Chapter 9
Decision-Making Technologies for Intelligent Maintenance and Management

Abstract Upon completion of bridge inspection, monitoring and analysis, the subsequent and crucial step is to formulate decisions for bridge maintenance, which should be logic or evidence based, optimal considering economic and environmental constraints, and feasible subject to resources at hand. There exists a situation that the decision-making is straightforward if the data and information are of low complexity. The reality is often the opposite, that is, data and information from the life-cycle inspection and monitoring processes, when brought to the maintenance engineers and managers, are often non-structured, high-dimensional, mutually dependent, and still 'big' in their volume. Recognizing these challenges, this chapter focuses digital technologies that can facilitate scientific and rational decision-making for bridge maintenance and management. Among them, Artificial intelligence (AI) technologies can facilitate decision-making taking the role of assisting human-based decision-making or of driving the decision-making. Two human–machine interfacing technologies are introduced, including virtual reality (VR) and augmented reality (AR), which provide advanced visual analytics for facilitate spatial–temporal understanding, logic formulation, and rational decision-making. General applications and specific applications of these technologies in the context of bridge maintenance and management are highlighted too in this chapter.

9.1 AI Based Decision-Making

9.1.1 Overview

Currently, bridge maintenance strategies primarily rely on bridge inspection results and reference to corresponding maintenance codes, such as the "Code for Maintenance of Highway Bridges and Culverts" (JTG 5120—2021), while taking into account the professional expertise and experience of the decision-makers. For instance, when dealing with crack damage in the substructure of a bridge, the bridge maintenance decision-maker may formulate a maintenance decision based on recommendations in the code and the results of on-site crack inspections, combined with

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their own maintenance experiences. This could involve counter-measures such as applying epoxy resin sealant or pressure grouting.

It is apparent that this process is filled with subjective uncertainties. Often, different decision-makers might propose different maintenance strategies for the same situation. This implies that the maintenance strategies formulated by different decision-makers will have variations in quality, leading to differences in reliability, remaining service life and other indicators of the bridge health after maintenance. In this context, if the subjective uncertainties introduced by the decision-makers themselves in the current decision-making process are not addressed properly, even with the use of various advanced technologies to address the issues in bridge inspection, there is no guarantee that the bridge, based on the current maintenance strategy, will continue to meet the requirements of normal use, ultimate load-carrying capacity and serviceability in a satisfactory manner. Therefore, the primary goal of bridge maintenance decision-making is to achieve a structured and standardized decision-making process, reducing subjectivity and ensuring quality of bridge maintenance.

Meanwhile, due to the existence of various objective factors, such as inability of AI technology to completely replace human involvement and inherent randomness in the external environment where bridges are located, the maintenance of different bridges still relies on the decision-makers' experiences. Therefore, formulation of bridge maintenance strategies cannot completely exclude involvement of the decision-makers. However, in order to better develop a system for formulating bridge maintenance strategies, it is necessary to track the effectiveness of the final maintenance decisions for each bridge, quantitatively evaluate the decision-making level based on the assessment results of post-maintenance inspections, and compile them into a database. This will facilitate continuous improvements in the later stages.

In addition, the current formulation of bridge maintenance strategies usually focuses on individual bridges, without considering the overall management, coordinated planning and formulation of maintenance strategies for other bridges within the same road network. As a result, bridge maintenance often requires long duration and frequent traffic closures, leading to a waste of time and money.

In summary, we need to reform the current bridge maintenance decision-making process to introduce more structured, standardized and objective decision-making methods and systems, and eliminate the subjective uncertainties introduced by the decision-makers themselves. At the same time, in the decision-making process, we should shift from considering individual bridges to considering the overall road network where the bridges are located. This allows for coordinated planning, avoiding unnecessary waste, optimizing resource allocation, extending the lifespan of bridge clusters, and ensuring the safety of people's lives and properties. Additionally, it is necessary to establish a reasonable evaluation system to quantitatively assess the bridge maintenance strategies formulated for each bridge. This will facilitate further improvement of the bridge maintenance strategy formulation system in the future.

With this background, coupled with the advancement of computer science, the concept of AI based decision-making has been proposed to overcome the current deficiencies in bridge maintenance by incorporating AI technology into the bridge maintenance decision-making process.

AI based decision-making, as the name suggests, refers to the introduction of AI technologies to partially or completely replace the role of humans in decision-making, eliminating subjective uncertainties, and enhancing standardization of decision-making. AI based decision-making can be divided into two aspects: AI-assisted decision-making and AI-driven decision-making, depending on the role and level of intelligence played by AI in the decision-making process.

9.1.2 AI-Assisted Decision-Making

AI-assisted decision-making refers to the role of AI technology in the entire bridge maintenance decision-making process to provide auxiliary supports. It falls within the domain of weak artificial intelligence and can replace humans in executing relevant stages of the decision-making process. However, the ultimate decision-making for maintenance is still made by humans, similar to the conventional bridge maintenance decision-making process. The introduction of AI technology can greatly improve decision-making efficiency and accelerate the retrieval, recording, and summarization of relevant data and information during the decision-making process. Although AI-assisted decision-making cannot completely solve the aforementioned problems, it can serve as a transitional stage towards achieving AI-driven decision-making.

In AI-assisted decision-making, humans remain the core decision-makers, and AI primarily operates based on instructions issued by humans. Its subjectivity is relatively weak, but it still has prominent advantages at this stage. For example, Siri, the intelligent voice assistant in Apple smartphones, is an AI-assisted technology that utilizes Natural Language Processing (NLP). The users can interact with their phones directly through voice commands. Similarly, NLP technology can be introduced into bridge maintenance decision-making, allowing the decision-makers to no longer rely on hardware such as keyboards and mice to interact with the systems. This eliminates the need for tedious mechanical tasks such as retrieving maintenance data, inputting text, performing data calculations and storage. It greatly enhances decision-making efficiency and enables automated and standardized archiving of bridge maintenance data, facilitating subsequent decision evaluation, and tracking the generation of future automated AI-driven decision-making systems.

The Touch and Talk (TNT) human–computer interaction system released by Smartisan Technology Co., Ltd. in 2018 exemplifies this concept. Although it is not yet mature and still has various issues, its global-based gesture and voice interaction system presents a highly promising AI-assisted decision-making approach. It has revolutionized the conventional computer's graphical user interface (GUI) interaction method and significantly improved the work efficiency. Furthermore, in recent years, the popularization of VR and AR technologies can be effectively applied in AI-assisted decision-making, assisting the decision-makers in data retrieval, on-site surveys and reinforcement solution selection.

In the future, the ideal state of AI-assisted decision-making systems would resemble J.A.R.V.I.S., the intelligent butler in the movie "Iron Man", capable of seamless communication with the decision-makers and fulfilling their various needs. Currently, there are already many technologies available for bridge-assisted decision-making, including the aforementioned Natural Language Processing (NLP) technology, VR technology, AR technology, and so on.

9.1.3 AI-Driven Decision-Making

Compared to weak AI-assisted decision-making, in AI-driven decision-making, AI has greater autonomy. It can autonomously make decisions and provide maintenance plans based on the current evaluation status of the bridge and relevant maintenance data, without human involvement. This falls within the domain of strong artificial intelligence. The Go-playing robots AlphaGo and AlphaZero, which have defeated various top Go players multiple times in the past, belong to the active decision-making systems. They can actively make autonomous decisions and formulate optimized strategies based on the current state of the game.

Compared to weak artificial intelligence in AI-assisted decision-making, active AI-driven decision-making belongs to the realm of strong artificial intelligence, but currently can only address some simple system problems. In the field of bridge maintenance, achieving the ideal goal of AI-driven decision-making is relatively challenging due to the complexity of bridge systems and the presence of significant uncertainties. However, in industries such as medicine, logistics, and urban planning, there have been preliminary prototypes of AI-driven decision-making systems for addressing some simpler problems. For example, in the field of medicine, there is the Clinical Decision Support System (CDSS), which is a human–computer interactive medical information technology application system. It learns from electronic medical record systems and internet databases to accomplish clinical decision-making and provide decision support to doctors and other healthcare practitioners.

Currently, to achieve AI-driven decision-making, techniques such as expert systems and reinforcement learning can be employed. By training learning systems with relevant domain knowledge and data, the system can learn and mimic the decision-making process of bridge maintenance decision-makers, thus achieving active decision-making. The next section will introduce the technologies involved in AI-assisted decision-making and AI-driven decision-making.

9.1.4 AI Technologies for Decision-Making

Interaction between the conventional bridge lifecycle management research and the non-destructive testing and structural health monitoring research is limited. Scholars in related fields are mostly conducting research within their respective domains, with different focuses and directions. The research achievements in various fields are difficult to integrate with each other, making it challenging to truly realize comprehensive bridge lifecycle management. As shown in Fig. 9.1, based on the development of emerging disciplines in computer science, this book proposes a new concept of intelligent lifecycle management by fully integrating technologies such as digital twins, big data, Internet of Things and AI into the processes of bridge monitoring, inspection, assessment and maintenance decisions. This aims to enhance scientific, objective and timely aspects of bridge management, bridging the limitations and deficiencies in current conventional bridge lifecycle management, and truly perform bridge management from a holistic perspective. It aims to meet the requirements of safety and applicability while considering durability and cost-effectiveness.

Currently, AI based decision-making in bridge maintenance, as the final component of intelligent lifecycle management of bridges, remains a cutting-edge research field. The research outcomes in this area are still relatively limited. In this section, we will introduce the relevant technologies that can be utilized for the development of AI based decision-making, as shown in Fig. 9.2. Among them, due to the relative maturity and significant implications for the development of AI based decision-making, VR technology and AR technology will be discussed in detail in the following two sections.

(1) Natural Language Processing (NLP)

NLP is dedicated to the study of various theories and methods that enable effective communication between humans and computers using natural language to serve as an interface between humans and machines. Applying NLP techniques to AI-assisted decision-making in bridge maintenance can improve the interaction efficiency between decision-makers and computers. Additionally, it facilitates retrieval, input, storage and management of relevant bridge maintenance decision data, thereby enhancing the level of bridge maintenance decision-making.

Among all living beings, only humans possess the ability of language. Various human intelligences are closely related to language. Human logical thinking takes the form of language, and the majority of human knowledge is recorded and transmitted

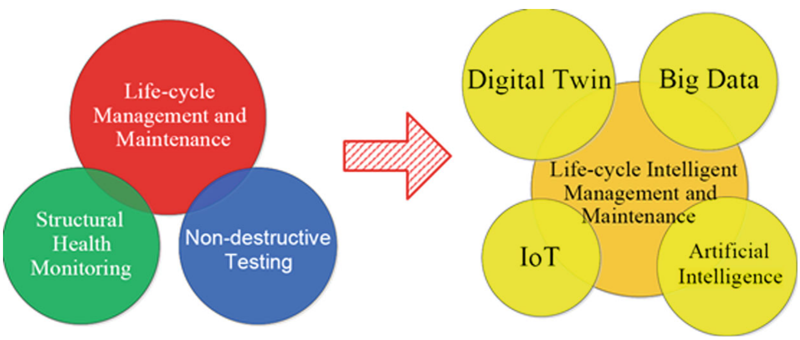


Fig. 9.1 Intelligent life-cycle maintenance and management

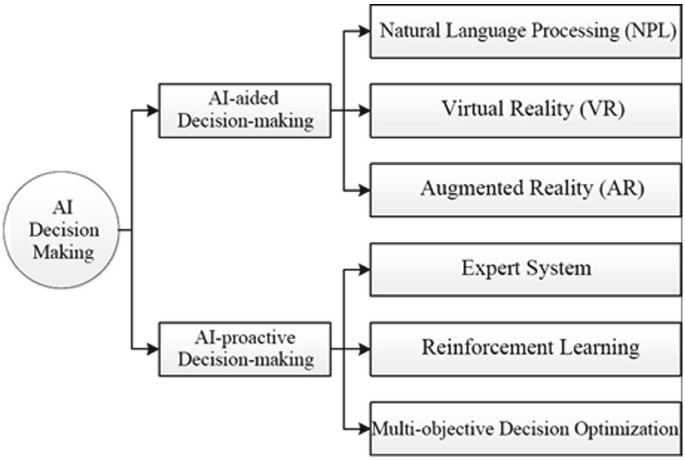


Fig. 9.2 Related technologies for AI based decision-making

in the form of language and text. Therefore, natural language processing is an important, even core, part of AI. Bill Gates has also stated that "Language understanding is the crown jewel of artificial intelligence."

The ability to communicate with computers using natural language has long been a pursuit of humanity. It holds significant practical value as it allows people to use their preferred language to interact with computers, without the need to spend a substantial amount of time and effort learning unfamiliar computer languages. Achieving natural language communication between humans and machines means enabling computers to both understand the meaning of natural language texts and express given intentions, thoughts and ideas in natural language texts. The former is known as Natural Language Understanding (NLU), while the latter is referred to as Natural Language Generation (NLG). Therefore, natural language processing involves two core tasks: natural language understanding and natural language generation.

Natural Language Understanding aims to enable machines to have the same language comprehension ability as humans. However, due to the many difficulties inherent in language understanding, machine understanding of natural language still lags far behind human-level comprehension. Firstly, language lacks strict rules and exhibits complex patterns. It allows for free combinations and can be composed into complex linguistic expressions. Secondly, language is an open set, allowing people to invent and create new ways of expression freely. Lastly, language requires the connection to practical knowledge and has a certain knowledge dependency. The use of language is based on the environment and context. Therefore, Natural Language Understanding needs to address five technical challenges: language diversity, language ambiguity, language robustness, language knowledge dependency and language context. In contrast to Natural Language Understanding, the purpose of Natural Language Generation is to bridge the communication gap between humans and machines, transforming non-linguistic data into language formats that humans can easily understand, such as articles and reports. It involves six steps: content determination, text structure, sentence aggregation, grammaticalization, reference expression generation and language implementation.

Natural language processing began in the 1950s. In 1954, researchers at Georgetown University attempted to automatically translate over 60 Russian sentences into English, claiming that the problem of machine translation could be solved within 3 to 5 years. However, the actual progress of this work fell behind expectations. It was not until the late 1980s that statistical machine translation systems were developed, marking a significant advancement in machine translation research. In the 1960s, one particularly successful natural language processing system was the SHRDLU system developed by MIT's Winograd, which was used to control the actions of robots. The system combined syntax analysis, semantic analysis and logical reasoning, greatly enhancing the system's capabilities in language analysis. Until the 1980s, most natural language processing systems were still based on a set of complex, manually crafted rules, resembling expert systems. However, starting from the late 1980s, machine learning algorithms were introduced to language processing, leading to innovation in natural language processing. Some of the earliest machine learning algorithms used, such as decision trees, were systems composed of hard rules, similar to previously crafted rules. However, research in natural language processing has increasingly focused on soft, probabilistic models for decision-making. These models are usually sufficient to handle unexpected input data, especially when there are errors in the input, and they produce reliable results when integrated into larger systems that involve multiple subtasks.

In recent years, natural language processing has entered a phase of rapid development. The increasing abundance of various resources such as lexicons, semantic grammar dictionaries and corpora, along with the rapid progress in technologies like word segmentation, part-of-speech tagging and syntactic analysis, and the emergence of new theories, methods and models, have propelled the prosperity of research in natural language processing. The trends of the internet, mobile internet and integration of the world economy and society have created an urgent demand for natural language processing technology, providing strong market impetus for the development of natural language processing research. Although achieving natural language understanding or natural language generation is currently not as simple as originally imagined, from the perspective of existing theories and technological status, a general, high-quality natural language processing system remains a long-term goal. However, practical systems with considerable natural language processing capabilities have already emerged for certain applications, some of which have been commercialized and even industrialized. Examples include multilingual database and expert system natural language interfaces, various machine translation systems, full-text information retrieval systems and automatic summarization systems. Among them, the most well-known products include Apple's widely-used personal assistant Siri, personal intelligent assistants from companies like Google, Amazon, Microsoft and Baidu, and the intelligent voice input method developed by iFlytek, which have greatly facilitated people's lives and work. From these products, it can be seen that applying natural language processing technology to bridge AI-assisted decision-making is highly feasible at the current level of technological development. Based on natural language processing technology, bridge maintenance decision-makers can directly store and retrieve bridge management data through human–machine dialogue, perform corresponding calculations and formulate final decisions.

(2) Expert Systems

Expert systems are a branch of AI that utilizes a vast amount of specialized knowledge to address problems that currently only experts can solve. Bridge decision-making based on expert systems refers to the intelligent software system that utilizes expert systems to mimic experienced experts and make maintenance decisions for existing bridges, following the relevant rules formulated in current bridge decision-making.

One of the pioneers of expert systems, Professor Edward Feigenbaum of Stanford University, defines expert systems as "intelligent computer programs that apply knowledge and reasoning to solve complex problems that only experts can solve." In other words, expert systems can be seen as a type of intelligent computer system that possesses a vast amount of specialized knowledge. They can utilize the specialized knowledge and experience provided by one or more experts in a specific field and employ AI reasoning techniques to solve and simulate various complex problems that are typically solvable only by experts. This allows experts' expertise to be accessible without being limited by time and space.

It is important to note that expert systems simulate the reasoning of experts in specific domains. For example, in the field of bridge maintenance decision-making, expert systems simulate the reasoning process of how experts derive maintenance decisions based on inspection and monitoring results, rather than simulating the problems themselves (i.e., modeling the problem domain through mathematical models). Expert systems only simulate the problem-solving capabilities of experts. Therefore, using this characteristic for bridge maintenance decision-making can effectively eliminate decision discrepancies caused by differences in decision-makers' professional knowledge and experience, thereby enhancing the standardization of bridge maintenance decisions.

In general, a basic expert system consists of six components: knowledge base, database, inference engine, explanation mechanism, knowledge acquisition and user interface, as shown in Fig. 9.3.

In an expert system, the knowledge base is its core component, consisting of factual knowledge and heuristic knowledge specific to the domain (such as the domain of bridge maintenance decision-making). The former refers to public and widely accepted facts, such as relevant indicators in bridge inspection and decision-making standards. The latter refers to the experiential and heuristic knowledge in the specific domain, such as the personal experience and decision-making expertise of bridge decision-making experts. The knowledge base of an expert system is a collection of multiple expert knowledge about a domain or specific problem. It can provide the users with expertise and knowledge of more than one expert, and can be continuously enhanced and improved over time. The performance level of an expert system depends primarily on the quantity and quality of knowledge it possesses. The

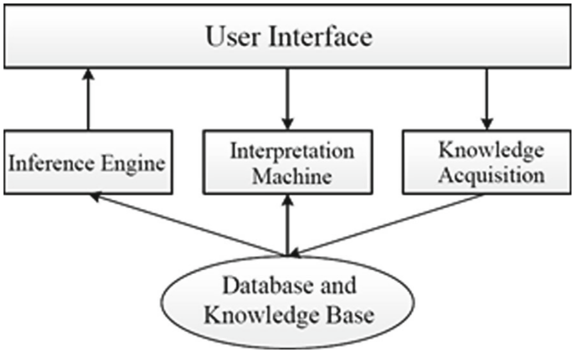


Fig. 9.3 Framework of an expert system

more higher quality knowledge an expert system has, the stronger is its problem-solving ability. The database, on the other hand, is used to store knowledge, input data, initial states and inference processes within the expert system, serving as the working memory area of the expert system.

Knowledge acquisition is an important learning function of expert systems. It is used to modify and add knowledge to the knowledge base, incorporating new knowledge to continuously enhance the system's expertise. It is similar to continuously "inputting internal force" into the system, allowing its "skill" to become more profound.

A reasoning engine is a set of programs used to control and coordinate the entire expert system. It utilizes the knowledge from the knowledge base, based on user input data (such as bridge defect data obtained through inspections and monitoring in bridge maintenance), and follows certain reasoning strategies (such as forward reasoning, backward reasoning and mixed reasoning) to solve current problems, interpret user requests and ultimately provide conclusions. When designing a reasoning engine, it should conform to the reasoning process of experts. Generally, the reasoning engine of an expert system is separate from the knowledge base, which not only facilitates knowledge management but also enables system generality and scalability.

The primary role of the explanation mechanism is to explain how an expert system deduces inferential conclusions based on input information and to answer user queries, enabling users to understand the entire reasoning process, and the knowledge and data applied during the process. The main reason for incorporating an explanation mechanism in expert systems lies in the fact that expert knowledge, in general, is mostly experiential knowledge accumulated by human experts in practice, and therefore, usually only the experts themselves have an understanding of it. Moreover, experiential knowledge is often derived from experience and lacks theoretical guarantees. Typically, this knowledge is not documented in textbooks or other professional books. Consequently, this knowledge remains unfamiliar to others and essentially constitutes proprietary knowledge of the experts. If an expert system only provides final conclusions without any explanations, it will inevitably affect the level of trust users have in those conclusions, especially when the system's conclusions contradict the users' own perspectives. Therefore, an expert system should possess explanatory functionality, allowing it to answer user questions and inform users about how it solves problems, which knowledge it utilizes, the content of that knowledge, its sources, its rationale, and so on, making the expert system "transparent" to the users. Good transparency also facilitates knowledge validation and modification, enabling the users to evaluate and discern the conclusions drawn by the system.

The final user interface provides a user-friendly interactive environment for the users, facilitating the exchange of information between the expert system and the users. The aforementioned six components constitute an integrated whole of the expert system. Through computer programs and initial knowledge learning and training, the expert system can simulate a highly skilled bridge maintenance and management expert, and achieve AI driven decision-making for bridges based on input inspection and assessment data. However, the current bridge decision-making based on expert systems can only address individual bridge decision problems and cannot yet achieve comprehensive decision-making for a group of bridges, failing to reach the level of holistic planning for the entire road network.

In an expert system, expert knowledge, as the core of the system function, has the following problems:

- Instability of expert knowledge. Expert knowledge is often heuristic in nature. Therefore, compared to logical knowledge, it is unstable. When faced with new situations or problems, human experts can readily revise existing knowledge or induce new knowledge to deal with these new issues. However, expert systems find it difficult to exhibit the same flexibility, which ultimately leads to ineffective decision outcomes.
- Difficulty in acquiring expert knowledge. The knowledge acquisition of expert systems generally involves a series of interactions between the domain experts (such as in the field of bridge maintenance decision-making), software engineers and computers. In this process, if the software engineer lacks expertise in the field of bridge maintenance, it becomes difficult to grasp the concepts, relationships and problem-solving methods used by the experts. As a result, the knowledge of the experts cannot be accurately input into the system, making it challenging for the expert system to replicate the logic and thinking process of the experts during decision-making.

More importantly, in most cases, the experts rely primarily on experience and intuition when making bridge maintenance decisions, making it difficult to accurately describe them using mathematical theories or other models. Furthermore, in order to solve problems in a specific field, the experts need to know much more than just principles and facts, including a significant amount of common knowledge from daily life. Therefore, it is impossible to expect the domain experts to compile all the knowledge they have in a short period of time.

To solve the aforementioned two types of problems, a relatively simple and effective method is to input the knowledge compiled by the domain experts into the system, continuously update and learn from it, and make the development of the expert system an iterative process. This also means that developing a successful expert system often requires extensive testing with practical engineering cases to identify and eliminate erroneous knowledge, as well as to continuously modify and expand the system to achieve high performance.

HP captured 1000 rules from 12 product series through two knowledge engineers, one programmer and three customer service experts, which further led to the development of the company's customer equipment diagnostic system. This system assists the customer service representatives in handling millions of phone inquiries each year. XCON, an expert system developed by Digital Equipment Corporation (DEC) and Carnegie Mellon University in the 1970s, is a commercial system used to devise hardware configurations for computer systems, resulting in significant economic benefits. Regarding the application of expert systems in civil engineering,

Kostem [1] developed an expert system for highway bridge evaluation in 1986. However, this system was essentially an interface for a bridge classification program developed using the conventional software approaches. Later et al. [2] developed a fuzzy expert system for bridge damage assessment, which combines genetic algorithms with neural networks and can be used for durability evaluation of reinforced concrete bridges. Melhem et al. [3] also developed an expert system for bridge condition assessment, which utilizes multi-dimensional decision models and fuzzy set theory to evaluate the condition of bridges. Mikami et al. [4] developed a learning-based expert system for repairing steel bridges in 1994, using a novel inference engine that can learn from user feedback. Subsequently, Wilson et al. [5] developed a decision support system for the entire life cycle of bridges, which evaluates various aspects of bridge design, construction, operation and maintenance.

The system proposes evaluation methods, calculation models, multi-parameter databases and knowledge systems with distributed interactive capabilities, considering factors such as bridge functionality, maintainability, operational cost, safety and environmental impact within its expected service life. However, due to various existing issues in the aforementioned expert systems and the complexity of bridge maintenance decision-making itself, there is currently no expert system that has been truly applied to bridge maintenance decision-making.

(3) Reinforcement Learning

Reinforcement Learning (RL) is a type of machine learning that enables computers to learn and solve problems autonomously. In the process of computer learning, humans only need to set a "small goal" for the computer, and the specific optimal strategy is obtained by the computer through continuous trial and error without human intervention. More precisely, reinforcement learning refers to the learning process of an intelligent agent that interacts with the environment and guides its behavior based on rewards obtained, aiming to maximize the overall reward gained by the agent.

A common model for reinforcement learning is the standard Markov Decision Process (MDP), where the next state of an agent depends not only on the current state but also on the action taken. The goal of reinforcement learning is to adjust the strategy to find the policy that maximizes the rewards and accumulates the highest total reward. Its basic elements include states, actions, state transition probabilities, rewards and policies (see Fig. 9.4). The problem-solving process of reinforcement learning can be roughly divided into two steps: (1) prediction, where a given policy

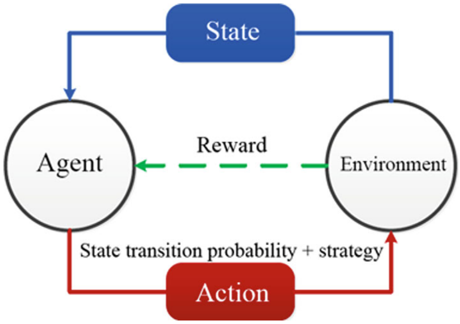


Fig. 9.4 Framework of reinforcement learning

is evaluated to estimate the corresponding state value function and the accumulated value obtained from rewards, and (2) action, where the optimal action for the current state is determined based on the value function. Depending on the given conditions, reinforcement learning can be categorized into model-based RL and model-free RL.

(1) Model-Based Reinforcement Learning

Model-based reinforcement learning is a method that uses dynamic programming to solve Markov Decision Processes. Depending on the policy, it can be divided into two methods: policy iteration and value iteration, both of which belong to dynamic programming. These methods require a comprehensive understanding of the rewards and state transition probabilities in the entire problem, and it is possible to store all the information of the Markov decision processes. However, in games like Go, the total number of states is 3 to the power of 19, which is extremely large and cannot be stored, making model-based reinforcement learning methods unsuitable.

The main idea behind policy iteration is as follows: first, randomly initialize a policy and calculate the value of each state under this policy. Then, based on these state values, derive a new policy. Calculate the value of each state under the new policy and repeat this process until convergence. In this process, calculating the value of each state under a policy is known as policy evaluation, and obtaining a new policy based on state values is called policy improvement. Compared to the two-stage policy iteration of policy evaluation and policy improvement, value iteration combines these two steps more closely. Firstly, through one round of policy evaluation, calculate the expected value of future states for each possible action in the current state. Select the action that leads to the state with the highest expected value and use this maximum expected value as the value of the current state for the next round of policy evaluation. Repeat this process until the value function converges. Value iteration is significantly faster than policy iteration.

(2) Model-Independent Reinforcement Learning

Compared to model-based reinforcement learning, model-free reinforcement learning refers to the approach where we have incomplete knowledge about the reward function and transition probabilities, and need to explore them ourselves. There are three main algorithms in model-free reinforcement learning: Monte Carlo

(MC) method, SARSA (State-Action-Reward-State-Action) method and Q-learning method.

The MC method generates policy samples randomly and calculates the corresponding state-action values based on these samples. It keeps track of the values and visit counts for each state-action pair. With an increasing number of random samples, the values and visit counts for each state-action pair are continuously updated. In contrast to the MC method, which requires complete policy samples, SARSA is a form of temporal difference (TD) learning that utilizes the Markov property and updates the value of the current state based only on the next state information. SARSA guides the system to explore according to a given policy and updates state values at each exploration step. The framework of Q-learning is similar to SARSA. Q-learning also guides the system to explore according to a policy and updates the state values at each exploration step.

The aforementioned methods mainly focus on solving reinforcement learning problems with discrete and small-scale state spaces. When facing more complex state spaces, including continuous ones, the conventional methods become computationally expensive. In such cases, deep reinforcement learning methods should be employed, with Deep Q-learning (DQN) being one of the classical algorithms. The basic idea of DQN algorithm originated from Q-learning, but it approximates the value function. Instead of directly calculating the Q-value based on the state-value (s) and action (a), it employs a Q-network composed of neural networks to compute the Q-values. Consequently, DQN has the capability to handle large-scale reinforcement learning problems. However, the DQN algorithm encounters an issue: it does not guarantee convergence of the Q-network. In other words, we cannot necessarily obtain converged Q-network parameters, leading to poor performance of the trained model. To address this problem, various variants of the DQN algorithm have been developed, such as Nature DQN, Double DQN and Dueling DQN. These methods still fall within the category of value-based learning algorithms. Although they have been successfully applied in many fields, they still exhibit limitations in handling continuous actions, addressing problems with restricted states, and resolving stochastic policy problems. To overcome these challenges, performance-based deep reinforcement learning algorithms can be employed, such as the Monte Carlo Policy Gradient (reinforce) algorithm, as well as methods that combine policy and value, such as Actor-Critic algorithms, A3C algorithm, and Deep Deterministic Policy Gradient (DDPG) method, to address the aforementioned issues.

In the field of reinforcement learning applications, the most well-known example is the Go AI program called AlphaGo, which has defeated numerous human Go masters. AlphaGo utilizes the deep reinforcement learning DQN algorithm to maximize reward accumulation through self-play, thereby determining the best moves in various game states. This algorithm aligns more closely with human decision-making in the real world and finds widespread applications in intelligent robot control, board game play, game completion, autonomous driving, and other decision-making and control problems. Similarly, in the domain of bridge maintenance, reinforcement learning methods possess remarkable potential with their human-like autonomous decision-making capabilities, enabling proactive maintenance decision advantages.

In the maintenance process, reinforcement learning algorithms (agents) act as bridge maintenance decision-makers, continuously interacting with the targeted bridge structures (environment), providing different maintenance strategies, and calculating corresponding bridge performance reliability indicators as environmental feedback and state evolution. Eventually, optimal bridge maintenance strategies are obtained to minimize the life-cycle cost while maximizing the bridge's service life. Currently, scholars have already attempted to optimize maintenance decisions for simply supported beam bridges and large-span cable-stayed bridges using the deep reinforcement learning DQN algorithm. The results have shown that the DQN algorithm can efficiently and autonomously select the optimal maintenance strategies for bridge structures with varying degrees of complexity. These cases illustrate the significant position and value of deep reinforcement learning technology in future bridge AI based decision-making.

It is worth mentioning that visualizing the decision results allows for a more intuitive observation of the changes occurring in the bridge before and after maintenance. Generative models are a novel and reliable approach to solving such simulation generation tasks. Generative models include auto-encoder network models and generative adversarial network models. The output of these models is no longer a classification or prediction result but rather a sample individual that conforms to the distribution space of the input samples. For example, it can generate 3D models or images of bridges after maintenance.

Generative Adversarial Networks (GANs) are primarily inspired by the idea of zero-sum games in game theory. They were first proposed by Ian Goodfellow in 2014 and have attracted widespread attention in the academic community. The principle of generating images using GANs is illustrated in Fig. 9.5.

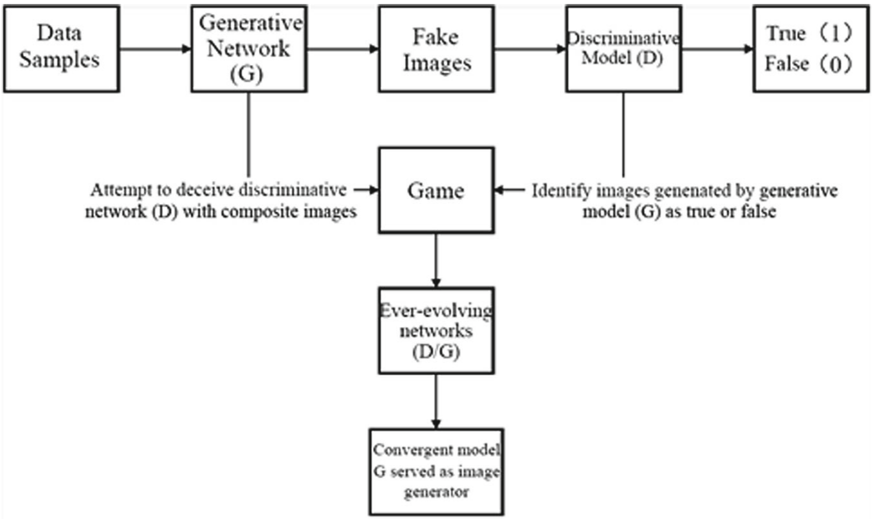


Fig. 9.5 Framework of antagonistic generative neural network

A GAN consists of two components: the generator model (G) and the discriminator model (D). The generator model learns the distribution of real data, while the discriminator model is a binary classifier used to distinguish between real and generated data. The generator model (G) generates data based on the sample data, and then both real and generated data are input to the discriminator model (D), which outputs the predicted class. The discriminator model is typically a binary classifier, assigning a label of 1 to the real images and a label of 0 to the generated images.

During the training process, the objective of the generator model G is to synthesize images to deceive the discriminator model D, making D classify them as real. On the other hand, the objective of D is to accurately distinguish between G's generated fake images and real images. Thus, G and D form a dynamic "game" where they continuously evolve. The generated images by G become increasingly similar to the real images, while the discriminator model D improves its ability to judge the authenticity of images. After a sufficient number of iterations, the generator model G reaches a converged state, leaving G as the sole generator of images. The generated images are statistically indistinguishable from the real images.

(4) Multi-objectives Optimization

The aforementioned technical methods mainly focus on AI-based bridge maintenance decision-making for individual bridges. However, in more practical scenarios, when formulating bridge maintenance decisions, it is necessary to consider the entire network of bridges. During the construction of the road network, the construction time of bridges along the route is relatively concentrated, resulting in similar service periods for these bridges. In this context, within a certain time period after completion of bridge construction, bridges of the same type in the road network may experience similar types of damages, leading to "shock-like" traffic paralysis and extensive maintenance demands. This highlights the significant importance of maintenance decision-making for a group of bridges.

Unlike the maintenance of individual bridges, bridge networks involve multiple maintenance targets, large maintenance volumes, diverse structural forms and complex environments. Simply applying the maintenance decision-making models for individual bridges to the maintenance decision-making for bridge networks would result in higher maintenance costs and waste of resources. To address this issue, it is necessary to optimize the maintenance decision-making for bridge networks. This optimization involves considering the different structural forms and environmental effects of multiple bridges within the road network and optimizing the maintenance decision-making accordingly.

Optimization of maintenance decision-making for bridge networks refers to selecting the optimal maintenance timing and measures at regular analysis intervals or within a certain time period. After maintenance, the degradation process of the structural performance of bridges is delayed or temporarily halted, resulting in a postponement for reaching the threshold of serviceability. The degradation process of structural performance after maintenance is generally considered to be a repetition of the degradation prior to maintenance. When optimizing maintenance decision-making for bridges, the extension of service life has an impact on maintenance benefits and costs: the greater the extension of service life, the better the maintenance benefits, but the required maintenance measures often come with higher costs. The purpose of optimizing maintenance decision-making is to comprehensively consider various factors that affect the optimization objective function based on the concept of intelligent bridge lifecycle management, such as the location of the bridge within the road network, degradation of the bridge's performance, assessment of the bridge's performance state, maintenance costs (including direct and indirect costs), etc. This allows for formulation of the optimal maintenance strategy under the current optimization objective. Depending on the number of objective functions in the maintenance decision-making optimization, it can be classified as single-objective optimization or multi-objectives optimization.

In mathematics, a single-objective optimization problem refers to computing the optimal solution for a specific objective under certain constraints. In the optimization of maintenance decision-making for bridge networks, the objective function is typically set as the minimum maintenance cost over the entire lifecycle of the bridge network. Common constraints would include the threshold value of structural failure probability, critical state level of the bridges, carrying capacity level or remaining service life. Alternatively, the maximization of maintenance benefits can be used as the objective function, with the constraint being the budget allocation for bridge network maintenance. This is because the fundamental and crucial question faced by bridge management authorities in formulating maintenance decisions for bridge networks is how to effectively utilize limited funds for maintenance. Renowned scholar Frangopol from Lihai University also believed that the goal of bridge network management is to achieve a balance between the total life-cycle cost and the overall life-cycle reliability by efficiently utilizing limited funds. In some existing bridge management systems like BRIDGIT and PONTIS, the minimum equivalent expected average cost (the ratio of total maintenance cost to expected service life) is adopted as the objective function for decision optimization. From the perspective of the number of objective functions, the optimization of bridge maintenance decisions using the cost–benefit ratio can be considered a single-objective optimization problem, which inherently takes into account both maintenance effectiveness and costs.

In contrast to single-objective optimization problems, multi-objectives optimization problems involve more than one objective function that needs to be simultaneously achieved. For example, in bridge maintenance decision-making, there are two optimization objectives: minimizing maintenance costs and maximizing maintenance effectiveness. Compared to single-objective optimization, multi-objectives optimization allows for considering more practical bridge management requirements and aligns better with the actual needs of bridge managers. Therefore, it represents the future research and development trend of bridge maintenance strategy optimization.

Compared to single-objective optimization, in practical problems, the goal of multi-objectives optimization is to obtain optimal values for different objective functions within the same value range. These objectives are generally interdependent, and even conflicting. To improve the adaptability of one objective function, it is necessary to compromise the optimality of other conflicting objective functions. In other words, it is impossible to simultaneously optimize all objective functions when solving multi-objectives optimization problems. The so-called optimal solution to multi-objectives optimization problems is a set of non-dominated solutions obtained through coordination among these objective functions. Therefore, the number of optimal solutions in multi-objectives optimization problems is often infinite, and the set of all optimal solutions is called the non-dominated Pareto solution set. Compared to the optimal solution in single-objective optimization, which appears as a point in the objective space, the Pareto solution set generally represents a continuous or dispersed surface in the objective space. In this context, the key challenges in solving multi-objectives optimization problems lie in ensuring that the obtained Pareto optimal surface is closest to the true optimal surface, that the distribution of optimal solutions is uniform and covers a comprehensive range. Additionally, since there are infinitely many Pareto optimal solutions, they cannot be directly applied. This requires decision-makers to select the most satisfactory solution from these non-dominated solutions based on practical considerations.

There are three main approaches for selecting the final solution: the first approach involves obtaining the final solution based on the requirements of the decision-maker using the non-dominated solution set already obtained; the second approach is the interactive method, where the final solution is gradually determined through dialogue between the analyst and the decision-maker; and the final approach involves transforming the multi-objectives problem into a single-objective problem through weighted combination, based on the decision-maker's prior knowledge and then solving it, which is essentially the same as the approach used in single-objective optimization mentioned earlier.

Currently, with the continuous development of mathematics, operations research, systems theory and other related disciplines, the methods used to solve multi-objectives optimization problems have become increasingly diverse and mature. These include goal programming, dynamic programming, linear and nonlinear programming, artificial neural networks, and various evolutionary algorithms such as genetic algorithms and particle swarm optimization.

Liu et al. [6] conducted multi-objectives optimization research on minimizing both bridge deck inspection and maintenance costs, and deterioration costs using genetic algorithms, which were applied to the optimization of bridge deck maintenance in a transportation network. Miyamoto et al. [7] proposed a multi-objectives maintenance optimization approach that minimizes inspection and maintenance costs, and maximizes structural durability based on an expert rating system using genetic algorithms for optimization. Furuta et al. [8] considered the lowest life cycle cost, maximum service life and maximum target safety performance in the optimization of civil engineering infrastructure inspection and maintenance. Peng Jianxin et al. developed maintenance strategies that minimize maintenance costs within the structural life cycle and maximize structural condition indicators, while satisfying structural performance requirements and budget constraints. Kim et al. [9] considered uncertainties in structural inspection and maintenance and optimized the inspection and maintenance time, plus measured by maximizing the structural service life and minimizing the inspection and maintenance costs. Frangopol and Liu [10] proposed a road network bridge management decision optimization framework based on multi-objectives optimization problems. They used a two-stage stochastic dynamic programming approach that considered the remaining service life of each individual bridge and its importance in the road network. In the first stage of the framework, optimal maintenance decisions for each bridge were obtained based on the objective of minimizing the life cycle maintenance cost. In the second stage, the available maintenance budget was allocated according to the importance of each bridge, while satisfying the optimal maintenance decisions obtained in the previous stage as much as possible.

9.1.5 AI-Based Decision-Making in Bridge Engineering

As shown in Fig. 9.6, Yuanfu et al. [11] applied the Bridge Maintenance Intelligent Assistant Decision Support System (BMIADSS) to the Xihoumen Bridge, the world's first segmented steel box girder suspension bridge in the Zhoushan Mainland-Continental Bridge Project. BMIADSS includes professional databases such as user professional database, information management system professional database and professional database for intelligent decision support system. Based on the inspection data and non-destructive testing results of the bridge, a complete set of bridge intelligent decision support system was established using advanced information processing technologies such as neural networks, fuzzy evaluation, genetic algorithms and immune genetic algorithms.

Based on the Jiangyin Bridge Structural Health Monitoring System, Zhenan [13] transferred the collected massive raw data to the database in the monitoring center for safety assessment. However, during the data acquisition process, there may be noise

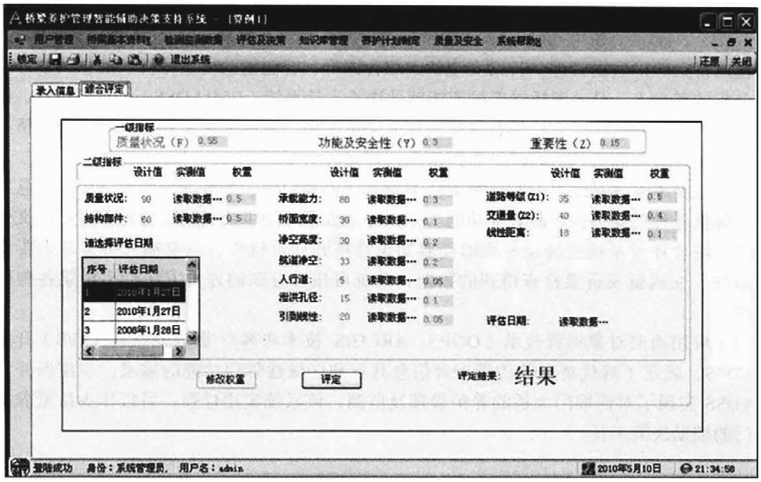


Fig. 9.6 Integrated rating user interface of BMIADSS [12]

interference, sensor failures or network transmission failures, resulting in a large amount of noise and faulty data in the raw data. To efficiently identify data anomalies and to distinguish structural anomalies from system anomalies, a deep learning-based method for data anomaly analysis in structural health monitoring systems was proposed. This method utilized the LSTM model to learn the feature relationships between time series, using historical monitoring data from the normal operation phase of the structure to train the model. Then, based on this model, the predicted response was obtained using the structural historical response, and combined with Dynamic Time Warping (DTW) distance calculation and Isolation Forest anomaly detection to successfully identify abnormal data in the bridge acceleration data. This method can differentiate structural anomalies from system anomalies through logical correlation analysis and multidimensional anomaly detection. It improved upon the previous methods that required manual threshold setting for data filtering, enabling continuous 24-h data monitoring and anomaly analysis to obtain higher-quality data content. It also enhanced the monitoring system's ability to provide early warnings and significantly improved the automation level of the structural health monitoring system.

Huang [14] applied statistical analysis to reveal the limitations of the Markov chain method, identified important factors affecting bridge performance deterioration, and developed an application for predicting the future state of bridges. Based on the historical inspection records, maintenance records and database data of bridge deck components in Wisconsin, bridge deck deterioration was selected as a significant factor. A bridge deck damage prediction model based on artificial neural networks was established using pattern classification methods, considering the potential nonlinear relationships between observation conditions and identification factors. The model consisted of an 11-5-5-5-5-5 neural network structure, involving 11 bridge attributes such as maintenance history, service time, design load and length. The structure has 5 hidden layers, with each layer containing 5 hidden neurons, and one layer served as the output layer with 5 output labels. In the Three Forks Cross-Validation, the neural network prediction model achieved classification rates of 84.66% for the training set and 75.39% for the test set, indicating that the backpropagation multilayer perceptron (BP-MLP) performed well in handling pattern classification problems and accurately predicted the bridge deck conditions, providing useful information for maintenance planning and decision-making. The research also highlighted the importance of maintenance and upkeeping records for effective bridge maintenance decision system, emphasizing the need for institutions to strengthen the collection and archiving of such data.

As shown in Fig. 9.7, Liqun et al. [15] designed a bridge structural health monitoring model (KPCA-SVM) based on data mining techniques. The model utilized wireless sensors to collect bridge structural health data. Kernel Principal Component Analysis (KPCA) was applied to preprocess the bridge structural health data, removing redundant features and reducing the dimensionality of the detection features. Subsequently, Support Vector Machines (SVM) were employed to learn from the bridge structural health data. SVM is a machine learning algorithm that minimizes structural risk while incorporating modern statistical theory. By fitting

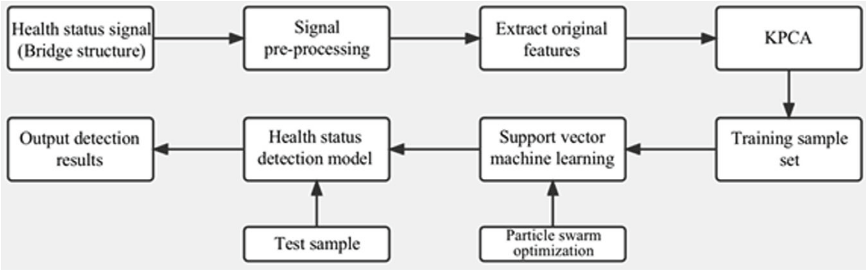


Fig. 9.7 Workflow of a data mining-based bridge structure health condition detection model

the relationship between the bridge structural state and feature values using SVM learning and training samples, the parameters of the bridge structural health monitoring model were determined using Particle Swarm Optimization (PSO) algorithm. This approach established an optimal bridge structural health monitoring model.

Guixuan et al. [16] developed a bridge intelligent decision support system (expert system) based on a bridge in Yamaguchi Prefecture, Japan. The system followed the maintenance management steps of inspection, evaluation and counter-measures. It consisted of three interconnected subsystems: bridge database management system, bridge aging evaluation system and bridge maintenance management plan optimization system. The bridge database management system was primarily responsible for including basic information about the bridge, inspection records, and maintenance and strengthening records. The bridge aging evaluation system transferred expert knowledge and experience into the computer, and data such as the bridge's basic elements, environmental conditions, traffic volume and inspection results. By setting up a hierarchical evaluation structure centered on the durability of the main beam, a five-layer feedforward neural network was used for inference. Deep learning was then performed using backpropagation algorithm to evaluate and predict the aging degree of the bridge based on durability and load-bearing capacity indicators. The bridge maintenance management plan optimization system employed genetic algorithms (GA) to simulate higher biological inheritance and evolution, as well as immune algorithms (IA) to emulate the immune system of living organisms so as to perform combined optimizations. It provided the optimal maintenance management plan within a certain time frame. The specific strategies included recommending appropriate maintenance and strengthening methods, determining suitable timing based on system judgment, and estimating the required budget. This system not only assisted bridge managers in handling large amounts of inspection data and evaluating the aging characteristics of existing bridges but also provided the best bridge maintenance management plan based on budget and construction conditions.

As shown in Fig. 9.8, Sidi [17] leveraged AI algorithms to address the problem of preventive maintenance decision-making for transportation facilities. The pavement condition index (PCI), which comprehensively indicated the functional state of the pavement structure, was selected as the core indicator for segment division. Seven types of pavement distress were considered as influencing factors for segment division, and a segment division model was established. A comparison was made between the original PCI values and the PCI values calculated by the probabilistic neural network. The correlation between the two reached 96.96%, and the correlation continued to improve with an increase in the number of samples. This clearly demonstrated that the accuracy of the preventive maintenance segment division model constructed based on the probabilistic neural network could fully met practical engineering needs. The probabilistic neural network classification method blurred the classification boundary values of the segments, automatically grouping similar distress types together, which facilitated the implementation of maintenance work. This method could quickly handle segment division cases with a large amount of data and allowed for real-time updating of data and results. It addressed the limitations of the conventional segment division methods, such as a small applicable scope, complex operations and low accuracy. It was suitable for large-scale network-level pavement segment division.

Furthermore, as shown in Fig. 9.9, a preventive maintenance decision-making model was constructed based on the multi-objectives backbone particle swarm optimization algorithm. Economic, social and environmental benefits were evaluated as the objective functions of the decision model, and an optimal maintenance strategy selection method based on fuzzy functions was proposed. Chen Sidi, based on the LTTP database, constructed a network-level preventive maintenance decision-making case with 20 sets of segment data. Through analysis of the case, the constructed intelligent pavement maintenance management model has achieved optimal choices for maintenance timing, maintenance segments and maintenance measures as it formulated the most scientific and efficient preventive maintenance plan within a specified period.

Ju [18] established a network-level funding optimization decision model based on the characteristics of rural road maintenance funds in Kunming City. The model aimed to maximize the effectiveness of fund allocation under the constraint of limited

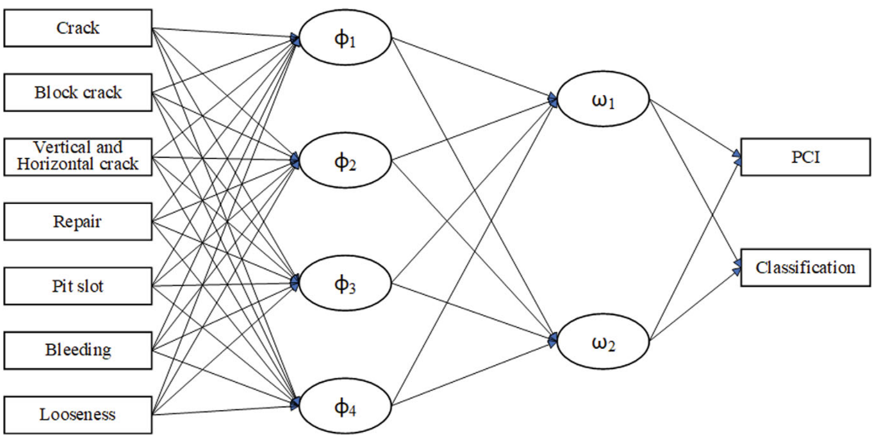


Fig. 9.8 Road segmentation model

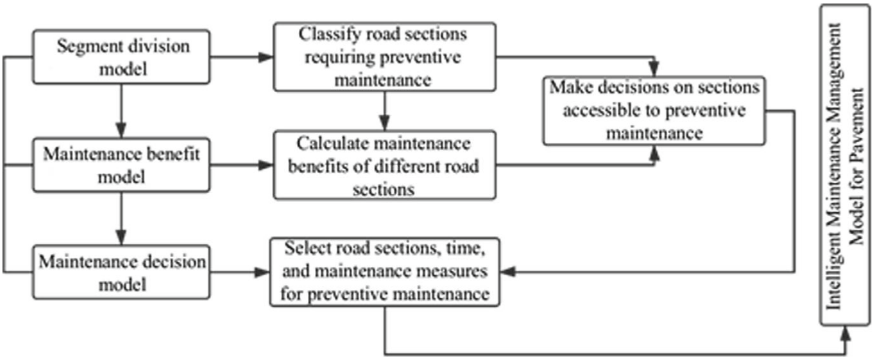


Fig. 9.9 Intelligent road surface maintenance management model

total maintenance funds by considering the pavement performance and the importance of roads in the road network as parameters. The Analytic Hierarchy Process was used to evaluate the maintenance benefits, including economic, social and environmental benefits. Considering the large total mileage and dispersed distribution of rural roads, as well as the road maintenance goals of "every road must be maintained" and "maintenance prioritization," various optimization decision-making methods were analyzed and compared. Ultimately, a multi-objectives optimization decision-making approach was adopted to establish the funding optimization decision model for rural road maintenance. For the case study of Kunming City's rural roads, two forms of funding optimization decision models were constructed: single-year model and multi-year model. The particle swarm optimization algorithm was used to solve the models and to provide the most reasonable maintenance plans, corresponding investment amounts, Pavement Quality Index (PQI) and social benefit scores, as shown in Fig. 9.10. The results indicated that the single-year funding optimization decision model yielded 14 Pareto optimal solutions, from which the maintenance department could directly select appropriate solutions for implementation based on the actual situation. The multi-year maintenance funding optimization model produced 20 Pareto optimal solutions, but most of the implementation plans were concentrated in the first year, which might lead to uneven allocation of management resources. However, considering the parameters set in this model, it represented the optimal maintenance decision-making plan. Finally, the results demonstrated that this model format could be further developed, and is worth applying in highway maintenance.

Deep Reinforcement Learning (DRL) is considered an important component of AI systems and has been applied to decision-making and control tasks in various engineering applications. From the perspective of AI, the problem of formulating maintenance decisions can be analyzed as a case of reinforcement learning. Efficient solutions can be achieved through a series of sampling algorithms to minimize maintenance costs and obtain optimal maintenance decisions. As shown in Fig. 9.11, Wei et al. [19] proposed a DRL-based model for automated decision-making in bridge maintenance. The input dataset of the model can be historical data from real

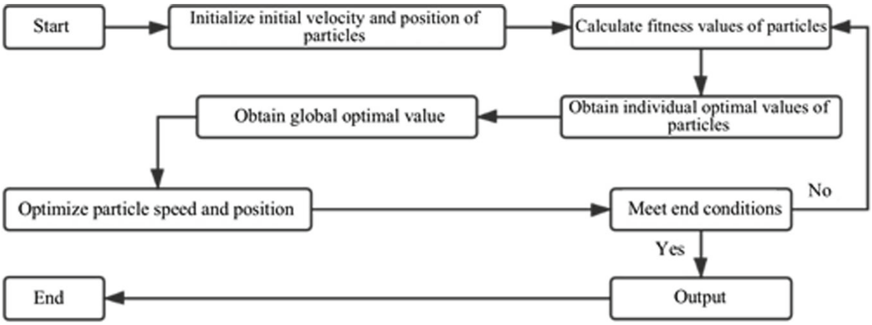
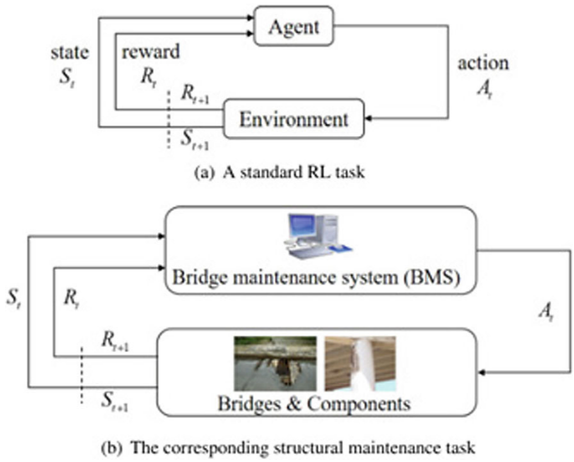


Fig. 9.10 Flow chart of particle swarm optimization algorithm

Fig. 9.11 Schematic diagram of the mapping of enhanced learning and bridge maintenance tasks: reward—economic cost of maintenance decisions and risk in some cases; action—some kind of bridge maintenance behavior



bridges or bridge data from virtual models. These two types of data models can also be merged into the same framework. In the model architecture, deep learning is responsible for evaluating the value function, while reinforcement learning is responsible for improving the mechanism. Through iterative learning in the evaluation and improvement stages, the model learns the optimal strategy. The structured agent of the deep neural network allows the model to be applicable to various bridge cases with minimal modifications.

9.2 Virtual Reality Technology

The conventional communication method between humans and computers involves viewing the results of information processing through the conventional output interfaces such as printing or screen display. The information obtained by humans from computers is often one-dimensional, resulting in a situation where humans have to adapt to computers and revolve around them. However, with the rapid development of social productivity and scientific technology, more challenges have been posed to adapt to the future information society. One of these challenges is to establish a multi-dimensional and visualized information integration environment that allows humans to participate in the process of information processing and decision-making through sight, hearing, touch and bodily forms. VR serves as the key technology that supports this multi-dimensional and visualized information space.

Virtual reality (VR), as an emerging technology that enables the creation and experience of virtual worlds, is a convergence of various technologies such as computer technology, sensor technology, multimedia technology, simulation technology, network technology and human–computer interaction technology. It is a challenging interdisciplinary field and a frontier research area, often hailed as the "new technology of the twenty-first century." VR showcases its broad application prospects and has been widely applied in various industries, steadily maturing over time. The application of VR in bridge engineering is also an important part of smart maintenance. Therefore, this section will provide a detailed introduction to the relevant concepts, characteristics, and applications of VR, as well as explore its application in bridge engineering.

9.2.1 Overview of VR

(1) Definitions and Features

In 1989, Jaron Lanier first proposed the concept of "virtual reality" and conducted defining and research on its content. The term "virtual" indicates that the environment or scene is not real but exists within the computer as an artificially constructed virtual world. "Virtual reality" immediately attracted the attention of scholars giving rise to a series of synonymous terms, such as "virtual environment" (VE), "artificial reality," "cyberspace," and so on. In 1992, experts and scholars at the US National Science Foundation Workshop suggested using "virtual environment" instead of "virtual reality." However, to this day, the academic community still commonly uses the term "virtual reality."

Brooks [20] defines "virtual reality experience" as any experience that effectively immerses the users in an interactive virtual world. This means that the users can "enter" this virtual environment, use a variety of new interactive devices and natural physical skills (such as turning their heads, waving their arms, etc.) to issue various commands to the computer, autonomously and dynamically control their viewpoint, and receive real-time feedback from the environment in terms of visual, auditory, tactile and other sensations, thus creating a sense of immersion in the corresponding real environment. Its essence lies in being an advanced computer user interface that provides the users with intuitive and natural real-time perceptual interaction methods, maximally facilitating user operations, thereby reducing user burden and improving the overall efficiency of the system. The fundamental goal of VR is to achieve realistic experiences and natural skill-based human–computer interaction. As a new comprehensive information technology, VR, with its real-time three-dimensional spatial representation capabilities, interactive operating environment and immersive experiences it brings to the users, has changed the tedious, rigid and passive nature of interaction between humans and computers.

Burdea and Coiffet [21] proposed the concept of "Virtual Reality Technology Pyramid," which succinctly describes the fundamental characteristics of VR systems—the three "I"s: immersion, interaction, and imagination, which ultimately distinguish VR against 3D animation:

Immersion refers to the ability to immerse and engage users in the computer-generated virtual environment. Users can see, hear, touch and even smell everything in the virtual scene just as they would in the real world, creating a sense of "presence."

Interaction refers to the ability for users to interact with objects in the virtual space, including manipulating various objects in the virtual scene and receiving real-time feedback from the virtual environment [22]. It encompasses degree of interactivity with objects, naturalness of feedback received from the environment and reasonable movement of objects in the virtual scene, among others.

- Imagination highlights the vast imaginative space offered by VR technology, expanding human cognitive capabilities. By immersing themselves in a "real" virtual environment, users can interact with and gain sensory and rational understanding from the virtual environment, deepening concepts and inspiring new ideas.

The 3I characteristics emphasize the pivotal role of humans in VR systems, where users are immersed in a virtual world created by computer software and hardware. Through the interactive means provided by the system's software and hardware, the users can interact with the system, fulfilling their real-world ideas while also triggering virtual imaginations. In addition to the 3I features mentioned above, VR also possesses multi-modality. It emphasizes that besides visual perception, which general computers possess, VR also includes auditory perception, tactile perception, motion perception and even includes gustatory and olfactory perception.

(2) Evolution of VR

The evolution of VR is shown in Fig. 9.12.

First stage (1950–70s): the exploration stage. The origin of the VR concept can be traced back to the simulator developed by Morton Heilig in 1956, which integrated a 3D display, stereo speakers, odor generator and vibrating seat. However, its bulky size prevented it from being commercially viable. In 1965, Ivan Sutherland, the founder of computer graphics, presented a report titled "The Ultimate Display" at the IFIP (International Federation for Information Processing) conference, proposing the use of a display screen as a window to observe the world, providing the observer with a sense of immersion. This was a milestone in the development history of VR technology. In 1968, Ivan Sutherland developed a helmet-mounted stereoscopic display using two cathode-ray tubes that could be worn on the eyes. This display

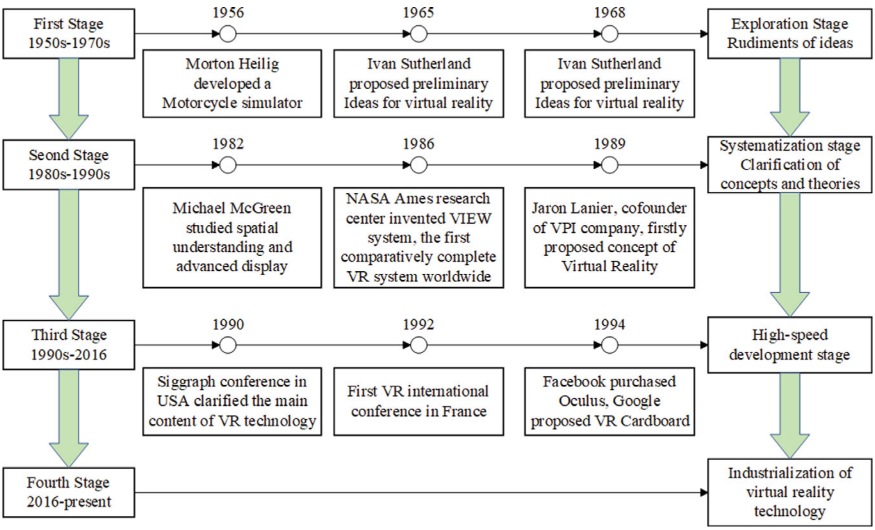


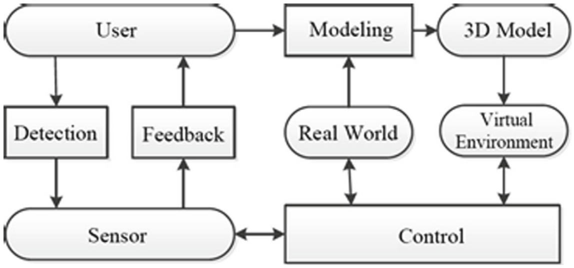
Fig. 9.12 Evolution of VR

became a foundational achievement in stereoscopic 3D display technology, providing a prototype and reference for the development of VR devices in the future. Overall, this stage of VR technology development progressed slowly and was in the stage of conceptual brewing.

Second stage (1980–90 s): the systematic stage. During this stage, the basic concepts, features, related theories and research on VR were gradually clarified. In 1981, Michael McGreevey began his research on the "spatial understanding and advanced display". In 1984, the first commercially available VR device, the RB2, was introduced. The development of NASA Ames Experiment Center's VIEW system in 1986 marked the world's first complete multi-purpose, multi-perception VR system. Jaron Lanier, one of the founders of VPL, introduced the term "virtual reality" in 1989.

Third stage (1990–2016): the rapid development stage. After the 1990s, with breakthroughs and rapid developments in scientific fields such as computer technology, high-performance computing, human–computer interaction devices, computer networks and communication, as well as the significant demand in important application areas like military training, aerospace, etc., VR technology entered a stage of rapid development. In 1990, the American Siggraph conference discussed VR technology and clearly defined its main components: real-time 3D image generation technology, multi-sensor interaction technology and high-resolution display technology, which set the direction for the development of VR technology. In 1992, the first international conference on VR technology was held in France, playing an important role in establishing the independent research status of VR.

Fig. 9.13 Functional modules of VR systems



Fourth stage (2016 to the present): the stage of industrialization and development. 2016 was a milestone year in the development of VR technology. Its products gradually gained popularity and started to infiltrate various vertical industries. At CES 2016, Oculus officially released the Oculus Rift head-mounted VR device, and other devices like HTC Vive and Samsung's Gear VR also emerged. Intel and Qualcomm started providing support for VR at the chip level. Game engines such as Unity, Blender, CryEngine, etc., announced comprehensive support for VR technology. In the gaming and entertainment industry, major game companies such as EA, Ubisoft, NetEase, Tencent, etc., released their representative works. From this year onwards, a large amount of capital poured into the VR market, leading to the emergence of more diverse VR device products. The VR content industry and technological support became more mature, and the user base continued to expand.

(3) Technology Components, Classification and Trends

Figure 9.13 illustrates the six major functional modules of VR systems.

Sensors are an important part of achieving human–computer interaction and serve two main tasks: (1) receive commands from the user and apply them to the virtual environment; and 2) provide the results of the operations to the user in various forms of feedback. The detection module is primarily used to detect the user commands and then apply them to the virtual environment through the sensor module. The feedback module is responsible for receiving information from the sensor module and providing real-time feedback to the user. The control module is mainly used to control the sensors, enabling interaction between the user, the virtual environment and the real world. The modeling module acquires three-dimensional data from the real world and establishes their three-dimensional models. 3D models are three-dimensional representations of the real world and constitute corresponding virtual environments.

A typical VR system consists of computer, input/output devices, application software and databases. The computer plays a crucial role in the VR system, responsible for real-time rendering calculations of the entire virtual world and real-time interaction calculations between the users and the virtual world. To achieve effective human–computer interaction in VR systems, special input devices are used to recognize various forms of user input, and real-time feedback generated is delivered to the users through the output devices. The implementation of a VR system also relies on various auxiliary software. For example, during early data collection and image organization, 2D software such as AutoCAD and Photoshop, as well as architectural drawing software, are used. For audio and video preparation, software like Audition and Premiere are utilized. In a VR system, the role of the database is primarily to store various data required by the system, including terrain data, scene models and various created models. Every object appearing in the VR system needs to have a corresponding model in the database. The data in a VR system can be classified into four categories based on their sources and roles, as shown in Table 9.1.

VR systems can be classified into four main types based on their implementation method: immersive, desktop, augmented and distributed VR systems [23]

- Immersive VR systems primarily utilize interactive devices such as head-mounted displays and data gloves to encapsulate the user's visual, auditory and other sensory experiences, enabling the user to truly become a participant within the VR system. Through these interactive devices, the users can operate and navigate the virtual environment, generating a sense of presence. Common immersive VR

Table 9.1 Classification of data in VR systems

Data	Definition	Generation
Platform data	Public platform data and administrative data to support system operation	Public support platform (computer system, network system, etc.)
Model data	The image of things in the real world in the digital space, the subject data in the VR system	Scanners, algorithms, axiomatic systems
Sense data	It is also called rendering data, which is applied to various output devices to make users see, hear, touch, smell, etc.	Rendering algorithm
Control data	User control and influence over the virtual environment through the data generated by the input device	Human–computer interaction devices (data gloves)

Fig. 9.14 Helmet-based VR display system

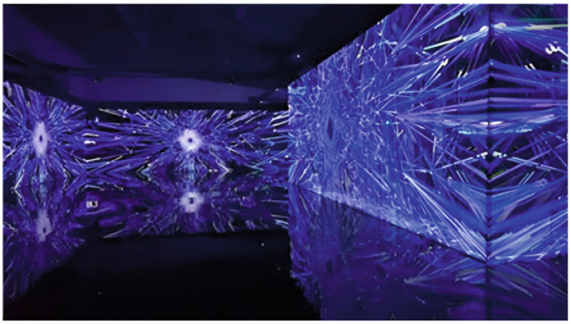


Fig. 9.15 Projected VR system

Fig. 9.16 Desktop VR system

systems include head-mounted display-based systems and projection-based VR systems (Figs. 9.14 and 9.15).

- Desktop VR systems (Fig. 9.16), also known as window VR systems, utilize devices such as personal computers or entry-level graphics workstations, using the computer screen as a window through which the users observe the virtual world. Although lacking the immersive effects of wearable displays, these systems are more widely used due to their relatively lower cost.
- Augmented VR systems (Fig. 9.17) do not require isolation from the real world. They allow the users to see the real environment while simultaneously viewing the virtual objects overlaid on the real world. It is a system that combines the real and virtual environments.
- Distributed VR systems (Fig. 9.18) are a combination of VR technology and network technology. The goal is to connect geographically distributed users or multiple virtual worlds through a network, building upon immersive VR systems. This allows multiple users to participate simultaneously in the same virtual space and interact with other users through networked computers, aiming to achieve collaborative work.

Recent research in VR technologies has followed the principle of "low cost, high performance" and has made rapid progress, exhibiting new characteristics and development trends, mainly manifested in the following aspects:

Fig. 9.17 Augmented VR system

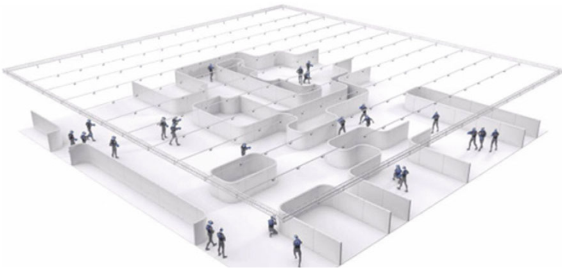


Fig. 9.18 Distributed VR system

Real-time 3D graphics generation and display technology: The technology for generating 3D graphics has become relatively mature. However, the key focus of research lies in how to generate graphics in real-time and improve the refresh rate without compromising the quality of graphics. Additionally, VR technology relies on the development of stereoscopic display and sensor technology. The existing virtual devices are unable to meet the system's requirements, thus necessitating the development of new techniques for 3D graphics generation and display.

Development of new interaction devices: The foundation for achieving immersive experience in VR technology, which enables free interaction between humans and virtual world objects, lies in the interaction devices. Common input/output devices currently include helmet displays, data gloves, data clothing, 3D position sensors and 3D sound generators. However, most VR devices are high-end products and come with a hefty price tag. Whether it is software or hardware, VR technology will only become mainstream when it becomes affordable for the ordinary users. Although recent versions of devices have entered the market at cheaper prices, they are still not sufficiently inexpensive as consumer-grade products. Therefore, the development of new, affordable, and robust data gloves and data clothing is an important direction for future research.

- 5G + VR: There are several reasons why VR has not yet become mainstream. One reason is that VR devices have always been expensive, and another reason is the lack of connectivity. In order to create a more realistic virtual experience, devices need to operate quickly and require high levels of storage and low latency. Sometimes, even a delay of a few milliseconds can significantly impact the effects presented in VR. With the arrival of the 5G era, network latency can be reduced to at least one-tenth of its original level, improving network efficiency and increasing traffic capacity by at least 100 times. This allows for more refined and smooth VR visuals and better integration with real-world products and services. Therefore, the introduction of 5G will provide developers with tools to greatly expand the scope of VR projects and create truly immersive and remotely accessible products.

(4) Application of VR

The emergence of VR technology has triggered significant changes in various techniques and methods, transforming outdated conventional technologies and improving the means of product design and development. It has significantly increased work efficiency, greatly reduced the difficulty of tasks, and effectively mitigated operational risks. VR technology was initially applied in the gaming industry. Currently, its application has expanded to various fields, including the military domain, industrial circle, agricultural field, medical field, education and architecture.

Military requirements have been the driving force behind the development of VR technology. Since the early 1990s, the United States has been at the forefront of using VR technology in the military domain. Subsequently, military organizations in many countries worldwide have adopted VR technology for military applications. In the military field, military training and exercises are considered essential measures to enhance combat capabilities. VR technology can effectively improve the quality of military training, reduce casualties in actual combat, save training costs and resources, minimize environmental pollution and destruction, and enhance command decision-making capabilities. VR technology is also applied in the development process of weapons to shorten the weapon equipment development cycle.

In industrial simulation, VR technology is used to perform various dynamic performance analyses on models and improve design solutions. It replaces conventional physical prototyping with digital representation, reducing product development costs and expenses while enhancing product quality and performance. The renowned Boeing 777 aircraft, for example, was successfully designed using VR technology.

VR technology finds broad applications in the agricultural sector, including scientific research, teaching, production, planning, agricultural resource allocation, commodity circulation, and agricultural machinery design and manufacturing. It enables the development of agricultural machinery, and the simulation of real environments and growth processes of living organisms. By utilizing sensors, it can collect biological information, reconstruct life processes, reproduce the occurrence and control of pests and diseases in crop production, and calculate pollution levels to eliminate pollution sources in crop production. This holds significant implications for food safety and security.

The application of VR technology in the medical field involves various aspects such as surgical simulation, skill training, surgical guidance and psychotherapy. For example, through surgical simulation, doctors can plan and train for surgeries, gain a deeper understanding of specific surgical procedures, and learn and explore new techniques. Medical students, for instance, can experience the actual process of operations through skill training, enabling them to quickly grasp clinical knowledge such as human anatomy.

In the field of education, VR technology can transform conventional teaching methods from passive learning to active learning, where learners acquire knowledge and skills through their interaction with the informational environment. Virtual laboratories allow students to experience activities such as space travel and the display of compound molecular structures, making the learning process more engaging and persuasive than the conventional teaching methods.

VR systems also play a significant role in the field of architectural engineering. By using VR technology, architects can visualize and "touch" design outcomes, facilitating convenient modifications at any time. Additionally, VR systems can be quickly and easily adjusted to accommodate changes in project plans, assisting architects in making decisions, thereby accelerating the speed and improving the quality of design solutions while saving substantial funds. Furthermore, VR finds extensive applications in the assessment of major engineering projects. Large-scale public buildings or important structures, such as stations, airports, bridges, ports and dams, often have a significant impact on the landscape and environment of a particular area once constructed. Due to the high construction costs and significant societal impact of these projects, evaluating their safety, economic viability and functional feasibility becomes even more crucial.

9.2.2 Applications in Bridge Maintenance and Management

(1) Bridge Safety Accident Restoration

With the rapid development of the economy, China's bridge industry has also flourished in recent years. However, as traffic volume increases and various natural and human factors come into play, the safety of bridges is receiving increasing attention from the general public [24]. While the construction of bridges in China has been rapidly advancing, there have been recurring incidents of bridge collapses, resulting in significant social and economic losses as well as casualties, and often causing severe negative social impacts.

On October 1, 2019, at 9:30 a.m., a bridge accident occurred at Nanfang'ao Bridge in Yilan County, Taiwan. The accident resulted in the collapse of three fishing vessels, causing six serious injuries, four minor injuries and five missing persons. Nanfang'ao Bridge, completed in 1999, was the only single steel arch bridge in the Taiwan region, with a length of 140 m and a width of 15 m. It was built at a cost of 250 million New Taiwan Dollars. The bridge featured a tourist viewing platform, an important local landmark. Preliminary investigations indicated that the accident was caused by the collapse of a bridge pier on the seaward side, resulting in the bridge structure dropping and fracturing. However, the exact cause of the incident has yet to be determined. Therefore, it was essential to conduct identification and analysis of bridge safety accidents in order to identify the main causes of such accidents and actively prevent the recurrence of similar bridge safety incidents.

The identification and analysis of bridge safety accidents require the use of computer simulation technology to accurately reproduce the process of bridge safety accidents in a scientific manner. Generally, researchers simulate the accident process using mathematical approximation methods, such as finite element analysis [25], whose accuracy has been proven by numerous successful cases. However, mathematical approximation simulations have certain limitations. Firstly, the relevant information about the bridge's environmental factors (such as terrain and landforms) is usually not considered in the mathematical approximation process. In many cases, after an accident occurs, it is necessary for professional engineers and experts to conduct on-site investigations to determine the cause of the bridge accident and take appropriate rescue measures. Additionally, the results presented through mathematical analysis simulations are simplified and abstract, making it difficult for researchers to have a comprehensive and intuitive understanding. Therefore, in the process of identifying and analyzing bridge safety accidents, in addition to necessary scientific and mathematical analysis, it is also crucial to provide a realistic presentation of the process and strive to accurately depict the entire accident sequence.

In terms of disaster simulation and reproduction, VR technology is playing an incredible role, such as in the simulation and analysis of mining accidents, fire reconstruction, aircraft crash simulation, traffic accident reconstruction and crime scene reconstruction. The "reproduction" and analysis generated by these VR technologies are of great significance in mitigating and preventing disasters. Introducing VR technology into the process of identifying and analyzing bridge safety accidents can effectively compensate for the limitations of the aforementioned mathematical approximation simulation methods. It can comprehensively integrate numerical analysis simulation, terrain, landforms and the surrounding landscape of the bridge, thus more comprehensively and accurately reproducing the process of the accident. Additionally, it can provide a sense of realism through various human–computer interactions and special effects production. Furthermore, the functionality of virtual scene simulation and scene roaming can maximize the satisfaction of observation and contemplation needs during the analysis process of bridge safety accidents, assisting in the identification of safety accidents and conducting more in-depth analysis. Researchers can focus on a specific process based on their own ideas, and depending on their individual expertise or experience, with each person's focus may varying. This is more conducive to the development of thinking and finding the main causes of bridge safety accidents (Fig. 9.19).

(2) Assistance in bridge maintenance and management

(1) VR assistance for engineers to quickly familiarize themselves with the basic information

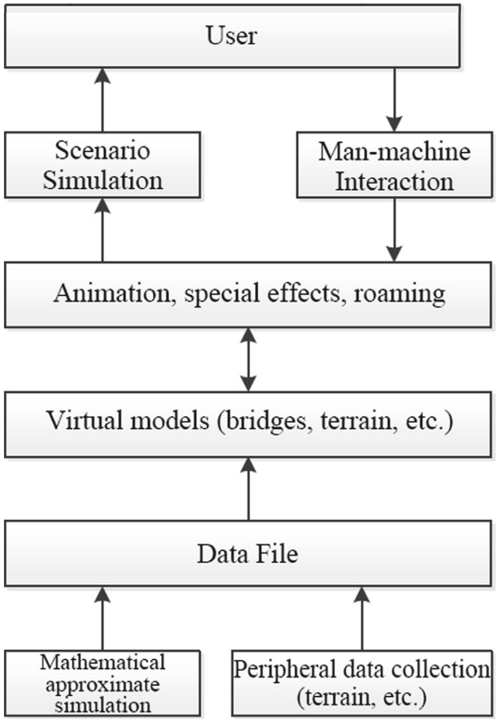


Fig. 9.19 Flowchart of bridge safety accident simulation process

① Application Background

After a bridge sustains damage, it often requires professional engineers and experts to conduct on-site investigations and monitoring to determine the cause of the bridge damage, and to make relevant repair and maintenance decisions. However, making accurate bridge repair and maintenance decisions based solely on on-site monitoring information is difficult. It is necessary to have prior knowledge of the basic information of the damaged bridge, including the bridge type, span and structural arrangement, and then combine it with the data obtained on-site to make effective decisions. For a long time in the design and construction process of bridges, plan drawings have been predominantly used. Plan drawings can help bridge maintenance engineers understand the structure and basic information of the bridge. However, plan drawings have two shortcomings. First, plan drawings lack intuitiveness, and engineers often need to combine multiple drawings to have a basic understanding of the bridge's structure, which makes the process of obtaining information complex and time-consuming. Especially for bridges that were constructed a long time ago, their design drawings and data may not be readily available, delaying the time and efficiency of on-site repair and maintenance decision-making. Second, plan drawings have poor visualization and cannot convey the detailed aspects of bridge design to the engineers. The damaged parts of the bridge are often in the details, such as bearings, cables and anchors, which are not well represented in plan drawings and lack visual characteristics.

② Application Route

In an era where intelligent design is constantly emerging, the emergence of VR technology can compensate for the shortcomings of plan drawings. As shown in Fig. 9.20, when designing bridges, engineers can use BIM technology and VR technology as the foundation to combine the immersive nature of VR with the digitization of BIM. Based on the BIM model environment, engineers can create a virtual "real" scene of the designed bridge using VR immersive perception. Subsequently, relevant data of the designed bridge's VR real scene can be stored in the smart bridge maintenance system to establish a bridge's big data VR real scene, truly realizing digitization, mobility and visualization of bridge design information. This provides convenience when making maintenance decisions for bridges. For a bridge that requires maintenance, engineers and experts can access the VR real scene of the bridge in the smart bridge maintenance system on their computers or mobile devices. By using VR glasses and other equipment, they can quickly familiarize themselves with the relevant information of the bridge and then combine it with the on-site surveys. This significantly improves the efficiency of bridge repair and maintenance.

(2) VR applied to skills training of bridge maintenance and management engineers

① Application Background

Before bridge maintenance engineers enter the actual bridge maintenance site, they should undertake job training. The current widely adopted training mode is "theory learning + mentorship." "Theory learning" refers to the engineers first engaging in theoretical learning through written materials or videos, while "mentorship" means

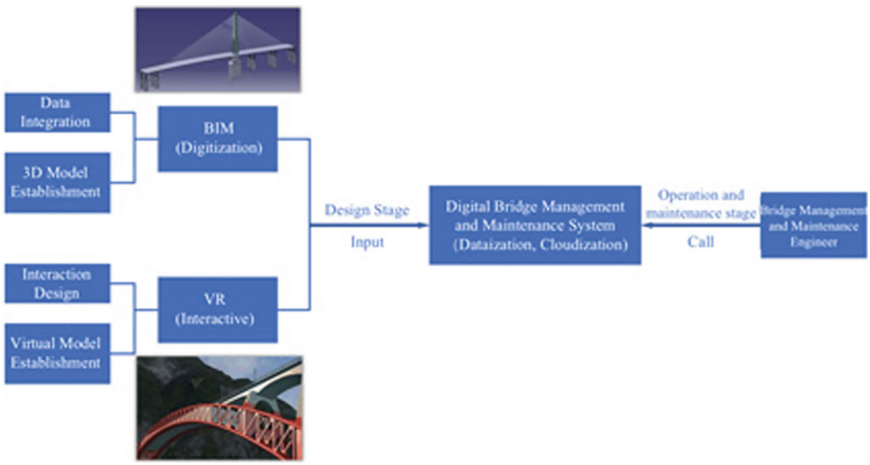


Fig. 9.20 VR assists engineers in familiarizing themselves with bridge information

that after completing the theoretical learning, experienced engineers will guide the new engineers in practical on-site operations. This mode has three major drawbacks: First, it can lead to a "disconnect between theory teaching and practice," where theoretical teaching and practical application are not synchronized, resulting in lower efficiency in skills training. Second, it can lead to a "reduction in on-site maintenance efficiency." Skills often require 10 to 20 practical exercises to become truly proficient. For more complex skills, the number of exercises may even reach 50 to 100 times. Therefore, newly employed bridge maintenance engineers may inevitably make mistakes, leading to a decrease in on-site maintenance efficiency. Third, the safety of this training mode is difficult to guarantee.

② Practical Training of Skills Using VR Technology

Nowadays, with the advancement of digital technology, digital technology based VR technology is highly favored and widely applied in various fields, especially in the areas of education and training. VR skill training refers to the use of various simulation environments and devices, combined with specialized VR courseware, to provide the trainees with highly realistic, systematic and professional training, enabling them to fully grasp the training content and practical operation essentials in a short period of time. Compared to the conventional skill training, VR skill training can significantly reduce the need for teaching resources, lower the requirements for training environments, and greatly avoid safety issues in certain hazardous skill training scenarios. Taking the conventional bridge maintenance operation training as an example, conventional training requires large space, multiple equipment investments, and high maintenance costs. Moreover, there are certain hidden risks during the training process. However, VR skill training only requires a single simulated device to provide training for multiple skills.

Compared to the conventional skill training, the advantages of VR training are self-evident. VR training can provide the learners with vivid and realistic learning environments, allowing them to interact with the virtual environment and to facilitate learning and consolidation. By incorporating VR technology into skill teaching, the cost of practical education can be effectively reduced, while significantly lowering the risks associated with practical training. By bringing immersive experiences into classrooms and other training environments, VR can enhance knowledge retention.

Today, major global companies have already started utilizing VR technology to train their employees, as they believe this technology can make training safer and more efficient. Moreover, this technology has tremendous potential in training employees' soft skills, such as empathy and teamwork. Retail giant Walmart has deployed nearly 200 VR training centers to prepare for Black Friday each year. Through VR devices, trainees can experience the busiest day of the year and learn how to address potential issues, such as inventory shortages, crowd control and customer conflicts. VR technology makes training more engaging and enjoyable, which is difficult to achieve in the real world.

Contrary to intuition, VR can even be used for soft skills training. For businesses, assessing and training soft skills, such as empathy, perceptiveness and teamwork, can be challenging, as these factors often determine individual success. VR technology can place the users in the perspective of another person and help them practice empathy. Doctors use perspective-based VR technology to understand patients' healthcare experiences, which can help change their approach to patient care.

③ Application Route

Based on VR skill training and the VR training system proposed by existing scholars [26], and in response to the practical needs of bridge maintenance, the authors present a bridge maintenance training platform based on VR technology, as shown in Fig. 9.21.

The VR training platform for bridge management comprises two major modules: platform structure module and platform function module.

1. Platform Structure Module

(a) VR Support Platform

The training platform is a software system that is created using a specialized VR development support platform, such as VRML. The VR support platform is the

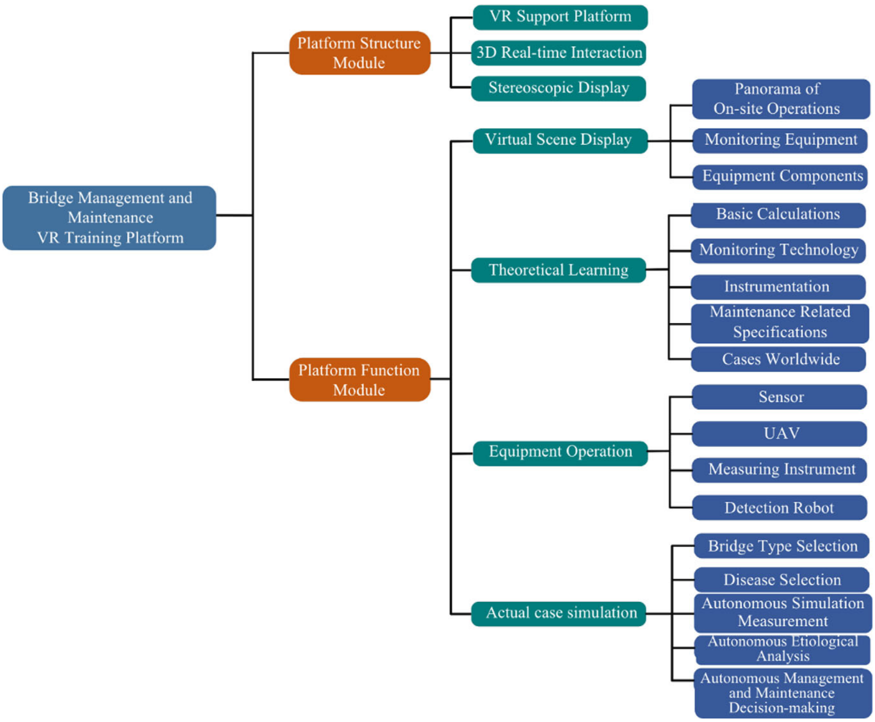


Fig. 9.21 VR-based training platform for bridge Maintenance and Management

essential component of the training platform, responsible for managing the data operations of the entire system.

(b) 3D Real-Time Interaction Part

The interactive system is a combination of conventional display devices and real-time motion capture systems, with data handling, position trackers, force feedback devices and other functions.

(c) Stereo Display Section

The stereoscopic display section is the display end of VR, providing the users with highly realistic, clear and immersive virtual environments, allowing the users to directly immerse themselves in a three-dimensional information space and freely use various information, thereby controlling the computer. The stereoscopic display section adopts a digital helmet, which can display and observe the 3D VR graphic signals in VR applications, and can also receive 3D VR graphic signals from the host by connecting to it. The usage mode is head-mounted, and the users can freely move within a three-dimensional space and observe the VR output effect through a three-degree-of-freedom spatial tracker.

2. Platform Function Module

The training platform encompasses four major functions: the virtual scene display, the theoretical learning, the equipment operation, and the actual case simulation.

(a) Virtual Scene Display Function

The user has the freedom to adjust their walking speed and viewpoint, allowing them to freely navigate and inspect the virtual scene. This scene encompasses a panoramic view of the bridge site operations, monitoring equipment utilized and even the individual components of the equipment.

(b) Theoretical Learning Function

In this feature, the users can systematically learn the theoretical knowledge related to bridge maintenance, including basic calculations of bridges, various commonly used bridge monitoring techniques, commonly used bridge inspection instruments, relevant specifications for bridge maintenance, and some typical domestic and international bridge maintenance cases. This feature eliminates the previous dull and inefficient theoretical learning mode, namely the “written + video” learning mode, and strives to present theoretical knowledge in a three-dimensional manner to the users, making it interactive, interesting and efficient.

(c) Equipment Operation Function

In this module, the users can learn the specific operation methods of bridge inspection instruments, including sensors, drones, measuring instruments, inspection robots and more. Learning the equipment operation methods in the VR training platform not only reduces the number of devices required, but also lowers maintenance costs. It also reduces the requirements for training time and physical space, achieving the true concept of "learning anytime, anywhere."

(d) Actual Case Simulation Function

The users can utilize this function to accumulate experience in on-site operational decision-making. The users can select different bridge types and different defects according to their needs, and the system will simulate realistic virtual scenarios for them to learn from. The users can independently conduct measurements, analyze bridge conditions and make maintenance decisions within this scenario, aiming to gain an immersive experience throughout the entire process.

9.3 Augmented Reality Technology

VR technology brought us the new human–computer interaction that provides the users with a strong sense of realism and presence in completely virtual environments. On the other hand, augmented reality (AR) technology overlays virtual objects onto the real world, offering a lightweight and highly immersive augmentation technology. Due to its realistic integration capabilities, AR technology serves as a powerful complement and enhancement to the real world, with vast application prospects and value. In this section, starting from the consideration of AR technology's application in future bridge engineering, we mainly introduce the relevant concepts, characteristics and applications of AR technology, and discuss and illustrate its application scenarios in bridge operation, maintenance and decision-making.

9.3.1 Overview of AR

(1) Definition and Features

The main scientific issues of VR include modeling methods, rendering techniques, human–computer interaction and devices; but there are currently common problems such as high workload of modeling, high simulation costs, insufficient match with the real world and low credibility [27].

In response to these situations, various VR augmentation technologies have emerged to combine the virtual and real environments for enhancement [28]. Among them, the technique of overlaying real objects onto a virtual environment is called Augmented Virtual (AV), while the technique of superimposing three-dimensional virtual objects onto the real world is called augmented reality (AR). These two types of technologies can be vividly distinguished as "virtual with reality" and "reality with virtual." It is widely recognized in the industry that there are two types of VR augmentation technologies, namely augmented reality and augmented virtual environment, that bridge the gap from the real world to the virtual environment. Internationally,

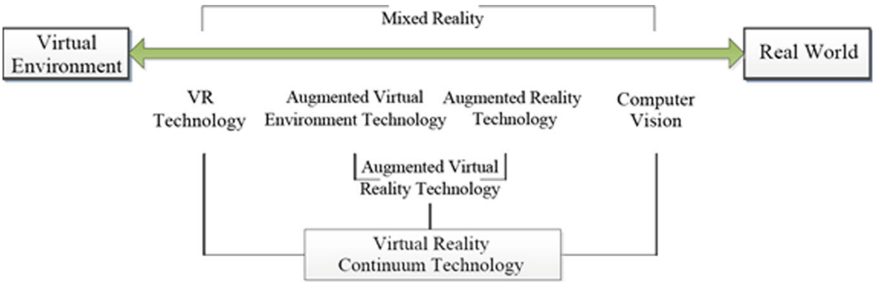


Fig. 9.22 VR Continuum

the real world (computer vision), AR, augmented virtual environment, and VR are commonly referred to as the VR continuum [29], with AR being considered as a part of mixed reality environments, as shown in Fig. 9.22. In this context, AR differs significantly from VR, as listed in Table 9.2.

Azuma [30] defined AR as a system with three essential characteristics:

- Integration of real and virtual worlds in a three-dimensional space. Unlike VR technology, AR technology does not separate users from the real world. Instead, it overlays computer-generated virtual objects and information onto the scenes of the real world, allowing the real world and virtual objects to coexist. This enables a more intuitive and in-depth understanding and interpretation of the real scene, facilitating comprehension of knowledge related to the real world within limited time and limited scenes. The augmented information can include non-geometric information related to real objects, such as videos and text, as well as geometric information, such as virtual 3D objects and scenes.
- Real-time human–computer interaction function. Using interactive interface devices in AR systems, users can interact with AR environments in a natural manner. This interaction needs to be real-time and achieve synchronous updates

Table 9.2 VR and AR comparison

	VR	AR
Technology	The scene is completely virtual	Overlaying digital images on the basis of real environment
	Emphasizing immersion and requiring complete isolation between one's feelings and the environment in which they are located	Allow users to perceive the real world while seeing the virtual environment
Device	Usually quite 'bulky'	Generally, it is mainly exquisite and compact
	More sensors, position positioning systems, motion capture systems and other equipment are needed	Cameras are essential, and products with cameras such as mobile phones, tablets, etc. can use AR technology

between the virtual world and the real world. In this way, AR technology can provide the users with a genuine experience of simulated objects in a virtual space within the real world, enhancing the enjoyment and interactivity of the experience.

- Three-dimensional registration. Three-dimensional registration refers to the process of locating objects in a scene, establishing a correspondence between computer-generated virtual objects and the real environment. It involves overlaying virtual objects onto the real scene based on accurate spatial relationships. Furthermore, the alignment between virtual and real objects is maintained as the user moves within the real environment. Detailed explanations about three-dimensional registration technology will be provided later.

(2) Evolution of AR

The research on AR technology can be traced back to 1968 when Ivan Sutherland became the first person to create an AR system using an optical head-mounted display [31]. This device, known as the first optical head-mounted display in the world, allowed real-time overlay and fusion of computer-generated images with the real scene. In the mid-1990s, Tom Caudell and his colleagues at Boeing introduced the term "augmented reality" while designing an AR system to assist workers in aircraft wiring systems. In the same year, L. B. Rosenberg developed one of the first operational AR systems called "virtual fixtures." It was not until 1994 when Paul Milgram and Fumio Kishino defined VR continuum, as shown in Fig. 9.22, as a continuous spectrum from the real environment to the virtual environment. AR and augmented virtual environment lie between the two, with AR being closer to the real environment and augmented virtual environment being closer to the virtual environment. In 1997, R. T. Azuma provided the widely accepted definition of AR in the industry.

At that time, due to various limitations, AR was not yet a widely popular technology. In 1999, the AR Toolkit, a marker-based AR system development kit, was successfully developed through collaboration between the University of Washington in the United States and Hiroshima City University in Japan. This development marked the emergence of AR from the laboratory and its gradual transition towards mass applications. The AR Toolkit has been maintained to this day and has greatly popularized AR technology, leading to the emergence of more related software applications and development systems.

In 2000, the first AR game, AR-Quake, was born. It was an extension of the popular computer game Quake and brought AR into real outdoor scenes. In 2012, Google released Google Glass, which was the world's first hardware device to truly implement AR technology, and it garnered widespread attention to mobile wearable AR devices. Following that, Microsoft released the HoloLens holographic glasses in 2015.

With the development of technology, especially the continuous updates of mobile devices such as smartphones, AR technology has gained more possibilities for application. In 2017, Apple introduced a new AR component called ARKit in iOS 11. This application is compatible with iPhone and iPad platforms, making iPhone the world's

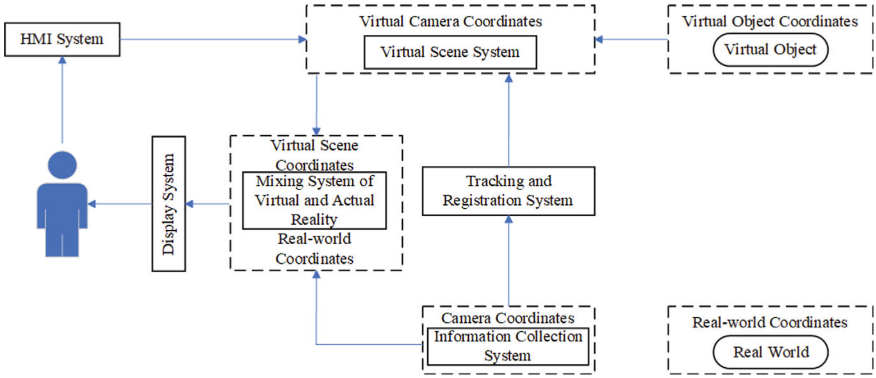


Fig. 9.23 Architecture of AR system

largest AR platform at that time. In 2023, Apple debuted their first-generation AR device – Apple Vision Pro.

(3) Technology Components

The typical structure of an AR system is illustrated in Fig. 9.23, which comprises six subsystems: information acquisition system, tracking and registration system, virtual scene generation system, virtual-real synthesis system, display system and human–computer interaction system [32]. Among them, the information acquisition system is responsible for collecting and acquiring information from the real world (such as the external environment); the tracking and registration system is used to track the user's head orientation and line of sight; the virtual scene generation system is responsible for generating the virtual objects to be added; and the AR system is intended for aligning and merging the virtual scene with the real scene.

As shown in Fig. 9.23, in an AR system, the input image is processed and used to establish the real-world space. The computer-generated virtual objects are embedded into the real-world space based on geometric consistency, forming an AR environment where the virtual and real are merged. This environment is then presented to the user through a display system, and the user interacts with the scene using interactive devices. Among them, the tracking and registration step that accurately combines the virtual and real is crucial. It serves as the foundation and key technology for AR.

Three-dimensional tracking and registration technology refers to the process of tracking and locating images or objects in the display scene, and then establishing the corresponding relationship between the virtual world and the real world coordinate system. As shown in Fig. 9.24, the mainstream three-dimensional tracking and registration technology can be divided into three types: hardware sensor-based tracking and registration technology, computer vision-based tracking and registration technology, and hybrid tracking and registration technology.

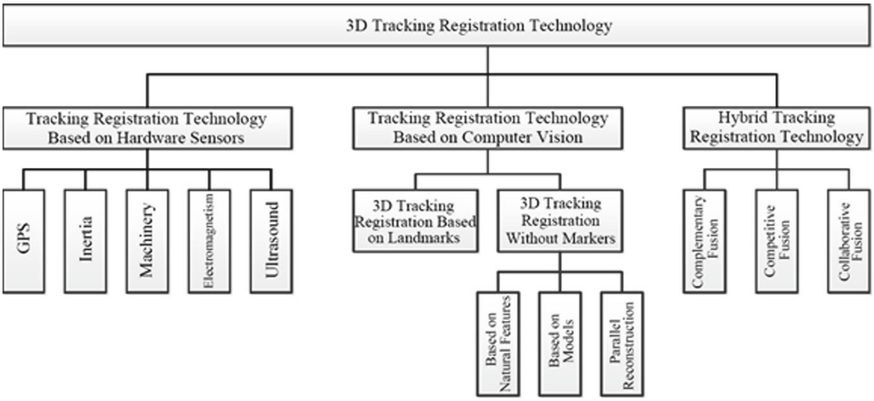


Fig. 9.24 3D registration tracing technology

(1) Hardware sensor-based tracking and registration technology relies on the coordinate information collected by various sensors to measure the position coordinates and orientations of the camera, thereby achieving camera calibration. It can be roughly divided into registration based on the Global Positioning System (GPS), inertial registration based on inertial sensors, mechanical registration based on mechanical sensors, electromagnetic registration based on electromagnetic sensors, and ultrasound registration based on ultrasound sensors. Hardware-based registration methods rely on external sensor support, having higher costs, larger size, poorer mobility performance and generally lower accuracy. Therefore, their development has been relatively slow.

(2) Computer vision-based tracking and registration technology is mainly realized through the use of computer vision algorithms [33]. The general process involves capturing real-world scenes using a camera and extracting feature points from the live scene using relevant algorithms. Then, based on the coordinate transformation, the position of virtual information in the real scene is determined, thus achieving the goal of virtual-to-real registration. The advantages of this approach include strong applicability, low cost, high accuracy and real-time performance. Depending on the presence or the absence of markers, computer vision-based registration methods can be divided into two types: marker-based 3D tracking and registration technology and markerless 3D tracking and registration technology.

① Marker-based 3D tracking and registration technology is a widely used and mature technology in current AR systems. It has low requirements for hardware processors and exhibits high robustness [31]. For this registration technique to take place, predefined markers are placed in the real scene. The camera identifies these markers and obtains their vertex information. Then, based on the principle of affine invariance, the pose change matrix between the predefined marker coordinates and the current scene marker coordinates is reconstructed to achieve the tracking and registration of virtual information. ② Markerless 3D tracking and registration technology can be roughly divided into three types: natural feature-based tracking and registration technology, model-based tracking and registration technology, and simultaneous localization and mapping (SLAM) based tracking and registration technology. Natural feature-based tracking and registration technology compensates for the limitations of marker-based 3D tracking and registration technology. It does not require predefined markers in the real environment. Instead, it computes the camera's pose information by utilizing natural features in the scene to achieve tracking and registration. Model-based tracking and registration technology uses virtual model information corresponding to the tracking and registration target as prior knowledge. It addresses the tracking and registration issues in environments with insufficient or no texture that natural feature-based tracking and registration technology may encounter. Simultaneous localization and mapping (SLAM) based tracking and registration technology does not rely on prior knowledge of the scene. It simultaneously tracks and reconstructs the 3D structure of the unknown scene during the registration and localization process.

(3) Mixed tracking and registration technology is a method that combines different types of tracking and registration techniques to obtain object poses. It effectively solves the technical challenges of achieving both high-precision tracking and robustness in AR systems but increases the complexity of the system. From the perspective of multi-sensor fusion classification, mixed tracking and registration technology can be divided into complementary, collaborative and competitive sensor fusions.

(4) Applications

AR can present virtual information in conjunction with the real world, forming a realistic integration that serves as a powerful supplement to the real world. It has broad application prospects and high commercial value. With the maturation of AR technology and the increasing number of applications, AR systems have become a new medium, gradually penetrating various fields, and are changing the way we shop, entertain and work.

(1) Digital Marketing: AR technology has opened up a new mode for digital marketing, allowing consumers to discover, understand and experience various products from a fresh perspective. Amazon is one of the brands that introduced AR technology early on, using AR to enable consumers to "try on" clothes online, providing unprecedented convenience for online shoppers. IKEA has developed an AR mobile application that allows customers to "place" IKEA furniture in their homes through the app before making a purchase, enabling them to see if the colors and sizes are suitable, thereby reducing the hassle of returns and exchanges.

(2) Architecture: In the field of architecture, AR technology allows architects, construction workers, developers and clients to visualize three-dimensional buildings and interior designs at any stage of construction. Additionally, AR technology can help to identify errors and issues during construction, pointing them out before they become difficult to resolve. AR technology can also assist in maintenance of buildings and facilities, providing remote assistance to clients during repair or maintenance processes.
(3) Tourism: With the help of AR technology, tourism brands can provide immersive experiences for their potential travelers. For example, through AR solutions, agents and destinations can offer visitors more information and directional signage. AR applications can help vacationers explore resorts and learn about destinations, and so on. Gansu Provincial Museum has introduced AR interactive technology into their exhibitions. When visitors use their mobile phone cameras to identify cultural relics, the relics can be presented in a more dynamic way, such as fish patterns "swimming" on painted pottery from the Yangshao culture, providing a better exhibition experience.
(4) Education: AR technology can assist educators in allowing students to use dynamic 3D models in the classroom, helping students understand relevant knowledge and stimulating their learning interests in an engaging way. Students benefit from the visual capabilities of AR, bringing concepts to life through digital rendering and accessing information anytime, anywhere, without the need for any special equipment.
(5) Healthcare: AR can provide real-time 3D digital images and key information to surgeons, allowing them to access important information during surgical procedures without leaving the operating area. The video optical perspective AR system developed by the Department of Information Engineering at the University of Pisa can overlay X-ray data onto a patient's body.
(6) Navigation Systems: By combining GPS technology with AR, navigation applications can improve safety and provide more comprehensive navigation information. Navion offers true AR navigation, being the first holographic AR navigation system designed for automobiles. As the surroundings of the vehicle change, the system continuously updates information to provide real-time navigation guidance. Hyundai Motor Group from Korea collaborated with a Swiss high-tech startup to introduce the world's first holographic AR navigation system at the 2019 International Consumer Electronics Show (CES).

9.3.2 AR Applications in Bridge Engineering

As one of the core components of bridge structural health monitoring systems, the data acquisition system is responsible for collecting relevant data for designers, managers and decision-makers. However, the data acquisition system is costly, and its operation is quite complex for untrained inspectors. Therefore, one of the major challenges in practical engineering is how to adopt new technologies for infrastructure maintenance and management, such as low-cost wireless smart sensors, AI approaches, machine learning algorithms, unmanned aerial systems, etc. However, these technologies cannot establish a direct connection between the inspectors and the structures. AR technology can effectively address this issue.

(1) Bridge Maintenance

Currently, there is a wide variety of bridges of different sizes across the country, and maintenance is still primarily conducted through paper-based records. Paper-based records suffer from issues such as inconsistent legends and inaccurate drawing information, which pose significant challenges to maintenance work, especially in the case of complex projects, presenting greater difficulties for the inspectors. Presently, inspection work typically involves manual on-site inspections, fault identifications and plan formulations. However, for bridge projects with incomplete drawings and insufficient existing data, correlation between the information and the actual site conditions is poor, making it difficult to conduct statistical analysis and identify hidden risks, thus reducing operational efficiency and increasing maintenance costs. By employing AR technology, data can be automatically collected, recorded, transmitted, processed and analyzed. Coupled with remote control capabilities, AR can help address on-site challenges and achieve intelligent bridge inspection and maintenance management. Furthermore, AR technology can be used to improve drawing materials, enhance the digitization of drawing information and enhance the guidance of remote inspection operations.

K. E. Ammar and A. Hammad proposed a BIM-based markerless mixed reality system framework (BIM3R), which integrates maintenance management systems, building information models and video-based feature tracking technology. This framework enables on-site information retrieval, visualization of maintenance work, and collaboration between on-site inspectors and office engineers. This AR application involves dividing the bridge into different small components and adding sequential identification numbers to these components during construction. During on-site inspection and maintenance work, the AR software confirms the identification numbers using the mobile device's camera, loads the 3D model of the component on the device screen, and allows gesture-based interaction to display relevant non-graphical data, including the component's dimensions, materials, construction information, model and more. Additionally, inspection and maintenance information can be recorded in text form within the software.

For the inspection of concrete bridge defects, Karaaslan et al. [34] proposed an AI-integrated AR system and developed a human-centered intelligent approach. They created an intelligent AR framework that can be integrated into wearable holographic headset devices, as shown in Fig. 9.25. The main objective was to assist the inspectors by expediting their routine tasks, such as measuring all cracks in defect areas, calculating spalling areas, conducting condition assessments and processing data for management systems. This potentially reduces the time and cost of infrastructure inspections. The system combines the inspector's professional judgment as

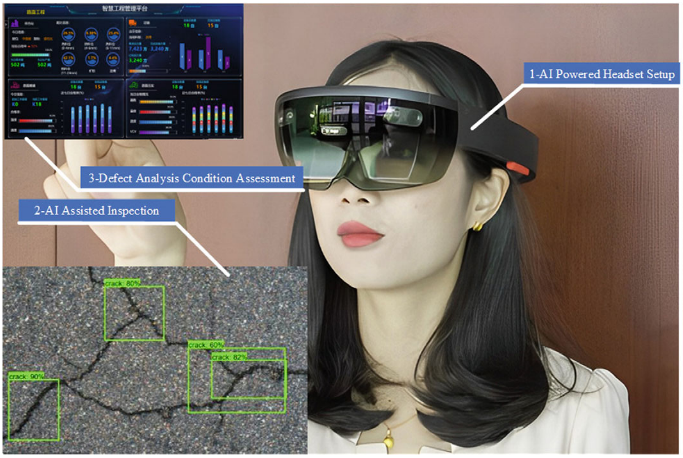


Fig. 9.25 Visual representation of an AI-driven MR system

being human-centric. Artificial intelligence helps the inspectors gather more quantitative and objective data, and the human-centered AI interacts with the inspectors. The collaboration between inspectors and AI aims to improve visual inspections rather than completely replacing human intervention in the inspection process. This research has made significant contributions to infrastructure inspection, maintenance, management practices and safety for bridge owners.

Based on the aforementioned related studies, a general bridge maintenance process based on AR technology can be summarized as shown in Fig. 9.26. Firstly, bridge inspectors use AR headsets during routine inspections of the infrastructure and walk around the bridge according to system guidance for regular or scheduled inspections. While the inspector performs routine inspection tasks, the integrated AI system in the headset continuously guides the inspector and displays potential defect locations. Once a defect is found, if the inspector confirms its location, the system proceeds with defect segmentation, characterization, determining the specific type of defect, and initiates analysis. If the defect boundaries require any correction or further subdivision, human inspectors can intervene and calibrate the analysis, displaying their annotations in the AR scene. Secondly, the inspectors record and mark defect elements or inspection information. If the inspector chooses to mark defect elements, the defect location information is automatically inherited from the BIM model and added as attributes. These attributes include the type of defect, severity of the defect, and any other annotations or observation results. All these data are saved in a database and immediately shared with the office for planning and consultation using the AV mode.

(2) Visualization of Structural Damage

In the conventional bridge maintenance methods, the detection of concrete cracking and spalling often relies on manual close-range visual inspection. This approach is time-consuming, labor-intensive and subject to significant subjectivity, making it

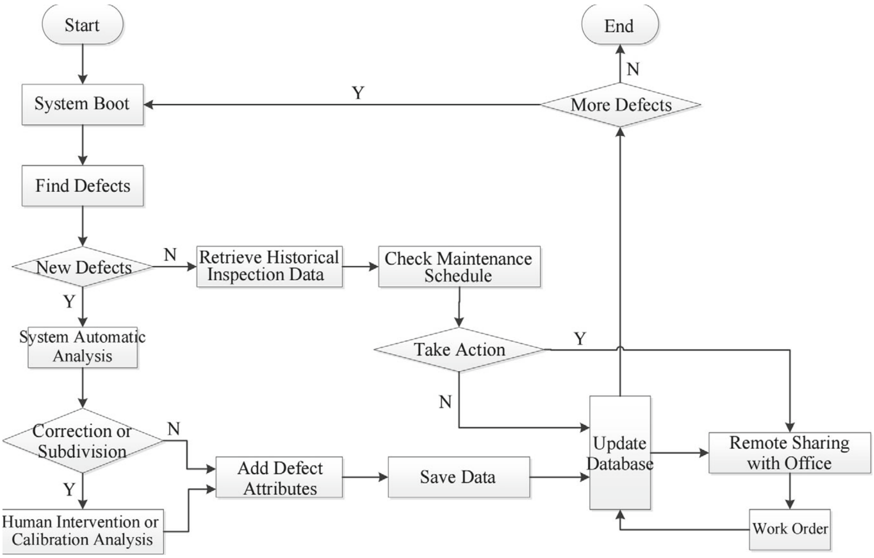


Fig. 9.26 Bridge maintenance process based on AR technology

difficult to identify small cracks and defects. In the future, with the development and maturation of AR technology, it can be combined with AI techniques and applied in bridge maintenance to achieve visualization of structural damages. This can assist the bridge inspectors in making faster and better decisions, as shown in Fig. 9.27.

Bridge inspectors need to conduct regular inspections of bridges, and in this case, they only need to wear a head-mounted AR display integrated with AI technology to go to the site, without the need for other complex equipment and tools. Upon arrival at the site, the inspector puts on the AR display, and the integrated AI system will guide the inspector to identify potential damage locations and annotate them using boundary wireframes in the AR device. The inspector then reviews the damage locations to check for any missed areas. If there are any, the system can re-annotate the damaged areas by manually adjusting the threshold. Once confirmed, the AI system performs damage segmentation within the boundary box and visualizes it in the AR system. For example, by highlighting the damage with colors, the inspector can visually identify the precise locations of the damage. Finally, through automatic analysis and computations by the AI system, the damage is quantified, and the results are added to the real environment through AR. Simultaneously, the on-site data is transmitted back to a remote terminal for analysis, to determine the development trends of concrete cracks and spalling. This information is then transmitted to the head-mounted display, allowing the inspector to understand the next steps in the development process of the cracking and spalling, thereby assisting them in making informed decisions based on scientific insights.

Compared to the conventional inspection methods, this method has three advantages: firstly, through AI searching and AR boundary line annotations, even small

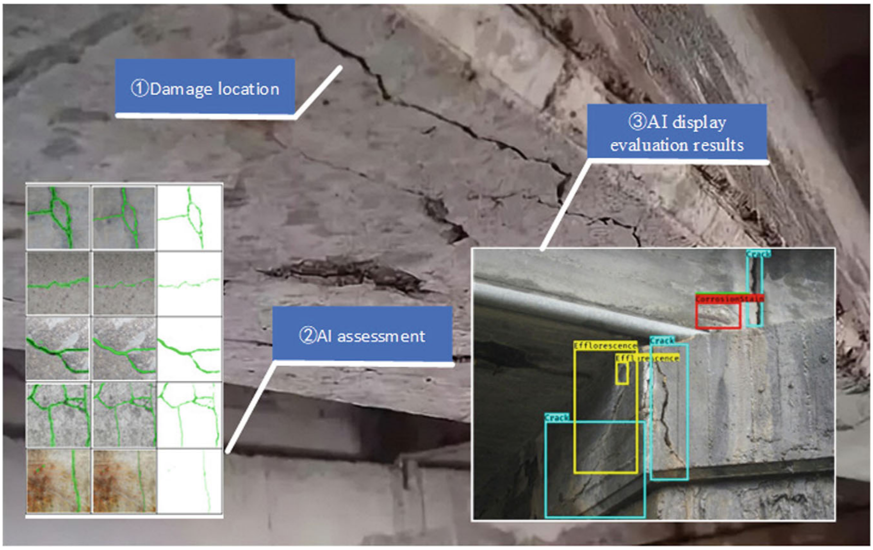


Fig. 9.27 AR technology for structural damage visualization

cracks and defects can be detected, avoiding the possibility of overlooking them due to negligence. Secondly, the AR zoom-in feature allows the inspection of damages from a distance, which is particularly significant for areas that are difficult to reach (such as bridge piers). Inspectors do not need to rely on other tools (such as bridge inspection vehicles or ladders); they only need to magnify and examine the relevant areas in the head-mounted AR display. Thirdly, by displaying the development trends of structural damages analyzed by a remote terminal through AR, the inspectors can quickly assess whether action needs to be taken.

The visualization of bridge structural damages and their development process using AR technology is just one of the many application scenarios in bridge maintenance. With technological advancements, bridge maintenance will undoubtedly progress towards greater intelligence.

9.4 Summary

AI, VR and AR, as representative technologies of the Fourth Industrial Revolution, are gradually changing our lives. The future decision-making and management of bridge maintenance will undoubtedly be digitized, visualized and intelligent. However, currently, these three intelligent technologies have not been widely applied due to maturity of the technology and cost, plus many issues still need to be addressed. In the future, it is hoped that more new technologies and concepts can be combined with the conventional techniques and applied to intelligent Maintenance and Management of bridges.

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