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A machine vision-based automatic inspection system for power station coal bunkers maintenance

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Abstract

Automation technologies can play a vital role in thermal power plants equipment maintenance, where coal bunker liner are critical parts in terms of functioning and safety. In this context, common issues involve the premature wear of fastening hardware (e.g. bolts) and lining edge warping. Current inspection approaches rely on manually driven visual detection of individual liners, resulting in low efficiency, low accuracy and prone to occupational health hazards. To overcome such drawbacks and to boost automated maintenance, this paper proposes a machine vision-based automatic inspection system endowed with a Cable-Driven Parallel Robot and a machine vision unit for the defect detection in coal bunkers. Considering the reflective characteristics of stainless-steel lining plate and the problems of uneven brightness and unequal focal length of images caused by camera motion during image acquisition, the proposed system utilizes a non-equidistant defect detection method based on improved template matching algorithm under diffuse reflection light source. A tailored light source unit is designed to preliminary reduce the reflection of the stainless-steel lining plate, allowing for high-quality images acquisition of the areas to be inspected. An automatic defect detection algorithm is developed to identify and locate the defects using the real-time spatial geometric position of the camera. The experimental results show that this method can effectively and efficiently detect a number of defects types in coal bunker lining plate. In this respect, compared with current manual inspection methods, the proposed approach can drastically reduce the inspection time whilst keeping an excellent detection accuracy capability.

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Keywords: automated maintenance; inspection system; machine vision; defects detection

1. Introduction

Due to the low price of coal-fired power generation, such energy source still dominates the global power production, accounting for 41.3% of the total global power generation in 2011 and 36.4% in 2019, with an average of 39.3%, as shown in Fig. 1 [1, 2]. In 2020, affected by the economic slowdown caused by COVID-19, China invested on coal-based electricity projects to boost the economy [3]. The development of coal power plants has therefore increased sharply, shifting backwards the decommissioning plan of coal power plants and leading to an increase in global installed capacity of coal and electricity [3]. At present, the installed capacity of coal plants in operation is 2059358 MW, and 179677 MW worth power plants is under construction worldwide [1, 2]. Moreover, a number of coal power plants have been reported to be poorly reliable, characterized by a low efficiency and high maintenance and operation costs [4, 5].

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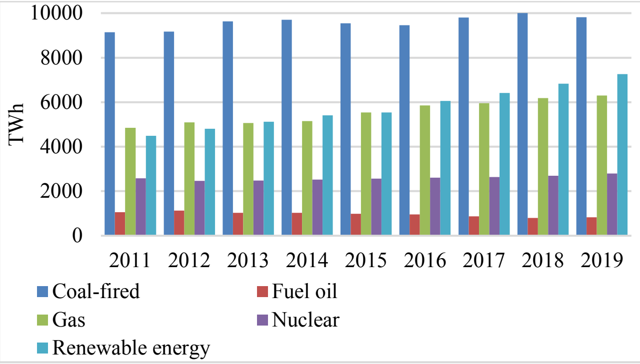


Fig. 1. Global power generation from 2011 to 2019 [1,2]


Fig. 2. Inside of coal bunker

In coal power plants, the raw material, is stored in a coal bunker (Fig. 2), generally realized in stainless-steel [6]. Generally, raw coal is fed through conveyor belt to a mill unit to be dried and grinded into powder. Pulverized coal is sorted and fed into a boiler furnace for combustion [6]. Environmental and mechanical factors can have a negative impact on the storage and feeding quality of coal through the plant. In this respect, high humidity can cause coal agglomeration yielding to the bunker clogging [7]. Concerning the mechanical stresses, due to the wear scratches caused by the long-term friction between the coal and the coal bunker surface, the fastener bolts and the welds between liners become vulnerable to the acid corrosion when exposed to the coal [8]. Such conditions can potentially clog the coal feeder inlet, and to ensure the safe and stable operation of the equipment, it is particularly important to regularly inspect the lining plates of the coal bunker. Defects such as fastener oxidation and corrosion and liner edge warping are recurrent in coal bunkers, requiring maintenance and repair in order to avoid inner wall damages, compromising the safe operation of the whole power plant. Automation technologies in coal power plants available in specialized literature are generally focused on the coal handling systems [9, 10].

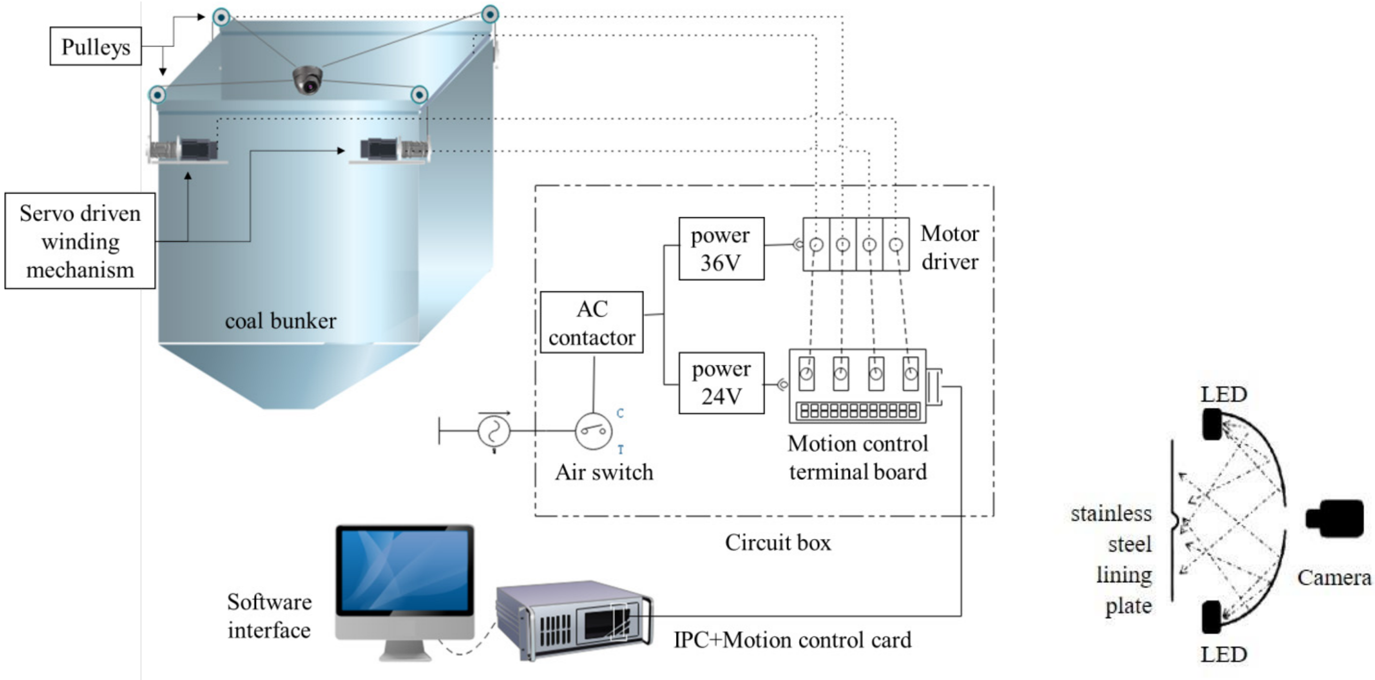
With reference to automated maintenance, limited contributions result available, mainly referring to robotic units based on infrared thermography have been used for conveyor belts maintenance [11] or to the structural properties of the bunker [12] while safety-oriented research contributions involve the temperature [13, 14] and the gas flow [15] monitoring. While civil infrastructures widely employ advanced computer vision – based monitoring systems for inspection and monitoring [16], the scarcity of technology availability both in terms of research and industrial practices forces most coal-fired power plants to choose manual inspection techniques as the main maintenance method. Extending the scope of computer vision – based maintenance and monitoring, learning-based approaches are used to classify defects in panelized walls steel frame manufacturing [17] and for quantitative assessment of visual detectability of different types of in-service damage in laminated composite structures [18].

An industrial practice survey carried out at Huaneng Coal Plant, Shantou, China, highlighted how the maintenance of coal bunker needs to be carried out in ta particularly dusty working environment. Due to the dark and heavy dust inside the coal bunker, the maintenance personnel currently need to build scaffolding and wear a headlamp to carry out inspection operations. In such circumstances, the Plant data report that it takes about 10 working days to complete the inspection of coal bunker liner, and during this period, the power plant needs to stop production [19]. This is not only time-consuming and expensive, but also has a great impact on the health of workers (e.g. pneumoconiosis, lung cancer etc.), and the maintenance personnel should also pay attention to the risk of falling into the bunker . In order to achieve a more efficient maintenance, save time, ensure the safety of workers, and improve the automation of coal bunker detection, a reliable and efficient automatic inspection system is required to replace the current manual inspection methods [17].

In this paper, the structure of the parallel mechanism with a camera and a light source is used to control the movement of the motor, so that the image acquisition subsystem can obtain the image of each stainless-steel liner through the visual inspection unit. Through the image processing subsystem and defect classification subsystem, the collected images are processed, and the defects are classified and counted. With the use of the supporting software, the detection progress and the location of each defect can be seen more clearly and conveniently, which is highly available and convenient to use. Considering the reflection characteristics of stainless-steel lining plate along with the uneven brightness and unequal focal length caused by camera movement in the process of image acquisition, a non-equidistant defect detection method based on improved template matching algorithm under diffuse reflection light source is adopted in the system. A tailored light source unit is designed to reduce the reflection of the stainless-steel liner, allowing for a high-quality image acquisition in correspondence of the area to be inspected. An automatic defect detection algorithm based on camera real-time spatial geometric position is proposed. A software endowed with a graphical user interface is designed to facilitate the automatic regular maintenance and repair of the coal bunker. By merging the images of each lining board, the internal status of the coal bunker can be accurately characterized, providing a reference for future maintenance [16].

2. Automatic inspection system experimental setup

In order to facilitate the image acquisition on the liner, the proposed inspection system enables the motion of the camera platform by controlling a four-cable-driven parallel mechanism [20].



(a) (b)

Fig. 3. Experimental setup (a) Inspection system scheme, (b) diffused dome light

Specifically, four pulleys are installed at the four top corners of the coal bunker, and the servo-driven winding mechanism is installed outside the coal bunker (as shown in the Fig. 3. Further details about the motion control system can be found in [20]. The motor winding speed of four corners is remotely controlled and programmable, and the camera position changes caused by the length change of the four cables, so as to control the movement of the camera moving platform. The images acquired by the camera are then tethered and displayed on a software interface in real time, as shown in Fig. 3(a).

The camera utilized for the experimental work in this paper is a Dahua@ 2 DH-SD2904-GN -axis Rotary camera with an image resolution of 1920*1080 pixels and a focal length of 2.8-11.2 mm. A detailed description of the experimental setup is reported in the next section.

2.1. Light source unit design

Due to the presence of coal at the bottom of the bunker, it is not feasible to use a more stable eight-cable-driven parallel robot structure, and the four-cable driven parallel robot is instead used in the proposed system. In this configuration, during the image acquisition process, the camera can oscillate causing the collected images to have different focal lengths. Even images taken at the same location may have slight differences due to camera oscillation. Moreover, due to the reflective characteristics of stainless steel, the reflection of camera pan tilt may appear on the stainless-steel liner, reducing the detection capabilities in terms of object features in digital images.

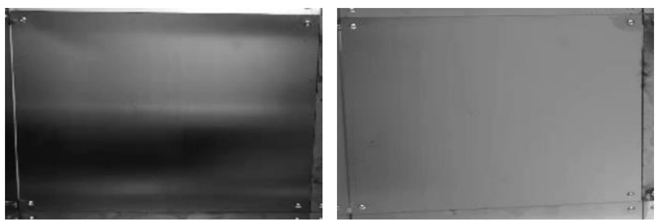
To overcome such issues, diffused reflection dome light source is used to aid the image acquisition process. According to the characteristics of specular light, diffused dome light source can be used to achieve uniform illumination in all directions [21]; the light is reflected multiple times through the diffused reflection plate of the hemispherical inner wall to realize the diffused reflection light illumination in the whole space area, which can eliminate the shadow as shown in Fig. 3(a). The mirror reflection is therefore eliminated indirectly. Fig. 4 shows the improvement due to the proposed light design. Such improvement can be quantified in terms of signal-to-noise ratio (SNR), defined as per Eq. (1).

$$SNR = \frac{\mu}{\sigma} \tag{1}$$

Where μ and σ represent the mean value and the standard deviation of the pixel intensities respectively [22]. With reference to Fig. 4, the SNR are respectively 1.71 for the image under natural light and 5.42 for the image under diffused light.

2.2. Image processing algorithm

The overall defect detection image processing algorithm is illustrated in Fig. 5. This paper focuses on the detection of two major defect types, i.e. the bolt corrosion and the edge warping in the lining plate. The raw image (Fig. 6(a)) is smoothed by using a Gaussian filter [20], with filter size $k = 3$ and standard deviation $\sigma = 0.8$. The Gaussian filtering result can be visualized in Fig. 6(b).



(a) (b)

Fig. 4. (a) Liner under natural light; (b) Liner under diffused light

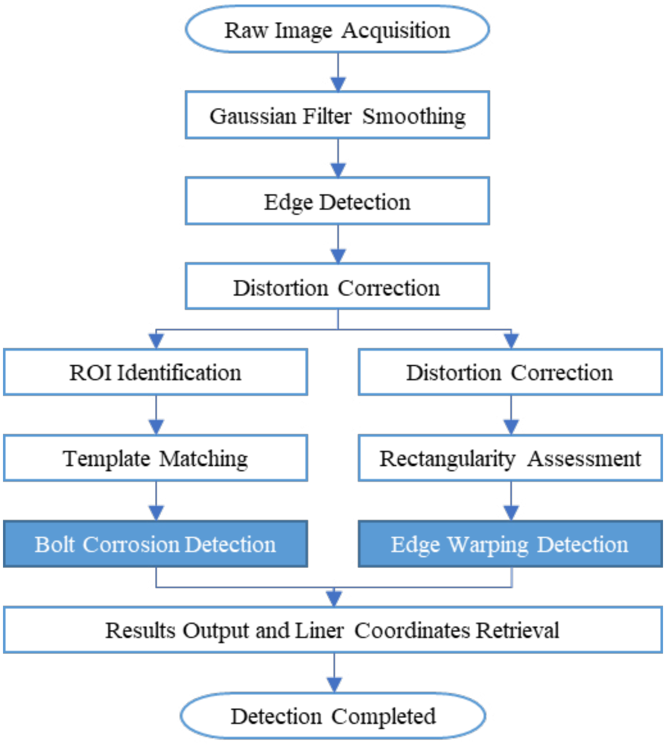


Fig. 5. Flow chart of defect detection algorithm for bolts and edges

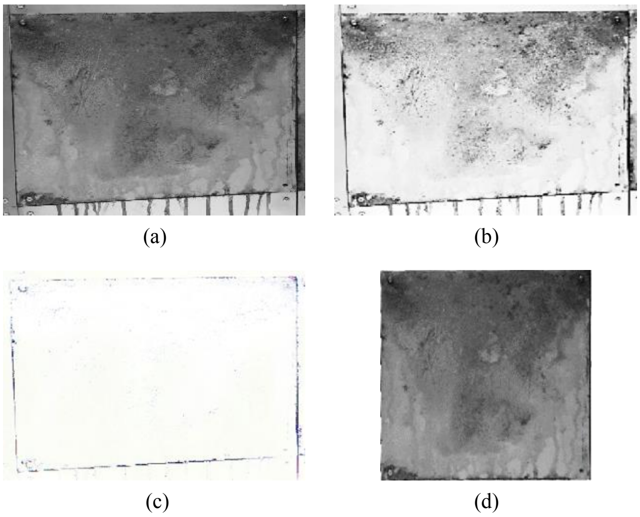


Fig. 6. Image pre-processing steps: (a) Raw image; (b) Gaussian filtered image; (c) Edge detection; (d) Distortion correction

Subsequently a Hough transformation [16] is applied to detect the liner edges (Fig. 6 (c)). This operation allows for an easier detection of image skew and distortion. If such conditions occur, a correction procedure is applied to the image instance. The final pre-processing result is illustrated in Fig. 6(d).

As regards the bolt corrosion detection, a customized template matching-based procedure is used [23, 24]. In this paper, the template matching is carried out by combining the geometric features such as the shape of the defect edge and object position coordinates. The specific algorithm can be summarized as follows:

Step 1: Load the pre-processed image instance and the bolt template image;

Step 2: Determine the search area within the image instance;

Step 3: Align the template image to the top-left corner of the image instance to be analyzed;

Step 4: Slide the template along the image instance from left to right and from top to bottom with a step equal to 1 pixel. At each sliding step, the similarity between the template and the corresponding image instance subset is computed in terms of Pearson's correlation coefficient R as per Eq. (2) [25].

$$R = \frac{\sum_i (x_i - x_m)\,(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\,\sqrt{\sum_i (y_i - y_m)^2}} \tag{2}$$

where x_i is the intensity of the i^{th} pixel in the template (acceptable bolt or corroded bolt), y_i is the intensity of the i^{th} pixel in the image instance, x_m is the mean intensity of the template, and y_m is the mean intensity of the image instance. Examples of acceptable and corroded bolts are reported in Fig. 7(a)-7(b).

Step 5: if the R coefficient results lower than the experimental threshold set to 0.99 the bolt is classified as corroded.

Concerning the detection of the edge warping, a rectangularity assessment is carried out [26]. Specifically, a rectangularity coefficient is computed with an acceptance threshold of 0.99, below which the lining plate edge is considered warped. An example of edge warping is illustrated in Fig. 7(c).

2.3. Defect location

In order to facilitate the maintenance personnel to find the damaged lining plate, once a defect is detected, the software provides the corresponding position information.

With reference to Fig. 3, one of the four corners on the top of the bunker is used as the origin, and the other three directions of the bunker structure are taken as the XYZ axis to establish the space rectangular coordinate system. An example of the real-time location reported in Fig. 8.

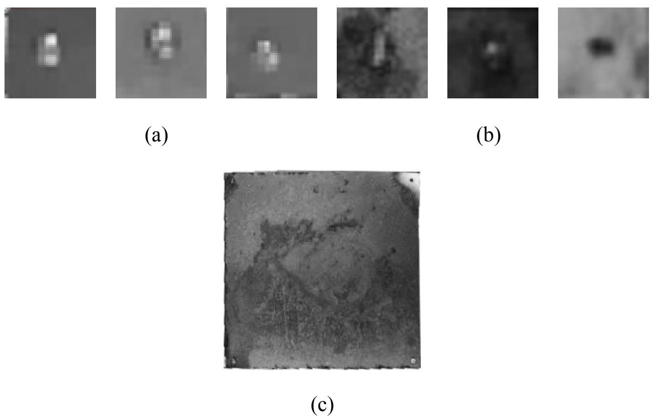


Fig. 7. (a) Acceptable bolts; (b) corroded bolts; (c) example of edge warping

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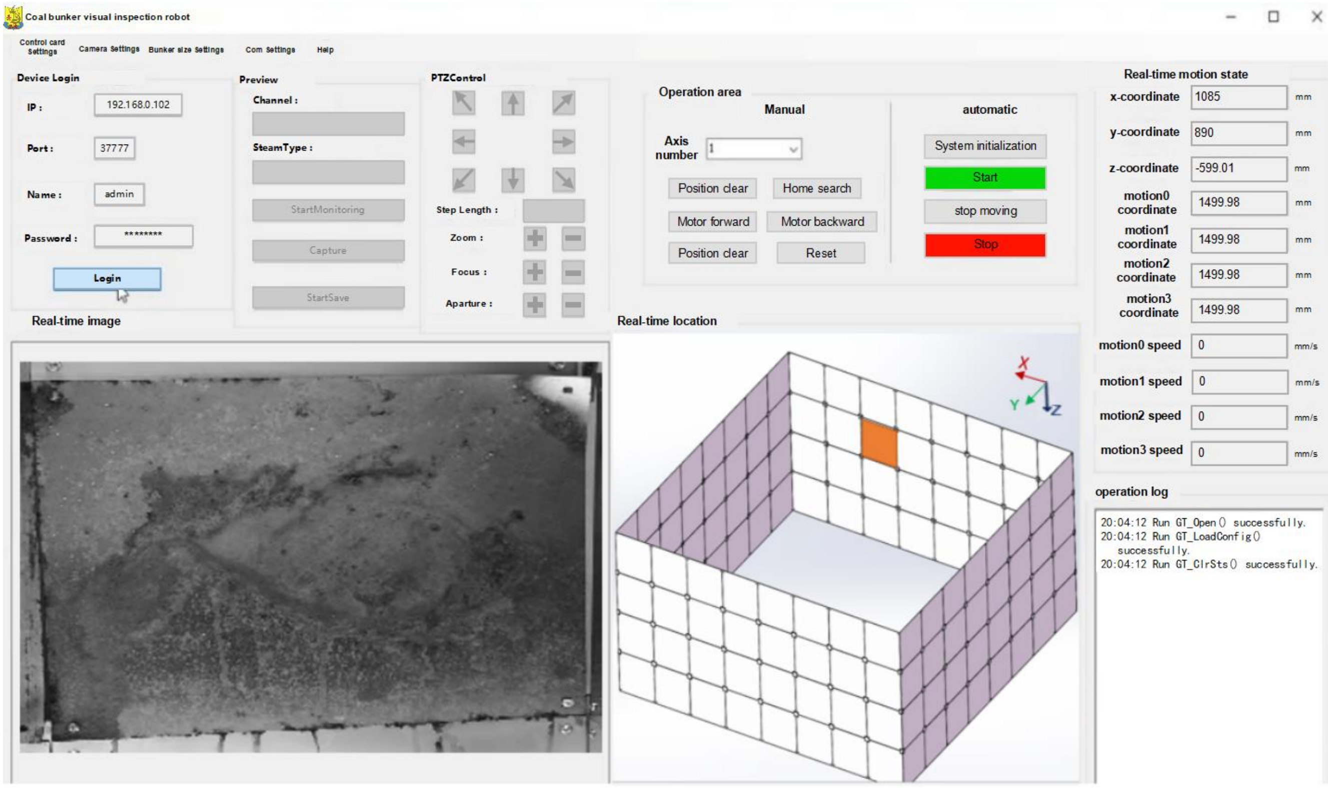

Fig.8. Graphic User Interface screenshot

2.4. Graphic User Interface

The proposed method is developed in a form of a software endowed with a graphic user interface (GUI) to allow for a proper handling. An example of the GUI is reported in Fig 8. showing the operation interface, the display interface and the camera settings interface [27].

The operation interface allows for the control of the camera login, pan tilt movement direction, camera angle, lens aperture size, lens zoom, lens focal length. This interface allows also for defect position retrieval The display interface allows for the visualization of robot spatial coordinates, motor position, motor running speed (dynamic refresh), real-time display of pictures collected by camera, system log and real-time position of robot. The graphic user interface allows for the custom settings in terms of camera field size, distance from the inner wall, coal bunker shape and size, motor speed, winding drum diameter and other operating parameters.

3. Experimental results and discussion

Experimental activities for this research have been carried out on a 1:5 scale coal bunker model of Huaneng Coal Plant, located in Shantou (China). The model is a cuboid with a length of 2 m, a width of 2 m and a height of 2 m. 256 stainless steel plates (25 cm × 25 cm) were installed on the inner wall of the model, which contained 1024 bolts and 1024 edges (Each plate has 4 edges and 4 bolts) to be detected. The defects, i.e. corroded bolts and warped edges were artificially created on the lining plates and then installed on the bunker model for experimental purposes. The experimental tests of image acquisition consisted in moving the camera unit clockwise along the inner wall of the coal bunker and acquiring a photo in correspondence of each panel. Once a cycle is complete the camera is moved downwards with a step of 24 cm for a new scanning cycle.

The distance from the camera to the wall is set to 50 cm. The defect detection results are displayed on the software interface and fed back to the maintenance personnel.

The experimental results shown in the confusion matrices reported in Tables 1 and 2 that the proposed method can effectively detect a variety of defects in the coal bunker liner. Specifically, the bolt corrosion detection was carried out with an overall accuracy of 96.5% and a missing rate of 11%, while the edge warping was detected with an overall accuracy of 99.6% with a missing rate of 2.99%. In terms of computation time, the proposed inspection system takes 288 s to detect the whole bunker surface.

Considering the scale of the model and the real size of the Huaneng Coal Plant bunker, the expected detection time for the bunker is about $288 \times 5 \times 5 = 7200\,s = 2\,h$.

Table 1. Confusion matrix for the bolt corrosion defect detection

Detection result		Output	
		Bolt corrosion	No defects
Target	Bolt corrosion	318	36
	No defects	0	670

Table 2. Confusion matrix for the edge warping defect detection

Detection result		Output	
		Edge warping	No defects
Target	Edge warping	134	4
	No defects	0	886

Considering an 8-hour working shifts and 10 days manual inspection duration, the automatic detection system proposed in this paper allows to save up to 97.5% of the time compared to the manual detection of coal bunker.

4. Conclusions

This paper proposes a machine vision-based automatic inspection system endowed with a Cable-Driven Parallel Robot, an image acquisition unit and an image processing unit for the defect detection in coal bunkers maintenance operations. A tailored light source is designed to reduce the reflection of the stainless-steel lining plate, allowing for high-quality images acquisition of the areas to be inspected. A campaign of experimental tests was carried out to detect corroded bolts and edge warping on the lining plates. Results demonstrate detection capabilities of the proposed system in a coal bunker environment. In this respect, compared with the current manual inspection, the proposed method can drastically reduce the inspection time whilst keeping a great detection accuracy and guarantee high health and safety standards. In this context, the proposed system can be further reconfigured with proper light sources, motion mechanism and specific templates for a complete automation of the inspection tasks. Current experimental activities are being carried out to improve the accuracy of the bolt corrosion detection as long as other types of occurring defects.

Acknowledgements

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