Application of bandelet transform to surface defect recognition of hot rolled steel plates

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Abstract

Surface defects are important factors to surface quality of steel plates. The detection and recognition of surface defects can provide effective information for production optimization. There are several types of surface defects on hot rolled steel plates which are covered by lots of scales. The purpose of this paper is to recognize eight kinds of typical surface defects from scales. Bandelet transform is applied to extraction of geometrical features. Firstly, each sample image is decomposed into multiple directional subbands at several scales by bandelet transform. Then, some statistical values of bandelet coefficients are calculated and combined into a feature vector from all subbands. In this process, several important parameters of bandelet transform are discussed and determined through experience and experiments. Finally, the feature matrices of training set and testing set are inputted into Support Vector Machine for classification. Experiments with sample images from a real production line of hot rolled steel plates show that bandelet transform is superior to curvelet transform and contourlet transform. Most of surface defects can be effectively recognized and the highest recognition rate of testing set is up to 96.07%.

1. Introduction

Surface defects are critical quality concerns in the production of steel plates. Recently, many on-line surface inspection systems based on machine vision have been developed to detect and classify various kinds of surface defects, as for information collection and production adjustment in time. Among which, feature extraction and image classification are key steps. The characteristics of images should be analyzed at first when choosing specific methods. For hot rolled steel plates, there are a large number of scales with unfixed shapes on the surface due to high temperature in rolling process, which makes recognition difficult. On the other hand, there are many types of surface defects of hot rolled steel plates and different kinds of defect images have different geometric characteristics, which is effective for defect recognition.

Though the algorithms of surface defect detection and recognition for hot rolled steel plates are seldom published because of commercial interests, there are some references for different types of steel plates. An approach based on multivariate discriminant function according to the maximum likelihood discriminant rule was developed to detect defective images from non-defective images for cold rolled steel strips [1].Wavelet transform was used to detect transverse corner cracks of steel plates by calculating the modulus and gradient direction of wavelet coefficients [2]. A detection method engineering-driven rule-based detection (ERD) was proposed to detect surface defect ("bleeds") generated in continuous casting processes [3]. The above-mentioned methods have gained some achievements, but the defect types are fewer and the defect recognition rates still need further improvement.

Bandelet transform is a major self-adaptive multiscale geometric analysis (MGA) method, which utilizes the known geometric information of images to improve the approximation ability. Compared with other widely used non-adaptive MGA algorithms such as curvelet transform [4] and contourlet transform [5], bandelet transform not only also has the characteristics of multiscale analysis, time-frequency localization, directionality and anisotropy, but also offers particular properties of strict sampling and adaptability which are very important for image representation. Because of the merits, bandelet transform can achieve asymptotically optimal representation of the image, especially for those with geometric structures. Based on an overall consideration of the characteristics of surface images of hot rolled steel plates and the advantages of bandelet transform, this paper presents a feature extraction method based on bandelet transform for surface defect recognition of hot rolled steel plates.

2. Surface defects of hot rolled steel plates

There are many types of defects that occur in the processing of hot rolling due to various factors like raw material, rolling equipment and processing technology. The background of hot rolled steel plates is complicated because of the effect of scales, water and illumination. Scales are often wrongly recognized as defects and have great influence on defect detection, so they are also seen as a type of defect. Figure 1 shows nine types of typical surface defects on hot rolled steel plates. They are cropped from original defective images checked with corresponding steel plates by workers from the steel plant.

As shown in Figure 1, different types of defects have different geometrical features:

Fig.1(a) and Fig.1(b) show the longitudinal crack and the transverse crack, which are along and perpendicular to the rolling direction respectively. They are two types of the most common surface defects of steel plates. The length of cracks is usually varying from a few to dozens of centimeters, but fairly deep longitudinal cracks even go through the whole steel plates which may lead to product scrapping. Cracks generally appear as continuous wavy-looking curves and their gray intensities are darker than the surrounding pixels in most cases.

Fig.1(c) shows the chap defect, which is shaped like a turtleback or a network of cracks. Chap is appearing periodically on the surface of steel plates and sometimes develops crack extension when dumpling for a long time.

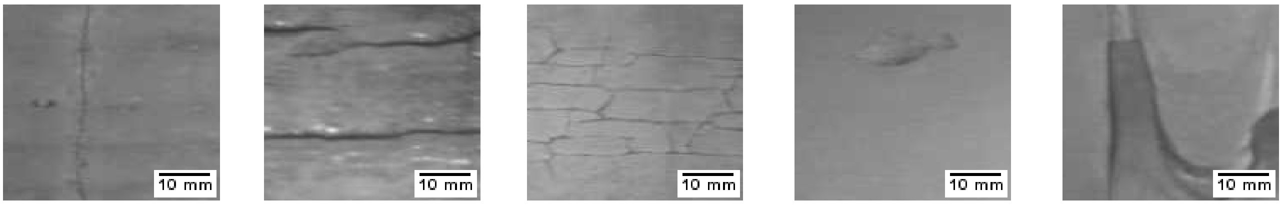
Fig.1(d) shows the roll imprint, which is a kind of concavo-convex defects with irregular shapes. It emerges alone or consistently within certain areas with similar sizes and forms.

Fig.1(e) shows the scar defect, which is irregularly distributed on the surface of steel plates appearing as tongue-shaped, blocky or scaly forms. Scar defects are variable in size and depth. The characteristic of scarring extends the rolling direction.

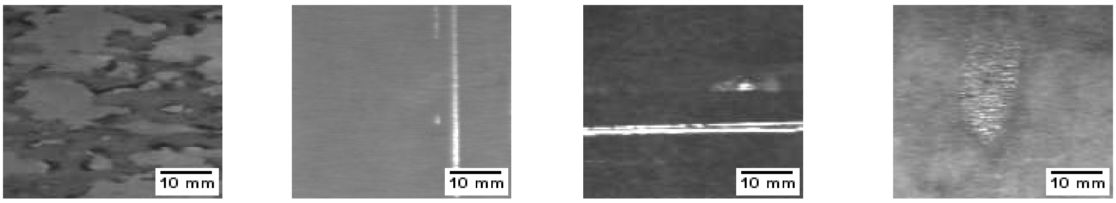
Fig.1(f) shows the scale, which is attached to the surface of steel plates in the form of fish scales, strips or dots. Scales vary considerably in size and form.

Fig.1(g) and Fig.1 (h) show the longitudinal scratch and the transverse scratch, which are along and perpendicular to the rolling direction respectively. They are similar to longitudinal crack and transverse crack in direction distribution. The difference is that scratches are straight lines and usually have higher brightness than the surrounding pixels. Also, scratches are of uncertain location and different in length.

Fig.1(i) shows the pockmark defect, which is characterized by local or continuous distribution on the surface of steel plates. Pockmarks are often gray white and observed as blocks with various areas.



(a) Longitudinal crack (b) Transverse crack (c) Chap (d) Roll imprint (e) Scar



(f) Scale (g) Longitudinal scratch (h) Transverse scratch (i) Pockmark

Figure 1. Surface defects of hot rolled steel plates.

3. Bandelet transform

In 2000, Pennec and Mallat advanced the first generation bandelet transform [6] based on 2-D separable wavelet transform. In order to overcome the disadvantages of repetitively sampling and curving in the first generation, Peyre and Mallat proposed the second generation bandelet transform [7] in 2004. It implements image decomposition through multiscale analysis and geometric direction analysis in stages and can represent basis functions in discrete domain directly. Compared to the first generation, the second generation bandelet transform is simpler, orthogonal and without border effect. So the latter has aroused extensive concern in several fields like image denosing, image fusion and image segmentation. In the respect of image feature extraction and recognition, the second generation bandelet transform has been used to detect human in still images [8]. But few researches have been conducted in applying bandelet transform to surface inspection of steel plates. In this paper, the second generation bandelet transform is used for feature extraction of surface images of hot rolled steel plates. The statistical values of bandelet coefficients will be calculated as the feature of sample images, combined with Support Vector Machine (SVM) classifier to classify and recognize nine kinds of typical surface defects for hot rolled steel plates.

The implement steps of the second generation bandelet transform are introduced briefly as follows [9].

Step 1: Multiscale transform with 2-D orthogonal or biorthogonal wavelets;

Step 2: Build the best quadtree decomposition for each high pass subband through quadtree division method and bottom-up CART (Classification and Regression Trees) algorithm;

Step 3: Find the best geometric flow direction for all obtained quadtree division blocks according to Lagrangian penalty function method;

Step 4: Apply a 1-D wavelet transform to the 1-D discrete signal acquired by orthogonal projection and reordering of wavelet coefficient according to the best geometric flow direction of each quadtree division block, thus get coefficients of the bandelet transform.

4. Experiments and discussions

4.1. Sample database

The sample images in experiments are obtained from a production line of hot rolled steel plates of a steel works. The acquisition of surface images of steel plates is performed by CCD cameras installed on an on-line surface inspection system developed by the authors. To construct sample database, the 128×128 pixel blocks are cropped from the captured images and contain both defects and pseudo-defects. There are nine types of surface images in the database including longitudinal crack (LC), transverse crack (TC), chap (Ch), roll imprint (RI), scar (Sr), scale (Sc), longitudinal scratch (LS), transverse scratch (TS) and pockmark (Po) shown in Figure 1. In experiments, the number of each kind of samples is selected roughly in proportion to its frequency. There are 1273 samples in total and the odd numbers of samples are used for training and the others for testing.

4.2. Parameter setting

In the paper, bandelet transform is applied to feature extraction of sample images and then Support Vector Machine (SVM) is used for classification. In the process, some important parameters should be set reasonably on the basis of many experiments. This paper addresses main parameter settings of bandelet transform including decomposition level L, the minimum and maximum depth of quadtree segmentation j_min and j_max, direction number of geometry flow θ and quantification threshold value T. Parameter settings should take into account both recognition effect and operating efficiency. Considering the characteristics of defect images of hot rolled steel plates and the computational complexity, geometry flow direction θ ranges from 0 to 7π/8 with a step of π/8. The maximum depth of quadtree j_max is set to 4 and the minimum depth j_min is also set to 4 if the decomposition level L is less than or equal to 3. When L is greater than 3, j_min should satisfy the condition that 2 to the power of j_min equals the length of the low-frequency coefficient matrix on the Lth level. Many experiments indicate that quantification threshold value T has few effects on experimental results and it is set to 15 in this study. The decomposition level L is an important parameter. Too few decomposition levels cannot fully utilize the merits of multiscale analysis, but too much will lead to high computational complexity and redundant information. So the decomposition level L is set to one, two, three, four and five for concrete comparison in experiments.

4.3. Results and discussions

In following experiments, Radial Basis Function (RBF) is selected to train SVM, and kernel parameter γ iterates through all values from 0 to 3 with step length 0.01 and error penalty parameter C is set to default value. After being decomposed by bandelet transform, each sample image gets an overall bandelet coefficient matrix which has equal size of the image. Computing the means and variances of all bandelet coefficient matrices on each decomposition level and combining them into a feature vector. The dimension of the feature vector equals 2(3L+1), where L denotes decomposition level. All feature vectors of training set and testing set are inputted to SVM for classification of sample images. The recognition rates of testing set under different decomposition levels are shown in Figure 2.

As shown in Figure 2, the recognition rate of testing set has been greatly improved as the decomposition level increases from one to four. However, there is no obvious improvement for recognition result when decomposition level increases to five and even a sharp decline when parameter γ is greater than 1.5 in comparison with four decomposition levels. Thus it can be seen that proper decomposition level is important for getting sufficient useful information and should be determined by experiments. In Figure 2, the highest recognition rate of testing set is up to 96.07% when decomposition level equals four and parameter γ equals 2.01. In addition, Figure 2 also shows that the recognition curves ascend quickly and then remain generally stable as parameter γ increases. This proves that bandelet transform is effective for surface defect recognition of hot rolled steel plates and has low sensitivity to kernel parameter γ.

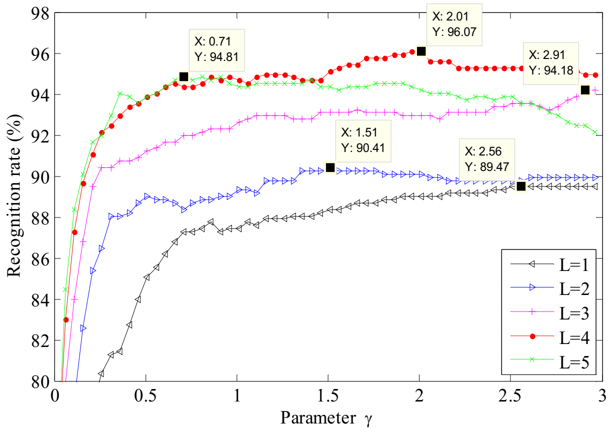


Figure 2. Recognition rates of testing set under different decomposition levels.

The comparison of the performance between bandelet transform and two of the most used non-adaptive MGA methods curvelet transform and contourlet transform is given in Figure 3 to show its advantage. The parameter settings of this experiment are as follows.

The decomposition level is set to 4 for all the methods. This level also gives the best results for curvlet transform and contourlet transform. The number of decomposition direction subbands is chosen by means of many experiments. The procedure of feature extraction of each method is the same as foregoing experiments. Also the means and variances of all the subbands of each sample image are calculated and combined into a feature vector. Specifically, for curvelet transform, the number of subbands from finest level to coarsest level is 1,8,16 and 1, respectively, and the feature dimension is 52. For contourlet transform, the number of the high-frequency subbands from finest level to coarsest level is 4, 4, 8 and 8, respectively. There are 25 subbands in total when adding the low-frequency subband and the feature dimension is 50. Besides, '9/7' and 'pkva' are selected as LP (Laplacian Pyramid) and DFB (Directional Filter Banks) filters respectively. Finally, for bandelet transform, the parameter settings are no different and the feature dimension is 26.

It can be seen from Figure 3 that each method can get a fairly good recognition rate when parameter γ equals suitable values. However, it is obvious that the performance of bandelet transform is better and more stable than curvelet transform and contourlet transform when applying to defect recognition of hot rolled steel plates. The reason is that bandelet transform makes full use of the geometrical characteristics of sample images which is helpful to extracting more distinctive information. In order to get more details of classification,

Table 1 lists the specific classification matrix of testing set as the recognition rate takes the maximum of 96.07% by bandelet transform.

From Table 1, it is observed that most of the sample images have fairly good results like transverse crack, scar, chap, scale, longitudinal scratch and longitudinal crack. However, the recognition rates of pockmark and roll imprint are lower. This because they have a small quantity of sample images which makes no sufficient unique features be extracted. Nevertheless, pockmark and roll imprint are rare in production line of hot rolling mill, so that the influence on overall recognition effect is small. Besides, the recognition rate of transverse scratch is not good enough and needs further improvement. This may be accomplished by increasing training samples or extracting more distinctive features. In addition, the processing time of each image was about 1.6s by using bandelet transform. In general, feature extraction method based on bandelet transform is effective for defect recognition of hot rolled steel plates.

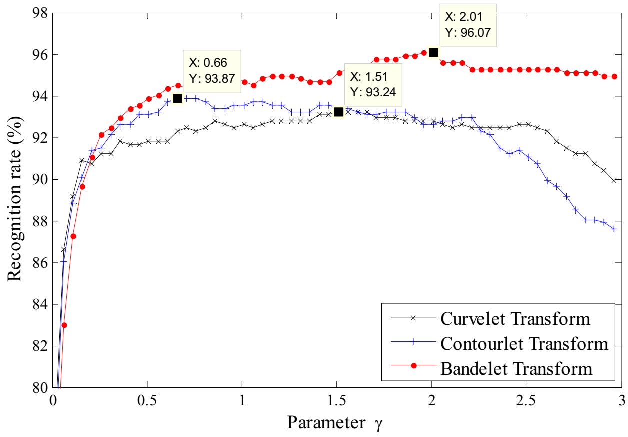


Figure 3. Recognition rates of testing set under different decomposition methods.

Table 1. Classification matrix of testing set with the recognition rate of 96.07%

Defect Type	TS	TC	Sr	Po	Ch	RI	Sc	LS	LC	Number of images		Recognition rate (%)
										Correct	Total	
TS	36	0	0	0	3	0	1	2	0	36	42	85.71
TC	0	130	0	0	3	0	0	0	0	130	133	97.74
Sr	0	0	15	0	0	0	0	0	0	15	15	100
Po	1	0	0	10	0	0	0	3	0	10	14	71.43
Ch	0	0	0	0	51	0	0	2	0	51	53	96.23
RI	0	0	1	0	0	8	0	0	3	8	12	66.67
Sc	0	0	0	0	0	0	95	4	0	95	99	95.96
LS	0	0	0	0	0	0	0	40	2	40	42	95.24
LC	0	0	0	0	0	0	0	0	226	226	226	100
Total	-	-	-	-	-	-	-	-	-	611	636	96.07

5. Conclusions

There are several types of defects on the surface of hot rolled steel plates. How to identify them effectively is important to quality control and production optimization. In the paper, bandelet transform is applied to feature extraction of sample images to get enough information at multiple scales. Several main parameters of bandelet transform are discussed and determined based on the characteristics of sample images and many experiments. Finally, feature matrices of training set and testing set are inputted into SVM for classification of defect images. Experimental results show that bandelet transform is effective to get useful features for surface images of hot rolled steel plates and the recognition result is pretty good.

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