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TOPICAL REVIEW

Applications of Machine Vision in Coal Mine Fully Mechanized Tunneling Faces: A Review

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ABSTRACT The realization of intelligent mining is the only method for realizing high-quality development in the coal industry. As the forefront working link in mine production, achieving automatic roadway tunneling control is key to improving production efficiency, enhancing intelligence, and reducing accident rates at fully mechanized tunneling working faces. Among various detection techniques, machine vision technology stands out with advantages of non-contact measurement, rich information acquisition, and high detection accuracy. The detection and control of tunneling equipment groups based on machine vision has become a research hotspot in the intelligence process of coal mines. This study first introduces the key technologies of a visual detection system, including camera calibration, image preprocessing, feature extraction, visual matching, target segmentation and recognition, visual measurement, and 3D reconstruction. It then elaborates on detection principles, workflows, limitations, precautions, and development status of various vision detection systems in practical application scenarios at tunneling faces, such as tunneling equipments, anchoring systems, transportation systems, and safety auxiliary systems, which significantly improve production safety and efficiency. Finally, considering challenging work conditions and strong interference in mines, the successful adaptation of machine vision to excavation sites relies on addressing technical challenges related to poor environment adaptability, limited imaging field of view, and low intelligence level. Furthermore, according to existing research results and the current technical status, this paper forecasts key technologies that need to be developed in the future for coal mine intelligent equipment systems based on machine vision, including multi-sensor information fusion, equipment group collaborative control, and digital twin-driven remote monitoring.

INDEX TERMS Machine vision, coal machinery equipment, detection and measurement, roadway fully mechanized tunneling faces, unmanned coal mine.

I. INTRODUCTION

According to the ''Global Energy Data'' published by the International Energy Agency, global coal production experienced a strong rebound of 6% in 2021 and a marginal increase of 0.9% in 2022, after a decline of 5.3% in 2020 due to the impact of Covid-19, which continues to supply approximately a quarter of the world's primary energy and over a third of its electricity [1]. As an indispensable energy source for industrial development, coal possesses advantages such as abundant reserves, high carbon content, convenient usability, and low cost compared to other energy sources. Despite the accelerated construction of clean and low-carbon energy systems in many countries, coal has maintained an irreplaceable core position in the energy structure for a significant period of time.

Throughout the entire coal production process, there are two main procedures: tunneling and coal mining. The tunneling procedure takes place at the tunneling face, marking the initial phase of mine excavation. It encompasses activities

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such as drilling, blasting, and excavation to establish underground tunnels and chambers, thereby creating pathways and areas for subsequent coal mining operations. The coal mining procedure takes place at the coal mining face and encompasses the extraction, loading, and transportation of coal from the coal seam within the excavated region. Coal mining is contingent upon tunneling, and tunneling, in turn, facilitates the coal mining process.

The automation level of mining technology and equipment is directly related to the efficiency and safety of mine production. Currently, the coal mining procedures has transitioned into an era of unmanned and automated working faces. However, the level of tunneling technology, equipment, and mechanization has significantly lagged behind that of coal mining. According to an investigation, in China, the largest consumer and importer of coal in 2022, the mechanization degree of mining faces all over the country has reached more than 85%, which exceeds the number of tunneling faces by 25% [2]. Consequently, the average monthly tunneling progress across the nation remains within 300 meters, with the required workforce for the tunneling process being approximately 3.1 times that of the coal mining personnel. Due to the outdated tunneling equipment and techniques, the pace of tunnel advancement fails to match the normal demands of coal mining. The resulting phenomenon of slow tunneling and rapid mining has given rise to the challenge of ''mining and excavation imbalance'', significantly hampering coal production efficiency. Moreover, these issues primarily stem from the constrained workspace and intricate operational procedures of the underground tunneling face, and the complexities in harmonizing ''tunneling, anchoring, supporting, and transportation'' activities. According to incomplete statistics, in the tunneling process, the time spent on anchorage maintenance is 2-3 times longer than that of cutting [3]. The anchorage speed has become the key factor limiting the roadway construction progress. Evidently, as a poor safety, heavy task, and low-automaticity working scene in the coal mine production, the technical indicators and intelligence degree of the fully mechanized tunneling face underground is urgently necessary to be advanced to meet the needs of safe and efficient mining.

With the rapid development of visual sensing, image processing, artificial intelligence, and other technologies, the application of computer vision to mine production processes has become a new trend in the development of intelligent mines. As early as 1992, Hurteau [4] and colleagues developed an optical detector using an industrial camera and artificial visual technology to measure the position deviation of a mining vehicle relative to the planned line. Since then, several machine vision systems had been developed and evaluated for safe and efficient coal mine production. With the excellent characteristics of non-contact sensing, multilevel information fusion, high-speed modeling and calculation, machine vision technology can commendably meet the requirements of a large production range, uninterrupted working, and timely feedback during mine production. To objectively reflect the application status, the number of selected publications per year was obtained by searching strings ''computer vision'' AND ''mining'' in the *Web of Science* database from 1998 to 2022 [5]. From the bar graph shown in Fig.1, it can be clearly seen that an increasing number of experts and scholars worldwide have paid serious attention to the application of machine vision technology in the field of coal mines in the last 25 years. In particular, the number of related studies has increased significantly since 2019. Owing to the development of pattern recognition and artificial intelligence technology, the application of machine vision technology in underground coal mines has gradually expanded from initial security and protection monitoring to position detection of coal mining equipment, target recognition, fault detection, three-dimensional (3D) scene reconstruction, safety monitoring, and many other aspects [6], [7].

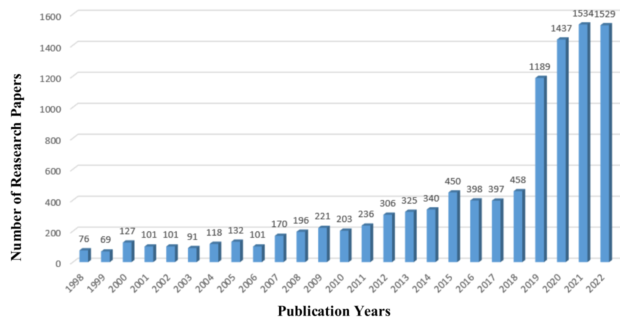


FIGURE 1. The number of selected publications per year in the last 25 years [5].

While numerous articles discuss the utilization of machine vision technology in mining, there remains a notable scarcity of comprehensive review papers in this field. As demonstrated in Table 1, existing review literatures cover a diverse range of applications, including mining rescue robots [9], underground autonomous driving [14], mineral processing [8], [12], and the identification and localization of mining equipment [11], [13], etc. However, there is a lack of systematic literature that specifically outlines the application of vision technology in a specific underground scenario, particularly in the domain of mechanized tunneling faces. Therefore, this paper endeavors to bridge this research gap. Through a meticulous exposition of relevant technologies, principles, workflows, and the prevailing challenges, it offers a comprehensive panorama and a profound comprehension to drive further research within this particular domain. The primary objectives of this review paper are as follows:

- Offer an in-depth introduction to the key technologies of visual detection systems designed for fully mechanized tunneling faces.
- Concentrate on clarifying the application principles and workflow of visual technologies within coal mine tunneling systems in recent years.

TABLE 1. Review studies related to machine vision applications in mining.

Literature	Year	Repository	Key words	Applications
S. Qin[8]	2023	MDPI	Image processing; CiteSpace; Mining; Visualization; Cocitation analysis theory; Path-finding network algorithm	Ore sorting; Particle-size detection; Mineral flotation.
G. Zhai[9]	2020	IEEE	Coal mine rescue robots; Binocular vision; Camera calibration; Stereo vision matching	Coal mine rescue robots.
M. Imam[10]	2023	MDPI	Anti-collision systems; Collision avoidance; Pedestrian detection; Underground mines; Computer vision; Deep learning; Artificial intelligence	Anti-collision systems for pedestrian detection in underground mines.
Y. Cui[11]	2021	SciELO	Coal mining; Underground positioning and navigation; Integrated navigation strategy; Inertial navigation; Positioning algorithms	Positioning and navigation of underground mining equipment and personnel.
J.T. McCoy[12]	2019	ScienceDirect	Machine learning; Artificial intelligence; Machine vision; Fault detection and diagnosis; Data-based modelling	Minerals processing: Sizing and sorting of particles and ore fragments; Flotation froth monitoring.
J. Ralston[13]	2014	ScienceDirect	Mining automation; Longwall mining; Longwall automation steering committee; Interoperability; Inertial navigation; Coal seam sensing	Longwall shearer localization; Coal seam spatial geometry.
M. Wang[14]	2022	MDPI	Mine unmanned driving; Perception; Positioning; Path planning; Vehicle control; Multi-vehicle scheduling	Mine unmanned driving: Personnel, equipment, and object recognition; Driverless vehicles positioning; Vision SLAM.
J. Shahmoradi[15]	2020	MDPI	Drones; Remote sensing; Surface mining; Underground mining; Abandoned mining	Geotechnical characterization recognition; Rock size distribution analysis; Mine rescue mission.

- Analyze various challenges and technical issues encountered during the underground on-site application of visual technologies.
- Highlight new directions that need to be emphasized for the future development of intelligent equipment systems in coal mines based on machine vision.

II. VISION SENSORS AND VISUAL ALGORITHMS IN COAL MINE FULLY MECHANIZED TUNNELING FACES

Machine vision technology plays a crucial role in intelligent roadway excavation. It utilizes explosion-proof cameras as information acquisition equipment and images as carriers to accomplish the identification and positioning of target objects through various operative algorithms, offering advantages such as easy installation, abundant information, and non-contact measurement.

A. VISION SENSORS

Vision sensors are essential components of a visual detection system. The quality of the acquired images depends on the system's hardware and environmental conditions. Image quality also determines the difficulty of late feature extraction and the detection accuracy of measured variables. In challenging underground coal mine environments, it is crucial to optimize the machine vision system using various strategies. These include designing a rational image acquisition scheme, selecting appropriate camera parameters, and compensating for illumination using artificial lighting. Commonly used vision sensors in underground coal mines can be classified into monocular cameras, binocular cameras, multi-camera vision systems, and structured light cameras. Table 2 provides an overview of their specific principles and applications of these different camera types.

1) MONOCULAR CAMERAS

The monocular vision system captures images based on the pinhole imaging model. Compared to other vision systems, it offers the advantages of a simple structure, low cost, and ease of calibration and identification. Furthermore, it also serves as the foundation for other types of visual systems, incorporating additional structures and measurement steps.

In fully mechanical tunneling operations, monocular cameras are commonly used for object recognition [16], pose detection [17], environmental monitoring [18], equipment condition detection [19], etc. However, a single camera is unable to extract 3D information from a single image. When employed for spatial pose measurements, it must be combined with other measuring devices or sensors [20]. Additionally, thermal cameras, distinct from visible light ones, utilize the principle of infrared thermal radiation to capture thermal images, thereby offering more valuable information for environmental monitoring.

2) BINOCULAR CAMERAS

The binocular stereo vision system consists of two monocular cameras. It mimics the optical parallax of human eyes to obtain depth information of objects. By comparing the images collected simultaneously by two cameras, it generates the parallax map of the target point based on the differences between the left and right imaging surfaces, and further calculates the spatial depth information of the point, which can be flexibly applied to various stereometric scenes.

Compared to the monocular system, the binocular system offers a straightforward approach to acquiring the spatial 3D coordinates of feature points. It has demonstrated significant experience and achievements in underground applications, such as target identification and positioning [21], parameter measurement [22], and 3D scene space reconstruction [23].

TABLE 2. Principle and application of different vision sensors.

Vision sensors	Principle	Advantages	Disadvantages	Applications underground
Monocular camera	Based on the pinhole imaging theory, it determines the depth information according to the scale invariance.	Simple structure; low cost; easy to be calibrated and identified.	The real size of the object cannot be determined in a single image.	Pose and position measurement, equipment condition detection and fault diagnosis, automated navigation and path planning, environmental monitoring and assessment, etc.
Binocular camera	Composed of two monocular cameras, it estimates the pixel spatial location on the basis of the triangulation principle.	Depth information can be easily obtained; can be used for indoor and outdoor; the measurement range increases with the baseline distance.	Complex configuration and calibration process; large amount of calculation; the depth range and measurement accuracy are limited by the baseline and resolution.	Stereo scene reconstruction, obstacle detection and avoidance, distance measurement and scale estimation, robot navigation and autonomous localization, etc.
Multi-camera vision system	Composed of multi-cameras, it obtains multiple views images and reconstructed spatial information based on the binocular measurement principle.	Obtaining rich information, it solves the matching polysemy problem with high matching and positioning accuracy.	More cumbersome configuration and calibration process; more complex matching algorithm; larger amount of calculation; worse real-time.	Multi-object tracking, trajectory prediction, parameter measurement, 3D reconstruction, etc.
Structured light camera	Composed of a camera and a projection device, it measures the distance according to the principle of TOF (Time of Flight) by transmitting and receiving structured light.	It can directly acquire RGB images and depth images with high measurement accuracy.	Narrow measurement range; large noise; easy to be disturbed by sunlight; unable to measure the infrared transmission material, mainly used indoors.	Tunnel morphology measurement, mining vehicle obstacle avoidance, pedestrian detection, coal flow monitoring, simultaneous localization and mapping (SLAM), etc.

Nevertheless, the confined space in coal mine roadways significantly constrains the practicality of binocular systems. There is still room for improvement in system calibration accuracy, stereo matching effectiveness, 3D reconstruction precision, and real-time performance.

3) MULTI-CAMERA VISION SYSTEM

Multi-camera vision system, also known as multi-view stereo imaging, is based on the principle of binocular measurement. It involves employing multiple cameras (often triple-eye cameras) to capture several images of the same target scene from different viewpoints and subsequently reconstructing the 3D information of the scene. This approach effectively expands the visual system's field of view. Moravec et al. [24] initially studied this system at Stanford University in 1980, where he developed a mechanical swivel "slider" to obtain multiple views for the visual navigation of the "Stanford Cart".

In underground coal mines, the application of multi-cameras primarily focuses on geometric parameter measurement [25], roadway 3D reconstruction [26], trajectory prediction [27], object surface reconstruction [28], etc. Multi-camera vision imaging offers abundant and high-precision information, making it especially well-suited for large-scale spatial 3D measurements. However, its calibration process and structural configuration are more complex than that of binocular systems [29], and its real-time performance is relatively lower. During practical implementation, it is crucial to consider the spatial constraints in underground scenes and strategically position the cameras to achieve optimal results.

4) STRUCTURED LIGHT CAMERAS

Structured light imaging belongs to the category of active measurement technology. By projecting specific light patterns or gratings onto the measured object and measuring the modulated light, structured light cameras can acquire the object's depth and 3D shape information with fast speed, high accuracy, and non-contact nature [30].

However, compared to other visual sensors, the utilization of structured light underground is relatively limited. Existing applications include obstacle avoidance for mining vehicles [31], pedestrian detection [32], SLAM [33], navigation and positioning [9], parameter measurement [34], and coal block morphology measurement [35]. Nevertheless, after several decades of development, structured light systems still have certain limitations, particularly in measuring complex surface shapes, highly reflective objects, and real-time measurements of dynamic objects.

B. MACHINE VISION ALGORITHMS

1) CAMERA CALIBRATION

Camera calibration refers to the process of determining the internal and external parameters of a camera by utilizing specific targets or scene characteristics. This allows for the mapping of the stereo space to the plane image [36]. The calibration methods for binocular cameras, multi-camera systems, and depth camera systems are all based on that of the monocular camera. Depending on the requirements of reference objects, existing monocular calibration methods can be divided into traditional calibration methods [37], self-calibration methods [38], and active calibration methods [39].

In recent years, with the widespread application of intelligent vision technology in mines, the structure and calibration methods of underground vision systems also require corresponding design and adjustments to adapt to the challenging mining environment [40]. For instance, plane explosion-proof glasses and optical ball covers are commonly employed to

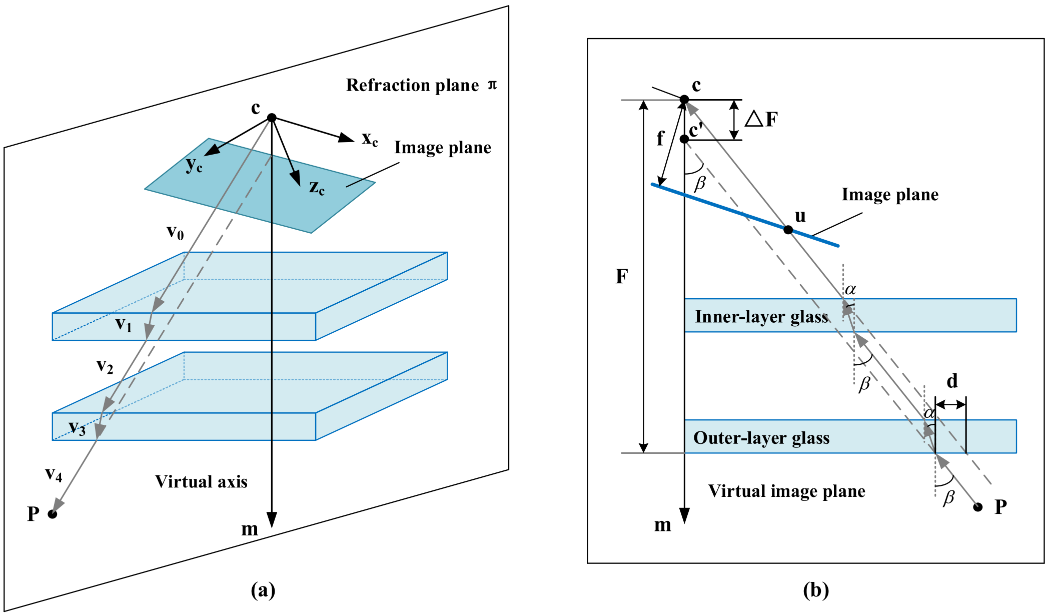


FIGURE 2. **(a) The entire light-path lies on the same plane of π. (b) The projective geometry in the refractive plane [41].**

protect the visual imaging system from dust and spray at the heading face. To address the impact of optical devices on the visual imaging system, Yang et al. [41] conducted a study on the refraction mechanisms of two glass types, as depicted in Fig. 2. They proposed corresponding noncentral refraction camera modeling and calibration methods based on a geometric-driven single-view mining camera imaging model. This approach realized the glass refraction correction of the mining camera and significantly improved the accuracy of the underground visual measurement system.

When designing a visual measurement system for the cutting head position, Zhang et al. [42] discovered that existing external parameter calibration methods often required swing the cutting arm to the middle position of the roadheader, relying on the operator's experience, which led to inaccuracies and potential fluctuations in the calibration results. To address this issue, they proposed an external calibration method based on multiple fixed points. In this method, the cutting arm was controlled to swing to the upper left, upper right, lower left, and lower right corners to capture target images at these four known limiting positions. Experimental results demonstrate that this approach effectively enhances the stability and precision of the calibrated external parameters.

2) IMAGE PREPROCESSING

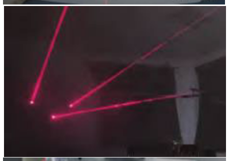
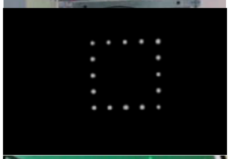
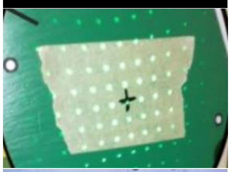
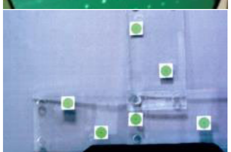
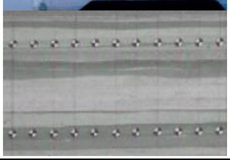
In the challenging environment of an underground complex coal mine, ensuring the quality of images captured by vision sensors becomes difficult due to factors such as high coal dust concentration, low illumination, and strong vibrations. Consequently, images obtained in such mines require additional preprocessing operations compared to a normal environment, aiming to eliminate interference information and enhance the salient features. Commonly used preprocessing operations include histogram equalization, image denoising, image enhancement, and frequency domain filtering. In underground engineering applications, numerous experts and scholars have proposed specific preprocessing methods according to the characteristics of actual captured images and the feature information that needs to be extracted.

In order to address the issues related to uneven illumination, unclear details, and poor contrast in coal mine images caused by large artificial light sources, Du et al. [43] put forward an edge feature detection method based on the Retinex theory and wavelet multiscale product after spectral analysis of low-illumination images. In addition, during image acquisition, camera vibrations may lead to inaccurate or even incorrect measurement results. To compensate for these deviations, Yang et al. [44] proposed an underground camera nonuniform blur model by researching the change in the imaging optical path under the influence of vibration. Furthermore, to mitigate the high-concentration coal dust interference, based on a detailed analysis of the visual characteristics in mines, Cui et al. [45] used four evaluation indices - *Energy of Gradient*, *Variance*, *Information Entropy*, and *Volhths* - to truly and objectively evaluate the image sharpness of five dehazing algorithms. It was concluded that the CLAHE algorithm exhibited the best dehazing effect in actual coal mine scenes.

3) FEATURE EXTRACTION

Feature extraction can compress image information by creating feature vectors, which plays a crucial role in image recognition. Commonly used features for visual recognition include color, texture, and shape [46]. However, underground

TABLE 3. Application examples of feature extraction underground.

References	Captured images	Artificial sources	Extracted features	Procedures for acquiring geometric parameters
Y. Du[21]		Artificial target with circular marks; Crossing laser sources	Circular-shaped patterns; Vertical intersection lines	Extracting circle center through edge points averaging; Straight line detection using Hough transform; Calculating the intersection of lines.
W. Yang[44]		Point laser sources	Laser spots; Laser beams	Extracting spot central point through gray values-based Gaussian fitting; Straight line detection using Hough transform.
Z. Huang[47]		Instruction laser	Laser spots	Extracting spot central point through morphological operations.
C. Zhang[48]		Infrared LEDs target	LEDs spots	Extracting spot central point through gray values-based Gaussian fitting; Linear fitting with the least square method; Calculating the intersection of lines.
P. Cheluszka[49]		Projected marker grid; Artificial middle cross marker	Circular-shaped patterns; Cross pattern	Morphological operations for marker segmentation and labeling; Geometric measurement for distortion determination.
C. Gan [50]		Artificial circular marks	Circular-shaped patterns	Color-based threshold segmentation; Extracting pattern centers with image moments.
J. Xu[51]		Artificial circular diagonal markers	Circular diagonal patterns	Elliptic fitting for the marker identification; Extracting marker central point based on the gray level distribution.

images possess distinct characteristics compared to aboveground images. For example, artificial lighting typically used underground causes the collected image illumination to be low and uneven. The presence of pseudo-edges caused by such illumination further complicates the extraction of meaningful features. In addition, symbolic objects in tunnels, such as the roadway wall surface and coal rock, often exhibit irregular geometric structures and inconspicuous texture characteristics. Consequently, these features prove difficult to utilize for target identification and positioning in later stages. As a result, extraction algorithms based solely on color or texture are not suitable for underground environments.

In mines, shape and geometric features, such as points, lines, and multi-feature fusion, are commonly used for visual measurement. Existing underground feature extraction approaches typically rely on artificial characteristics, including laser points, laser lines, straight lines, circles, and intersection points. With the aid of appropriate targets and light sources, easily extracted points or line features, and the established parameter solution model, feature extraction and target positioning can be smoothly completed with high detection accuracy and reliability. Table 3 provides some actual examples of underground artificial feature extraction. Compared to the natural features in mines, these artificial geometric features are easier to extract, and helpful for later parameter acquisition and target positionings.

4) VISION MATCHING

The function of the vision-matching algorithm is to identify and align the target in different pictures to determine its spatial position. It has been widely utilized in various fields such as target identification, navigation and positioning, and multicamera registration. There are three main types of vision matching algorithms based on the feature information to be matched: grayscale-based, transformation domain-based, and image feature-based algorithms [52].

Compared to the other two methods, the image feature-based matching method requires the least amount of information and offers faster matching speed. It uses the points, lines, angles, edges, or other easily obtained features to complete the recognition and matching of target objects in different images with high accuracy and low complexity. Due to these advantages, it has also been widely applied in mines. In the process of the roadheader cutting head position, [53] improved the MVM algorithm with skipping and multiple matching penalties for the binocular system, so that the algorithm can not only complete the multiple (one-to-many or many-to-one) mapping but also skip existing outliers in the matching sequence. As a result, it addresses the issue of mismatching caused by the deformation of the same contour from different perspectives. To realize stereo-vision matching for a coal mine rescue robot, He et al. [54] proposed an improved census algorithm by converting the original image into a census image, which achieved a good balance in terms of resource occupancy, processing speed, and matching accuracy. During the roadway panoramic map acquisition procedure, to improve the image registration accuracy and splicing effect, [55] employed the AANAP (Adaptive As-Natural-As-Possible) algorithm to align and stitch the images.

5) TARGET SEGMENTATION AND RECOGNITION

Target segmentation and recognition technology is also an important technique for realizing visual detection. Based on vision matching technology, it obtains space information of the target object or point through the recognition of image features extracted by various visual processing algorithms. In recent years, remarkable advancements have been achieved in the field of object recognition in complex mining environments, all due to the adoption of deep learning-based algorithms [56]. Representative models include R-CNN (Convolutional Neural Network), Faster R-CNN [57], SSD, YOLO, and GoogleNet [58].

For instance, after employing the depth-wise separable convolution method to reduce the parameter count in the SSD algorithm, [59] identified and detected possible foreign bodies in the process of coal mine belt transportation, which effectively avoided the damage of foreign bodies to the belt and reduced economic loss. Similarly, [60] and [61] improved YOLOX and YOLOv5, respectively, for foreign objects recognition on coal mine belt conveyors. Additionally, to address the problem that traditional tunnel boring machine (TBM) cutters cannot be automatically replaced by robots, [62] proposed a cutter feature recognition and extraction algorithm based on YOLO-SIFT. Reference [63] presented a DL scheme to assist the navigation of Micro Aerial Vehicles by using a CNN, which can be further utilized as a supervised image classifier that has the ability to process the image frames from a single on-board camera and to prevent mine tunnel wall collisions. The above recognition algorithms based on deep learning have greatly improved the recognition accuracy and efficiency of targets in various complex images, and have also become current research hotspots and frontiers.

6) VISUAL MEASUREMENTS AND 3D RECONSTRUCTION

During fully mechanized roadway tunneling, the realizations of many construction procedures are inseparable from the distance information (depth) acquisition, such as roadway construction according to the preset path, automatic and accurate formation of roadway sections, IIID reconstruction of unstructured environment, personnel localization, and target object positioning [64]. As shown in Fig. 3, 3D vision reconstruction technology can be classified into passive and active visual measurements, depending on the presence or absence of projection sources during the measurement process. Passive methods include monocular vision, binocular vision, and multi-vision. The active ones mainly refer to structural-light measurements. By eliminating the need for physical contact with the measured object, many defects in the contact measurement can be effectively avoided. Hence, active visual measurements have been widely used in ranging, obstacle avoidance, positioning, 3D reconstruction, and other fields underground.

During 3D reconstruction, the quality of point cloud data acquisition and processing determines the final space reconstruction effect. Recently, the research focus has shifted towards addressing outlier and mismatching points, aiming to improve point cloud registration accuracy and obtain dense point clouds within a high-precision world coordinate system. Noteworthy methods, such as Clustering Views for Multi-view Stereo(CMVS) [65] and Patch-based Multi-view Stereo(PMVS) [66], can transform estimated sparse point clouds into denser ones, which significantly improves the modeling effect and makes the models resemble real scenes more closely. For example, [26] demonstrated a rapid photogrammetric reconstruction method for tunnels using a 360-degree camera positioned at 27 locations. They reconstructed a 3D model of a tunnel section in an Underground Research Laboratory in Finland using Structure-from-Motion Multi-View Stereo (SfM-MVS) photogrammetry. Similarly, Zhang et al. [67] proposed a dense reconstruction method for tunnels using deep learning and double-line parallel photography techniques, which overcomes the limitations of conventional photography methods not having enough venues to lay the baseline in a narrow environment.

III. APPLICATIONS AND STATUS OF MACHINE VISION IN COAL MINE FULLY MECHANIZED TUNNELING FACES

In the entire coal mine production process, fully mechanized roadway excavation stands at the forefront. It represents the most challenging and high-risk stage of production. Achieving intelligent and precise tunneling construction is an essential step towards efficient unmanned mining and aligns with the ongoing trend of technological advancements. Additionally, the tunnel fully mechanization is a systematic project

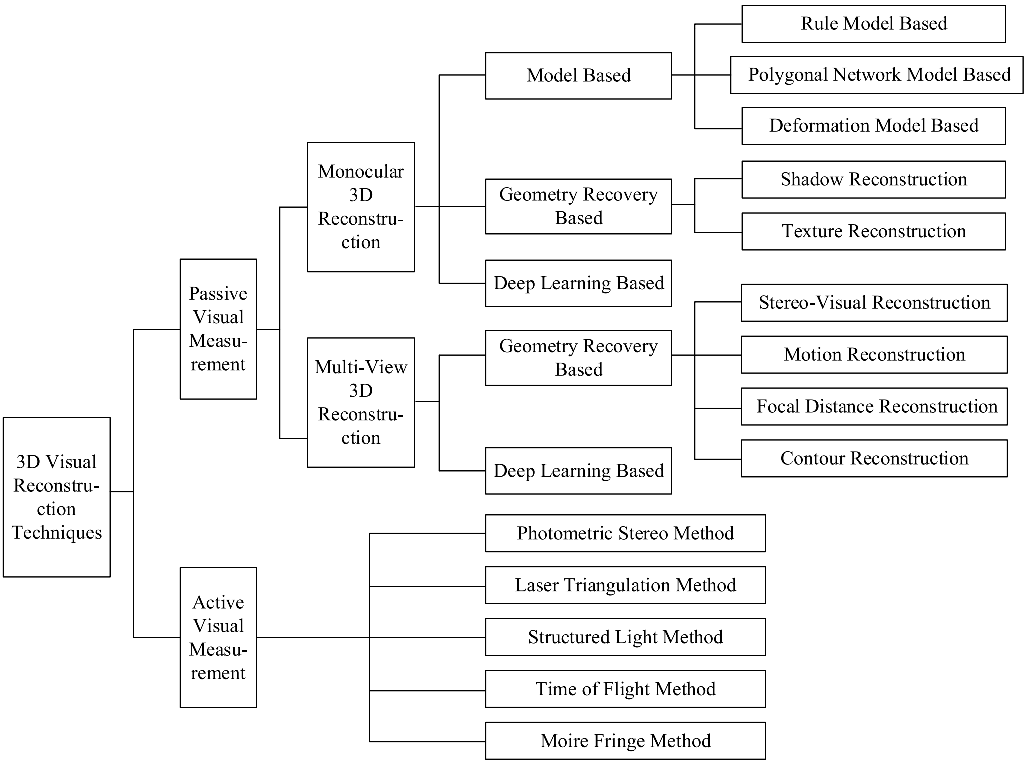


FIGURE 3. Classification of 3D visual measurement methods [64].

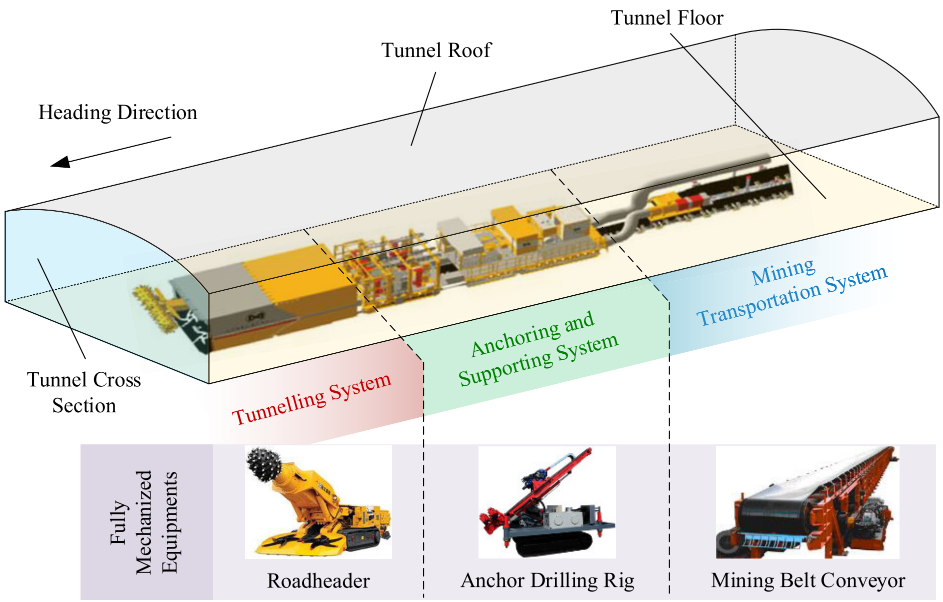


FIGURE 4. System composition of coal mine tunneling face and a part of fully mechanized equipments [own development].

that takes the roadheader as the key equipment and fuses multiple functions, including excavation, anchor protection, transportation, and dust removal. Through the coordinated efforts of various mechanized equipment, it becomes possible to achieve continuous, balanced, and efficient coal production.

As presented in Fig. 4, the tunneling face predominantly encompasses three significant systems: the tunneling system, the anchoring and supporting system, and the transportation system [68]. The primary function of the tunneling system lies in employing specialized equipment like boom-type roadheader for executing cutting operations along pre-established

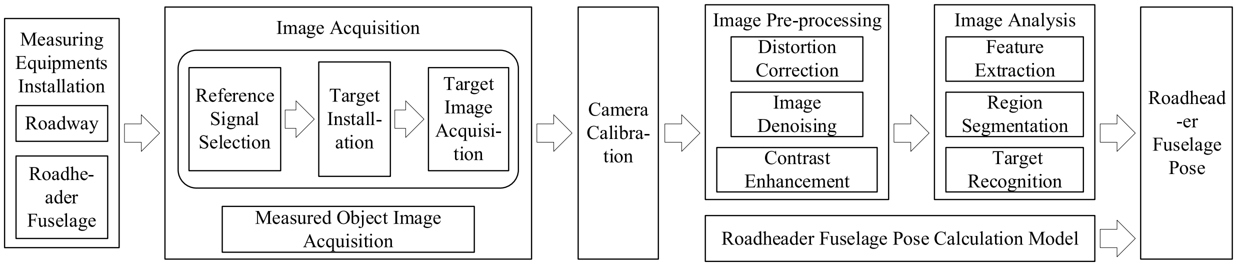


FIGURE 5. **Schematic diagram of roadheader position based on machine vision technology [own development].**

paths, thereby forming tunnels or chambers. The anchoring and supporting system concentrates on implementing support technologies like rock bolts, steel sets, and shotcrete, to ensure the stability and safety of the excavated space, preventing potential roof falls or sidewall accidents. Responsible for the efficient movement of coal and other materials within the tunneling face, the transportation system employs mechanisms like conveyor belts and shuttle cars. As can be seen from the above figure, realizing the cooperative operation of "tunneling-supporting-transportation" is of great significance for improving overall tunneling efficiency. Furthermore, the application of machine vision technology in fully mechanized tunneling faces necessitates the design of appropriate visual systems that cater to diverse detection requirements, in combination with the equipment structure, detected object characteristics, measurement parameters, environmental factors, and more. Therefore, this section introduces the current development status of machine vision technology in fully mechanized tunneling faces from four different application scenarios: tunneling equipment, bolt supporting system, transfer and transportation system, and safety assistant system.

A. BOOM-TYPE ROADHEADER

A boom-type roadheader is a fully mechanized tunneling machinery that incorporates various functions, including independent walking, coal rock cutting, loading and transportation, and spray dust control. As a crucial equipment for roadway tunneling, its performance significantly impacts tunneling efficiency and driving footage.

During the construction operations of a boom-type roadheader, the walking mechanism propels the crawler to push the body forward, while the cutting mechanism adjusts the cutting head's position using hydraulic cylinders. By coordinating these actions, the cutting head can perform drilling operations. Consequently, achieving automatic roadway section cutting in accordance with the requirements necessitates resolving the spatial pose perception of the roadheader's body and the location of its cutting head. Currently, the utilization of machine vision technology in boom-type roadheaders predominantly focuses on these two aspects [69].

1) ROADHEADER BODY VISUAL DETECTION

Real-time and automatic detection of the roadheader body pose is an urgent problem to be solved in intelligent mining. Existing detection methods, such as those based on total station measurements, inertial sensors, and radio waves [70], are vulnerable to adverse environmental factors encountered underground. In the past decade, machine vision technology has emerged as a viable solution due to its non-contact nature, real-time performance, and ability to acquire comprehensive information. As a result, it has been widely adopted for roadheader fuselage positioning [71]. A schematic diagram of the roadheader position based on machine vision technology is as shown in Fig. 5.

As indicated above, the measuring equipment used for image acquisition should be installed and fixed on the roadway roof or the fuselage in accordance with the principle of roadheader body pose positioning. Depending on the captured image's content, existing methods can be categorized into direct and indirect measurement schemes. In the direct scheme, an image of the measured object is acquired directly. On the other hand, the indirect scheme can only collect the target image (not the measured object) after completing the reference-signal selection and target installation. Once the image is collected, it undergoes preprocessing following vision system calibration, including distortion correction, image denoising, contrast enhancement, and other operations. Subsequently, image feature analysis takes place, involving tasks like feature extraction, region segmentation, and target recognition. Finally, by combining the established roadheader fuselage pose calculation model, the fuselage's pose parameters are determined. Key technologies employed in this process include image denoising, image enhancement, feature detection and recognition, and the pose calculation model building based on the camera projection. According to the number of vision sensors, the current roadheader pose detection techniques utilizing machine vision can be categorized as monocular or binocular.

The monocular measurement scheme uses a single camera to capture mine images during the detection process. After camera calibration, image processing, and other necessary operations, the roadheader's real-time six degrees-of-freedom pose parameters in the tunnel space can be determined when combined with the established fuselage

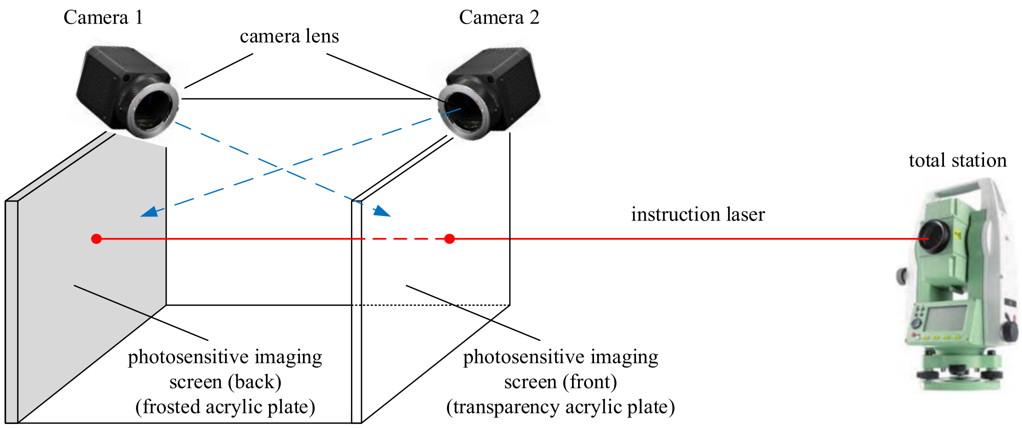


FIGURE 6. **Dual camera target structure and posture detection principle [47].**

posture solution strategy. For instance, Chi et al. [72] installed a chessboard target at the rear of a tunneling machine to capture the laser ray from the starting point. The offset of the machine can be calculated by segmenting the target markers and laser spot in a single monocular image and detecting their coordinates. In addition, the team led by Professor Xuhui Zhang at Xi'an University of Science and Technology [73], [74] utilized the monocular visual measurement principle and laser point-line characteristics to construct different types of roadheader position solution models. To address the issue of unsharp images captured by fixed-focus lens cameras at varying working distances, the authors of [75] used an autofocus camera to ensure image sharpness at any distance. Then, they proposed a multiscale variational autoencoder-aided convolutional neural network model to estimate the current poses of the tunneling machine, which was robust to different camera intrinsic parameters and did not require access to camera parameters.

Compared to the monocular system, depth feature information can be obtained more easily in the binocular stereo-visual system. In addition to calibrating the internal parameters of each camera, the acquisition of external parameters for the binocular system and stereo vision matching must be completed prior to body positioning. The calibration accuracy and matching effectiveness of these two key technologies significantly impact the positioning accuracy and 3D reconstruction precision [9]. In a study by [21], two cameras were used to capture double cross-lasers projected onto left and right laser targets. By setting up a machine body position calculation model and employing space matrix transformation, it achieved the real-time automatic machine pose detection. Although this method employed two cameras, it does not strictly qualify as a binocular system. By analyzing laser spots projected by the total station in two images and performing Euler angle calculation, the method proposed in [47] successfully measures the machine's spatial deviation for guidance. Fig.6 illustrates the measurement setup, comprising two cameras and two photosensitive imaging screens installed in opposite directions. In [48], a binocular system was fixed on the roadheader with a lens directed toward the afterbody, which was convenient for capturing images of the infrared-led targets behind the fuselage. To overcome the limited distance of binocular vision measurement, a dual-target moving measurement strategy was designed to realize continuous and uninterrupted measurements.

In addition, RGB-D (red, green, blue, and depth) cameras offer advantages over monocular and binocular cameras as they are unaffected by ambient lighting changes and textures. Using active ranging technology, the authors in [76] collected environmental data with an airborne RGB-D camera and constructed the RANSAC+ICP model for autonomous pose measurement, which can effectively solve the difficult positioning and orientation problem of roadheaders in a restricted space.

When it comes to target positioning, identification, and tracking, the single-source measurement scheme suffers from certain drawbacks, including low accuracy, low credibility, time lag, weak robustness, and limited measurement dimension. In contrast, the multi-source combined measurement and positioning scheme often yields better results [77]. As a result, experts and scholars worldwide have been exploring the integration of visual sensors with other types of sensors to achieve multisensor combination positioning of the roadheader body. Some examples include visual/inertial combinations [45], [78], [79], visual/lidar combinations [76], visual/infrared combinations [17], [80], and visual/inertial/lidar combinations [9]. These combinations aim to leverage the strengths of different sensors to enhance the overall positioning performance and address the limitations associated with single-source measurements.

Different visual position measurement systems adopt specific techniques and projection models based on their requirements and the nature of the measurements. In current researches, various types of visual position measurement systems exist. In addition to the image-processing algorithm, the key technology lies in establishing the pose calculation

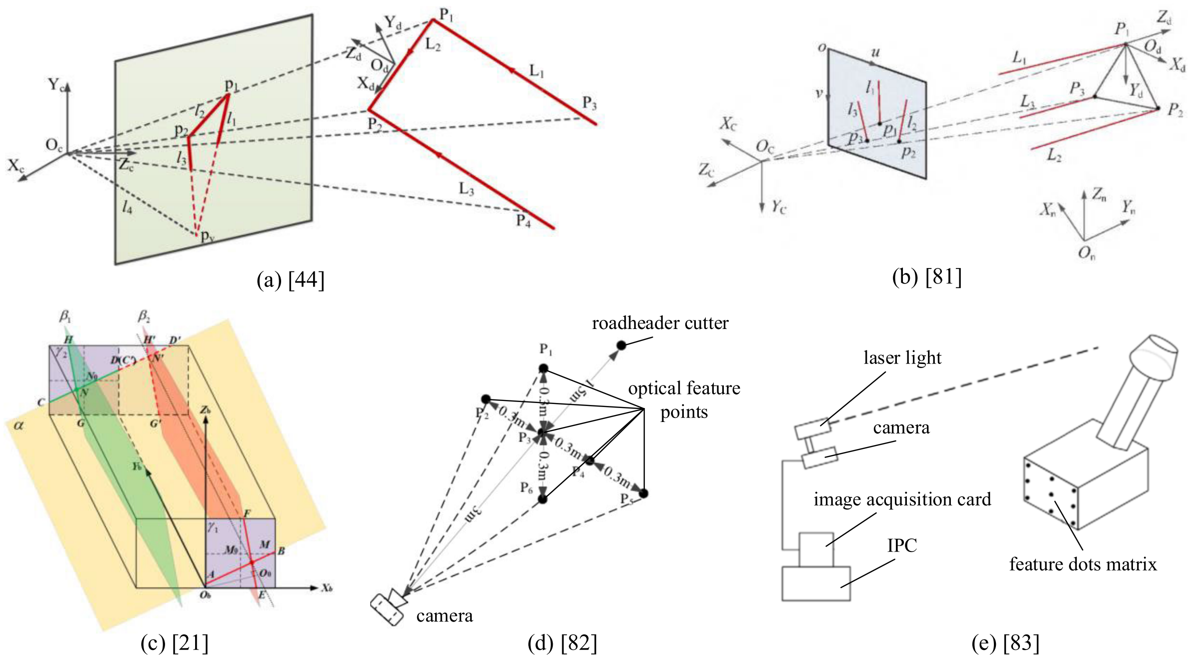


FIGURE 7. **Perspective projection models for the roadheader pose detection in different literatures.**

model. As depicted in Fig. 7, different optical systems use different perspective projection models for the parameter measurements. The contents of the collected images also vary. According to statistics, the images collected by existing roadheader body pose measurement systems include targets with light sources, targets receiving laser projection, line lasers, and point lasers (projected onto the lane wall).

In Fig. 7 (a), Pro. Zhang's team fixed two laser-pointing instruments parallel to the roof of a roadway [44]. By constructing a monocular visual position measurement model called 2P3L (two-points-three-lines) for a dynamic target in a coal mine based on the characteristics of laser points and lines, they calculated the position and attitude parameters of the boom-type roadheader fuselage. However, maintaining the parallelism of the two laser beams during the measurement process is challenging in actual underground projects. Additionally, the external parameter calibration process for the visual system is complex and difficult. Therefore, there is a need to further improve positioning accuracy and stability through algorithm optimization. Building upon previous research, [81] constructed a three-point three-line (3P3L) pose estimation model (shown in Fig. 7 (b)) utilizing three line-lasers as positioning references. By segmenting and extracting laser beam dot-line features, they effectively improved the accuracy and stability of the system. In addition to point lasers, line lasers are also frequently used references in mines. Fig. 7 (c) illustrates two cross-lasers in different colors (red and green) as positioning references [21]. The system captures the coordinates of ten characteristic points projected by the cross lasers on the double targets to obtain the fuselage position through coordinate transformation. When a target with light sources is affixed to the measured object, the position of the moving object can be obtained from the target position using coordinate transformation. On the basis of back shield pose in real time, [82] measured the position and orientation between the front and back shields of a double-shield universal compact TBM by designing a spatial distribution model consisting of six crossing optical characteristic points (as shown in Fig. 7 (d)). Similarly, as the first roadheader visual positioning model (Fig. 7 (e)), the model in [83] consisted of a 3 × 3 feature-dot light source matrix (the light target) mounted at the fuselage afterbody, which belongs to the passive measurement mode. In practical applications, the above models should also be robust enough to handle mining vibrations, dense dust, and low-illumination environments underground [45].

On the working surface of a coal mine roadway excavation, the real-time position perception of boom-type roadheaders serves as the foundation for unmanned fully mechanized tunneling. Accurate positioning of the fuselage enables various operations and research to be conducted, including real-time positioning of the cutting-head, roadheader trajectory planning, path tracking [76], [84], and simultaneous localization and mapping (SLAM) [33], [80]. These capabilities are essential for efficient and effective excavation processes in coal mine roadways.

2) CUTTING HEAD VISUAL DETECTION

The ultimate operational goal of the boom-type roadheader is to ensure that the roadway section can be cut off and formed precisely in accordance with the predetermined trajectory. The cutting process involves the roadheader body rotation

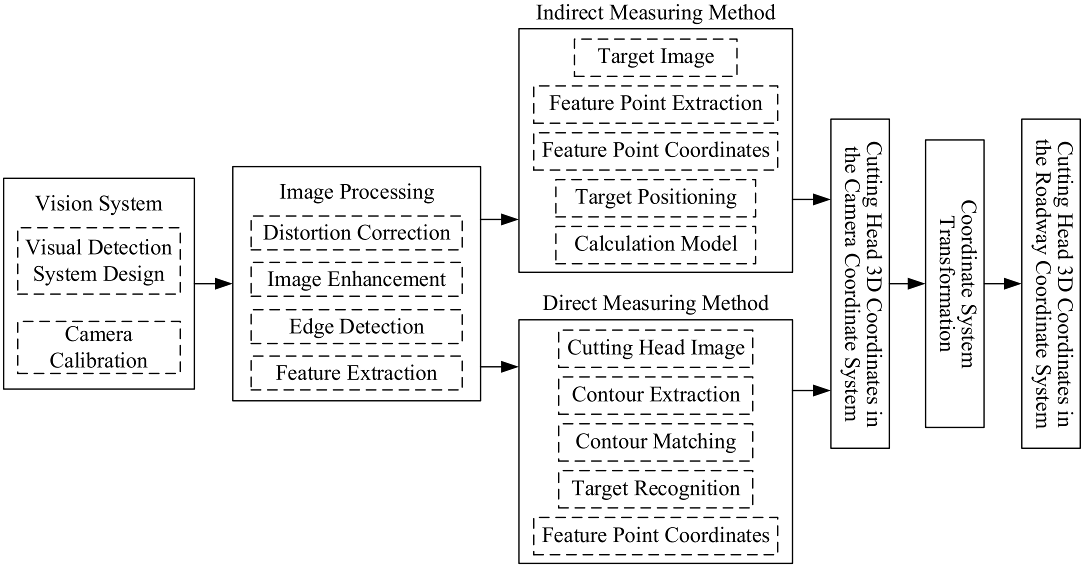


FIGURE 8. **Schematic diagram of roadheader cutting head position based on machine vision technology [own development].**

and the all-direction turning of the cutting arm, which collectively shape the cutting section of the tunnel. Therefore, it is necessary to accurately measure the cutting head position and realize the local positioning of mining equipment, even under complex working conditions. It is of great significance to improve the section-forming quality and tunneling efficiency of the roadway. Fortunately, many existing visual detection techniques for cutting mechanisms have also focused on this field.

Existing methods can be classified into contact and non-contact ones. In the contact measurement method, various sensors are installed on the cutting arm, such as inertial, inclination, and cylinder displacement sensors. It has been widely used and has shown promising application results. However, it is susceptible to device vibrations and other harsh underground working conditions, which can lead to data instability or sensor failure [85], [86]. Among non-contact measurement methods, visual systems are the most prominent. As early as 2003, to avoid cost-intensive corrections at the customer site, [87] developed a vision measurement system for testing the cutting profile of roadheaders during the final stages of machine assembly at the manufacturer's facility. The visual-based system does not require any structural modifications to the roadheader, but only needs to install a camera in an appropriate position to obtain cutting head images, which exhibits strong adaptability to the harsh environment, with high accuracy and low cost. It is particularly significant for numerous boom-type roadheaders that are already in service. Fig. 8 illustrates a schematic diagram of the vision-based roadheader cutting head positioning system.

Furthermore, according to the target objects in the camera's field of view, visual-based cutting-head positioning techniques can be divided into direct measurement and indirect measurement. Direct measurement directly collects the cutting head image and determine its position in real time without the need for additional equipment. As an illustration, [53] employed matching algorithms to directly discern the outline of the cutting head. Through binocular camera disparities calculation and coordinate transformations, they successfully achieved real-time and precise positioning of the cutting head within the roadway coordinate system. However, during tunnel excavation, the cutting head often becomes indistinguishable from background elements, substantially intensifying the recognition challenge. By contrast, indirect measurement relies on a reference object, such as a target, installed on the cutting mechanism. It obtains the real-time position of the cutting head indirectly by calculating the relative pose between the camera and the reference object. The method in [17] utilized an infrared LED rectangular target mounted on the roadheader cutting arm to address low-illumination, high-dust, and complex background conditions. By collecting the image of the square infrared dot array on the target through a monocular camera, it can obtain the attitude angles of the cutting head using the pre-constructed calculation model. Nevertheless, there are various types of roadheader, which may not provide a suitable position for infrared target installation. In addition, the target may be occluded during the measurement process. Therefore, it is necessary to adjust the target installation position according to the actual roadheader structure in practical applications.

To improve the efficiency and quality of roadway tunneling, after the cutting mechanism positioning, many other advanced technologies are employed to realize the automatic formation of coal mine roadway sections, such as cutting trajectory planning [88], servo control, and digital twin. In the European Commission-supported research project "Advance drivage and roadheading intelligent systems (ADRIS, 2007-2010)" [89], an automatic cutting path planning algorithm was proposed based on real-time coal rock identification using laser scanners. Cheluszka et al. [90] from the Silesian University of Technology, Poland, discussed the concept of automatic control for the cutting head movement of a boom-type roadheader, which can reduce the cutting energy consumption and improve the machine's dynamic performance. The team led by Prof. Xuhui Zhang introduced several notable contributions in this field, such as the visual servo cutting control system for the cantilever roadheader [91], the digital twin-driven remote automatic formation and cutting control [92], and the automatic cutting speed control system [93]. These studies can provide an inspiration for the monitoring and control of underground roadway tunneling.

In addition to cutting head pose detection, machine vision has various other applications in roadheader cutting mechanisms. In an underground potash mine near Barcelona, Spain [94], researchers employed visual techniques to analyze rock structures. This approach enables the automatic mining of rocks with varying hardness. In [61], a TBM cutter-changing robot was designed using binocular visual recognition and positioning. In Poland, extensive research has been conducted on the application of machine vision technology in roadheader cutting institutions. For instance, [95] discussed the possibility of utilizing a stereovision system to calculate the distance between the pick holder base and the roadheader cutting head side surface. Similarly, [49] and [96] presented a method for detecting the side surface shape of the cutting head. They also determined the boom [97] and cutting head [98] vibrations of the roadheader during cutting based on an analysis of the time-lapse pictures of the recorded footage obtained from high-speed cameras using dedicated TEMA 3D software. The aforementioned studies significantly contribute to enhancing the intelligence level of tunneling equipment and enabling automatic mining of underground roadways.

B. ANCHORING AND SUPPORTING SYSTEM

In addition to roadway excavation, roadway support is also a crucial technique in underground coal-mining engineering. As depicted in Fig. 9, the current coal roadway supporting methods encompass both passive and active supporting techniques [99]. Among various methods, the bolt-supporting system is the most widely used one at present, accounting for over 60% of the proportion in China. In some coal mines, this proportion has even exceeded 90% [100]. The bolt support involves several operation steps, such as net-lapping, steel belt installation, drilling, anchoring agent loading, and bolt nut pre-tightening. Among them, many require manual operation, which reduces support efficiency and significantly restricts the speed of roadway tunneling. Therefore, improving the automation of coal mine support operations is an important task in the coal mine intelligence process [101].

According to statistics in the literature, the application of machine vision technology in tunnel anchoring systems can be roughly divided into two categories: bolting support theory and bolting support equipment. The first method uses the digital image correlation (DIC) method to explore roadway bolt support theory and investigate the mechanism of anchor-solid characteristics in different environments. The other focuses on applying machine vision technology to anchoring protection equipment to improve the intelligence level of underground anchoring engineering.

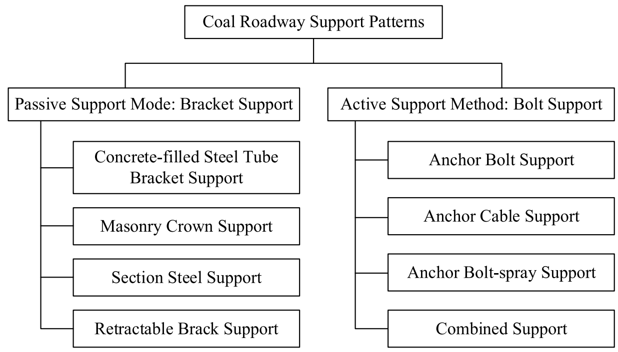


FIGURE 9. Coal roadway support patterns [99].

During the tunnel anchoring operation, various factors inside the coal rock will affect the strength and stability of the anchoring effect, such as rock creep deformation, corrosion factors, rock cracks [102], and the surrounding rock loose circle. Therefore, it is necessary to study the characteristics of anchor solids and bolting support theory. The digital image correlation (DIC) method can determine the correlation between the deformed and undeformed images of the object [103], which has also been widely used in the study of anchor solid characteristics. For instance, to investigate the reinforcement effects of specimens containing a single fissure, [104] employed the DIC method to monitor the displacement fields, strain fields, and other parameters of unreinforced and reinforced specimens, respectively. To study the anchoring characteristics of anchors in a non-uniform restricted state, which often exists in anchoring engineering, [105] used DIC technology to establish an indoor half-anchor model and obtained the load-displacement relationship and failure mode in a pull-out test. The above studies on the mechanism of anchor solids in deep-rock geomechanics play a positive guiding role in practical projects of bolt support in underground engineering. They contribute to the development of relevant theories and enhance the effectiveness of anchoring systems in real-world applications.

In roadway construction, the extensive use of tunneling equipment has greatly improved the tunneling speed. However, as described above, the process of anchoring and supporting is intricate and time-consuming, contributing to the occurrence of the "mining and excavation imbalance" phenomenon, which significantly affects the efficiency of coal production. Therefore, many enterprises and researchers at home and abroad are actively researching anchorage technology and equipment, seeking solutions to these challenges, and improving the automation and intelligence degree of anchorage operations [106].

The application of machine vision technology in automatic and intelligent anchorage construction primarily focuses on two aspects. One is the automatic renovation of traditional anchoring techniques. For example, [107] proposed an improved YOLOv5s model to realize intelligent identification and spatial positioning of the steel belt anchor hole during roadway support. Coincidentally, [108] proposed a YOLOv7 bolt mesh-detection algorithm combining the image enhancement and convolutional block attention module. In the anchoring process of rock bolting jumbos, it is essential to consider deformation errors caused by mechanical arm loads and dead weights. Through real-time monitoring of the compliance deformation of the boom, [109] completed the bolting jumbo boom positioning, ensuring the efficiency and quality of roof bolting construction. After tunnel anchoring, with the passage of time and the progress of production, the bolt support function might decrease or even fail, posing risks to miners' safety. Utilizing a roadway inspection robot as the platform, [110] proposed a rapid visual bolt-anomaly detection method that assesses whether the bolt is loose by measuring changing characteristics of the bolt.

With the proposal of the "Mine Equipments Robotization" strategy, the other application direction of machine vision in the automatic bolt construction is to abandon traditional technics and develop new anchoring equipments, such as the integrated tunneling supporting machine, drilling anchor robot, etc. Employing a laser radar sensor and camera, Professor Ma's team [111] designed a gantry drill-anchor robot to calculate the motion control quantity of each part of the robot to avoid collisions between the boring crown and the anchor network and ensure the accurate alignment of the drilling rig. Based on the principle of monocular vision, [112] proposed a method of body positioning measurement of a bolting robot, laying the foundation for the localization control of the mining face and the automation and unmanned bolting. In the process of "mine equipment robotization", the anchoring operation robot still has plenty of room for further development.

With the rapid development of vision recognition and processing technology, the visual measurement technique has also been applied to monitor the roadway surrounding rock deformation. For instance, [113] proposed a visual multi-dimensional deformation monitoring system for tunnel primary support, which can monitor and analyze the crown settlement 2D deformation, peripheral convergence, and the 3D overall supporting effect. Focusing on the research goal of "intelligent sensing of roof quality at coal entry tunneling", [114] constructed a fully automatic statistical system for discontinuity parameter analysis based on digital image processing technology and verified the reliability of this system through industrial tests.

C. MINING TRANSPORTATION SYSTEM

As one of the three major tunneling systems, the mining transportation system mainly consists of the main transportation and auxiliary transportation systems. The main transportation system is responsible for conveying the coal and gangue cut by the roadheader, while the auxiliary transportation system handles the transportation of support materials. Depending on the excavation line, commonly used transportation equipment in fully mechanized tunneling faces can be categorized into two types: belt conveyors and mineral shuttle trucks. Belt conveyors are suitable for long-distance and high-volume transportation with high reliability. While, mineral shuttle trucks are suitable for short-distance and low-volume transportation, offering convenient turnover.

With the proposal of the "Intelligent Mine" concept, advanced technologies such as the Internet of Things, big data, sensing detection, and information processing can be utilized to ensure safe, reliable, green, and efficient operation. In the process of intelligent transportation, fault monitoring plays a crucial role. Perception of transportation parameters, such as coal flow and belt speed, forms the basis for intelligent speed regulation of the belt conveyor [115]. In addition, it is necessary to improve the intelligence level of auxiliary technologies, including energy-saving, transportation scheduling, and personnel safety behavior monitoring. The specific workflow of the visual intelligent monitoring system in the transfer and transportation system in a mine is shown in Fig. 10, encompassing three main steps [116]. First, target-detection technology is used to extract target objects from the collected images. The objects are then automatically classified according to the extracted features. Finally, event identification technology is employed to determine whether the detected information triggers a set of event identification rules. If triggered, alarms and control actions are initiated. Otherwise, cycle detection continues.

1) ANOMALY INTELLIGENT MONITORING

As the main transportation equipments in mine production, belt conveyors can easily get out of order when operating continuously under high intensity in the harsh environment of a coal mine. For instance, the wire rope core inside the conveyor belt may tear or become damaged due to driving tension. Prolonged usage can also result in longitudinal tearing, scratching, off tracking, skidding, roller damage and other faults. Any issues can disrupt normal production and even threaten miners' safety. Therefore, automatic fault monitoring of conveying systems is crucial for ensuring the realization of intelligent transportation system operation. Equipment safety is also a critical aspect of mine video monitoring and management [7]. At present, machine vision technology is widely applied in intelligent fault monitoring of transfer and transportation systems, with the following key applications.

(1) Identification and positioning of longitudinal tearing of conveyor belt.

In the material transportation of coal mines, hard impurities like schistose gangue and metal anchors may scratch or even break the conveyor belt, leading to longitudinal tearing. In general, the damage distance of the belt increases rapidly if the damaged part cannot be detected or repressed in

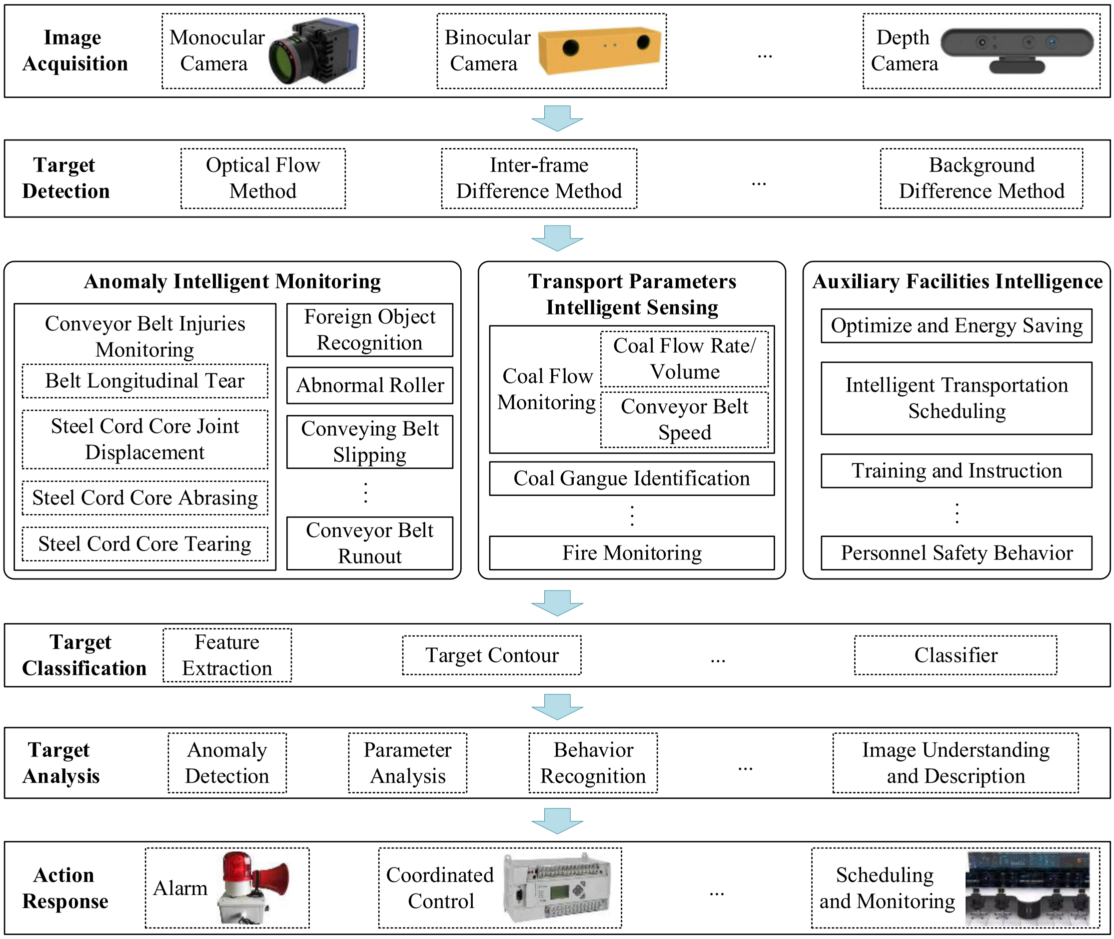


FIGURE 10. The workflow of visual intelligent monitoring system in the transfer and transportation system in mine [116].

time. Subsequently, during maintenance, the entire belt must be removed and replaced, resulting in prolonged production interruptions. In recent years, machine vision has emerged as a popular research direction for identifying and locating longitudinal tears in conveyor belts. Ponsa et al. [117] used four area array cameras to capture conveyor belt images and developed a computer-vision detection system. Li et al. [118] proposed a modified SSR algorithm for detecting tear features. Yang et al. [119] proposed an algorithm to obtain and analyze the characteristic function of a longitudinal tear by transforming a grayscale image into a one-dimensional vector. Some deep learning algorithms have also been applied [120]. By deeply integrating the Mobile Net and Yolov4 networks, [121] identified multiple types of belt damage, such as belt tearing and surface wear. The lightweight network design enables identification speeds of up to 70.26 FPS. However, due to the challenging underground working conditions, as well as the presence of surface residual coal and belt surface scratches, it is hard to achieve good detection effects robustly, if the edge or region is directly extracted from the original images. To address these issues, researchers have explored various new visual detection methods, as depicted in Fig. 11.

The utilization of thermal imaging [122] in the mining industry offers a wide range of research opportunities in view of heat production, simultaneously reducing the influence of environmental interference factors. Tiezhu Qiao's team at Taiyuan University of Technology in China has conducted extensive research on this topic. For example, [19] used an individual infrared camera to extract the connection domain of tear features for early warning of conveyor belt longitudinal tearing. Reference [123] proposed an integrated binocular visual detection (IBVD) method to highlight the characteristics of the longitudinal tear part by merging synchronously collected infrared images and visible light images. Soon afterwards, [124] proposed a dual-band infrared detection (DBID) method to extract tear features by combining the complementary characteristics of mid-infrared and long-infrared vision. The experiments verified that DBID achieves higher accuracy in dark environments compared to the previous IBVD method. Besides, to improve the robustness caused by drastic changes and uneven illumination, Wang et al. [125] proposed

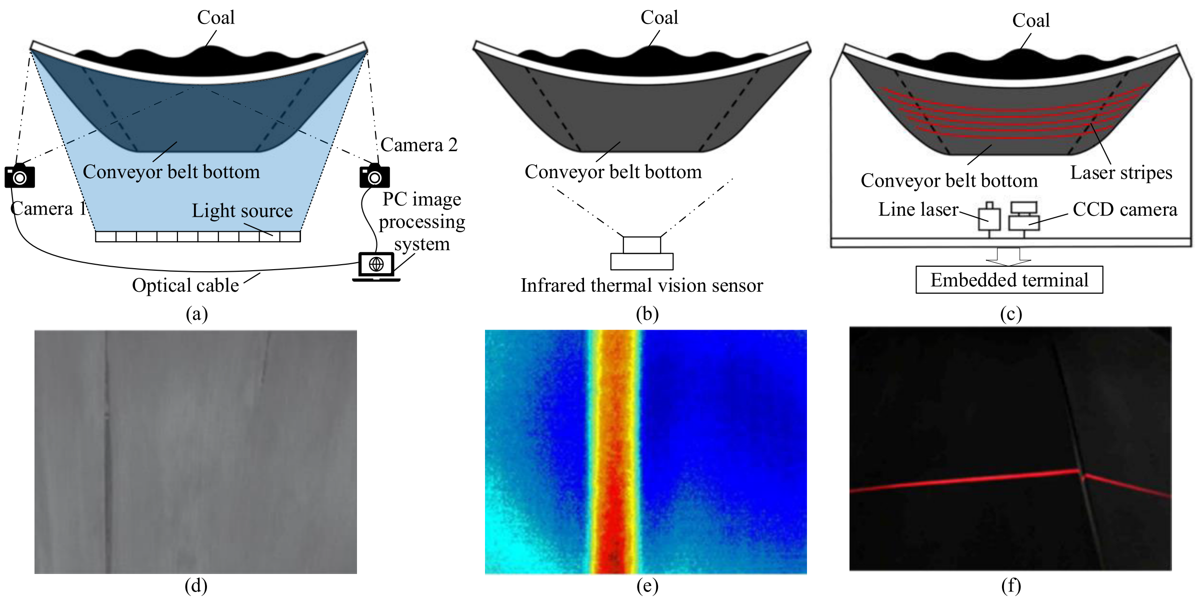


FIGURE 11. Visual detection methods of conveyor belt longitudinal tearing. (a) visible light imaging [120], (b) thermal imaging [19], (c) line laser detection [127], (d, e, f) detection results of above methods.

a classifier training method based on the Haar-AdaBoost and Cascade algorithm.

In addition to thermal imaging, another approach is the utilization of a line laser as a strong light source to minimize the impact of environmental interference factors. When a longitudinal tear occurs in the conveyor belt, the contour line formed by the laser source presents fracture features. A visual recognition system, incorporating both laser and area light sources, was designed in [126] to prevent longitudinal tears based on multi-feature information such as abrasions, incomplete tears, and complete tears. Li et al. [127] designed a monitoring system based on a line laser and ARM. In this system, the skeleton representation of the stripe centerline was first extracted using the maximum pixel value method. By employing multiple sets of lasers, the algorithm presented in [128] effectively expanded the detection area, capturing complete and more pronounced tear characteristics. To further improve detection accuracy, deep learning methods can be used to identify conveyor belt damage. The audio-visual fusion (AVF) detection method in [129] used both a visible light CCD and a microphone array to collect images and sounds of the conveyor belt in different running states. Then, the principal component analysis (PCA) method was employed to merge and classify the image and sound features, which improves the detection accuracy and reliability.

(2) Deviation monitoring of the conveyor belt

In addition to belt tearing, belt-off tracking and skidding are among the most common and influential faults in the belt conveyor operation process. As early as 1990, Australian scientist Pro. Harrison [130] conducted an extensive study on this topic. He emphasized that when the belt center deviates from the original geometric center line, it results in uneven force distribution across the belt, leading to deviations in the driving direction, material leakage, belt tearing, or skidding. To effectively reduce pecuniary loss, the belt off-tracking fault should be detected and restrained as soon as possible. In recent years, machine vision technology has also been applied to the deviation detection of belt operation. The process typically involves three steps:1) conveyor belt area segmentation, 2) edge contour extraction, and 3) linear feature extraction and deviation determination of the conveyor belt edge. Literature [131] proposed a belt deviation detection system based on computer vision by increasing the mine conveyor image clarity under high dustiness. Collecting real-time images of the conveyor belt using a linear-array CCD camera, [132] proposed the average graying method as a rapid image segmentation algorithm and designed a deviation feature vector composed of deviation degrees and offsets to inspect the belt offset. Treating two vertically aligned laser beams as reference lines, [133] measured the distance between the conveyor belt edge and them to provide an intuitive indication of belt deviation.

Although the machine vision detection method has made some progress in detection accuracy, timeliness is not guaranteed owing to the large amount of calculation. Consequently, deep learning has been gradually employed for comprehensive fault detection in coal conveyor belts. Reference [134] tackled the challenge of rapidly extracting features and determining deviations in conveyor belt edges within complex backgrounds by enhancing the general-purpose object detection network YOLOv5. Similarly, [135] presented a real-time conveyor belt detection algorithm that relies on a multi-scale feature fusion network. This algorithm showcases outstanding performance, particularly in accurately segmenting the conveyor edge with minimal breakpoints.

(3) Damage detection of conveyor belt wire rope core

Steel rope core belts are widely used to enhance the tensile strength of long-distance mining belt conveyors. However, after prolonged usage, they are susceptible to various forms of damage, such as internal steel core rust, core fractures, or conveyor joint elongation. These failures can lead to major safety accidents and significantly impact production. To effectively conduct nondestructive testing and maintenance of wire rope core conveyor belts, numerous researchers worldwide have conducted extensive researches [136]. Aport [137] proposed an artificial neural network diagnostic method based on image processing for identifying belt splices and damages, which was successfully implemented at the Richards Bay Coal Terminal in South Africa. With the rapid development of X-ray detection and image processing, many scholars have attempted to detect wire rope cores and joints using X-rays [138], [139].

(4) Fault diagnosis of belt conveyor roller

The belt conveyor roller is also a critical structural component responsible for transporting and carrying materials. It rotates by friction with the conveyor belt, playing the role of material bearing and reducing friction during the transporting process. In a noisy environment at the tunneling face, commonly used roller-running state detection methods, such as sound-, pressure-, and temperature-based detection, might fail. Therefore, noncontact measurement technologies, such as thermal imaging and computer vision, have emerged as the primary research focus for detecting roller faults. Utilizing an infrared thermal imager to capture images of key mechanical components of the conveyor, [140] realized the automatic classification and identification of the motor, cylinder, and roller based on the improved regional growth method. Obtaining infrared (IR) and RGB videos of a conveyor system from a mobile robot, [141] proposed an automated method to determine overheated idlers. In a similar vein, [142] employed an inspection robot to take video of the roller, enabling fault diagnosis by comparing the estimated linear velocity of the roller from the video with the actual belt speed. Analogously, [143] designed a conveyor inspection robot based on a UGV platform. It combined RGB images and IR data to segment the area of overheated rollers.

(5) Foreign object recognition of belt conveyor

Belt tear testing primarily focuses on early detection of longitudinal tears in order to promptly mitigate their length and impact on mine production. However, it cannot fundamentally prevent the problem of longitudinal belt tearing [144]. During normal delivery, this phenomenon rarely occurs. They typically occur only when the belt seriously deviates or when external sharp objects, such as anchor rods, angle steel, or large gangue, penetrate the belt, potentially causing scratches and tears [145]. Therefore, in line with the cause of the accident, if the foreign object can be accurately detected and removed in the early stage, it can effectively prevent longitudinal tearing to a certain extent and ensure the safe and stable operation of belt transportation [146]. Traditional foreign body detection methods for coal mine belt conveyors include manual, metal, and radar detection. However, these methods suffer from low detection efficiency, limited applicability, and high cost. In recent years, with the continuous research on machine vision [147] and deep learning, vision-based detection has become the mainstream method in the field of artificial intelligence. Another approach [148] used a multimodal imaging system (polarization camera) to generate two images and differentiate the material and color properties of foreign objects from the raw coal conveyor belt. Reference [149] proposed a modified YOLOv4 algorithm for foreign-object detection on a belt conveyor in a low-illumination underground environment. Similarly, based on the SSD algorithm, [59] proposed the video detection of foreign objects on a belt surface.

As can be seen from the above, target identification and positioning based on machine vision technology have rapidly developed in the field of fault monitoring of conveyor belts and their components. To realize intelligent fault monitoring of the transfer and transportation system, in addition to installing detection devices within the machinery, if the field environment is spacious, an autonomous robot can be employed for auxiliary detection. For example, [150] used an autonomous legged inspection robot to monitor the belts of conveyors in particularly dangerous and inaccessible locations. Moreover, based on an Unmanned Aerial Vehicle (UAV), [151] used a thermographic inspection and signal processing technique to automatically identify belt conveyor roller failures in the mining industry. Similarly, [143] proposed an Unmanned Ground Vehicle (UGV) platform as a virtual miner that will ride along the belt conveyor and collect information about conveyor operation using infrared thermography for belt conveyor maintenance.

2) TRANSPORT PARAMETERS INTELLIGENT SENSING

The intelligent perception of transportation parameters and states is the basis for ensuring the safe and stable operation of the transportation system. It is also the premise of realizing an ''Intelligent Mine''. According to statistics in the literature, the applications of vision in the transportation parameters of intelligent sensing mainly include coal flow parameter monitoring and coal gangue identification.

(1) Coal flow parameters monitoring

In the main transportation system, the coal flow parameters serve as key indicators for measuring the transport capacity and regulating system speed. Realizing the parameter online detection can effectively reduce operating costs and achieve energy conservation and emission reduction goals [152]. The coal flow parameters encompass height, sectional area, volume of the coal pile, and coal flow movement speed. Monitoring methods based on vision can be divided into monocular, binocular, and structured light methods.

The monocular vision monitoring method uses only a single camera to complete positioning tasks, which limits its depth perception ability. However, it offers a wide field of vision. By employing the Swin Transformer attention

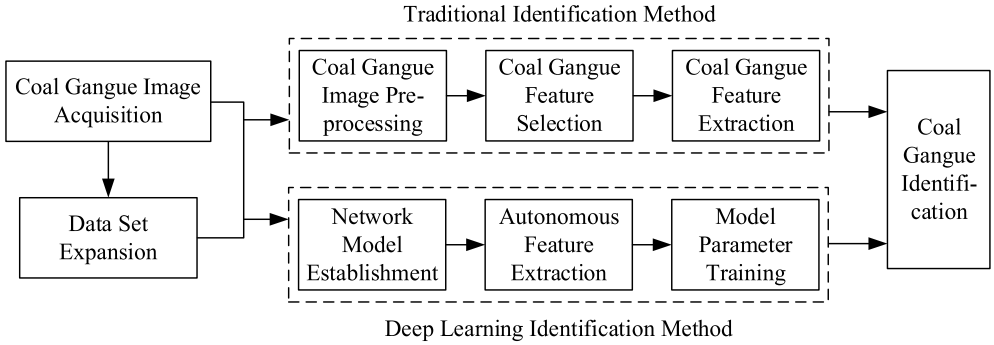


FIGURE 12. Vision recognition methods of coal and gangue [160].

mechanism to address the limitations of the traditional convolutional receptive field, [153] introduced an enhanced YOLOv5 real-time coal flow detection algorithm. This improvement aims to prevent power loss and belt damage. Nevertheless, the monocular method can only carry out qualitative detection of coal flow to realize coal amount classification. Quantitative detection cannot be achieved, which can only be used for belt conveyor fuzzy control.

Applying binocular vision method to coal flow volume measurement [20], it is easy to calculate the coal flow rate with the advantages of simple operation and light equipment. Based on the mathematical model of the coal quantity distribution of the entire coal flow transportation system, an intelligent control system with a self-learning function developed in [154] can make the belt operate at the most economical speed. By accurately measuring the instantaneous coal quantity and belt speed, energy savings and green production can be achieved. Reference [155] developed a coal weight detection system using 3D scene reconstruction and T-S fuzzy reasoning based on a binocular 3D information extraction module. Although the binocular visual method can realize the quantitative detection of coal flow, it is currently not suitable for practical applications due to its low measurement accuracy and slow speed.

The structured light vision method [156] first actively projects structured light to the surface of the measured object and subsequently determines its size parameters by measuring the pattern deformation before and after the modulation. On the basis of 3D point cloud reconstruction of the coal stack and yard in the absolute coordinate system, volume calculation and weight estimation systems were established in [157] based on image processing. Reference [34] used point cloud data collected through a speckle-structured light acquisition system to calculate the volume of the coal mass and monitor the coal flow of the conveyor. Using an industrial camera to collect dynamic images of a conveyor belt irradiated by a laser transmitter, [158] presented a method for coal quantity detection and classification based on machine vision and deep learning. In order to improve the accuracy and efficiency, the structured light vision method can also be combined with monocular or binocular vision. Li et al. [159] employed a method that combines binocular stereo vision with structured vision to calculate coal flow rate by uniformly sampling and integrating coal pile point clouds within a given time frame.

(2) Coal gangue identification

In the coal quality management system undermines, the quality management of the tunneling face is much more difficult than that of the mining face. During the tunneling process, to ensure roadway height and stability, sometimes a part of the roof rock must be broken additionally, resulting in more gangue mixed with coal [160]. According to statistics, the coal output of the tunneling face generally accounts for 10% to 20% of the total mine output. It is estimated that owing to the influence of the tunneling face, the ash content of the coal in the entire mine can increase by 1% to 2%. This demonstrates that the mixing of coal and gangue in the heading face directly affects the coal quality of the mine. Therefore, it is essential to implement feasible measures for the identification and sorting of gangue in the heading face.

Commonly used methods for coal gangue separation include radiation identification and visual identification [161]. According to the degree of intelligence, visual identification methods can be further divided into traditional methods that require artificial feature extraction and intelligent methods that can automatically extract characteristics through deep learning and neural networks. The specific steps are illustrated in Fig. 12 [160].

Traditional recognition methods achieve the purpose of distinguish coal and gangue by extracting artificially selected image features. In 2009, Ma [16] used wavelet moments to extract gangue histogram characteristics, laying the groundwork for automatic gangue separation. Applying least squares support vector machine (LS-SVM) as the image classifier, [162] trained three classifiers using the features of grayscale, texture, and the joint feature combining skewness with contrast to reduce the average coordinate errors for coal and gangue sorting robots. To avoid the shortcomings of traditional methods (radiation, pollution, etc.) effectively, [163] proposed a new solution for the recognition of coal and gangue using multispectral imaging. By combining LBP feature extraction with GS-SVM, the model achieved a prediction accuracy of 96.25%.

In contrast to traditional methods, deep learning recognition methods efficiently identify coal and gangue by independently extracting features and learning network parameters through a deep learning convolutional neural network model. Reference [164] proposed an improved YOLOv4 algorithm as a classic deep learning method for the intelligent and highly accurate recognition of coal and coal gangue. By applying cluster analysis to different datasets, this approach achieved better anchor values. Reference [165] improved the classic convolution neural network LeNet-5 from the input sample size, activation function, network depth, size and number of convolution kernels, classification function, etc., to solve the problems of traditional coal gangue image recognition methods, such as difficult extraction of artificial features and low accuracy of recognition. For segregating coal and gangue, in [166], based on a powerful trained image recognition model, VGG16, the concept of transfer learning was introduced to build a custom CNN model. This approach overcame the challenges of massive trainable parameters and limited computing power linked to the building of a brand-new model from scratch. Coal gangue identification methods based on deep learning exhibit higher efficiency than traditional methods. However, because of the specificity and complexity of the gangue classification environment, it is still necessary to build efficient gangue datasets and conduct extensive research on the generalization, real-time performance, and robustness of recognition algorithms.

3) AUXILIARY FACILITIES INTELLIGENCE

Ensuring the safe, reliable, and energy-efficient operation of the transportation system is crucial for the overall production of a mine, making it an important aspect at the fully mechanized tunneling face. Apart from system failures, intelligent monitoring, and parameter perception, improving the intelligence level of auxiliary facilities is necessary. This includes optimizing energy savings, transportation scheduling, and monitoring personnel safety behavior.

For a coal mine transportation system, the essence of vision applications in optimal energy saving still lies in the monitoring of coal flow information. Based on the actual coal flow on the belt conveyor, conveyor frequency control can be realized to achieve energy savings in the main transportation system of coal mines. Reference [167] proposed an optimized energy-saving control system for a mine belt conveyor based on laser-assisted binocular vision technology, which can adjust the belt's operating speed intelligently according to the coal flow size through a PLC fuzzy controller.

In terms of intelligent transportation scheduling, [168] devised a video-assisted monitoring system with the capability to extract vehicle information using license plate data from the control system's database This functionality enhances decision-making support for intelligent scheduling.

In coal production, there are also many conveyer-transportation accidents caused by unsafe personnel behavior. Utilizing infrared images, [169] applied the enhanced Lucas-Kanade optical flow method to extract the motion characteristics of moving objects. This approach facilitates the detection of moving personnel for trackless rubber-tyred vehicles in coal mines, thereby ensuring personnel safety. Addressing personnel management in belt and winch lanes, Ma et al. [170] applied their designed intelligent monitoring and recognition system underground. This system achieves personnel intrusion identification, personnel crossing detection, and personnel presence recognition, ensuring the safety of individuals throughout the production process.

Equipment robotization is also an important development direction for intelligent transportation systems. To address this, [171] proposed a novel robotic method for belt conveyor structure inspection with a set of sensors, including a microphone, accelerometers, laser, and cameras. To achieve coal gangue image recognition and robot sorting control, [172] presented an automatic coal and gangue separation robot system based on visual information, machine learning, and deep learning. With the in-depth development of mine intelligent construction and the continuous improvement of mining management level, it is gradually possible to realize green energy saving and efficient intelligent operation of the transfer and transportation system at the tunneling face by using new materials, processes, and technologies.

D. SAFETY AUXILIARY SYSTEM

The comprehensive mechanized rapid tunneling of roadways is a systematic project that involves the coordinated operation of tunneling, anchoring, and transportation equipment, forming an integrated "Dig-Anchor-Transport" system. These three equipment components work together to achieve continuous, balanced, and efficient production of coal mine roadways. However, in automation and intelligence processes, various factors restrict the development of fully mechanized tunneling technologies at the working face. Apart from the performance of large-scale equipment, the advancement of safety assistance equipment also plays a crucial role. Machine vision technology has found applications in underground tunneling safety auxiliary systems, including personnel safety monitoring, tunnel deformation monitoring, and fire monitoring and prevention.

1) PERSONNEL SAFETY MONITORING

In recent years, the safety production techniques of coal mines have been greatly improved, resulting in a reduction in mining accidents to some extent. However, due to the high-risk nature of the industry and the challenging underground environments, ensuring coal mine safety remains a persistent challenge. Mining accidents continue to occur. Ensuring personnel safety remains a primary task of mining. The high concentration of dust and noise produced in the roadway tunneling process will make it difficult for the staff to effectively identify people and objects in their surroundings. The dreadful condition keeps the machine driver and persons in the vision limited vision zone in dangerous environments because it can easily cause casualties or damage. In addition, some dangerous areas in coal mines are prohibited from entering. Therefore, effective personnel detection methods are essential to ensure safety. Machine vision technology has been widely applied in underground personnel safety and security systems, primarily focused on disaster prevention through personnel identification and tracking. After comprehensively considering various actual influencing factors, such as large vibration, high dust concentration, and explosion suppression, [173] proposed a personnel identification system at the tunneling face to monitor workers in hazardous areas during operations, aiming to reduce safety accidents like squeeze injuries. To meet the demands of real-time monitoring and precise localization of underground mining personnel, [174] introduced an enhanced YOLOv4 network based on thermal infrared images, enabling the recognition of underground personnel identities. Similarly, [175] devised a real-time video analysis system for coal mine surveillance. Through collaborative cloud-edge processing, they notably improved the AP value of the FL-YOLO single-scene pedestrian dataset to an impressive 80.7%. Based on the real-time acquisition of a human skeleton point map by depth vision, [176] constructed a sphere-swept convex hull collision detection model for auxiliary personnel. Then, a human-machine safety collision avoidance method was proposed from the perspective of the drilling anchor robot control system. Evidently, these methods effectively ensure personnel safety through personnel identification and detection.

2) TUNNEL DEFORMATION MONITORING

The pressure exerted by surrounding rocks on roadways increases as mining depth increases, which easily causes strata deformation and failure and hinders underground transportation and ventilation. When the situation is serious, it may result in equipment damage and even personnel casualties. Therefore, it is of great significance to ensure the safe production of coal mines by timely monitoring roadway deformation and accurately assessing the state and changing trends of the surrounding rock. Machine vision technology enables the monitoring of roadway deformation by observing the 'target' within the visual field. Based on the 'target', which could be either an artificial or existing structural feature, commonly used application methods can be divided into the indirect and direct types.

Indirect methods need to preinstall markers, LED lamps, or targets with special patterns on the roadway surface and indirectly monitor the deformation of the roadway by analyzing changes in artificial features in the captured video. As a result, the obtained data points are relatively sparse. However, compared to the direct method, the amount of data is smaller, and the processing speed is faster. Xu et al. [177] proposed a real-time monitoring method based on monocular vision. This method utilized fixed circular diagonal markers on the roadway wall as the information transmission medium to reflect tunnel deformation. By restoring the geometric characteristics and deformation parameters of the roadway section, deformation indices were acquired and processed. Subsequently, they [178] extended their approach by utilizing indicators such as surrounding rock deformation, velocity, and acceleration as parameters to enable real-time tunnel monitoring. This was undertaken with the aim of achieving early warning for surrounding rock dynamic deformation and potential failure in deep roadway. By using monocular vision to detect the 3D coordinates of designed artificial target points coated with fluorescent paint, [50] achieved automatic and accurate monitoring of roadway surface displacement during TBM tunneling.

In contrast, direct methods use cameras to capture tunnel images directly. After performing feature matching and point cloud registration, these methods reconstruct the tunnel's 3D information, offering a visual representation of roadway deformation. The accuracy of monitoring and information obtained through direct methods is notably higher than that achieved through indirect methods, which, in comparison, demand more intensive computational processing capabilities [179]. By harnessing DIC, [180] introduced an innovative approach using the image coefficient of variation (ICV) to detect early signs of surrounding rock damage, thereby presenting a novel warning indicator for tunnel instability. In a similar vein, [181] employed a handheld structured light scanner for precise 3D mapping within mining environments. Addressing the challenges posed by low-light conditions on point cloud quality, [182] proposed a Zero-reference Deep Learning model customized for underground scene 3D reconstruction, achieving an impressive reconstruction accuracy of up to 98.58%. Meanwhile, [183] employed a Kinect depth camera for image capture, accompanied by an improved iterative closest point algorithm, facilitating 3D reconstruction in mining contexts. Additionally, [184] collected mining data and reconstructed point clouds using RGB-D cameras to repair the holes in the original point clouds obtained from 3D laser scanner. Moreover, [185] applied machine vision reconstruction methods to underground patrol robots to monitor deformation in coal mine tunnels.

3) FIRE MONITORING AND PREVENTION

Mine fires pose a significant threat to the safety of coal production. According to the cause and formation conditions, they can be categorized into two main types: spontaneous combustion fires and exogenous fires [186]. Spontaneous combustion fires account for approximately 90% of the total number of mine fires in China, as reported by survey statistics. On the other hand, exogenous fires mainly refer to electrical fires, which mostly occur in electromechanical chambers, conveyor belts, and electric cables.

For detecting spontaneous coal combustion, the primary methods mainly involve using infrared thermal (IR) imaging cameras for identifying fire sources. Reference [187] improved monitoring production capacities with portable thermal imaging cameras, which greatly simplified the efforts and costs associated with coal self-ignition prevention. While infrared detection is highly sensitive to temperature measurements compared to other methods, its accuracy can be influenced by factors such as detection depth and radiation heat from coal self-ignition. Moreover, it can detect many other temperature changes that are not caused by spontaneous combustion, leading to potential misjudgments. Therefore, to enhance monitoring accuracy, it is necessary to employ a multi-sensor information fusion technology to fuse it with others.

Electric sparks in mines can lead to thermodynamic disasters, including leakage electric sparks, induction electric sparks, and electric sparks in the shell. Detecting these sparks promptly allows for the implementation of preventive measures and control actions to reduce or even avoid disaster accidents. To efficiently identify early fire sources, [188] employed an infrared CCD as a sensor. By inputting the extracted flame characteristics into a neural network, real-time fire detection can be accomplished. During transportation, the friction between the belt conveyor tape and coal or gangue generates heat, which also poses a hidden risk of fire [189]. Nevertheless, the accuracy of fire identification and positioning may be affected by some factors, such as high-concentrate smoke, long measurement distance, uneven illumination, and even red clothes, which need to be further improved by intelligent algorithms. Reference [190] applied an artificial neural network to mine conveyor fire detection, which effectively improved the accuracy of the existing methods.

Coal mine fires are often accidental. Rapid and accurate detection of early fires is of great practical significance for reducing disasters. In this regard, [18] designed a structure for early fire detection based on image and video processing. By utilizing color information to extract the flame region and employing the Bayes classifier to recognize dynamic fire features, the accuracy of early fire prediction in coal mines was significantly improved. Similarly, [191] also found that video-based fire detection (VBFD) is a more effective and robust approach for providing timely fire detection and warning than traditional CO detectors in typical Australian underground mines. Another study [192] treated smoke as an indicator of early fire and employed the optical flow method to predict the predominant motion direction of smoke. By studying the characteristics of underground smoke and training an SVM smoke classifier, it successfully predicted early coal mine fires.

In addition to using fixed devices to monitor fire sources, if the underground environment and space permit, coal mine fire inspection robots can be employed to perform environmental detection tasks [9]. For instance, [193] employed the high-definition camera mounted on an inspection robot to capture video images. By extracting and analyzing multiple flame features and integrating information from an infrared thermal imager and a smoke sensor, precise recognition and monitoring of smoke and flames within mines were successfully achieved. Similarly, [194] utilized a particle system-based simulation algorithm to process flame images, offering an efficient fire hazard early warning for intelligent patrol robots in mines. In the past decade, although fire inspection robots have been extensively researched, developed, and applied on a small scale, most of these efforts remain in the initial exploration stage. Accordingly, achieving intelligent unmanned inspection of the entire mine still requires further advancements.

IV. RESEARCH CHALLENGES AND FUTURE PERSPECTIVES OF MACHINE VISION IN FULLY MECHANIZED TUNNELING FACES

A. RESEARCH CHALLENGES

1) LOW ENVIRONMENTAL ADAPTABILITY

Obtaining complete, effective, and clear image information is crucial for accurate detection in the visual system. However, the unique underground environment in coal mines presents challenges for machine vision systems. The fully mechanized tunneling process often requires artificial lighting to compensate for the lack of natural light underground, resulting in images with low light levels and uneven illumination distribution compared to surface environments. In addition, during coal rock cutting, the strong vibration from the roadheader and the presence of high-concentration mine dust contribute to noise and reduced image resolution. These harsh conditions make later feature extraction and image processing more challenging. Therefore, when applying visual technology to coal mines, it is essential to consider the influence of complex environmental factors on the system. Furthermore, during the design and selection process, it is beneficial to choose systems that not only meet explosion prevention requirements but also have functions such as dust removal, image stabilization, and illumination adaptation. These features can improve the quality of digital images and reduce the difficulty of feature extraction.

2) NARROW FIELD OF VIEW FOR IMAGING

In mines, the narrow roadway space and the presence of large construction equipment often result in incomplete images with missing information, as the light path can be easily blocked. One approach to address this challenge is to use extreme wide-angle lenses, which can effectively expand the perspective to some extent. However, this may introduce significant nonlinear distortion and increase the difficulty of camera calibration. Another solution is to employ a movable and rotatable visual platform or increase the number of cameras to enhance the imaging range of the visual system by improving its degree of freedom. However, in the subsequent stages, the collected images need to undergo motion decoupling, feature extraction, and matching. Therefore, it is currently a technical challenge to expand the perspective of image acquisition equipment in order to efficiently capture more scene information within a short measuring range.

3) IMPROVEMENT OF INTELLIGENCE DEGREE

The core technology of visual detection at the tunneling face is to obtain effective information through image feature extraction, and then work out relevant parameters with the parameter solution model, or complete the detection and recognition of the target object using the artificial intelligence algorithm. In the feature extraction stage, most existing algorithms use fixed parameters that are unable to adapt to changes in the environmental parameters. To ensure detection accuracy, the parameters should be adjusted in real-time according to the actual situation. Therefore, in this stage, an urgent problem to be solved is how to improve the intelligence degree of the algorithm so that it can automatically adjust the parameters according to the roadway environment, thereby increasing the precision and stability of feature extraction. In the parameter solution stage, existing methods primarily rely on predetermined solution models to determine relevant parameters by utilizing extracted feature information. However, these solution models can fail when effective feature information is partially occluded or cannot be collected. Thus, a technical bottleneck in this stage is accurately calculating specific parameter values using early-stage collected images and intelligent algorithms when the manually established solution model is inadequate. In the target detection and identification stage, existing recognition algorithms exhibit limited adaptability in complex and unstructured mine environments. This limitation hampers their ability to meet high real-time requirements, and they often exhibit hysteresis and uncertainty. Consequently, the technical challenge in this stage lies in improving the accuracy and efficiency of target object recognition by incorporating new technologies such as artificial intelligence algorithms, deep learning, and big data.

B. FUTURE PERSPECTIVES

Despite the challenges faced by machine vision applications in underground coal mines, the future holds promising developments. Research is progressing towards multi-sensor information fusion, equipment group collaborative control, and digital twin-driven remote monitoring, as discussed below.

1) MULTI-SENSOR INFORMATION FUSION TECHNOLOGY

Applying machine vision to roadway fully mechanized tunneling working faces offers several advantages, including non-contact measurement, rich information acquisition, high precision, and fast speed. However, the rugged environment in mines, such as low illumination, uneven light distribution, high coal dust concentration, and a large amount of water mist floating in the air, can impact the quality of collected images and limit the generalization of the visual system to some extent. To address these challenges, underground visual detection systems can be equipped with additional sensors, such as photoelectric sensors, ultrasonic sensors, inertial measurement components, and electronic total stations. By formulating the detection scheme of ''Visual Measurement +'' and utilizing the sensor information fusion technology with high robustness, it becomes possible to effectively compensate for the limitations of visual measurement, such as easily blocked measurement lines and poor reliability. This approach improves the overall stability and environmental adaptability of the detection system. Various methods can be employed for sensor information fusion, including neural networks, Bayesian estimation, Kalman filters, and D-S evidence theory. In addition, for the problems of poor SNR and limited visual field range of a single vision sensor, a multiple-view system can be employed to form an informative synthetic image by integrating the original captured images. This approach expands the visual coverage and improves the overall understanding of the environment. Nevertheless, it is important to note that there are still many difficulties in multisensor information fusion. It has become a hot topic of current research on how to effectively use redundant information obtained from multi-source heterogeneous sensors by combining their location, dynamic characteristics, attribute parameters, and parameter selection or fusion to form a reliable decision. These advancements will contribute to the development of more reliable and accurate decision-making systems in roadway fully mechanized tunneling working faces.

2) EQUIPMENT GROUP COLLABORATIVE CONTROL TECHNOLOGY

The intelligent fully mechanized tunneling system in a coal mine takes the roadheader as the leader, assisted by other auxiliary equipment, to complete the roadway excavation and the tunneling section accurate formation. Classified by different work tasks, the system is comprised of various subsystems, including the cutting system, temporary supporting system, drilling anchor system, transportation system, and ventilation and dust removal system. According to the production process of ''tunneling-supporting-transportation'', realizing parallel operation between multiple systems has been an effort direction for mining industries to improve the efficiency of roadway tunneling. To achieve efficient and intelligent completion of tasks in the multi-task and multi-system environment, several challenges need to be addressed, such as multi-task optimal matching, multi-task parallel control and multi-system collaborative control. Therefore, in addition to single-subsystem intelligent control, achieving parallel operation of multiple tasks and intelligent collaborative control among subsystems has become a crucial focus in intelligent coal mine tunneling research. In view of the above problems, the existing research methods mainly include reinforcement learning, genetic algorithms, agent algorithms, P-learning, and PSO algorithms.

3) DIGITAL TWIN DRIVEN REMOTE MONITORING TECHNOLOGY

The traditional remote control systems for roadway tunneling mostly rely on surveillance videos and 2D planar information. The forming quality of the roadway section depends entirely on manual operation experience with low reliability. Recently, digital twin-driven remote monitoring technology has been widely considered. It refers to creating a virtual model of the physical system through virtual reality technology, incorporating various sensors to gather equipment data. The running state of the equipment is then replicated in the virtual scene, enabling stable, reliable, and intuitive remote monitoring. At present, in the field of coal mine equipment remote control, digital twin technology has also obtained certain research results, such as the remote control systems for coal winning machines and roadheaders [92]. While the original remote monitoring systems relied on a single information source with minimal transmitted data and low security risks, digital twin-driven remote monitoring systems primarily rely on visual sensors to obtain data source, supplemented by numerous other sensors, which greatly increases the amount of information data. As a result, there is a growing demand for improved transmission speed, data quality, and information security. Therefore, enhancing image transmission efficiency and real-time data processing through computer science, image compression, and other technologies, as well as establishing a robust information security system, have become crucial directions for advancing digital twin technology. These advancements are essential to ensure the safe production of roadway excavation.

V. CONCLUSION

Due to the complex environment and low production efficiency in fully mechanized mining working faces, the adoption of intelligent and unmanned tunneling is becoming an inevitable trend in the coal mining industry. Machine vision technology, in the field of automatic detection, offers advantages such as non-contact measurement, comprehensive information acquisition, and fast data processing. Its application in the roadway fully mechanized tunneling working face holds great significance in improving the efficiency of fully mechanized mining, ensuring personnel and equipment safety, and reducing accidents. This study focuses on the application of machine vision technology in tunneling, anchorage, transportation, and safety assistance equipment based on task divisions at the tunneling face, supported by specific engineering cases. By analyzing the structure and detection principles of various visual detection systems in different application scenarios, the technical performance, workflow, merits, and drawbacks of machine vision technology in mines are clarified. However, due to the harsh underground environment of coal mines, visual technology encounters several challenges in specific applications, such as environmental adaptability, narrow imaging fields, and insufficient intelligence. To address these challenges, the future development of machine vision technology is expected to focus on multi-sensor information fusion, equipment group collaborative control, and digital twin-driven remote monitoring technologies. As artificial intelligence algorithms and image processing continue to advance rapidly, machine vision technology will find wider applications in various aspects of underground coal mines. These applications may include equipment or personnel positioning, tracking, gauging, navigation, fault detection, disaster monitoring, and rescue operations, enabling more efficient detection and intelligent feedback control. In the future, the intersection and integration of machine vision with various new technologies will continue to evolve, leading to innovative outcomes and ultimately achieving the goal of unmanned intelligent mining.

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