Y. F. JIANG, X. ZHOU, W. Y. ZHANG

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A SURFACE DEFECT DETECTION METHOD FOR ROLLING MAGNESIUM ALLOY SHEET BASED ON COMPUTER VISION

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In the rolling process of magnesium alloy sheet, defects such as edge crack, fold and ripple are easy to appear on the surface of the sheet. These defects will affect the product yield and quality, and cause waste of resources. In this paper, computer vision technology is used to analyze the image of rolling magnesium alloy sheet in real-time, extract its defect features, and Bayesian classifier and Random Forest (RF) classifier are used to identify defects. The experimental results show that the comprehensive defect recognition rate of the RF algorithm is up to 92,4 %, which is much higher than the accuracy of Bayesian classifier, and it is more suitable for the recognition of surface defects of magnesium sheet.

Key words: rolling, magnesium alloy, sheet, defects detection, computer vision

INTRODUCTION

In the process of rolling magnesium alloy sheet, the poor quality of slab to be processed, the low accuracy of main equipment of rolling mill and improper control parameters such as rolling speed and press force directly result in low surface quality of sheet and seriously reduce the yield of rolled sheet. Therefore, how to do non-destructive, real-time and accurate surface defect detection for magnesium alloy rolling sheet has great practical significance.

In the early stage of thin plate surface defect detection, manual visual sampling method is generally used, which is slow in detection speed and high in missing rate. The method does not satisfy industrial production requirements anymore. Therefore, some experts and scholars have successively proposed eddy current testing, infrared testing, magnetic flux leakage testing and other surface defect detection methods, but there are still many limitations, such as low detection accuracy, few types of detectable defects, etc. With the development of computer vision technology, the method of thin plate surface defect detection based on digital image processing has become a research hotspot. The core of this method is how to choose high-speed image processing algorithm and high accuracy recognition algorithm. In recent years, according to the characteristics of sheet metal surface defects, various scholars have put forward many defect recognition methods, such as artificial neural network, support vector machine and the method of maximum variance between classes [1]. However, most of these algorithms are based on static defect images of magnesium sheet, and do not consider the problems of light, production speed and repeated sampling in the actual production of magnesium sheet, and cannot be applied to the actual magnesium sheet production line for defect detection. In this paper, a real-time automatic defect detection technology based on computer vision is adopted. This method can detect the surface defects of magnesium sheet quickly and efficiently in real-time.

Y. F. Jiang, X. Zhou, W. Y. Zhang, School of Computer Science and Software Engineering, University of Science and Technology Liaoning, China. Corresponding author: W. Y. Zhang (zhangwenyu8518@126.com)

CAUSES OF SURFACE DEFECTS OF THIN PLATES

The dataset used in this paper includes five common surface defects of magnesium sheet:

Edge Crack (EC): The edges of one or both sides of magnesium sheet are unevenly cracked, mostly in serrated shape. The main cause is the tearing at the edge of magnesium strip under high tension rolling conditions.

Oil Stain (OS): Oil stains are attached to the surface of magnesium sheet. The main causes are the oil stain in the slab itself, and the oil stain attached to the rolling equipment drips on the thin plate during the rolling process.

Ripple (R): The surface of magnesium sheet is uneven, which is mainly caused by the dislocation of rolls working for a long time under the pressure.

Fold (F): Crease occurs in the local area on the surface of magnesium sheet. The main reasons are that the slab itself has corrugated defects and the thin strip off-tracking.

Scratch (S): The surface of magnesium sheet is linearly marked with metallic luster. The main reason is that the surface of the roll is not smooth or adheres to foreign bodies.

The five defect type images are shown in Figure1.

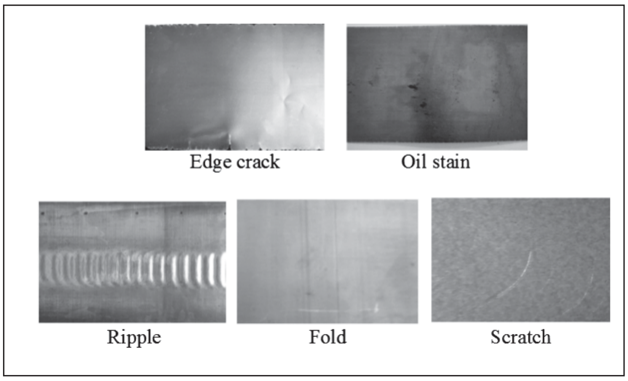

Figure 1 The five defect type images

DEFECT IMAGE FEATURE SELECTION AND EXTRACTION TECHNOLOGY

In the process of rolling magnesium sheet, the image acquired by computer in real-time is not perfect due to limit of sensor material, limit of electronic component, motion blurring and the imperfection of transmission medium and recording equipment in the process of image signal transmission. This will cause some noise in the image and result in image blurring, which will greatly increase the false detection rate of the algorithm. Therefore, it is necessary to pre-process the image before extracting the features of the image by removing noise and enhancing the contrast of the image.

After the image is captured, the image is grayed firstly to reduce the computational complexity to meet the real-time requirements. Secondly, perform histogram equalization can increase the dynamic range of the gray value of the pixel and enhance the contrast of the image, thus highlighting the defects. The median filter can reduce the interference of the surrounding environment and lighting, and keep the edge information of the image well. Next, image binarization is processed, and the adaptive threshold is selected to decide whether to retain or directly remove a pixel to reduce the noise interference. Then, morphological operations are performed on the image to reduce the noise caused by motion blurring. Finally, the retrieval contour can focus on the defect area to extract defect features.

After pre-processing, if there are defects such as edge cracks, oil stains, folds, etc., the pixels in the defect area will have significant difference from those around them, the defect part will have obvious geometric characteristics, and there will be also some differences in the gray level representation of the image defect. Therefore, geometric features and texture features are synthetically selected to reflect the shape and gray characteristics of defects, in order to further abstract the shape features of defects, and finally define the defect information given by the classifier so that the computer can automatically identify edge cracks, oil stains, ripples and other defects.

Geometric feature is one of the basic features that can describe sheet defects relatively intuitive [2]. The selected geometric features need to simply describe the location, size, shape and other information of defects. In this paper, five basic geometric features, including area, circumference, centrifugal rate, roundness and normalized moment are selected.

In order to more comprehensively represent the essential attributes of defects, another kind of feature, called texture feature, is also used.

Texture feature in image analysis refers to the digital feature of gray level change. This paper chooses four texture features: entropy, angular second moment (ASM) energy, contrast and correlation through comprehensive consideration to better represent the gray features of defect information.

Entropy. Entropy of an image measures the richness of information contained in an image, which is a representation of the non-uniformity level or complexity of texture information in images [3]. In this algorithm, in order to reflect the spatial characteristics of the image gray distribution, the spatial characteristic quantity is added to represent the two-dimensional entropy of the image based on the one-dimensional entropy which can represent the aggregation feature. In this theory, the spatial characteristic quantity of image gray distribution is represented by the neighborhood gray value of the image, which forms a feature tuple together with the pixel gray value of the original image, which is marked as (i, j). The Formula (1) for calculating image entropy is:

$$H = \sum_{i=0}^{255} P_{ij} log P_{ij} \tag{1}$$

In this formula, i is the gray value of the pixel ($0 \leq i \leq 255$); j is the mean gray value of the neighborhood ($0 \leq j \leq 255$); P_{ij} is the quotient of the occurrence frequency of characteristic binary (i, j) and the total number of pixels in the image.

ASM energy. ASM energy is an eigenvalue to measure the uniformity of gray distribution and texture thickness in an image. The larger the ASM energy value of the image is and the more uniform the image texture pattern is, the more regular the image texture change is. In image processing, its representation is:

$$ASM = \sum_{i=0}^{255} \left[P(i) \right]^2 \tag{2}$$

In this formula, P (i) is the first-order histogram of the image, it is the quotient between the total number of pixels with gray level i and the total number of pixels in the image.

Contrast (*CON*). Image contrast is the characteristic value to measure the clearness of image and the depth of texture grooves [4]. The contrast computation formula is:

$$CON = \sum_{i=0}^{255} i^2 P(i) \tag{3}$$

In this formula, P(i) has the same meaning with the formula (2).

Correlation (*COR*). The correlation of image is the characteristic value of local gray pixels in image; it concerns with the similarity level of elements in the row or column direction in the spatial gray level co-occurrence matrix.

The expression formula of its correlation is shown in formula (4):

$$
\begin{aligned}
COR &= \sum_{i=0}^{255}\sum_{j=0}^{255}\frac{ijP_{ij}-\mu_i\mu_j}{\sigma_i\sigma_j}\\
\mu_i &= \sum_{i=0}^{255}\sum_{j=0}^{255} i\cdot P_{ij}\\
\mu_j &= \sum_{i=0}^{255}\sum_{j=0}^{255} j\cdot P_{ij}\\
\sigma_i^2 &= \sum_{i=0}^{255}\sum_{j=0}^{255} P_{ij}(i-\mu_i)^2\\
\sigma_j^2 &= \sum_{i=0}^{255}\sum_{j=0}^{255} P_{ij}(j-\mu_j)^2
\end{aligned}
\tag{4}
$$

In this formula, i, j and P_{ij} have the same meaning with the formula (1).

Based on the above nine features, we can extract the size, shape, gray distribution, texture and other features of defects, so as to highlight the mathematical characteristics of defects, and make full preparations for the next step of defect sample matching and defect classification and recognition in the classifier.

DESIGN OF CLASSIFIER

The training time and the judgment time should be considered in the selection of classifiers, and prediction accuracy is also very important. Bayesian classification is fast because of its clear relationship between conditional attributes and decision categories. It has been successfully applied to many fields such as Web document classification [6] and product failure rate classification. Random Forest (RF) algorithm has high prediction accuracy and good tolerance for outliers and noise. It is not easy to appear over fitting phenomenon, and it has a wide range of applications in various fields. Therefore, this paper establishes the RF model and Bayesian model for comparative experiments.

Design of Bayesian Classifier

Bayesian classification is based on probabilistic reasoning, it completes the corresponding reasoning decision under various uncertainties according to the probability of each condition. In this paper, area, circumference, centrifugal rate, roundness, normalized moment, entropy, ASM energy, contrast and correlation nine features of defects in surface image of magnesium sheet are extracted as Bayesian network features, and in formula we use *S, L, e,* R_0, H_u, *H, ASM, CON, COR* to represent them. The conditional probability of defect type under given defect characteristics is:

$$
P\left(Defect|S,L,e,R_0,H_u,H,ASM,CON,COR\right)=\frac{P\left(S,L,e,R_0,H_u,H,ASM,CON,COR|Defect\right)\cdot P\left(Defect\right)}{P(S,L,e,R_0,H_u,H,ASM,CON,COR)}
\tag{5}
$$

In the formula (5), *(S, L, e,* R_0, H_u, *H, ASM, CON, COR)* is the eigenvector of the sample. *Defect* is a collection of defects in different feature spaces. *P (Defect)* is a prior probability of *Defect*. *P(S, L, e,* R_0, *H, ASM, CON, COR)* represents the conditional probability of *(S, L, e,* R_0, H_u, *H, ASM, CON, COR)* features under *Defect* conditions.

Design of RF Classifier

RF algorithm is an integrated machine learning algorithm which establishes by multiple decision trees and synthesizes the result of each tree to obtain the final classification results. The Gini index was used in this paper to judge the optimal classification feature. The formula of Gini index can be expressed as:

$$
\mathrm{Gini}\left(T\right)=\sum_{k=1}^{n}p^k\left(1-p^k\right)k=1,2\cdots \mathrm{N}
\tag{6}
$$

Where p^k is the probability of the kth class, n is the number of categories in dataset T. After classification by a certain eigenvalue t, the Gini index can be expressed as:

$$
\mathrm{Gini}\left(T,t\right)=\sum_{k=1}^{n}\frac{|T^k|}{T}\mathrm{Gini}\left(T^k\right)
\tag{7}
$$

The smallest Gini(T, t) was selected as the segmentation point for classification.

EXPERIMENTAL VERIFICATION

In this experiment, 150 samples of each of the five defects mentioned above were collected, and a total of 750 pictures were taken as dataset, the Bayesian prediction model and RF prediction model were established respectively.

Table 1 **Accuracy comparison table**

Subject of entry	Algorithm	Defect type					In total
		EC	OS	R	F	S	
Recognition rate / %	Bayes	86	82	92	80	78	83,6
	RF	98	90	96	92	86	92,4

500 images in the data set were used for training, and the other 250 were used for testing. The accuracy comparison between Bayes and RF classifiers is shown in Table 1.

From Table 1, we can see that the recognition rate of ripple defects is the highest among the five kinds of defects by using Bayesian classifier, which reaches 92 %. However, the overall recognition rate is only 83,6 %, which represents that the Bayesian network cannot meet the practical application requirements.

In addition, it can be seen from table 1 that the prediction accuracy of RF model is 92,4 %, which is higher than that of Bayesian model on the surface defects detection of magnesium alloy sheet. It shows that the RF algorithm has a good effect on the prediction of surface defects of magnesium alloy sheet.

CONLUSION

In this paper, according to the characteristics of magnesium alloy sheet surface defects, Bayesian algorithm prediction model and RF prediction model are designed respectively. From the experimental results, the overall accuracy rate of Bayesian model is only 83,6 %. The overall accuracy rate of RF is 92,4 % on the surface defects of magnesium alloy sheet. Therefore, the RF algorithm is more suitable to predict the surface defects of magnesium alloy sheet. In later research, the rolling parameters of magnesium alloy sheet will be automatically modified by expert system to reduce the defects, so as to realize the overall automation of rolling process.

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Note: The responsible translator for English language is Lihua Cai-University of Science and Technology Liaoning, China