Automated On-line Fast Detection for Surface Defect of Steel Strip Based on Multivariate Discriminant Function

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Abstract

Surface inspection of steel strips is of great importance to improve the quality because it is mainly affected by the defects on the surface. Digital image processing methods have been developed for defect detection for past few years. As to an automated on-line detection system, the research on rapid defect detection is quite significant. In this paper, an approach to detect surface defects of steel strip based on multivariate discriminant function is discussed. By subdividing the images into blocks and extracting related features, tiny defects are effectively detected. With the inspection of the defects, a multivariate discriminant function model has been established. Persuasive experiments results were obtained which prove the feasibility and accuracy of the proposed method. Thus, this research is quite practical and lays a solid foundation for the future study.

1. Introduction

Rapid defects detection for steel strip has been motivated by the need of fast defects recognition and classification, real-time quality examination and report, as well as the improvement of detection efficiency and accuracy. Conventional detection is mostly completed by human beings, which is slow, expensive, limited and inaccurate. Therefore, the application of rapid on-line defect detection based on machine vision will be undoubtedly a better substitution.

One of the advantages for rapid defect detection is to save much of storage capacity and promise the real time of the inspection. When the surface digital images have been acquired without defect detection, all of them need be processed in the subsequent steps such as image filtering, image transformation, image segmentation and so on. Such processing will be not only time consuming but also take up a large part of the limited storage capacity. In other words, by defect defection images acquired can be preliminarily determined defective or non-defective. Keep the defective ones and send them to the following stage to make an accurate defect assessment. Therefore, the research on rapid defect detection to determine whether the images contain defects is quite significant.

Generally, steel strip surface image can be regarded as a typical statistical texture image [1]. Various approaches for texture defect detection have been proposed in the past two decades. Fourier-domain features have been used for the detection of texture defects because of the high degree of texture periodicity [2-4]. On the one hand, it is difficult to qualify the contribution of spectral components since the Fourier bases are of infinite length. On the other hand, spectral-domain features are generally less sensitive to noise than spatial-domain features. Thus, Fourier analysis is not suitable for detection of local defects that occur in the small areas of the image inspected [5]. Detection of local texture defects requires multi-resolution decomposition of the image inspected across several scales. That is why texture features based on multi-scale wavelet decomposition have been applied [6-8]. An image can be decomposed into a hierarchy of localized subimage at different spatial frequencies by discrete wavelet transform (DWT). It divides the 2D frequency spectrum of an image into a set of lowpass (smooth) subimage and a set of highpass (detail or noise) subimage. The textural features are then extracted from the decomposed subimage in different frequency channels and different resolution level. Nevertheless, defect detection for steel strip surface is still a topic deserves further research though different algorithm have been presented. For the purpose of reducing cost and improving detection speed, a novel automated on-line rapid defect detection approach has been proposed in this paper.

The approach proposed in this paper mainly applies multivariate discriminant function to realize fast defect detection of cold rolled steel strip. Essential statistical data (difference, mean, and variance), which decrease the influence of steel strip texture on the detection, are acquired locally after image noise suppression. This is quite crucial to improve detection accuracy. A defect detection model was established by use of multivariate discriminant function. Implementations and tests were taken on a number of surface images of cold rolled steel strip. The results have proved that the proposed approach

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can provide an accurate identification to the surface defects in a visual inspection system.

The remainder of this paper is organized as follows. Section 2 presents the proposed detection algorithm which uses block-based features extraction and multivariate discriminant function analysis techniques in detail. Experiments results are shown in Section 3, and conclusions are given in Section 4.

2. Detection algorithm

In this section, the proposed detection algorithm, which aims at detecting the steel strip surface defects correctly, is described in detail. This algorithm consists of four stages: steel strip image acquisition, image noise suppression, statistical features extraction, and defect detection modeling. Figure 1 shows the whole research steps for the image processing which are sequentially linked together.

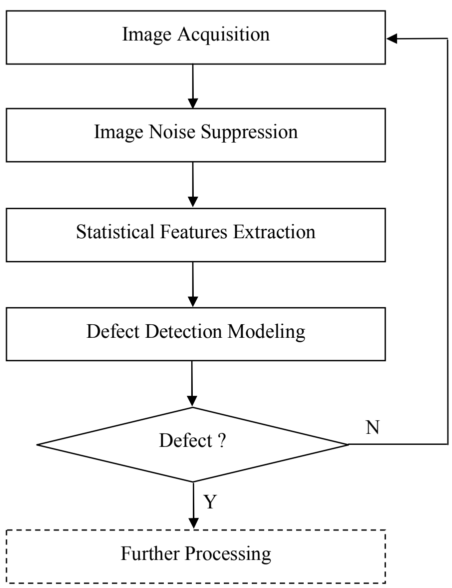
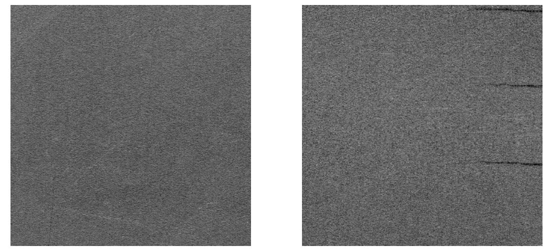


Figure 1 Flow chart of the research method for defect detection

2.1 Steel strip image acquisition

Charge couple device (CCD) cameras are used to take steel strip surface images in this stage. Then, two kinds of image data sets will be created: the defective group and the non-defective group.

Defective group is defined as the images containing tiny defects. Since large defects can be easily detected so that detecting large ones will be not a critical matter if the small defects are detected clearly. The benefits lie in that it can improve the accuracy and efficiency of defect detection. In this research, 20 digital images are selected from each group and used as statistical data for defect detection modeling. Figure 2 shows the examples of defective and non-defective images.



(a) (b)

Figure 2 Illustrative cold rolled steel strip surface images ((a) non-defective image; (b) defective image)

2.2 Image noise suppression

Impulse noises are inevitable when digital images are acquired [9-12]. With the objective of reducing impulse noise, noise suppression is necessary and significant. Through the processing of this stage it will produce an output image without noisy pixels while preserving details required for defect detection. Generally, such impulse noises tend to be misclassified as defects. Consequently, it is assumed in this paper that most impulse noises are generally smaller than the defects, and it is these impulse noise pixels that disturb the local homogeneity of steel strip texture. The noise suppression algorithm applied in this stage has been presented and illustrated in our previous studies [13], which is based on local similarity analysis and neighborhood evaluation.

2.3 Statistical features extraction

In statistical features extraction stage, the image is subdivided into blocks of size $w \times w$, and then a number of local statistical data are extracted from each block. It should be mentioned here that the main focus of the algorithm is to detect defects that disturb the local homogeneity of the images. To attenuate background texture, three descriptive statistic feature values are selected to characterize the shape of the plot. They are: the difference (d_g), the mean (m_g), and the variance (v_g). Those simple statistical features have been chosen in such a way that a fast and accurate on-line system can be devised, which can be defined as follows.

$$d_g(i,j) = \max_g(i,j) - \min_g(i,j) \tag{1}$$

$$m_g(i,j) = \frac{1}{w^2}\sum_{k=-w/2}^{w/2}\sum_{l=-w/2}^{w/2} g(i+k, j+l) \tag{2}$$

$$v_g(i,j) = \sqrt{\frac{1}{w^2}\sum_{k=-w/2}^{w/2}\sum_{l=-w/2}^{w/2}\left[g(i+k,j+l) - m_g(i,j)\right]^2} \tag{3}$$

where,

$$\max_g(i,j) = \max(g(i+k, j+l)) \text{ for } k,l \in [-w/2, w/2] \quad (4)$$

$$\min_g(i,j) = \min(g(i+k, j+l)) \text{ for } k,l \in [-w/2, w/2] \quad (5)$$

where, g(i, j) denotes a gray value of pixel located at coordinate (i, j) in the image.

How to divide the images into blocks is very important in this stage. When the block size parameter has been chosen, following basic requirements must be satisfied:

1. The block size must be small enough so that the defect area can be localized precisely.

2. The block size must be large enough. One aspect is that the result can not be influenced by the deterministic part of the steel surface texture. On the other, the effect of minute unimportant or false defects such as dust and minute particles can be neglected.

3. The defects needed to be detected must be taken into consideration when block size is determined. Large defects need large block size while small ones need small size.

In the proposed algorithm, a block size of 40 × 40 pixels was found to satisfy the previous conditions.

2.4 Defect Detection Modeling

After statistical features extracted from the previous steps, defect detection for steel strip surface follows. In this operation, multivariate discriminant analysis techniques are applied. Multivariate discriminant function is a very useful method to separate two or more groups and assign a new observation to one of groups. Therefore, it has been applied widely in many fields [14]. In this research, a successful discriminant function model is established on the premise of appropriate feature variables.

(1) Maximum likelihood discriminant rule

The densities of each population Π_j are denoted by $f_j(x)$. The maximum likelihood discriminant rule (ML rule) is given by allocating x to Π_j maximizing the likelihood $L_j(x) = f_j(x) = \max_i f_i(x)$. If several f_i give the same maximum then any of them may be selected. Mathematically, the sets R_j given by the ML discriminant rule are defined as [14]

$$R_j = \{x : L_j(x) > L_i(x) \text{ for } i = 1, \ldots, J, i \neq j\} \quad (6)$$

For the simplicity and high efficiency of the problem solutions, it is assumed that the data of objective groups come from multivariate normal distributions $N_p(\mu_i, \Sigma)$. As shown in Figure 3, according to the ML rule x is allocated to R_1 if $x < x_1$, or $x > x_2$, else x is allocated to R_2.

THEOREM 1 Suppose $\Pi_j = N_p(\mu_i, \Sigma)$. The ML rule allocates x to Π_j, where $j \in \{1,\ldots, J\}$ is the value minimizing the square Mahalanobis distance between x and μ_i :

$$\delta^2(x, \mu_i) = (x - \mu i)^T \Sigma^{-1}(x - \mu_i) \text{ for } i = 1,\ldots, J. \quad (7)$$

For $J = 2$, theorem 1 says that x is allocated to Π_1 if

$$\delta^2(x, \mu_1) \leq \delta^2(x, \mu_2) \quad (8)$$

$$(x - \mu_1)^T \Sigma^{-1}(x - \mu_1) \leq (x - \mu_2)^T \Sigma^{-1}(x - \mu_2) \quad (9)$$

Rearranging terms leads to

$$-2\mu_1{}^T\Sigma^{-1}x + 2\mu_2{}^T\Sigma^{-1}x + \mu_1{}^T\Sigma^{-1}\mu_1 - \mu_2{}^T\Sigma^{-1}\mu_2 \leq 0 \quad (10)$$

which is equivalent to

$$-2(\mu_2 - \mu_1)^T\Sigma^{-1}x + (\mu_1 - \mu_2)^T\Sigma^{-1}(\mu_1 + \mu_2)^T \leq 0 \quad (11)$$

$$(\mu_1 - \mu_2)^T\Sigma^{-1}\{x - \frac{1}{2}(\mu_1 + \mu_2)\} \geq 0 \quad (12)$$

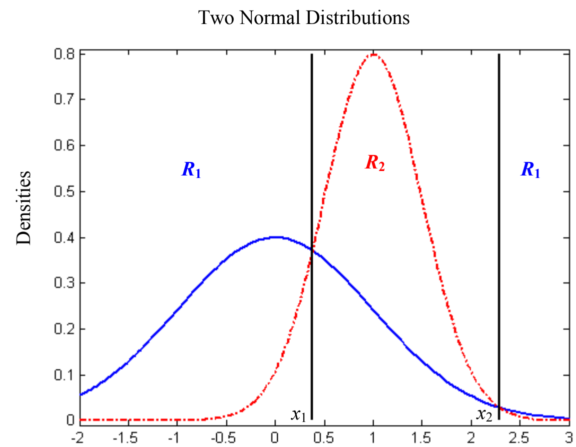


Figure 3 Maximum likelihood rule for normal distributions

(2) Defect detection modeling

There are two groups in this research, defective group (Π_1) and non-defective group (Π_2), the corresponding number of sampled data is respective n_1 and n_2. To estimate μ_i and Σ, sample mean vectors ($\bar{x}_i$) and covariance matrices (S_i) are defined as follows.

$$\bar{x}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} x_{ij} \quad \text{for } i = 1, 2 \quad (13)$$

$$S_i = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}(x_{ij} - \bar{x}_i)(x_{ij} - \bar{x}_i)^T \quad \text{for } i = 1, 2 \quad (14)$$

The common covariance matrix can be estimated by

$$S_u = \sum_{j=1}^{2}(n_j - 1)\left(\frac{S_j}{n-2}\right) \quad (15)$$

where, $n = \sum_{j=1}^{2} n_j$.

The discriminant function for two normal groups is defined as follows.

The new observation of x_0 is allocated to Π_1 based on Eq. (12), if

$$h(x_0) = (\bar{x}_1 - \bar{x}_2)^T S_u^{-1} x_0 - \frac{1}{2}(\bar{x}_1 - \bar{x}_2)^T S_u^{-1}(\bar{x}_1 + \bar{x}_2) \geq 0 \quad (16)$$

3 Experimental results and discussion

In our test, forty 400 × 400 pixel size real cold rolled steel strip images were used to model the multivariate discriminant function for recognizing the existence of defects. As described in section 2, if the value of $h(x_0)$ in a given image block is positive, it means the image is defective. Otherwise, it is allocated to the non-defective group.

In this research, sample mean vectors of Π_1 and Π_2 groups are prepared according to Eq. (13). They are:

$$\bar{x}_1 = \begin{bmatrix} v_{g1} \\ d_{g1} \\ m_{g1} \end{bmatrix} = \begin{bmatrix} 25.6086 \\ 165.6250 \\ 97.1049 \end{bmatrix} \quad (17)$$

$$\bar{x}_2 = \begin{bmatrix} v_{g2} \\ d_{g2} \\ m_{g2} \end{bmatrix} = \begin{bmatrix} 22.4661 \\ 146.6250 \\ 102.9999 \end{bmatrix} \quad (18)$$

Covariance matrices of two groups are calculated according to Eq. (14).

$$S_1 = \begin{bmatrix} 1.8239 & 2.7537 & -3.3789 \\ 2.7537 & 166.8393 & -9.9455 \\ -3.3789 & -9.9455 & 11.1162 \end{bmatrix} \quad (19)$$

$$S_2 = \begin{bmatrix} 0.3483 & 0.6879 & 0.3177 \\ 0.6879 & 27.4107 & -1.4263 \\ 0.3177 & -1.4263 & 1.9020 \end{bmatrix} \quad (20)$$

The common covariance matrix is:

$$S_u = \frac{1}{2}(S_1 + S_2) = \begin{bmatrix} 1.0861 & 1.7208 & -1.5306 \\ 1.7208 & 97.1250 & -5.6859 \\ -1.5306 & -5.6859 & 6.5091 \end{bmatrix} \quad (21)$$

According to Eq. (16), the multivariate discriminant function to recognize the existence of defects is created as follows.

$$h(x_0) = [2.3442 \quad 0.1405 \quad -0.2316]\, x_0 - 55.1131 \geq 0 \quad (22)$$

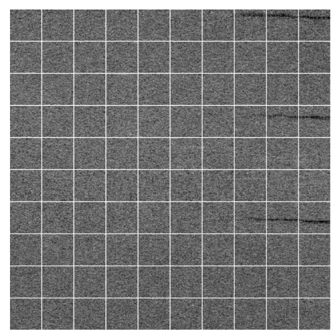
where, $x_0 = [v_{g0} \quad d_{g0} \quad m_{g0}]^T$.

If the value of $h(x_0)$ in a given image block is positive, it means the image is defective. Otherwise, it is allocated to the non-defective group.

It is the value of the block size w, which is determined in the statistical features extraction step, controls the sensitivity of the detection algorithm. Smaller value of w would detect minute defects but it could also result in false detection. Larger values of w would decrease the sensitivity of the algorithm and only localize large defects. Therefore, w will have to be freely adjusted both according to the required sensitivity and defects types in the inspection sites. For all the samples we used in this implementation, a value of 40 was chosen for w. It was chosen using a trial and error approach so that satisfactory results could be obtained for different defects.

Figure 4 shows one of sample images and its multivariate discriminant function values. Figure 4 (a) is the image subdivided into blocks of size 40 × 40, which represents a kind of defects called "wrinkles on the surface". Figure 4 (b) shows the multivariate discriminant function values of each block. If the value is positive, it means that the relevant block is defective. By contrasting with Figure 4 (a), it can be seen that the proposed algorithm is effective and accurate in identifying major defects.

The proposed approach was tested with a number of non-defective and defective cold rolled steel strip samples and satisfactory results were achieved (91% success, 7% false defects being detected and 2% failure to localize the defects).



(a)

-4.61	-6.19	-1.67	-1.82	-8.62	-6.68	-1.85	**8.55**	**7.83**	**11.69**
-5.43	-6.45	-5.38	-3.72	-9.26	-4.35	-5.76	-5.26	-6.83	-7.19
-8.81	-5.65	-6.14	-7.15	-5.90	-7.58	-7.00	-10.66	-6.91	-10.45
-7.24	-6.87	-6.05	-8.03	-8.45	-7.73	-7.42	**0.61**	**1.08**	**6.69**
-4.54	-4.75	-8.83	-6.39	-3.73	-7.14	-4.98	-7.60	-7.97	-10.60
-3.47	-2.84	-2.95	-7.62	-8.66	-5.04	-8.39	-1.81	-10.12	-6.46
0.03	-4.01	-3.68	-5.94	-8.51	-6.37	-4.09	**1.07**	**3.27**	**8.53**
-6.03	-8.72	-6.92	-5.31	-6.80	-4.45	-6.59	-7.03	-6.84	-9.70
-5.33	-7.82	-7.45	-4.95	-9.17	-8.17	-6.76	-9.83	-7.95	-9.26
-8.79	-2.00	-3.56	-9.43	-6.58	**0.92**	-7.22	-9.61	-8.02	-4.70

(b)

Figure 4 Defective image and its $h(x_0)$ values

4. Conclusions

In this paper, a new fast defect detection approach has been investigated to inspect the surface of steel strip. Neighborhood noise evaluation was firstly applied in order to attenuate the influence of impulse noises. After that, a description of detecting tiny defects was given where the image is subdivided into blocks and corresponding features are extracted. According to the maximum likelihood discriminant rule, a successful discriminant function model has been established which was tested and validated by inputting a new observation into this model. Experimental results prove the feasibility and accuracy of the approach presented. Take practice application into consideration, this detection and classification system proposed in this paper lays a solid foundation for the future study.

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