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Surface Quality Inspection of Plate and Strip Steel Based on Support Vector Machine

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Abstract

The types and distribution of surface defects in the production process of strip steel vary greatly, and the detection and classification of surface defects can greatly improve product quality. This article proposes a machine learning based surface quality inspection system for strip steel, including the hardware and software structures of the system. Applying machine learning theory to provide effective methods for detecting and classifying surface defects in steel. Design a support vector machine classifier based on radial basis function (RBF) kernel function, which can achieve an average detection rate of 88.2% for 6 types of defects on the surface of plate and strip steel, ultimately achieving the goal of automatic detection of surface defects on plate and strip steel.

Keywords: Quality Inspection; Support Vector Machine; Plate and Strip Steel; Machine Learning.

1. Introduction

On the steel production line, the quality of steel billets, production process, equipment conditions, and environmental factors all play a decisive role in the surface quality of strip steel. The types and distribution of surface defects on strip steel vary greatly. Although some defects are subtle and difficult to detect, they can also affect the size, ductility, wear and corrosion resistance, and service life of the steel to a certain extent. Therefore, it is necessary to conduct a specific analysis of the types of defects on the surface of the strip steel, and design a defect detection system based on the characteristics and causes of different defects.

In the late 1990s, the American company Congnex designed a Smart view system [1], which is based on machine learning algorithms for classifiers [2]. It first learns from training samples and then achieves defect recognition through pattern matching algorithms. Users can design the software and hardware structure of the system according to their own ideas.

In 1997, the German company ParsyTec designed a classifier based on artificial neural networks and developed HTS-2 [3] and HTS-2W [4] on the basis of area array CCD imaging. A few years later, a Parsyte5i system was introduced for the first time, which combines surface CCD and linear CCD, greatly improving the reliability of defect recognition.

In 2011, TolbaAS designed a probabilistic neural network classifier based on Log Gabor filtering [5]. The basic idea is to first pass the image through a Log Gabor filter, and then put it into a probabilistic neural network for training.

At the beginning of the 21st century, Beijing University of Science and Technology, in collaboration with Wuhan Iron and Steel Company, put surface array CCD technology into practical production and developed China's first CCD imaging steel plate surface quality inspection system. Extract feature information from the images collected by the array CCD to achieve defect classification [6].

In 2002, researchers such as Xu Ke from Beijing University of Science and Technology cleverly utilized the changes in brightness and darkness of reflected light during camera imaging to design a defect detection device based on "bright field illumination" and "dark field illumination" [7]. According to the differences between the surfaces of ordinary carbon steel and stainless steel, "bright field illumination" and "dark field illumination" were applied to the three-dimensional defect detection of both surfaces, using two different methods to improve the pertinence and effectiveness of defect recognition.

In 2004, Xu Daofeng and Di Xiaojuan conducted research on feature extraction methods based on defect image shape, texture, projection, and histogram, and designed a classifier based on LVQ neural network [8].

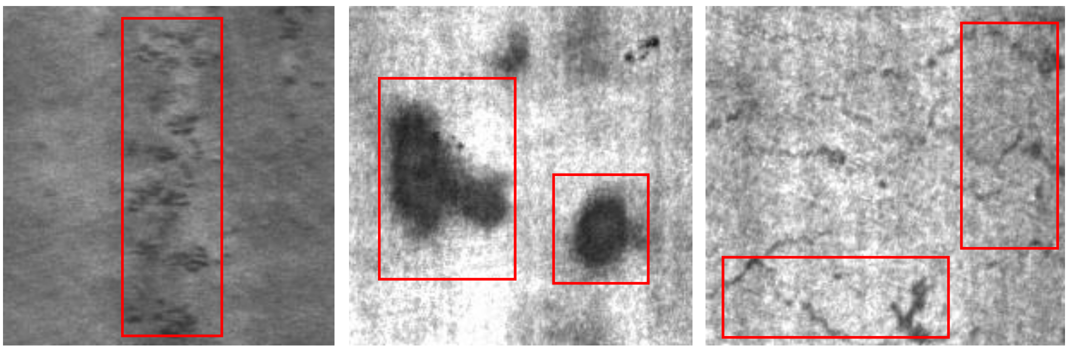
In 2005, Liu Hongbing designed a classifier based on feedforward neural network [9]. Fei Jianghua et al. proposed a combination classification algorithm [10]. They train the feature quantities extracted by different algorithms, and then compare the recognition results of different classifiers to obtain the category with the highest probability.

In 2015, Han Yingli et al. designed a steel surface defect detection system based on an optimized quantum particle swarm radial basis function network [11]. The system utilizes the QPSO algorithm's ability to automatically find the optimal parameters, which enhances the learning efficiency of the neural network.

However, there are currently problems with outdated detection equipment and low detection accuracy in the quality inspection of steel plates and strips. By using existing computer image processing technology and combining it with pattern recognition technology, applying machine vision to steel production practice can effectively compensate for the shortcomings of traditional detection methods, improve the quality and efficiency of steel plate inspection, and enhance the overall quality of steel production. Therefore, this article studies the basic principles of support vector machine (SVM), designs a support vector machine classifier based on radial basis function (RBF) kernel function, and ultimately achieves the goal of defect detection.

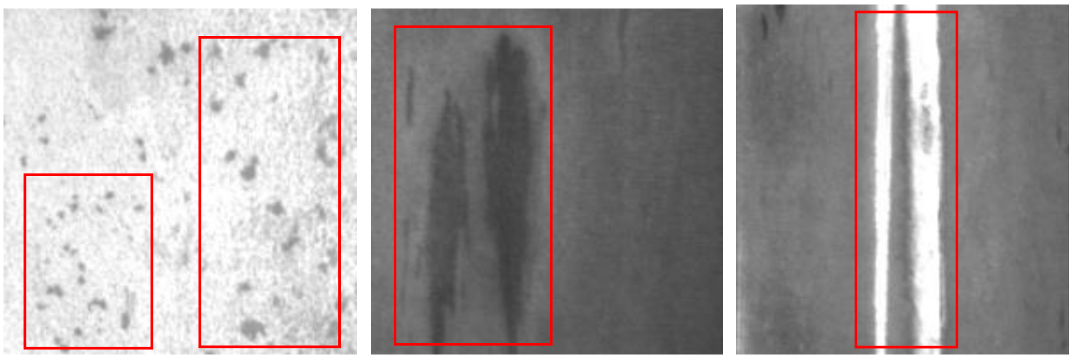
2. Analysis of Defect Types on the Surface of Plate and Strip Steel

This article selects six typical surface defects of strip steel from the NEU surface defect database [12].As shown in Figure 1.



(a) oxide skin (b) plaque (c) crack

Fig.1 Defect Types



(d) pitting (e) inclusion (f) scratch

Fig.1 Defect Types (cont.)

Take 6 samples from each of these 6 types of defects and arrange them in sequence as shown in Figure 2. Observe the comparison between inter class defects and intra class defects from both horizontal and vertical perspectives.

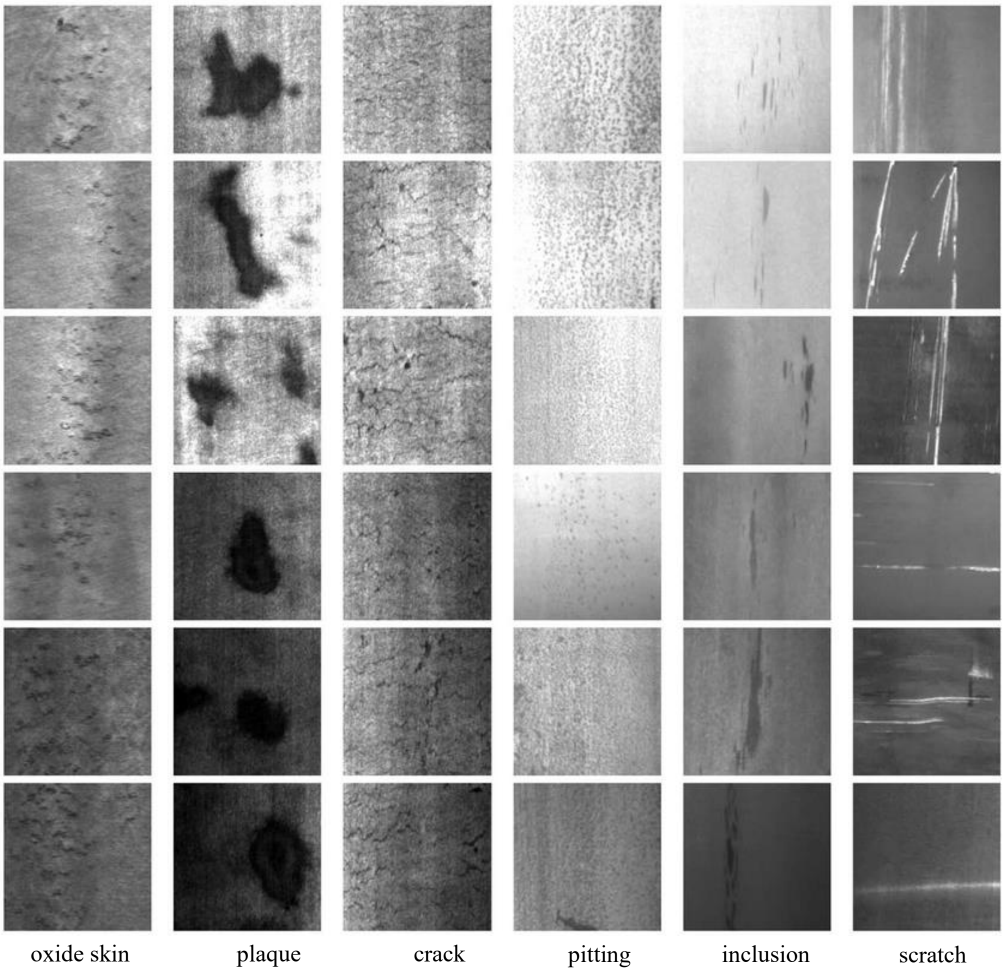


Fig.2 Comparison of inter class defects and intra class defects

From Figure 2, it can be seen that not only do different types of defects have different characteristics, but different samples of the same type of defect may also have significant differences in grayscale, size, shape, and roughness. In short, when distinguishing various types of defects, we encounter two difficult challenges: intra class defects have significant differences in appearance, while inter class defects have similar aspects, and defect images are affected by lighting and material changes. This requires us to design a classifier with higher accuracy.

3. Design of Surface Defect Detection System for Plate and Strip Steel

3.1. System Hardware Structure Design

The hardware structure of the machine learning based surface quality inspection system for strip steel is shown in Figure 3. The entire system consists of an infrared lighting device, a detection table, a detection system, an image processing computer group, and a control center. The lighting system adopts infrared light source directly controlled by the control center, which has the advantage of providing the lighting conditions required for high contrast image inspection. The inspection platform sends the strip steel along the direction of the assembly line to the bottom of the inspection system. The detection system consists of several high-speed array CCD cameras, the number of which is determined by the size of the strip steel and is directly managed by the control center.

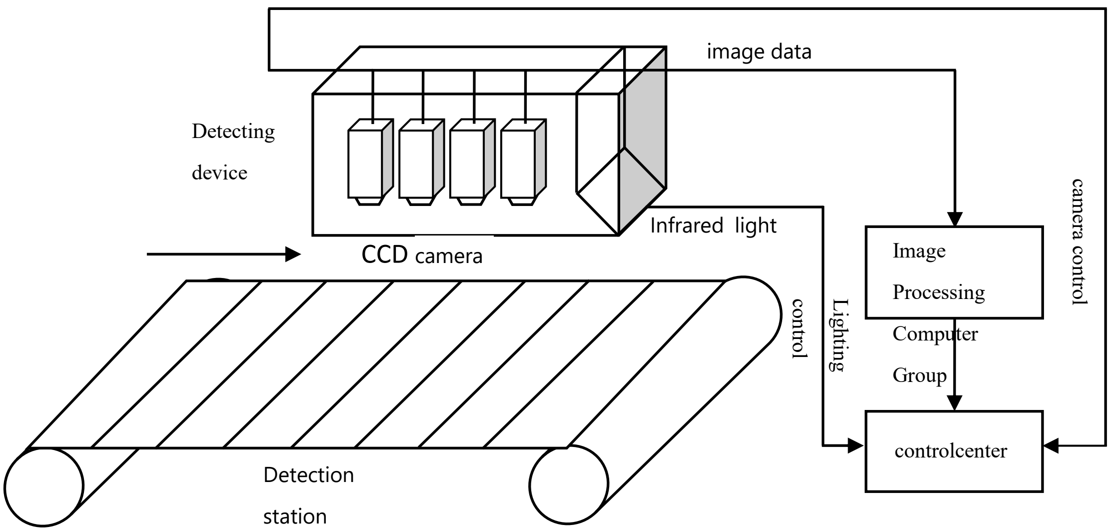


Fig.3 Schematic diagram of system hardware structure

The image processing computer group directly receives the steel surface image captured by the CCD camera from the detection device. The image processing computer can send signals to the control center according to the actual situation, and adjust the parameters of the camera and lighting device as well as the speed of image capture through the control center, ensuring that independent and high-quality steel surface images can be obtained. The image processing computer team uses image processing algorithms to filter out noise interference and segment defect areas (ROIs), which are then fed into the classifier. The defect images after classification are then transmitted to the control center, stored in the control center's database, and displayed on the control center screen.

3.2. System Software Architecture Design

The software structure of the machine learning based surface quality inspection system for strip steel is shown in Figure 4. From the figure, it can be seen that the image signal after image acquisition needs to go through four steps of processing, namely image filtering, image segmentation, feature extraction and selection, and defect classification.

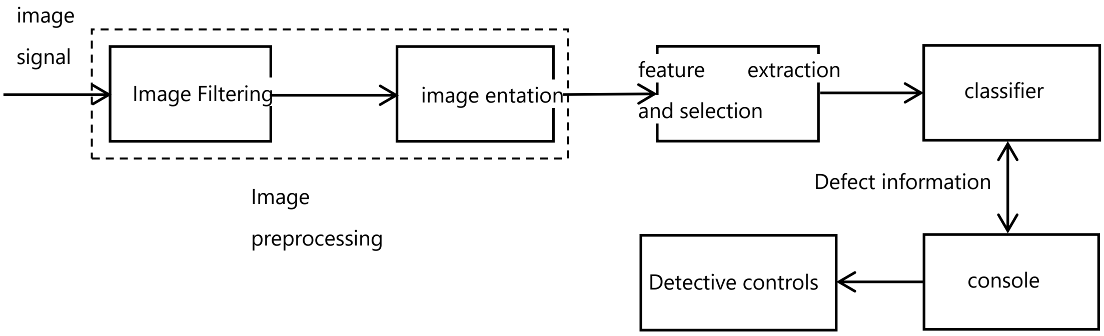


Fig.4 Schematic diagram of system software component structure

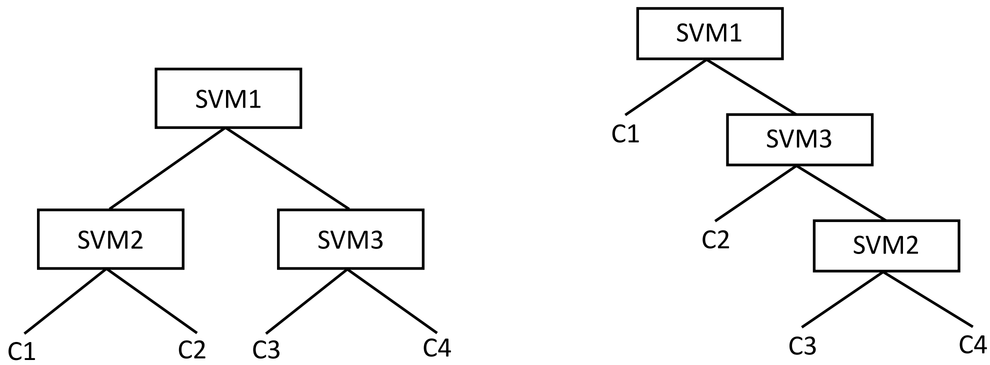
4. Surface Quality Inspection of Plate and Strip Steel Based on Support Vector Machine

4.1. Classifier Design Based on Support Vector Machine (SVM)

SVM is a linear binary classifier with outstanding training performance for small samples. The use of kernel function greatly reduces the possibility of dimension mutation during the operation process. The penalty factor and relaxation variable used to some extent solve the common problems in model recognition such as overfitting.

1) Multi class SVM

A regular SVM classifier can only perform two classifications. In this system, there are a total of six defect categories involved, so it is necessary to design an SVM that can achieve multi classification. Usually, there are three main methods for SVM to achieve indirect multi classification. Including 1-a-r type, 1-a-1 type, and multi-level classification. The main idea of the 1-a-r type is that each class has a matching SVM, and each SVM can only distinguish the sample data into that class or other classes; The main idea of the 1-a-1 type is to set one SVM for every two classes, and repeat setting a total of C_k^2 SVMs; The basic idea of multi-level classification is to use a fully binary tree or a partially binary tree, and the specific classification situation is shown in Figure 5.



（a）complete binary

（b）Partial binary

Fig.5 Multi level SVM

Considering the actual situation, this system adopts the 1-a-1 type as the multi classification model.

2) Selection of kernel function

The polynomial (POLY) function and radial basis function (RBF) discussed in equations 4.38 and 4.39 belong to global kernel functions and local kernel functions, respectively. Considering the high accuracy of local kernel functions in typical situations, SVM based on RBF function is selected as the classification system for surface quality detection of strip steel, taking into account various factors.

3) Surface Defect Image Dataset of Plate and Strip Steel

The data sample used in this project is the NEU surface defect database. Randomly select 434 grayscale images of surface defects on strip steel as training samples, as shown in Table 1.

Tab.1 Training Sample Quantity Table

Defect type	oxide skin	plaque	crack	pitting	inclusion	scratch	No defects	Total
Number	75	89	60	40	65	80	25	434

4.2. Analysis of SVM classifier test results

The accuracy of a kernel function is greatly influenced by its parameters, and the most difficult part of classifier design is how to determine its optimal parameters. Due to the fact that the "RBF" kernel function we selected only has one parameter "gamma" and the penalty factor "C" is independent of "gamma", it greatly facilitates us in determining its optimal parameter.

We first randomly determine 'C=10', at which point we only need to change the value of 'gamma' and find its relationship with accuracy. Traverse the 'gamma' from 0.0001 using the self multiplication method of 2, and the final result is shown in Figure 6. From Figure 6, we can clearly see that within the range of -4 to -1 for Log (gamma) values, it is directly proportional to accuracy; When the value of Log (gamma) exceeds -1, the accuracy actually decreases.

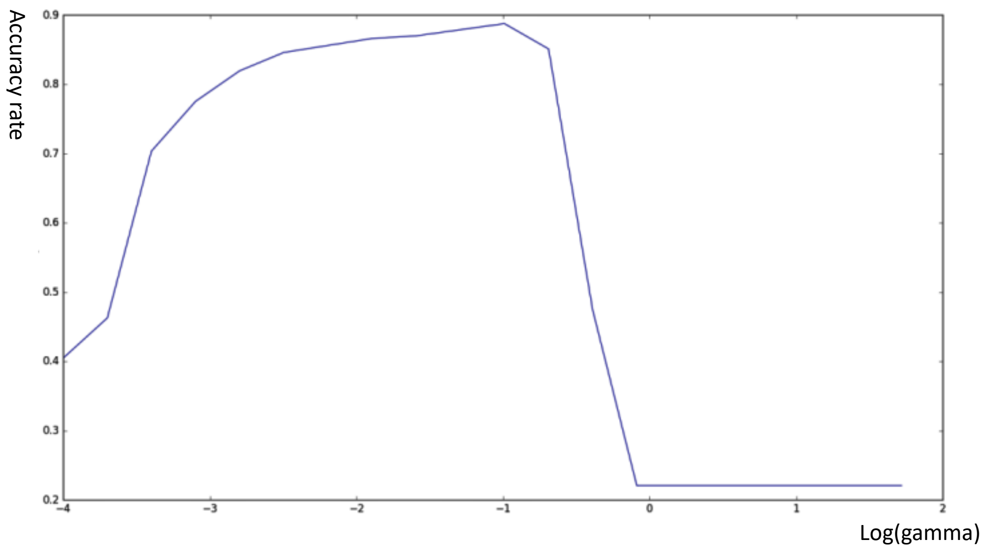


Fig.6 The Effect of Gamma on RBF

After determining the relationship between "gamma" and accuracy, we also need to determine the optimal value of "C". Select a highly accurate "gamma" value of 0.1024 from Figure 6, and similarly traverse "C" from 0.001 using the self multiplication method of 2. The final result is shown in Figure 7. From Figure 7, we can clearly see that within the range of -1.5 to 0 for Log (C) values, it is directly proportional to accuracy; When the value of Log (gamma) exceeds 0, the accuracy no longer changes.

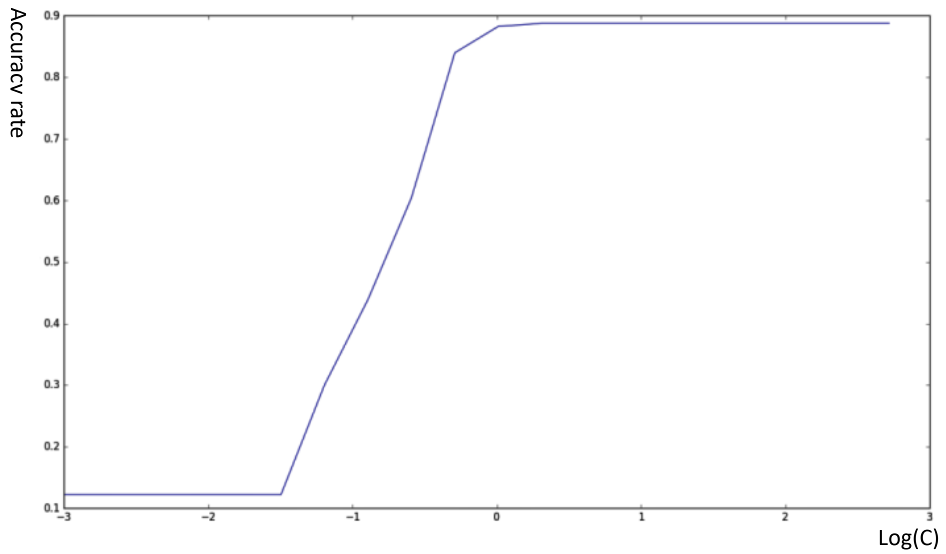


Fig.7 The Effect of C on RBF

Next, we select "C=6" while ensuring accuracy, and find the corresponding "gamma" value with the highest accuracy within the range of 0.05-0.15. The final result is shown in Figure 8. From Figure 8, we can clearly see that the accuracy has been fluctuating between 0.87785 and 0.89033.

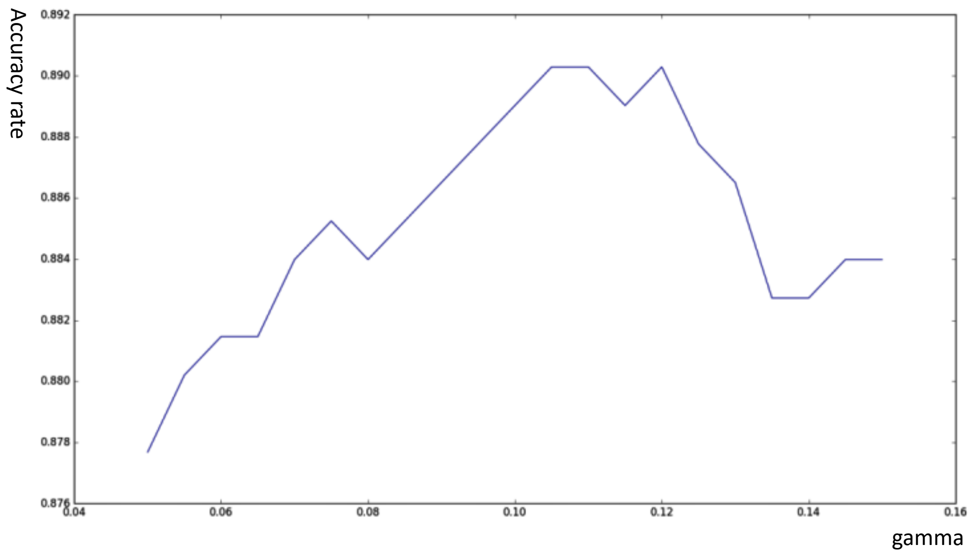


Fig.8 RBF small-scale test parameter gamma

The number of test samples and test results are shown in Tables 2 and 3, respectively.

Tab.2 Test Sample Quantity Table

Defect type	oxide skin	plaque	crack	pitting	inclusion	scratch	No defects	Total
Number	210	140	150	110	160	200	30	1000

Tab.3 Test Results Table

Defect type \ Recognition result	oxide skin	plaque	crack	pitting	inclusion	scratch	No defects	Total	Recognition Rate
oxide skin	190	11	2	3	2	2	0	210	90.5%
plaque	1	129	1	7	1	1	0	140	92.1%
crack	2	2	128	4	4	10	0	150	85.4%
pitting	1	6	1	101	1	0	0	110	91.8%
inclusion	3	7	2	8	137	3	0	160	85.6%
scratch	3	2	11	1	7	176	0	200	88.0%
No defects	2	1	1	2	2	1	21	30	70.0%
Total	Correct quantity : 882							1000	88.2%

From Table 3, we can clearly see that the final detection accuracy for six types of surface defects on the strip steel, including oxide scale, plaque, cracking, pitting, inclusions, and scratches, is 90.5%, 92.1%, 85.4%, 91.8%, 85.6%, and 88.0%, respectively. Among these six types of defects, the recognition rate is significantly lower than the other types, and the overall reason may be due to the high similarity between inter class defects, such as cracking and scratches. Defect free is greatly affected by noise, so the accuracy is only 70.0%. Overall, the average detection rate of the six types of defects on the surface of the strip steel is 88.2%, which basically meets the expected accuracy requirements.

4. Conclusion

We proposes a machine learning based surface quality inspection system for strip steel, including the hardware and software structures of the system. Design an SVM classifier based on radial basis function

(RBF) kernel function, determine its parameters, and accurately distinguish the six main types of defects studied. The average detection rate of the final 6 defects is 88.2%, which basically meets the expected accuracy requirements. The experimental results indicate that machine learning theory provides an effective method for detecting and classifying surface defects in steel.

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