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# A Review in Automatic Visual Inspection for Railway Overhead Contact Line Systems based on Image Processing

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## ABSTRAK

Inspeksi sistem overhead catenary meliputi pemeriksaan pada geometri kawat kontak, interaksi antara kawat kontak dan pantograf, cacat pada komponen, komponen yang aus, dan jarak bebas sangat diperlukan untuk memastikan keandalan, ketersediaan, pemeliharaan keselamatan infrastruktur dan operasi kereta api. Teknologi inspeksi visual otomatis pada sistem overhead catenary dapat meningkatkan efisiensi, efektivitas biaya, dan presisi jika dibandingkan dengan metode inspeksi konvensional. Makalah ini memberikan gambaran umum dan kontribusi penelitian yang dilakukan oleh para ahli di bidang ini, serta aplikasi dan kemajuan teknologi inspeksi visual otomatis untuk sistem overhead catenary kereta api. Proyeksi arah penelitian di masa depan untuk sistem inspeksi otomatis dalam kegiatan inspeksi sistem catenary overhead juga akan dibahas.

*Kunci: Sistem Overhead Catenary, Inspeksi Kereta Api, Visi Komputer, Inspeksi Otomatis.*

## ABSTRACT

*Inspections of overhead catenary systems include checks on the geometry of contact wire, the interaction between contact wire and pantograph, defects in components, worn components, and clearance are necessary to ensure the reliability, availability, maintainability, and safety of railways infrastructure and operation. An automatic visual inspection technology of overhead catenary systems can improve conventional inspection methods' efficiency, cost-effectiveness, and precision. This paper provides an overview and contributions of the research made by scholars in this field, as well as the application and advancement of automated visual inspection technology for railway overhead catenary systems. The projection of the future research direction for automatic inspection in overhead catenary system inspection activities was also provided.*

*Keywords: Overhead Catenary Systems; Railway Inspection; Computer Vision; Automatic Inspection.*

## 1 INTRODUCTION

Overhead Contact Line System (OCS) transmits electric power from the traction substation to electric trains as the primary energy. Various types of OCS are implemented according to the operating system and its purpose, such as simple catenary, stitched catenary, compound catenary, and rigid catenary or conductor rail [1][2][3]. The growth of OCS networks worldwide is increasing rapidly. Their reliability, availability, maintainability, and safety must be maintained because degradation of the existing OCS network equipment due to continuous operations and exposure to environmental conditions will reduce performance over time [4][5]. Increasing inspection frequency is one way to maintain OCS reliability, but their availability will decrease due to frequent inspection activities [6]. Moreover, if inspections are conventionally performed, complications may arise due to the massive number of assets that should be inspected, driven maintenance costs, and some inspections may endanger workers. Some railway companies perform condition-based maintenance to maintain OCS performance as one of the solutions [7][8]. Furthermore, predictive maintenance can be performed after consistently collecting historical data from many inspection activities [9][10][11]. Therefore, an automatic inspection method based on computer vision is needed to enhance the maintenance methods mentioned.

Computer vision is a technology that can be utilized for non-contact measurement. Several studies on railway inspection using computer vision have been widely developed. Some authors have reviewed the use of computer vision for railway inspection purposes. Liu et al. summarized the use of image processing technology for detecting faults and defects in railway tracks, pantographs, catenary networks, train body parts, and infrastructure inspections such as stations, crossings, and tunnels [12]. Besides that, Gao et al. provide a general overview of the automatic detection and monitoring system for the pantograph and catenary system in China's high-speed railways. There are six types of inspection equipment and their applications, which are: (1C) comprehensive pantograph and catenary monitoring, (2C) catenary checking video monitoring, (3C) catenary checking online monitoring, (4C) high precision catenary checking monitoring, (5C) pantograph and catenary video monitoring, and (6C) ground monitoring for catenary and power supply equipment. This 6C system can identify potential defects and assess the pantograph and catenary system's operational efficacy to ensure safe operation [13][14].

Danijela et al. present a review analysis of obstacle detection and distance estimation techniques for railways. This discussion aims to reduce the number of collisions between trains and particular objects. The explanation focuses on the currently used sensors, particularly vision sensors, and categorizes the methods into traditional Computer Vision-based and Artificial Intelligence-based methods. Each classification entails three key aspects: (1) Rail track extraction, (2) Identifying obstacles on or near rail tracks, and (3) Estimating distances between onboard cameras and identified obstacles [15]. Although the discussion presented by the author is still about obstacles in the track area, there are still possibilities to be applied to the OCS system. Unlike before, Long et al. analyzed existing computer vision techniques focusing on two critical areas: measuring overhead contact wire parameters and identifying overhead contact wire conditions. The overhead contact wire geometry parameters can be precisely measured using methods based on stereo vision, except in particularly extreme conditions such as train motion caused by the sway, vibration, rotational angle on train body dynamics, and environment variation or complex background [4]. Then the next chapter will discuss in more detail the research progress in OCS inspection on railways.

A common setup camera is mounted on the rail vehicle roof or driver's cabin train to capture the object of inspection, such as the pantograph, OCS component, and state of the OCS line ahead. Various intelligent image recognition analyses will process the acquired image or video data to obtain the needed parameters and utilize some algorithms to identify abnormalities. Some methods have even pinpointed abnormal locations and automatically generated reports. Generally, to support the computer vision-based automatic inspection process, it uses equipment such as cameras, illumination, optical devices: filters and lenses, processing computers, communication interfaces, and mounting equipment. The differences in the specifications of the equipment installed must be adapted to meet the inspection requirement and the object to be inspected, including camera orientation, angles, and even image processing methods to achieve the best results and enable all weather conditions. Some studies on OCS inspection using computer vision may have pros and cons results that still need to be discussed, such as measurement accuracy, precision, robust detection method, and fast computing processes for online real-time control conditions that require improvement.

Study on the details specific to OCS inspection is still very limited. Thus, several methods regarding automatic visual inspection for railways OCS especially based on computer vision will be discussed in detail. This study aims to provide information on the development of OCS inspection, then insight into the most viable and frequently used methods to obtain good results depending on the object inspected and the software and hardware implemented so far.

## 2 RAILWAY OCS AND ITS INSPECTION

### 2.1 Object of OCS inspection

The OCS determines power traction supply performance. There are three main objects: OCS, pantograph, and the interaction between OCS and pantograph [5]. OCS inspections are normally performed to check: geometry parameters, supporting equipment, insulator, contact wire wear, wind deviation, abnormal fitting, foreign object, and the interaction between OCS and pantograph (contact force, arch, and collector strips) [16]. The current collection process requires maintaining the geometric parameters of the contact wire within specified limits. The geometry parameter constraint ensures that the contact point between the contact wire and the current collector remains in its proper position. So, this is the reason why the inspection of several aspects above is imperative.

The initial inspection object is the contact wire's geometry parameter (CGP). CGP is generally divided into stagger and height [17], creating risks if poorly maintained. The stagger of the contact wire refers to the lateral displacement of the wire point of contact from the rail track center. The stagger of contact wire is set up in a zigzag shape to prevent local wear on the current collector strip pantograph. The contact wire's stagger is also maintained to avoid exceeding lateral displacement from the permissible limits that can cause the contact wire not to be in its proper position. If the contact wire has excess stagger, it may lead to poor current conductivity, cause a spark over or arcs, and even break the contact wire. Besides, it is essential to maintain the contact wire's height to prevent contact loss. The contact wire's height refers to the vertical distance from the rail track's top surface to the contact wire's lower surface while measured perpendicularly. The contact loss of contact wire also may lead to poor conductivity. Conversely, if the contact wire's height is too low, it may lead to intense friction on the contact point and accelerate wear, causing arcs and even the pantograph to stop operating. An illustration of the CGP is shown in **Figure 1** - Contact wire’s height and pantograph interactions and **Figure 2** -Contact wire's stagger and contact point. The typical nominal CGP parameter for simple catenary is shown in **Table 1**.

The second inspection object is the OCS supporting equipment, which acts as a support structure that helps maintain the performance of the OCS. OCS support equipment includes various components such as insulators, pins, bolts, clamps, and tension fittings. The essential activity of this inspection is to recognize the type of component and its condition, for example, loosening or missing pins and bolts, broken clamp and tension fitting, fracture, or corroded insulator, deflection of arm and other supporting structure. This type of inspection is also often implemented to assess new installations.

The next inspection object is the sliding condition between the pantograph and the contact wire. Specifically, observe the interactions on the current collector strip of the pantograph and the contact wire when the train is running. Some phenomena that will occur during sliding are arcs, hot spots, and contact force. An electric arc is a current flow through an air gap between a contact strip and a contact wire, usually indicated by intense light emission. Arc occurs due to poor geometric adjustment and excessive friction, which was previously briefly explained, sometimes caused by improper static contact force, incorrectly set aerodynamics, and worn components [18].

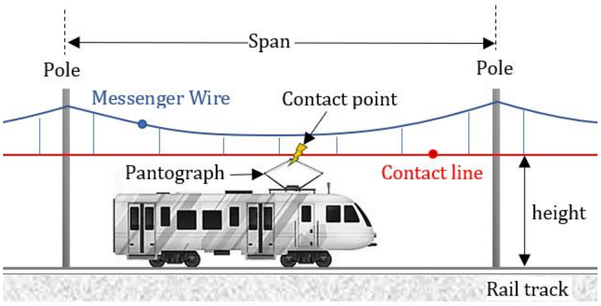

**Figure 1** Contact wire’s height and pantograph interactions.

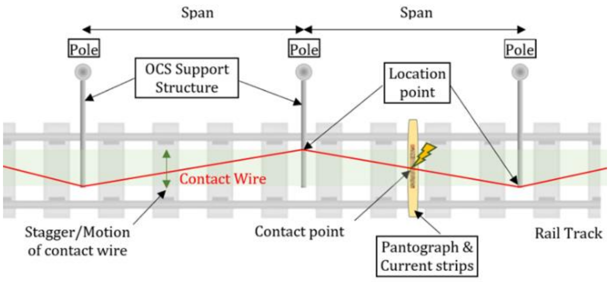

**Figure 2** Contact wire's stagger and contact point [19][20]

**Table 1** Nominal CGP parameter on simple type OCS [21]

| Simple Type Catenary Geometry Parameter | Nominal | Unit |
|---|---|---|
| Span length | 50-60 | m |
| Contact wire stagger (straight) | 200 | mm |
| Contact wire stagger (Curve) | 300 | mm |
| Contact wire height | 4.3 – 5.7 | m |
| Max. gradient | 6 | ‰ |
| Max. change in gradient | 3 | ‰ |

Midya et al. explained a comprehensive study of arcs and their mechanisms. They do laboratory-scale experiments to test many parameters that may cause arcs on the pantograph [22]. As well as the vertical force of the pantograph called the pantograph's contact force. The way to determine the presence of contact force is by measuring the sudden acceleration of vertical displacement on the pantograph, or it can also be by measuring the contact wire supporting structure uplift. Using a finite element model, Bai et al. analyzed the effect of contact wire design parameters such as contact wire span length, height, and tension on contact force at various speeds. The results show that the longer the span, the higher the contact force, and the lower the trolley wire tension, the higher the contact force. However, the difference in structure height has no significant effect on contact force [23].

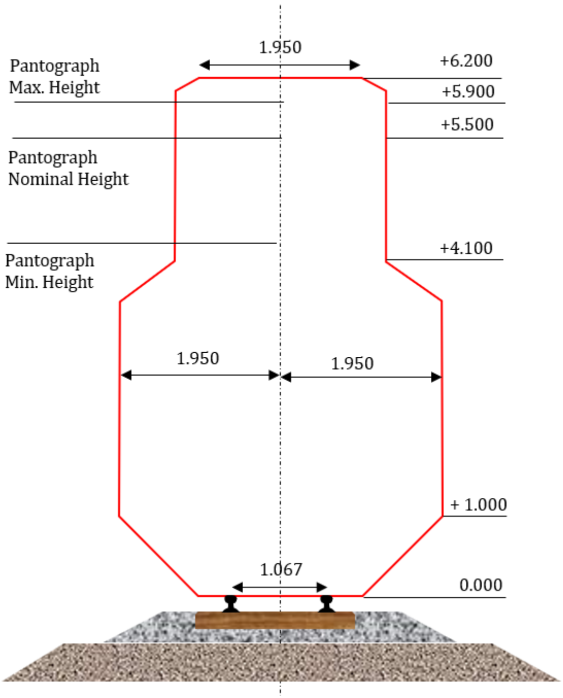

**Figure 3** Rollingstock clearance-narrow gauge [24]

The last inspection object is OCS's clearance and intrusion. OCS's clearance is the safe distance between live parts of contact lines and the supporting structures or rail vehicles. Sometimes the building structures from property development and some vegetation or tree branches around the railway track could interfere with train operations. Figure 3 describes the common clearance between vehicle and the environment.

## 2.2 Development of OCS Inspection

Utilizing measurement devices is integral to the pantograph and catenary inspection activities. Some traditional detection, contact detection, non-contact detection, and combined detection methods already provide many advantages. Conducting efficient, precise, real-time detection and monitoring to acquire accurate information regarding OCS operation is crucial to ensuring system safety. The resulting data can be used to perform maintenance and address any unfavorable conditions promptly. The development of pantograph and catenary detection has followed a progression of four different phases, as shown in Figure 4. Jing et al. have reviewed the various uses of inspection robots in the railway field. The sensors used are various, such as Computer vision, Digital Image Correlation, Ultrasonic, Laser-vision System and laser distance, Light Detection and Ranging (LiDAR), Accelerometer, thermal sensor, Eddy Current, Electromagnetic Acoustic Transducer (EMAT), and soon [25].

The conventional detection approach to identifying issues with pantograph and catenary relies on manual work. The inspector walks and utilizes insulated poles or so-called Hot-Sticks to measure the stagger and the height of the contact wire [17]. At the same time, the inspector checks the environmental conditions around the OCS. Some advantages of manual detection are that it offers greater versatility and enables the identification of diverse failure modes, but it suffers from low efficiency and inadequate security. Moreover, the long duration of conventional inspection shall be scheduled to not coincide with train operation time. Furthermore, subjective human factors can impact detection outcomes, such as the experience of the personnel involved.

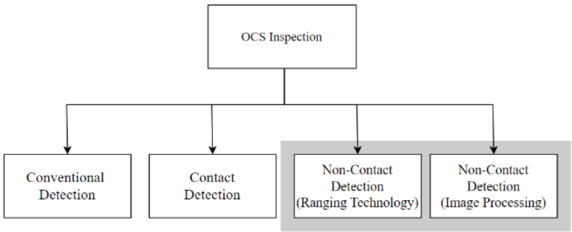

**Figure 4** Hierarchy of OCS inspection methods.

The contact detection method on inspection is to check the kinds of parameters using measurement equipment in direct contact with the pantograph or catenary. The contact detection method on inspection is to check the types of parameters using measurement equipment in direct contact with the pantograph or catenary. The contact detection method evolved with the advancement of railway electrification. Switch sensors mounted on the pantograph can detect stagger. For example, when the contact wire has excess stagger, the contact wire passes through the adjacent switch sensor. Then it emits a signal that can be used as information to calculate and measure the stagger value. Like stagger detection, a displacement sensor can detect the contact wire's height by detecting the tilt change. The variation in contact wire height will cause a difference in the angle of the pantograph's arm and the horizontal plane, which can help calculate and measure the height value [16].

Abdullah et al. conducted a laboratory experiment by creating a scale model to identify the performance of the dynamic interaction of contact wire and pantograph using load sensors and displacement sensors that combined with a laser to detect contact force. The data collected is used to trigger the actuator as active control of the pantograph [26]. Donnell and Sing et al. have developed an inspection system called PANDAS (Pantograph damage assessment system).

This module system is integrated into the pantograph to detect and monitor wear and damage that occurs [27]. Besides that, Marco et al. implement optical fiber sensors for strain measurement, enabling real-time monitoring to detect contact force. There are two types of fiber sensors, which are fiber brag gratings sensors (FBGs) and interferometric schemes[28][29]. Sung et al. conduct a study using a load cell and accelerometer to measure contact force on a pantograph by considering the aerodynamic lifting force [30]. The inspection system in the contact detection method is only able to detect one object. This method has some disadvantages in durability and operation safety due to poor temperature characteristics and unstable connectors of the sensors, so it is feared that it can interfere with the measurement results, and additional devices must be used if the inspection is needed for different objects. Therefore, non-contact methods were introduced.

Non-contact detection methods using ranging technology such as laser, infrared sensor, or camera and ultrasonic are kept advancing. Many non-contact detection methods have become widely employed for pantograph and catenary system detection. Peng et al. implement an optical system that employs the laser phase ranging technique to inspect contact wire gradients. This system will be installed on the low-voltage side of the locomotive top and measure the distance target on the pantograph [31]. Ötslund et al. propose a technique for condition-based maintenance of the pantograph current collector strip employing photodiodes. By establishing a relationship between the intensity of arc light, DC components, and the running distance, the wear of the current collector strip of the pantograph is well predicted and increases availability more than the previous method, which is limited to mileage intervals only [6].

Puschman et al. proposed the technology of measuring the lateral position of the trolley wire using ultrasonic and dedicated software called OVHWizard and FMA. This tool has a high accuracy compared to a laser, depending on the speed during measurement, but its weakness is that it cannot be further than 50 cm from the contact wire [32]. Non-contact measurement using ranging technology provides many advantages and guarantees detection activities with high efficiency and little traffic disruption. However, the simple features and lack of accuracy of the sensors, as well as the complicated data processing, require more working time for inspectors. Therefore, non-contact methods using camera technology were developed.

The latest is a non-contact detection method using image processing. Image processing technology has a remarkable impact on the automated visual examination of OCS. The inspected objects depend on the part of OCS that needs to be periodically checked. The image data acquired from the inspection will be processed in real-time or sent to the office to be analyzed offline. The automatic visual inspection of OCS requires stages such as (1) data acquisition by taking pictures of an object using a camera or video, (2) pre-processing by refining data or images adjustment, (3) segmentation by selecting the focused object, (4) feature extraction to take reference of the image for image matching, (4) object detection and object recognition by training or labeling the input data, (5) processing data to produce good qualitative or quantitative output as desired [33]. Researchers use specific methods to produce the desired output under different parameters and environments at each stage. For example, Ge et al. propose a computer vision system encompassing a modified version of faster R-CNN specific for the subway in real-time to inspect pantograph interaction. Their research findings indicate that their approach has achieved impressive results, with about 94.9% detection precision [34]. Successful image detection of OCS components such as pantographs is important for further inspection tools-based computer vision development. The next subsequent segment will discuss how researchers utilize computer vision technology on various objects on OCS inspection. Some recent research reviews have even used a combination of non-contact detection methods, both with audio and video as input, and use Deep Learning to detect defects in the field of railway maintenance [35][36].

## 3 METHOD AND REVIEW OF RAILWAY OCS INSPECTION BASED ON COMPUTER VISION

This review utilizes a narrative approach to present a synthesis of the latest knowledge related to automatic visual inspection of railway overhead contact systems based on image processing. The research integrates various relevant literature to provide a comprehensive overview of the technological advancements in this field. The literature selection process involved a thorough search across multiple academic databases using relevant keywords, and the chosen articles were evaluated based on their contribution and relevance to the discussed topic. Through this approach, we aim to offer a comprehensive understanding of how image processing technology has been used to enhance the efficiency and accuracy of railway overhead contact line inspections.

The general approach to computer vision is to make the computer equipment recognize an object and perform specific tasks according to the user's purpose. **Figure 5** shows the components of the computer vision system are a sensing device and interpreting device [37]. **Figure 6** shows how computer vision on railway OCS inspection conducted. **Figure 7** illustrates clearance detection using image processing that showing another method that applied on Railway OCS inspection. The importance of conducting inspections is the standard as a reference to avoid the subjectivity of the inspector, so the several types of inspection discussed earlier are regulated in BS EN 50317.

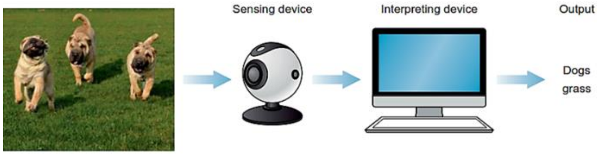

**Figure 5** Diagram of how computer vision generally works.

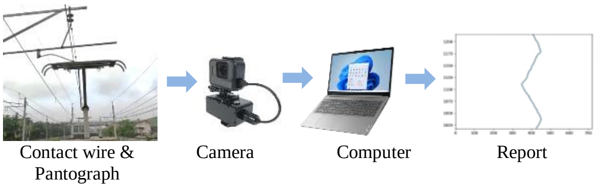

**Figure 6** Diagram of how computer vision measures stagger on contact wire

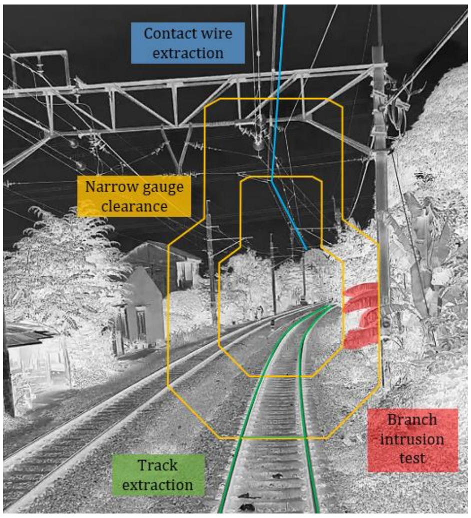

**Figure 7** Illustration of clearance inspection [38]

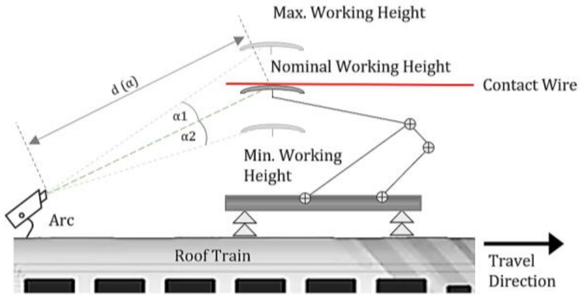

**Figure 8** Arcs Detector location on roof of vehicle BS EN 50317 [39]

**Figure 8** shows the installation of an inspection detector on the roof of a rail vehicle. Not all types of inspections in the railway OCS can be replaced using computer vision, such as detailed geometry measurements on cross-over equipment and power quality performance tests. However, most visual and measurement activities can be replaced by computer vision. The following sub-sections will review some measurement parameters that can be performed using computer vision.

### 3.1 Geometry Parameter Inspection

Aydin et al. successfully implemented some methods for monitoring anomalies on the pantograph and contact wire. They combined some methods, such as mean-shift for object tracking on contact wire [19]. In other research, they also apply a modified kernel-based method, blob analysis to detect arcs, and S-transform to detect irregularity of contact wire simultaneously. Gaussian mixture models (GMMs) are also used to detect the foreground in each frame [40]. Cho et al. propose a novel technique for the dynamic stagger of contact wires utilizing a video monitoring methodology. This approach addresses the limitations of traditional methods, which may result in significant inaccuracies when applied to tilting trains. They are adding feature-based image matching techniques such as the scale-invariant feature transform (SIFT) algorithm and gradient local affine invariant feature extraction (G-LAIFE) that are resilient to changes in camera viewpoint. The experimental video data was obtained from a camera placed on the roof of the Korean Tilting Train Express (TTX) and linked to the monitoring center within the train. Processing image data is currently employed offline, showing a correct detection rate of approximately 85% [41].

Stela et al. proposed an intelligent software application that can accurately determine the status of contact wires and perform maintenance work based on system-generated indications. The zigzag pattern was determined using a camera to capture geometry measurements and conducted using the NI MyRIO acquisition board [42]. The intelligent software application will analyze the measured data and provide two types of decisions: immediate interventions at locations where defects are detected, based on the most recent measurement, and predictions regarding the future development of contact wire conditions [43]. Liu et al. have developed a high-precision detection of catenary geometry parameters based on computer vision for electric railways. They utilize laser-emitted spotted images to determine the coordinates of the wire. The tracking and locating spotted image method used is particle swarm optimization - Generic particle filter algorithm (PSO-GPAF). Then added, the Kalman filter (KF) method was used as a correction factor from the geometry parameter values in the form of stagger and contact wire height that has been defined. The resulting judgment of root mean square error (RMSE) after correcting for contact wire height is 0.7 mm, and for stagger is 1.3 mm [20]. As previously, Zhan et al. used a binocular vision camera (BVC) integrated with a line scan camera (LSC). The method used is based on a 1-D target combined with a 1-D displacement platform and adding a vibration compensation method (MDOF) to reduce the vibration error of the vehicle. The resulting judgment of root mean square error (RMSE) for contact wire height is 1.5 mm, and for stagger is 2.20 mm [44].

Huang et al. proposed a novel method for detecting contact points (CPD) between the pantograph and catenary with complex infrared images with high accuracy. The method comprises three primary elements: (1) separating single input called horizontal-vertical enhancement (HVE) approach to be two model outputs, (2) the vertical output model for point detection of the pantograph, and (3) the horizontal output model for point detection of the contact wire. Then both components were detected using improved random sample consensus (RANSAC) to obtain their contact points. All infrared data for this study were obtained from the CRH2A electric multiple unit (EMU) at the Nanchang Passenger Transport Section. The proposed scheme is efficient and robust, with an average pixel error of 0.48 and an average accuracy of 99.6% in two datasets comprising 12,000 frames. Explicit recognition of the point of contact plays a significant role in monitoring the operation of EMU trains [45]. Zang et al. present a robust method for monitoring the condition of pantograph and catenary interaction based on a combined deep convolutional network with modified features to enhance the stability of contact point detection in the presence of complex backgrounds, such as messenger wire, portal structure, vegetation, tunnel environments with cloud, glare, and other complex backgrounds. The modified features are the deep pantograph detection network (DPDN) and the deep pantograph segmentation network (DPSN). The proposed method achieved outstanding results with a segmentation performance of about 90.2% mIoU and 5.5% error detection [46].

### 3.2 OCS Component Defect Detection

The number of catenary component image databases is important for training machine learning. Wang et al. completed a database of catenary components for visual inspection during construction encompassing diverse catenary components, defect types, and inspection time conditions. Some defects were deliberately pre-made, and a total image was taken as many as 21024 images or 87.1 kilometers equivalent. Eighteen high-resolution cameras were installed on a catenary ladder in various viewing directions during the day and night conditions. Of course, the data can be used as training for automatic visual inspection when the OCS is already operating in the future [47]. Liu et al. have introduced a method to detect fastener defects on catenary support devices based on computer vision. The method consists of three stages: (1) localize the joint of catenary supporting structures using single shot multi-box detector (SSD) framework, (2) localize the fasteners using You Only Look Once (YOLO) as a classifier, (3) diagnose a defect of fasteners using deep convolutional neural networks (DCNNs). Some fasteners, such as two screws, puller bolts, α-pin, β-pin, and nut, were successfully detected. The experiment data was taken by XLN4C-01 imaging inspection vehicle during the night, and the proposed DCNNs have achieved an impressive accuracy of 92.78 mAP. This method was also successfully applied for contact point detection [48][49]. Gao et al. present a novel system for detecting defects on insulator surfaces. This basic system employs some methods such as faster R-CNN to localize the main component containing the insulator, supervised deep material classifier (DMC), and unsupervised deep denoising autoencoder (DDAE) to classifier the score of anomalies. The data set used in this study consists of approximately 18,000 images taken by KCIS-01 catenary inspection vehicle during the night and processed offline. The experiment features TensorFlow deep learning framework, and the results achieved an F1 score of 0.95 [50]. Ding et al. propose a catenary defect detection algorithm for high-speed railways. The method consists of pixel region cutting and tilt correction as pre-processing image, faster and mask R-CNN to localized object detection, and using gradient, texture, and grey feature fusion (GTGFF) and K-means clustering analysis model to detect the defects such as broken insulators, foreign bodies, dirt, and flashovers. The insulator defect detection algorithm was evaluated using 1500 isolator image datasets taken by an inspection vehicle and demonstrated exceptional results, achieving a Recall of 99.0% and a Precision of 92.5% [51].

### 3.3 Contact Force and Arcs Detection

The interaction between the pantograph and the contact wire in the OCS is inseparable. When an arc occurs, excess or lack of contact force can be one of the causes. Landi et al. utilized a thermo-camera to facilitate the monitoring of pantographs from overheating and arcs. They also combine cany edge, and Hough transform methods to detect irregularity of contact wires, as discussed before [52][53]. Koyama et al. present a novel approach to quantify contact force using a line sensor camera (LCS). The pantograph panhead is marked by black strips to notice the vertical displacement. The vertical displacement can be determined with normalized cross-correlation (NCC) as pattern matching. Additional equipment, such as load cells and illumination, is also necessary to verify this method. The experimental findings showed good results, with a measurement accuracy of 91.5% [54]. Aydin et al. presented a method to maintain contact force between the catenary system and the pantograph by managing the height of the pantograph. They applied the canny edge detection algorithm and Hough transform to detect the height of the running pantograph. The experiment was processed in MATLAB Simulink and was suitable to simulate the vertical movement of the active control of the pantograph in real-time operation requirements [55]. Another way that Aydin et al. do. They propose methods to detect pantographs and arcs using a firefly optimization algorithm, integral image, and Haar-like feature as fitness detection functions. Based on the findings, the firefly-based method has achieved a satisfactory detection performance, with an accuracy rate of around 96%, which is suitable for practical purposes. The method is observed in the laboratory but could be effectively implemented in real-time scenarios [56]. Arthington et al. utilized an onboard camera to detect contact force. The method works by detecting two markers mounted on the outer side of the pantograph that travels up and down according to the trajectory. Dynamic pantograph modeling is required to perform force estimation, and the results are optimized again using a Kalman filter to reduce noise. The resulting output is quite good, approaching the actual force [57]. Karakose et al. presented a novel approach employing Deep Learning based on Convolutional Neural Network (CNN) for detecting arc. They applied the five pooling layers architecture of CNN in this method. Remarkably the experimental findings demonstrate significant accuracy results, with 97% of the arc area correctly identified [58].

### 3.4 Clearance and Intrusion Detection

Moller et al. describe a method to detect catenary obstacles using a tri-ocular camera sensor system. The catenary obstacle detected consists of wooden knots, plastic film, crime acts, and defective components such as down hanging, ripped-off droppers, bonding, and broken insulator. This method aims to retract the pantograph immediately after an obstacle is detected to avoid pantograph damage. Three progressive scan cameras record the scene with zooming lenses to capture the scene about eighty meters ahead of the train. An algorithm based on Helmholtz shears is employed to detect contact wire. In order to acquire the operating speed of the train within 120-330 km/h, the transfer rate data requires 30 Mbytes / sec. This proposed method results in 80% corrected detection of an obstacle [59]. The illustration of pantograph clearance intrusion is shown in Error! Reference source not found.. Wu et al. proposed a method to detect bird nests. They employed a novel framework as follows: (1) adaptive binarization, (2) trunk/branch detection, (3) hovering point detection, (4) streak extraction, and (5) pattern learning. They also utilized the histogram of the orientation of streaks (HOS) to capture the distributions of orientations and the histogram length of streaks (HLS) to the distances of detected twig streaks. The patterns of bird nests are learned with SVM. The proposed method has been evaluated, and the results have shown promising performance with a precision of 35.82% and a recall of 91.06%. The intrusion of bird nests is illustrated in **Figure 10** [60]. Tian et al. proposed a method of object detection in the railway environment that aims to improve the safety of railway operations. The method used is Variable focus multi-scale augmentation (VCMF) with functions to detect objects at various scales. Then the feature extraction and fusion neural network architecture using CentreNet (FFCN) serves to improve object detection abilities. This method was tested using the PASCAL VOC2007 database and obtained an 81% mAP score[61].

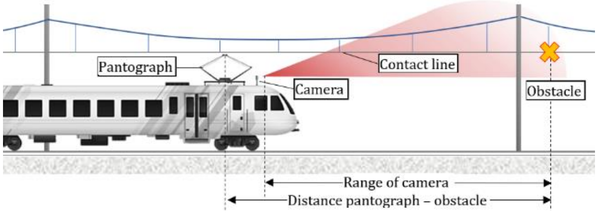

**Figure 9** OCS's obstacle detection [59].

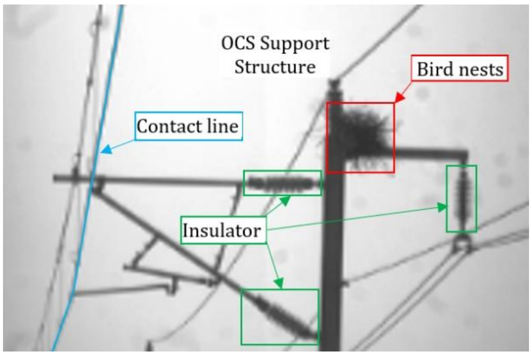

**Figure 10** Bird nests detection on OCS [60].

## 4 DISCUSSION

Based on several articles we reviewed, we have compared the advantages and disadvantages of conventional methods versus camera-based methods as shown in the Table 2.

Table 2 **Comparation of Advantages and Disadvantages between Conventional Inspection**

| Aspect | Conventional Method | Computer Vision Method |
|---|---|---|
| Advantages | Simplicity: Straightforward implementation [25] | Efficiency: Quick inspection of large areas |
| | Cost-Effective: Lower initial investment [25] | Consistency: Standardized inspection criteria [25] |
| | Reliability: Established procedures and protocols | Detail and Precision: High-resolution imaging for detailed analysis [62] |
| | Human Judgment: Nuanced decision-making based on experience | Safety: Reduces human exposure to hazards [63] [64] [25] |
| Disadvantages | Time-Consuming: Slow and labor-intensive [65][64] | Initial Cost: Investment in high-quality cameras and systems [60][8] |
| | Subjectivity: Variable results depending on inspector's skill and fatigue [65] | Technical Expertise: Specialized knowledge required [66] |
| | Limited Accessibility: Difficult to inspect hard-to-reach areas [60] | Data Management: Needs robust storage and processing capabilities [62][67] |
| | Safety Risks: Potential hazards for inspectors in dangerous environments | Initial Setup: Time-consuming calibration and setup [62] [68] |

## 5 CONCLUSIONS

OCS inspection methods continue to evolve as technology develops. Inspection with traditional methods that are very simple requires much inspection time and endangers the inspectors requiring more effective methods such as contact measurement methods. Contact measurement methods are often less reliable and endanger railway operations, so non-contact methods are developed using ranging technology and cameras. Researchers sometimes combine non-contact methods for specific purposes, such as accuracy improvement and self-calibration. Computer vision has the potential capability to detect objects and can be utilized mainly in any OCS inspection activities. Sometimes additional or modified methods are required depending on the inspection object type to obtain promising results. Each method has advantages and disadvantages depending on the parameters of the object to be measured. The challenge in the future is to improve the shortcomings of the methods that have been implemented, especially in accuracy, precision, computation time cost, robust detection on more complex backgrounds, and faster computing. This challenge is needed to fill real-time online measurements to speed up the inspection process significantly. Computer vision measurement methods will evolve as computer vision algorithms and hardware features advance.

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