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Automatic Recognition of Surface Defects on Hot-rolled Steel Strip using Scattering Convolution Network ⋆

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Abstract

Automatic recognition method for hot-rolled steel strip surface defects is extremely important to the steel surface inspection system. In order to improve the tolerance ability of local deformations for current feature extraction methods, a scattering operator is applied to extract features for defect recognition. Firstly, a scattering transform builds non-linear invariants representation by cascading wavelet transforms and modulus pooling operators, which average the amplitude of iterated wavelet coefficients. Then, an improved network named the scattering convolution network (SCN) is introduced to build large-scale invariants. Finally, a surface defect database named the Northeastern University (NEU) surface defect database is constructed to evaluate the effectiveness of the feature extraction methods for defect recognition. Experimental results demonstrate that the SCN method presents the excellent performance of defect recognition under the influence of the feature variations of the intra-class changes, the illumination and grayscale changes. Even in the less number of training, the SCN method can still achieve the moderate recognition accuracy.

Keywords: Surface Defect; Automatic Recognition; Feature Extraction; Scattering Convolution Network

1 Introduction

In recent years, the visual-based inspection technology, as a kind of non-contact inspection method, has become a research hotspot in the field of steel surface defects inspection such as steel bar [1], steel billet [2], raw steel block [3], and continuous casting steel [4]. Meanwhile, some researchers focus on a single type of defect such as residual oxide scale [5], periodical defects [6], and crack defects [7].

In order to improve the recognition accuracy of the steel surface inspection system, a wide variety of feature extraction methods have been developed. Wu et al. [8] introduced the fast Fourier transform (FFT) to extract features and used the genetic algorithm to optimize the feature set. Since the FFT method not characterized the information in the spatial domain,

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Medina et al. [9] applied the Gabor filters to extract features. However, applying the Gabor of every rotation and scale to an image patch could not tolerate local deformation well. Recently, Ghorai et al. [10] evaluated the performance of a number of different wavelet feature sets and developed an automated visual inspection system in real time. Meanwhile, Xu et al. [11] employed the multi-scale geometric analysis (MGA) to produce a high-dimensional feature vector and used the graph embedding algorithms to reduce the feature vector.

Despite the wavelet-based method and the MGA methods mentioned above have achieved moderate results, these extracted features are not seem to be stable to local deformations. In this work, to improve the tolerance ability of local deformations, a scattering operator [12, 13] is applied to extract features for defect recognition. A scattering transform builds non-linear invariants representation by cascading wavelet transforms and modulus pooling operators, which average the amplitude of iterated wavelet coefficients. The scattering transform is Lipschitz continuous to deformations. To further build large-scale invariants, an improved network named the scattering convolution network (SCN) is introduced. Furthermore, a surface defect database named the Northeastern University (NEU) surface defect database is constructed to evaluate the performance of the method.

2 Scattering Transform

For feature classification, translation invariant representation is an indispensable property. Although the Fourier transform can represent translation invariant, it is not stable to small deformations at high frequencies. In order to avoid the Fourier transform instabilities, wavelets were employed to build invariant representation. Unfortunately, wavelet transforms are not invariant but covariant to translations. To steadily represent the translation invariant, Bruna et al. [12] proposed the scattering transform, which is locally translation invariant and linearizes deformations. The scattering transform computes local image descriptors with a cascade of wavelet decompositions, complex modulus and a local averaging. In the scattering transform, each scattering coefficient is invariant to a translation. Furthermore, the scattering is Lipschitz continuous to deformations as opposed to the Fourier transform modulus.

3 Scattering Convolution Network

To further build large-scale invariants, Bruna et al. [13] proposed an improved network named the scattering convolution network (SCN). In the SCN, to avoid losing crucial information, several layers are constructed to present large-scale invariants. It is should be noted that the first-order coefficients are equivalent to SIFT coefficients for appropriate wavelets. While the second-order scattering coefficients are computed with a second wavelet transform that performs a second frequency subdivision.

Fig. 1 shows the scattering coefficients of six kinds of typical surface defects. The first row presents six kinds of typical surface defects images. The first order scattering coefficients and the second order scattering coefficients are shown in the second row and third row respectively.

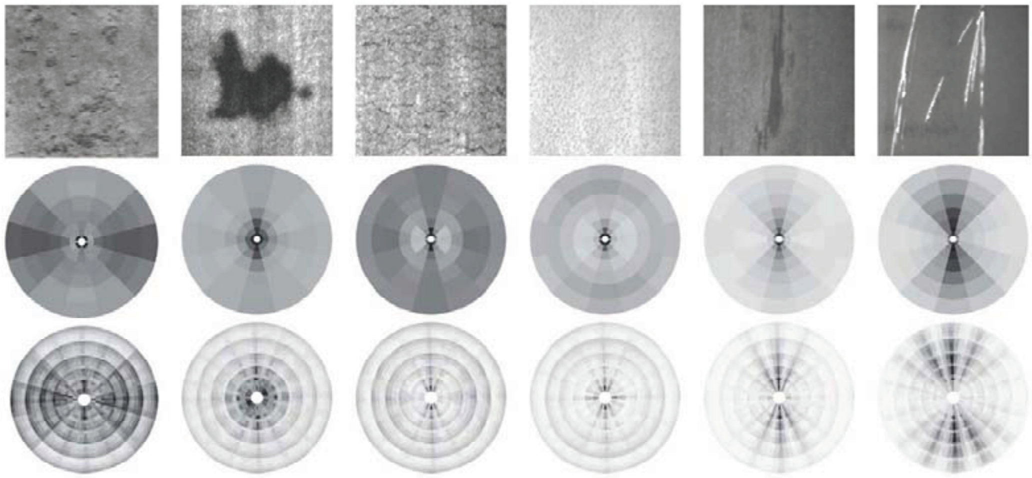

Fig. 1: The scattering coefficients of six kinds of typical surface defects. The first row presents six kinds of typical surface defects images. The first order scattering coefficients and the second order scattering coefficients are shown in the second row and third row respectively

4 NEU Surface Defect Database

In order to demonstrate the effectiveness of the feature extraction methods for defect recognition, a surface defect database named the Northeastern University (NEU) surface defect database is constructed. In this database, six kinds of typical surface defects of the hot-rolled steel strip are collected, i.e., rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In) and scratches (Sc). The database includes 1,800 grayscale images: 300 samples each of six different kinds of typical surface defects. Fig. 2 shows the sample images of six kinds of typical surface defects, the original resolution of each image is 200×200 pixels. From Fig. 2, we can clearly observe that the intra-class defects existing large differences in appearance, for instance, the scratches (the last column) may be horizontal scratch, vertical scratch, and slanting scratch, etc. Meanwhile the inter-class defects have similar aspects, e.g., rolled-in scale, crazing, and pitted surface. In addition, due to the influence of the illumination and material changes, the grayscale of the intra-class defect images is varied. In short, the NEU surface defect database includes two difficult challenges, i.e., the intra-class defects existing large differences in appearance while the inter-class defects have similar aspects, the defect images suffer from the influence of illumination and material changes. The NEU surface defect database can be down load from our homepage: `http://faculty.neu.edu.cn/yunhyan/NEU_surface_defect_database.html`

5 Experimental Results

In this section, the SCN method is compared with other feature extraction methods of surface defect on the NEU surface defect database.

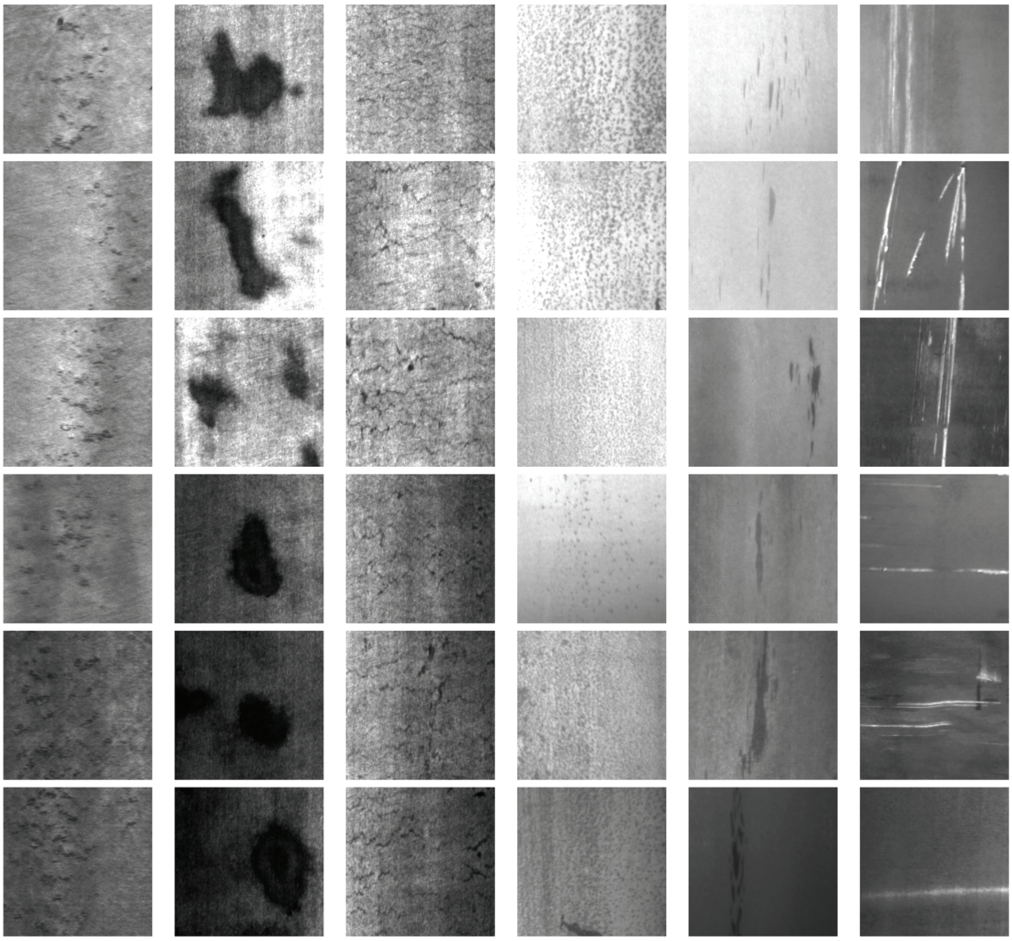

Fig. 2: Samples of six kinds of typical surface defects on NEU surface defect database. Each row shows one example image from each of 300 samples of a class

5.1 Compared methods and implementation details

Compared methods: In view of the LBP-based methods have achieved the state-of-the-art results in texture feature extraction, the SCN method has been compared with those feature extraction methods such as local binary patterns (LBP) [14], local ternary patterns (LTP) [15], and completed local binary patterns (CLBP) [16]. In this work, the rotation invariant uniform patterns are used under multi-scale scheme, i.e., $LBP^{riu2}_{8,1+16,2+24,3}$, $LTP^{riu2}_{8,1+16,2+24,3}$, and $CLBP\_S^{riu2}_{8,1+16,2+24,3}/M^{riu2}_{8,1+16,2+24,3}/C$.

Implementation details: To classify the extracted features of defects, the nearest neighbor classifier (NNC) and the support vector machine (SVM) are used to assign the defect class. In the nearest neighbor classifier, the chi-square distance is used. In the SCN method, the numerical computations are performed with K=6 rotation angles, invariant scale J=3, and the order m=2. The user-specified threshold t of LTP is set as 5. Furthermore, 150 samples per class are randomly elected for training and the remaining for testing. All the results of the SCN method and other methods are reported over a hundred random partitions of training and testing sets. Then the average classification accuracy and the standard deviations are calculated on the NEU database.

5.2 Experimental results and analysis

The average recognition accuracy and the standard deviations on NEU surface defect database are shown in Table 1. From the produced results, it is observed that the SCN method achieves the best average recognition accuracy (98.60%) in the methods of comparison with SVM classifier. Moreover, in the experimental results of these methods, it is observed that the performance of SVM classifier is slightly better than that of the NNC. Additionally, these results demonstrate the excellent performance of the SCN method even in the difficult challenges.

Table 1: The recognition accuracy (%) on the NEU surface defect database

Method	Classifier	Accuracy
LBP	NNC	95.07±0.71
	SVM	97.93±0.66
LTP	NNC	95.93±0.39
	SVM	98.22±0.52
CLBP	NNC	96.91±0.24
	SVM	98.18±0.51
SCN	NNC	97.24±0.27
	SVM	98.60±0.59

In order to investigate the recognition results for six different kinds of typical surface defects in detail, the confusion matrix of the SCN method on the NEU surface defect database is shown in Table 2. In this experiment, 150 defect samples of each class are randomly elected for testing and the NNC is used here. From Table 2, it is observed that the RS defects achieve the best result (the recognition accuracy is 100%). Although the total recognition accuracy of the SCN method is 97.22%, the experimental results of the In defects and Sc defects are slightly better than that of the PS defects which is the lowest one.

Table 2: The confusion matrix of the SCN method on the NEU surface defect database

	RS	Pa	Cr	PS	In	Sc
RS	150	0	0	0	0	0
Pa	0	149	1	0	0	0
Cr	1	1	148	0	0	0
PS	3	2	3	138	3	1
In	0	0	0	2	145	3
Sc	1	0	0	2	2	145

On the whole, the SCN method presents the excellent performance of defect recognition under the influence of the feature variations of the intra-class changes, the illumination and grayscale changes. In addition, Fig. 3 shows the relationship between the recognition accuracy of different methods and the number of the training test for each class. It reveals that the recognition accuracies of all the methods are decreased as the number drops. However, the SCN method achieves the recognition accuracy of 92% even in the number is 30.

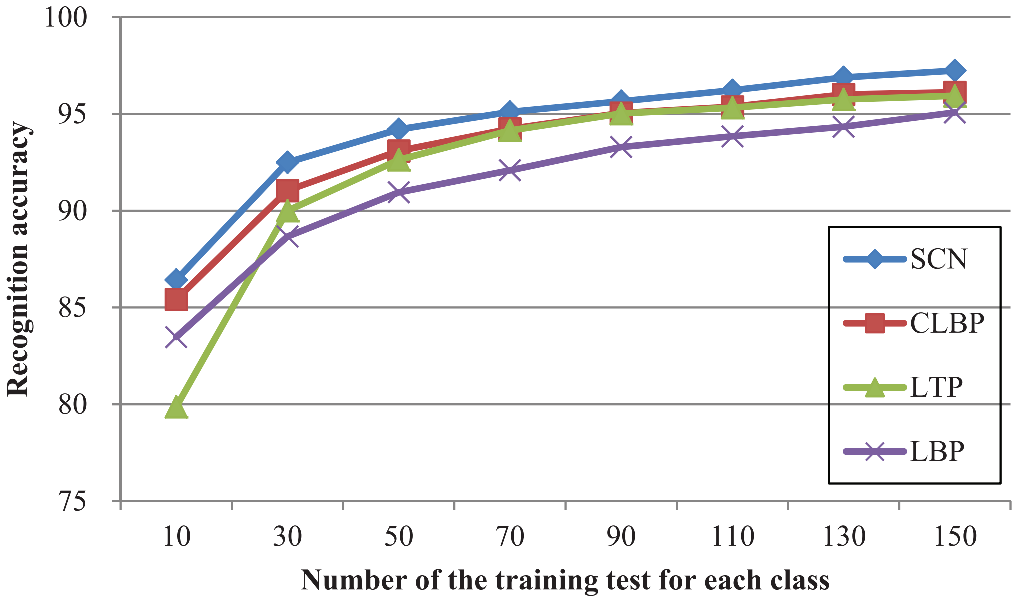

Fig. 3: The recognition accuracy (%) with different number of the training test for each class

6 Conclusion

To improve the tolerance ability of local deformations, a scattering operator is applied to extract features for defect recognition in this work. The scattering transform is Lipschitz continuous to deformations. Furthermore, an improved network named the scattering convolution network is introduced to build large-scale invariants. In addition, a surface defect database named the Northeastern University (NEU) surface defect database is constructed to demonstrate the effectiveness of the feature extraction methods for defect recognition. Experimental results demonstrate that the SCN method not only presents the excellent performance of defect recognition under the influence of the feature variations of the intra-class changes on the NEU surface defect database, but also achieves the moderate recognition accuracy in the less number of training.

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