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Review on Full Perception Intelligent Pantograph-Catenary System in Electrified Railways

Z. Liu, H. Yang and Y. Song

**School of Electrical Engineering, Southwest Jiaotong University
Chengdu, China**

Abstract

High-speed railways have gradually shifted from the infrastructure era to the operation and maintenance era in China, which puts forward higher requirements for the safe and reliable operation of high-speed railway traction power supply system equipment. As a railway power transmission channel, the pantograph-catenary system is an important part of the traction power supply system. However, the operation has shown that most abnormal states come from the pantograph-catenary system (including contactors and pantographs). The Power supply safety monitoring system for high-speed railways (6C system) is a comprehensive system that can measure the dynamic and static geometric parameters related to the catenary and detect the faulty working status and running status of the components in the pantograph-catenary system. The active control of the pantograph can also effectively improve the current collection quality of the pantograph-catenary system. The paper provides a detailed introduction to the overall architecture of the 6C system, pantograph active control technologies, and pantograph active control simulation platform. Finally, combining multi-source data fusion, UAV monitoring, fiber optic sensors, and other technologies, a prospect is given for the full-sensing intelligent detection of pantograph-catenary on electrified railways.

Keywords: pantograph-catenary system, active control, 6C system, data fusion, UAV, fiber optic sensor.

1 Introduction

By the end of 2023, China's high-speed railway had an operating mileage of more than 42,000 kilometers and could circle the earth's equator. China's high-speed rail development has gradually transitioned from the construction phase to the operation and maintenance phase. The pantograph catenary system of electrified railways serves as the power transmission channel for railways and is an essential component of high-speed railways. Field experience has shown that catenary support structures that are affected by complex factors such as external environment and train vibration, and may experience loosening, missing, breakage, cracks, and other defects or failures (as shown in Figure 1), leading to a decline in their structural reliability.

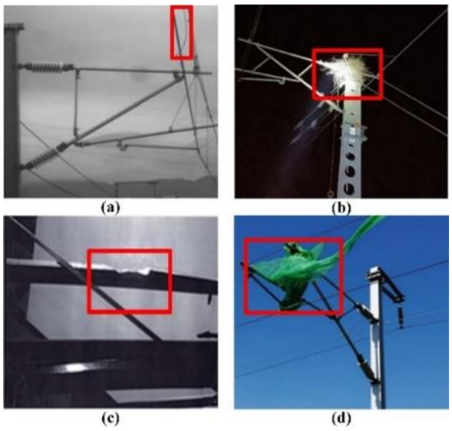

Figure 1. Different types of faults in the pantograph-catenary system. (a) dropper falling; (b) bird’s nest; (c) damage on the pantograph; (d) foreign body.

2.1 Catenary Detection Technology

Early research on overhead catenary inspection using computer vision techniques focused on target localization and defect judgment based on manually designed feature detectors. Xu et al. [1] proposed an improved feature extraction method using LBP-HOG features for identifying and locating rotating double-ear regions in overhead catenary images. Wu et al. [2] conducted the potential occurrence of bird nests in the catenary positioning system. They first used the Hough transform to extract the linear segments of branches on the outer side of the bird nests. Then, using histogram statistics, they analyzed the lengths and directions of all extracted segments to create a characteristic description of the bird nests. Finally, they employed an SVM classifier to locate the bird nests. However, these methods struggle to meet the demands of overhead catenary inspection under complex conditions. In recent years, the overhead catenary inspection has witnessed rapid advancements, driven by the burgeoning development of deep learning techniques, such as deep convolutional neural networks (CNNs) [3]. These advancements have opened possibilities for intelligent overhead catenary inspection, offering enhanced capabilities and performance. For component localization, several studies [4] have employed the original Faster R-CNN network to achieve accurate localization of different overhead catenary components, including single-category components, rotating double-ears, and equipotential lines. In the realm of fine-grained region extraction, Ref. [5] has employed segmentation models YOLACT to perform pixel-level region segmentation on cropped component patches extracted from object detection results. These approaches have been successfully applied to segment components such as pins, positioning line clamps, inclined strut sleeves, and their tightening bolts. In anomaly detection, Zhang et al. [6] employed the instance segmentation algorithm YOLACT++ to extract masks of support sleeves and their tightening bolts and nuts. They then analyzed the existence of these masks and their geometric relationships to detect loose fasteners.

2.2 Active Pantograph Control Technology

When an electric locomotive travels at high speeds, pantograph-catenary vibrations cause fluctuations in the contact force between the pantograph and the catenary, resulting in poor current collection, reduced locomotive performance, and even damage to electrical equipment. To suppress pantograph-catenary coupling vibrations and improve the current collection capacity of high-speed trains, the active pantograph is one of the most promising methods. Over the years, to reduce contact force fluctuations and improve current collection quality, people have conducted extensive research and analysis on the pantograph-catenary relationship both domestically and internationally [7]. Various measures have been proposed, such as optimizing the catenary structure [8], optimizing the pantograph structure [9], optimizing the spacing between double pantographs [10], and optimizing the static uplift force of double pantographs [11]. However, these measures have certain limitations. Catenary structure optimization can only be implemented on the built lines. Applying it to existing lines requires much manpower and resources, resulting in high costs. Early researchers proposed using active control technology to improve the pantograph's tracking ability. First, active control of the pantograph does not target any specific type of catenary or pantograph. With the control algorithm determined, adjusting the control parameters can be applied to any pantograph-catenary structure. Second, the cost of active control for pantographs is relatively low, requiring only appropriate modifications to the pantograph without optimizing or modifying any parameters or structures of the catenary. Therefore, it can be applied to various catenaries, from low-speed to high-speed, and from existing to newly built lines. Finally, active control of the pantograph requires only a small amount of state information, such as real-time contact force, displacement, and speed of the pantograph head and frame, depending on the control algorithm. This characteristic indirectly enhances the system's anti-interference capability. Research on controllable pantographs has gradually become an important topic in pantograph research. G. Poetsch et al. [12] were the first to propose various structures and active control concepts for active pantographs. Therefore, guiding the active control of pantographs based on sensor data obtained from the pantograph-catenary full-sensing monitoring system is also an important way to ensure the quality of the current collection.

2.3 Multi-Source Data Fusion Technology

Data fusion aims to utilize statistical methods and feature engineering to integrate information from different sources, thereby obtaining higher quality, more comprehensive, and useful information. Compared with single-source tasks, the advantages of data fusion include increasing confidence, reducing system uncertainty, expanding spatiotemporal perception, enhancing system fault tolerance, and improving model judgment accuracy. Data fusion methods are classified into different levels within a system, including data-level, feature-level, and decision-level fusion.

Typical traditional data fusion methods include Kalman filtering [13], D-S evidence reasoning [14], and neural networks [15]. The Kalman filtering method achieves real-time fusion representation of redundant data by using the statistical characteristics of the measurement model to recursively estimate multi-source data. It is a classic data-level fusion algorithm [16], but it can only handle linear problems and has low observability, making it prone to divergence. D-S evidence reasoning uses Dempster's rule of combination to merge individual pieces of evidence into a new body of evidence, employing uncertainty intervals and probability intervals to determine the likelihood function in multi-evidence situations. Based on this, it performs reasoning and fusion and is a typical decision-level fusion algorithm [17]. This algorithm is suitable for fusing imprecise and incomplete information but struggles to handle inconsistent information. Deep neural networks have powerful feature extraction and integration capabilities and can effectively fuse unstructured, high-dimensional, and heterogeneous data through representation learning methods. Jiao et al. proposed a deep coupled dense convolutional network (CDCN) with complementary data that integrates information fusion, feature extraction, and fault classification for intelligent diagnosis [18].

It is worth noting that although the above methods perform well in multi-modal data fusion tasks, most of them adopt a "divide and conquer" approach (extracting features of different data with different networks and then performing feature fusion) without considering the interaction between modalities. To address this issue, inspired by domain adaptation [19], some studies have introduced adversarial learning mechanisms into multi-modal data. Bhagat et al. proposed a new spatially constrained adversarial autoencoder for the fusion of spatial features of data images and spectral features of infrared images [20]. Liu et al. introduced an effective adversarial tri-fusion hashing network (ATFH-N) aimed at cross-modal retrieval, representing one of the initial endeavors utilizing adversarial learning for managing multi-modal data. [21]. Therefore, introducing multi-source data fusion technology into the pantograph-catenary intelligent detection system is an important means to improve the monitoring performance of the pantograph-catenary state.

2 The 6C Perception System: From Equipment to Industry

As shown in Figure. 2, the 6C system is divided into six parts: the Pantograph and Catenary Comprehensive Monitoring System (CPCM-1C), the Catenary Inspection Video Monitoring System (CCVM-2C), the Catenary Inspection Online Monitoring System (CCLM-3C), the High-Precision Catenary Inspection Monitoring System (CCHM-4C), the Pantograph and Catenary Video Monitoring System (CPVM-5C), and the Catenary and Power Supply Equipment Ground Monitoring System (CCGM-6C). Additionally, the data collected by the 6C system is transmitted through a three-tier data center, gradually transferring from the power supply section to China Railway Corporation. Furthermore, each subsystem is equipped with devices or apparatus, and algorithms specifically are designed for its purpose and location.

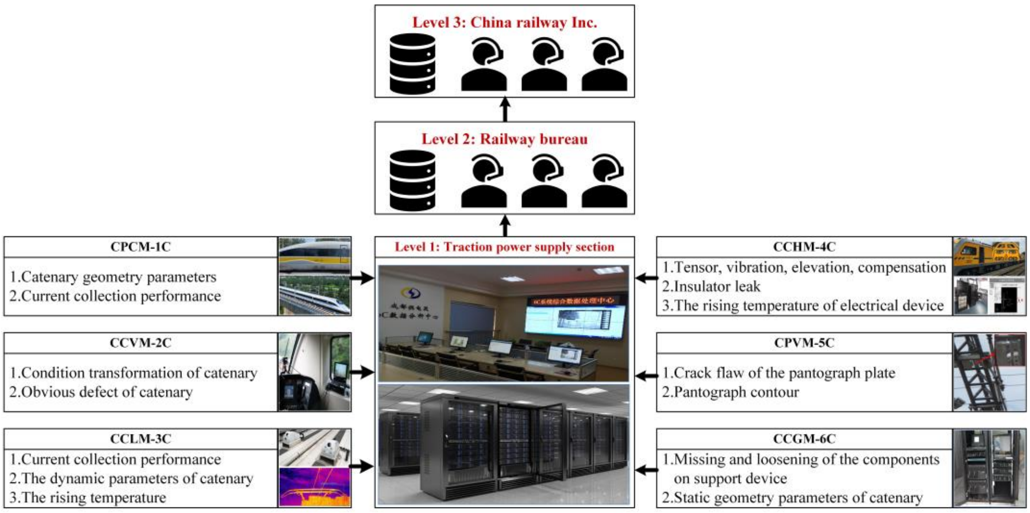

Figure 2. The architecture of 6C system. It contains six detecting components and a three-level data processing center.

2.1 CPCM-1C

CPCM-1C is a fixed detection device installed on the roof of a high-speed comprehensive inspection train [22], which can effectively measure various equipment parameter indicators under dynamic environments and conditions. The primary function of the high-speed 1C device is to measure the parameters of the catenary and pantograph, providing guidance for the operation and maintenance of the catenary. The results include catenary status parameters, real-time pantograph status, pantograph-catenary current parameters, catenary component image detection, and related power supply equipment status. The catenary status parameters mainly contain the height of the contact wire, stagger value, hard points, pantograph-catenary contact force, speed, and kilometer markers. The layout of the high-speed comprehensive inspection train and roof arrangement is shown in Figure. 3.

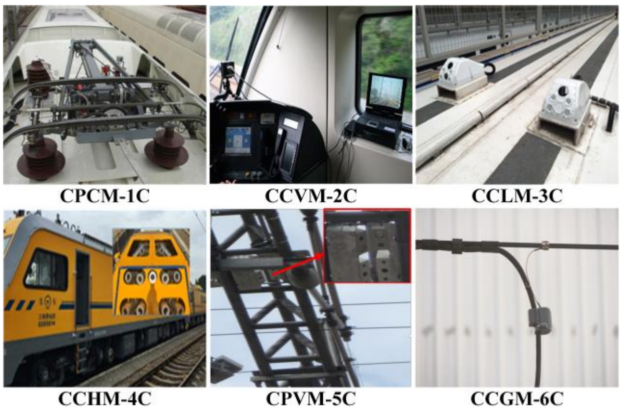

Figure 3. The layout of the 6C device.

The CPAM-1C equipment includes detection sensors, pantograph-catenary video surveillance equipment, signal transmission equipment, power supply equipment, signal acquisition equipment, and data processing computers. Its functions are as follows: (1) Real-time processing, analysis, and storage of raw test data, reading data in standard formats, and continuous real-time display of test data and waveforms; (2) Establishing an inspection database and generating defect reports and inspection reports using the inspection data; (3) Comparative analysis of historical inspection data from the same location. In summary, the 1C device is used for the comprehensive detection of the dynamic geometric parameters and current collection quality of the pantograph-catenary system on inspection trains. It employs measures such as nonlinear distortion compensation and dynamic tilt correction to make sure the accuracy and robustness of the inspection train under high-speed and severe vibration conditions.

2.2 CCVM-2C

The CCVM-2C system is designed to detect the technical status and external environment of the catenary system and perform statistical analysis on its technical status to guide the maintenance of the catenary. Its detection targets include significant changes in the catenary system, such as bird nests, tree invasions, fallen contact wires, and disconnected contact wires [22]. The detection method involves using a portable video acquisition device installed on the train driver's bridge to monitor the status of the catenary system, as shown in Figure 3. Additionally, this equipment features functions such as image browsing, video retrieval, image marking, and positioning of poles (suspension poles). The CCVM-2C equipment includes high-definition cameras with night vision capabilities, a synchronization control module, a power management module, a portable computer, cables, and an image processing computer (offline). It can effectively determine the external environment that pose threats to the safe operation of the catenary power supply equipment. The system segments the video based on the information from the catenary poles (or suspension poles) and records the detected defects along with their corresponding kilometer markers (or pole numbers) and other positioning information. Additionally, it can establish a "one-pole-one-image" database, allowing for comparative analysis with historical inspection results taken at the same location. In summary, the 2C system is deployed in EMU (Electric Multiple Unit) inspections to detect changes in the contact suspension and foreign object invasions, such as bird nests and tree damage. The 2C system uses portable video acquisition equipment for fixed-point status detection, temporarily installed on the driver's cab of the EMU. It captures video of the catenary status, analyzes the video, and evaluates the condition of the suspension components. CCVM-2C primarily detects and identifies significant changes in the catenary system through methods such as template matching (HOG, SIFT), machine vision, and deep learning.

2.3 CCLM-3C

CCLM-3C is an electrified railway overhead catenary status monitoring system that provides full coverage and dynamic detection. The detection parameters of the 3C device mainly include contact line height, pull-off value, horizontal distance between the two contact lines, arc burning time, and overhead catenary temperature [22]. The 3C system is mainly installed on the roof of the train in front of the pantograph, as shown in Figure. 3 CCLM-3C can monitor the operation status of the catenary and track mileage data. According to the needs, the system can also perform the following tasks: (1) Use wireless transmission or wireless call transmission to transmit detection data in real-time; (2) Use a mobile hard disk method or wireless transmission method to transfer data to the train; (3) It allows for fast query and segment detection data, including high-definition video. High-definition video is employed for monitoring the status of the catenary. Among them, the primary utilization of real-time data is to analyze and process the contact between the pantograph and the catenary arc, the temperature of the catenary, the dynamic geometric parameters of the catenary, and the operation status of the catenary. In addition, real-time data can also automatically identify abnormal pantograph-catenary arcs, abnormal catenary temperatures, and suspicious geometric defects. In summary, the 3C is installed on EMUs with speeds of over 200 km/h to obtain dynamic geometric parameters such as height, offset, line spacing, catenary arc (arc rate, arc energy, number of arcs), contact head suspension temperature, etc.

2.4 CCHM-4C

Maintaining the overhead catenary system is challenging due to the harsh working environment and the large number and variety of supporting components [22]. CCHM-4C is a promising system [23] that can help address this challenge. The 4C inspection vehicle runs at a stable speed on the line to photograph overhead catenary components. The system can measure the static geometric parameters of the overhead catenary by imaging and data analysis of the overhead catenary components and provide guidance for the operation and maintenance of the overhead catenary. In addition, the device continuously measures the geometric parameters of the catenary, including the precise position of the catenary arm support (or catenary mast), the images of the front and rear sides of the equipment, the images of the contact suspension (hanger, wire clamp, etc.), and the images of the additional suspension area. As shown in Figure. 3, the equipment of CCHM-4C mainly consists of a static geometric parameter detection system, high-definition cameras, an anchor point automatic identification module, compensation optical equipment and display, and operating equipment. In summary, the 4C is designed as a contactless system to assess static geometric parameters and detect multiple components on the support and suspension devices. The images of the suspension devices are recorded by cameras mounted on top of the inspection vehicle. The latest deep learning and other computer vision algorithms are employed to detect multi-scale and diverse components under various conditions.

2.5 CPVM-5C

CPVM5C is installed at the exits and intersections of railway stations to monitor the status of pantographs in real time [24]. To monitor the status of pantograph skids, CPVM-5C needs to be installed in important areas (local boundaries, section boundaries, etc.). CPVM-5C can promptly detect abnormal conditions of pantograph skids, narrow the detection range, and provide guidance for the maintenance of the overhead catenary. CPVM-5C, as shown in Figure 3, includes a high-speed camera array, a pantograph recognition module, a compensation light source device, a monitoring computer, a network transmission control module, and a high-performance server terminal. It can perform the following tasks: (1) Monitor the status of pantographs and the pantograph angle of the working pantograph using image acquisition equipment; (2) Remotely transmit monitored images or videos via wired or wireless methods; (3) Automatically analyze and process the status of pantograph skids, identify abnormal conditions like pantograph skids damage or breakage, and alarm in real time; (4) Automatically identify the car number of the monitored pantograph. In summary, 5C monitors the status of pantographs at station exits and junctions as a video patrol for special overhead catenary sections such as high-speed railway stations, mobile depot entrances, station throats, important tunnel entrances, turnouts, and bifurcations. It is an important device for detecting abnormal overhead catenary conditions based on pantograph skid status.

2.6 CCGM-6C

CCGM-6C is installed on specific sections of the overhead catenary and traction substations. The CCGM-6C device monitors parameters such as catenary tension, vibration, lift, line temperature, and displacement of compensation devices [22]. It can detect the technical condition of power supply equipment including insulators, cables, and accessories, The monitoring data obtained can be utilized to guide the operation and maintenance of the overhead catenary and power supply equipment. As shown in Figure. 3, the 6C equipment consists of highly sensitive sensors, a wireless or wired transmission network, front-end data acquisition, storage and transmission devices, power supply as well as power management, high-performance server terminals, etc. In summary, 6C is mainly used to install monitoring equipment in special overhead catenary sections and traction substations to monitor the overhead catenary and power supply equipment in real-time, guide maintenance work, and monitor objects such as overhead catenary tension, vibration, lifting weight, temperature, and insulation status.

3 Active Pantograph Control Technology

The core of the active pantograph lies in the control algorithm that considers a comprehensive optimization objective and can guarantee safe operation under various emergency conditions. Developing a fast-computing and easy-to-implement rational controller is challenging, especially during high-speed operation, as the increasing number of uncontrollable factors such as vibration and electromagnetic interference complicates the study of control algorithms [25]. Advanced and sophisticated controllers can consider the variations in contact wire stiffness and employ robust control methods to achieve adaptive control [26]. In general, the comprehensive optimization objectives proposed by researchers include three aspects: offline arc, contact force, and dynamic uplift of the contact wire. Numerous researchers have investigated the effects of different control algorithms on flow quality [27]. These algorithms include Proportional-Integral-Derivative (PID) control [28], Sliding mode control [29], Robust control [26], Fuzzy control [30], Optimal control [31], Linear quadratic regulator (LQR) [32], Adaptive robust fault-tolerant control [33], Model predictive control (MPC) [27], Feedforward control [25]. The implementation of most controllers that require contact force as feedback is challenging because sensors cannot be directly installed on the pantograph, which serves as the power transmission channel (25KV). In contrast, measuring the displacement and acceleration of the pantograph frame can be achieved relatively easily by using non-contact measurement techniques [22]. Wang et al. [34] proposed a novel pantograph control strategy that relies on deep reinforcement learning (DRL), which overcomes the complex modeling problem of PCS and optimizes behavior strategies through trial and error to complete tasks under a given cost function. In addition, they proposed a dual pantograph control strategy that considers catenary vibration and wave propagation through process learning and reward propagation channels.

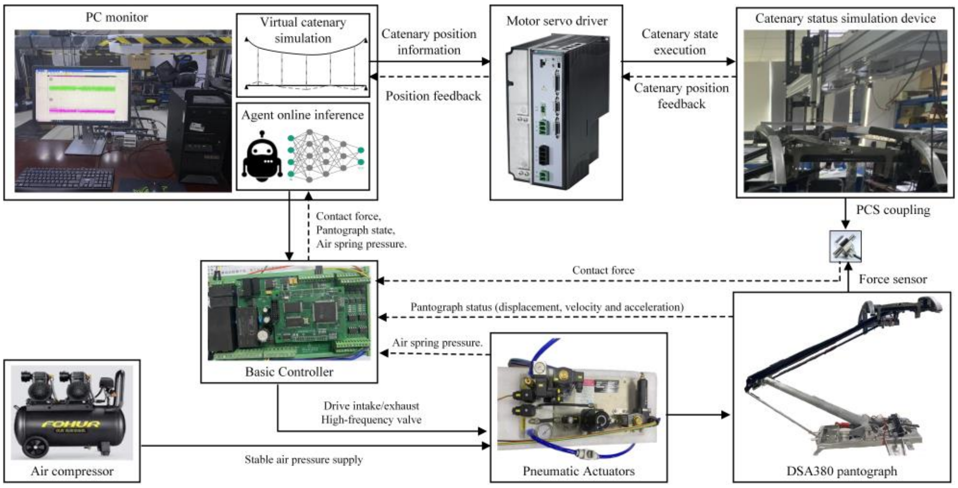

Figure 4. Active pantograph HIL experiment platform workflow and the system alternates between collecting operational status and executing control actions.

Furthermore, the selection of a suitable actuator that can meet the on-site installation conditions and address application bottlenecks is of utmost importance. Actuators mainly include airbags (air springs), motors (electromagnetic actuators), hydraulic actuators, and deflectors (aerodynamics) [35,36]. Servo motors are known for their rapid response to low-power control commands but are susceptible to environmental factors such as electromagnetic interference and temperature [35]. Cylinders or hydraulic cylinders have a wide adjustment range and are easy to install using the original pantograph lifting mechanism, but there is an execution delay [36]. Finally, HIL test benches are an effective tool for verifying the performance of active pantographs and controllers before actual railway line tests. They are composed of a virtual catenary, an actual pantograph, and a virtual locomotive excitation system [37]. Figure 4 shows the Active Pantograph HIL experiment platform established by Southwest Jiaotong University, in which a computer and an electromagnetic servo excitation system are employed to simulate the dynamics of the virtual catenary. The computer simulates the PCS contact position in real-time through numerical simulation software. The electromagnetic servo excitation system executes motion commands and generates excitation to drive the pantograph collector. Although testing on existing lines is difficult, active pantographs also need to undergo extensive practical testing on HIL test benches before they can be further developed and promoted [38].

4 Emerging technologies: from UAV and fiber optic sensors to full-sensing monitoring systems

With the progress of science and technology, emerging technologies such as unmanned aircraft technology (UAV), fiber optic sensors (sensor networks, etc.), and pantograph active control technology have been developed rapidly. How to effectively integrate these technologies to build a more efficient electrified railroad pantograph-overhead catenary total sensory monitoring system is the next important research direction.

4.1 Emerging technologies

UAV technology has been widely applied to inspection tasks in various industrial fields due to its flexibility, such as power system inspection, geological exploration, firefighting search, and rescue. Among them, it is especially popularized in power transmission line inspection tasks. Liu et al [39] introduced an improved K-means++ algorithm in RetinaNet to align the Anchor to match the actual dimensions of the power line components such as towers, fixtures, insulators, etc. Zhao et al [40] applied K-means to cluster the visual shapes of objects. Then, shape semantics are generated to help faster RCNN detection and inspection of power line bolts. Miao et al [41] modified the fine-tuning strategy for insulator detection by inserting an intermediate fine-tuning stage that narrows the domain gap between the common and electrical tasks. The method smoothed the transfer process from ordinary tasks with large datasets to specific tasks with small datasets. Fortunately, the power transmission system is like the overhead catenary system, so these studies can provide ideas for pantograph inspection in electrified railroads.

The development of fiber optic sensor technology has revolutionized our daily life with a wide range of applications including physical sensors (temperature, pressure, vibration, etc.), gas sensors (NH_3, CO, NO_x, etc.), and automation (vehicles, doorway security, safety uses, etc.) [42]. Fiber optics sensors play a vital role in sensing because of their excellent inherent properties such as resistance to electromagnetic interference (EMI), large bandwidth, information security, and flexibility in sensor head design. In addition, fiber optic sensors are free from crosstalk problems, EMI problems, and the ability to develop multiple sensors on a single optical fiber to detect different signals such as temperature, pressure, strain, and vibration [43]. Liu et al [44] proposed a fiber optic-guided motorized rotary laser line scanning thermography (FMRLST) system aimed at rapidly detecting impact-damaged cracks in composite laminates of unknown orientation. Inspired by this, fiber-optic sensors can be implanted into pantograph equipment to monitor the "in-situ information" of the pantograph equipment all the time.

4.3 Electrified railway pantograph-catenary full-sensing intelligent monitoring system based on multi-source heterogeneous data fusion

As can be seen from the above, the 6C system suffers from the problems of limited monitoring perspectives and incomplete monitoring periods. Fortunately, UAVs can be deployed flexibly and perform monitoring tasks from different angles around the clock. In addition, the fiber optic sensing network can provide “in-situ information” of the pantograph equipment, which can provide more comprehensive detection information. Therefore, the integration of UAV aerial images and in-situ information from fiber-optic sensing network to optimize the existing 6C system is crucial for the development of future 6C systems. Data fusion technology is an effective solution to the above problems. However, the heterogeneous gap between 6C, UAV, and fiber optic data makes traditional data fusion methods difficult to apply. Deep learning-based methods are widely used in the field of data fusion due to their flexibility and efficiency in network design. Among them, how to simultaneously preserve the modal specificity and modal non-deformation of different data sources in the data fusion process is a key issue in fusing heterogeneous data. To this end, adversarial learning and distance metric constraint methods can be utilized to perform the extraction and fusion of modal invariance and modal specificity features for heterogeneous data from multiple sources. We have made some attempts to propose the following framework of cross-domain clustering fusion algorithm for multi-source heterogeneous data based on constrained hierarchical neural networks, as shown in Figure 5.

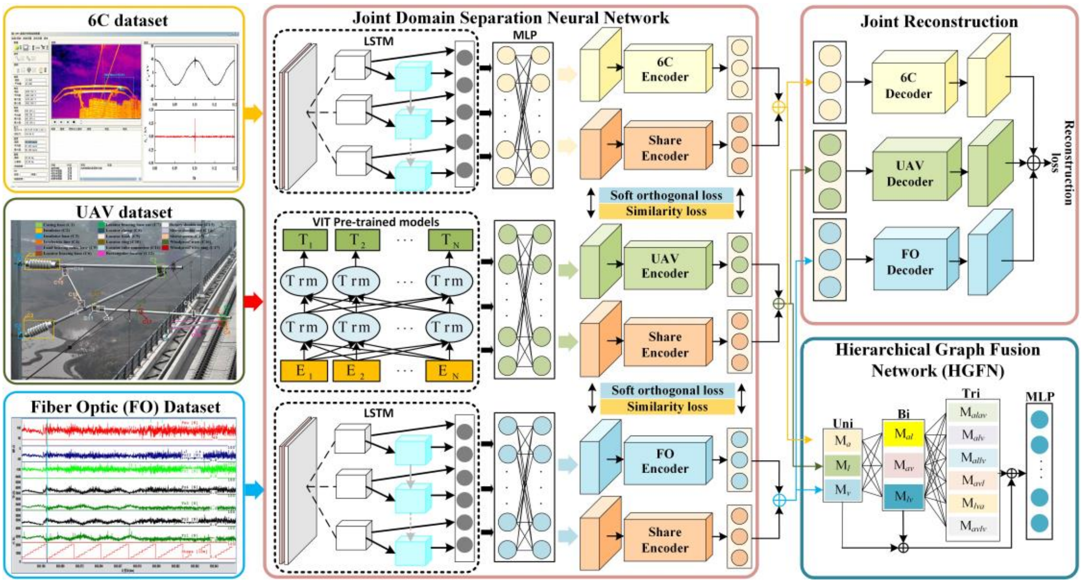

Figure 5. Fusion framework for multi-source heterogeneous data.

First, the data from different data (6C, UAV, and FO) are extracted by different neural networks, and then the modal specificity and modal invariance between different data modalities are extracted using constraints (soft orthogonality constraints, and similarity constraints). Finally, the modal invariance features and specificity features are inputted into a feature fusion network (e.g., a hierarchical graph fusion network) equipped with adaptive weighting capabilities to perform the fusion task. Further, the fused data are synchronized to the 6C data fusion center for further analysis [24].

5 Conclusion

This paper presents a brief review of the current research on catenary detection technology, active control technology for pantographs, and multi-source data fusion technology. Next, it gives a detailed introduction to the key equipment and technology of China’s high-speed railway pantograph-catenary automatic detection and monitoring system (6C system), including the Pantograph and Catenary Comprehensive Monitoring System (CPCM-1C), the Catenary Inspection Video Monitoring System (CCVM-2C), the Catenary Inspection Online Monitoring System (CCLM-3C), the High-Precision Catenary Inspection Monitoring System (CCHM-4C), the Pantograph and Catenary Video Monitoring System (CPVM-5C), and the Catenary and Power Supply Equipment Ground Monitoring System (CCGM-6C). Then, it introduces the active control technology for pantographs, the active control simulation platform, and proxy models. Finally, the research status of UAV technology and optical fiber sensing technology is introduced, and the outlook for a fully perceptive intelligent detection system for the pantograph-catenary system based on these two technologies and multi-source data fusion is presented. Specifically, in the future, combining the advantages of flexible deployment, scheduling, and shooting angles of UAVs with the all-time, comprehensive monitoring characteristics of the optical fiber sensing network to complement the deficiencies of the existing 6C system is an important means to optimize the intelligent monitoring system of electrified railways.

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