Research on scratch defect detection for steel bar

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Abstract

With the increase of requirement for the quality of raw materials in industry, surface defect inspection of steel bar has been an essential part of industrial production. In order to detect steel bar surface scratch defects, a detection algorithm based on wavelet transform was proposed. The images were decomposed by wavelet transform, so the location of defects could be found accurately. Subimage was processed with Gaussian convolution. This could keep the edge characteristics of defects. Then image binaryzation was carried. The whole defects image was obtained by open operation and close operation.

Keywords

Red steel rod; Surface defects; Machine vision; Inspection algorithm.

1. Introduction

With the development of industry, the steel bar surface quality is becoming more and more important. Since the surface defect frequently encountered in the hot bar rolling of steel can easily lead to a fatal manufacturing defect during the secondary cold forging process of bar stocks, it is necessary to inspect it in-time. In steel surface defects detection, machine vision is widely used [1-3]. In order to inspect the defects occurred on the steel bar surface, we need to know the type and characteristic of the surface defects.

Scratches often occur during the rolling process as shown in Fig.1. It often comes into being along the longitudinal direction of steel bar. It may include one or more line defects parallel to the axes.

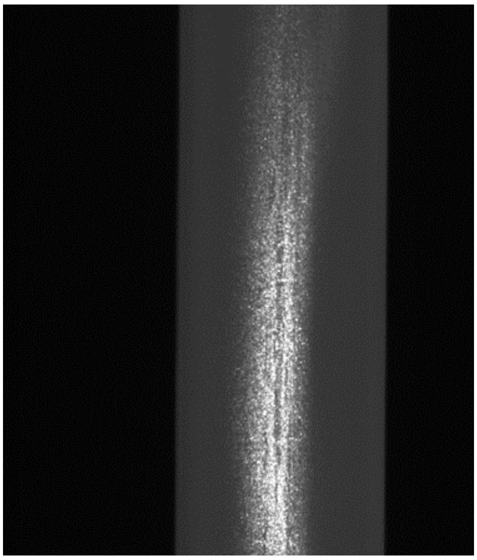

Fig. 1 Scratches defect of steel bar surface

2. Characteristic analysis of steel bar surface image

From Fig. 1, we can see that the image captured in actual rolling line includes two parts: background and object image. So the segmentation is needed when detecting this image. Besides, the image of steel bar contains some pit defects in it. Now we analyze the details of the image.

The gray level shows irregular distributions in whole image while relatively uniform in local areas. The defect areas exhibit a low gray-level in comparison to the neighboring background pixels. The steel bar surface image is bright in the center and getting darker towards two sides. The defects in the middle have an obvious contrast with the local background. Besides, the image is a little twisty because of the shake of bar when rolled. When the characteristic of the steel bar surface image is clear, we can inspect its surface defect in time.

The pixels in one line of the scratch image are chosen. The distribution of gray level is shown in Fig.2. The area whose gray level is low in two sides and has little change in the trend belongs to black background. There is one area whose slope is large which is called steep slope area. Slope crest is real edge of steel bar. The beginning of this area is gentle. In this area, the light is not reflected to the camera. The area in which the light changes greatly is called bright area. The scratch defect is labeled in Fig.2.

Through the analysis of the scratch defect characteristic, we can find that the noise signal in dark area is weak while the scratch defect area has obvious low gray level in the middle bright area. But the bright area has also much noise signal which has low gray level. This disturbs the detection of defect in great level. Therefore, we need to inhibit the noise signal so that the defect could be detected easily.

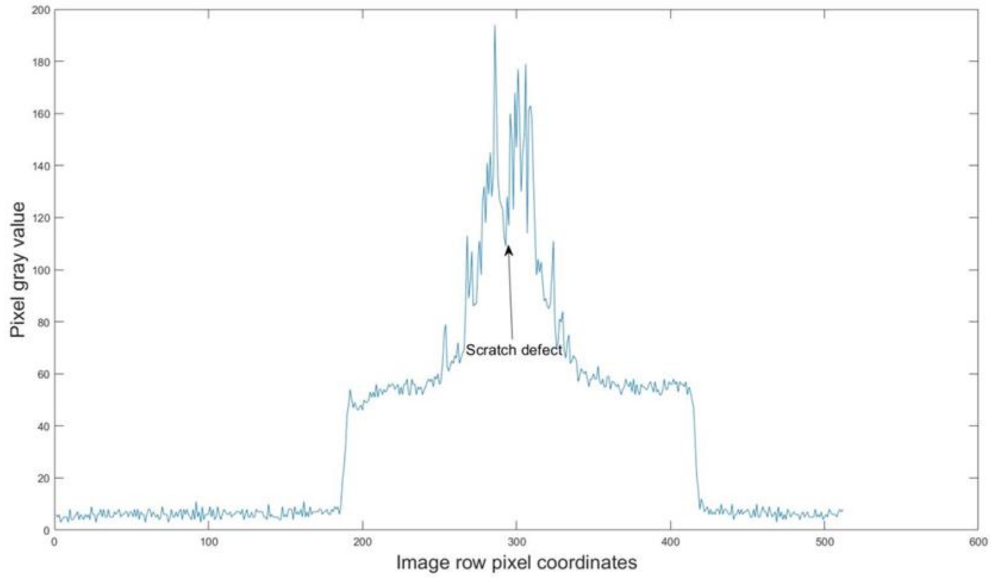

Fig. 2 Gray level distribution of scratches defect on steel bar surface

3. Scratch defect detection algorithm

Wavelet theory has a wide application because of its great advantage in digital signal processing. This paper introduces the translational invariant wavelets in scratch defect detection.

Traditional wavelet translation is shown in Fig.3.

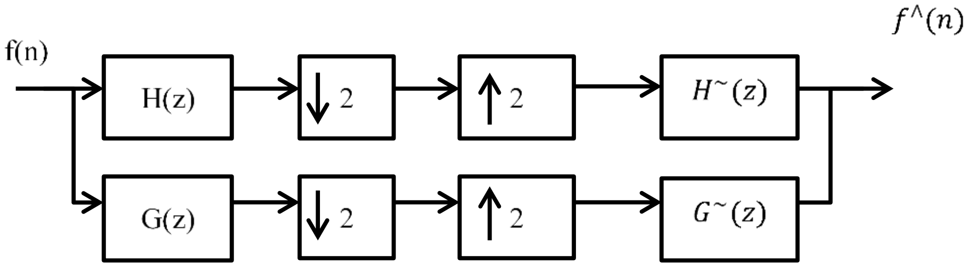

Fig.3 Sampling wavelet of traditional wavelet translation

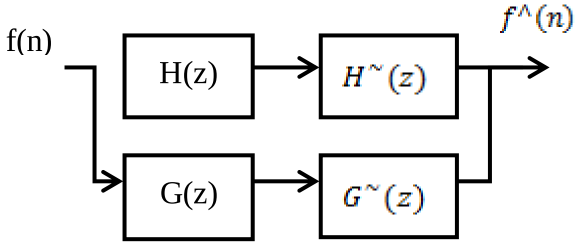

Fig.4 Non-sampling wavelet of traditional wavelet translation

Low frequency decomposition and high frequency decomposition are both realized through lower sampling. Wavelet reconstruction is finished by higher sampling. Every translation makes the image to half size of original image in width and height. We assume that the scratches can be detected, but the accurate location could not be found, so this has some disadvantage. Hence, we use non-sampling wavelet transformation to detect scratch defects.

In non-sampling wavelet transformation, every image is divided into four sub images. But these sub images have the same size with original image. The difference between traditional wavelet transformations is that every filter coefficient is inserted to some series of zero elements. The formula is:

$$h_{0,k}^{[j]} = h_{0,k} \uparrow 2^j = \begin{cases} h_{0,k/2^j} k = 2^j m, if m\epsilon Z \\ 0, else \end{cases} \tag{1}$$

$$h_{1,k}^{[j]} = h_{1,k} \uparrow 2^j = \begin{cases} h_{1,k/2^j}, k = 2^j m, if m\epsilon Z \\ 0, else \end{cases} \tag{2}$$

In the formula, h_0 is lower filter coefficient while h_1 is higher filter coefficient. j is the scale of wavelet transformation. The sub image in j+1 level could be obtained through the image in j scale. The formulas are:

$$A_{j+1}(m,n) = \sum_k \sum_l h_{0,k}^{[j]} h_{0,l}^{[j]} A_j(m+k, n+l) \tag{3}$$

$$W_{j+1}^{LH}(m,n) = \sum_k \sum_l h_{1,k}^{[j]} h_{0,l}^{[j]} A_j(m+k, n+l) \tag{4}$$

$$W_{j+1}^{HL}(m,n) = \sum_k \sum_l h_{0,k}^{[j]} h_{1,l}^{[j]} A_j(m+k, n+l) \tag{5}$$

$$W_{j+1}^{HH}(m,n) = \sum_k \sum_l h_{1,k}^{[j]} h_{1,l}^{[j]} A_j(m+k, n+l) \tag{6}$$

In the formulas, $A_{j+1}(m,n)$ is general outline of original image. The three images $\mathrm{W}_{j+1}^{\mathrm{LH}}(\mathrm{m},\mathrm{n})$, $\mathrm{W}_{j+1}^{\mathrm{HL}}(\mathrm{m},\mathrm{n})$ and $\mathrm{W}_{j+1}^{\mathrm{HH}}(\mathrm{m},\mathrm{n})$ are horizontal details, vertical details and diagonal details coefficients.

In order to design the orthogonal wavelets suitable for their own specific applications, the wavelet filter coefficient is parameterized so the wavelet function could be obtained.

We assume that h(i)'s Z-transformation is:

$$\mathrm{H(z)} = \sum_{i=0}^{2N-1} h(i) z^{-i} = H_0(z^2) + z^{-1} H_1(z^2) \tag{7}$$

$$H_0(z) = \sum_{i=0}^{N-1} h(2i)\, z^{-i} \tag{8}$$

$$H_1(z) = \sum_{i=0}^{N-1} h(2i+1)\, z^{-i} \tag{9}$$

In the formulas, H_0 (z) and H_1 (z) are called multiphase component of h(i). H_0 (z) is lower filter while H_1 (z) is higher filter. Two of them are energy Complementary. The condition of small wave base orthogonal is:

$$H_0(z)H_0(z^{-1}) + H_1(z)H_1(z^{-1}) = 1 \tag{10}$$

$$\begin{gathered} H_1(-1) = 0 \\ H_1(1) = 0 \end{gathered} \tag{11}$$

The binaryzation effect of the sub image depends on the set threshold. Traditional single threshold method has weak effect in this application. If the threshold is too high, some defects may be missed detection. If the threshold is too low, some non-defect areas may be error detection. Therefore, the double threshold method is applied to this scratches defects detection. The double threshold method is expressed as bellows:

$$\text{if } T_{high} < E(x,y), \begin{matrix} then\ B_{high}(x,y) = 1 \\ else\ B_{high}(x,y) = 0 \end{matrix} \tag{12}$$

$$\text{if } T_{low} < E(x,y), \begin{matrix} then\ B_{low}(x,y) = 1 \\ else\ B_{low}(x,y) = 0 \end{matrix} \tag{13}$$

4. Experiment results and analysis

In order to verify the effectiveness, the surface of red steel was tested by wavelet decomposition algorithm. We test performance of the algorithm by evaluate the index of dent defects. The image 2000 is selected that the no defect and the image 48 is scratch defects from actual rod production line. The test results are show in the table 1.

Table 1 Algorithm test results

Image of detection	Test results		
	success	failure	accuracy
defective	43	4	90.7%
Non-defects	2000	27	98.85%

As we can see from table 1, wavelet decomposition algorithm has higher detection rate to the scratch defects. As the same time, the low error rate is maintained. Because of the scratch defect discontinuity, the discontinuities or the defect edge is not obvious, a part is masked by the noise signals that result in defect leak detection, and the reason for error checking is the noise signal in the image is not completely removed, it being treated as a defect that oxide layer formed on the surface of red steel.

5. Conclusion

The algorithm proposed in this paper is realized through Matlab programming. Its advantage is good at mathematical calculation and graphic output. Therefor the execution efficiency is not high. So the scratches defects could not be detected in real-time. In the future, we would program this algorithm with c++ and optimize it to detect the defect in real-time.

Acknowledgments

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