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Research Progress of Intelligent Detection Technology and Equipment for Diseases in Cable-Supported Bridge Systems

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ABSTRACT

Bridges are important infrastructure for China's modernization. Currently, China's bridge construction scale, technical level, especially the construction level of long-span bridges, has leapt to the forefront of the world. Cable-supported bridges include cable-stayed bridges and suspension bridges. For bridge projects with a span exceeding 1000 m, cable-supported bridges are the only bridge type choice. Many early-built long-span cable-supported bridges at home and abroad have experienced service performance degradation during their service life. The actual service life of bridges is far shorter than the design life, one of the important reasons being the lack of management and maintenance. The domestic mainstream bridge maintenance management method is manual inspection, which is relatively passive, time-consuming, and has high repair costs. In recent years, UAV technology, robotics, machine learning algorithms, and LiDAR point cloud-based 3D reconstruction technology for buildings have made significant progress. Researchers have developed various bridge disease detection equipment and methods, some of which have been applied in practical engineering. This paper mainly introduces the main disease forms of cable-supported bridges and some research directions and achievements of intelligent detection technology, and analyzes the advantages and disadvantages of different intelligent detection technologies and equipment.

KEYWORDS

Cable-supported Bridges; Intelligent Detection Technique; UAV; Robot; Machine Learning Algorithm; Point Cloud; 3D Reconstruction.

1. INTRODUCTION

Since the 14th Five-Year Plan, the strategy of building a strong transportation nation has become an important support for the cause of socialism with Chinese characteristics in the new era. China is a major bridge-building country, and bridges are an important means of transportation. By the end of 2022, there were 1.0332 million road bridges in China, with a total length of 85.7649 million meters, an increase of 72,000 bridges and 11.9627 million meters over the end of the previous year. Among them, there were 8,816 extra-large bridges (16.2144 million meters) and 159,600 large bridges (44.3193 million meters).Among the many bridge structural forms, cable-supported bridges are known for their large spanning capacity, especially when the span exceeds 1000 m. Cable-supported bridges, including cable-stayed bridges and suspension bridges, are the only bridge type choice. Currently, China is in a period of concentrated construction of long-span cable-supported bridges. In recent years, a number of world-class bridges with spans exceeding one kilometer have been planned, are under construction, or have been completed. As of April 2022, among the world's top 10 cable-stayed bridges with the largest main spans, 7 are from China, and among the top 10 suspension bridges, 5 are from China. The designed service life of these bridges is as long as or exceeds 100 years.The completion of long-span cable-supported bridges has greatly promoted regional economic

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development, but also brought new challenges to their maintenance and management. During service, bridges are inevitably affected by the environment and traffic, leading to material performance degradation, component damage and defects, structural functional deficiencies, etc. These not only affect the normal operation of the bridge, but may also change the overall service performance of the main bridge structure, posing safety hazards and shortening the actual service life of structures or components. The Golden Gate Bridge in the United States has anti-corrosion and reinforcement, and its suspender cables have been replaced. Cracks in the flat steel box girder of the Severn Bridge in the UK were successively discovered in the 1970s and 1980s, leading to reinforcement. After 2006, severe corrosion and broken wires of the main cable were found, and a main cable dehumidification protection system was installed. The Yibin Nanmen Bridge over the Jinsha River was completed in July 1997, and on November 7, 2001, a serious collapse accident occurred. The fracture of the cable-stayed bridge's cables was the main cause of the accident, resulting in casualties[1]. In May 2020, the Humen Bridge in Guangzhou experienced multiple vortex-induced vibrations. Although the analysis concluded that the event had no impact on the bridge's structural safety, it attracted widespread attention and discussion. On January 18, 2022, a fork-end screw rod of an upstream suspender of the Chongqing Egongyan Rail Bridge, which had been in operation for just over two years, fractured and ceased to function, leading to the suspension of rail transit in the affected section.China's cable-supported bridges have undergone more than 30 years of development and are gradually entering the stage of maintenance, repair, and performance improvement. However, the detection of apparent diseases of cable-supported bridges is still mainly based on manual visual inspection, which relies on inspection platforms to approach the area to be inspected. The inspection data is greatly affected by human factors. Obviously, traditional inspection methods can no longer meet the increasing demands and increasingly dangerous bridge maintenance and inspection tasks.With the rise of a new round of technological revolution and industrial transformation, 5G technology, cloud computing, IoT technology, UAVs, robots, intelligent sensing, imaging systems, artificial intelligence and other emerging technologies will become key technologies for refined bridge design, construction, operation, and maintenance. Therefore, researchers at home and abroad have conducted extensive research on using UAVs and robots as platforms for collecting bridge disease images and on computer vision-based automatic disease image recognition technology. In addition, the significant development of oblique photogrammetry modeling technology and LiDAR point cloud-based 3D reconstruction technology has provided strong support for the entire bridge and full-span inspection, localization, recording, and description of apparent diseases. This paper discusses the main forms of cable bridge diseases and the difficulties of their detection in a review format, summarizes some current research achievements on intelligent detection technology and equipment for diseases of cable-supported bridges, and evaluates the advantages and feedback issues and shortcomings in practical application, hoping to provide valuable references for future research.



Fig 1. Fracture of the fork-end screw rod of the suspender of the Egongyan Rail Bridge

2. MAIN DISEASE FORMS OF CABLE-SUPPORTED BRIDGES

Cable-supported bridges are mainly divided into suspension bridges and cable-stayed bridges. The main load-bearing structure of a suspension bridge consists of towers, high-strength flexible cables (main cables) suspended from the towers, suspenders, stiffening girders, and anchorage structures. Modern suspension bridges generally consist of towers, main cables, anchorages, suspenders, stiffening girders, and cable saddles. Cable-stayed bridges are self-anchored structural systems. The stay cables exert beneficial compression on the main girder of the bridge span structure, improving the stress state of the main girder. The main structure of a cable-stayed bridge consists of three components: the main girder, the pylon, and the stay cables. The suspenders, main cables, pylons, and box girders of suspension bridges and cable-stayed bridges are the main parts where corrosion, cracks, and other diseases occur.

2.1. Main Cable or Stay Cable Diseases

Due to the existence of gaps between the main cable wires, cable band gaps, and saddle gaps, the main cables of suspension bridges are practically open cables. Water and oxygen can enter the interior of the main cable wires unimpeded through these gaps and the wire gaps at the splay sections, causing rusting. For stay cables of cable-stayed bridges, after the external protective device of the cable body cracks, the cable body is affected by rain, snow, sunlight, wind, etc., leading to electrochemical corrosion on the surface. At the same time, the huge tensile force on the cable body exacerbates the corrosion[2].

2.2. Pylon Diseases

The pylon not only bears its own weight and the weight of the main girder deck system transmitted through the stay cables, but also bears the vertical and horizontal loads of the deck system. The tension forces of the stay cables on both sides of the pylon are unbalanced, and the tower column itself is susceptible to external forces, temperature, wind, and other environmental factors. If the offset and displacement deformation of the tower body exceed specified limits, the structural stress of the pylon may be damaged, and in severe cases, the safety of the bridge may be endangered.

2.3. Steel Box Girder Diseases

Steel box girders boast the advantages of light self-weight, high bending stiffness, excellent wind resistance, and convenient and rapid hoisting. A large proportion of long-span cable-supported bridges that have been completed or are under construction in China adopt steel box girders as their main girders. However, due to the inherent characteristics of steel box girders, problems such as scratches on surface coatings and welding burns are prone to occur during their fabrication and installation. Meanwhile, long-span bridges are exposed to harsh natural environments and subjected to long-term dynamic loads including vehicle loads and wind loads, making them susceptible to corrosion and fatigue damage[3]. Typical defects of steel box girders include coating deterioration, steel corrosion, and structural damage. Among them, coating deterioration is mainly manifested as chalking, blistering, cracking, spalling, and rusting. Steel corrosion mainly includes pitting corrosion, uniform corrosion, and crevice corrosion. Structural damage to steel box girders mainly consists of fatigue cracks, excessive component deformation, and connection defects.

3. EFFICIENT DETECTION EQUIPMENT AND TECHNOLOGY FOR APPARENT DISEASES

3.1. Bridge Inspection Robots

A bridge inspection robot is a robotic device that can be used for bridge inspection engineering, autonomously identifying bridge problems. Robots can reach inspection blind spots that are typically difficult for inspectors to access, reducing inspection costs and ensuring inspector safety. Currently, mainstream bridge robots mainly include cable-climbing robots and wall-climbing robots.

3.1.1. Cable-climbing Robots

Cable-climbing robots work on cables, moving vertically upward and downward, belonging to one-dimensional motion robots. Cable-climbing robots are high-altitude robots and are affected by wind during operation.IPC Corporation in the United States developed a cable-climbing inspection robot weighing 48 pounds. The robot is equipped with four cameras, and the images captured by the cameras can detect surface defects, but installation is complex. Kyeong Ho Cho et al. in South Korea designed a tracked cable-climbing robot for climbing on steel wire ropes. The robot adopts a box structure; the external frame makes the robot more robust and stable, the three-sided tracked clamping design ensures stable climbing, and guide wheels are installed at the front. The tracks are pressed tightly against the steel wire rope through a linkage mechanism, so the robot has good adaptability to the diameter of the steel wire rope[4].

Research on cable-stayed bridge cable inspection robots started relatively late in China. The research group of Professor LYU Tiansheng at Shanghai Jiao Tong University successively developed three generations of cable maintenance robots: pneumatic peristaltic type, electric continuous type, and electric hydraulic type. The main problem with these three generations is their excessive weight, all exceeding 100 kg[5].

XU Fengyu at Southeast University first studied key technologies in the field of cable-stayed bridge robots, proposed multiple portable robot solutions such as gripping peristaltic mobile robots, multi-legged walking robots, tracked walking robots, and wheeled mobile robots, designed modular excitation flaw detection equipment, proposed attachment mechanisms using magnetic adsorption and spring support, and built a robot prototype[6].



Fig 2. Two or more references

3.1.2. Wall-climbing Robots

DAI Suya focused research on the robot's attachment mechanism and proposed a parallelogram structure and a quick-release mechanism. The quick-release structure makes it easier to install the robot on the cable and simplifies the magnetic flux leakage detection device[7].WEI Wu et al. at South China University of Technology designed a snake-like robot for bridge cable inspection, using a climbing gait generation method during climbing to improve the robot's climbing flexibility and safety during operation[8].

WANG Xiaolin et al. at Liuzhou OVM Machinery Co., Ltd. improved a cable-climbing robot using lightweight carbon fiber material. The most notable feature of this robot is its use of carbon fiber material, which reduces the robot's weight, extending its endurance. It adopts a two-part frame structure for easy disassembly and can be adjusted according to different cable diameters, with a maximum load[9].

Wall-climbing robots are a type of biomimetic robot that can not only move quickly on the ground but also adhere to vertical walls, ceilings, and other different normal planes for flexible operation. Currently, wall-climbing robots are mainly used for cleaning high-rise building glass, dock rust detection, petrochemical storage tank inspection, as well as firefighting, reconnaissance, etc. Their application in bridge inspection is still in its early stages. Leveraging their small size, flexibility, and convenience, they can reach blind spots that traditional inspection cannot access.The overall load capacity of a wall-climbing robot is one of the key factors affecting its application in bridge inspection. In 2010, Ozgur Unver[10] developed a tracked wall-climbing robot capable of overcoming 16 mm obstacles, using elastic adhesion to achieve fast, vibration-free movement on walls, but its load capacity was only 300g, insufficient to carry inspection devices for routine bridge disease detection.LIN Renjun et al. at Beijing Institute of Technology developed a silicone-tracked wall-climbing robot that uses ducted fans to generate positive pressure adhesion and silicone tracks to generate greater friction, allowing it to walk vertically on bridge surfaces of various materials. H. Peel at the University of Leeds used a small mobile robot for visual inspection of bridge bearings. Dikai Liu at the University of Technology Sydney designed a bionic inchworm robot for inspecting complex and confined environments of steel bridges, focusing on motion planning and control, and conducted inspection experiments on the Sydney Harbour Bridge[11].

In 2014, DAI Qifan[12]proposed a wall-climbing robot for bridge inspection. The system hardware consists of a wall-climbing robot and a visual inspection device. The visual inspection device uses a zoom camera with a resolution of 1280*960. The robot can complete inspection tasks on concrete component surfaces, successfully crossing 2cm wide grooves, with crack detection accuracy reaching 0.5mm in width. In 2016, CHEN Yao[13] proposed a bridge crack image detection method based on a wall-climbing robot, reducing image blur caused by relative motion between the robot and the component. They improved upon the KD-tree method and used an SVM decision tree algorithm to classify cracks, ultimately achieving crack extraction and classification.



Fig 3. Two or more references

3.2. Unmanned Aerial Vehicles

UAVs are unmanned aircraft operated by radio remote control equipment and onboard program control devices. UAVs generally use multi-rotor drones with stable takeoff and landing, facilitating data collection and observation. The data transmission system is used for transmitting system control signals and inspection data. The ground station system is used for real-time monitoring of UAV flight and inspection image capture, facilitating timely flight path correction and detection of obvious bridge diseases[14].

Infrastructure Preservation Corporation in the United States was the earliest in the world to offer commercial UAV-based bridge inspection services. In China, transportation departments such as China Merchants Chongqing Communications Technology Research & Design Institute Co., Ltd.,

and the provinces of Hunan and Jiangsu have begun attempting to use commercial UAVs for bridge maintenance inspection. However, due to the lack of satellite navigation signals under bridges, the current primary method of UAV bridge inspection is manual remote operation.In 2018, ZHANG Ping et al.[15]used a W6 six-rotor UAV equipped with a 20-megapixel zoom camera to inspect concrete components of the Wanzhou Yangtze River Highway Bridge for cracks, damage, rebar exposure, and corrosion. They found multiple cracks, rebar corrosion, and other diseases, with crack detection accuracy reaching 0.2mm in width.In 2020, LIU Wei et al.[16]used a DJI M200 quad-rotor UAV equipped with a DJI Z30 lens (2.13 megapixels) to inspect the entire bridge along 8 pre-planned inspection routes, achieving crack detection accuracy of 1mm in width.In 2020, SUN Lele[17] used a DJI M210-RTK industrial-grade UAV to collect crack disease information. After six steps including grayscale conversion, median filtering, convolutional gradient calculation, crack edge connected component extraction, crack identification, and crack scale calculation, the final crack scale information was obtained, with crack width detection accuracy reaching approximately 0.25mm.In 2021, MA Xuezhi et al.[18] used a DJI Matrice M300 UAV with a 20-megapixel zoom Zenmuse H20 camera. Tests were conducted on the Zhulonghe Railway Bridge on the Shuohuang Railway. The test results showed that the system could detect cracks as narrow as 0.25mm.

3.3. Steel Box Girder Disease Detection Methods

The main methods for daily inspection and maintenance of steel box girders include manual visual inspection, ultrasonic testing, magnetic particle testing, and eddy current testing. In recent years, many scholars have conducted research on intelligent detection methods for steel box girders, but most research has focused on the detection of external diseases of steel box girders. The intelligent detection of internal diseases of steel box girders still needs improvement and refinement.

3.3.1. Ultrasonic Testing

Ultrasonic waves reflect at heterogeneous interfaces, and the reflected echoes are received by a receiver. The detection principle is shown in Figure 4. Based on this principle, ultrasonic methods are applied to structural flaw detection[19] and structural thickness measurement[20]. Ultrasonic testing can detect internal diseases of steel box girders without affecting traffic. However, due to equipment limitations, it cannot inspect some critical parts of the steel box girder. Additionally, the high cost of the testing instruments limits the application of this method.

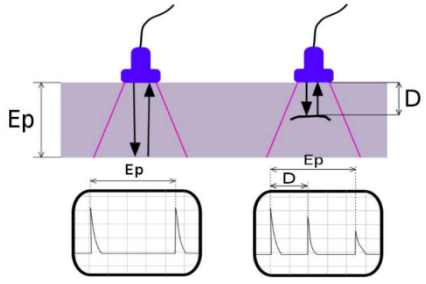


Fig 4. Principle of ultrasonic testing

3.3.2. Magnetic Particle Testing

In magnetic particle testing, magnetic particles are sprinkled on the test piece. If there are no cracks on the test piece and the material is continuous, the magnetic field lines on the surface and near-surface do not change, and the magnetic particles are uniformly distributed. If cracks or other defects exist, a change in magnetic resistance occurs, magnetic flux leakage at the crack, distortion of the magnetic field lines, and accumulation of magnetic particles. Magnetic particle testing is generally used to detect surface cracks, grooves, and protrusions on steel box girders[21]. It is simple to operate, reliable, and low-cost, effectively detecting surface cracks in steel without causing any damage to the steel box girder during testing. However, this method requires a high degree of surface smoothness

of the test piece, has a slow detection speed, demands high technical skill and experience from the inspector, and cannot detect internal cracks in steel.

3.3.3. Eddy Current Testing

Eddy current testing is based on the principle of electromagnetic induction. When a coil carrying alternating current is placed on the surface of steel, if a crack exists in the steel, the eddy current field changes, causing a change in the coil's impedance or induced voltage[22]. Eddy current testing is mainly used for detecting surface diseases of steel box girders. During eddy current testing, the coil does not need to be in direct contact with the test object, allowing for high-speed testing and easy automation. However, it is not suitable for parts with complex shapes, can only detect surface and near-surface defects in conductive materials, and the test results are susceptible to interference from the material itself and other factors[23].

3.3.4. Development of Portable Equipment for Steel Box Interiors

The development of bridge inspection equipment is trending towards intelligence, miniaturization, lightweight, and multifunctionality. Some scholars have developed new intelligent inspection equipment for the special environment inside steel box girders.WU Mengdi et al. at Shanghai Institute of Technology[24] invented an automatic inspection trolley for intelligent patrol of internal diseases in box girders.

The trolley is installed on pre-laid tracks inside the box girder and is slidably connected to the tracks. The trolley body includes a frame, detection module, control module, communication module, and power module. By automatically patrolling inside and outside the box girder, the detection module collects damage information from inside the box girder, which can significantly reduce labor intensity and inspection costs compared to manual and traditional inspection methods, facilitating daily maintenance of box girders.LI Yi, FENG Liangping et al.[25] invented a robot for inspecting apparent diseases on the inner surface of bridge steel box girders. The inspection robot consists of a robot body, a mobile module, an image acquisition module, a laser scanning module, and a data transmission module. The inspection images are attached to a 3D model of the steel box girder interior to form a 3D model of the inner surface of the steel box girder. Then, based on the as-built drawings of the steel box girder, a standard 3D model of the steel box girder is created. By comparing it with the 3D model of the inner surface of the steel box girder, the location of apparent diseases on the inner surface of the steel box girder can be quantified.

3.4. 3D Laser Scanning

3D laser scanning technology, also known as "reality capture technology", uses a non-contact measurement mode to accurately and effectively collect 3D coordinate data of irregularly shaped and complex structured entities, enabling rapid depiction and quantification of complex spatial entity geometric information. 3D laser scanning technology features non-contact, high speed, wide scanning range, penetrability, and full automation, and is widely used in geographic mapping, 3D modeling, digital cities, etc.

Using 3D laser point clouds, 3D information of bridge apparent diseases can be obtained quickly and accurately, significantly reducing fieldwork intensity and time, shifting more effort to data processing indoors. By processing and analyzing point cloud data, automated detection and evaluation of bridge apparent diseases can be achieved, improving inspection efficiency and accuracy.

Many cases of applying 3D laser scanning technology to detect the apparent quality of bridges have emerged, mainly due to the advantage of 3D laser scanning technology in acquiring overall bridge structure data at once. Zogg[26]and Lõhmus et al.[27] found that terrestrial laser scanning (TLS) achieves millimeter-level accuracy, sufficient for general structural deformation measurement requirements. Ye[28] and Kim et al.[29] applied TLS to bridge construction and maintenance and

validated the methods. GUO et al.[30]combined UAV imagery with LiDAR point clouds to make deformation monitoring of long-span steel structures more detailed and comprehensive.

WANG Xun[31]used a Leica MS50 3D scanner to scan bridge deck deformation under three modes and used Geomagic Qualify for data comparison. However, due to the accuracy limitations of the 3D scanner used, the test was only effective for bridge structures with large spans and deformations greater than 3mm.

GENG Lu[32]summarized the application of 3S measurement, 3D laser scanning, and measurement robots in bridge deformation detection. Compared to traditional measurement methods and 3S methods, 3D laser scanning offers advantages such as high automation, non-contact operation, and powerful output capabilities. However, the high-precision instruments are very expensive, and data processing is relatively complex.

4. IMAGE CLASSIFICATION AND RECOGNITION TECHNOLOGY FOR APPARENT DISEASES

After acquiring structural apparent disease images using intelligent inspection equipment, it is also necessary to combine computer vision-based structural apparent disease recognition methods to intelligently and automatically perform feature analysis on disease images, identifying the disease type and location. Machine vision-based automated defect detection methods not only reduce manpower, cost, danger, and the subjectivity required for manual inspection but also improve work efficiency and can cover areas difficult to reach by conventional inspection. They are playing an increasingly important role in multiple aspects of bridge operation, maintenance, and repair[33].

Image classification represents the attribute classification of diseases, allowing for accurate and efficient screening of images of different apparent disease types, thereby avoiding focusing on a large number of non-disease type images and reducing subsequent resource consumption. Therefore, conducting research on computer vision-based apparent disease classification is of great significance. Existing computer vision-based apparent disease classification methods can be roughly divided into the following two categories: traditional feature engineering combined with classifier methods, and deep learning-based automatic feature extraction methods.

4.1. Disease Identification Methods Using Feature Engineering Combined with Classifiers

Disease identification methods using feature engineering combined with classifiers can be considered traditional "shallow" machine learning models, where feature construction requires human participation or expert knowledge. Prasanna et al.[34] proposed an automatic crack classification algorithm called STRUM, which classified hundreds of crack regions collected from two bridges and achieved 95% accuracy. CHEN Yao et al.[35] proposed a crack classification method based on images collected by a wall-climbing robot, using a KD-tree for crack region connection and finally classifying cracks using a Support Vector Machine (SVM). Chen et al.[36]processed each frame of crack image extracted from a video through grayscale conversion, histogram equalization, and mean filtering, then extracted Local Binary Pattern (LBP) texture features from the preprocessed crack grayscale images, and achieved 95.12% crack classification accuracy using an SVM classifier. CHEN Feifei et al. extracted grayscale histogram features, color moment features, and texture features from disease images and used SVM to classify three disease types: cracks, rebar exposure, and spalling. The disadvantage of classifier-based image recognition methods is that for complex background images of multiple bridge diseases (such as large areas of concrete spalling, rebar exposure, etc.), noise in the background is easily misjudged as disease, resulting in poor anti-interference ability. Moreover, noise caused by uneven illumination, blurring, and distortion in actual inspection environments also severely affects results[37].

4.2. Deep Learning-based Disease Identification Methods

In recent years, with major breakthroughs in the field of artificial intelligence, deep learning-based methods, represented by Convolutional Neural Networks (CNNs), have become a research hotspot in both academia and industry for further analyzing the large number of disease images collected by intelligent inspection equipment. As the number of layers in deep neural networks increases, the features described by the networks become more abstract, and the ability to identify disease features gradually improves[38]. Moreover, CNNs have a strong ability to filter out background noise, sufficient to overcome noise generated by handwriting, stains, occlusion, and uneven illumination on the surface of reinforced concrete bridges. The development of CNNs has led to deep learning-based detection techniques gradually replacing traditional methods.

Cha et al.[39] introduced CNNs into structural crack detection, using CNNs to distinguish concrete cracks from the background without manually designing defect features. The designed CNN was trained on 40,000 images with a resolution of 256×256 pixels, and the results showed that the CNN achieved a classification accuracy of 98% and strong robustness. Zhang et al.[40]proposed a CNN-based road crack classification method, demonstrating that CNNs have better crack identification performance compared to traditional manual feature extraction methods such as SVM and Boosting. Xu et al.[41] proposed an improved fused convolutional neural network structure for recognizing cracks and handwriting in images containing complex interference information inside steel box girders.

MA Weifei et al.[42] applied CNNs to detect bridge cracks in images captured by UAVs, combined with an improved sliding window algorithm for bridge crack detection, achieving a crack classification accuracy exceeding 97%. However, dividing the bridge crack image into 16×16 cells was too fine, increasing detection time. HAN Xiaojian et al.[43] applied CNNs to classify surface diseases of bridge structures, training and fine-tuning an AlexNet model through transfer learning, constructing a disease classification model for three categories: cracks, corrosion, and defects. SHA Aimin et al.[44] applied CNNs to road surface disease identification and measurement, designing three CNNs for road surface disease identification, crack feature extraction, and pothole feature extraction, respectively. The classification accuracy for crack and pothole disease levels reached 98.99% and 95.32%, respectively.

5. 3D MODELING TECHNOLOGY

5.1. UAV Oblique Photogrammetry Modeling

Oblique photogrammetry technology has significant advantages in engineering surveying and 3D modeling applications. UAV oblique photogrammetry technology is not subject to the various limitations of traditional aerial survey imagery, allowing multiple sensors to collect data from different angles, greatly improving collection efficiency, while also ensuring the real-time nature, validity, and authenticity of the data, meeting the current industry demand for 3D information[45].

Key technologies for oblique photogrammetry image processing typically include: high-precision calibration of non-metric cameras, image preprocessing, regional network block adjustment, multi-view image matching, DSM generation, true orthorectification, and 3D modeling.

Non-individual models (also called oblique models): 3D models fully automatically produced using system software. Based on multi-view image data, considering various systematic errors, joint block adjustment is performed, first generating a high-density point cloud, then automatically generating a TIN mesh model, and finally producing a 3D model with realistic textures. Its greatest advantages are full automation and realistic textures. The disadvantage is that each building cannot be modified, including its texture information.

5.2. LiDAR Point Cloud-based Modeling

Point clouds are typically acquired through 3D laser scanners. After scanning selected target objects or environments, 3D laser scanners can quickly acquire high-resolution 3D coordinate data of the surface of the scanned object over a large area. During the 3D laser scanning process, point cloud data acquisition is often affected by factors such as object occlusion and uneven illumination, which can easily create scanning blind spots in areas of complex-shaped objects, forming holes. Also, due to the limited scanning range, multiple scans are necessary for large objects or large scenes. Therefore, the scanning results are often multiple point cloud datasets with different coordinate systems and containing noise, which cannot meet the requirements for realism and real-time digital models. Thus, 3D point cloud data needs preprocessing such as denoising, simplification, registration, and hole filling. Through data preprocessing, noise and outliers in the point cloud can be effectively removed, point cloud data can be simplified while preserving geometric features, and point clouds scanned from different angles can be unified into the same coordinate system, providing a robust data foundation for subsequent surface reconstruction and 3D solid model generation.

5.2.1. Data Registration

Point cloud data registration, also known as point cloud data stitching or coordinate correction. Due to the complexity of the target object, it is usually necessary to scan from different directions over multiple stations to fully scan the target. Each station's scan data has its own coordinate system. 3D model reconstruction requires correcting the scan data from different stations to a unified coordinate system. The main point cloud stitching methods include target-based stitching, point cloud-based stitching, and control point-based stitching.

5.2.2. Data Denoising

When scanning a target with a 3D laser scanner, the point cloud data inevitably contains some noise due to factors such as the scanning equipment, surrounding environment, human disturbance, and target characteristics, preventing the data from accurately representing the spatial position of the scanned object.

5.2.3. Data Simplification

Data simplification is the process of reducing the quantity of point cloud data within accuracy tolerances, extracting effective information. It is generally divided into two types: redundant data removal and thinning simplification.

Redundant data is data from overlapping areas after data registration, mostly useless data that greatly affects modeling speed and quality and should be removed. Thinning simplification refers to situations where the scanned data density is too high, and the quantity is too large. Some of this data is of little use for later modeling, so it is simplified while meeting certain accuracy requirements and preserving the geometric features of the scanned object. This improves data operation speed, modeling efficiency, and model accuracy.

5.2.4. Data Segmentation

For complex scanned objects, direct point cloud data modeling can be difficult, and the mathematical representation of the 3D model becomes complex. Therefore, for complex modeling objects, point cloud data is generally segmented first, then each segment is modeled separately, and finally combined. The main methods for point cloud data segmentation include edge-based segmentation, surface-based segmentation, and clustering-based segmentation.

5.3. Multi-source Fusion Modeling Technology

Currently, the production of detailed 3D reality models of bridges mostly relies on close-range photography using multi-rotor UAVs, requiring high-precision positioning technology assistance. He

et al.[46] proposed a collection method combining global and local UAV flight paths, improving the reconstructed model quality by 46.7%. SUN Baoyan et al.[47]obtained high-precision 3D reality models of detailed cable-stayed bridge tower nodes by designing stepwise circular flight paths. The emergence of close-range photography has to some extent increased the detail of 3D reality models. However, due to the location limitations of bridges, there is a lack of safe space for flight path planning. Unreasonable camera angle settings may cause missing textures at bridge nodes, recesses, anchorages, and other details. Moreover, due to the light difference between the underside of the bridge and the outside, overexposed images are easily captured, causing failure in aerial triangulation calculations and resulting in model misalignment or large-area texture loss at the bridge bottom.

Domestic research on multi-source data fusion-based 3D reality modeling started relatively late. However, with the comprehensive advancement of 3D reality China construction, many domestic scholars have conducted various studies on 3D reality modeling technology and have also carried out some explorations in the field of multi-source data fusion modeling technology. At the same time, certain research results have been achieved in multi-source data fusion at the image fusion level, point cloud fusion level, model fusion level, and image + point cloud fusion level.

Using 3D laser scanners to quickly acquire high-precision ground 3D information solves the problems of low efficiency and insufficient density of ground close-range data acquisition. Mohammadi et al.[48] established detailed point cloud models of a small two-span wooden truss bridge using both aerial photogrammetry and terrestrial laser scanning, analyzing the advantages and disadvantages of the two modeling methods. ZHOU Yong et al.[49] proposed a data fusion modeling method integrating UAV oblique photogrammetry technology and 3D laser scanning technology for UAV oblique point clouds and vehicle-borne laser point clouds, completing 3D reconstruction of a bridge. Experimental results showed that multi-source data fusion modeling technology can ensure bridge accuracy while providing new ideas for digital bridge restoration. LI Xiaobin et al.[50] proposed a 3D reality fusion modeling technology combining laser scanning and oblique photogrammetry. Experimental results showed that compared to single data source modeling methods, the fusion modeling method has advantages in efficiency, accuracy, and cost, and offers better value. SUN Baoyan et al.[51]proposed an air-ground multi-data complementary fusion 3D model reconstruction method, completing a detailed 3D model electronic archive of a large arch-style ancient building, providing new ideas for the protection and health monitoring of ancient buildings. HUANG Liming[52] used multi-source data fusion 3D reality reconstruction technology, fusing point cloud data to build a 3D reality model with high geometric accuracy, clear and complete textures. The model results were applied to building deformation monitoring. CHENG Chang[53] proposed a detailed 3D reconstruction method integrating oblique photogrammetry and terrestrial 3D laser scanning technology. Experimental results showed that this reconstruction method can obtain high-precision, comprehensive real information of buildings, compensating for the shortcomings of single modeling technology.

6. CONCLUSION

Considering the research on disease inspection equipment for cable-supported bridges at home and abroad, it can be found that although wall-climbing robots and cable-climbing robots have the advantages of high automation and the ability to carry inspection equipment into complex and confined environments, problems such as excessive self-weight, insufficient load capacity, and inadequate adhesion make it difficult to carry out full-bridge, full-span inspection, localization, recording, and description.

UAV oblique photogrammetry technology can quickly scan large areas of bridge surfaces in a relatively short time, greatly improving inspection efficiency. The high-resolution and high-precision image data obtained help detect and identify fine diseases on bridges. However, the difficulty and challenge of achieving global bridge disease detection using only UAVs are still significant. UAV

operations are greatly affected by weather, and when UAVs are shaded under or near bridges, satellite positioning signal reception may be affected, leading to inaccurate positioning. Fusing UAV imagery and 3D scanning technology to establish detailed 3D models is feasible and can overcome the limitation of 3D laser scanners easily causing loss of texture information on the top surfaces of targets. The characteristic of synchronous operation can further improve the efficiency of detailed modeling.

As the main girder of cable-supported bridges, the external and internal disease detection of steel box girders cannot be ignored. The development of portable intelligent inspection equipment for the interior of steel box girders requires further in-depth research.

Computer vision-based structural apparent disease recognition methods can automatically perform feature analysis on disease images, identifying the disease type and location. Early research mostly focused on classifier-based methods, which are "shallow" machine learning models. In contrast, deep learning models represented by convolutional neural networks can describe features more abstractly and have a stronger ability to filter out background noise, gradually becoming a hot research direction in disease image recognition.

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