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Application of Shearlet transform to classification of surface defects for metals ☆

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ABSTRACT

Surface defects are important factors of surface quality of industrial products. Most of the traditional machine vision based methods for surface defect recognition have some shortcomings such as low detection rate of defects and high rate of false alarms. Different types of defects have special information at some directions and scales of their images, while the traditional methods of feature extraction, such as Wavelet transform, are unable to get the information at all directions. In this study, Shearlet transform is introduced to provide efficient multi-scale directional representation, and a general framework has been developed to analyze and represent surface defect images with anisotropic information. The metal surface images captured from production lines are decomposed into multiple directional subbands with Shearlet transform, and features are extracted from all subbands and combined into a high-dimensional feature vector. Kernel Locality Preserving Projection is applied to the dimension reduction of the feature vector. The proposed method is tested with the surface images captured from different production lines, and the results show that the classification rates of surface defects of continuous casting slabs, hot-rolled steels, and aluminum sheets are 94.35%, 95.75% and 92.5% respectively.

1. Introduction

Surface quality control is one of the most important issues in metal industry. In recent years, computer vision based surface inspection systems have become the mainstream research. With the characteristics of non-contact and fast response, the systems have been widely used in modern manufacturing fields in order to obtain high-quality products. The inspection systems capture surface images of industrial products with CCD cameras under specific lighting conditions; then various algorithms of image processing are applied to the images, and surface defects are identified and classified using the algorithms for the defect detection and recognition. The algorithms are crucial for the inspection systems.

Recently, various algorithms for the defect detection and classification have been developed for the metal surface inspection systems. For example, an algorithm combined with discrete wavelet transform and morphological analysis was developed to detect corner cracks of steel billets from oxide scales [1]; Gabor filters were used to detect thin and corner cracks in raw steel block by minimizing the cost function of energy separation criteria of defect and defect-free regions [2]; defects of structural steel plates were detected using Discrete Fourier Transform Spectral Energy and Artificial Neural Networks [3]; an approach based on 3D profile data of steel slab surfaces was developed for an automated on-line crack detection system, and morphological image processing and logistic regression based statistical classification were integrated in the system [4]; a framework with multiple views was applied to detecting flaws in aluminum castings, and information gathered from multiple views of the scene was combined for the flaw detection [5]. Although the above methods achieved high detection rates of some defects, they were restricted to some specific products or defects, and classification rates of common defects were generally limited. There is a real need to develop algorithms for the detection and classification of common defects with wide-ranging versatility.

There are various defects generated by the same or different production lines of metals; the comprehensiveness and universality of the image features associated with the defects are essential to the classification of these defects. More information of images, including those retrieved from different scales and directions, can help improve the comprehensiveness and universality of the image features. The images are usually represented by low-level feature descriptors focusing on different types of information, such as color, texture, and shape [6]. Traditional methods for multi-scale signal analysis, such as Wavelet and Gabor transforms, are extensively applied to image processing applications. However, these methods fail to effectively extract the directional features due to their isotropic support and limited directional sensitivity. Multi-scale geometric analysis (MGA) is proposed to decompose images into different scales and directions [7]. The most common methods of MGA are Curvelet transform [8,9] and Contourlet transform [9,10]. Curvelet transform is not directly constructed in the discrete domain, but the implementation is more

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involved with less efficiency. Contourlet transform is a combination of a multi-scale and a directional filter bank in the discrete domain, and it has less clear directional features than Curvelet transform. Curvelet transform and Contourlet transform are both non-adaptive methods of MGA, which means that they cannot deal with images directly without information of image edges and contours. Except the non-adaptive methods, there are adaptive methods of MGA, which utilize known geometric information of an image to improve the approximation ability of the image transform. Bandelet transform is a major adaptive method of MGA [12,13]. Compared with Curvelet transform and Contourlet transform, Bandelet transform not only has the characteristics of multi-scale analysis, time-frequency localization, directionality and anisotropy, but also offers particular properties of strict sampling and adaptability which are very important for image representation. However, Bandelet bases are regular functions with compact support, and the algorithm of searching the best Bandelet basis is very complicated [14].

Shearlet transform is a relatively new method of MGA [15,16]. Compared with other methods of MGA, Shearlet transform can set up different direction numbers at different decomposition scales. Furthermore, Shearlet transform is optimal in approximating 2D smooth functions with discontinuities along C2-curves, and it yields nearly optimal approximation properties. So Shearlet transform is suitable to analyze image textures with complex background.

Kernel Locality Preserving Projections (KLPP) is introduced as a method of dimension reduction. Locality Preserving Projection (LPP) is a well-known dimensionality reduction method, which can project high-dimensional input data into a low-dimensional subspace by linear transformation [17,18]. KLPP is the implementation of LPP in kernel space. Combined with Shearlet transform and KLPP, a feature descriptor called DST-KLPP is proposed in this article. Surface images of metals are decomposed into different scales and directions with Shearlet transform, and KLPP is employed to reduce redundant information and improve the operating efficiency. In order to test the generality and efficiency of the proposed method, sample images acquired from three different production lines were analyzed. Results of the proposed method were compared with the other methods.

The rest of the paper is organized as follows: Section 2 depicts the characteristics of surface images of metals, including the defects and some background information. Section 3 introduces three methods of MGA, which are Curvelet transform, Contourlet transform, and Shearlet transform. Section 4 describes the DST-KLPP method in detail. Experimental results with three typical metal surface images and discussions are presented in Section 5, followed by conclusions in Section 6.

2. Surface images of metals

As we know, there are three procedures of metal production, including continuous casting, hot rolling and cold rolling. In each procedure, metals are in different states, and have various defects with different features. In the paper, surface images of continuous casting slabs, hot rolled steels and aluminum sheets are used as samples because they represent three typical defect detection and classification problems to be resolved: 1) surfaces of the continuous casting slabs are very complicated; 2) there are many types of defects with the hot rolled steels; and 3) defects of aluminum sheets are small in size and contrasts of their images are usually low. All these image samples were collected from the production lines with the surface inspection systems developed by the authors [19–21]. Line-scan CCD cameras were used to capture the images with different illuminations. The dimension of the images is 4096 by 1024 pixels or 2048 by 1024 pixels, depending on the CCD cameras used in the system. However, all sample images are cropped to 128 by 128 pixels for image classification. There are noises, non-uniformed lighting effects in the images, which may affect the final results of classification.

Fig. 1 shows four types of sample images of continuous casting slabs, including cracks, non-uniformed lighting effects, scales and slag marks. Cracks are the genuine defects in the samples of Fig. 1, and the other three types of samples are the pseudo-defects. Cracks are the most common defects and may lead to quality accidents of slabs. However, cracks are very difficult to be detected as non-uniformed lighting effects, scales, and slag marks are sometimes similar to cracks. The most important task of defect detection for continuous casting slabs is to detect cracks from the complicated image backgrounds.

The slabs are inspected immediately after the flame cutting of casting, and the surface temperature is about 1000 °C. As demonstrated in Fig. 2, the slabs are illuminated with green linear laser lighting [20]. The wavelength of lasers is 532 nm, which is far away from spectrum of high-temperature radiation of slabs. Furthermore, a color filter of narrow band is added to the camera lens, and the central bandwidth of the filter is 532 nm. As a result of using the laser lighting and the narrow band filter, most of the high-temperature radiation is filtered out, and only lights of lasers reflected by the slab surface enter into the CCD cameras. Therefore, images with high contrast can be captured from the high-temperature slabs. Three line-scan CCD cameras with 4096 pixels are used together to inspect one side of the slab with width of 2500–2800 mm, and the scanning width of each camera is 1000 mm. So the resolution of image width in Fig. 1 can be calculated as $1000/4096 = 0.25$ mm. The resolution of image height, which is

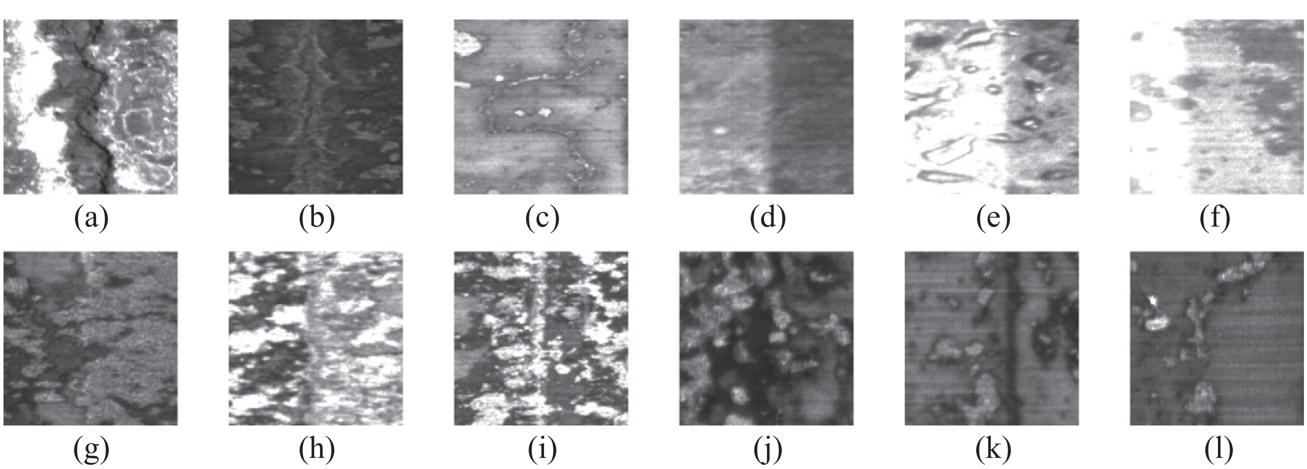

Fig. 1. Sample images of continuous casting slab: cracks [(a)–(c)], non-uniformed lighting effect [(d)–(f)], scales [(g)–(i)], and slag marks [(j)–(l)].