Design of Belt No-load Detection System Based on Image Processing Technology

Jiali Sun, Shaochuan Xu, Dehua Liu and Jing He

***Abstract*—Belts are mainly used for transporting coal. During the conveying process, the belt may be idling. Manual inspections not only lead to reduced efficiency, but also pose safety hazards. As a result, it is proposed a belt no-load monitoring system based on the improved algorithm of support vector machine. The belt is used for on-site monitoring of belt idling problems. An initial image of the belt is acquired by a camera unit and the image is preprocessed. According to the belt images of different working conditions, feature selection is performed for images affected by external light sources, belt surface trace features and ore state distribution. Then support vector machine models using different kernel functions are constructed to classify the belts. Therefore, the belt no-load detection method proposed in this paper can to a certain extent solve the problem that artificial cannot monitor the belt status in real time and timely warning. This method reduces the chance of belt conveyor failures and makes the belt work more efficiently.**

***Index Terms*—belt conveyor, no-load detection, support vector machine, feature selection**

I. Introduction

Belt conveyor is one of the universal conveying equipment. It has the advantages of large conveying distance, small power consumption and long continuous working time. It is widely used in metallurgy, coal mine and other industries. Because the belt work site transportation environment is extremely complex. The belt operates over a wide range of areas. If you rely on staff, you will not be able to detect and stop belt failures in a timely manner. Not only does it cause unnecessary damage, but it also puts staff in a dangerous environment [1]. Therefore, this paper designs a system to detect the belt no-load and reduce the risk of belt failure.

At present, many scholars have studied the phenomenon of belt failure. Many methods have been proposed for belt fault detection. For example, Zhang, Xu, and Wang proposed a deep learning based belt deflection detection method under complex working conditions. The features of belt and rollers are extracted by convolution neural network. Thus, the belt and the rollers are positioned and the degree of belt deflection is calculated [2]. Wu et al. proposed a method to detect belt deflection using machine vision technology. Utilizes a combination of RFID and wheel odometers to accurately locate belt deflection [3]. Xu et al. proposed a real-time belt deflection detection method [4]. Zhu et al. proposed a YoloX - ECA damage detection method based on YoloX to improve the detection of conveyor belt damage [5]. Wang et al. proposed a visual detection method YOLOv4 - BELT based on deep learning, which effectively solves the problem that complex samples are difficult to recognize [6]. Nowadays, most of the belt failures are detected as belt deflection, belt damage and belt tears. However, it is neglected that the detection of belt no-load can reduce the frequency of failures.

Belt transmission mainly depends on friction force. It can effectively cushion the load impact. When the belt is overloaded, it is easy to cause the problem of belt slip. When the belt is not tightened, the material will pile up more and more, causing the belt to become clogged. Therefore, this paper designs a belt no-load detection method based on the improved algorithm of support vector machine to monitor the working status of the belt in real time and avoid the belt failure. The contributions of this paper are: Firstly, a feature selection method is proposed and the result of feature selection is used for support vector machine classification. Secondly, by establishing the classification model of support vector machine, Gaussian kernel function is introduced to build the belt no-load detection system to detect the belt no-load. At present, this system in the mine has been through a large number of experiments to prove that the accuracy of the method is high and can meet the requirements of the actual working conditions.

II. Classification and Analysis of Belt Load in Complex Environment

Due to the complexity of the field environment, the unstable lighting environment will affect the selection of the eigenvalues and feature areas. The distribution state of the discharge is variable during transportation of the belt. In addition, the belt transportation process inevitably darkens the belt color. Some belt images are difficult to distinguish between material or no-load. It also causes wear on the belt and affects the surface characteristics of the belt. Under load conditions, the captured belt images are categorized. It can

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be affected by the external light source, the characteristics of the belt surface traces, and the distribution of the ore state.

A. Analysis of Working Conditions

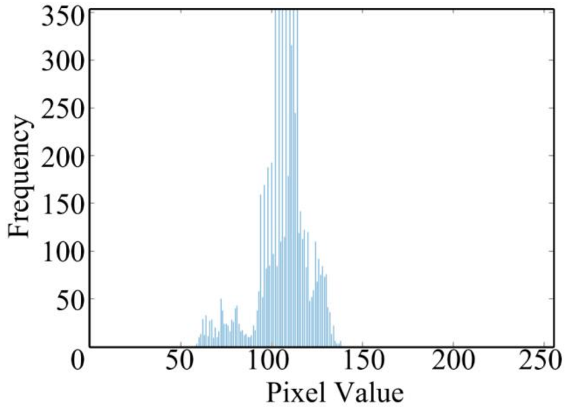
The first category is influenced by external light sources. Belt images are categorized into indoor and outdoor images under different lighting environments. Indoor images are categorized into images illuminated only by non-natural light and in a closed state, and images with windows that are affected by both natural and non-natural light. In this case, the detection of images of belts in a closed state is more stable. Indoor belt images with windows can produce light spots on the belt due to natural light variations. However, there are not enough natural light sources indoors in the early morning or late afternoon. At this point, it is necessary to use unnatural light indoors for supplemental lighting. Outdoor images are also affected by natural and unnatural light, similarly to indoor situations with windows. The belt state of natural light at the same belt at different time periods is shown in Fig. 1.

(a) Daytime unloaded

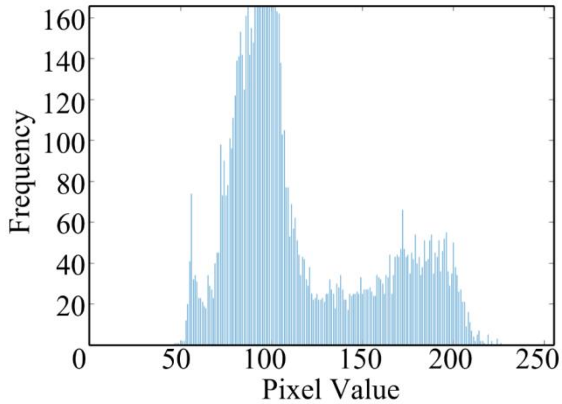
(b) The morning is full of material

(c) The afternoon is full of material
Fig. 1. Belt status for different time periods

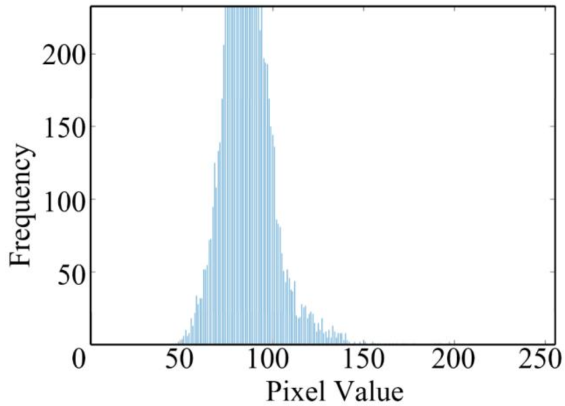
As shown in Fig. 1, the belt has a poor light source in the afternoon, and the red-framed area in Fig. (a) is selected. As shown in Fig. 2, which shows the grayscale distribution of the belt image at different time intervals. Comparing Fig. (a) with the distribution of the same belt in no-load condition, it is observed that the grayscale levels of no-load are mainly distributed in the range of 60 to 140. The range of gray scale distribution of the material is more similar to that of the material when the light source is poor, which is prone to miscalculation. Therefore, the subsequent data processing requires a reasonable selection of eigenvalues to make the classification effect better, thus reducing miscalculation.



(a)Daytime unloaded



(b)The morning is full of material



(c) The afternoon is full of material
Fig. 2. Gray scale distribution of belt images for different time periods

The second category is influenced by the characteristics of the belt surface traces. Due to the corrosive nature of the coal material, the belt will change the colour of the belt surface when transporting coal for a long period of time. At the same time, the long-term work of the belt conveyor also leads to belt wear, and the wear and scratches on both sides of the belt are extremely serious. This type of belt image affects the size of the eigenvalue when selecting the feature area. It is difficult to distinguish whether the belt is no load or not. As shown in Fig. 3. Belt scratches compare the image of a belt with distinctive surface trace characteristics with the image of the belt when there is material.

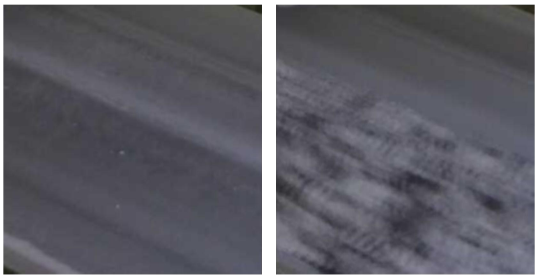
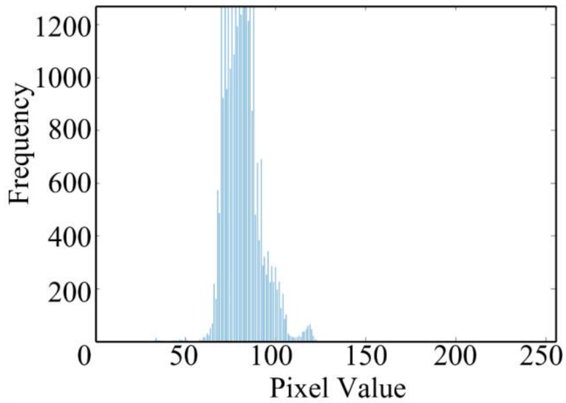
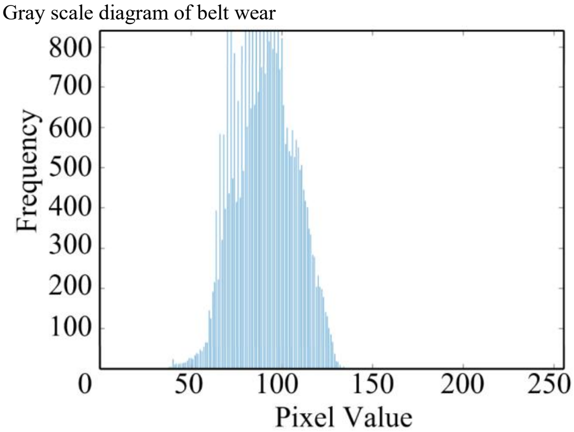


Fig. 3. Images of belt wear and material

As shown in Fig. 4, the grayscale level of the belt is within 125 for both no-load and with material. It is found that the range of grayscale distributions of such images is similar. Subsequent processing of the data requires the selection of appropriate feature areas. Otherwise, it is easy to misjudge.



(a) Gray scale diagram of belt wear



(b) Gray scale diagram of belt with material

Fig. 4. Gray scale image of belt wear and presence of material

The third category is influenced by the distribution of mineral states. The direction and position of the ore fall can lead to uneven distribution of the ore on the conveyor belt. Uneven distribution not only causes belt deviation problems, but also has an impact on belt detection. It is difficult to distinguish the condition of the belt due to the dark color in the middle of the belt caused by the corrosion of the mineral material. The best classification results are obtained when the middle and edge regions of the belt are selected as feature regions. However, it is more difficult to select and classify the features of no material in the middle of the belt, no material on both sides of the belt and coal material covered the belt. It is difficult to find a suitable location by manual effort when selecting features for the above cases. If the edge position is selected as the feature area, it may be judged as no-load when the belt is covered with ore. Whether or not there is coal in the centre cannot be identified either. If the middle of the belt is selected as the characteristic area, it is easy to be judged as having material when there is no material on both sides. Therefore, take the example of no material in the middle and some material on the sides. The red-framed area as shown in Fig. 5 is selected as the feature area.

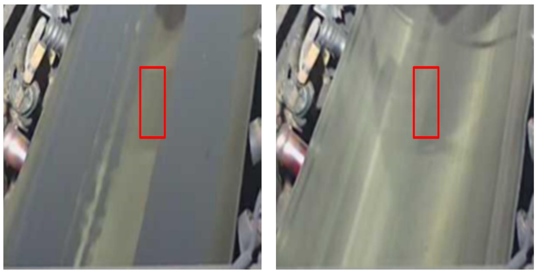
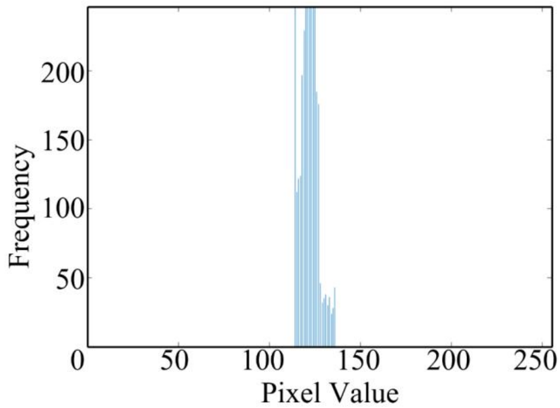
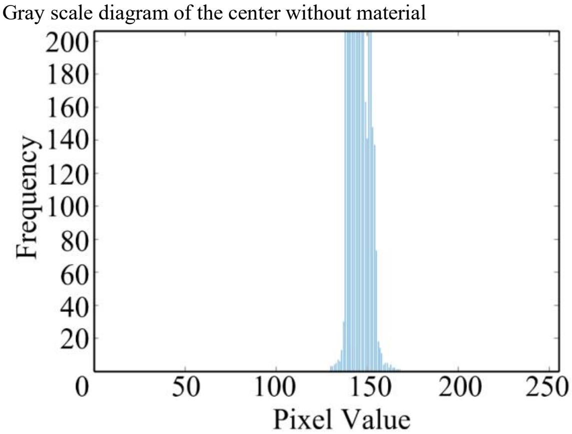


Fig. 5. Belt image with no material and no load in the center

Compare the image with the same belt in the same condition with no load. The distribution maps of the two belt images are similar in range. The corresponding grayscale plot is shown in Fig. 6.



(a) Gray scale diagram of the center without material



(b) Gray scale diagram of an unloaded

Fig. 6. Gray scale plots of no material and no load in the center

In complex working conditions, it is difficult to determine whether a belt is no load or not by a single decision criterion. In this paper, the acquired images are analyzed according to the external light source, the belt surface trace characteristics and the distribution of the ore state, respectively. The appropriate feature regions are selected for the classification of the support vector machine model.

B. Basic System Composition

In this paper, it is designed a belt no-load detection system based on machine vision. The functional structure of the system is shown in Fig. 7. The acquisition of belt image information is carried out by means of a camera device at the belt transport site. The belt image is obtained. Preprocessing operations are then performed on the image. According to the specific analysis of the working conditions in which the belt is operating, the characteristic area is selected and the characteristic values are read. The respective image information data of each belt is obtained to construct the data set. The training set is imported into a support vector machine based on different kernel functions for training. A classification model for the support vector machine will be obtained [7]. The test set is categorized by a classification model of support vector machine. The accuracy of the test set will be obtained. If the test set is not highly accurate, check the training samples. If there is no error sample in the training sample, the image of the error sample is imported into the training set and retested.

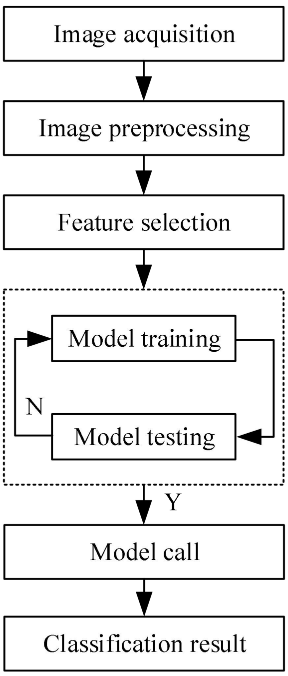


Fig. 7. System function structure diagram

Nowadays, most of the belt testing is belt fault detection, ignoring the fact that belt no-load can cause failure to the belt conveyor. Therefore, this paper proposes a machine vision based belt no-load detection system. The improved method of support vector machine is used for classification.

III. Belt No-load Detection Method Based on Support Vector Machine

It can be known from the analysis of the above classification of belt working conditions. Feature selection is influenced by many factors. It is difficult to distinguish the obtained datasets for better classification. In addition, belts for different categories need to be selected according to specific characteristics. When the feature area is selected manually, it can lead to some errors in detecting belt no-load. Therefore, several experiments with different types of belts are needed to achieve optimal detection.

A. Image Preconditioning

In practical terms, the belt can be affected by the influence of external factors. As a result, the captured images can also have quality issues. Thus, it affects the size of the eigenvalues. The result is that the detection results of belt no-load are affected. Therefore, image preprocessing is required in the belt no-load detection process. The dark channel defogging algorithm is used to remove the haze from the image and increase the defogging effect. However, this algorithm has low contrast. It is hard to discern belt condition. Image decomposition, logarithmic transformation, removal of lighting effects, and color enhancement are performed on the image by the single-scale Retinex algorithm. It improves the brightness, contrast and colour saturation of the image. However, the image is not clear at night [8]. Therefore, it is possible to combine the two algorithms to obtain a clearer image of the belt. The image is grayed out using the weighted average method. Belt images with more distinctive features can be obtained. The average value method of grayscale processing is shown in Fig. 8.


Fig. 8. Mean value method of graying

B. Eigenvalue Selection

The feature values are chosen mainly to reduce the dimensionality and improve the efficiency of model training. The region selected for the eigenvalues needs to be the same between different samples. The stability and generalization of features can be improved. Regarding the feature value selection for the belt image, the feature selection region is kept constant. The pixel data within the feature area is extracted and the data set collection is constructed. The image is characterized by the first-order moments, second-order moments, third-order moments, and grayscale covariance matrices of the image within the feature region [9].

Where the first order moment of the image is the average of the gray values of all pixels in the feature region [10]. The expression is shown in Equation 1.

The second-order moments of the image are used to measure the dispersion of the data using the mean and variance measures. The expression is shown in Equation 2.

The third order moments of the image are a measure of how skewed the data is. The expression is shown in Equation 3.

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1}$$

$$\sigma_i = [\frac{1}{N}\sum_{j=1}^{N} (P_{ij} - \mu_i)^2]^{1/2} \tag{2}$$

$$\varsigma_i = [\frac{1}{N}\sum_{j=1}^{N} (P_{ij} - \mu_i)^3]^{1/3} \tag{3}$$

The rows and columns in the gray level covariance matrix of an image represent the gray level of the image. The element represents the number of occurrences of a particular gray level difference pixel pair. Texture feature information such as contrast, correlation, and energy can be extracted [11].

In fact, some experience is required in selecting the feature areas. When the belt edge position is selected as the feature area, the part of the edge with material is basically selected for the computation of the eigenvalues in the first-order moments, second-order moments, and the greyscale covariance matrix. The portion of the belt that is free of material is generally computed by choosing the correlation in the third order moments and greyscale covariance as the eigenvalues. The feature area is the red boxed area. The part of the feature area without material is area 1, and the part of the edge with material is area 2. As shown in Fig. 9.

Fig. 9. Feature area selection diagram

A belt is randomly selected as an example and three feature areas are chosen. As shown in TABLE I. Four belt images are selected for daytime and nighttime no-load and with material conditions. It is expressed as daytime with material, daytime no-load, nighttime with material and nighttime no-load.

C. Feature Region Selection

The selection of the belt image feature area needs to be representative and important. When selecting feature regions, common principles are fixed regions, regions of interest, learning selection and other selection principles. In this case, the region of interest needs to be selected as the feature region to determine whether the belt image is no-loaded or not. The area of interest is automatically selected with an image of the belt with the differentiated no-load and under-load. Therefore, the principle of region of interest selection is used for feature region selection for belt images.

First, the belt images are categorized into indoor and outdoor images due to the influence of light source variations. Images where the room is closed, shadows and light spots created by unnatural light have less impact on the belt image. In the case of an indoor window, natural light will shine through the window and create a light spot on the belt. When there is occlusion, shadows are created. The area and position of light spots and shadows change over time. If the natural light in the room is dim, lighting will be used to supplement the lighting. The distribution of light sources is relatively stable, and after two types of contrasting lights can be used as a characterization area. The outdoor image is placed on the outdoor belt in natural light. Belt image features are difficult to categorize due to the high variation of light sources outdoors. When the situation is completely outdoors, the daytime is similar to the indoor environment with windows. Therefore, both lights and belt surface features can be used as feature areas. In addition, it should be noted that the selection of the feature area should try to avoid the location of the belt shadow boundary and the location of frequent changes due to the external light source.

In addition, due to the corrosive nature of the ore, the belt transports the ore for a long period of time making the middle of the belt darker in color. Wear and scratches on both sides can also affect the belt color to change. In this case, the feature area should be selected as the middle position and the edge position of the belt. The difference in textural information on the edges of the ore is more pronounced when there is material. It is necessary to constantly observe the belt and select different positions in the central area based on experience.

When judging whether the belt is no-load or with material, the state of the belt can be detected based on the eigenvalues as well as the selection of the eigenareas. Under ideal conditions, it is easy to distinguish the condition of the belt. However, it is easy to misjudge belt no-load as material and material as no-load under complicated working conditions. Therefore, a consistent light source as well as the location of the edge and centre of the ore can be selected to determine whether the belt is no-loaded or not. It is easier to judge the belt condition by manual inspection. However, there are significant safety concerns. Therefore, in this paper, we classify the belt images by using the improved algorithm of support vector machine in machine learning to make the results more accurate and efficient.

TABLE I
EIGENVALUES OF DIFFERENT CHARACTERISTIC AREAS OF THE BELT

Belt Condition	Mean Value 1	Variance 1	Mean Value 2	Variance 2	Mean Value3	Variance 3
Daytime with Material	79.645	36.655	76.211	21.828	125.843	65.025
Daytime No-load	90.174	23.271	118.072	20.979	156.261	65.531
Nighttime with Material	105.248	25.065	113.759	24.998	156.858	33.381
Nighttime No-load	127.725	48.635	144.104	40.943	165.72	59.059

D.Improved Algorithm of Support Vector Machine

Support vector machines are a model algorithm that classically solves binary classification problems that can be supervised [12]. The basic model is to find a unique optimal hyperplane in the feature space that can classify the data into different types. The support vector machine hyperplane is shown in Fig. 10. Improved algorithms using support vector machines are well suited to solve classification problems for high-dimensional, nonlinear, small and medium-sized complex datasets. Therefore, the improved algorithm of support vector machine can be applied to the belt no-load detection problem.

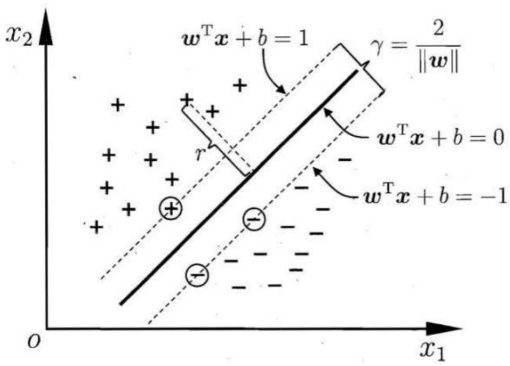


Fig. 10. Support vector machine hyperplane

When dealing with linearly indivisible problems, low-dimensional features are mapped to high-dimensional features, and kernel functions should be introduced. The regularization parameter can be used to balance the optimization problem for support vector machines. The smaller the value of the penalty factor, the greater the chance of misclassification. Overfitting can be effectively prevented. In this paper, it is designed a classification algorithm with support vector machine for the purpose of belt no-load detection, which categorise the belt images into two types, either in with material state or in no-load state. The data set training models obtained from the selected feature values and feature regions are compared. The data set for selecting a more appropriate support vector machine training model. In addition, the selection of the kernel function affects the performance of the support vector machine model. Therefore, different kernel functions need to be selected for model training and testing, resulting in the best performance support vector machine model.

IV. Results and Analysis of Results

A. Models Comparison

With the development of machine learning, the problem of classification has been widely used in various fields. The classification is a fundamental problem in machine learning. In deep learning, common algorithms include logistic regression, support vector machine, and decision tree. In this paper, both logistic regression and decision tree methods are used to compare with support vector machine methods. The same belt was selected for testing using each of the three methods. It is observed that the accuracy of the method of support vector machines is higher. Therefore, the support vector machine model is selected for classification in this paper. The classification results of different models are shown in the TABLE II.

TABLE II
Classification Results of Different Models

Model	First Category	Second Category	Third Category	AP
LR	83.10%	94.37%	98.04%	91.84%
DT	90.20%	88.24%	98.04%	92.16%
SVM	92.16%	94.12%	93.80%	93.36%

B. Belt No-Load Detection Model Validation

For the three types of belts, there are different kernel functions quoted in this paper to use for the training of support vector machine models. The reasonable parameters are adjusted and compared for each type of belt. At the same time, the three kernel functions make a comparison. Thus, the Gaussian kernel function is chosen for detecting the belt in this paper. The training results for different kernel functions are shown in TABLE III.

TABLE III
Training Results for Different Kernel Functions

Type of Working Condition	Kernel Function	Parameter	Identify the Correct Quantity	Number of Misjudgments
First Category	Gaussian	40	1037	1
		30	1035	3
		20	1010	28
	Polynomial	40	560	478
		30	478	560
		20	478	560
	Linear	40	1036	2
		30	1034	4
		20	1008	30

Type of Working Condition	Kernel Function	Parameter	Identify the Correct Quantity	Number of Misjudgments
Second Category	Gaussian	40	709	4
		30	708	5
		20	673	40
	Polynomial	40	594	119
		30	587	126
		20	579	134
	Linear	40	680	33
		30	678	35
		20	650	63

Type of Working Condition	Kernel Function	Parameter	Identify the Correct Quantity	Number of Misjudgments
Third Category	Gaussian	40	513	6
		30	511	8
		20	508	11
	Polynomial	40	487	32
		30	476	43
		20	453	66
	Linear	40	510	9
		30	506	13
		20	493	26

The belts were classified into three categories based on the analysis of the working conditions and the data set was constructed for experiments. The first category consists of images of belts that are affected by an external light source. The second category is influenced by the characteristics of the belt surface traces. The third category is influenced by the distribution of mineral states. The distribution of belt samples for the three types is shown in the TABLE IV.

TABLE IV
DISTRIBUTION OF BELT SAMPLES

Type of Working Condition	Number of Test Samples	Identify the Correct Quantity	Number of Misjudgments	Misjudgment Rate
First Category	1038	1036	2	0.0019
Second Category	713	709	4	0.0056
Third Category	519	513	6	0.0117

In order to validate the belt no-load detection model, this paper tests the training set by introducing three different kernel functions. The mean value of the eigenvalues is quoted as an evaluation metric for the support vector machine classification model.

The results of different kernel functions to classify the model are shown in TABLE V.

TABLE V
CLASSIFICATION EFFECTS OF SUPPORT VECTOR MACHINE MODELS WITH DIFFERENT KERNEL FUNCTIONS

Kernel Function	Accuracy	Precision	Recall	F1
Linear	91.29%	91.19%	91.31%	91.25%
Polynomial	96.38%	96.16%	96.54%	96.35%
Gaussian	97.48%	97.39%	97.22%	97.30%

The average performance of the three kernel function trained models is analyzed. The higher the value of recall, the lower the probability of misclassification [13]. Also the closer the value of F1 is to 1, the better the classification performance of the model [14]. The linear kernel function has the lowest average performance parameter. The polynomial kernel function and the Gaussian kernel function are almost close to each other in terms of performance parameters [15]. However, the Gaussian kernel function performs better. The Gaussian kernel function works best when a new test set is obtained after training the model. Therefore, a Gaussian kernel function training model with high performance parameters should be selected for belt no-load detection [16].

The average results obtained by performing classification tests on the test set. As shown in TABLE VI.

TABLE VI
TEST SET CLASSIFICATION EFFECT

Kernel Function	Accuracy
Linear	90.58%
Polynomial	96.26%
Gaussian	97.53%

C. Analysis of Results

According to the experimental results, there may be several reasons for misjudging the belt image. The sample size is small. The dimension of the belt image feature selection is too high. The wrong parameter was selected. All of these reasons can lead to support vector machine overfitting problems [17]. It is difficult to discern the condition of the belt due to a variety of factors. The feature values and feature areas of the belt images were selected with bias based on inexperience. The parameters of the Gaussian kernel function in support vector machines are not optimal kernel functions. The performance metrics for belt no-load detection could perhaps be even higher.

Based on the analysis of the results, the detection of part of the image affected by the light source is more accurate. Belt images show belts with less material, uneven distribution of mineral material and severe scratches on the belt surface. Detection of such cases is more prone to bias. In addition, the features in this experiment were selected based on human experience. The parameters of the Gaussian kernel function are also chosen empirically by hand. The Gaussian kernel function gives good classification results. However, further experiments on feature selection and kernel function selection are needed to achieve higher detection correctness.

V. DESIGN AND IMPLEMENTATION OF BELT EMPTY LOAD DETECTION SYSTEM BASED ON SUPPORT VECTOR MACHINE

A. System Function Module

In this paper, the design of belt no-load detection system has four main modules: Image acquisition and pre-processing module, feature selection module, belt no-load detection module and alarm module. The image acquisition and pre-processing module is used to acquire the belt image through the camera unit and pre-process the initial image. The feature selection module is to select suitable feature values and feature regions for the preprocessed image. The belt no-load detection module is to classify the processed belt images to produce detection results. The alarm module is an alarm for belts that appear to be no-loaded as a result of the detection. The functional modules of the system are shown in Fig. 11.

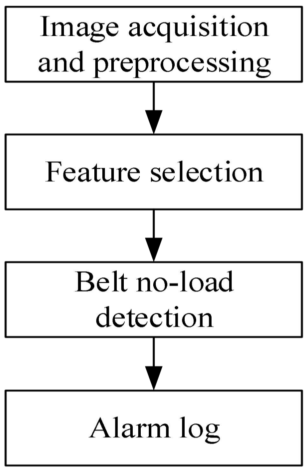


Fig. 11. System functional module diagram

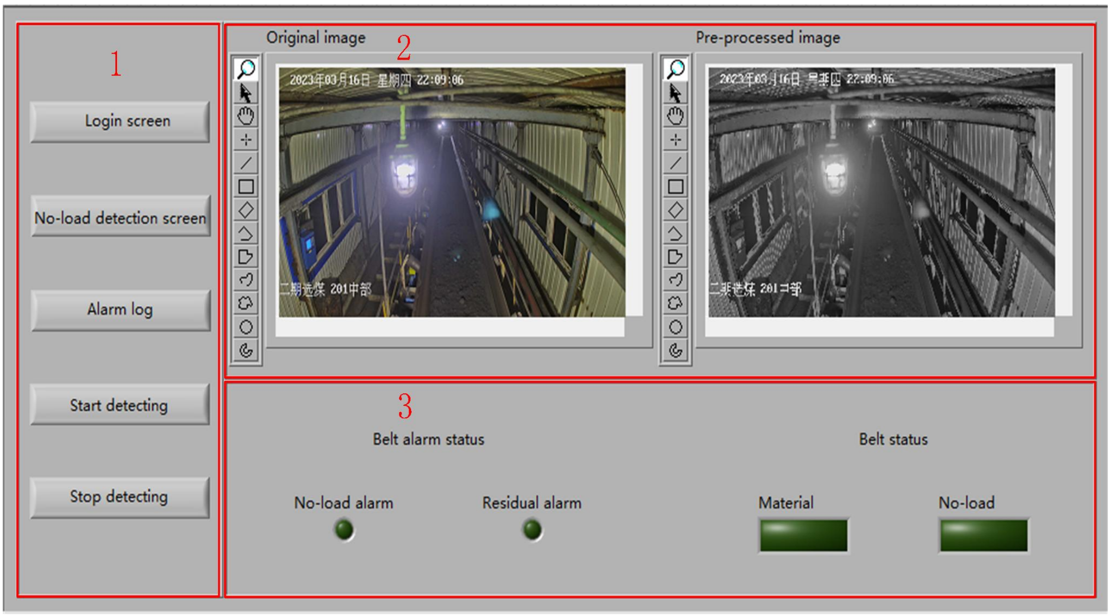


Fig. 12. Belt no-load detection system interface design

B. System Interface Design

In this paper, the interface of the belt no-load detection system is designed by using LabVIEW software. According to the needs of belt no-load detection system, this system is designed with login interface, belt no-load interface, alarm device interface and switch button interface. The interface design of the belt no-load detection system is shown in Fig. 12. The button in the area labelled 1 is used to switch the function of belt detection. The region labelled 2 previews the initial image and pre-processes the initial image. Then, feature selection is performed on the preprocessed image. Marked as 3 zones, it sets no-load alarms and residual material alarms to avoid unnecessary impacts caused by belt idling. Moreover, an indicator is used to set the status of the belt image. This system can meet the needs of belt no-load detection after testing in the field, and play a certain important role in the belt transportation process.

VI. Conclusion

In this paper, a collection of images of the belt is obtained based on the placement of a fixed camera. A support vector machine based classification method is designed as a monitoring system to detect whether the status of the belt is no-load or not. In real working conditions, the belt image is preprocessed. According to the belt images affected by the external light source, belt surface trace characteristics and ore state distribution, the same position in different images is selected as the feature area. The feature values within the feature area are read and the data set is thus obtained. A support vector machine classification model is built by introducing a kernel function. The accuracy of different kernel functions is compared to determine whether the detection of belt no-load is the best result. The final system accuracy is 97.53%. After actual field tests, the belt no-load detection system proposed in this paper can be used in field applications. The system enables work to be done efficiently under different operating conditions. And, it is more practical to ensure that staff are in a safe situation.

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