The State Inspection of Upper Supporting Roller of Conveyor in Service with Structural Pattern Recognition and Cluster Norm Algorithm of Failure

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ABSTRACT

In thermal power generation, coal transportation is an important link in the production process, and coal transportation by corridor conveyor is a common technical method. In order to ensure the normal and continuous supply of coal, it is necessary to inspect the corridor facilities, especially the working status of conveyor rollers, and timely find and deal with abnormal situations. It is difficult to meet the requirements of modern thermal coal transportation inspection due to the heavy workload and high labor intensity. According to the performance requirement, operation mode and function of space orbit, a kind of inspection robot instead of manual is proposed. The robot system by CCD detection, convention scanning way, classifier design and abnormal structure pattern recognition algorithm, the displacement of conveyor roller state, center, do not turn, abstraction of severe abrasion and crack, form the state vector, through clustering algorithm of norm, judgment and determine the roller on the working state, the robot real-time condition monitoring alarm with abnormal situation.

Keywords: *State vector, Structural pattern recognition, Machine vision, Conveyor upper roller state, Cluster norm algorithm*

1. INTRODUCTION

In thermal power generation, corridor conveyor coal transportation is a common technology for coal supply. In order to ensure the accurate and reliable transportation of coal through the corridor, the corridor conveyor and other equipment should be inspected. The roller on the conveyor becomes the core object of inspection because of bearing and transmission power. It is difficult to meet the requirements of modern thermal power coal transportation inspection due to the heavy workload and high labor intensity.

The development direction of conveyor inspection is mainly using robot technology. According to the operating environment and inspection objects, the robot is designed and adopted by using machine vision, sensor technology, logical judgment algorithm, combined with kinematics and dynamics analysis. The inspection includes temperature and humidity in corridor space, dust concentration, movement direction of conveyor, idler status and leakage with or without coal, etc.

At present, the research and application of machine vision and robot inspection have made some progress. Alhassan, Ahmad Bala et al. [1] studied the aerodynamic stability of a light-armed transmission line detection robot under the influence of wind. Shi Congling et al. [2] Study on laser positioning system of downhole detection robot based on signal reflection principle. Xu, Wei et al. [3] designed a modular detection robot based on substation. Meet the needs of different substations. Teng, Yun et al. [4] proposed the application of intelligent inspection robot system in sutong GIL comprehensive pipe corridor project. Wu, Gongping et al. [5] proposed an automatic docking charging control method for testing robots. Dehne, Andre et al. [6] proposed the so-called MARWIN: a mobile autonomous robot for maintenance and inspection in a 4D environment. Li, Peng et al. [7] proposed an active screw driven robot for pipeline detection. Dubreuil, L et al. [8] integrated the detection program into the processing process and proposed a calibration method based on the measurement of parts, which was completed through the 3D features of parts and synchronized with the machining operation, so as to realize the Monte Carlo simulation and evaluation of 2D feature recognition in the real environment.

Szydlowski, M et al. [9] proposed a milling cutter wear detection method based on machine vision and wavelet extended depth of field image reconstruction, which can achieve careful positioning of the cutting edge and accurate measurement of geometric quantity. In the process of image acquisition, variable light intensity is used to detect the regions with different reflection characteristics, and then geometric information and reflection characteristics are used to evaluate tool wear. Wang, ZX et al. [10] realized a robot for capacitor quality detection based on machine vision, which is mainly used to accurately detect the appearance defects and capacity values of safety capacitors and can automatically eliminate defective devices. Wang, Su-Mei et al. [11] proposed a machine vision system based on vehicle data recorder and image signal processing to automatically evaluate rail curvature in view of the long distance of railway lines, which makes it difficult to detect track state effectively and accurately. The proposed machine vision system consists of four modules: video acquisition module, image extraction module, image processing module and trajectory state assessment module. According to the dashcam video, the coordinate system of train and track is defined in Lagrange space, and the track curvature is estimated by the string offset method and double measurement method. Seokjae-hacho, Myeong-woo [12] Proposed a detection system for LED press based on machine vision in this study. In this system, two cameras are used to detect epoxy point position and two cameras are used to detect patch status. A new visual processing algorithm is proposed and its effectiveness is verified by field experiments. The measurement position error is less than X: -29 ㎛,Y: -32 ㎛ and rotation error :3 °using the proposed visual algorithm. The results show that the proposed machine view is based. Joshi, K, et al. [13] proposes a machine learning method based on machine vision, the method based on texture analysis technology based on vision is the principle of characterization of surface texture, and then USES the multi-layer feedforward neural network for supervised machine learning, fitting response by back propagation (surface roughness) input (based on visual texture parameters). The performance of texture analysis techniques based on histogram, gray level co-occurrence matrix, Fourier transform and wavelet transform for training data generation and training algorithm for training network are compared. This method can be used to estimate the surface roughness of industrial parts. Boby, RA et al. [14] adopted four different algorithms for defect detection, namely Fourier filtering, automatic median method, image convolution method and single-step threshold method, and compared their performance with the efficiency and speed of defect classification. This paper introduces the whole process, analysis and results of different image processing algorithms for defect detection. Moo,Huh Kyung [15] proposed an enhanced histogram matching algorithm to correct distorted histograms caused by illumination changes. We use a resolution adjustment method to optimize the matching of input histograms and reference histograms and reduce quantization errors during digitization. This algorithm not only improves the accuracy of defect detection, but also is robust to illumination changes in machine vision detection. Experimental results show that the proposed method can keep consistent detection error rate under the condition of large illumination changes, while the results of traditional detection methods are inconsistent under the same illumination conditions. Yang, Y [16] designed a set of online inspection system for welding quality based on machine vision on the basis of studying welding inspection methods. Singh, R.et al. [17] carried out ;some examples of reliability testing of automatic measurements using grey scale digital images of mining structures is described. A CCD (charged coupled device) based active triangulation system is combined with image understanding algorithms to provide machine vision capability and for automatic measurement of the textureless and featureless surface of sandstone strata. Yang, Tang Wen et al. [18] studied real-time algorithms to detect the power lines in the UAV video images, in that video images are converted into binary images through an adaptive thresholding approach, Hough Transform was used to detect line candidates in the binary images, and a fuzzy C-means (FCM) clustering algorithm is used to discriminate the power lines from the detected line candidates. Horn, David [19] discussed the use of advanced neural networks to expand the field of machine vision systems for commercial application. In addition to routine inspection of products and control of robots for routine tasks, advances have been made in lighting technology, application-specific software, and computer chips. Guo, BHW et al.[20]the objectives of this paper are to: (1) investigate the current status of applying computer vision technology to construction safety, (2) examine the links between computer vision applications and key research themes of construction safety, (3) discuss the theoretical challenges of applying computer vision to construction safety, and (4) recommend future research directions. A five-step review approach was adopted to search and analyze peer-reviewed academic journal articles.Mittal, V and Bhushan, B[21] described an in-depth survey of problems faced in existing computer vision applications and to present AI on the Edge along with OpenVINO toolkit as the solution to those problems. We redefine the workflow for deploying computer vision systems and provide an efficient approach for development and deployment of edge applications. Furthermore, we summarize the possible works and applications of AI on the Edge in future in regard to security and privacy.Mite-Baidal, K et al.[22] aimed at identifying the techniques or computer vision algorithms used to assess fermentation index of cocoa beans for quality control, as well, the main physical and chemical characteristics of the cocoa beans identified through the computer vision algorithms. Feng, MQ and Leung, RY[23] demonstrated a novel application of the computer vision technology to solve a challenging vehicle WIM problem. Requiring no sensor installation on the roadway or the vehicle, this cost-effective non-contact computer vision system has demonstrated a great potential to be implemented.. Tsotsos, J et al. [24] examined the distribution of sensor settings in vision datasets, only one potential dataset bias, and performance of both classic and deep learning algorithms under various camera settings. This reveals a strong mismatch between optimal performance ranges of theory-driven algorithms and sensor setting distributions in common vision datase.

According to the performance requirements, operation mode and function of space orbit, this paper proposes a kind of inspection robot instead of human operation by using machine vision, sensor technology, logical judgment algorithm, combined with kinematics and dynamics analysis. By means of insight into the properties of materials of the upper supporting roller assembly and with CCD detection, conventional scanning mode, classifier design and abnormal structure pattern recognition algorithm, the status, center displacement, non-rotation, severe wear and crack of conveyor idler are monitored and warned online, and the real-time status monitoring and abnormal situation alarm are realized.

2. STRUCTURAL STATE OF CONVEYOR AND BASIC FAILURE TYPE ANALYSIS OF THE UPPER ROLLER

Continuous and effective transportation of coal is an essential guarantee for thermal power generation. The direct support for the normal working state of the coal conveyor is the position and state of the rollers on the conveyor as shown in figure 1. For durance of the conveyor system, stress materials have been selected for the assembly of the rollers, premium steel for the frame and strong alloy for shafts, reinforced rubber for the rollers themselves, and double-row thrust bearings being adopted.

In order to monitor the working state of the conveyor in real time, it is necessary to check the upper roller supporting the conveyor to confirm its normal state and failure or potential failure form. On the basis of actual production site investigation and abstraction, three typical failure modes are formed:

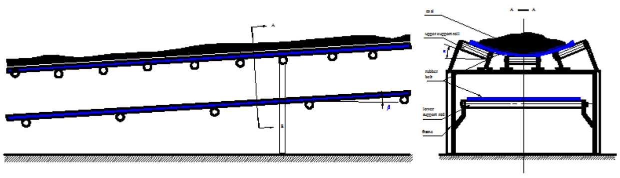

Figure1. Conveyor working system and supporting roller of coal conveying gallery bridge

2.1 Overall deviation of the upper roller

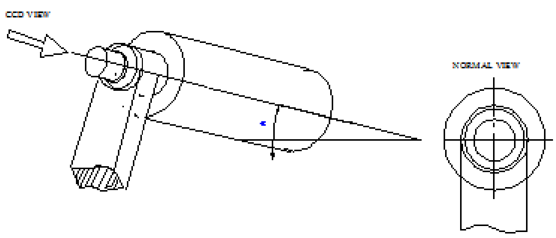

Figure 2. Structure of the upper roller

The upper roller is in direct contact with the conveyor, which not only plays a guiding role, but also exerts a supporting role, is subjected to friction, dynamic load and so on. Therefore, the loads of the upper roller should be

$$S_F : \{ \vec{F}, q_l, M_l, M_a, F_a \sin \omega t\} \qquad (1)$$

where the elements in above set respectively represents the concentrated force, distributed force, torque by beam, torque by rotational shaft and cyclic load.

The working states of the upper roller are complicated, but the result of the action makes the roller leave the original ideal positions, as shown in figure3.

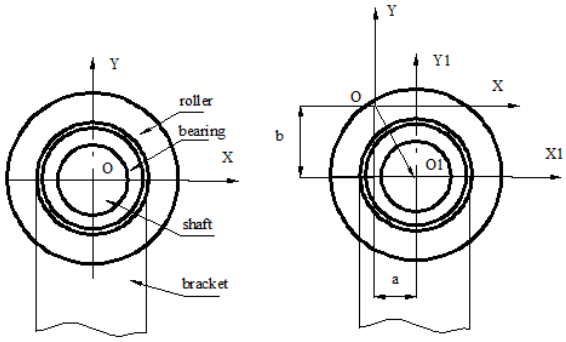

Figure 3. Working state of the upper roller and significant center displacement of the roller

2.2 Rotation-failure of the upper roller

The upper roller cannot operate normally due to excessive resistance of rotary mechanism.

Set the instantaneous linear velocity of the conveyor (desirable average value) as vc, and the rotation speed of the idler under normal working condition is

$$n_r = \frac{v_c}{\pi d} \qquad (2)$$

When the lubrication is poor, foreign particles enter the working raceway of the bearing, the rolling body is broken, or the idler is blocked by external objects and cannot rotate normally, rotation stops or the speed is very low, it can be regarded as a rotary fault.

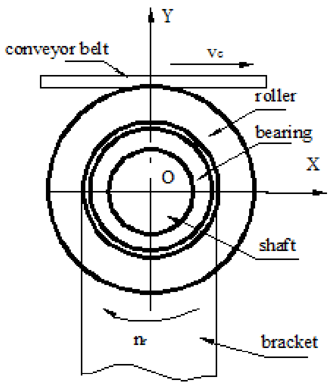

Figure 4. Failure in rotation

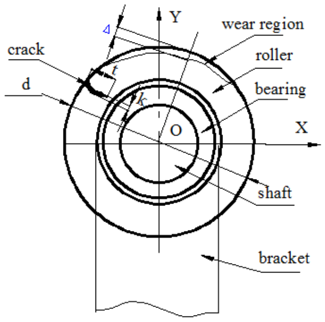

Figure 5. wear and crack of the upper roller

A certain interval, such as flag "+", can be marked at the appropriate position of the end of the roller. When the time interval is Δt and the above symbol is detected, the roller speed can be determined:

2.3 Wear and crack on upper roller face

Working roll is subjected to alternating stress load for a long time, at the same time by the conveyor surface action under the lower surface of the convey bent, subjected to a large percentage of rolling friction and small percentage of sliding friction continuously, can cause local crack and wear. When this kind of crack and wear becomes visible, consequences maybe faced for the transportation of the coal, and actions must be taken in time for repair or replacement. This situation is depicted as shown in figure 6.

Cracks may be described as A_c=a × b;

Expressions of wear may be by W_c=Δ.

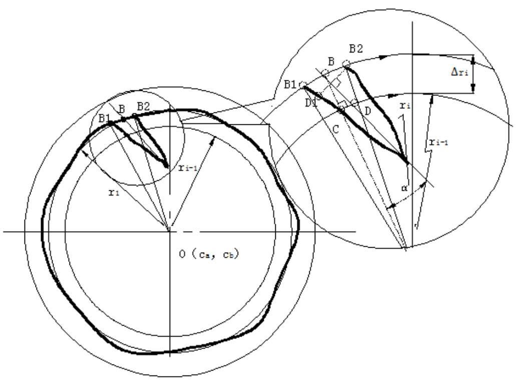

Figure 6. Inspection of wear and crack on roller working face

3. STRUCTURAL PATTERN RECOGNITION STANDARD MODEL AND CLUSTERING NORM ALGORITHM FOR UPPER ROLLER ASSEMBLY

3.1 Standard model (error-free classifier)

It is assumed that the roller components are all in the original ideal state: no deformation (displacement), no wear, no crack, and the rotation of the roller is also in the ideal state. At this point, the state vectors can be used to describe the states of the monitored objects, denoting as the standard states:

$$S_{is}(E_{js}) = \{e_{i\,js}\}, i = 1,2,3.....n;\ j = 1,2,3.....m \tag{3}$$

where, $S_{is}(E_{js})$ ——The standard states of the monitored objects. There are n monitored objects in the system, and the state vectors of each monitored object has j components

$\{e_{ijs}\}$ —— element expressions of state vector of the monitored object

For a system that uses m components to describe n objects, it can be expressed by the matrix $n \times m$.

As an example, the standard (ideal) working state model vector of the rotary center of the above roller is

$$S_{1s}(E_{js}) = \{e_{1\,js}\},\ j = 1,2,3.....m$$
$$= \{e_1(\mathrm{x}), e_1(\mathrm{y}), e_1(z), e_1(t)\} = \{x_{co}, y_{co}, z_{co}, T_o\} \tag{4}$$

where, $\{x_{co}, y_{co}, z_{co}\}$——ideal position coordinates

T_o ——durance of the upper supporting roller

3.2 Instantaneous state structure pattern recognition

Similarly, the instantaneous state vector of the monitored object of the system can be described.

$$S_i(E_j) = \{e_{i\,j}\}, i = 1,2,3.....n;\ j = 1,2,3.....m \tag{5}$$

Different from the standard state, the parameters reflecting the state of an object are no longer the standard values, but the parameters reflecting the instantaneous working state through structural pattern recognition. When represented as a state vector, it is in the same form of the state vector of the standard model and can equally be manipulated as a vector. This provides conveniently a theoretical and technical basis for the clustering norm algorithm to judge the working state of monitored objects.

For example, the rotation center of the above roller, its standard (ideal) working state model vector is

$$S_1(E_{js}) = \{e_{1j}\},\ j = 1,2,3.....m$$
$$= \{e_1(\mathrm{x}), e_1(\mathrm{y}), e_1(z), e_1(t)\} = \{x_{11}, y_{12}, z_{13}, T_{14}\} \tag{6}$$

where, $\{x_{11},\ y_{12}, z_{13}\}$ ——the instantaneous working position coordinates of the roller

T_{14} ——the rest of the durance of the roller after a period of working time

3.3 Clustering norm algorithm for state classification and failure judgment

According to the failure type, the ideal state has been described as the respective standard type when checking the state of the roller. Once the coal conveyance system is put into operation, the state of roller will change from "standard type" to "instantaneous type", thus deviating from the original ideal position. With the lapse of time, the above deviation degree gradually increases, and even crosses the threshold and enters the "failure type".

The "standard type" has been explained in the above part, and the instantaneous state and failure state of each monitored object are given here.

According to the cluster analysis method, suppose there are n test objects of the roller, and the instantaneous state of a specific test object can be described by m state parameters, then the state vector of the standard model is expressed with equation (3), and the state vector of the instantaneous working model is in terms of equation (5).

The mathematical norm is introduced to compare and calculate the "distance" between the instantaneous state and the ideal state for the inspected object. When the distance exceeds the working domain, the failure state is entered. Take the distance norm

$$d_n = \left|S_i(E_j) - S_{is}(E_{js})\right| \le \delta \tag{7}$$

As soon as the inequation (7) is failed to set up then the object enters the failure state, that is

$$\left|e_{ij} - e_{ijs}\right| > \delta \tag{8}$$

4. CLASSIFIER DESIGN BASED ON GRAYSCALE EDGE ALGORITHM

The core of using CCD to capture and examine the scene is to distinguish the required "foreground" and eliminate the "background". On this basis, the state of the foreground is picked up and compared with the standard template. When the "consistency rate" reaches the threshold value, the "state appearance" can be identified. We use grayscale to realize structural pattern recognition.

4.1 Classification and state discrimination of roller center

From figure 2, the roller, conveyor, and the large background can be detected by CCD. By differentiating gray level, the edge of roller may be found to determined the center of roller.

Calibration of roller center after installation

Set the coordinate of original center Co as (cao,cbo), that is, the position of idler in no-load state is determined and recorded into the database. "Row scanning method" is adopted, and the row spacing is set as Δδ, as shown in figure 7.

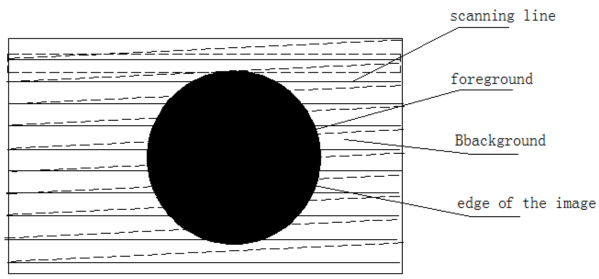

Figure 7. Row scan in the foreground

In a row scan, the previous pixel grayscale with $e < \mathrm{i}$

$$q < k \tag{9}$$

where,k——foreground grayscale

And there is an alternating gray step situations within $i \le e \le j$. while the pixel gray scale is reduced to $q < k$.

When the pixels are dense enough, a clear edge of the full circle can be obtained.

Take three pixels (x1, y1), (x2, y2) and (x3, y3) that are sufficiently spaced apart.

The plane circle and the center of the circle can be obtained. In order to improve the reliability of positioning, the concentric circle scanning method is used to verify and correct the row scan result.

Ideally, the scan path is a set of concentric circles

$$x^2 + y^2 = R_i^2,\ i = 1,2,3\ldots n \tag{10}$$

Take the scanning interval in the concentric circle scanning method $\Delta R_i = R_i - R_{i-1}$.

To begin with the large enough circle, the scan runs with the graduate reduction of radius according to, arithmetic progression,then it is certain that the gray scale of the i-th scanning circle will change suddenly or change alternately.

So. The coordinates of the circle and center of circle obtained by "row scan method" can be improved and modified:

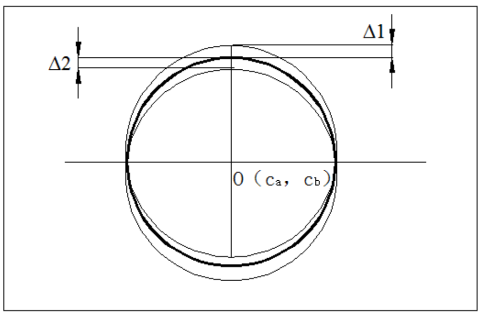

Figure 8. Correctness of the center of the roller

Then we take

$$c_b = c_b \pm \Delta i \tag{10-1}$$

If the large grayscale value appears earlier, the above equation is calculated with mark "+"; otherwise, use a "- ". Similarly, coordinates of the circle center will be treated in the x direction. Now we have

$$\begin{cases} x_{modified} = a_c \pm \Delta_{xi} \\ y_{modified} = b_c \pm \Delta_{yi} \end{cases} \tag{11}$$

According to equation (6) and figure 3, the center of the roller is significantly displaced

$$\begin{aligned} \Delta C &= \left| o_{\Delta C} - o_O \right| \\ &= \sqrt{(x_{modifies} - c_{ao})^2 + (y_{modified} - c_{bo})^2} \\ &= \sqrt{((a_c \pm \Delta_{xi}) - c_{ao})^2 + ((b_c \pm \Delta_{yi}) - c_{bo})^2} \end{aligned} \tag{12}$$

when ΔC exceeds the working threshold, the significant displacement of the roller center can be approved.

4.2 Classification and discrimination of roller cracks and edge wear

In triangle BCD, see figure 6, angle ∠BCD is a right, α is the included angle between crack direction and radial direction. Points B1 and B2 can be obtained from the edge of the crack (according to the gray level) when the scanning sequence is from the large circle to the small circle, i.e. the center of the circle with points. C1 and C2, etc. Now we have a relative orientation of crack

$$\alpha = \text{arctg}\left(\frac{CD}{BC}\right) \tag{13}$$

The crack width

$\overline{D1B2} \approx \overline{B1B2}\sin\alpha$

Crack length

When take the maximum radius and minimum radius of the scanning ring parameters

$$\overline{BD} = \frac{\overline{BC}}{\cos\alpha} \tag{14}$$

then $\overline{BD}$ may be regarded as the crack length.

By using machine vision, starting with a concentric circle scanning, the basic method is so-called "concentric circle scanning method", the concrete operation process of it is as follows:

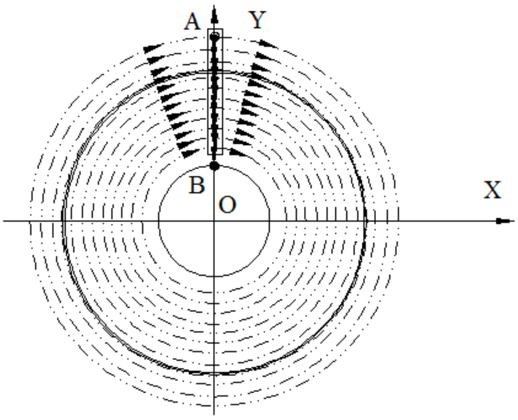

Figure 9. Concentric circle scanning method

According to equation (11), start with a value slightly larger than the diameter of the roller for the concentric circle scanning, and undertake

$$x^2 + y^2 = R_1^{\ 2},\ R_1 = d_o / 2 + \Delta Ri \tag{15}$$

Ensure that the scan includes parts of the background, and scan as far as to the position of the roller radius small enough so that the foreground and edges are marked by grayscale contrast. The concentric circle scan starts with point A, through a whole circle and then comes back to point A and turns to next concentric circle whose radius is less than ΔRi. and so on, until approaching point B.

In this process, the grayscale of foreground, background and idler forms contrast, crack and background contrast obviously, edge is clear; but the gray contrast of roller's edge of wear is not obvious, so the crack and edge wear are judged together.

4.3 Classification and status discrimination of the roller

A certain interval can be marked at the appropriate position of the end of the roller, such as "+". When the time interval is noted in terms of Δt and the rotation angle is Δβ , then the above symbols are detected, and the instantaneous roller rotation speed can be determined by

$$n_i = \frac{1}{360} \times \frac{\Delta\beta}{\Delta t} \tag{16}$$

Let nr be the ideal rotation speed, if the instantaneous roller rotation speed is much less than that of the ideal rotation speed, then the failure of rotation speed of the roller may be recognized

$$\left| n_i - \frac{n_r}{10} \right| = \left| \frac{1}{360} \times \frac{\Delta\beta}{\Delta t} - \frac{v_c}{10\pi d} \right| \leq \varpi \tag{17}$$

Or

$$\left| n_i \right| \leq \lambda \tag{18}$$

where， ϖ、λ ——infinitesimal positive numbers.

So, the failure of rotation of the roller may be determined.

5. CONCLUSIONS

A special inspection robot was proposed and developed for the monitoring the upper supporting roller of the thermal power corridor coal conveyor through the principle of machine vision, structure, pattern recognition and cluster norm algorithm is used to build the conveyor roller working state inspection and failure diagnosis system, to ensure timely find out failure roller and failure forms, timely report to the police, timely maintenance, to maximize the guarantee normal operation for the coal supply..

Based on the analysis of the structure state and the failure or potential failure forms of the conveyor roller, three failure forms of the roller are abstracted: the macro displacement of the roller center, the roller failure of rotation, and the significant wear and crack of it. The working state vectors are adopted to describe the three failure modes, and the engineering problem is transformed into a mathematical problem.

By analyzing and calculating the distance norm between the instantaneous working state vector and the ideal state vector, the clustering norm algorithm has been proposed and employed to reflect the working state of the roller and determine the failure form of the roller effectively in real time.

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