Development and Application of Modern Intelligent Control Theory

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Abstract. Modern intelligent control theory has experienced multi-stage development from classical control to fuzzy control, neural networks, and model predictive control, which not only improves the flexibility and adaptability of control systems but also promotes interdisciplinary research. With the advancement of science and technology and social development, intelligent control theory will be further combined with machine learning, big data, and other fields in the future to promote industrial automation and technological innovation. This article reviews the development history of modern intelligent control theory, its main theories, and its applications in robot manufacturing, power electronics, and other fields. It also discusses the current challenges and future development trends in the field of intelligent control.

Keywords: Modern intelligent control theory; Fuzzy control; Neural network control; Model predictive control; Machine learning.

1. Introduction

With the rapid development of science and technology, modern intelligent control theory has attracted widespread attention and research in the field of control systems. The rise of this trend stems from a deep understanding of the limitations of traditional controllers in complex, highly dynamic systems. In the past, control systems mainly relied on the classic PID control method. This traditional method has limitations in dealing with nonlinear and time-varying systems. In order to better solve these challenges, modern intelligent control theory came into being. From the fuzzy set theory of fuzzy control to the bionic learning of neural networks to the timing optimization method of model predictive control, intelligent control theory continues to evolve, providing more flexible and intelligent solutions to system control problems. [1]

In this era of digitization and automation, intelligent control theory is not only at the forefront of scientific research but also an important tool to promote engineering practice. The rise of emerging technologies such as deep learning has injected new vitality into intelligent control theory. At the same time, modern intelligent control theory has been widely used in many fields, such as robot intelligent manufacturing, machinery manufacturing, and power electronics. [2]

This article will deeply analyze the specific application cases of modern intelligent control theory in different fields, analyze the challenges and opportunities faced by modern intelligent control theory, look forward to the future development direction, and provide ideas for research in the field of intelligent control, which is of great significance.

2. Development of Modern Intelligent Control Theory

The evolution of modern intelligent control theory stems from a deep understanding of the limitations of traditional control methods, whose roots can be traced back to the middle of the last century. In the 1940s and 1950s, the univariate system control theory represented by the frequency method was gradually developed and successfully used in radar and fire control systems, which resulted in the formation of the "Classical Control Theory.". Traditional controllers showed some difficulties in dealing with the nonlinearity, uncertainty, and time-varying nature of complex systems, so intelligent control theory came into being. In the 1960s and 1970s, mathematicians dominated the development of control theory, forming the "modern control theory" represented by the state-space method [3]. In 1971, Chinese-American scientist Jingsun Fu put forward the idea of combining artificial intelligence and automatic control, laying the foundation for the development of intelligent control theory. Subsequently, in 1977, American scholar G. N. Saridis further proposed the idea of combining artificial intelligence, cybernetics, and operations research, paving the way for the theory to enter a new era [4]. Since then, many intelligent control methods, such as self-tuning and parameter tuning PID, have been developed on the basis of the conceptual simulation of artificial intelligence, with the main theoretical support of "large system theory" and "intelligent control theory." Later on, the development of practical intelligent control algorithms is the main focus, especially neuron networks, which are the most prominent [5]. The research results in this period have promoted the continuous deepening of intelligent control theory.

Entering the 21st century, the emergence of deep learning technology has become an important driving force in the field of intelligent control. With its excellent data processing and feature extraction capabilities, deep learning has demonstrated its unique advantages in the modeling and control of complex systems. Meanwhile, the introduction of emerging technologies such as reinforcement learning has further expanded the research field of intelligent control theory. Intelligent control theory has gradually evolved into an interdisciplinary and diversified field, providing a new paradigm for solving complex system control problems.

Modern intelligent control has a high degree of flexibility, which can flexibly respond to complexity and uncertainty and realize automatic control; it has adaptivity, which can make autonomous decisions to solve multi-objective conflicts and show self-organizing and coordinating functions; it has theoretical intersectionality, which can be combined with other technologies to make the system design more diversified and the scope of application more extensive; and it has real-time, which makes the intelligent control system capable of responding to environmental disturbances and uncertain factors and realizing real-time response. [6]

In the future, modern intelligent control theory will be more integrated with machine learning, computer vision, natural language processing, and other fields to form a more comprehensive and interdisciplinary research direction. At the same time, more attention is paid to real-time and the effectiveness of adapting to a variety of practical engineering application scenarios, especially in the fields of automatic driving and industrial automation. [7][8]

3. Application of Modern Intelligent Control Theory

3.1 Fuzzy Control

As an intelligent control method, fuzzy control theory has been widely used in many industries and fields, showing its unique advantages and wide application potential. The origin of fuzzy control theory can be traced back to the 1960s. American professor Zadeh formally proposed fuzzy logic in 1965 and gave the definition of fuzzy logic control and related theorems in 1973. In 1974, British professor Madani applied it to steam engine control for the first time, marking the birth of fuzzy control theory. Since then, fuzzy control theory has developed rapidly, especially the Takagi-Sugeno (T-S) model and single-case fuzzy system, which have greatly enriched the method and application scope of fuzzy control.

The principle of fuzzy control is based on fuzzy set theory and fuzzy logic, and the control of complex systems is realized through four steps: fuzzification processing, establishment of fuzzy rules, fuzzy reasoning, and defuzzification. [9]

The fuzzification and defuzzification are implemented by the control of the affiliation function. An affiliation function is used to determine the extent to which an input value belongs to a fuzzy set, commonly known as a triangular affiliation function, a trapezoidal affiliation function (Figure 1), and so on. The fuzzification process can transform the input values into fuzzy linguistic quantities through the affiliation function. The defuzzification then calculates the output value based on the shape and affiliation distribution of the fuzzy output set and scales it.

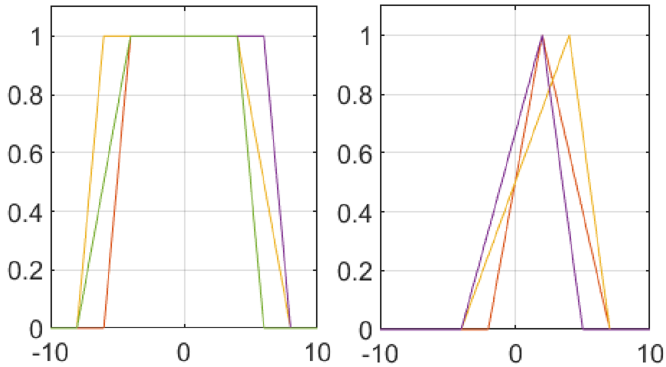

Figure 1 Triangular membership function and trapezoidal membership function

Fuzzy rules, or "IF-THEN (premise-conclusion)" rules, are constructed on the basis of expert knowledge and experience, defining the relationship between input fuzzy sets and output fuzzy sets. Fuzzy reasoning uses fuzzy logic operations to process the premise part of the rule and then generate fuzzy output values based on the activation level of the rule and the conclusion part of the rule.

The exact input variables are quantized and fed into the fuzzy controller, where the fuzzification process is converted into fuzzy sets, fuzzy reasoning is implemented by fuzzy logic operations, and finally the fuzzy reasoning results are converted into output quantities through the de-fuzzification process, which are output from the fuzzy controller [10]. The control block diagram of this process is shown in Figure 2.

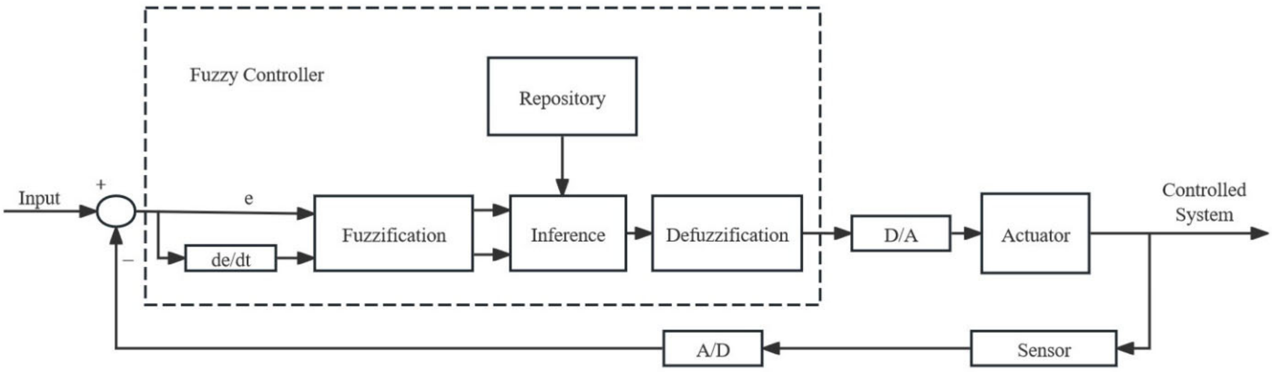

Figure 2 Block diagram of fuzzy control

Generally, fuzzy systems are categorized into three types based on the IF-THEN rule: the Mamdani-type fuzzy system, the T-S fuzzy system, and the singleton fuzzy system [11].

Mamdani fuzzy system is a model-free control method based on experts' experience, where the output fuzzy set is obtained by reasoning through fuzzy rules and the input fuzzy sets using fuzzy inference mechanisms, usually using the principle of maximum affiliation.

The Takagi-Sugeno (T-S) fuzzy system, on the other hand, uses a linear model to represent the fuzzy rules, and the T-S model is capable of accurately approximating complex dynamical systems in the form of segmented linear or nonlinear systems.

Singleton-type fuzzy systems are simpler and more intuitive; each rule has only one affiliation function, and the principle of maximum affiliation is used for fuzzy inference.

As an important branch of modern intelligent control theory, fuzzy control realizes efficient control of complex systems through flexible fuzzy sets and fuzzy logic operations. Its wide application in aerospace, automobiles, electric power, and other fields has achieved remarkable results.

The state of a jet airplane during landing is controlled by fuzzy tracking of a linear dynamic system. The dynamics of the aircraft are described by a set of differential equations that linearize the equilibrium flight conditions. Selection of appropriate state variables and treatment of the system of fuzzy differential equations through the concept of particle differentiability allow tracking of the input values and control of the longitudinal motion of the aircraft in the presence of perturbations [12].

In recent years, the introduction of methods such as non-singular terminal sliding mode control has brought new design ideas for fuzzy control. For example, in robotic systems, uncertainty and external interference are compensated by an adaptive fuzzy system, which improves control accuracy and system robustness. Meanwhile, the fuzzy PID control system analyzes the qualitative properties within the fuzzy number space through generalized Hukuhara differentiability and fuzzy function integration, which enhances the flexibility and adaptability of the control system. The integration of these techniques not only improves the accuracy and robustness of the control system but also broadens the application of fuzzy control in different fields. [13][14]

3.2 Neural Network Control

Neural network control is an intelligent control method based on artificial neural networks, the concept of which is inspired by the network of neurons in the human brain. Neurons are the basic processing units of neural networks.

The artificial neuron model is a simplification and abstraction of the biological neuron, which is generally a multiple-input, single-output unit, and its structural model is shown in Figure 3:

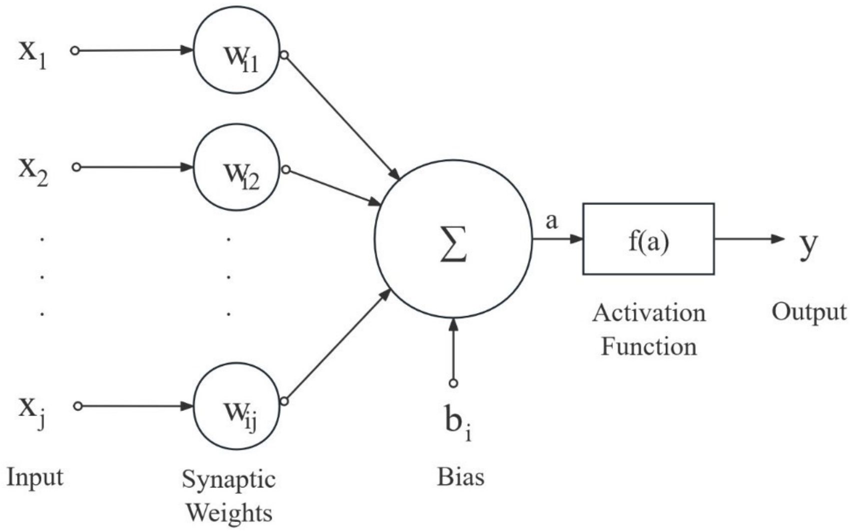

Figure 3 Neuron Structure Model

It receives a set of input signals ($x_1, x_2, \ldots, x_n$), each of which is weighted b by a weight ($w_1, w_2, \ldots, w_2$) to reflect the importance of different inputs. These weighted input signals are accumulated and a bias term is added to form the total input of the neuron, which is then processed by an activation function to produce the output of the neuron y. For example, the mathematical relationship between the input and output of a convolutional neural network can be expressed as follows [15]:

$$y = f\left(b_j + \sum_{i=1}^{n} x_i \times w_{ij}\right) \tag{1}$$

A neural network usually consists of multiple layers, including an input layer, a hidden layer, and an output layer. Each layer contains multiple neurons (or nodes), and neurons are connected by weights. Its structure is shown in Figure 4.

The input layer receives input data and passes it directly to the next layer. Each neuron corresponds to one input data. The number of neurons and the number of layers in the hidden layer are determined by the complexity of the problem. The input of each neuron is the weighted sum of the output data of the previous layer, and then an activation function is used to process the information. The output layer also applies an activation function to process the input data. The number of neurons in this layer is equal to the number of output variables of the entire network.

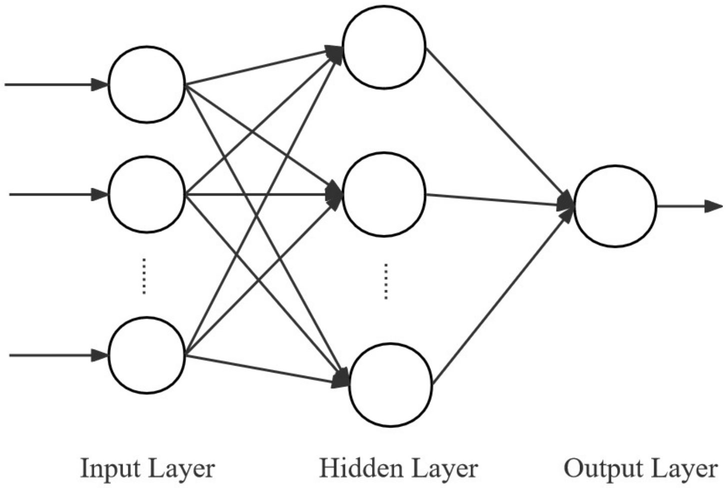

Figure 4 Structure of Neural Network

From the perspective of neural network structure, neural network systems are generally classified into the following categories [16][17]:

(1) Feedforward Neural Network (FNN), which is the most basic type of neural network. Information propagates unidirectionally in the network without feedback.

(2) Recurrent Neural Networks (RNNs), whose basic structural unit is the recurrent unit, which can feed back information from the output of the previous moment to the input of the current moment.

(3) Self-Organizing Maps (SOMs), which is able to map high-dimensional input data into a usually two-dimensional, topology-preserving mapping space while maintaining the topological structure of the input data.

When the number of network layers exceeds three, a deep learning neural network model is formed. As the number of network layers increases, more free elements can be used for function fitting, and its training process also requires a large amount of sample data.

As an important part of modern intelligent control theory, neural network control has made remarkable achievements in various fields with its learning ability, real-time performance, and adaptability. For example, in terms of robot control, dynamic neural networks are used for real-time learning and control without relying on physical models, and control strategies can be dynamically adjusted to adapt to environmental changes. As shown in Figure 5, in this system, excitation noise is injected into the control channel to promote effective learning, ensuring that the estimation error can converge to zero even in the presence of excitation noise. [18]

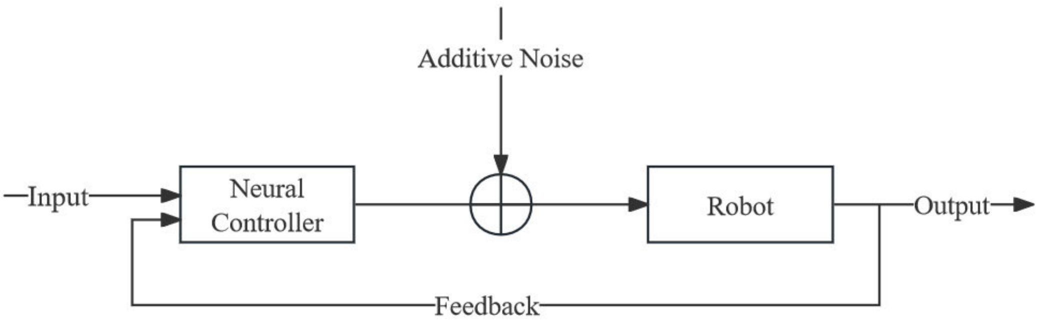

Figure 5 Control Block Diagram of a Neural Network Controlled Industrial Robot

The neural network control system is real-time through parallel processing and distributed learning and is suitable for control tasks that require rapid response. In model predictive control (MPC), it uses a mathematical model of the system to predict system behavior over a period of time in the future and optimize control signals to achieve control goals. Neural networks learn complex nonlinear relationships from data, allowing MPC to control systems that are difficult to accurately describe with traditional models. Make control decisions more quickly and accurately by updating the model in real time to reflect the latest system status and dynamics. [19]

3.3 Genetic Algorithm

A genetic algorithm is a type of evolutionary algorithm that was proposed by John Holland in the early 1970s and inspired by natural selection and genetic mechanisms to solve optimization problems by simulating the process of biological evolution through iterative searches with operations such as selection, crossover, and mutation [20]. The process is shown in Figure 6:

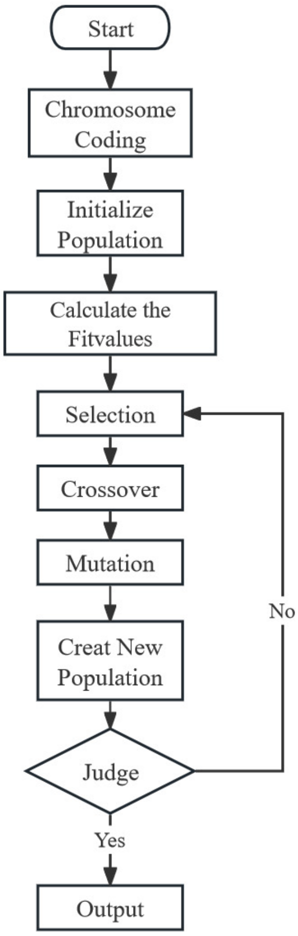

Figure 6 Basic flow of genetic algorithm

A randomly generated initial population is the basis for a genetic algorithm to begin the search process, where each individual is referred to as a chromosome and each element on the chromosome is referred to as a gene. In the genetic algorithm, the n-dimensional decision vector is represented by a X string $X_i\left(i=1,2,\ldots,n\right)$ consisting of n symbols .

$$X = X_1 X_2 \ldots X_n = \left[X_1, X_2, \ldots, X_n\right]^T \tag{2}$$

Each symbol X_i represents a gene X and a chromosome. Genes are usually encoded in the form of binary strings, with 0 and 1 corresponding to alleles.

Genetic algorithms search for optimal solutions by modeling the natural evolutionary process. The algorithm consists of three main genetic operators: selection, crossover and mutation. The selection operator is responsible for selecting individuals from the current population according to some criteria so that they can generate offspring based on individual fitness. Common selection methods include roulette selection, tournament selection, and elite selection [21]. Genetic algorithms utilize a fitness function $f(x)$ to evaluate the fitness of each individual, that is, the quality or merit of the solution, and individuals with high fitness have a higher probability of being selected to participate in the reproduction of the next generation. There are three common methods for designing fitness functions: direct evaluation, penalty, and multi-objective optimization [22].

Crossover, on the other hand, simulate biological reproduction, where two individuals generate offspring by exchanging genetic information to increase the diversity of solutions. Common crossover methods include single-point, multi-point, and uniform crossover [20]. For example, two new offspring are generated by dividing the genes of two parent individuals at a specific crossover point (c), and the expression is

$$o_1 = p_1[1:c] + p_2[c+1:end] \tag{3}$$

$$o_2 = p_2[1:c] + p_1[c+1:end] \tag{4}$$

Among them, $p_1 p_2$ are the two individuals of the father, $o_1 o_2$ and are the offspring individuals obtained by the crossover operation of the two father individuals. The process is shown in Figure 7.

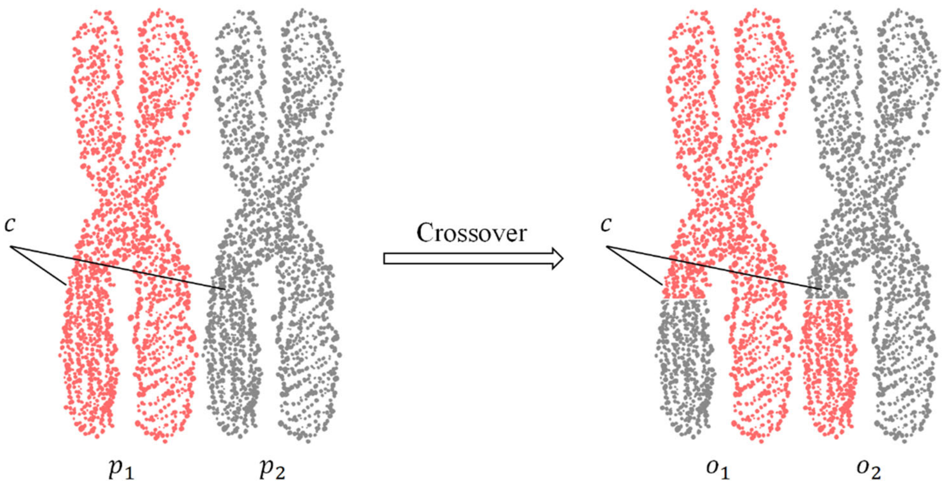

Figure 7 Schematic Diagram of Crossover

The mutation operation introduces new genetic mutations by randomly changing the values of certain genes, helping the algorithm avoid local optimality and expand the search space. The algorithm's termination condition is usually reaching the set number G_{max} of iterations or finding a satisfactory solution. Through these processes, genetic algorithms can effectively find optimal solutions in complex search spaces.

In the field of intelligent control, the applications of genetic algorithms include parameter optimization of system models, design and optimization of control strategies, fault diagnosis and fault-tolerant control, etc. Genetic algorithms can be used to automatically adjust the parameters of control system models such as PID controllers to optimize system performance; used to optimize control strategies to improve the system's adaptability and response efficiency to complex environments; and used in intelligent diagnostic systems to optimize diagnostic strategies to improve the accuracy and efficiency of fault detection [23].

Genetic algorithms are applied to optimize the membership function parameters of the fuzzy controller input variables. Each individual represents a set of membership function parameters, which are optimized through the evolutionary process of the genetic algorithm. This process can automatically optimize the membership function parameters, reduce human intervention, and enable the servo control system to achieve the desired performance. Genetic algorithms are also used to improve PID controller parameters and dynamically select the best performance parameter combination to solve the optimization problem. This method not only saves computing time but also shows better performance than the existing state-of-the-art algorithms when solving a variety of test problems. [24]

In mobile robot path planning, genetic algorithms are used to optimize the path of an autonomous mobile robot from a starting position to a target position while avoiding obstacles and optimizing specific criteria such as minimizing path length, maximizing safety, and shortening trajectory execution time [25]. For example, by improving the fitness function while considering the shortest path, the safety and efficiency of the path are also taken into account to more effectively find feasible paths in different environments. [26]

3.4 Model Predictive Control

Model Predictive Control (MPC) is a process control method widely used in industrial processes and system engineering. Its basic principle is to use the mathematical model of the system to predict system behavior in the future and optimize the control input at the current moment based on these predictions to achieve the desired control effect. The core steps of MPC include the establishment of the prediction model, the definition of the cost function, and the selection of the optimization algorithm [27].

A predictive model describes how a system responds to input signals to predict its future behavior. This model can be a deterministic model based on physical principles, an empirical model, or a data-driven model. The model should describe the system's response to the control input accurately enough, usually expressed as a set of difference or differential equations, as follows:

$$x_{k+1} = f\left(x_k, u_k, w_k\right) \tag{5}$$

Among them , x_k is the system state at the time step k, u_k is the control input , w_k is the possible system disturbance, and $f(\cdot)$ represents the system dynamics.

The cost function defines what the control system is trying to achieve. The cost function typically reflects expectations of system performance, such as minimizing energy consumption, maintaining the system state on a desired trajectory, and reducing the variability of the control action.

The cost function in model predictive control generally consists of two components: process cost and end cost. The process cost $L(x,u)$ calculates the contribution of each control action and system state to the total cost over the prediction horizon and is commonly used to evaluate the extent to which the system state deviates from the desired trajectory and the magnitude of the control action. The end-state cost $\phi(x)$ reflects the deviation of the system state from the target state at the end of the prediction horizon, helps to ensure that the system state will eventually converge to the desired state, and is sometimes used to ensure system stability. Common forms of cost functions include quadratic cost functions and linear cost functions. The quadratic cost function is the most commonly used form of cost function, especially in linear systems and quadratic programming problems. In some applications, it may only be necessary to minimize the control action or the absolute value of the state deviation, in which case a linear cost function can be used.

The optimization algorithm is responsible for solving for the minimum value of the cost function in each control cycle and determining the optimal control inputs. In the MPC framework, the optimization algorithm is responsible for solving an optimization problem to minimize the cost function while satisfying all constraints. The complexity of the optimization problem depends on the nature of the system model, the form of the cost function, and the type of constraints present. The commonly used optimization algorithms are linear programming, quadratic programming, and mixed integer programming.

The main advantages of MPC are its explicit treatment of constraints and the optimal control strategy achieved through future behavior prediction. It is particularly suitable for dealing with complex systems, multivariable systems, and systems characterized by nonlinearity or uncertainty. In robotics research, the combination of whole-body impulse control (WBC) and MPC can effectively realize the high-speed dynamic motion of the robot, and the overall control framework of this system is shown in Figure 8. This control system optimizes the motion state of the robot and realizes the complex dynamic gait by predicting the optimal ground reaction force contour in the future period and calculating the corresponding joint dynamics response [28].

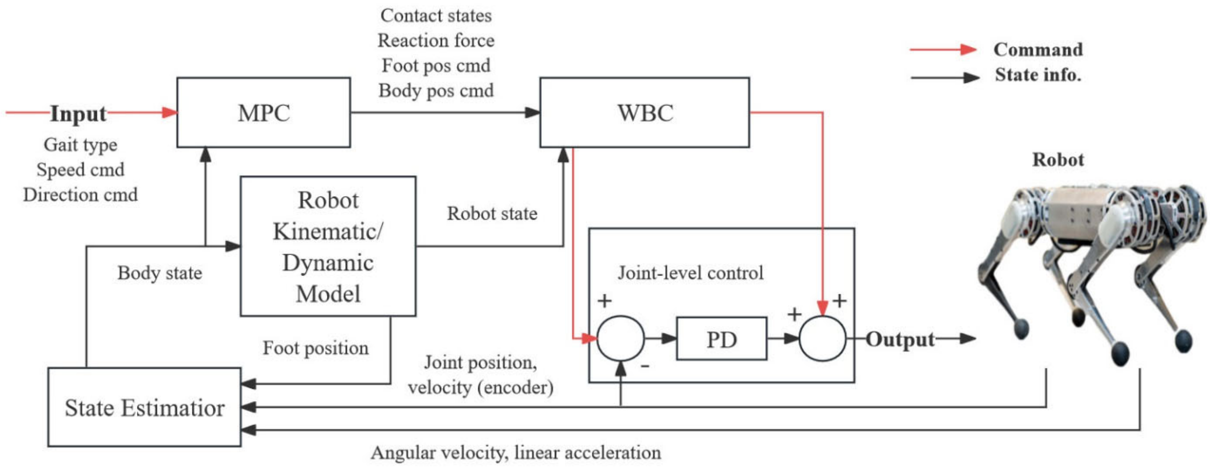

Figure 8 Control System Framework for Quadruped Robots

In the application of automatic landing of unmanned aerial vehicles (UAVs), the MPC approach performs UAV guidance by integrating vision-based target localization, optimal localization performed by the Kalman filter, and achieving an accurate and stable landing of the UAV on the mobile platform. During this process, MPC is responsible for predicting and optimizing the flight path and speed of the UAV to ensure that it can accurately dock to the mobile platform [29], demonstrating the advantages of MPC in real-time path planning and control.

Another application of MPC in recent years is in building energy efficiency and comfort optimization to effectively reduce energy consumption while improving indoor thermal comfort. The system employs a dynamic artificial neural network with a nonlinear autoregressive exogenous structure (NARX) to adaptively predict the dynamic response of the building and adjust the heating, ventilation, and air conditioning (HVAC) system in real time within the MPC framework [30]. This not only demonstrates the potential of MPC in optimizing energy use and improving quality of life, but also highlights its broad applicability in interdisciplinary applications.

4. Future Development Trends of Modern Intelligent Control Theory

The development of modern intelligent control theory is in a period full of potentials and challenges, and its future trends are mainly influenced by the progress of new technologies, the deepening of interdisciplinary cooperation, and the expansion of application fields. First of all, new technologies such as the fusion of artificial intelligence and machine learning and the wide application of Internet of Things (IoT) technology will greatly improve the performance of intelligent control systems [31].

Meanwhile, interdisciplinary cooperation is also a key factor in promoting the development of intelligent control theory. For example, drawing on the self-organization and self-adaptation mechanisms in biology, as well as combining psychology to understand the human decision-making process in order to design more humane interaction interfaces, can provide new ideas and methods for the development of intelligent control systems. [32][33]

In terms of application prospects, the applications of intelligent control theory are rapidly expanding, covering a wide range of fields from self-driving cars to intelligent manufacturing to sustainable energy systems. These applications not only demonstrate the great potential of intelligent control theory in improving productivity, optimizing resource allocation, and promoting sustainable development, but also point in the direction of future research and development.

Overall, with the continuous development of new technologies, the deepening of interdisciplinary cooperation, and the emergence of new application scenarios, the development of modern intelligent control theory will continue to move forward.

5. Conclusion

This paper accomplishes the following work for the development of modern intelligent control theory and its application in various fields:

(1) The development of intelligent control theory is summarized, ranging from fuzzy control to neural network control to model predictive control, etc., and the theoretical foundations and technological advances at each stage are described in detail.

(2) Examples of applications of intelligent control theory in different fields are analyzed, including aerospace, automobile manufacturing, and electric power systems, showing how intelligent control theory can solve practical engineering problems and improve system performance and safety.

(3) The challenges and future directions of the intelligent control field are discussed, especially how to combine the latest technology to further promote the innovation and application of intelligent control theory.

The continuous development of intelligent control theory not only promotes technological innovation but also provides more flexible and efficient solutions for dealing with complex systems. The research in this paper not only provides valuable reference materials for academic research but also provides theoretical support and practical guidance for technological upgrading and product innovation in industry.

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