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ROBOT SYSTEM



Hui LIU

Time Series Predictive Control in Robotics

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Time Series Predictive Control in Robotics

Hui LIU

This book presents the latest advances for the frontier cross disciplinary field of robotics, intelligent control and learning. Seven chapters are provided to cover the key common theories and technologies of robots, including the robot mapping and navigation, robot recharging and smart power management, robot arm manipulation, unmanned vehicle control, intelligent manufacturing systems, etc. The book proposes a unique new perspective using time series prediction to control robots. Especially with the fast increasing of various data in robotics, this new robot control mode using time series prediction has become very important. The book provides the complete cases for the most popular application scenes of robot predictive control. By this first monograph on the topic of robot time series predictive control in the world, author provides important references for the engineers, scientists and students in the field of robotics and artificial intelligence.

Hui LIU is Professor and Vice dean of the School of Traffic & Transportation Engineering, Central South University, China. His main research interests include computational intelligence, intelligent robotics in traffic & transportation engineering, and nonlinear signal modeling & forecasting. He holds double Ph.D degrees from China (Traffic & Transportation Engineering, from Central South University in 2011) and Germany (Automation Engineering, from University of Rostock in 2013), and obtained his professorship degree in Automation Engineering from University of Rostock in 2016. He has published more than 100 international research papers and authorized beyond 100 invention patents in the field of robotics, data science, and time series predictive control, as the first inventor.

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Preface

With the expansion of the robot market, the working environment of robots is diverse and complex. Various environmental challenges have profound effects on robot perception, navigation, planning, and control. With the development of artificial intelligence technology, intelligent autonomous robots have attracted attention, which have environmental adaptation and self-learning capabilities to complete more complex and dangerous tasks. In the current form of rapid development of the intelligent autonomous robotic system, it is necessary to publish an international book on planning and predictive control applications in smart robots. Therefore, the author completed the writing of this book based on their decades of research achievements and practical experience in the fields of data science and smart robots.

Based on the big data generated during the operation of smart robots, this book originally proposes the time series predictive control theory of smart robots to achieve high-precision control and application of various smart robots. This book focuses on the three mainstream robot configurations: mobile robot, robot arm, and wearable robot. The decomposition, modeling, prediction, and control of the navigation position, onboard power, motion, and other key elements that affect the application performance of the robot are carried out to provide readers with a detailed and complete theoretical basis and practical guidance.

This book provides the basic principles and advanced knowledge of data science and predictive control methods in the field of smart robotics. It plays an important role in enhancing the industrial competitiveness of the field of smart robotics and is of great significance in improving the intelligence of robots in autonomous decision-making, planning, and control. This book integrates a variety of cutting-edge theories and technologies, including big data, robotics, and artificial intelligence, and provides an important reference for future interdisciplinary collaborative development in the fields of robotics, intelligent manufacturing, automation science, and computer science.

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Prof. Dr. -Ing. habil. Hui Liu
Changsha, China
October 2022

Abbreviations

AdaBoost	Adaptive Boosting
ADF	Augmented Dickey-Fuller
AE	Autoencoder
AFSA	Artificial Fish Swarm Algorithm
AIC	Akaike Information Criterion
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
AR	Autoregressive
ARIA	American Industrial Robot Association
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BGA	Binary Genetic Algorithm
BIC	Bayesian Information Criterion
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
CWC	Coverage Width-based Criterion
DBN	Deep Belief Network
DT	Decision Tree
ECG	Electrocardiogram
EEG	Electroencephalogram
ELM	Extreme Learning Machine
EMG	Electromyogram
ENN	Elman Neural Network
EOG	Electrooculogram
ESN	Echo State Network
EWT	Empirical Wavelet Transform
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBDT	Gradient Boosting Decision Tree

GMDH	Group Method of Data Handling
GNSS	Global Navigation Satellite System
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
GWO	Grey Wolf Optimization
HAL	Hybrid Assistive Limb
IMU	Inertial Measurement Unit
KF	Kalman Filter
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mean Error
MLP	Multi-Layer Perceptron
MPC	Model Predictive Control
NAR	Nonlinear Autoregressive
NB	Naive Bayes
PCA	Principal Component Analysis
PICP	Prediction Interval Coverage Probability
PINAW	Prediction Interval Normalized Average Width
PRM	Probabilistic Road Map
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
RBM	Restricted Boltzmann Machine
RELM	Regularized Extreme Learning Machine
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RTK	Real-Time Kinematic
SARIMA	Seasonal Autoregressive Integrated Moving Average
sEMG	Surface Electromyogram
SSA	Singular Spectrum Analysis
SVM	Support Vector Machine
SVR	Support Vector Regression
VMD	Variational Mode Decomposition
WPD	Wavelet Packet Decomposition
XGBoost	Extreme Gradient Boosting

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Chapter 1

Introduction

1.1 Robotics and Control Technology

Since the middle of the 20th century, robotics has matured along with the rapid development of mechatronics, sensing technology, computer technology, and control theory. Robots have assisted or replaced human work in different scenarios. The emergence of new technologies such as 5G networks, cloud computing, and artificial intelligence in Industry 4.0 has brought about a new era of robotics development. Recently, China has become the world's largest market for robotics applications, and its market size of industrial, service, and specialized robots has grown steadily.

Robots were developed worldwide in the mid-20th century. They had simple structures, low control accuracy, and limited functions. Therefore, they could only serve humans to a certain extent and hardly perform complex operational tasks independently. Robots at this time fell far short of the expectations of scholars, prompting them to invest more research efforts in this area. By the 21st century, robotics has become relatively mature, with perfect functional composition, adaptation to various complex environments, and high mechanical control accuracy. Currently, the emergence of new technologies such as time-series prediction, human–robot interaction, and pattern recognition has brought new opportunities for robotics.

The predictive perception capability of robots requires improvement to overcome the influence of the work environment with complex uncertainty. Time series prediction technology is used to predict the trajectory, electrical energy, and joint coordinates of robots and performs feedback controls on the robot, realizing the functions of active obstacle avoidance, intelligent scheduling planning, and early error correction. Consequently, robot predictive control can improve their intelligence, reliability, and accuracy, which is crucial for building automated smart cities and improving human life qualities.

1.1.1 Robotics

The term robot first appeared in 1920, and it was not until 1940 that the science fiction writer Asimov gave a concrete definition of the concept of robots. Robot research began in the middle of the 20th century, and three generations of robots

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have evolved (Li *et al.*). The first-generation robots were teaching robots. The second-generation robots are sensory robots equipped with sensors to adapt to certain changes in the external environment, such as sweeping robots. Intelligent robots are the third generation, which obtains external information through sensors and measuring equipment, use intelligent technology to identify and judge, and make corresponding planning decisions (Fan and Destech Publicat, 2016). It is an advanced robot that can act autonomously to achieve predetermined goals. Figure 1.1 shows the development history of robots.

In the 21st century, robots have been commonly used in industrial production, life services, and hazardous operations in human society, being of great importance to human production activities. Many countries and regions are committed to the development of robotics. Robotics is the science of designing, manufacturing and applying robots, and it consists of robot structure, kinematics, dynamics, control, machine perception, machine vision, robot language, decision-making, and planning (Brogardh, 2009). The current research hotspot aims at fully using big data technologies to study and control robot systems to help build an intelligent human society.

The history of robot development is shown in figure 1.1. Besides technological innovation, modern robot research also focuses on improving interactivity and adaptability, considering the human and environmental factors that interfere with it, which has also given birth to a new concept-robot system. The robot system comprises robots, work objects, and environments, including mechanical, drive, perception, and control systems (Angeles *et al.*, 2003). The robot system is a typical mechatronics system that is highly unified, intelligent, and flexible. It can achieve highly interactive work between the robot and the environment by applying advanced sensing, signal processing, and intelligent control technologies. The robot system is dedicated to helping robots complete operations under complex working conditions with higher efficiency and improving their perception, planning, and collaboration capabilities. Therefore, it improves human industrial production and brings convenience to human life.

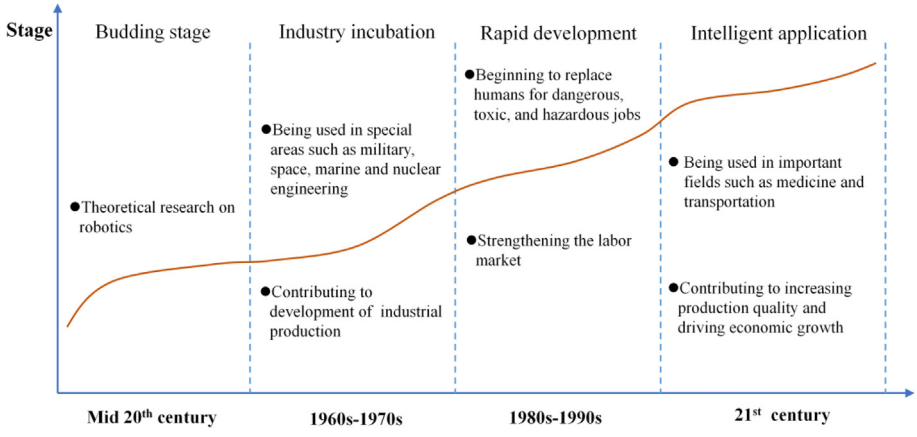


FIG. 1.1 – History of robot development.

Robots are technologically advanced, highly integrated, and rich in variety. Therefore, the classification of robots is very complex. No unified classification standard has been prescribed in previous studies (Dobra, 2015). This book attempts to cover a more comprehensive field and presents a rational classification based on four criteria, including robot control model, application scenario, working mode, and kinematics, as shown in figure 1.2.

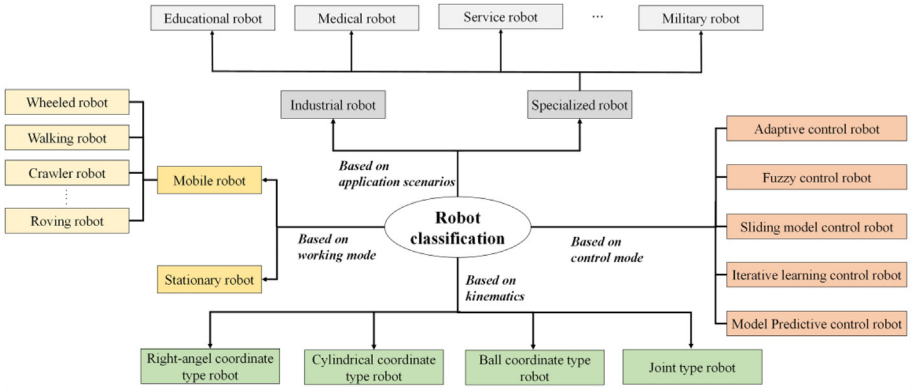


FIG. 1.2 – Robot classification.

A. *Control mode*

Robots can be classified into five categories according to their control methods: adaptive control, sliding model control, fuzzy control, iterative learning control, and model predictive control (Wu *et al.*, 2022). These controls are possible in both joint space and Cartesian space, with the corresponding physical quantity information transmitted by sensor acquisition. The control in joint space is for the variables at each joint of the robot, and the control in Cartesian space is for the variables at the end of the robot.

B. *Application scenario*

The application scenarios from robots can be divided into two main categories: industrial robots and specialty robots (Hodges and Hallam, 1990). This is widely recognized by scholars internationally. Industrial robots are robots with robotic arms or multiple degrees of freedom for industrial applications. Specialized robots are generally used in professional fields to serve, assist, or replace humans in performing tasks, such as service, medical, and military robots.

C. *Working model*

With the development of robotics, the functions of stationary robots are difficult to meet the increasingly diverse needs of humans. In the late 1980s, many countries began to focus on mobile robots with autonomous planning, self-organization,

self-adaptive capabilities, and the ability to adapt to complex unstructured environments (Siegwart *et al.*, 2011). They can be divided into wheeled, walking, crawling, and swimming robots according to the movement mode.

D. *Kinematics*

Robots can be divided into four types according to the form of motion. The right-angle coordinate type can move along three right-angle coordinates. The cylindrical coordinate type can lift, turn, and telescope. The ball coordinate type can turn, pitch, and telescope. The joint type has multiple rotating joints (Coiffet and Chirouze, 1982).

1.1.2 Robotics Control Technology

With the rapid development of robotics and the various application scenarios, robots have been equipped with intelligent functions, such as sensing, planning, decision-making, and control, satisfying accuracy requirements in robot operations. For robots to accurately perform various tasks and actions, advanced control technologies are required for manipulation. As a key technology for computer systems, robot control technology includes a wide range from robot intelligence to motion control and self-service control, which is shown in figure 1.3. Much research has been done on robot control technology to propose robot control strategies and schemes, achieving accurate machine motion and reasonable control performance (Durmus *et al.*, 2009).

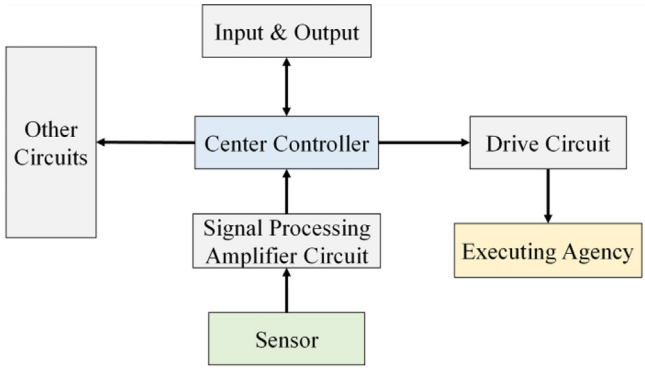


Fig. 1.3 – Robot control system structure.

The earliest robots were controlled by remote control, and the control actions were performed manually. Later, along with the development of computer technology, robots began to use computer systems to synthesize the functions of mechatronics devices and adopt the control method of demonstration and teaching. The recent development of information and control technologies has led to the

development of robot control technology toward intelligence, with new technologies such as off-line programming, task-level language, multi-sensor information fusion, and intelligent behavior control (Gerald and Feitian, 2020b). Intelligent robots obtain information about the environment through various sensors, use intelligent technologies to analyze it, make planning decisions, and finally achieve predetermined goals. The basic methods of existing robot control are divided into two types: Joint space control and Cartesian space control (Gerald and Feitian, 2020a). However, both types of control methods are susceptible to uncertainty, so more advanced and intelligent control techniques are needed to reduce errors in robot applications.

Artificial intelligence plays a key role in the development of future robots. The four major technologies of artificial intelligence, including memory technology, perception technology, action planning, and machine learning, have been fully developed in recent years, and these technologies can be transplanted into robots to form a complete, autonomous, and networked closed-loop control system (Ren and Bao, 2020). To solve the problems of low real-time control accuracy, susceptibility to environmental factors, and low fault tolerance of existing robot control technologies, time series prediction is a method with great potential. Many time series variables exist in the control process of robots, such as movement trajectory, electrical energy storage, joint displacement, and user intention. By deep information mining of historical data sequences, relevant potential laws can be obtained to accomplish complex control of robot trajectory planning, error correction, and human–robot interaction, promoting the development of intelligent robots.

1.2 Time Series Forecasting in Robotics Control

1.2.1 Time Series Forecasting Objectives

Time series forecasting is a powerful tool, and its importance has been proved by a large number of publications and extensive applications over the years (Tealab, 2018; De Gooijer and Hyndman, 2006). For example, using historical time series to predict the future state of wheeled mobile robots by obtaining their simulation models (Vagale *et al.*, 2021). As shown in figure 1.4, through time series prediction, the uncertainty of the robot system can be reduced enormously, and the modeling of unknown and complex items can be avoided. Consequently, the calculation cost can be greatly reduced. In addition, through the dynamic feedback structure of the predicted results, the robot's action and posture can be corrected in time, and the operation accuracy can be increased. Summarize the recent research and classify it based on the prediction objectives.

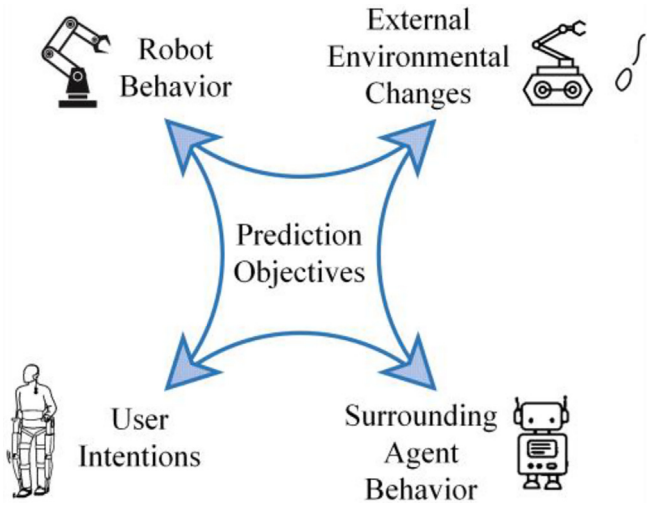


FIG. 1.4 – Objectives of time series prediction.

(1) *Predicting robot behavior*

Because the robot control simultaneously considers factors such as gravity load, attitude-related structural dynamics, and strong nonlinear interference of joint reducer, it is extremely difficult to predict the trajectory information using physical models (Chiu *et al.*, 2016). Therefore, the time series prediction method is required. The difference between the predicted and the actual trajectory can be analyzed by predicting the time series of robot behaviors. Then, the uncertainty of a robot system can be reduced, improving its moving accuracy. For example, a Temporal Convolutional Network (TCN) is used to predict the joint tracking error of industrial robots, and the pre-compensation method is adopted based on the prediction error to improve the joint tracking accuracy (Tan *et al.*, 2023).

In addition to predicting the motion trajectory of the robot's parts, time series prediction can also predict the power of the robot itself. Kerstin Thurow uses Wavelet Packet Decomposition (WPD) and Bidirectional Long Short Term Memory (BiLSTM) based on deep learning to predict the battery power and voltage of transport robots. The prediction results show the hybrid model's effectiveness and strong generalization ability for robot power prediction (Thurow *et al.*, 2019). There will be a sudden voltage drop in the early and late stages of battery discharge. However, in the middle stage of discharge, the battery voltage will change little, and the point of voltage drop will change with the use of the battery. Therefore, it is extremely difficult to calculate the battery power and battery level in the late stage of discharge. The traditional method is to warn when there is still some battery energy left and charge in advance. However, using time series prediction, we can know the battery level more accurately and reduce the number of charges while ensuring that the robot is not powered off.

(2) *Predicting external environment changes*

The robot system needs to interact with the surrounding physical world constantly. However, the physical world is complex and dynamic with unquantifiable items. The spatiotemporal evolution prediction for unknown dynamic information is essential for autonomous robot operation. The research shows that the heat convection–diffusion system and the fluid dynamical system can be effectively predicted by using the HybridNet integrated with a data-driven Deep Neural Network (DNN) and using Cellular Neural Network (CeNN) to solve model-driven calculations (Long *et al.*, 2018).

The prediction of external environmental changes can help robots respond to environmental changes in advance, such as avoiding falling rocks, collapsing rubble, and incoming floods. Researchers have already proved the feasibility of the Radial Basis Function (RBF) neural network. The RBF predicts the position of the dynamic obstacle at the next moment so that the avoidance problem of the dynamic obstacle can be converted into the avoidance problem of the static obstacle (Li *et al.*, 2008).

(3) *Predicting user intentions*

The wearable robot is an important part of the robot field. It is equipped on the user's body and reacts according to the user's intention. Predicting user intention through time series measurement can effectively avoid human–computer confrontation (HRC) in motion control, thus ensuring information interaction between humans and computers (Liu *et al.*, 2023). Unlike the previous physical-based human–computer cooperation, robots need to perceive the future actions of human beings in advance in prediction-based human–computer cooperation. This can improve the flexibility and smoothness of human–computer cooperation and reduce the security problems caused by HRC.

In addition to wearable robots, smart home robots also need to predict user intentions. In one study, multiple sensors were installed on different furniture to predict the furniture used in the next five minutes based on the furniture used in the past 45 min. This study also compared the prediction accuracy of multiple hybrid models based on Deep Belief Network (DBN) according to the prediction results (Choi *et al.*, 2013).

(4) *Predicting surrounding agent behavior*

The uncertainty of the robot system comes from other agents. For example, driverless vehicles need to predict the trajectory of surrounding vehicles or pedestrians to plan safe routes. However, unlike ordinary time series prediction, because the prediction object is another agent, they usually update their actions according to the actions of the predictor (Agarwal *et al.*, 2022). Therefore, the prediction of other agents can not only rely on historical time series but also take into account the content of the game theory.

1.2.2 Time Series Forecasting Methods

(1) *Time series*

There are time series in the fields of science and daily life, such as finance, physics, biology, medicine, meteorology, etc. Time series analysis is important to understand the objective world and natural phenomena. Generally speaking, the Autoregressive (AR) model proposed by British statistician George Udny Yule in 1927 is considered the origin of modern time series analysis (Yule, 1995; Nerlove, 1990).

The application of real-time online forecasting algorithms can better identify sensor information in an uncertain environment to improve the dynamic response frequency of the robot.

(2) *Traditional statistical forecasting method*

Traditional time series analysis methods mainly include descriptive time series analysis and time series analysis based on mathematical statistics (Aliev *et al.*, 2006). The descriptive analysis method mainly analyzes by directly comparing and observing the differences between the data or drawing images to explore the hidden laws between the sequences. It is characterized by convenient operation, intuitive, and efficient.

Traditional time series forecasting methods can be divided into three commonly used categories as follows:

(a) Trend extrapolation forecasting technology (Martino, 1969). According to the existing and systematic mature methods to estimate the future data curve trend method. There are many kinds of trend extrapolation forecasting techniques, such as the Peel curve model and linear biexponential trend prediction model.

(b) Regression prediction technology (Hoskuldsson, 1994). Regression forecasting technology is based on historical data. It is a forecasting method that establishes a regression equation through regression analysis. Scholars have studied various regression analysis techniques, such as linear regression, logistic regression, and least square regression. The regression model process is shown in figure 1.5.

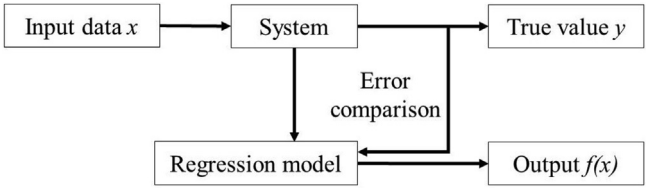


Fig. 1.5 – Regression model framework.

(c) Grey forecasting technology (Xie and Wang, 2017; Deng, 1991). This technology is mainly aimed at variable data with uncertain factors and predicts future data. It is a type of model that is commonly used in small sample data. The advantage of this forecasting technology is that it can simplify complex forecasting problems into problems with exponential changes in data and establish and solve differential equations. Its disadvantage is that the prediction accuracy is unsatisfactory in the case of non-exponential changes in data.

The traditional forecasting method based on mathematical statistics is widely used even today. Its main idea is to take the historical data of time series as the observation value, use mathematical statistics to study the historical trajectory of the time series, and establish a model to fit future data. Commonly used Traditional statistical forecasting methods include the Autoregressive (AR) model, Moving Average (MA) models, Autoregressive Moving Average (ARMA) model, Autoregressive Integrated Moving Average (ARIMA) model, Naive Bayes (NB) model, Decision Tree, Hidden Markov Model (HMM), Random Forest (RF) model, etc.

(3) *Intelligent forecasting method*

Artificial neural networks were first introduced in 1943 (Huang *et al.*, 2009; McCulloch and Pitts, 1990). The structure of the artificial neural network is a model to simulate the information processing mechanism of the nervous system (Dorffner *et al.*). These networks can learn the complex relationship between their input and output vectors. So far, many different artificial neural networks, such as feedforward, recurrent, spiking, Kohonen self-organization, and radial basis function, have been expanded (Askari and Keynia, 2020; Ghosh-Dastidar and Adeli, 2009; Bebis and Georgiopoulos, 1994).

The advancement of artificial intelligence has brought people's attention to intelligent prediction methods. Because the intelligent model has a strong nonlinear fitting ability, its performance in classification and regression is better than the statistical model. Commonly used intelligent models include Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Extreme Learning Machine (ELM), Radial Basis Function (RBF), Elman Neural Network (ENN), Generalized Regression Neural Network (GRNN), etc.

The deep neural network with multiple hidden layers stacked can significantly enhance the learning ability and strengthen the feature extraction ability (Li, Zhang, and Ding, 2019; Li, Zhang, Ding, *et al.*, 2019). Because deep learning has a strong learning ability and performs well in many directions, many frameworks integrate relevant content. These frameworks are compatible with many platforms and have excellent portability. However, deep learning is highly dependent on data. The larger the amount of data, the better its performance. Especially in image recognition, facial recognition, NLP, and other fields. Therefore, only scientific research institutions or enterprises with relatively strong economic strength can use in-depth learning for cutting-edge and practical applications.

At present, Commonly used deep learning models include Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) network, Gated Recurrent Unit (GRU), Deep Belief Network (DBN), etc.

(4) *Hybrid forecasting method*

The main idea of the hybrid prediction method is to integrate various algorithms, methods, or models to make full use of their advantages, further improving the prediction performance. The prediction method can be combined with other algorithms or methods to optimize the prediction results at any stage.

Before the establishment of the basic prediction model, the data can be pre-processed, such as Wavelet Packet Decomposition (WPD), Empirical Wavelet Transform (EWT), Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Factor Analysis (FA), Singular Spectrum Analysis (SSA), etc. The main purpose of pre-processing is to reduce noise interference, reduce the dimension of complex data, or extract data characteristics.

When building the model, various optimization algorithms can be used to optimize the model parameters, such as the number of hidden layers, learning rate, etc. Commonly used optimization algorithms include the Binary Genetic Algorithm (BGA), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), Simulated Annealing (SA) Algorithm, etc. These optimization algorithms can find better model parameters and improve generalization ability and prediction accuracy, which are especially helpful for models that are greatly affected by initial parameters.

After the model completes the prediction, the optimization method can also optimize the prediction results. For example, the error analysis method is used to analyze the error to correct the prediction error. In addition, ensemble learning can combine the prediction results of multiple weak learners according to a certain combination strategy. It obtains more significant generalization performance and higher prediction accuracy than a single learner.

1.3 Predictive Control in Robotics

1.3.1 Uncertainty Problems in Predictive Control of Robotics

Uncertainty Science is the product of the second scientific revolution in the last century (Evans and Rosenthal, 2004). As one of the active fields in human intelligence research, uncertainty science is a key technology for computer intelligence systems to become practical (Voorbraak, 1995). Uncertainty science studies systems with fuzzy structural concepts, incomplete information in calculations, unclear (black box) or incompletely clear (gray box) original data, energy dissipation, or material changes during the movement of things.

For mobile robots, the main content of uncertainty research is as follows: the abstract processing of uncertain knowledge or information, that is, how to effectively characterize data or information; the problem of multi-information integration and fusion, especially uncertainty information processing and fusion issues; image recognition and understanding in the uncertain environment of mobile robots,

real-time obstacle avoidance and path planning; the adaptability and robustness of reasoning models, and the error and performance analysis of different models; under uncertain environments, environment perception and environment modeling, and real-time positioning and navigation problems; the robot's self-reasoning and self-learning capabilities. Figure 1.6 analyzes the uncertain factors in mobile robots (Wang *et al.*, 2020; Scaglia *et al.*, 2015; Kim *et al.*, 2003).

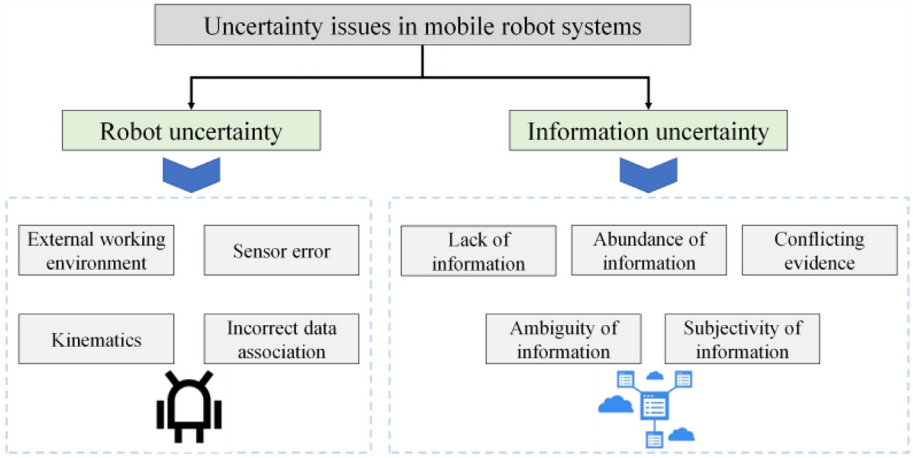


FIG. 1.6 – Uncertainty issues in the mobile robot system.

Uncertain factors in robot uncertainty are described as follows:

(a) Uncertain factors in the environment

The external working environment in which the robot is located is uncertain (Gasos and Rosetti, 1999). The existing algorithm research mostly assumes a static environment, while the real environment is constantly changing, such as the movement of people on the highway and the door opening in the home environment. These dynamic obstacles cause a series of errors due to the mismatch of map information during the robot's movement.

(b) Uncertain factors in sensors

The sensor of the robot system itself has accuracy errors in the measurement process, such as the cumulative track estimation error of the gyroscope, and it will also be affected by external interference factors, such as the influence of different surface characteristics and angular resolution of lidar (Chatila and Laumond, 1985). So, the perceived outside information contains much uncertainty.

(c) Uncertain factors in kinematics

The uncertainty that caused by the kinematics model (Santolaria and Gines, 2013). The mobile robot can obtain the current pose based on the kinematics model through sensor measurement. The kinematics model is a simplification of the real