A Fast Detection Method for Region of Defect on Strip Steel Surface

Rongfen GONG,1) Maoxiang CHU,1)* Anna WANG2) and Yonghui YANG1)

1) School of Electronic and Information Engineering, University of Science and Technology Liaoning, Gaoxin District, Anshan, 114051 China.
2) College of Information Science and Engineering, Northeastern University, Heping District, Shenyang, 110819 China.

(Received on July 6, 2014; accepted on September 11, 2014)

In order to meet the increasing demands of high efficiency and accuracy for strip steel production line, a fast detection method for region of defect (ROD) on strip steel surface is proposed in this paper. Firstly, the efficiency requirement of ROD detection algorithm is described. Secondly, mean filter improved in speed is used to filter noise. Then, five statistical projection features are extracted from detection region on surface image. Finally, based on distinct feature vector dataset, extreme learning machine (ELM) classifier, region of background (ROB) pre-detection and classifiers selection are combined together to realize two-class classification of ROD and ROB. Experimental results show that the novel method proposed in this paper not only is of high detection accuracy and efficiency but also can satisfy on-line ROD detection.

KEY WORDS: strip steel surface; defect detection system; ROD; statistical projection features; ELM.

1. Introduction

Surface defect detection is an important technical measure to ensure the quality of strip steel products. Technologies of strip steel surface defect detection have developed very fast with the endeavor of researchers, such as magnetic flux leakage detecting, infrared detecting, eddy current detecting and visual inspection based on charge coupled device (CCD).1−3) To mention that, line-scan CCD visual inspection system has been adopted widely.4,5) It acquires image through line scanning, which is fit for the strip steel surface moving on production line.5) Moreover, this system with high acquisition speed and accuracy is easy to realize. Detection system mainly includes two parts: hardware system and detection algorithm. Different hardware structure corresponds to different algorithm efficiency. So the relationship between them is the premise of detection algorithm design.

In general, the algorithm of strip steel surface defect detection system includes two parts: region of defect (ROD) detection and defect type recognition. Defect type recognition is used to realize defect segmentation, defect feature extraction and defect classification.6) Because its processing objects are defect images cached in the memory, defect type recognition can be handled in semi-real-time. However, the processing objects of ROD detection algorithm are surface images being collected in real time. So ROD detection is required to keep up with acquisition. ROD detection can distinguish between surface images with defect and without defect, and save surface images with defect. Because most of surface images have no defect, ROD detection can greatly reduce the number of surface images without defect. Perfect background method and projection method are often used in ROD detection.7) Perfect background method can separate ROD and Region of background (ROB) according to perfect background threshold. In projection method, gray values in the two-dimensional surface image are projected as one-dimensional dataset along X and Y axis. It also uses threshold to detect ROD. Though these two methods are both fast, they also have two problems. One is that it is hard to select a proper threshold. The other is that the detection result is always disturbed by noise seriously.6) Used decision tree to realize fast detection. Whereas, its classification accuracy is affected by the number of training samples and its anti-noise performance is poor. Then, ROD detection algorithm based on local annular contrast is proposed in reference.9) This algorithm is of high speed and accuracy for ROD, but it can merely detect steel bar defects, such as pit, overfill and scratches. Ref. 10) Adopted support vector machine (SVM) to inspect seam defect of steel bar surface. However, its accuracy is subjected to parameters selection.

A fast ROD detection method is proposed for strip steel surface in this paper. On one hand, the efficiency requirement of ROD detection algorithm corresponding to a detection system with distributed architecture is described. On the other hand, three parts of ROD detection algorithm: noise filtering, feature extraction and two-class classification of ROD and ROB are realized respectively. In detail, mean filter is improved in speed to filter noise. Five statistical projection features are extracted fast from detection region on surface image. Then, distinct feature vector (DFV) dataset is extracted. Based on the dataset, ROB pre-detection, classifiers selection, and extreme learning machine11) (ELM)
classifier are combined together to realize two-class classification of ROB and ROD. This paper is structured as follows. The efficiency requirement of ROD detection algorithm is described in section 2. Section 3 focuses on fast ROD detection algorithm. Testing experiments and results analysis are done in section 4. Some conclusions are drawn in section 5.

2. The Efficiency Requirement of ROD Detection Algorithm

In general, strip steel surface defect detection can be realized by using computer vision system that includes CCD cameras, light sources, acquisition boards, acquisition interfaces, transfer interfaces and computers. The distributed architecture of detection system is often applied, just as Fig. 1. This type of system acquires and processes data in parallel, which reduces the requirement of efficiency for ROD detection algorithm. This parallel processing makes the efficiency of ROD detection algorithm has close relationship with the speed of strip steel, the pixel resolution of surface image and the number of CCD cameras.

Suppose that the width and the speed of strip steel are \( w \) mm and \( v \) mm/s respectively. And there are \( n \) line-scan CCDs on up or down strip steel surface. Pixel resolution of surface image in width is \( a_w \) mm and in height is \( a_t \) mm. Then acquisition speed and transfer speed of acquisition board are \((w \times v)(a_w \times a_t \times n)\) Bps. Suppose the size of the image is \( M \times N \), then ROD detection algorithm need process \((w \times v)(a_w \times a_t \times n \times M \times N)\) images per second. Take \( w = 1600 \) mm, \( v = 15,000 \) mm/s, \( a_w = 0.5 \) mm, \( a_t = 0.5 \) mm and \( n = 4 \) for example, then both linear acquisition speed and transfer speed are 22.9 MBps. Computer systems can cache about 59 images with size of \( 800 \times 512 \) per second. Then, ROD detection algorithm need process 59 images with size of \( 800 \times 512 \) per second. That is to say, it takes less 16.9 ms to process an image.

3. Fast Detection Algorithm based on ELM

3.1. Noise Filtering

Strip steel surface image will be inevitably corrupted in the process of acquisition. These noises are derived from production environments, photovoltaic conversion of CCD, transmission channel and electrical devices. So, it is an essential step to filter noise. Gaussian noise is the main kind of noise. Of course, there is a small part of impulse noise. Filtering algorithm must be real-time for strip steel surface image.

Standard mean filter can effectively filter noise. However, it blurs image while filtering. In this paper, transfinite neighborhood mean method is used to improve standard mean filter. Suppose the gray for every pixel is \( f_k \) \((k = 1,2,\ldots,12)\), which is shown in Fig. 2. For the first \( 3 \times 3 \) window, the gray \( g_5 \) of central point can be obtained through transfinite neighborhood mean method:

\[
M_5 = \frac{1}{9} \sum_{k=1}^{9} f_k \quad g_5 = \begin{cases} 
M_5 & \text{if } |M_5 - M_s| > T \\
M_s & \text{else} 
\end{cases} \tag{1}
\]

Where, \( M_s \) is mean value. \( T \) is a threshold which is determined according to real problem. Transfinite neighborhood means method can not only filter noise effectively but also reduce image blur. However, it will take 8 times of addition operation and 1 time of division operation to calculate the mean value \( M_s \). In order to improve its efficiency, data correlation between neighboring filter windows is used to reduce the times of addition in this paper. For the first \( 3 \times 3 \) window in Fig. 2, the mean value \( M_s \) of the central point can be obtained by calculating \( S_i = \sum_{l=1}^{3} f_i \) \((i = 1,2,3)\). Obviously, the mean value is \((S_1 + S_2 + S_3)/9\). It takes 8 times of addition and 1 time of division to calculate the mean. For the second \( 3 \times 3 \) window, the mean value of the central point can be obtained by calculating \( S_k = \sum_{i=3}^{12} f_i \). The mean value is \((S_2 + S_3 + S_4)/9\). It takes 4 times of addition and 1 time of division. Similarly, for all the other \( 3 \times 3 \) windows, the mean value \( M_s \) of the central points can be obtained by calculating 4 times of addition and 1 time of division based on neighboring window. Obviously, this method can improve the efficiency of mean filter.

3.2. Feature Extraction

Effective feature extraction is the basis for ROD detection. In order to capture ROD on the strip steel surface image, detection window is used in this paper. And feature vectors for detection window are extracted. The size of detection window should be small enough for small ROD and large enough for effective feature extraction. The size of the window is determined as \( 16 \times 16 \) by analyzing strip
Then horizontal projection gray \( (f_L)_p \) and vertical projection gray \( (f_V)_p \) can be calculated just like the following:

\[
(f_L)_p = \frac{1}{16} \sum_{i=1}^{16} f(i, p), \quad (f_V)_p = \frac{1}{16} \sum_{i=1}^{16} f(i, p) \quad p = 1, 2, \cdots, 16
\]

\[
(f_L)_p = \frac{1}{16} \sum_{i=1}^{16} f(i, p+1-i), \quad p = 1, 2, \cdots, 16
\]

\[
(f_V)_p = \frac{1}{16} \sum_{i=1}^{16} f(p+1, 16-i), \quad p = 1, 2, \cdots, 16
\]

\[
(f_L)_p = \frac{1}{16} \sum_{i=1}^{16} f(i+16-p), \quad p = 1, 2, \cdots, 16
\]

\[
(f_V)_p = \frac{1}{16} \sum_{i=1}^{16} f(p+16-i), \quad p = 1, 2, \cdots, 16
\]

Then, Based on the above four types of projection grays, 5 local statistical projection features, such as projection mean \( M \), horizontal projection variance \( V_L \), vertical projection variance \( V_V \), +45° projection variance \( V_4 \), and –45° projection variance \( V_{-4} \) can be defined. These statistical projection features can be calculated as the following.

\[
M = \frac{1}{16} \sum_{i=1}^{16} (f_L)_p
\]

\[
V_L = \frac{1}{16} \sum_{i=1}^{16} ((f_L)_p - M)^2
\]

\[
V_V = \frac{1}{16} \sum_{i=1}^{16} ((f_V)_p - M)^2
\]

\[
V_4 = \frac{1}{31} \sum_{i=1}^{31} ((f_4)_p - M)^2
\]

\[
V_{-4} = \frac{1}{31} \sum_{i=1}^{31} ((f_{-4})_p - M)^2
\]

It can be seen from the above equations that mean value for every type of projection grays is \( M \). On one hand, projection mean feature can reflect the average value of projection gray levels. On the other hand, four projection variance features can reflect the variance of projection gray levels. Moreover, projection grays can improve the efficiency of statistical features extraction.

3.3. ELM

ELM proposed by Huang et al. is a high effective learning algorithm for single hidden layer feedforward neural network.\(^{11}\) ELM is of good global approximation property.\(^{13}\) Its initial parameters can be selected at random, that is to say, its parameters learning does not need iteration. So ELM is characterized by easy parameters selection and fast learning.

Feedforward neural network architecture based on ELM is shown in Fig. 3. Suppose there is a training dataset \( X = \{(x_i, y_i)|i=1, 2, \cdots, N\} \) with \( N \) samples, and \( x_i \in \mathbb{R}^{n_{in}} \) is the input sample and \( y_i \in \mathbb{R}^{n_{out}} \) is the output label. Then ELM can be described as the following linear equations:

\[
H \beta = Y \hspace{1cm} (4)
\]

Where, the hidden layer output matrix \( H \in \mathbb{R}^{N \times N} \), the output label matrix \( Y \in \mathbb{R}^{N \times 1} \) and the weight matrix \( \beta \in \mathbb{R}^{n_{out}} \) connecting hidden layer and output layer are as follows:

\[
H = [h(x_1), h(x_2), \cdots, h(x_N)]^T
\]

\[
= \begin{bmatrix}
g(w_1^T x_1 + e_1) & \cdots & g(w_1^T x_1 + e_a) \\
\vdots & \ddots & \vdots \\
g(w_a^T x_N + e_1) & \cdots & g(w_a^T x_N + e_a)
\end{bmatrix}
\]

\[
\beta = [\beta_1, \beta_2, \cdots, \beta_n]^T, \quad Y = [y_1, y_2, \cdots, y_n]^T
\]

Where, \( g() \) is an activation function, \( w_i \in \mathbb{R}^{n_{in}} \) is the weight vector connecting input layer and hidden layer, and \( e(i = 1, 2, \cdots, a) \) is the threshold value for hidden node. Huang et al. have proved that parameter \( (w_i, e_i) \) can be selected at random in \( \mathbb{R}^2 \times \mathbb{R}^a \) space if \( g() \) can be infinitely differentiable in arbitrary boundary. And \( \beta \) can be calculated as the following:

\[
\beta = H^+ Y \hspace{1cm} (6)
\]

Where, \( H^+ \) is the Moore-Penrose generalized inverse of \( H \). \( H^+ \) can be estimated through minimum norm least squares solution, and its result is:

\[
H^+ = (H^T H)^{-1} H^T \hspace{1cm} (7)
\]

Suppose \( \text{sign}() \) is sign function. Then for sample \( x \), the output of ELM can be represented as:

\[
y = \text{sign}(h(x) (H^+ H) \cdot H^T Y) \hspace{1cm} (8)
\]

Take two-class classification for example, \( y = [y_1, y_2], y_1, y_2 \in \{-1, 1\} \). The sample \( x \) is assigned to the class +1 or −1 depending on output label \( y \):

\[
x \in \begin{cases} 
\text{class } +1 & \text{if } y_1 > 0, y_2 < 0 \\
\text{class } -1 & \text{other wise}
\end{cases} \hspace{1cm} (9)
\]
3.4. Fast Detection Algorithm

7 types of defects for strip steel surface will be detected in this paper. They are dent, fold, scarring, scale, bruise, hole and damage. 7 types of defect images and non-defect image are shown in Fig. 4. Because acquisition instrument is used in consistent environment and fixed location, backgrounds of all surface images are same. So, ROD detection can be realized through two-class classification of ROD and ROB. In this paper, ELM is used to realize the two-class classification of ROD and ROB.

Just as Fig. 5(a), three steps are needed to realize ROD detection. Firstly, surface image should be filtered through fast mean filter. Then, surface image is divided into many 16 × 16 detection windows. And 5 statistical projection features are extracted for every detection window. Finally, the feature vector composed of 5 statistical projection features is used by ELM to realize fast two-class classification of ROD and ROB. In subsections 3.1 and 3.2, noise filtering and feature extraction methods have been described respectively. For two-class classification of ROD and ROB, the algorithm flow chart based on ELM is shown in Fig. 5(b). It has 3 steps: ROB pre-detection, classifiers selection and ELM-τ classification.

3.4.1. ROB Pre-detection

Because most regions on surface image belong to ROB, distinct background can be firstly detected by ROB pre-detection algorithm. And the other undetermined regions can be detected in the following step. ROB pre-detection can improve the efficiency of ROD detection.

Suppose is the feature vector dataset of ROB extracted from surface images. is a feature vector sample in and . Firstly, calculate the density of every sample in with the following equation:

\[ \rho_i = \sum_{j=1}^{b} \exp(- \| B_i - B_j \|_2^2) \quad i = 1, 2, \ldots, b \quad \ldots \ldots (10) \]

Where \( \| \cdot \| \) denotes L2 norm. It can be seen from the equation that \( \rho_i \) is determined by all the Euclidean distances between sample \( B_i \) and all samples in \( B \). The bigger the \( \rho_i \) is, the closer the samples in \( B \) are to \( B_i \). It can be concerned that samples with high density compose the DFV dataset of ROB.

Firstly, sort all \( \rho_i \) in an ascending order. Then delete 25 percent of samples with low density from \( B \) according to the interquartile range (IQR). The remaining samples compose the DFV dataset \( \overline{B} \) of ROB. The number of samples in \( \overline{B} \) is \( \overline{b} \). Define the DFV space is a hyper-sphere with center \( \overline{B} \) and radius \( \overline{R} \). To mention that, \( \overline{B} \) is the center of all samples in \( \overline{B} \) and \( \overline{R} \) is the average distance of all distances between \( \overline{B} \) and samples in \( \overline{B} \). The calculating equations of \( \overline{B} \) and \( \overline{R} \) are:

\[ \overline{B} = \frac{1}{\overline{b}} \sum_{B_i \in \overline{B}} B_i, \quad \overline{R} = \frac{1}{\overline{b}-1} \sum_{B_i \in \overline{B}} \| B_i - \overline{B} \| \ldots (11) \]

\( \overline{B} \) and \( \overline{R} \) are obtained during the process of training. The speed of training does not affect the efficiency of on-line ROD detection algorithm. During the processing of on-line detection, a feature vector sample \( x \) that has fallen into DFV space of ROB is concerned to be ROB by ROB pre-detection algorithm. Its equation is:

\[ x \in \begin{cases} \text{ROB}, & \text{if } \| x - \overline{B} \| < \overline{R} \\ \text{Undetermined region}, & \text{else} \end{cases} \ldots \ldots (12) \]

3.4.2. Classifiers Selection

Most regions on surface image have been detected and some undetermined regions need be detected after ROB pre-detection. ELM classifier which can realize the classifica-
tation of ROD and ROB is adopted to detect undetermined regions. If samples with 7 types of ROD are concerned as a whole training dataset, the training samples and hidden nodes of ELM classifier are too many. This will reduce the efficiency of the ELM classifier. So, independent ELM-τ (τ ∈ {1, 2, ..., 7}) classifier is constructed in this paper. The training dataset of ELM-τ classifier only includes feature vector samples of ROB and feature vector samples with the single type of ROD. In this way, the number of the training samples and hidden nodes of the ELM-τ classifier are both reduced, which improves the efficiency of classification. Moreover, independent ELM-τ classifier can also improve the accuracy of classification.

Classifiers selection determines which ELM-τ classifier is adapted to detect the feature vector of undetermined regions. Suppose \( D^j \) \((j = 1, 2, ..., 7)\) is the dataset with one type of ROD extracted from surface images dataset. \((D^j)\) is a feature vector sample in \( D^j \) and \( (D^j) \in R^{5\times l} \) \((i = 1, 2, ..., d^j)\), where \( d^j \) is the number of samples in \( D^j \). According to subsection 3.4.1, DFV dataset \( D^j \) of ROD and center samples \( (D^j) \), can also be obtained.

During the process of on-line detection, the distance between a feature vector sample \( x \) and \( (D^j) \), is calculated through classifiers selection algorithm. And ELM-τ classifier is determined according to the minimum distance, just as:

\[
\tau = \arg\min_{j} \| x - (D^j) \|, \quad \tau = \arg\min_{j} \| x - (D^j) \|, \quad \tau = 1, 2, ..., 7
\]  

(13)

3.4.3. ELM-τ Classification

A feature vector sample \( x \) is detected by ELM-τ classifier which can realize the classification of ROD and ROB. The architecture of ELM-τ classifier is shown in Fig. 3. It is composed of 5 input nodes, 2 output nodes and 10 hidden nodes. Those input nodes represent 5 feature values of sample, and those output nodes represent two-class classification labels of ROD and ROB.

Corresponding to 7 types of ROD, there are 7 ELM-τ classifiers. The parameters of each ELM-τ classifier need be trained in training dataset. For every ELM-τ classifier, DFV dataset \( X^\tau \) used as training dataset is composed of \( B \) and \( D^\tau \). And parameter \( \tau \) can be determined with Eq. (6). The number of samples in \( X^\tau \) is greatly reduced compared with that in the whole training dataset and that in the training dataset composed of \( B \) and \( D^\tau \). Moreover, noise samples have been eliminated. So, both the efficiency and accuracy of ELM-τ classifier are improved by using \( X^\tau \). Parameters of ELM-τ classifier are determined according to Eq. (6).

During the process of on-line detection, two-class classification label of ROD and ROB for a feature vector sample \( x \) is determined according to Eqs. (8) and (9).

4. Experiments and Results Analysis

In order to testify the performance of the fast ROD detection method proposed in this paper, some experiments and results analysis are done. Testing types of defects for strip steel surface obtained from hot rolling production line are shown in Fig. 4. Suppose that the width and the speed of strip steel are 1 600 mm and 15 000 mm/s respectively. Pixel resolution of surface image in width is 0.5 mm and in height is 0.5 mm. Hardware architecture is constructed as Fig. 1. So the size of strip steel surface image is 800 × 512. Then ROD detection need process at least 59 images per second. ROD detection algorithm is realized on Microsoft Visual C++ 2010.

Firstly, for 7 types of defect images and non-defect image, the results of fast ROD detection are shown in Fig. 6. To mention that, binarization method is used to highlight the ROD detection result. Gray of ROD is set as 0 and gray of ROB is set as 1. The white region in Fig. 6 is ROD. It can be seen that the shape of ROD in Fig. 6 is slightly different with that in Fig. 4. However, ROD detection algorithm is used to fast judge whether the surface image has defect or not. That is to say, the above mentioned difference will not affect the result of ROD detection.

Secondly, 3 200 images with 7 types of defects and without defect are tested. The size of these images is 800 × 512. There are 2 240 samples for training dataset and 960 samples for testing dataset. There are 280 samples in training dataset and 120 samples in testing dataset for every type of defect and ROB. In order to test the accuracy, the fast ROD detection algorithm is compared with the other similar detection algorithms: perfect background, projection, and decision tree. In perfect background algorithm, a perfect threshold can be obtained through statistics for 280 background images. In projection algorithm, the threshold can be obtained through exhaustive method. And decision tree algorithm can be found in reference.4 The accuracy of these detection algorithms is shown in Table 1. It can be clearly

---

Fig. 6. The results of fast ROD detection for 7 types of defect images and non-defect image.
of feature extraction. This novel feature extraction method which is based on 1-dimensional projection grays and 5-dimensional statistical features is of high efficiency and accuracy. The two-class classification of ROD and ROB can recognize defect image. ROB pre-detection algorithm is used to detect most regions of surface image, which can improve the efficiency. For undetermined regions, DFV dataset, Classifiers selection, ELM classifier are combined together to realize classification of ROD and ROB with high efficiency and accuracy. Testing experiments also show the high efficiency and accuracy of the fast ROD detection algorithm. The accuracy of the novel algorithm is over 97.5% for ROD detection and 99% for ROB detection. And the total execution time is 12.9 ms. This means that the novel algorithm can process 77 surface images per second. So, the fast ROD detection scheme proposed in this paper can satisfy not only the requirements of high efficiency and accuracy but also on-line detection for ROD on strip steel surface.

Acknowledgment
The authors give thanks to sponsor and support from University of Science and Technology Liaoning Foundation (No. 2014QN05).

REFERENCES

Table 1. The accuracy of four detection algorithms for eight types of images.

<table>
<thead>
<tr>
<th>ROD algorithm</th>
<th>Dent</th>
<th>Fold</th>
<th>Scarring</th>
<th>Scale</th>
<th>Bruise</th>
<th>Hole</th>
<th>Damage</th>
<th>Non-defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perfect background</td>
<td>99.2</td>
<td>92.5</td>
<td>95.8</td>
<td>93.3</td>
<td>92.5</td>
<td>100</td>
<td>94.2</td>
<td>89.2</td>
</tr>
<tr>
<td>Projection</td>
<td>100</td>
<td>92.5</td>
<td>97.5</td>
<td>95.8</td>
<td>91.7</td>
<td>98.3</td>
<td>93.3</td>
<td>91.7</td>
</tr>
<tr>
<td>Decision tree</td>
<td>100</td>
<td>95.8</td>
<td>98.3</td>
<td>96.7</td>
<td>95.8</td>
<td>100</td>
<td>93.3</td>
<td>96.7</td>
</tr>
<tr>
<td>ROD detection</td>
<td>100</td>
<td>97.5</td>
<td>99.2</td>
<td>98.3</td>
<td>98.3</td>
<td>100</td>
<td>99.2</td>
<td>99.2</td>
</tr>
</tbody>
</table>

Table 2. Execution time of fast ROD detection algorithm.

<table>
<thead>
<tr>
<th>Execution time</th>
<th>Noise filtering</th>
<th>Feature extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum time</td>
<td>3.512 ms</td>
<td>6.353 ms</td>
</tr>
<tr>
<td>Minimum time</td>
<td>3.512 ms</td>
<td>6.353 ms</td>
</tr>
<tr>
<td>Average time</td>
<td>3.512 ms</td>
<td>6.353 ms</td>
</tr>
<tr>
<td>Total time</td>
<td>12.9 ms</td>
<td></td>
</tr>
</tbody>
</table>

seen that fast ROD detection algorithm is much better than the others for eight types of images.

Finally, the efficiency of the fast ROD detection is tested with 960 testing samples. The execution time is tested for every step of fast ROD detection. Moreover, the maximum execution time, the minimum execution time and the average execution time of the algorithm are tested in this experiment. The experimental results are shown in Table 2. It can be seen that the execution time of noise filtering and feature extraction for different detection regions is fixed. But 3 types of time for classification of ROD and ROB are quite different. Most ROB can be detected through ROB pre-detection algorithm, which saves the time to be used on the classifiers selection and ELM classifier. So the time for detection of ROB is minimal and the time for detection of ROD is maximal. To mention that, most regions of surface image are ROB, so the average execution time is closer to the minimum execution time. The execution time of ROD is 17.5 ms, which can be calculated from Table 2. This execution time cannot satisfy the throughput requirements. However, ROD is far smaller than ROB on surface image. Fortunately, buffers in computers can solve this worst condition that may appear in a short period of time. Table 2 also shows the total execution time of fast ROD detection algorithm. The total execution time (12.9 ms) is the average execution time for 960 images. It means that fast ROD detection algorithm can detect 77 images per second, which can meet the strip steel speed of 19 000 mm/s.

5. Conclusions
For a detection system with distributed architecture, the efficiency requirement of ROD detection algorithm is firstly described. In order to improve the accuracy and efficiency of defect detection, a novel fast ROD detection algorithm is proposed. The algorithm includes 3 steps: noise filtering, feature extraction and two-class classification of ROD and ROB. Mean filter improved in speed is used to filter noise. And 5 statistical projection features are extracted in the step