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A contactless measuring speed system of belt conveyor based on machine vision and machine learning

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Keywords: belt conveyor; contactless measuring speed; image processing; polynomial linear regression

Abstract:

During the operation of the belt conveyor, measuring speed of the belt conveyor is vital to the safe and efficient operation. In the existing measuring speed system, the measurement instrument is required contacting with the surface of the belt. The contact measurement method cannot avoid the occurrence of measuring error caused by slipping on the contact surface and wear of the measurement instrument. In order to solve the problems mentioned above, a new contactless measuring speed system is proposed in this paper. The system uses the CCD camera to capture the side image of belt. The speed of belt conveyor can be obtained by measuring the regularity of image texture. The proposed measuring system can meet the requirement of measuring speed in long running process of belt conveyor. Experimental results show that the measuring accuracy indicators can reach RMSE of 0.018 m/s and MAE of 0.010 m/s.

1. Introduction

Belt conveyor is widely used in industry field because of strong conveying capacity[1], especially it is the key part of the production and transportation system of the coal mine enterprise[2]. The speed control of the belt conveyor is the core of the machine operation[3]. In the process of operation, measuring speed play a significant role in the speed control of belt conveyor[4].

The solution of measuring speed has been developed together with the dynamics of belt conveyor system for many years[5]. A series of studies have already produced promising result. For instance, the methodology of the magnetoresistance sensor has been put forward[6], which has very high availability and strict reliability in measurement speed; the system of the self-calibrating rotary encoder has been put forward[7], which uses the self-calibratable rotary encoder to achieve highly reliable and reproducible; the widely used speed measuring system is optical encoder[8], which uses the incremental optical encoder to have advantages of high accuracy and easy-to miniaturization; the Jadavpur university proposed a method to measure the speed of the incremental photoelectric encoder[9], the measurement results are stable and have good real-time performance. These methods have good performance to meet the requirement of speed measurement in many fields. However, the current research still faces some limitations in the field of belt conveyors. Firstly, the phenomenon of slipping between the measuring instrument and the surface of belt is a potential problem in long running process of measurement. It can cause the error of measurement. Secondly, due to a long period of friction on the contact surface, the wear problem of measuring instrument may occur. It can shorten diameter of measuring instrument to result in measurement errors. Thirdly, the contact surface of belt may be scratched when the measuring instrument is accidentally damaged. The scratch problem can affect the normal operation of belt conveyor.

Because of the advantage of stability, accuracy and cheapness[10], machine vision has become one of the development tendencies in the field of measurement. X.W. Ye, Ting-Hua. Yi, C.Z. Liu, et al., have proposed a vision-based structural displacement measurement[11], which integrated with a digital image processing approach to develop vision-based structural displacement measurement system. X.W. Ye, Ting-Hua. Yi, C.Z. Liu, et al., have proposed a multi-point displacement monitoring of bridges using a vision-based approach[12], which demonstrated that the vision-based system for multi-point structural displacement measurement has good accuracy and reliability. In the field of measuring speed, many measurement systems have been proposed. The University of Tokyo designed a visual encoder that enables high resolution and high stability in 2016[13]. This method realized the separation of the CCD camera and the encoder. However, this method requires the encoder to be attached to surface of the measured object. The problems of slippage and wear cannot be solved in the field of belt conveyor. Therefore, it is necessary to realize a new contactless measurement system to solve the above problems.

In this paper, a new contactless measurement system for measuring speed of belt conveyor is proposed to solve the above limitation based on machine vision and machine learning. The system combines ROI (region of interest) selection, image edge detection, image texture description and Polynomial Linear Regression machine learning algorithm to solve the problems in the contact measuring speed system.

ROI selection[14] can eliminate redundant information to shorten processing time. Image edge detection is responsible for extracting image edge information in order to benefit image texture description. The speed of belt conveyor can be obtained by calculating the data of entropy based on the image texture description. Polynomial Linear Regression[15] machine learning algorithm can enhance performance of anti-interference by building an excellent fitting model based on a data set of the entropy.

Based on the experimental platform in the laboratory, experiments are carried out to test the performance of the measurement system in a horizontal belt conveyor. Experimental results demonstrate that, the measuring accuracy indicators can reach RMSE of 0.018 m/s and MAE of 0.010 m/s. The contactless system can avoid above problems of the contact measurement system and meet the requirement of measuring speed in long running process of belt conveyor.

In this paper, section 2 describes the principle of the measuring method (image selection, image edge detection, image texture description and Polynomial Linear Regression machine learning algorithm) used in the system. Section 3 illustrates the hardware design and system process. Section 4 shows the experimental design and the analysis of experimental results. Section 5 concludes the contribution and future development of the research.

2. The measuring speed method

In the actual measuring environment, the CCD camera is set up on the side of belt. The height of the CCD camera is level with the belt so that images can be captured. Some software algorithms are used to process images to obtain measuring results. Firstly, ROI selection can select the image part of the belt side. Secondly, image edge detection is responsible for extracting edge features. Thirdly, the GLCM entropy is calculated to obtain measuring speed results. Fourth, a machine learning algorithm is responsible for enhancing the performance of anti-interference. Each part is described in the following section.

2.1 ROI selection

The original image is mainly composed of the belt and the background. Furthermore, the part of belt involves the surface area and the side area. ROI should only contain the side area of belt. After selecting, ROI can replace the original image to continue the next step of image processing. The main part of the ROI selection is threshold segmentation. The method of threshold segmentation is used to detect the contour of side area. More specifically, the Otsu's method[16] as the core algorithm is applied in the threshold segmentation. The advantage of the Otsu's method is that the image can be effectively segmented when the area of target is not much different from the area of background. In this paper, the selection of ROI is used to establish the foundation for measurement.

There are massive random images used to test whether the selection of ROI is valid. The part of side area is marked with a green rectangle and shown in the Fig. 1. Based on the above principle, ROI selection can effectively overcome the interference of background information.

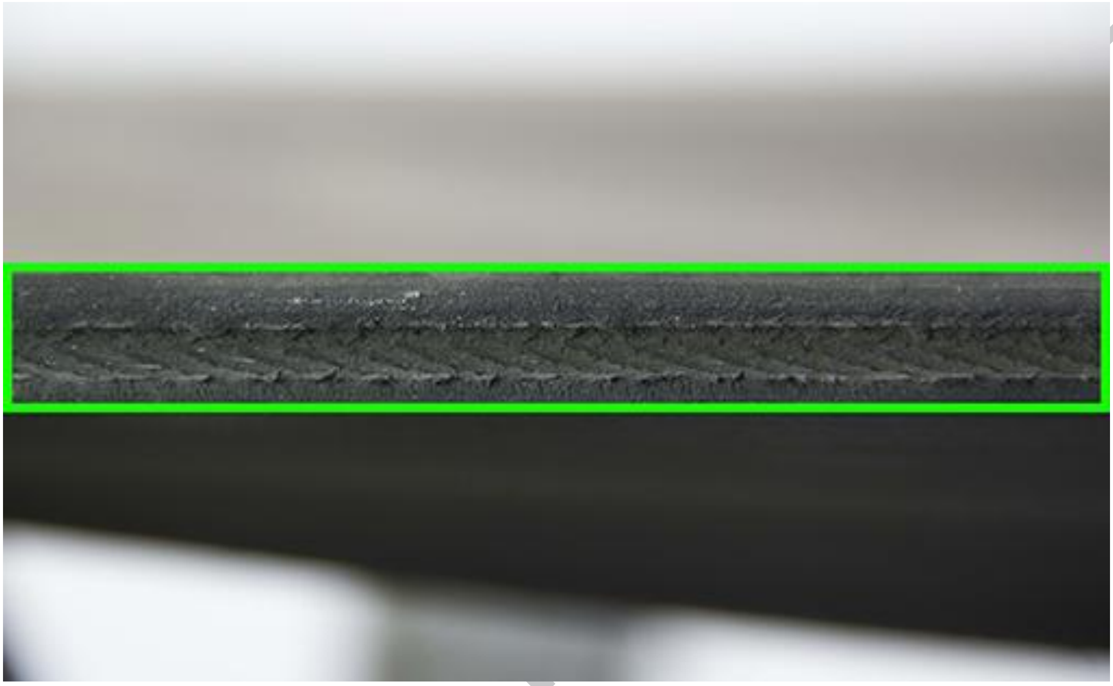
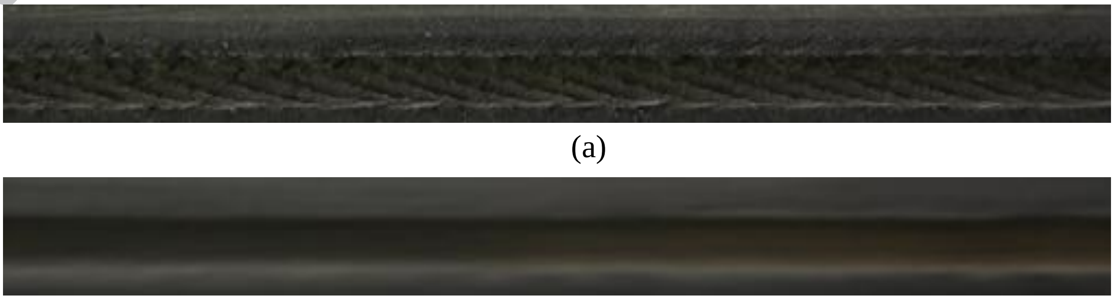


Fig. 1. The part of side area is marked with a green rectangle.

2.2 Image edge detection

During the operation of belt conveyor, the speed of running can be adjusted at any time. The CCD camera is used to capture images according to the preset configuration (manual focus, f-stop f/5.6, shutter speed 1/10 sec, ISO 200). When the belt conveyor at different speeds of running, the image of the belt side may appear clear or blurry. The images of belt conveyor at different speeds are shown in Fig. 2. The image of relatively slow running speed usually appears clear. On the contrary, there are significant differences between the image of relatively fast running speed. The image of relatively fast running speed usually appears blurry.



(a)

(b)

Fig. 2. The images of different speeds at (a) slow and (b) fast.

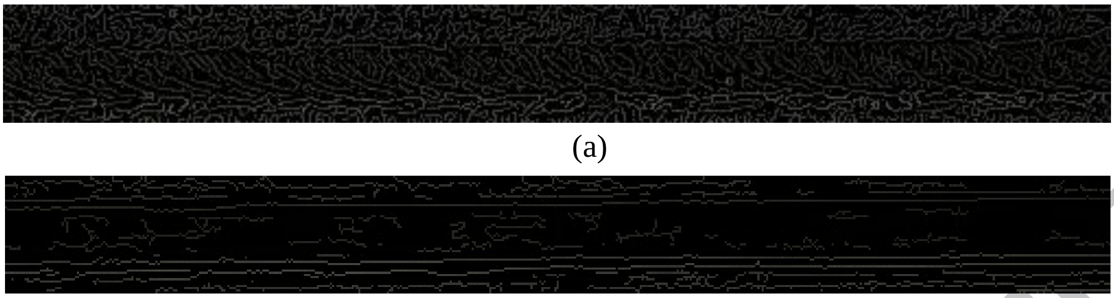


Fig. 3. The Fig. 3(a) and Fig. 3(b) are obtained using the Canny algorithm based on Fig. 2(a) and Fig. 2(b) respectively.

The image of relatively slow running speed has more edges than the image of relatively fast running speed. The image edge detection method is used to extract edge of image. The core algorithms include Bilateral high-pass filter[17] and Canny edge detection algorithm[18]. The Bilateral high-pass filter can attenuate the low-frequency components without disturbing high-frequency information to achieve edge preserving. The Canny edge detection algorithm is used to accomplish the edge detection based on three primary objectives (low error rata, edge points should be well localized and single edge point response). The images obtained using the above algorithms are shown in Fig. 3. The Fig. 3(a) is processed based on the source image of relatively slow speed and it has rich edge details. The Fig. 3(b) is processed based on the image of relatively fast speed, whose edge details is less.

2.3 Image texture description (GLCM and entropy)

After image edge detection, the difference of edge details between the images at different speed is already appearing. An important approach to this difference description is to quantify its texture content. This is important when describing texture, the texture-analysis process is to consider not only the distribution of intensities, but also the relative positions of pixels in an image. The difference of the relative positions of pixels also appears in Fig. 3. Therefore, the image can be transformed to the grey-level co-occurrence matrix(GLCM)[19] to describe texture. The advantage of the GLCM is that the texture can be described by studying the spatial correlation properties of gray scale.

As shown in Fig. 3(a), the texture has the regularity from macroscopic view. On the contrary, the irregularity and randomness distribution characteristics of texture can be found in the Fig. 3(b). Therefore, measurement of texture regularity can be used to realize the measurement of speed. The randomness of the elements of GLCM represents the regularity of the corresponding images. Specifically, the entropy value indicates the complexity of the gray level distribution of the image. When all values of GLCM are equal or the pixel values of image exhibit maximum randomness, the entropy value is the largest. Therefore, the entropy[20] is responsible for measuring the randomness of the elements of GLCM.

The formula of entropy is shown as follows.

$$-\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}\log_2 p_{ij} \tag{1}$$

In formula, p_{ij} is an estimate of the probability that a pair of point satisfying Q will have values, and Q is an operator that defines the position of two pixels relative to each other.

The image texture description guarantees that measurement system can get the corresponding indicator of entropy at different speeds of belt conveyor. Thus the contactless measuring speed method can be achieved effectively. Besides, the data of the entropy is involved in machine learning as the important parameter.

2.4 Machine learning based on Polynomial Linear Regression

According to the methods described above, the measurement system can obtain the corresponding feature of image texture of different speeds. However, the image texture description is too idealistic to adapt to complex measurement environment (interference factors include the variation of illumination[21] and the jitter phenomenon of belt). Firstly, the changing illumination generally refers to the reflected light. The surface of belt side cannot realize uniform reflection of illumination in a few cases. This problem can reduce the accuracy of the image texture description. Secondly, the jitter phenomenon of belt may occur during the fast running of belt conveyor. Some extreme jitter situation so strongly that ROI cannot be selected. In order to improve the robustness of measurement, some machine learning algorithms have been proposed[22]. The Polynomial Linear Regression[23] machine learning algorithm is adopted to solve the above problems based on its satisfactory data fitting and mathematical modeling performance. The advantage is that a linear causal relationship between the two sets of variables is established for analysis.

The establishment of the fitting model can be achieved by analyzing the relationship between input samples (image features) and output samples (measurement results) based on machine learning. The Polynomial Linear Regression fitting model can be established to reach the goal of the optimum fitting of data. The optimal fitting model should have the feature that minimize the Euclidean distance between all sample points in the dataset and the fitting curve of model. Minimizing the Euclidean distance can be achieved by calculating parameters the corresponding to the fitting model. Fitting and modeling of data requires two key parameters: the speed of belt conveyor (range from 0 to 3 and unit is m/s) and the data of entropy (indicator of image texture and range from 0 to 1). The two parameters can be used to form a two-dimensional parameter-space because of the correlation. In the process of machine learning, the training samples are used to fit a cubic curve model according to the method of Polynomial Linear Regression. The cubic curve model is chosen because it can avoid the problem of under-fitting and over-fitting. The cubic curve fitting model is shown in the Fig. 4. Through extensive samples training, the fitting model is in line with expectations.

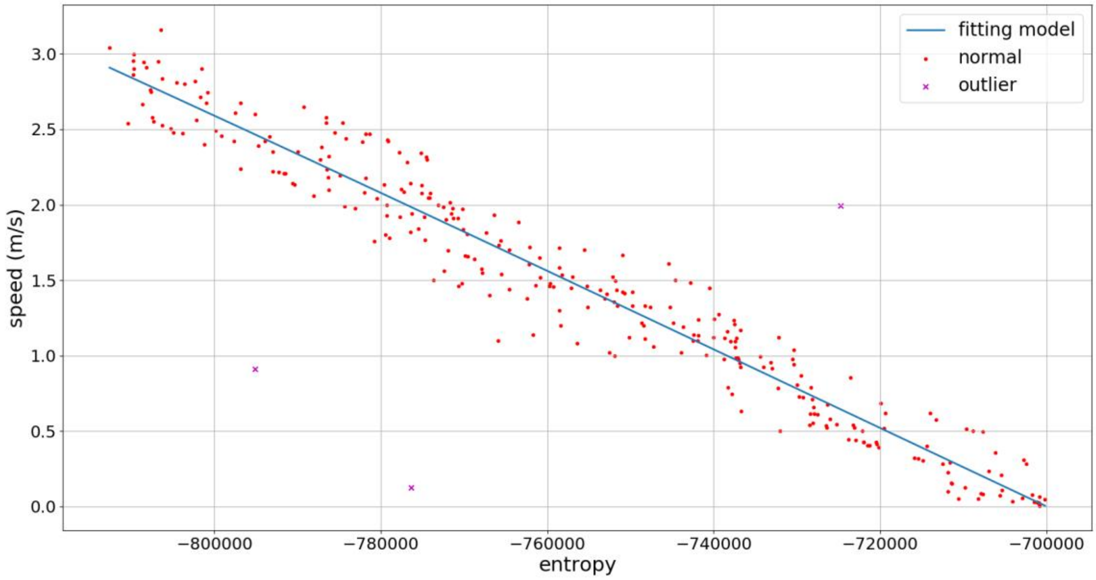


Fig. 4. The fitted model of every key parameter.

Crucially, the measurement system can eliminate some outliers caused by interference factors in the fitting model. Three obviously outliers are shown in Fig. 4. The judgment rule of outliers: In the machine learning model, the point (the value of the measurement result) can be regarded as the outlier by judging whether the Euclidean distance of the point and the linear regression fit curve exceeds the threshold value.

The detailed description of the polynomial linear regression algorithm is as follows. The task of algorithm is fitting a M-degree polynomial function which is generated by known training data. In the parameter space, the existing sample training dataset is T $=\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, $x_i, y_i \in R$, x_i indicates the data of entropy and y_i indicates the speed of belt conveyor.

According to the existing data, selecting the most suitable M-degree (M=3) polynomial can avoid the problem of over-fitting and under-fitting effectively.

$$y=\sum_{j=1}^{M} w_j x^j\ , \quad M=3 \tag{2}$$

For a given piece of data x, it is a key that using the suitable w that minimize the error to match y. The formula for determining w is shown as follows.

$$L(w)=\frac{1}{2}\sum_{i=1}^{N}\left(\sum_{j=0}^{M} w_j x_i^j - y_i\right)^2 \tag{3}$$

$$set\,\frac{\partial L(w)}{\partial \omega_k}=0 \tag{4}$$

The parameter of w can be gradually adjusted to reduce the error with the process of persistently repeating formula (3) and (4). After adding new samples, the formula (2) can be corrected iteratively using with the new w for calculating new fitting model.

With the increasing number of size of training data, the measurement accuracy of Polynomial Linear Regression machine learning algorithm is constantly improved. Experimental result shows that this machine learning algorithm effectively eliminates the measurement error which caused by interference factors, and it is able to adapt to the complex measuring environment.

3. System design

Design of the speed measurement system can be divided into two parts: hardware design and system process.

3.1 Hardware design

The system is composed of three parts: image acquisition subsystem, image processing subsystem and central monitor subsystem. The image acquisition subsystem consists of large area light source (500mm*300mm) and HR (high resolution) CCD camera (image source, 10 million pixels). The image processing subsystem consists of IPC (industrial personal computer, I7 7700HQ, 8G memory) and central monitor (DELL). The image acquisition subsystem is installed on the side of belt conveyor. The light source illuminates the side of belt at an angle of 45 degrees. The HR camera is parallel to the side of belt. The IPC is installed in the central control room which is adjacent to the production workshop. The installation of system is shown in Fig. 5.

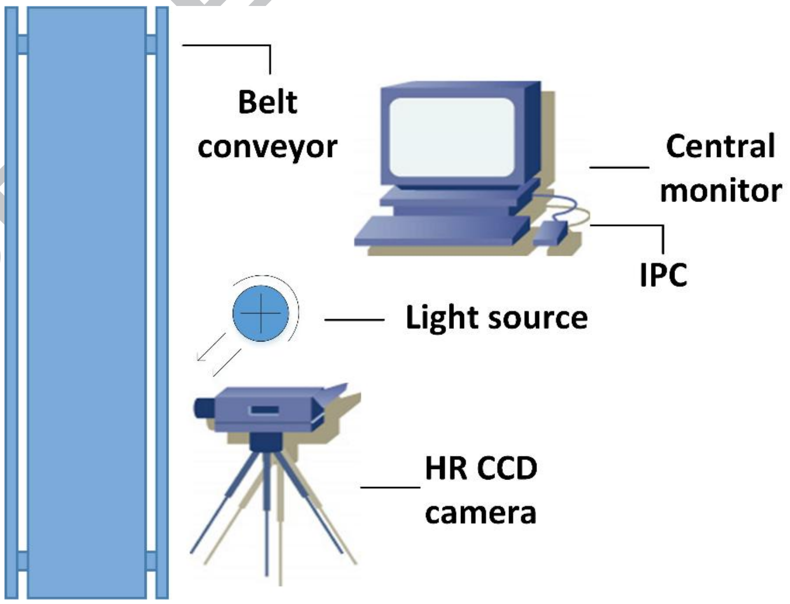


Fig. 5. Installation of the whole system

3.2 System process

The large area light source provides adequate illumination for the side of belt to highlight the stripe of belt. The HR CCD camera is responsible for capturing the image when the belt conveyor running. Subsequently, the HR CCD camera transmits images to IPC. After receiving and image processing, IPC obtains the measurement result based on calculating the entropy, and adds the measurement result to the dataset. The machine learning fitting model judges whether the new sample is the outlier data. The outlier can be cleaned to guarantee long-term stable operation of the measurement system. Finally, IPC displays the measurement result on the central monitor in real time. The structure diagram of whole system is shown in Fig. 6.

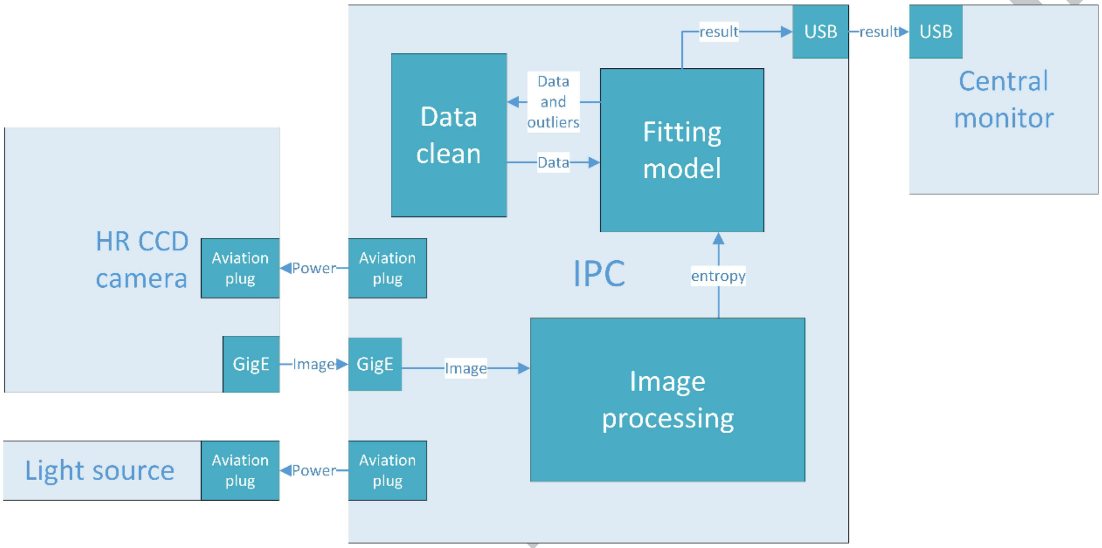


Fig. 6. Structure diagram of the whole system

4. Experiments

Experiments are carried out to test and verify the performance of designed system. The whole contactless measuring speed system and conveyor belt are installed in the laboratory. The testing platform is set up as shown in Fig. 7. The experimental design and results analysis are described as follows.

Fig. 7. The testing platform.

4.1 Experiment design

In order to facilitate the evaluation of the accuracy and performance of the new measurement system, the contactless measuring speed system is compared to the results of the optical encoder measurement system which is existing widely used traditional measuring method. In the process of experiment, existence of minimal probability, the measurement result may be incorrect. Therefore, two evaluation indicators will be highlighted in this paper. First of all, the designed experiment will focus on the accuracy of speed measurement. The accuracy is regarded as the core reference index to evaluate the performance of the designed system. In another aspect, the main purpose of speed measurement is to achieve real-time speed regulation. The average processing time of measurement will directly affect the speed regulation efficiency. Thus it should be another key index of concern in the experiment.

Before the test begins, the IPC invokes the large area light source, the HR CCD camera and returns self-inspection report. After confirmation, the belt conveyor runs and the measurement system starts. The operating environment of the belt conveyor is mostly in the underground environment. The dark underground environment of the belt conveyor is simulated in the laboratory. The experimental platform supplemented the stable light source on purpose, so anti-interference treatment was performed on the influence of the lighting condition. In addition, machine learning methods can remove erroneous measurements that are affected by environmental factors. During system operation, the measurement result is displayed in real time. The experimental flow chart is shown in Fig. 8.

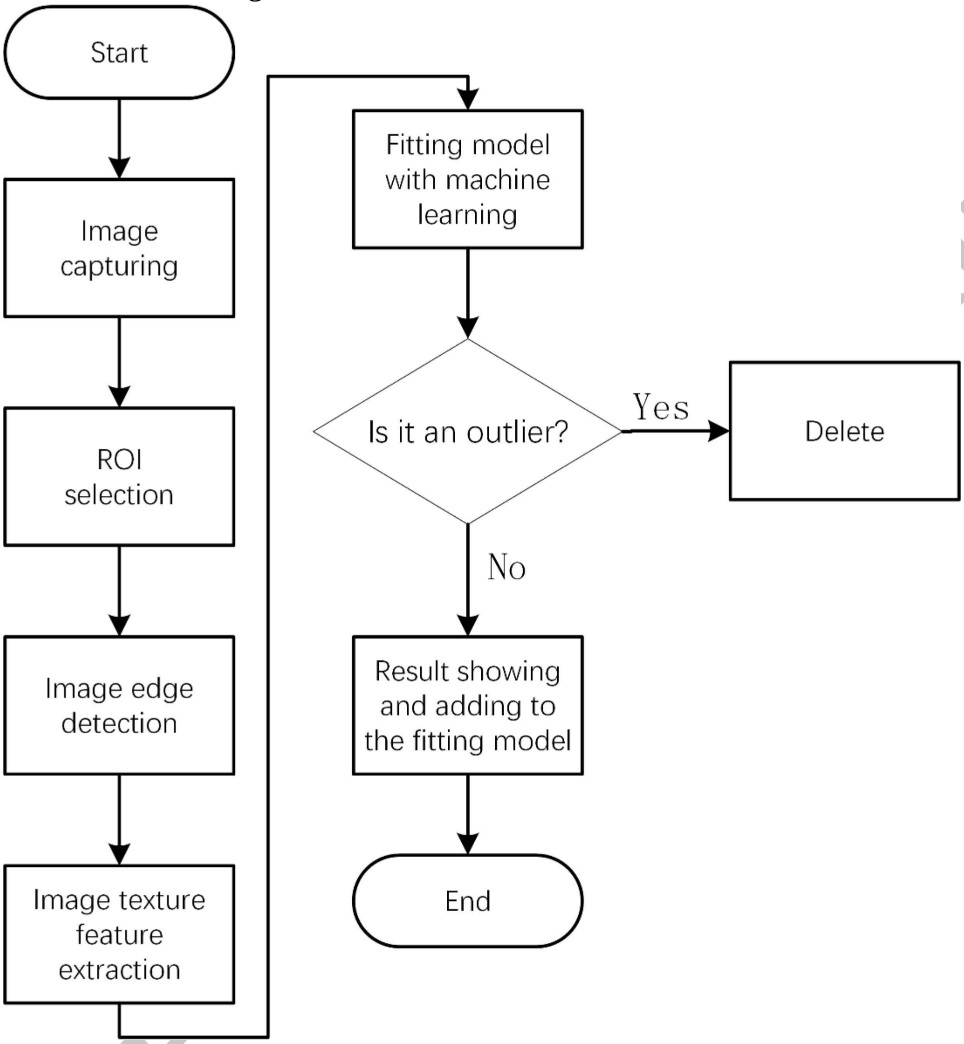


Fig. 8. The experimental flow chart

4.2 Experimental results and analysis

The existing contact speed measuring equipment (rotary encoder) of the laboratory is used as the real speed of the belt conveyor. The measurement result of the speed measuring system is compared with it. The performance of the designed contactless speed measurement system is validated by the contrast experiments between traditional speed measurement method and contactless method. The traditional method experiment and the contactless method experiment are performed simultaneously in progress. The samples of the above experiment are controlled in the test range (0-3 m/s). All of experiments, the system increases the test speed from 0m/s to the maximum with the speed interval of 0.1 m/s and compares the testing results (the accuracy and average processing time of measurement) with the traditional method. The measurement can be completed at least five times per second to meet real-time requirements. Each speed measurement needs to keep the results stable for one minute. The measurements should be taken at least 300 times per minute. Each speed level of measurement takes 10 minutes. The values recorded in the table are stable values of the measurement results. After the first experiment, the system repeats the experiment according to the preset (test range is 0-3 m/s and interval of 0.1 m/s). The purpose is to verify that the accuracy of measurement system based on machine learning is improved. The experimental results without machine learning are shown in Table.1 and the experimental results with machine learning are shown in Table.2.

Table. 1. The experimental result without machine learning.

Increment (m/s)	Speed (m/s)					
	0.0	0.5	1.0	1.5	2.0	2.5
0.1	0.133	0.636	1.153	1.599	2.130	2.621
0.2	0.222	0.697	1.226	1.711	2.211	2.701
0.3	0.324	0.817	1.324	1.839	2.322	2.822
0.4	0.405	0.898	1.403	1.915	2.395	2.900
0.5	0.516	1.013	1.530	1.998	2.523	2.986

● Increment refers to use the speed interval of 0.1m/s to divide each one-sixth of the total test range into five parts.
● Speed refers to divide the total test range (0-3 m/s) into six parts.
● The table parameters show the measurement results of samples.
● The RMSE is 0.022 m/s
● The MAE is 0.017 m/s

In the experiment without machine learning, effectiveness of the proposed contactless method has been validated by experiments. Compared with the traditional system, the overall accuracy did not decrease obviously and the average processing time of measurement did not increase significantly. Concretely, we calculated the root mean square error (RMSE)[24] of the speed measurement as RMSE= $\sqrt{\Sigma(measurements-actual)^2/N}$ (N is the number of samples). The RMSE is the square root of the ratio of the square of the deviation between the observed value and the true value and the number N of observations. It is generally recognized that the superior measuring performance should try to keep RMSE as small as necessary. The RMSE is 0.022 m/s. In the meantime, the method of mean absolute deviation (MAE) is also used to make error analysis as MAE= $\frac{1}{m}\sum_{i=1}^{m}\left|(y_i-\hat{y}_i)\right|$. MAE is the mean of the absolute values of the deviations of all individual observations from the arithmetic mean. MAE can accurately reflect the actual prediction error. It is generally assumed that the measuring with better of MAE is qualified. The MAE is 0.169 m/s. According to the above results, the most of measurement error occurred when there are influenced by interference factors. In addition, the CCD camera can take 10 shots a second and use manual focus to fix the focus points according to the preset. The average time of image processing by IPC is about 100ms. Thus the total processing time which includes the time of image acquisition and image analysis can be limited to 200ms or less. The measurement time is not predetermined, but continues until the result is stable and remains for one minute.

Table. 2. The experimental result with machine learning.

Increment (m/s)	Speed (m/s)					
	0.0	0.5	1.0	1.5	2.0	2.5
0.1	0.009	0.608	1.114	1.611	2.092	2.609
0.2	0.201	0.712	1.209	1.707	2.197	2.690
0.3	0.303	0.802	1.302	1.813	2.295	2.805
0.4	0.408	0.890	1.403	1.906	2.403	2.910
0.5	0.506	1.006	1.501	2.003	2.515	3.024

● Increment refers to use the speed interval of 0.1m/s to divide each one-sixth of the total test range into five parts.
● Speed refers to divide the total test range (0-3 m/s) into six parts.
● The table parameters show the measurement results of samples.
● The RMSE is 0.018 m/s
● The MAE is 0.010 m/s

In the experiment with machine learning, testing system performance by comparing above two evaluation indicators. With the support of machine learning fitting model, the results show that the system performance has been significantly improved with the RMSE reduced to 0.018 m/s and the MAE reduced to 0.010 m/s. During the operation of belt conveyor, the measurement error caused by interference factors is reduced. On the other hand, the unchanged average processing time means system performance can be guaranteed.

5. Conclusion

In this paper, a contactless measuring speed system of belt conveyor has been proposed. The system mainly measures image texture to establish a relationship between the speed of belt and image based on machine vision and machine learning. With respect to machine vision section, the system employs a HR CCD camera with a light source to capture images. The image processing subsystem is called to calculate the image texture in order to obtain the speed of belt conveyor. With respect to machine learning section, according to the result of image texture, a polynomial regression model can be fitted to eliminate interference in order to enhance applicability of industrial environment. The results of experimental show that the proposed system is able to achieve the contactless speed measurement. Moreover, the measuring system still has room to expand. Due to images will become extreme blurry when the belt conveyor at the excessive fast speed, most measuring results of high speed are hardly to be distinguished from each other based on image texture alone. The measurement of high speed is the prominent problem in the future research.

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- Realized contactless speed measurement of belt conveyor.
- The speed can be obtained by measuring the regularity of image texture.
- Some measurement errors can be eliminated based on machine learning.
- The measuring accuracy can reach RMSE of 0.018 m/s and MAE of 0.010 m/s.