closed-loop control system. However, the unknown parameter matrix A in the control in (6) prevents the ideal controller from being obtained, so the design of a global sliding mode controller using a new double hidden layer feedback neural network is proposed to solve this problem. The DHLRNN, which consists of multilayer perceptions, has two hidden layers and a dynamic cyclic connection that represents memory elements. The DHLRNN is a four-layer network embedded with two hidden perceptron and an external feedback connection. The initial layer is designated as the input layer, comprising signal-receiving nodes. A distinguishing feature of this layer is the capacity of its neurons to receive components from the output layer through the signaling neural structure, facilitated by the neurons. The second layer constitutes the initial hidden layer, which maps the signal from the input space to a higher-dimensional hidden space where the signal features are linearly differentiable and the computation of the Gaussian function is performed. The signal is subsequently mapped to the third layer, and the Gaussian function is once again computed. The fourth layer, designated as the output layer, serves to finalize the computation of the neural network's output for a variety of inputs. The output signals will be propagated to return the results to the input layer neurons through an external feedback loop after completing the computation of the output signals for the current round.

$$U_{eq} = (CB)^{-1}\left[f_0(t) - CAX - CF + CX_d\right] \tag{5}$$

$$U = (CB)^{-1}\left[f_0(t) - CAX - C\dot{X}_d - Ksgn(S)\right] \tag{6}$$

In this system of equations, $A \in R^{N\times N}$, $B \in R^{N\times N}$ denotes the parameter matrix, $C \in R^{N\times N}$represents the non-singular matrix, $X \in R^N$is the state vector, $F \in R^N$is the uncertainty term, $f_0(t)$applies to the function that reaches the global sliding surface, and K is the sliding gain.

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3.3. Reinforcement learning

Reinforcement learning is a machine learning method that learns optimal strategies through the interaction of an intelligent body with its environment. It uses a Markov decision process to model the decision-making process. The optimization goal is to find the optimal strategy to maximize the expectation of accumulating rewards [9]. The classical reinforcement learning model is shown in Fig. 3. The fundamental premise of the Markov decision process is that the subsequent state is contingent solely on the present state and action (history-independence), i.e.: $P(s_{t+1}|s_t, s_a) = P(s_{t+1}|s_0, a_0, \cdots, s_t, a_t)$, thereby reducing the computational complexity of state transition. Reinforcement learning has found application in a variety of fields, including gaming AI (e.g., the AlphaGo series, DOTA2, OpenAI Five), robotics (e.g., the footed robot Boston Dynamics Atlas, which is capable of walking on complex terrains via RL), intelligent transportation (e.g., the Hangzhou City Brain project, which has led to a 25% increase in access rate), and intelligent healthcare (e.g., da Vinci Surgical Robotics).

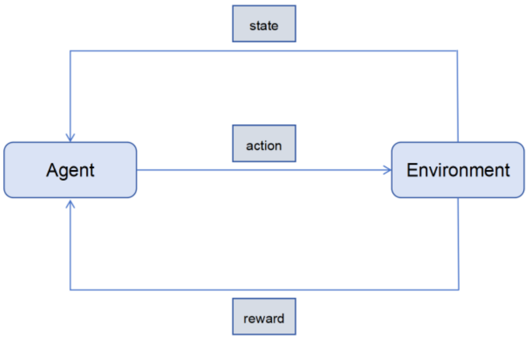

Figure 3: The classical reinforcement learning model

As indicated in the relevant literature, contemporary reinforcement learning (RL) agent models demonstrate a propensity to encounter challenges in their capacity to adapt to dynamic and uncertain conditions. [11] has drawn attention to the fact that prevailing approaches, including incremental learning [12], gradient descent methods [13], the generation of RL detection agents [14], and transfer learning, Adaptive self-learning dynamic planning is limited in scope due to its predominantly goal-oriented nature, which often disregards the learning process as a means of balancing skills and challenges. This tendency towards over-adaptation or the failure to retain accumulated knowledge can compromise the model's performance when confronted with increasingly complex challenges. In addressing these limitations, the concept of flow has been proposed as a potential solution to enhance the range of performance in the field of artificial agents. The concept of flow is inherent in the task itself, which commences at a specific challenge level and skill level, designated as initial level (α). The agent incrementally augments its skill level (Step 1) until the boredom value at the challenge level surpasses the boredom threshold (Step 2). In the event that the boredom threshold has been surpassed and the experience level corresponds to the system's anticipated final level (step 3), the system successfully concludes the learning process. Conversely, the system augments the complexity of the challenge by increasing the difficulty level (step 4) and reverting to the learning phase. The fundamental framework of [11] comprises two primary algorithms: the stream-based reinforcement learning algorithm 1 and the boredom calculation algorithm 2. The modified Flow-based reinforcement learning algorithm 1 initially initializes the Q-table and the state of the solution at the current challenge level. It then balances exploration and utilization to select actions using the decaying ε-greedy Q-learning method. In the initial learning rounds, random actions with relatively high probability are selected, and the probability of exploration is gradually reduced during the learning process to increase the chance of utilizing the most appropriate actions. Subsequent to ascertaining the solution for each challenge level, a boredom value is calculated based on all the state and action pairs accessed by that solution. This value is then compared with a predefined threshold to determine whether the agent has exited the Flow region and issued a command. The boredom calculation algorithm 2 is based on Equation (7), which determines the frequency of accessing state-action pairs ((s; a)) over multiple runs. At the conclusion of each iteration, the algorithm recalibrates the number of visits and action pairs for each state to determine the level of boredom. The frequency with which a given combination is accessed across multiple rounds has been demonstrated to inversely correlate with its perceived novelty and increase its boredom value. The boredom value is defined to range between [-1,0], with 0 indicating a completely novel solution and -1 indicating a solution with no novelty whatsoever. The mean boredom value of all possible combinations is utilized in Algorithm 1 to compare with the boredom threshold. In the initial phase of each challenge, solutions are initiated with a value of 0. In the absence of novelty in the state and upon attaining a value of -1 by the action pair, the challenge is escalated to the subsequent level.

$$b_t(s,a) = \left(\lambda_1^{n_t(s)} + \lambda_2^{n_t(s,a)}\right)\Big/_2 - 1 \tag{7}$$

Furthermore, reinforcement learning typically employs reward functions to train the agent's behavior to execute a designated task. The complexity of environments can impede the construction of reward functions, a challenge that can be effectively addressed by leveraging human preferences. [10] proposed a weakly supervised human preference for deep reinforcement learning that allows for human input dynamics and weak preference levels. The authors developed human preference scaling models to reflect human behavior and reduce the number of human inputs to established human presentation estimators. The developed model for human preference reinforcement learning has been demonstrated to achieve higher cumulative reward values than current fixed human preference models. This finding lends support to the hypothesis that reinforcement learning can reduce the amount of dynamic and weakly preferred human inputs by up to 30% without significantly sacrificing reward values. In [10], human preferences were modeled using a Bayesian-based method for learning strategies from trajectory preference queries, the synthetic prophet. The model developed in [10] is predicated on synthetic human preferences and modifies the design of the preference interface in [15] to accommodate weaker human preference conditions. Scale-based preferences provide a scaling model that inputs dynamic scores by assigning any value between 0.0 and 1.0 to the preference segments. The range of z is set to [0.0,1.0], and a z value of 1.0 indicates that humans exhibit a strong preference for the left trajectory segment, while a z value of 0.0 indicates an equal preference for both segments, and a z value of 0 indicates a preference for the right trajectory segment. The value of 5 indicates an inability on the part of humans to differentiate between the two trajectory segments under consideration. The data indicates a weak preference for σ_1 at values between 0 and 0.5, as well as a weak preference for σ_2 at 0.5 to 1.0. This provides the reinforcement learning agent with more accurate human preference information and with a specification of the degree of dominance. [10] developed a human demonstration estimator that was based on previous human inputs. This was an extended version of the above preference scaling method with a regression model for supervised learning. The regression model used was either linear regression or support vector regression (SVR) combined with a radial basis function (RBF) kernel. This approach had two advantages. First, it reduced the number of human inputs, n. Second, it maintained a good performance without sacrificing cumulative rewards. The database, which has been meticulously compiled, comprises n-fold preference scaling for preference estimators derived from prior human inputs. Additionally, it incorporates supervised learning regression models for human demonstration estimators, which are

DOI: 10.54254/2755-2721/160/2025.TJ23498

employed to predict specific human preferences. The database is structured in the following format: $(\sigma_1,\sigma_2,\hat{z})$.

4. The application of intelligent control

"Intelligent control" refers to systems that adapt and optimize on their own in complex environments thanks to technologies like artificial intelligence and machine learning. These versatile systems are used in automated robot control, transportation, energy systems, healthcare, and more.

4.1. Automated robot

Intelligent control solves problems in automated robotics, such as sensor inaccuracy, adapting to dynamic environments, and nonlinear system control. For example, a fault-tolerant tracking problem of time-varying formations in multi-robot systems was studied in [5]. A fuzzy adaptive formation tracking control system was developed using fuzzy logic systems (FLS) to approximate uncertain nonlinear dynamics, enabling formation collision avoidance and stay-connected, and a predetermined performance method was used to address the constraint of distance and angle. In human-robot interaction, robots can recognize human emotions. A method was proposed in [18] to analyze multimodal emotions using a coupled network. This network divides emotion recognition into two layers, extracting features using a fusion network of broad and deep learning and correlation analysis.

4.2. Energy system and smart grid

Many countries are quickly developing new energy sources to meet rising electricity demand, focusing on solar energy. Currently, the lack of inertia response and changing behavior have a negligible effect on frequency stability. The solar system is designed to maximize power injection into the grid, but this is limited by solar capacity. Synchronizers, which simulate inertia, are essential for integrating solar energy and grid stability. However, current synchronizers lack capacity to accommodate adaptive damping or digital controllers crucial for solar input management. A novel fuzzy logic controller (FLC) framework is proposed in [16] to control Dp in real time, balancing speed and stability, and correcting frequency errors based on the frequency difference. This enables synchronizers to operate in grid-connected solar systems, addressing frequency stability issues.

4.3. Medical and healthcare

Intelligent control has found widespread application in the domain of healthcare, particularly in surgical robots, intelligent diagnosis of medical images, and the optimization of drug development. Prominent examples include the da Vinci surgical robot, the ET medical brain, and the lower limb exoskeleton robot. [17] provides a concrete illustration of the implementation of fuzzy control in the context of medical imaging intelligent diagnosis. When employing neuroimaging analysis for the automated diagnosis of Alzheimer's disease, traditional deep learning (DL) models encounter challenges related to data inaccuracy, stemming from ambiguous expert annotations, difficulties in data collection, such as data harmonization issues, and constraints in device resolution. These issues hinder the accuracy of analysis, interpretation of results, and comprehension of complex symptoms. The integration of fuzzy logic with deep learning, known as "fuzzy deep learning" (FDL), has emerged as a significant development in data management and analysis. This approach effectively addresses the challenges posed by imprecise data, offering interpretable insights that facilitate more accurate and nuanced decision-making.

4.4. Transportation

[19] conducted a review of the components of the autonomous driving task in which reinforcement learning can be implemented. These components include controller optimization, path planning and trajectory optimization, motion planning and dynamic path planning, the development of advanced driving strategies for complex navigation tasks, scenario-based highways, reward learning for intent prediction through inverse reinforcement learning from expert data, and ultimately policy learning for ensuring safety and performing risk assessment. The authors implemented DRL (DDPG) for autonomous driving using a full-size self-driving car [20], which was initially trained in a simulated environment and subsequently trained in real time using an on-board computer. The vehicle demonstrated the ability to learn to follow lanes and successfully completed real-world trials on a 250-meter stretch of road. This paper demonstrates the promising future of reinforcement learning in the domain of autonomous driving.

5. Challenges and development trends of intelligent control

The field of intelligent control, a fusion of artificial intelligence and automation technology, has shown significant advantages in many industries. Intelligent control systems can mimic the learning, reasoning, and decision-making process of humans, optimize the control strategy through continuous feedback, deal with nonlinear, high-dimensional, or uncertain problems through knowledge bases and fuzzy logic, and achieve fault tolerance through redundant data and self-correction mechanisms. However, the field faces challenges, including reliance on high-quality data, insufficient or noisy data, opaque decision-making processes due to "black box" big models, hardware and cost limitations, such as the cost of LIDAR and computational chips required for autonomous driving, and integration complexity, which has led to the need for unified standards and interfaces for cross-domain systems. The industry is lacking specifications and frequently encounters compatibility issues. There are also data privacy and machine ethics dilemmas yet to be resolved.

In the future, intelligent control will continue to integrate technology and upgrade with AI by combining multimodal data and integrating reinforcement learning and environment perception technologies. It will enhance human decision-making and use AI more as a supporting tool. It will promote international AI guidelines and require transparency and traceability of high-risk scenarios. A unified interface specification is an inevitable trend for future intelligent control, and the industry will promote cross-field data standards to solve system compatibility issues. It will develop specialized control systems for specific scenarios.

6. Conclusion and outlook

This paper summarizes and introduces recent methods in intelligent control and their applications, including fuzzy control, neural network control, reinforcement control, and deep learning. It analyzes the development of intelligent control according to its advantages and challenges. Intelligent control technology improves the autonomous decision-making and self-adaptive capability of complex systems by integrating fuzzy logic, neural networks, learning control, and other artificial intelligence methods. Future research should focus on technology integration, greening, standardization, and ethical governance, while deepening vertical scenario applications. Academia and industry should collaborate to promote intelligent control towards higher autonomy, safety, and sustainability, and support intelligent manufacturing, smart cities, and other fields.

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