Application of SOCP-SVM Algorithm on Strip Steel Surface Defect Recognition

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Abstract

Aiming at the problem that the recognition accuracy is not high and the recognition speed is slow in the classification and recognition of the strip surface defects, a classification and recognition algorithm based on the support vector machine with two order cone programming is proposed. First, the strip image is extracted, and the defect image is determined. Then, the defect images are pre processed. Finally, the defect images are extracted using the support vector machine with the two order cone programming (SOCP-SVM) algorithm. Simulation experiments show that the recognition accuracy of the proposed algorithm is higher than the traditional SVM algorithm and RVM algorithm. The recognition speed is faster than that of the SVM algorithm and RVM algorithm. The proposed algorithm is practical and real-time. It can be used for the identification of strip surface defects effectively.

Keywords: support vector machine; two order cone programming; surface defect recognition

1. Introduction

The strip surface defect recognition features and the defects types are complex, which have considerable complexity. The research on defect classification algorithm is mainly focused on the method of image recognition and machine learning. There are many theories and methods based on image recognition, which mainly include: statistical analysis, syntactic recognition and fuzzy recognition etc al. Machine learning method are divided into different types according to the different types of classifiers, such as neural networks, support vector machines, etc. The strip surface defect classification recognition methods include[1-7]: the multi-level classification of strip surface defects based on expert experience and decision tree classifier, the classification based on neural network, the classification based on combination feature reduction and clustering. However, the above classification method, or the need to know a priori knowledge and model structure, but, in dealing with the actual problem, the structural model is often not clear; Or in order to minimize the risk of empirical risk, in the practical application, the number of samples tends to infinity. So the application of the above classification method is very limited.

Hence we proposed a novel classification recognition method based on the SOCP-SVM algorithm to recognize the defect of steel strip surface from flatness defect image[8-10]. The hyper parameters of SVM model are optimized by the second-order cone programming (SOCP) algorithm. So that we can solve the optimization of SVM kernel function parameter and overcome the limitations of single core function for building the SOCP-SVM strip steel surface defect classification recognition model.

2. Application of SOCP-SVM Algorithm on Defect Recognition

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2.1 The Principle of SOCP-SVM

In order to solve the problem of the optimization of the kernel function parameters and the limitation of the single kernel function in the defect image recognition modeling, a new method based on SOCP-SVM is proposed. Given an un classified test data, that is, $S = \{x_i\}_{i=1}^n, x_i \in \mathbb{R}^m$, Optimization of kernel function in the SVM algorithm plays a decisive role on the classification accuracy [11-14]. In this paper, the kernel function of SVM algorithm is optimized using SOCP algorithm , and then the strip surface defect classification recognition model using SOCP-SVM algorithm is established.

The key problem of this algorithm (SOCP-SVM) is constructing the multi kernel function SVM based on the idea of multi kernel function, and transforming it into a convex optimization problem, and then using SOCP to solve. This can further improve the accuracy of the identification of defect types.

2.2 The Diagram of Strip Steel Surface Defect Recognition Based on SOCP-SVM

The diagram of strip steel surface defect recognition is shown in Fig. 1 to Fig.2.



Fig. 1. The diagram of SOCP-SVM training. Fig. 2.



The whole classification recognition algorithm is divided into two parts: the SOCP-SVM model training part (off-line part) and the strip surface defect classification recognition part (online identification part).

The training part of the SOCP-SVM model is mainly for the selection of the training sample set. The main steps are as follows:

(1) image preprocessing

Strip surface defect sample information should be accurate, comprehensive, as far as possible to ensure that the selected information is not repeated.

(2) feature extraction

On the strip surface defect image feature extraction, the feature parameters include three types features such as the geometric features (stretching length, rectangular degree, area, perimeter, seven order invariant moments), the gray level features mean value, mean square value, gray entropy), the texture features (energy, correlation, deficit moment, coarseness, contrast, direction).

(3) training of two order cone programming support vector machine model

In multi kernel SVM, the 3 radial basis kernel functions are constructed through linear combinations .The selected parameters are $\gamma_1 = 0.01$, $\gamma_2 = 0.1$, $\gamma_3 = 1$ respectively. Then the coefficients are solved using the two - degree cone programming method. The kernel function combination coefficients are 0.0710,0.0161 and 0.9862 respectively. In the SOCP-SVM model, the optimal penalty parameter C of SVM, the kernel parameter γ and the kernel weight u_i to be optimized are solved using SOCP algorithm. So as to get a good training SOCP-SVM classification recognition model.

(4) On-line defect recognition using the trained SOCP-SVM model

The steps of strip surface defects classification recognition are as follows:

(1) Image preprocessing and defect discrimination of steel strip surface defects:

First, the input image is preprocessed, and a two value image is obtained. Then the obtained image is processed by the median filter. Second, the two value image is processed to judge whether there is a defect in the image.

If there are defects in the image, the defect features are extracted, so that the features can be fed into the trained defect classification recognition model. If the defects does not exist, then enter the next frame.

(2) defect feature extraction

The defects features of strip surface defect image are extracted. The feature parameters include three types features such as the geometric features (stretching length, rectangular degree, area, perimeter, seven order invariant moments), the gray level features (mean value, mean square value, gray entropy), the texture features (energy, correlation, deficit moment, coarseness, contrast, direction). Then the selected features are fed into the SOCP-SVM model for classification recognition.

(3) SOCP-SVM recognition and output results:

The strip surface defect images are recognized using the trained SOCP-SVM model and output the results, so as to perform the corresponding operation.

3. Experiment and Effect Analysis

In this paper, a SOCP-SVM model is established based on the principle of SOCP-SVM, and the strip surface defects recognition classifier is constructed.

Finally, four kinds of typical defects such as folds, pyramid, iron oxide pressed and hem was selected as the research objects in the recognition simulation experiment, and 300 samples for each defect is selected. Among them, 200 samples are selected as the training set and 100 samples are taking into account as the testing set. Gaussian radial basis kernel function is selected as the kernel parameter. The SVM, RVM and SOCP-SVM algorithms are tested and simulated in the experiment. The hardware requirement of the experiment is as follows: CPU is Intel Core i5 760 3.3 GHz, 8 GB memory, and the software platform is the Windows7 operating system, and the simulation software is Matlab7.0.

The experimental strip defect images are collected in a steel factory. The collected image data set is composed of a data set, and the image preprocessing is performed, and then the algorithm is trained by the SOCP-SVM algorithm.

The most common 4 kinds of defects are as the typical research objects: folds, pyramid, iron oxide pressed and hem. As shown in Fig. 3 (a) to Fig. 3 (d).



(a) Folding (b) Pyramid (c) Iron oxide pressed (d)Hem Fig. 3. Defect map.

The three types of features such as the geometric features, the gray level features and the texture features are selected. As shown in Tab.1.

types	Feature parameters					
the geometric features	stretching length, rectangular degree, area, perimeter, seven order invariant					
	moments					
the gray level features	mean value, mean square value, gray entropy					
the texture features	energy, correlation, deficit moment, coarseness, contrast, direction					
* 10 ⁴ Hetagram of biding	4 10 ⁴ Histogram of pyramd 9 Using an of pyramd					
Fig. 4. Histogram of Defects.						

Table 1. Feature parameters of surface defect image

Fig. 5. Binarization image after the median filter.

According to the above method, the feature extraction of multiple images is carried out, and the defect data set is set up, and the feature information is acquired as much as possible to construct the dimension matrix, so as to obtain a better classification sample. By using the feature information mentioned above, the database is established, and the 20 dimensional feature training set is formed.

On the basis, 4 kinds of defects are simulated respectively using SVM, RVM and SOCP-SVM, 300 samples are selected for each defect. The first 200 pieces are used as training samples, and other 100 pieces are selected as test samples. The results are shown in table 3. SVM algorithm is realized by Libsvm and Libsvm and MATLAB interface program package, and the Gauss radial basis function is selected in RVM and SVM algorithms. The parameters of the Gauss radial basis function are $\gamma_1 = 0.01$, $\gamma_2 = 0.1$, $\gamma_3 = 1$ respectively, which are linear combination. The combination coefficients of the kernel functions are 0.0710,0.0161,0.9862 respectively solved through the two order cone programming

method.

Types		Folding	Pyrami d	Iron oxide pressed	Hem
The geometric features	stretching length	0.7553	0.8796	0.9794	0.6798
	rectangular degree	1.1714	1.2020	0.7644	0.3349
		7.8183e	1.2332e	4.4209e+0	7.2133e+0
	area	+003	+004	04	03
	• .	5.9843e	8.6888e	2.3680e+0	5.5986e+0
	perimeter	+003	+003	04	03
	one order invariant	2.7846	2.7719	3.0272	2.7070
	two order invariant moments	7.3570	6.5833	7.2239	6.4299
	three order invariant moments	10.3556	9.4944	11.8128	9.3157
	four order invariant moments	10.0423	9.6418	11.2506	9.2212
	five order invariant moments	20.3601	19.2487	23.0317	19.0676
	six order invariant moments	13.8680	13.0298	15.2416	13.3102
	seven order invariant moments	20.4289	19.6028	22.8651	18.5054
The	mean value	46.4784	83.8107	140.7380	40.9109
gray level	mean square value	60.8878	43.1957	66.0513	55.9317
features	gray entropy	2.0088	2.2148	2.2375	1.9482
The texture features	energy	0.0066	0.0014	0.0065	0.0075
	correlation	116.680 2	-0.6847	-93.5389	39.0686
	deficit moment	0.0720	0.0013	3.1608e-0 04	0.0682
	coarseness	43.5529	47.2789	45.9985	45.4885
	contrast	38.8981	39.9486	55.2481	35.2261
	direction	0.3084	0.1146	0.0265	0.3707

 Table 2. Defect feature parameters.

From the above experimental results, the average recognition time and the recognition accuracy of SVM, SOCP-RVM, RVM algorithms are compared. Experimental results show that in the same radial basis function, the average recognition time of SVM is 75.375ms, the average recognition time of RVM is 114.815ms, while the average recognition time of SOCP-SVM is 72.2ms, the recognition speed is improved; The recognition accuracy of SVM is about 97.75%, the recognition accuracy of RVM is about

98.25%, and the recognition accuracy of SOCP-SVM is 99.5%. Therefore, the recognition accuracy of the presented method is the highest. In contrast, the application of SOCP-SVM algorithm for strip surface defect recognition can get higher recognition accuracy, but also can get faster recognition speed.

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Types		Foldi	Pyram	Iron	Hem	
		ng	id	oxide pressed		
SVM -	Recognition accuracy	97%	98%	100%	96%	
	Average recognition time (ms)	69.3	73.1	78.5	80.6	
RVM -	Recognition accuracy	97%	99%	100%	97%	
	Average recognition time (ms)	98.6	110.3	119.1	128.6	
SCOP-SVM -	Recognition accuracy	99%	100%	100%	99%	
	Average recognition time (ms)	65.1	70.4	73.1	80.2	

Table 3. Comparison results of defect recognition using three algorithms

3. Conclusions

The multi kernel support vector machine model based on two order cone programming is used to classify and recognize the strip steel defect images in this paper. This algorithm can improve the classification accuracy and generalization ability of support vector machine. Multi dimensional feature parameters are extracted from the strip defect image. The simulation experiments prove that this method can reduce the time of defect recognition and improve the recognition accuracy. Compared with the traditional SVM and RVM algorithm, the proposed method has better recognition performance, which has important significance for improving the quality of the strip surface defect detection.

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