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Surface defect classification in large-scale strip steel image collection via hybrid chromosome genetic algorithm

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ABSTRACT

In this paper, hybrid chromosome genetic algorithm is applied to establishing the real-time classification model for surface defects in a large-scale strip steel image collection. After image preprocessing, four types of visual features, comprising geometric feature, shape feature, texture feature and grayscale feature, are extracted from the defect target image and its corresponding preprocessed image. In order to use genetic algorithm to optimize classification model based on hybrid chromosome, the structure of hybrid chromosome is designed to seamlessly integrate the kernel function, visual features and model parameters. And then the chromosome and the SVM classification model will be evolved and optimized according to the genetic operations and the fitness evaluation. In the end, the final SVM classifier is established using the decoding result of the optimal chromosome. The experimental results show that our method is effective and efficient in classifying the surface defects in a large-scale strip steel image collection.

1. Introduction

The past several years have witnessed the rapid development and deployment of professional image devices in strip steel product line. The real-time quality surveillance systems have collected a tremendous amount of unstructured strip steel surface images and have formed the strip steel industry image big data. The surface defect of strip steel is the major factor causing the poor quality of strip steel. Therefore the classification of surface defects in the acquired large-scale strip steel image collection is of high importance in the quality assurance. On the other hand, the accuracy and performance of the surface defect classifier in the strip steel industry image big data are also very crucial to not only the quality control in the strip steel production process, but also to the real-time production process improvement of the strip steel sector. In fact, the same classification problem faced in the strip steel product line is also encountered in the intelligent transportation [18], such as the illegal traffic image identification from the big data captured by the real-time intelligence transportation systems.

The surface defect classification is the task to assign one class or category to the surface defect manually or automatically. There are many types of defects in the strip steel industry image big data during the producing and processing of strip steel, such as roller mark, rust spot, emulsion spot, side mark, scrape, dent, hole and damage. In this paper, we investigate on five types of surface defect images in the following experiments. Typical examples of these five types of defects, selected from the large-scale image collection, are illustrated in Fig. 1.

Surface defect is usually characterized via visual appearances, such as color, grayscale, edge, shape, texture and geometric. In this paper, the image geometric, shape, texture and grayscale features are taken into consideration in the automatic surface defect target image classification.

The machine learning [26], a branch of artificial intelligence, intends to make computer simulate and evolve human behaviors based on different types of empirical data. A major focus of machine learning research is to automatically identify complex patterns and make intelligent decisions based on the observations. The machine learning methods can be divided into several types based on their desired outcome, including supervised, unsupervised, semi-supervised and weakly supervised [28,27]. Furthermore, machine learning methods have achieved great success of classification in the context of big data [24].

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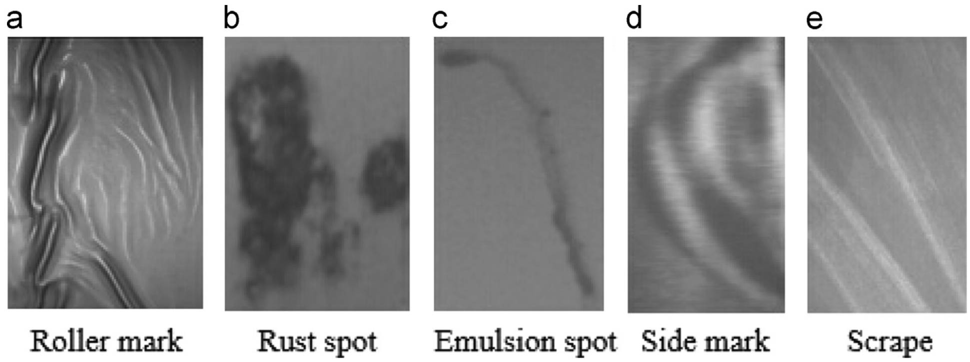

Fig. 1. Illustration of five typical types of defects.

In this paper, two kinds of typical machine learning methods, genetic algorithm (GA) and support vector machine (SVM) [3], are unified to classify the large-scale surface defect image collection obtained from the strip steel product line. When the SVM model is applied to classifying the strip steel defect images, the visual features, the kernel function and its corresponding parameters, and the penalty factor of the SVM model will affect the classification accuracy and efficiency. Moreover, kernel function [29] and visual feature selection play an important role in not only the classification accuracy but also the classification efficiency.

In order to improve the classification accuracy and real-time efficiency of the large-scale image big data, hybrid chromosome genetic algorithm (HCGA) is proposed to optimize the SVM classification model in this paper. In HCGA, the extracted visual features, the kernel function and its corresponding parameters and the penalty factor of SVM model are mixed and encoded in the same chromosome, and the GA based on hybrid chromosome is used to optimize the visual feature selection, the kernel function selection, the kernel parameters and the penalty factor of the SVM model. In the end, the optimized SVM classifier will be established using the decoding result of the optimal chromosome. In fact, on the other hand, the classification model can also be used to promote the selection of the genetic algorithm evolutionary direction.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the strip steel surface defects classification model based on HCGA. Section 4 discusses the four kinds of visual features in the defect image classification. Section 5 shows the structure of the hybrid chromosome. The HCGA is utilized to optimize the SVM model in Section 6. Section 7 presents experiments and discussions, followed by conclusions and future work in Section 8.

2. Related work

In this section, we will briefly discuss the related work on the visual feature selection, the model parameters optimization of SVM and the surface defect classification in large-scale image collection.

The feature selection and high-level feature integration have recently been paid more attention. Wang et al. [21,20,22] proposed the methods based on multigraph or hypergraph to tackle the curse of dimensionality in unified schemes. Nie et al. [14] presented a scheme to enhance web image reranking for complex queries by fully exploring the information from simple visual concepts and integrating three layers of relationships. Yu et al. [25] obtained the multiview distance metrics from multiple feature sets and the labels of unlabeled cartoon characters simultaneously under the graph-based semisupervised learning. Wang et al. [19] combined intra-group and inter-group to solve the online group feature selection problem. Cheng et al. [4] addressed the problem of learning compact hashing codes of multiple modality with a semi-supervised Multi-Graph Hashing (MGH) framework. Hong et al. [7] adopted the multi-view locality sensitive sparse coding to avoid the high dimensionality of image features in image-based 3D human pose recovery. Zhang et al. [30] presented a new multi-modal feature integration framework to model the high-order relations among multimodal features. Ahmad et al. [1] proposed feature subset selection for network intrusion detection mechanism using genetic eigenvectors. The performance analysis of genetic algorithm with K Nearest Neighbor (KNN) and SVM for feature selection in tumor classification was discussed by Gunavathi et al. [5]. In addition, Bhuvaneswari et al. [2] put forward a new fusion model for the classification of the lung diseases using genetic algorithm in which extracted features are selected by applying genetic algorithm which selects the top ranked features.

Huang et al. [10] proposed a GA-based feature selection and parameters optimization for support vector machines. This method applied genetic algorithm to SVM parameters optimization and the feature vector selection at first. And then the parameters and selected features were used to optimize support vector machine classification. Zhao et al. [33] committed feature selection and parameter optimization for support vector machines based on genetic algorithm with feature chromosomes. Moreover, Wong et al. [23] used the genetic algorithm to fine tune the support vector data descriptor for the classification of monocotyledon and dicotyledon weeds. In their study, weed seedlings were discriminated using support vector data descriptor to identify monocotyledon weeds from a mixture of monocotyledon and dicotyledon weeds. The feature selection and parameter fine tuning were performed using GA. However, their methods have not implemented the SVM kernel function yet.

For image classification, Zhang et al. [31] proposed a new fine-grained image categorization system in which multiple cells are combined into cellets, and a linear-discriminant-analysis-like scheme is employed to select discriminative cellets. Zhang et al. [32] also presented a novel architecture style recognition model by introducing blocklets. Shen et al. [16] aimed to identify spam image based on multiple visual properties extracted from different levels of granularity and comprehensive signature of spam images generated by the random forest and linear discriminative analysis. Nie et al. [14,15] accomplished the prediction of the relevance probability of each image with a query-adaptive graph-based learning based on the visual content in a large-scale image dataset. For strip defect image classification, researchers have proposed some classification methods. Masci et al. [12] applied Max–Pooling convolutional neural network approach for supervised steel defect classification. Suvdaa et al. [17] classified the surface defect images of steel strip by using SIFT and voting strategy, in which SIFT was used for defect regions detection and features extraction and a